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Financial strength ratings: Evolution, split ratings, and market impact within the insurance sector

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Financial strength ratings: Evolution, split ratings, and market impact within the insurance sector

By Sandy Perez-Robles

PhD thesis

BANGOR UNIVERSITY

Declaration and consent

‘Yr wyf drwy hyn yn datgan mai canlyniad fy ymchwil fy hun yw’r thesis hwn, ac eithrio lle nodir yn wahanol. Caiff ffynonellau eraill eu cydnabod gan droednodiadau yn rhoi cyfeiriadau eglur. Nid yw sylwedd y gwaith hwn wedi cael ei dderbyn o’r blaen ar gyfer unrhyw radd, ac nid yw’n cael ei gyflwyno ar yr un pryd mewn ymgeisiaeth am unrhyw radd oni bai ei fod, fel y cytunwyd gan y Brifysgol, am gymwysterau deuol cymeradwy.’

Rwy’n cadarnhau fy mod yn cyflwyno’r gwaith gyda chytundeb fy Ngoruchwylwyr ’.

‘I hereby declare that this thesis is the results of my own investigations, except where otherwise stated. All other sources are acknowledged by bibliographic references. This work has not previously been accepted in substance for any degree and is not being concurrently submitted in candidature for any degree unless, as agreed by the University, for approved dual awards.’

I confirm that I am submitting the work with the agreement of my Supervisors’.

Abstract

The insurance sector has witnessed a considerably changing landscape in terms of regulation and the role of Credit Rating Agencies (CRAs). The coverage of these issues in the academic literature has been limited. In particular, prior studies on insurers' Financial Strength Ratings (FSR) are scarce, notwithstanding the role of insurers as a key pillar of the global financial system. Further, very little prior research has investigated the rating dynamics across all four major CRAs active in the insurance sector. A high quality long-run dataset is constructed for this thesis. The primary aims of the research are to investigate FSR dynamics following three perspectives: (i) FSR evolution and sources of rating changes; (ii) examining the effect of split ratings on rating migration; and (iii) analysing the stock market impact of FSR actions.

The first empirical chapter analyses rating trends of U.S. Property/Casualty (P/C) insurers for the four major CRAs. The chapter reports that AM Best has the least amount of rating activity during the sample period from 2000-17, whereas S&P is the most active CRA. This chapter confirms that the effect of the financial crisis on FSRs of P/C insurers was uneven. However, climate-related events are revealed as a discernible and important factor. The second empirical chapter analyses how split ratings can affect subsequent rating changes. The results show that split ratings among the four major CRAs are influential on each other's future rating migrations. Moody's is the CRA that appears most influenced by the other three CRAs in both upgrades and downgrades. AM Best is influenced by all three other CRAs for upgrades.

The third empirical chapter examines the impact of FSR actions of U.S. P/C insurers on the share prices of the parent companies. The chapter presents evidence that negative FSR actions have a greater impact on the stock market compared to positive actions. The strongest market reaction is observed for negative FSR actions by Fitch. For S&P, the market reacts to negative Outlook, for Moody's to negative Watch actions while for AM Best, a slight yet significant reaction to positive FSR actions, specifically upgrades, is revealed.

This thesis provides many original contributions to the literature. Novel perspectives on FSR are presented. Due to the high quality dataset, new insights are revealed. In comparison to the broader literature on CRAs, the thesis draws attention to the unique role of AM Best as a key additional player in insurance company ratings. This study provides policy insights within the wider context of Solvency II regulations, climate change as a factor with serious implications for insurers, and the current debate on insurers' systemic risk.

A mis adorados padres Juana y Tomas, y a mis

hermanas Saray y Samia que me han acompañado aún en la distancia

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Abbreviations and acronyms

AM Best	A.M. Best Rating Services, Inc.
AIG	American International Group
CRAs	Credit Rating Agencies
COEF.	Coefficients
DBRS	Dominion Bond Rating Service
DOWNS	Downgrades
EU	European Union
EJR	Egan Jones Ratings Co
Eq. (s)	Equation(s)
FSR	Financial Strength Ratings
FC	Foreign currency
GDP	Gross Domestic Product
IMF	International Monetary Fund
KBRA	Kroll Bond Rating Agency
LC	Local currency
LT	Long-Term
ME	Marginal effects
NAIC	National Association of Insurance Commissioners
NRSRO	Nationally Recognized Statistical Rating Organization
NA	Not applicable
P/C	Property/Casualty
Obs.	Observations
OCR	Office of Credit Ratings
OECD	Organisation for Economic Co-operation and Development
ROAE	Return on Average Equity
S&P	Standard & Poor's
SEC	U.S. Securities and Exchange Commission
Std. Dev.	Standard deviation
U.S.	United States
U.K.	United Kingdom
UPS	Upgrades

Chapter 1. Introduction

1.1 Introduction

During and after the financial turmoil of 2007-10, default risk received intense attention from policy makers and academics due to the financial distress faced by banking and insurance institutions (Ciumaş et al., 2015). Particularly for insurers, the traditional idea of a (re)insurance industry with low risk of potential failure and inconsequential interconnectedness has been challenged (Park and Xie, 2014). The default of American International Group (AIG) triggered the need for updated regulatory oversight (OECD, 2010), and has reignited a debate about the potential systemic risk associated with insurers (Bierth et al., 2015; Caporale et al., 2017). Meanwhile, the role of Credit Rating Agencies (CRAs) in assessing default risk has been subject to increased scrutiny. Conflicts of interest have been claimed to be inherent in the credit rating industry (Bolton et al., 2012; Opp et al., 2013), and a lax rating attitude towards some structured finance instruments (pre-2007) is widely recognised (Becker and Milbourn, 2011; Mathis et al., 2009).

Despite the criticism, CRAs still exert a highly significant influence on economic activity (Cornaggia et al., 2017). Specific to the insurance industry, ratings are particularly important because of the reliance that policyholders place on insurers being solvent when a claim arises (Bierth et al., 2015) and that investors place when taking decisions about insurers' bonds and other debt (Miao et al., 2014). In fact, insurance firms play a central role in financial markets allowing stakeholders to transfer risk for a premium. Insurers use Financial Strength Ratings (FSR) within product promotion and consumers/investors utilise FSR as a source of information in their policy buying/investing process.

The inspiration for this thesis arises from the regulatory developments proposed to remedy the evidenced weaknesses during and after the financial crisis of 2007-10. These include Solvency II (SII) in Europe and updates of the Risk-Based standards by the National Association of Insurance Commissioners (NAIC) in the U.S. The Dodd-Frank Wall Street Reform and Consumer Protection Act (2010) was passed by the U.S. Congress in July 2010 to reform the CRA market, while in the European context, an introduction of several initiatives were presented to reform the CRA industry via the European Securities and Markets Authority (ESMA). These regulatory measures have also intended to answer the critics on conflicts of interest in the rating industry and to reinforce competition among CRAs (Vu et al., 2021).

While exploring this topic, revealed gaps in the literature motivate and provide relevance for embarking upon the directions of this investigation. Although a new strand of research has emerged to examine the financial stability of the insurance industry and its potential to pose systemic risks (e.g., Park and Xie, 2014, Billio et al., 2012, Caporale et al., 2017), there remains a scarcity of recent academic literature focused on insurance ratings. This contrasts markedly with a major emphasis in the CRA literature on the sovereign, structured finance and corporate segments after the global financial crisis.

The main literature strands for insurance ratings are the determinants of financial strength (e.g., Adams et al., 2003, Gaver and Pottier, 2005, Florez-Lopez, 2007), causes of split ratings (e.g., Pottier and Sommer, 1999, 2006), competition effects (e.g., Doherty et al., 2012) and the market impact of CRAs' actions (Singh and Power, 1992; Halek and Eckles, 2010; Wade et al., 2015). Amongst these strands, it is on the determinants where academic interest has been strongest, while split ratings, explanations about other behaviours among CRAs, and market impact have received very little recent attention. On competition, Doherty et al., (2012) is the only study examining how the entry of S&P to the insurers' rating market served by AM Best – a monopoly at the time –, changes the information content of ratings. This highlights how any differences in CRAs' standards are likely to create confusion and decrease the precision of information. Another academic interest lies in the regulatory sphere e.g., systemic risk (Asimit et al., 2016; Bierth et al., 2015), insolvency risk of insurance companies (Caporale et al., 2017) and the effects of regulatory frameworks such as SII in Europe (e.g., Höring, 2013; Laas and Siegel, 2016; Mezöfi et al., 2017) and regulatory changes in U.S. (e.g., Dimitrov et al., 2015).

Considering the voids in the rating literature, the overarching goal of this thesis is to provide empirical contributions on the intersection between the insurance sector and CRAs. Specifically, the empirical analyses in the thesis are based on a unique dataset of credit ratings from U.S. Property/Casualty (P/C) insurers. The choice of the country reflects the fact that about 65% of the global insurance market is in the U.S. and that institutional differences may affect empirical results when including data from different countries (Iannotta, 2006). Moreover, studies such as Adams et al., (2019) describe the P/C insurance sector (non-life) as the one with a much wider range of insurance product-types compared to life insurance whose products tend to mainly cover mortality-type personal lines of insurance based on standardized actuarial tables. This portrays P/C as a more information asymmetric sector than life insurance because of the prevalence of actuarial technology for assessing the accuracy of mortality risks in that sector.

The final sample of this thesis contains Financial Strength Ratings (FSR) of firms, which are rated by at least two of the four major CRAs for insurers. The CRAs are Standard and Poor's

(S&P), Moody's Investors Service (Moody's), Fitch Ratings (Fitch), and A.M. Best Rating Services, Inc. (AM Best). S&P has traditionally focused on rating individual debt issues, Moody's and Fitch are growing players in insurance rating market, while AM Best is the established CRA that has specialized in insurers' ratings. The fact that AM Best is included among the major CRAs in this sector creates a unique case for this analysis and adds to the originality of this thesis.

Furthermore, the use of data and a longer time period from four CRAs is a particular contribution of this study, since the vast majority of the related literature uses data from one or two CRAs (e.g., Doherty and Phillips, 2002; Florez-Lopez, 2007; Pottier, 1997; Pottier and Sommer, 2006). Please refer to Table 4.7 in Chapter 4 for more detail. The thesis uses a uniquely comprehensive ratings dataset. In empirical studies, the credit ratings scale is typically transformed into a 20-point numerical scale (Aaa/AAA =1, Aa1/AA+ =2, …Caa3/CCC- =19, Ca/CC to C/SD-D =20). It is at this stage where a unique challenge arises with FSRs across four CRAs. There is a lack of rating comparability in the number of points on the FSR rating scale when comparing AM Best with the other three CRAs. Hence, this thesis proposes three alternatives to map the 20-point numerical rating scale with the 13-point scale of AM Best. Congruently, the process is inversed by mapping the 13-point numerical scale used by AM Best and translating it towards its peers (Aaa/AAA =1, Aa1/AA+ =2,…Caa3/CCC- =11, Ca/CC to C/SD-D =13).[1]

Building upon the prior elements, three research questions are defined in this thesis to address diverse perspectives arising from the gaps in literature on ratings for insurance companies. Firstly, by examining the FSR evolution and drivers of rating changes assigned by S&P, Moody's, Fitch, and AM Best in U.S. P/C insurers (Chapter 5). Second, by focusing on the relationship between split ratings assigned by S&P, Moody's, Fitch, and AM Best and the impact of those disagreements on future rating changes (Chapter 6). Third, by analysing the impact of FSR actions related to U.S. P/C insurers (subsidiaries) on the share price of their respective parent company (Chapter 7).

Chapter 5 examines the differences in rating trends towards insurance companies among the big four CRAs using a sample of 1384 U.S. P/C insurers during 2000-2017. As the objective is to examine the FSR evolution, Chapter 5 incorporates rating transition matrices (RTM) to distinguish patterns among the FSR evolution across the four CRAs. The research question is:

[1] See Chapter 4 for a detailed explanation of the database construction used in this thesis.

what are the differences in rating trends for insurance companies among the big four CRAs?. The goal is also to offer insights on the effects of the global financial crisis 2007-2009 (GFC) on the FSR of U.S. P/C insurers. This chapter employs the mentioned 20-point rating transformation scale but also incorporates robustness checks using an alternative 13-point transformation. The chapter also assesses to what extent insurers in U.S. states that were affected by a higher frequency of natural catastrophes had more volatile rating evolution. Indeed, as stated by AM Best (2021), for most P/C insurers, environmental factors such as climate risk may pose a severe threat to the balance sheet, as they may result in material, rapid, and unexpected consequences for capitalization, as well as higher operating performance volatility. Linking that with FSR, the impact of Environmental Social and Governance (ESG) factors on financial strength over the short and long term is likely to vary depending on the nature of the company.

Chapter 6 investigates the impact of split ratings upon future insurers' rating changes by employing a binary probit approach (e.g., Morgan, 2002). It uses a sample of 904 U.S. P/C firms for the period from 2003 to 2017. The research question is: 'Is there any relationship between split ratings and subsequent rating migration for U.S. P/C insurers' ratings?'. Consistent with Chapter 5, this chapter employs the different empirical specifications to produce robust results.

Chapter 7 examines the information content of FSR for the stock market. Using a unique set of FSR actions associated with 346 U.S. P/C insurers from January 2003 to December 2017, the goal is to examine whether the disclosed information affected the stock market returns of the 30 parent companies associated with them. The research question can be expressed then as: 'Do FSR actions induce stock market reactions?'. The chapter employs an event study methodology and extends the analysis with a multivariate regression to capture the influence of parent companies' characteristics on the stock market impact.

Overall, the key findings of the empirical chapters are as follows. Chapter 5 reveals that numerous FSR actions occur before the crisis. Downgrades are more frequent than upgrades before and during the financial crisis, while after the crisis, upgrades and downgrades are quite balanced. Using a 20-point rating scale, RTM points that AM Best has the least amount of rating activity during the whole period 2000-2017, S&P seems to be the most active CRA, while Moody's and Fitch have quite similar amount of activity. Fitch is notable in assigning more downgrades during the financial crisis. This is a somewhat surprising finding since insurer ratings historically have been criticized for being inflated or overly positive (Ciumaş et al., 2015; Klein, 1992). However, even with Fitch rating levels can often remain in superior categories. In addition, from the RTM estimations, single and multi-notch rating changes (e.g., AA- to AA+) are more common over one year than changes within a whole category across CRAs. Alternative specifications using the 13-point rating scale based on AM Best is mostly aligned with the main results, and plentiful directions can be derived from this chapter for the future research.

To find attributable reasons for more rating activity before the crisis, this thesis draw upon some authors who focus on the insurance industry's performance before and during the crisis. For instance, Baluch et al., (2011) highlight the uneven effect of the financial crisis on the insurance industry, with life/health (L/H) insurers probably more affected than P/C insurers. Bernal et al., (2014) conclude that the insurance sector displays the largest risk contribution in the U.S. while in the Eurozone, banks are found to be systematically riskier than the insurance sector. Others have attributed institutional efforts by the states, federal regulators, and the National Association of Insurance Commissioners (NAIC) as factors that helped limit the effects of the crisis (GAO, 2011).

On the other hand, prior to the crisis, the P/C exhibited hard market conditions, and several man-made and climate-related events occurred. CRAs have argued that P/C insurers have been resilient enough to meet their obligations after natural catastrophes, thus not affecting rating levels majorly. Nevertheless, the frequency and severity of catastrophe events are increasing, which motivates the sector to keep monitoring its financial strength and anticipating future impacts of climate change.

Chapter 6 sheds light on the correspondence between the different CRAs' categories for insurers' ratings. Results suggest that split ratings among the four CRAs are influential on each other's future rating migrations. This is in line with prior work from Alsakka and ap Gwilym (2010a), Livingston et al., (2008) and Martin-Merizalde (2020), whose work on other rating segments motivates this research. The insurance literature contains very few examples of investigations on split insurers ratings (Pottier and Sommer, 1999, 2006). This chapter takes an original and unique direction by analysing the dynamic of the four CRAs and a much more recent and extensive time period.

The results of Chapter 7 corroborate that CRAs play a relevant role in providing valuable credit and financial strength information to investors, and other stakeholders. It favours the information content hypothesis and the asymmetric reaction of the stock markets to good and bad news. Briefly, the results indicate that negative FSR actions by Fitch exhibit the largest stock market reactions across CRAs. S&P's strongest market reactions arise from negative Outlook actions while Watch actions generate the strongest reaction for Moody's. This chapter does not find a substantial market reaction from AM Best FSR actions, except for a slight yet significant market reaction to upgrades. Similar to findings in Miao et al., (2014), it is rather surprising to find that FSR actions from Fitch elicit the largest market reaction. As AM Best is the CRA that is most commonly associated with the insurance sector, one might have expected stronger reactions to AM Best rating actions. Miao et al., (2014) refer to Doherty et al., (2012) to help elucidate their finding. Doherty et al., (2012) investigate the effect of competition between CRAs within the insurance rating market. They posit that, for a given rating by an incumbent CRA, new rating companies often require higher standards. Hence, it is possible that the greater market reaction to Fitch actions (a relatively late entrant to the insurer rating market) is an echo of the market's recognition of these differences.

This thesis adds to the existing literature in several ways. Firstly, it contributes to the literature about the role of insurer CRAs, specifically as a measure of insurance company performance. Second, the thesis makes a particularly unique contribution by identifying split ratings as a valuable factor affecting the probabilities of insurers' future rating changes. Lastly, this thesis contributes to the existing literature on the role of FSR in addressing the insurers' opacity, on the literature about the information content of ratings, and adds some elements about the parent-subsidiary relationship.

1.2 Thesis structure

Figure 1.1 illustrates the organisation of the remainder of the thesis. Chapter 2 provides a background and discusses concepts which are used throughout the remainder of this thesis. This is complemented by Chapter 3, which provides a review of prior empirical findings arising from examining financial strength ratings and insurer credit ratings. Chapter 4 explains the database construction, the selection of the U.S. as the main country of analysis and the selection of Property/Casualty (P/C) insurance as the main industry focus. The empirical Chapters 5, 6, and 7 contain the main contributions of this thesis via three perspectives. Chapter 5 examines the evolution of FSR across CRAs, in particular by employing rating transition matrices. Chapter 6 investigates how split ratings influence future rating migrations. Chapter 7 adopts an event study approach to capture the effect of the FSR actions associated with U.S. P/C insurers on the parent company share price. To close, Chapter 8 presents the conclusions and suggestions for future research.

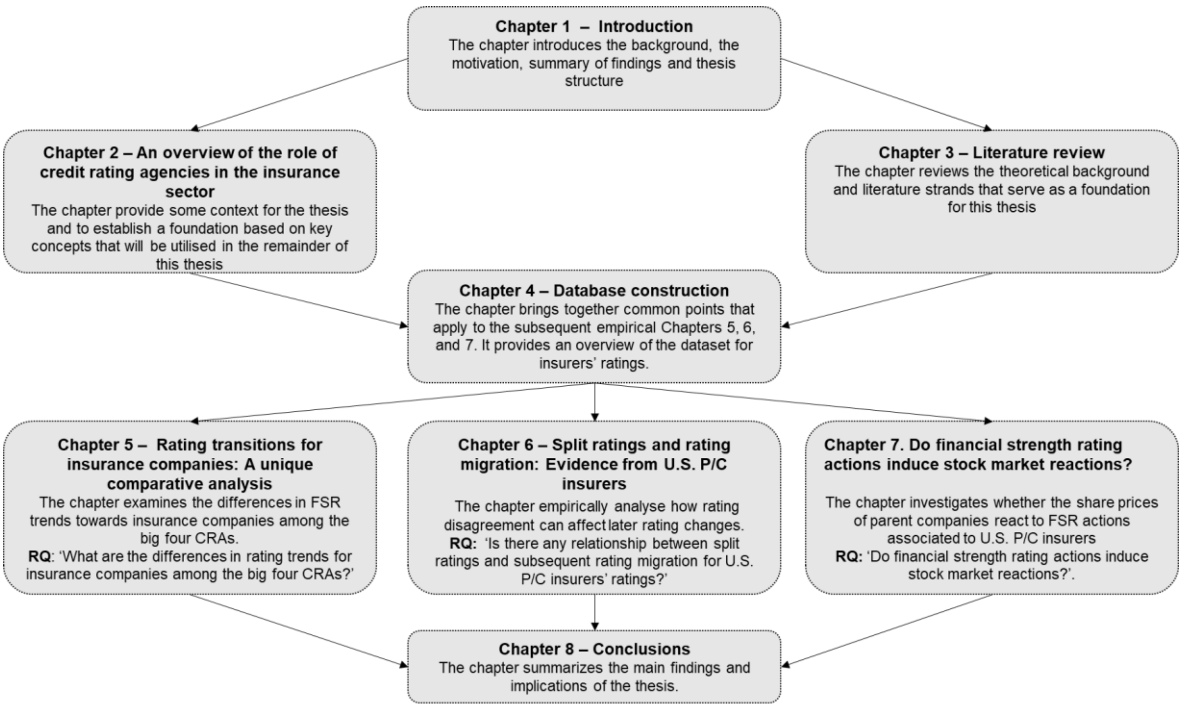

Figure 1.1 Structure of the thesis

This figure illustrates the contents of the thesis as a means to navigate the document.

Chapter 2. An overview of the role of credit rating agencies in the insurance sector

2.1 Introduction

The purpose of this Chapter is to provide some context for the thesis and to establish a foundation based on key concepts that will be utilised in the remainder of this thesis. In particular, this Chapter outlines the structure and role of Credit Rating Agencies (CRAs) in the insurance sector and specifically develops the concept of Financial Strength Ratings (FSR), which are a core element of the empirical analysis within this thesis. By discussing the CRAs that operate within the insurance industry, the characteristics of CRAs and the ratings they offer, this Chapter supplements the literature review developed in Chapter 3 and the rating scale transformation presented in Chapter 4. The combination of these elements establishes the setting for the investigations in the empirical chapters.

The academic literature on credit ratings is focused on the operation of the largest global CRAs: S&P Global Ratings (S&P), Moody's Investors Service, Inc. (Moody’s), Fitch Ratings, Inc. (Fitch), and for insurers, A.M. Best Rating Services, Inc. (AM Best). Moreover, it is focused on analysis of two of the different types of available ratings for insurance companies: Issuer Credit ratings (ICR) and more specifically, FSR. ICR involve long-term and short-term ratings to issuers, and both ICR and FSR can be applicable in foreign and local currency. The Chapter also provides an overview of the features of the insurance industry, the contributions to the global and U.S. economy, and highlight some major events that expand the context to the empirical results of this thesis.[2]

The remainder of this Chapter is organised as follows: Section 2.2 presents the composition of the insurers’ credit rating industry. Section 2.3 introduces the concepts of ICR and FSR and the differences across the four relevant CRAs. Section 2.4 provides a brief review of the main relevant concepts associated with the insurance industry, its major business lines and key events, and Section 2.5 concludes.

[2] Some insurers can also have short term FSR but those are very few.

2.2 Structure of the insurers' credit rating industry

For insurers, CRAs provide an assessment about both their capacity to repay corporate debt, and also their ability to repay claims from policyholders' contracts (Milidonis, 2013). By evaluating the ability of the insurer to meet its obligations, the CRAs' role becomes even more significant since insurance is considered one of the most opaque industries (Morgan, 2002). As mentioned in Chapter 1, investors and consumers use ratings as a source of information in their policy buying/investing process but also regulators use them in their oversight process.

Two primary regulators within the U.S. and European contexts supervise the operation of CRAs: The Office of Credit Ratings (OCR) from the U.S. Securities and Exchange Commission (SEC) and the European Securities and Markets Authority (ESMA) (Martin-Merizalde, 2020). The OCR was created in June 2012 under the Dodd-Frank Act which was passed by the U.S. Congress in July 2010 to enhance the regulation, accountability, and transparency of nationally recognized statistical rating organizations or "NRSROs" (Dimitrov et al., 2015). The OCR has responsibility for monitoring CRAs that are registered within the category of NRSROs. By means of its monitoring, OCR aims to promote compliance with statutory and SEC requirements. In particular, for the insurance sector, the 2010 Dodd-Frank Act also established the Federal Insurance Office (FIO) to monitor all aspects of the insurance industry, including identifying issues or gaps in the regulation of insurers that could contribute to a systemic crisis in the industry or the U.S. financial system.

Regarding Europe, ESMA is responsible for the registration and direct supervision of CRAs. ESMA was established in July 2011 and aims to achieve supervisory convergence across financial sectors by working closely with the other European Supervisory Authorities competent in the field of banking (EBA), and insurance and occupational pensions (EIOPA). In particular, EIOPA was established in the aftermath of the financial crisis with the purpose to rebuild trust in the financial system, supervise and bring about more harmonised and consistent application of the rules for insurance and occupational pensions sectors in Europe (EIOPA, 2021).[3]

In the U.S. scenario, there are additional institutions worth mentioning. The National Association of Insurance Commissioners (NAIC), founded in 1871, is a standard-setting

[3] CRAs are also recognized as an External Credit Assessment Institutions (ECAI) by the European Banking Authority (EBA) (Martin-Merizalde, 2020).

organization that provides data and analysis for insurance commissioners to regulate the industry. Attached to the NAIC, the Rating Agency (E) Working Group (RAWG) was formed on February 11, 2009, to conduct an evaluation of state insurance regulatory use of the credit ratings of NRSROs. Because of the financial crisis, RAWG recommended the reduction of the regulatory reliance on NRSRO ratings especially when evaluating new, structured, or alternative asset classes. Despite such recommendations, the NAIC still continues to rely on CRAs for other asset classes (NAIC, 2021a).[4,5]

Likewise, in order to increase competition, improve transparency and reduce barriers to entry in the credit rating industry, the U.S. Congress, eliminated the SEC's existing no action process and passed the Credit Rating Agency Reform Act (CRARA) of 2006. This resulted in an increase of the number of NRSROs from five in 2006 to nine rating agencies certified as NRSROs by SEC. According to SEC (2020), nine CRAs qualify as NRSROs as follows: AM Best; DBRS, Inc.; Egan-Jones Ratings Co. (EJR); Fitch; HR Ratings de México, S.A. de C.V.; Japan Credit Rating Agency, Ltd. (JCR); Kroll Bond Rating Agency, Inc. (KBRA); Moody's and S&P. As of December 2019, the percentage of each NRSRO's credit ratings of the total outstanding within the insurance companies category was AM Best (34.2%), S&P (32.3%), Fitch (15.7%), Moody's (12.0%), EJR (4.2%), DBRS (0.8%), JCR (0.4%) and KBRA (0.5). Considering these percentages, it is noticeable that the major CRAs within the U.S. insurers' rating industry are AM Best, S&P, Fitch, and Moody's.[6]

[4] Alongside the RAWG, there are additional initiatives to move away from ratings for mortgage-backed securities. For instance, the 'Structured Securities Project' was initiated in 2009 to assist state insurance regulators in establishing a new methodology to determine risk-based capital (RBC) requirements for the residential and commercial mortgage-backed securities held by insurers. In addition, as part of the NAIC, the Center for Insurance Policy and Research (CIPR) is a body that provides analysis on important insurance issues through research, data and education among policymakers, stakeholders, and in this thesis, it becomes an important source when understanding the sources of rating changes.

[5] Another NAIC initiative to highlight is the Group Capital Calculation (GCC) started to be develop by the NAIC's Group Capital Calculation (E) Working Group since 2015 and implemented in November 2020. GCC is as an additional solvency evaluation tool in assessing group risks and capital adequacy to complement the current holding company analysis in the U.S. The GCC is part of an update of the "Insurance Holding Company System Regulatory Act" and it is a reflection of the work started at the beginning of 2008 in terms of group supervision (NAIC, 2021c).

[6] As of December 2017, the percentage of each NRSRO's credit ratings of the total outstanding within the insurance companies category was AM Best (35.0%), S&P (31.6%), Fitch (15.9%), Moody's (12.1%), EJR (4.2%), DBRS (0.8%), JCR (0.5%) and KBRA (0.2%) (SEC, 2018). At the time, Morningstar Credit Ratings, LLC (Morningstar) was another NRSRO. However, it was not registered in the insurance rating category. In 2019, Morningstar completed an acquisition of DBRS and the two NRSROs began integrating their operations. Regarding the European context, ESMA (2021) recorded 13 EU registered CRAs providing insurers credit assessments. Those are S&P Global Ratings Europe, Moody's, Fitch Ratings, DBRS, Scope Ratings, KBRA, AM Best Europe Rating Services, Assekurata, Axesor Risk Management, ARC Ratings, BCRA-Credit Rating Agency, Rating-Agentur Expert, and EuroRating.

Unlike other industries, the insurers' rating industry was entirely dominated by AM Best. However, the industry experienced the entry of S&P in the 1980s (Doherty et al., 2012), and gradually the entry of more CRAs has followed. AM Best was incorporated in 1899, with its founder creating the concept of 'financial strength ratings' in 1906 (AM Best, 2021a). The CRA was initially dominant in the U.S. and has expanded globally. AM Best's monopoly position started to erode after attracting critics during the 'liability insurance crisis' of the mid-1980s and several natural catastrophes in the 1990s that bankrupted various insurers (Doherty et al., 2012). Despite AM Best is losing its monopoly, it's still recognized as the CRA that is placed uniquely among the CRAs that evaluate insurers (Singh and Power, 1992). Indeed, the insurance literature commonly focuses on AM Best rating alone (e.g., Doherty and Phillips, 2002; Epermanis and Harrington, 2006; Halek and Eckles, 2010; Wang, 2010).[7]

The second major CRA in insurers' ratings is S&P. According to Doherty et al., (2012), S&P entered the market in three phases, (i) in the late 1980's announcing it would publish 'claims paying ability' ratings on insurers, (ii) in 1991 when S&P announced its 'qualified solvency rating' service, and (iii) in late 1994, when S&P relaxed the 'BBB' ratings ceiling on qualified ratings. 'Qualified solvency ratings' were an unsolicited service based solely upon publicly available information and based on the condition that no insurer could receive a rating above 'BBB'. Thus, when S&P removed the latter, its ratings demand increased in a scenario where AM Best was still the only CRA providing insurers' ratings. [8, 9]

The third CRA is Moody's which was established in 1900, ceased to exist during the market crash of 1907 and then restarted operations in 1909 (Chorafas, 2004a). During the mid-1980s through the 1990s, Moody's started offering insurers' ratings and with time, the CRA has gained a solid reputation for reliability and proficiency in its work (Ciumaş et al., 2015). The final CRA is Fitch, whose origins traced back from IBCA, an agency incorporated in 1978 that merged with Fitch in 1997. By 2000, Fitch acquired Duff and Phelps Credit Rating Co. and Thomson Financial Bank Watch (Livingston and Zhou, 2016). Similar to Moody's and S&P,

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[7] For further details on the U.S. liability crisis please refer to Winter (1991) who provides an overview of the crisis faced by the insurance market between 1984 and 1986.

[8] It's worth noting that S&P is the oldest NRSRO. Poor's Publishing was stablished in 1860. In 1941 merged with Standard Statistics to form Standard and Poor's, and now is division of McGraw-Hill (Chorafas, 2004a). On the other hand, it's worth mentioning that, in a NAIC/CIPR webinar, Ahern and Painter (2016) claim that in 1971, S&P introduced Financial Strength Ratings on insurance companies.

[9] Similar to S&P, several CRAs originally used the phrase "claims-paying ability ratings" to refer to Financial strength ratings (Angell et al., 2000; Fitch, 2016). For example, DBRS withdraw the use of the claims paying ability scale and introduce the rating scale using the term financial strength ratings in December 17, 2015 (DBRS, 2013).

Fitch added insurers into their ratings coverage through mid-1980s towards the 1990s (Fitch, 2016).

Across the four CRAs, the ratings business model has faced major critics especially after the financial crisis 2007-10. There are two main models, the issuer-pays and the investor-pays model. Briefly, the issuer-pays model consists of CRAs that are compensated by the companies/issuers they rate, while in the investor-pays model the CRAs collect fees from investors who use their ratings for their investment decisions. In general, the major CRAs operate under the issuer-pays model when rating issuers in the insurance industry (Milidonis, 2013). For a more thorough explanation about the business models and associated criticism, refer to Alsakka (2010) and Jones (2019).

Another important element of the structure of the insurers' rating market is the regulatory framework that is in place. Indeed, looking at the U.S. and European markets such as the U.K., there are some features that distinguish the U.S. insurance market. First, the U.S. is considered an utterly competitive market, whereas P/C lines in the U.K. tend to be supplied by a small number of composite insurers (Upreti and Adams, 2015). Second, U.S. states are the primary regulators, where each state can define its own set of laws and rules (Adams et al., 2019); and third, the U.S. federal government plays an important role by offering assistance and funding through a range of agencies and programmes (see more details in Section 3.3.3 in Chapter 3 and Section 5.2.1 in Chapter 5).

According to Weiss and Chung (2004), the state-based insurance regulation has some particular features. For example, states can impose higher capital maintenance requirements on so called 'alien' (or foreign) reinsurance companies in contrast to U.S.-owned reinsurers, or they can impose regulatory limits on premiums (e.g., New York). Meanwhile, the U.K. regulatory framework does not discriminate between reinsurance companies according to their domicile, and it is defined as a unitary fiscal environment (Upreti and Adams, 2015). Klein (2005) claims that ideally, regulators in various countries will increase their cooperation and coordination to facilitate the appropriate supervision of international insurers. Likewise, the International Association of Insurance Supervisors (IAIS) is playing an important role in facilitating communication and promoting best practices among insurance regulators in different countries.[10, 11]

These institutional differences are relevant since premium rates, reinsurance, and taxes have a direct effect on the insurers' product-market strategies and underwriting capacity (Upreti and Adams, 2015). However, from a credit rating market perspective, the CRAs studied in this thesis operate globally and do not have an identifiable "home region" (Alsakka and ap Gwilym, 2012a). S&P, Moody's, Fitch and AM Best have global rating definitions/principles, and methodologies that may need to be complemented in specific cases. For instance, S&P says "*S&P Global Ratings uses a principles-based approach for assigning and monitoring ratings globally. These broad principles apply generally to ratings of all types of corporates, governments, securitization structures, and asset classes. However, for certain types of issuers, issues, asset classes, markets, and regions, S&P complements these principles with specific methodologies and assumptions"*.

Likewise, AM Best (2019, 2021b) asserts that for their evaluations, they rely primarily on information provided by the rated entity, although other sources of information may be used in the analysis. For example, financial statements used for their rating process are those presented in accordance with the customs or regulatory requirements of the country of domicile. Other documents may be reviewed, such as interim management reports on emerging issues, regulatory filings, investment guidelines, internal capital models, Own Risk and Solvency Assessment (ORSA) reports, or other supplemental information requested by them.

Furthermore, Feldblum (2011) presents several aspects from CRAs rating process that may help to clarify the CRAs attitude towards institutional framework and organizational structure. On one hand, CRAs analyse organizational structure of the insurer to determine the subsidiaries or affiliates, whether there is any used for pricing (various rates by legal entity), which ones are intended for operations in specific states or countries, among others. Feldblum (2011)

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[10] According to Klein (2005), alien insurers must meet a number of requirements to operate on a licensed or authorized non-admitted basis in the U.S. However, this does not prevent U.S. citizens and firms from purchasing insurance from alien companies on a direct basis. Such transactions are not subject to U.S. regulatory protections.
[11] In the U.S., when an insurer is licensed and authorized to do business in a particular state, it is known as an "admitted" insurer. It is also considered "domiciled", and "domestic" in the state that issued the primary license. Likewise, the insurer may seek licenses in other states as a "foreign" insurer. Finally, insurers incorporated in a foreign country are called "alien" insurers in the U.S. states in which they are licensed (III, n.d.).

documents that CRAs evaluate each legal entity, and then increase or lower the rating for benefits or liabilities of the corporate group.

On the other hand, Feldblum (2011) posits that CRAs check if the insurer lobbies in state and federal extents or depend on trade organizations. For instance, CRAs examine whether the insurer have rate filings and class plans approved by state insurance departments, or whether it relies on bureau filings and class plans. In this thesis, the empirical analysis will be based on U.S. Thus, role of the U.S. institutional features are used to help elucidate and get a better understanding of the empirical results in Chapter 5, 6, and 7.

2.3 Credit rating scales

2.3.1 Rating categories

Each CRA has its specific policies and terminology relating to assigning credit ratings. This section sheds light on the different rating categories applied by CRAs with special attention to FSR. Overall, three major types of ratings are offered to insurers: Issuer Credit Rating (ICR); Issue Credit Ratings (IR); and FSR. Issuer and issue ratings are often called the "traditional credit rating" (S&P, 2018), and FSR are exclusive to insurance companies. In general, ratings are given in the form of a letter scale ranging from AAA/Aaa for the highest credit quality or financial strength to C/SD/D for the lowest (see more detail on the rating scale in Section 4.5 in Chapter 4). Table 2.1 presents the definition of ICR across CRAs, while in a nutshell, issue ratings can be defined as the credit risk inherent in a specific insurance corporate bond issue (Milidonis, 2013).

Across CRAs and categories, ratings can be short- or long-term and local currency (LC) or foreign currency (FC). Short-term ratings are generally assigned to those obligations considered short-term maturity (less than a year) while long-term ratings relate to an entity's ability to meet its ongoing senior financial obligations (maturing in more than a year). LC (FC) ratings relate to an issuer's capacity to meet its debt obligations denominated in its local (foreign) currency (S&P, 2018). In Chapter 4, most ratings available when constructing the database for this thesis correspond to a LC designation from the CRA.

Ratings can also be based on national rating scales where the CRA provides an opinion about the relative creditworthiness of the issuers within a specific country. These are not used in this thesis. Ratings can also be solicited or unsolicited. 'Solicited ratings' refer to those when a firm requests and pays for a rating while 'Unsolicited ratings' involve a CRA rating a firm mainly from public information even though the firm has not asked for a rating (Poon and Firth, 2005).

For the insurance rating market, Cole et al., (2017) studies both unsolicited and solicited ratings from AM Best, S&P, Moody's, Fitch and Demotech. They argue that data related to unsolicited FSR is somewhat limited. They state that CRAs have generally discontinued this practice or narrowed the type of insurers to which they assign these ratings. For example, Fitch announced that it will no longer issue unsolicited ratings, called 'q' ratings, though it may issue 'q' scores if demanded by the market in the future (Fitch, 2009). However, in recent reports, Fitch (2019) also clarifies that unsolicited ratings do not happen when public information is insufficient to support a rating and that the solicitation status has no effect on the level of the credit ratings assigned. Additionally, in a guide to their ratings, AM Best (2019) states that a credit rating may be produced at their discretion (i.e., unsolicited) or in response to a request (i.e., solicited). However, in the same guide, AM Best states that they do not currently produce ‘unsolicited credit ratings’.

Table 2.1 Definition of issuer credit ratings by CRAs

CRA	S&P (2018)	Moody's (2019)	Fitch (2018)	AM Best (2019)
Abbreviation	ICR	Issuer Rating	IDRs	ICR
Definition used by CRA	Forward-looking opinion about an obligor's overall creditworthiness. Obligor's capacity and willingness to meet its financial commitments as they come due.	Opinions on the ability of entities to honor senior unsecured debt and debt like obligations. These ratings do not reflect the risk that a contract or other non-debt obligation will be subjected to commercial dispute.	Opinion on an entity's relative vulnerability to default on financial obligations offering an ordinal ranking of issuers based on the agency's view of their relative vulnerability to default, rather than a prediction of a specific percentage likelihood of default.	Independent opinion of an entity’s ability to meet its ongoing financial obligations and can be issued on either a long- or short-term basis.

This table contains a brief definition of issuer credit ratings by CRAs. Fitch denominates its ratings as long-term (LT) and short-term (ST) “Issuer Default Rating - IDR”. Moody’s expresses its Issuer Ratings as either LT Issuer rating, or ST issuer rating.

2.3.1.1 Financial strength ratings (FSR)

Financial Strength Ratings (FSR) were introduced in response to policyholder interest following several failures and an increasing desire for more accurate information regarding insurers’ insolvency risk in the late 1980s and early 1990s (Halek and Eckles, 2010). Prominent studies define FSR as the summary measures of insolvency risk (Pottier and Sommer, 1999; Wang and Carson, 2014), ratings with long-term basis assessments (Florez-Lopez, 2007) and ratings that despite its voluntary nature (Adams et al., 2003), have been associated with market discipline in the insurance industry (Epermanis and Harrington, 2006).

Table 2.2 presents the definition, abbreviations, and rating scale points of FSR across CRAs. The top of the scale represents the best possible rating and therefore the opinion of an insurer able to meet its ongoing obligations, and the scale works down towards C and D to discern on insurers with poor ability or that have defaulted. From Table 2.2, it is evident that the rating points and symbols are very similar across S&P, Moody’s, and Fitch, whilst AM Best’s rating scale is noticeably different. More details on this matter will be discussed in Chapter 4.

Furthermore, it is worth noting that S&P also offers ‘Insurance Financial Enhancement Ratings’, these ratings contain a forward-looking opinion about the creditworthiness of an insurer with respect to insurance policies or other financial obligations that are predominantly used as credit enhancement and/or financial guarantees. According to S&P (2018), FSR and financial enhancement rating, if any, are identical to the ICR.[12]

Moody’s use the denomination “Insurance Financial Strength Ratings – IFS” to refer to FSR when evaluating insurance companies. FSR are opinions of the ability of insurance companies to pay punctually senior policyholder claims and obligations and reflect the expected financial loss suffered in the event of default (Moody's, 2019). According to Ciumaş et al., (2015), FSR ratings for Moody’s are based on the analysis of industry regulatory trends and an assessment of an insurer's business fundamentals (this focuses mainly on financial aspects, such as capital adequacy, investment risk, return and liquidity management or organizational structure).

Regarding Fitch, the CRA use the denomination “Insurer Financial Strength – IFS Ratings” as equivalent of FSR. FSR rating reflects both the ability of the insurer to meet obligations on a timely basis and expected recoveries received by claimants in the event the insurer stops making payments, due to failure or some form of regulatory intervention (Fitch, 2018). Concerning AM Best, they use the denomination Best’s Financial Strength Rating (FSR) and describe them as an opinion of an insurer's ability to meet its obligations to policyholders. AM Best use the approach of “Rating units” and a quantitative measure called Best’s Capital Adequacy Ratio (BCAR) to build its ratings. BCAR is designed to capture the risks inherent in the rating unit’s investment and insurance operations relative to its available capital (AM Best, 2017a).

To define a rating unit, AM Best consider the features of the organization such as pooling arrangements, intra-group reinsurance contracts, guarantee and net worth maintenance agreements, and other connections (branding, type of business written, manner of distribution, geography. For more detail about rating units, please refer to AM Best (2017a) methodology.

[12] S&P (2018) state “*FSR equals the ICR unless the present default risk leads to a rating conclusion of 'CCC+' or lower, or unless policyholder obligations, but not other financial obligations, are supported by a more creditworthy counterparty”.*

Table 2.2 Definition of financial strength ratings by CRAs

CRA	S&P (2018)	Moody's (2019)	Fitch (2018)	AM Best (2019)
Abbreviation	FSRs	IFS	IFS	FSR
Definition by CRA	Forward-looking opinion of the financial security characteristics of an insurer with respect to the ability to pay under its insurance policy or contracts in accordance with their term.	Forward-looking opinion of the insurer's ability to punctually pay senior policyholder claims and obligations.	Reflect the ability of the insurer to meet both obligations on a timely basis and expected recoveries received by claimants.	Independent opinion of the insurer's ability to meet its ongoing insurance policy and contract obligation
Rating scale points and symbols	21-points AAA to SD-D	21-points Aaa to C	19-points AAA to D	13-points AA++ to D
Rating categories	Extremely strong, very strong, strong, good, vulnerable, marginal, weak, very weak, extremely weak,	Highest quality, high quality, upper-medium grade, medium-grade, speculative, speculative and are subject to high credit risk, speculative of poor standing	Exceptionally strong, very strong, strong, good, moderately weak, weak, very weak extremely weak distress	Superior, excellent, good, fair, marginal, weak, poor

This table defines financial strength ratings (FSR) across CRAs and shows the abbreviation used by them. AM Best has also non-rating designations are E, F, S, NR.

2.3.2 Different rating activity by CRAs

Overall, CRAs aggregate quantitative and qualitative information about an issuer (in this case, insurers), and use rating actions, as a means by which they signal permanent changes in an issuer's credit quality and/or financial strength. However, CRAs also develop secondary rating actions to communicate potential or temporary changes in credit quality, which are named Outlook and Watch actions. Table 2.3 presents these supplementary rating actions within the major four CRAs of the insurance sector, which have a few differences especially from AM Best.

According to Alsakka and ap Gwilym (2012b), an Outlook action states the likely direction that a credit rating may take over the next one- to two-year period, and it can be positive, stable, negative or developing. Meanwhile, a Watch action is a statement about the future direction of a credit rating within a relatively short horizon (ex-ante target of 3 months). Similar to Outlook, Watch categories are: Watch for upgrade (positive Watch); Watch for downgrade (negative Watch); and Watch with direction uncertain.

Table 2.3 Secondary rating actions across CRAs

Actions/CRAs	S&P	Moody's	Fitch	AM Best
Outlook	Positive Negative Stable Developing Not meaningful. (N.M.)	Positive (POS) Negative (NEG) Stable (STA), and Developing (DEV) Rating(s) Withdrawn (RWR) Confirm	Positive Negative Evolving Affirmed	Positive Negative No Change After Receipt of Annual Financial Statement (Affirmed)
Watch	Positive Negative Developing	Review for upgrade (UPG), downgrade (DNG), or more rarely with direction uncertain (UNC).	Positive Negative Evolving	AM Best has no Watch actions. However, it employs Under review modifier as shown below
Modifiers	**S&P**	**Moody's**	**Fitch**	**AM Best**
Under review	Under Criteria Observation (UCO) identifier	Rating(s) Under Review (RUR) Modifier	Under review Modifier	Under review (u) modifier with positive and negative implications

This table shows the terminology of the secondary rating actions performed by CRAs.

Besides secondary rating actions, CRAs have rating modifiers, qualifiers, suffixes, identifiers, prefixes or a combination. Overall, these aim to provide supplementary information that may help clarify the scope of a rating or provide additional information. Across CRAs, one particular modifier/identifier of interest is 'Under Review' as shown in Table 2.3. For S&P, Moody's and Fitch, the meaning of Under Review' is similar whereas for AM Best it has variations. S&P (2018) define under review as an identifier called 'Under Criteria Observation' or 'UCO' identifier. The 'UCO' identifier was an EU regulatory requirement and it is assigned to credit ratings under review as a result of a criteria revision. Regarding to Moodys (2019), they use a designation of RUR (Rating(s) Under Review). RUR indicates that an issuer has one or more ratings under review, which overrides the outlook designation. For Fitch (2018), Under Review is also a modifier and it is applicable to ratings that may undergo a change in scale not related to changes in fundamental credit quality.

A key difference to report from Table 2.3 is that AM Best does not conduct Watch actions. However, AM Best uses the under review modifier (hereafter 'under review' actions), which refers to ratings that has the potential for a near-term change (normally six months) given a recent event or unforeseen change in the financial condition of the entity. Halek and Eckles (2010) argues that AM Best added 'under review' actions to its services in 1995 as a response to the desire for more accurate information regarding insurer insolvency risk in late 1980s and early 1990s. Under review actions can be with positive (negative) implications, or developing.

A key consideration in comparing Outlook, Watch and Under Review is the differing time horizons which relate to each of these signals.

It is important to clarify that in this thesis, the use of the rating actions in Chapters 5 and 6 only consider upgrades and downgrades whereas, for Chapter 7, Outlook and Watch are included in the analysis. Likewise, under review actions by AM Best are included in Chapter 7 as part of the investigation to look at the information content of FSR actions in the stock markets.

2.4 Insurance industry characteristics

This section considers terminology relating to the insurance industry to ensure a common understanding of the concepts used throughout this thesis. According to Chorafas (2004b), a key component of the insurers' behaviour across business lines is the fact that compared to banks that transact credit risk as intermediaries; insurers take technical risks as part of their business and face expected and unexpected risks (e.g., catastrophe risk: climate related events). The ability of the insurers to model both types of risk and absorb them in its balance sheet, as well as the evolution of their investments determines how the insurer can sustain over time.

2.4.1 Major business lines

There are three main business lines or insurance subsectors: (i) Life/health (L/H), (ii) Non-life and, (iii) reinsurance. Across regions of the world, different terminology is used to refer to the non-life subsector. In the U.K., general insurance is the equivalent of non-life insurance, while in the U.S., Property/Liability or Property/Casualty (P/C) is sometimes used. In this thesis, P/C will be the term used throughout the document. Depending on the line of business, the risks insurers face may vary. Indeed, Caporale et al. (2017) assert that there are huge differences between the subsectors that make it inappropriate to mix them together when embarking on certain empirical studies.

Concisely, L/H insurers mainly offer products associated with two segments: life insurance and annuities which protect against the risk of financial loss associated with an individual's death; and accident and health products which focus on covering in an event of disability (FIO, 2017). Regarding P/C, the concept can be broken down. Property insurance is described by NAIC (2021) as *coverage against loss or damage to real or personal property from a variety of perils, including but not limited to fire, lightning, business interruption, loss of rents, glass breakage, tornado, windstorm, hail, water damage, explosion, riot, civil commotion, rain, or damage from aircraft or vehicles*. Likewise, NAIC defines casualty insurance as a form of liability insurance that covers negligent acts and omissions such as workers' compensation, errors and omissions, fidelity, crime, glass, boiler, and various malpractice coverages.

With regards to reinsurance, often called insurance for insurance companies, NAIC (2021) refers to it as the agreement between two insurers to share financial consequences of a loss. The agreement protects the first insurer or "primary insurer" against large claims, and agreements are commonly placed with other direct insurers frequently holding internationally diversified portfolios (Doherty and Tinic, 1981). Upreti and Adams (2015) claim that reinsurance provides a more comprehensive and easily accessible source of information on insurers' prospects for interested parties. Therefore, future studies on the reinsurance sector would be a way to continue the investigations which are conducted later in this thesis.

2.4.2 Other developments in the industry: Takaful insurance

There is another form of insurance that can be considered as another "insurance subsector". Takaful is a form of Cooperative Insurance that has become a growing segment of the Islamic finance industry. Takaful is a word derived from the Arabic verb kafala meaning 'to guarantee', and refers to guaranteeing each other (Bisani, 2011). The concept is introduced in Sudan in late 1970s and 1980s in Malaysia (Kassim, 2005). Takaful is based on the concepts of *tabarru* (conditional and irrevocable donation or gift), taawun' (mutual protection), and *verteran* (mutual assistance), which are involved in the operational activities and must ensure *Shariah* (islamic law) compliance.

Several features distinguish Takaful from conventional insurance. Primarily, the nature of the contract. Second, level of uncertainty (ghara). Third, gambling (Masur) and fourth, interest (riba). AM Best also highlight the following aspects: two separate funds, solidarity principle and equal surplus distribution, restricted investments and, establishment of a Shariah board (AM Best, 2017b). Certainly, the differences with conventional insurance have required that CRAs published a specific methodology to rate this subsector.

2.4.3 Economic importance of the insurance sector

The insurance industry, and in particular, insurers' solvency is important to the stability of the global financial system given the contingent nature of an insurance promise, the implementation of long-term contracts, and the carrier role of many financial risks (Eling and Jia, 2018).

According to FIO (2017), the U.S. remains the world's largest insurance market by direct premiums written ($1.3 trillion in 2016), with 29 percent of the global market, while the European Union (EU) has similar figures if viewed as a single market. Likewise, the report asserts that China is now the third largest insurance market, after the U.S. and Japan. Becker and Ivashina (2015) argue that U.S. is also the largest institutional holder of corporate and foreign bonds since in 2010 insurance companies' holdings represented $2.3 trillion, or more than the bond holdings of mutual and pension funds taken together.

Figure 2.1, Panel A, presents insurance spending, a ratio that reflects the relative importance of the insurance industry in the domestic economy, and insurance penetration (Panel B), a ratio used as an indicator of insurance sector development within a country. From the 1990s, U.S. has been above OECD countries positioning at 11.2% in 2017 compared to 8.91% for the OECD average. Interestingly, among Europe, the U.K. has a greater percentage of 12.80% in 2017, making the industry another important market to study. In Figure 2.1, Panel B, the insurance penetration of non-life insurers is also a point to highlight with 6.78% versus 4.39% of life insurers in 2017. Indeed, by subsector, the P/C insurance in the U.S. is economically important as it contributes more than 4% to U.S. GDP, but also an important source of capital to financial markets, for instance, via the investment of collected insurance premiums on outstanding insurance contracts (Ben Ammar et al., 2018).

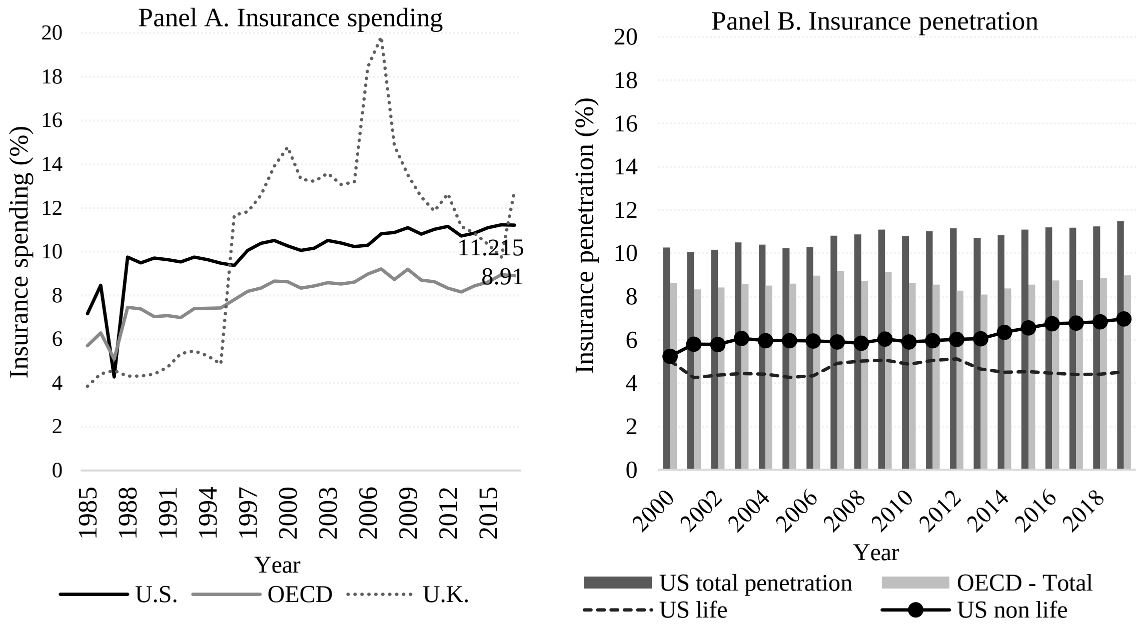

Figure 2.1 Insurance spending and insurance penetration

This figure presents two insurance industry indicators. Panel A presents insurance spending which is defined as the ratio of direct gross premiums to of gross domestic product (GDP) during 1985-2017. This indicator is expressed as a percentage GDP. Panel B presents insurance penetration which is the ratio of total insurance premiums to GDP in a given and it is a percentage. Source: OECD (2020).

2.4.4 Major events in the insurance industry

To understand the reasons why the insurance industry has evolved in a certain way, it is relevant to consider the main events that affected the industry. To find a detailed review of insurance crisis before the credit turmoil in 2008, Baluch et al. (2011) compiles among others the following events: U.S. liability insurance crisis, the near collapse of the 300-year-old Lloyd's insurance market in the 1990s in Europe, and the Hurricane Andrew that hit Florida in 1992. Until Hurricane Andrew, the industry had thought USD 8 billion was the largest possible catastrophe loss. According to Swiss Re (2018), total global economic losses from natural disasters and man-made catastrophes were USD 337 billion in 2017.

After the financial crisis 2007-10, renewed attention to the concept of systemic risk has been the focus as well as the regulatory oversight. Billio et al. (2012) refers to the concept of systemic risk as the collection of interconnected institutions that have mutually beneficial business relationships that can quickly propagate during periods of financial distress. Within the discussion about systemic risk, there are two main broad views about the insurance sector. In one group, recent studies claim that insurance companies have become riskier due to the extensive business ties that insurers have been developing over the last decade with hedge funds, banks, and brokers/dealers (Becker and Ivashina, 2015; Billio et al., 2012; Koijen and Yogo, 2016). Certainly, Chorafas (2004b) claims that the merging of financial instruments and insurance changes the perspective of technical risk at the frontline of the insurance industry.[13]

In the second group, Geneva Association (2010) argues that the insurance sector is fundamentally different from the banking sector, and thus the systemic risk posed by reinsurers seems to be less significant. The only possible source of systemic risk posed by the insurance/reinsurance industries is through their non-core activities (e.g., Credit Default Swaps, financial derivative trading, short-term funding, and security lending) as happened with the American International Group (AIG) case. In that respect, Billio et al., (2012) argue that is precisely the latter that has activated channels through which adverse shocks affecting the insurance economy may harm the real economy. Above this debate, Bernal et al., (2014) bring points from both views and conclude that the insurance sector displays the largest risk contribution in the U.S. while in the Eurozone, banks are found to be systematically riskier than the insurance sector.

In terms of subsectors, it is argued that the P/C insurance industry may be subject to systemic risk because of its heavy dependence on reinsurance and the complexity of the reinsurance market (Cummins and Weiss, 2014). Nevertheless, Park and Xie (2014) bring together an analysis of the interconnectedness between reinsurers and U.S. P/C insurers showing that the likelihood of systemic risk caused by reinsurers is relatively small for the P/C industry.

[13] See Silva et al., (2017) for an analyses and classification of 266 articles regarding systemic financial risk.

2.5 Conclusions

Chapter 2 provides an overview of the particular features of the insurers' credit rating industry as well as key characteristics of the insurance industry based on the literature and the available information from CRAs. The investigation is divided into three aspects: i) the composition of the insurers' credit rating industry, ii) the description of CRAs' rating scales with a special focus on the concept of FSR definition across CRAs, and iii) insurance industry features considering the complexity and the opacity of the industry.

The largest supervisors of the credit rating industry are the SEC for the U.S. and ESMA for Europe. These supervisors regulate the rating practices of CRAs. CRAs offer long-term and short-term ratings to insurers, and are offered in foreign and local currency. The industry has two compensation models, issuer-pays model and the investor-pays model. Each has advantages and drawbacks that have been studied by the credit rating literature, but this will not be a focus in this thesis.

This chapter has laid an important foundation for the empirical chapters of the thesis. Chapter 5 examines the differences across time and CRAs on the FSR evolution. Chapter 6 investigates the effects of rating disagreements on future rating changes, and Chapter 7 explores whether FSR actions induce stock market reactions. Thus, the estimations in all chapters incorporate the long-term local currency assigned by all four major CRAs. The next Chapter presents a literature review of the studies relevant for this thesis, further complementing the outline of the insurers' credit rating industry developed in the current chapter.

Chapter 3. Literature review

3.1 Introduction

The focus of this Chapter is to review the pertinent literature and theories that support the proposed research questions of this thesis. A crucial objective is to define the gaps in knowledge that this thesis will address. Section 3.2 examines the role of Credit Rating Agencies (CRAs) in the insurance setting and presents the available literature on the determinants of Financial Strength Ratings (FSR).

Two theories serve as a foundation, namely information theory and the theory of financial intermediation. Information theory suggests that in the presence of information asymmetries, investors possess imperfect information about the companies in which they invest. Thus, credit ratings have an overall effect on the welfare of market participants (Bae et al., 2015) by uncovering new information about firms' performance (Miao et al., 2014). Aligned with the information theory, the theory of financial intermediation states that the principal role of CRAs is the reduction of ex-ante uncertainty or informational asymmetry about a firm's economic value and probability of financial distress (Millon and Thakor, 1985). Consequently, ratings act as a means to achieve information economies of scale and solve principal-agent problems (Gonzalez et al., 2004), and CRAs gain a relevant role as they reduce ex-ante uncertainty about the probability of financial distress (Pottier and Sommer, 1999). In the insurance industry context, the financial intermediation theory is also linked with the role of insurers in financial markets, which are systemically important regulated financial intermediaries (Upreti, 2014) that allow stakeholders to transfer risk for a premium.

Regarding the determinants of FSR, measures of profitability, liquidity, leverage, size, business activity are typically found to be significant influences. The review of the literature in this section is pertinent for Chapter 7. Section 3.3 provides the available research surrounding FSR as a mechanism for market discipline. The section draws upon critiques of CRAs and comprises the regulatory frameworks that apply in Europe with Solvency II, and U.S. regulatory updates as a response to the global financial crisis of 2007-10. The findings in this section are particularly valuable for Chapter 5 in the effort to explain the evolution of FSR across time and across CRAs.

Section 3.4 incorporates the available research on the different market dynamics across CRAs such as leads and lags, herding behaviour, and split ratings. The review shows that rating disagreements have informational value for investors and are a significant influence on rating migrations. The findings on split ratings are especially relevant for Chapter 6. Finally, Section

3.5 presents the academic debate surrounding the market impact of credit rating actions in numerous rating segments i.e., sovereigns, corporate, banks, and ultimately, insurers. There is a strong set of prior evidence that rating downgrades affect equity and bond prices more significantly compared to upgrades. This argument is re-examined in Chapter 7 in an empirical setting for insurers.

Overall, the review of the available research exposes the scarcity of literature on insurance ratings in academic journals. With the current scenario of interconnected financial markets, a need exists for much more recent studies on FSR, on market dynamics among CRAs, and the market impact of FSR actions. In the effort to comprehend these issues, contributions to knowledge could arise from a high quality dataset (see Chapter 4). Research on these aspects has the potential for insights that can inform stakeholders and future regulatory developments.

3.2 Market discipline and reputation of CRAs

Market discipline features in academics and regulators' discussions as it has exhibited important flaws during the financial turmoil in 2008-2009. Failings from CRAs when assessing complex financial products have made the market' shortcomings even more noticeable. Theoretically, market discipline is referred as a means to distribute resources effectively and efficiently (Eling and Schmit, 2012) proposing manners of preventing or mediating excessive risk-taking by financial institutions either by market participants or indirectly by regulators using market prices as signals of developing problems (Bliss, 2014).[14]

Overall, research on market discipline's notions has been focused on the banking industry (Eling and Schmit, 2012). Dimitrov et al. (2015) serve as an example with their study about the U.S. Dodd-Frank Act's effects on rating levels. Concisely, Dodd-Frank Act's entail aspects such as an increase in CRAs liability for issuing inaccurate ratings and authorize the SEC to impose sanctions on CRAs. Dimitrov et al. (2015) test the changes in rating characteristics before and after Dodd-Frank regulation in the U.S., contrasting reputation and disciplining concerns. Their results indicate that CRAs lower their ratings after Dodd-Frank when their reputation is more valued. [15]

Market discipline becomes relevant for this thesis bearing in mind the role that credit ratings have constituted as a key information channel among market participants (Becker and Milbourn, 2011; Alsakka and ap Gwilym, 2010a). Even more with the scrutiny of CRAs and updates in regulatory frameworks after the financial crisis. In Europe, Solvency II (SII) denotes the influence of clients, CRAs, and investors on insurance firms' behaviour in the purpose of building a strongly solvent industry. In the insurance research literature, Adams et al. (2003) stand out again by using topics related to market discipline when investigating CRAs' practices in the U.K (Eling and Schmit, 2012). Epermanis and Harrington (2006) also become a prominent paper advocating that FSR impose market discipline in the insurance industry, and provide an analysis of the relationship between insurance premium growth and changes in AM Best FSR for a large sample of U.S. P/C insurers. They generally found economically and

[14] See the case of AIG that has constituted AIG Financial Products Corp in Ciumaş et al., (2015)

[15] Jones (2019) defines the reputation hypotheses as the case when CRAs may respond to increased scrutiny by lowering ratings to protect and rebuild their reputation. Meanwhile, the disciplining hypothesis states that the increased legal and regulatory demands will motivate CRAs to invest in improvements to their methodologies, due diligence, and performance monitoring.

statistically significant premium declines in the year of and the year following rating downgrades.

Recent forays in the insurance literature offer implications rather than direct tests of market discipline (Eling and Schmit, 2012). For instance, there are studies about insurance companies' investment strategies either standalone (e.g., Gatzert and Martin, 2012; Höring, 2013; Christiansen and Niemeyer, 2014; Asimit et al., 2016; Mezöfi et al., 2017; Bølviken and Guillen, 2017), or alongside comparisons with other regulatory frameworks (e.g., Gatzert and Wesker, 2012; Laas and Siegel, 2016; Eling et al., 2008; Dacorogna, 2018 in Table A 3.2).

3.2.1 Reputational theories and rating levels

As previously mentioned, CRAs have experienced widespread criticism during and after the 2007-09 financial crisis. The most recurrent critics are: i) a lax rating attitude towards some structured products (Becker and Milbourn, 2011; Mathis et al., 2009); ii) biased and inflated ratings arising from the business model (Agarwal et al., 2016; Bolton et al., 2012; Dimitrov et al., 2015); iii) Lack of transparency in their methodology (Dilly and Mählmann, 2016); and iv) partial responsibility for the subprime crisis (Eling and Schmeiser, 2010; Lugo et al., 2015; Mathis et al., 2009).

In responding the criticism, CRAs have defended themselves with the argument that reputation is their main asset, thus, behaviour such as issuing inflated ratings would put their reputation at risk (Lugo et al., 2015). Consequently, CRAs' actions and their drivers remain within a current debate among academics and regulators with appealing and open research questions.

Within the discussion of CRA reputation, a strong background is provided by Dimitrov et al. (2015), Opp et al. (2013), and Cheng and Neamtiu (2009). The latter concludes that CRAs react by improving their credit analysis when there is increased regulatory intervention or reputation concerns. Nevertheless, limitations are found in Dimitrov et al. (2015) since they have contrasted reputational versus disciplining hypothesis providing predictions on rating levels with not enough delineation between the two hypotheses.

3.2.2 Solvency II in Europe

An important element to comprehend the evolution of FSR (Chapter 5), the relationship between rating disagreements and rating migration (Chapter 6), and market impact of FSR (Chapter 7) is the regulatory framework that is in place. The three major regulatory frameworks worldwide are Solvency II (SII) for Europe, Swiss standards (SST) and U.S. Risk Based Capital (U.S. RBC) standards. This section and the following will expand on SII and U.S. RBC standards since both cover the two largest insurance markets in the world, containing about 70 per cent of the global life and non-life premiums in 2006 (Holzmüller, 2009).

The relevance of providing the literature about regulation is to shed light on the additional factors that can influence the financial strength of insurers. Agreeing with Klein (2019), depending on how it is structured and managed, insurance regulation can improve market performance, have no impact, or cause significant problems in the market (e.g., higher premiums).

Following the 2008 financial crisis there was renewed scrutiny of CRAs and rules in several financial industries. Basel II & III in the banking industry have aimed to redress the identified weaknesses of the industry by providing new guidance on capital requirements (Gatzert and Wesker, 2012). Mimicking the banking industry, Solvency II (SII) has been developed by the Omnibus directive – the EC - to harmonize regulatory standards across Europe tailoring the framework to insurance industry risks (Bryce et al., 2016; Laas and Siegel, 2016). Solvency II has been in effect since January 1, 2016, setting out various reporting requirements for insurance companies (Mezöfi et al., 2017). Hence, supervision has profoundly been reformed by forcing insurance undertakings to provide capital reserves to protect policyholders.

With the entrance of SII in the regulatory landscape, new research themes arose in connection with the implementation. Overall, SII was built upon a total a market value approach; Value at Risk methods; capital requirements and risk management models (van Bragt et al., 2010). Briefly, the framework is based in three pillars. The first pillar carries the calculation of Solvency Capital Requirement (SCR) (which holds a 99.5% interval of confidence) and Minimum Capital Requirement (MCR) over a one-year span (Ferriero, 2016); Pillar II shots to enhance procedures of governance and supervision; while Pillar III is based on disclosure through the reproduction of solvency and financial reports (Gatzert and Wesker, 2012). Relative to credit ratings, SCR could use credit ratings in its calculation, while MCR is an absolute floor and is not based on external credit ratings aiming to reduce rating overreliance (Tran, 2015). Up to the Q2 2017, insurers have healthy solvency positions on average. The SCR ratio of the majority of solo insurance undertakings is above 200% and hence twice as much as the regulatory requirement (100%) (EIOPA, 2017).

In line with SII, several authors are converging to provide technical interpretation of SCR where Christiansen and Niemeyer (2014) and Mezöfi et al., (2017) are highlighted. Mezöfi et al. (2017) provides support for the square-root formula used for the SCR calculation. Bølviken and Guillen (2017) on the contrary, propose SII enhancements by using a log-normal distribution in the calculations. On the other hand, Laas and Siegel (2016) and Gatzert and Wesker (2012) compare SII against Basel II/III for banks in terms of SCR and MCR. On ratings, Höring (2013) stands as they endeavour the effect of SII on insurers investment strategies by comparing the restrictions of SII's capital requirements –which pursuits a 99.5% confidence level- with the restrictions for an 'A' rating by S&P that targets 99.4%. He found that SII is less restrictive, and S&P is only more restrictive for equities, alternatives and European sovereign debt. Despite the above literature progresses, potential effects of SII on European insurance ratings remain as a likeable and open question.

To this respect, CRAs have manifested that FSR on insurers will likely be unaffected. For instance, S&P arguments that they base their view on capitalization mainly on their risk-based capital model unless they determine a significant risk of breaching the MCR. What S&P recognize as a possible impact is the rating on hybrid instruments. If an issuer's solvency ratio comes under stress due to the regulation, it could lower the hybrid ratings to reflect the increased risk of coupon non-payment.

On the other hand, it is worth mentioning that with Brexit, the government has been reviewing the SII insurance capital rules for the U.K. and is likely to make changes to them in what would be the first big post-Brexit adjustments in U.K. financial regulation. Certainly, the U.K. had the same transposition deadline as the rest of the EU to 31/03/2015 but they were a member state until 31.01.2020. So far, U.K. insurance industry has been strident for the rules to be diluted arguing for cuts to the capital buffers they are required to hold (Financial Times, 2021). Therefore, the study about the particular case of U.K. and SII is another open area for future research.[16]

3.2.3 U.S. regulatory framework: State regulation and NAIC RBC standards.

As briefly mentioned in Chapter 2, there are some institutional features that distinguish the U.S. insurance market. One of the main features is that the primary regulators of the business of insurance are the fifty states, the District of Columbia, and the five U.S. territories. Each state has an insurance official/commissioner which are coordinated through the National Association of Insurance Commissioners (NAIC), a voluntary and non-profit organization

[16] Brexit refers to the withdrawal of the U.K. from the European Union (EU) and the European Atomic Energy Community (EAEC or Euratom) at 23:00 31. More information can be found in https://www.gov.uk/brexit.

established in 1871. In parallel, U.S. federal government plays an important role by offering assistance and funding through a range of agencies and programmes. For instance, the addition of the Federal Insurance Office (FIO) within the Treasury as established by part of the 2010 Dodd-Frank Act.[17]

State-based regulation implies that insurance commissioners oversee insurers' admission and licensing; underwriting; products and prices; claims handling; solvency and investments; transactions among affiliates; reinsurance, among others. At the same time, commissioners are not autonomous and face a number of constraints in exercising their authority (Klein, 2005). III (n.d.) argues that while the regulatory processes in each state vary, three principles guide every state's rate regulation system: adequate rates to maintain insurers' solvency, but not excessive to lead to exorbitant profits and nor unfairly discriminatory.

On the other hand, Cummins et al., (2015) argues that since 1980, there have been no major changes in state regulation except for the adoption of the risk-based capital (RBC) system in the early 1990s. U.S. RBC standards were introduced in 1994 by the NAIC driven by a series of large-company insolvencies in the late 1980s and early 1990s (NAIC, 2020). The Solvency approach is based on a current/target comparison between the available (adjusted) capital and the required (risk-based) capital as at the balance sheet date. Intervention by the regulator is permitted at various 'trigger levels'. i.e., company action, regulatory action, authorized control and mandatory control levels.

The standards aim to incorporate the size and risk profiles of insurers when determining capital requirements. To account for the differences between lines of business, the framework contains three separate formulae to calculate the required capital for P/C and L/H insurers. By subsector, the P/C formula includes charges for underwriting, credit, asset and growth risk (Holzmüller, 2009). The formulas are reviewed annually to keep up with the evolving landscape and overall, the RBC system is periodically updated to meet the changing regulatory environment.

With the 2010 Dodd-Frank Act, insurance state-based regulation was covered by the creation of the Federal Insurance Office (FIO). It also included some reinsurance reform and changed the basis for regulation and taxation of surplus lines insurers (NAIC, 2011). The FIO was

[17] The U.S. state-level regulatory nature stems from the McCarran-Ferguson Act in 1945, and the Financial Services Modernization Act of 1999, currently known as the Gramm-Leach-Bliley Act. The Gramm-Leach-Bliley Act affirmed that states should regulate the business of insurance by declaring that the McCarran-Ferguson Act remained in effect (NAIC, 2011).

granted limited authority to enter into covered agreements with other nations on insurance regulatory matters and represents the U.S. at the International Association of Insurance Supervisors (IAIS). For example, FIO (2020) documents the ongoing dialogues projects; EU-U.S. Insurance Dialogue Project and U.S.-UK Insurance Dialogue Project. Nevertheless, the primary state insurance regulatory functions remain as they have been since the enactment of McCarran-Ferguson in 1945. This allows states to perform solvency oversight of the U.S. insurance industry and to regulate insurer behaviour in the marketplace.

It has been argued that actions by state and federal regulators and the NAIC, among other factors, helped limit the effects of the financial crisis. Many in the insurance industry regard the current state system as overly complex, anticompetitive and unduly burdensome (III, n.d.). Thus, it wouldn't be surprising to observe reform proposals in the U.S. insurance industry in the long term.

Considering both market discipline and reputational theories, a summary of some of the previously cited literature is collated in Table A 3.2. The table is evidence that regulatory regimes vary widely throughout the world, and therefore regulators' financial strength criteria vary accordingly.

3.3 The role and determinants of insurers' credit ratings

One of the major research themes relevant to this thesis is the role of FSR, their determinants, and the probability to be rated. From the literature strand about FSR determinants, the most cited studies are Pottier (1997), Pottier and Sommer (1999), and Adams et al., (2003). Pottier (1997) provides a foundation for subsequent research with their study on the relationship between insurer risk and ratings for U.S. life insurers rated by AM Best. His results show that higher liquidity, lower leverage, large and mutual insurers are likely to receive higher ratings while insurers that invest in affiliate companies, common stock, real state, and non-investment bonds are likely to receive lower ratings. With regard to profitability, the effect on ratings is unclear.

Building upon his research, Pottier and Sommer (1999) extends out in three major areas, i) factors influencing the decision to obtain one or multiple ratings, ii) the determinants of FSR by AM Best, S&P, and Moody's, and iii) reasons for rating disagreement among CRAs (see Section 3.4.4). Above those areas of research, Pottier and Sommer (1999) install the view that insurers' ratings are important to market participants. They assert that FSR is a tool used by insurers in their advertising strategy to convince buyers of the firm's strength, a tool used by brokers to avoid recommending unrated insurers or insurers with ratings below a cut-off point of financial strength, and a tool employed by consumers in their insurance policy buying process. Several studies have continued adding arguments to the importance of FSR, e.g., Doherty and Phillips (2002) who argue that FSR is used as a signal of the firm's financial strength, and Wade et al., (2015) focus on the effect of FSR announcements.

Common issues spring from Adams et al., (2003). These authors focus on the likelihood to be rated and determinants of financial strength of insurers in the U.K. finding that lower values of leverage and amount of reinsurance push higher ratings, whereas greater values of profitability, liquidity, growth, company size, and organizational form impulse higher ratings. In addition, mutual insurers are more likely to be rated than stock ones. Breaking down their results by CRAs, findings for AM Best indicate that higher levels of profitability and liquidity lead to higher ratings as well as mutual insurers compared to stock insurers. Meanwhile, for S&P, higher levels of profitability and liquidity lead to higher S&P ratings while the negative relation of low leverage and ratings indicate lower leverage push a higher S&P rating. This last finding suggests that S&P places more weight on leverage in determining FSR compared to AM Best.

Consistent with prior studies Gaver and Pottier (2005) discuss that FSR is also relevant since they influence the price insurers can charge for their policies, thus an understanding of the rating process is beneficial for the insurance firms themselves, regulators, stockholders, and consumers. Their main results indicate that capitalization proxy by ‘equity/assets’ ratio, liquidity using ‘cash flows/assets’ ratio, profitability measure by ‘dividends/income’ relation and size of the insurer are associated with higher ratings. A relevant implication of their results and particularly linked with Chapter 7 of this thesis is that financial characteristics are found to be relevant in individual firm ratings but also apply to consolidated group ratings assigned by AM Best.[18]

Latter developments came with Florez-Lopez (2007). They propose a new methodology for the analysis of rating determinants. The study claims that research on insurance firms is limited and does not offer very clear results about feature selection, models, methods, and accuracy results. Using a three-step model that performs a selection process mixing statistical, Bayesian, and machine learning approaches, they employ the proposed model into a sample of S&P “pi” ratings from European insurers. Results indicate that seven financial ratios are relevant, regarding liquidity, profitability, and size of the firm.[19]

More recently, Wade et al., (2015) draws upon Pottier and Sommer (1999)’s work regarding the importance of FSR in their effort to examine a subset of short-sellers around FSR announcements (see more in Chapter 7). They distinguish the fact that during the individual insurance purchasing process, brokers and agents recommend coverage based on the ratings provided for a specific company, whereas corporate insurance consumers require that all their insurers be highly rated. To end, Caporale et al., (2017) contribute to the discussion on determinants with a special focus on the systematic risk of insurers. They found that size is one of the most important factors in determining credit risk, where, large firms exhibit greater levels of diversification, income, and loss absorbing capacity. Insurance-specific risk factors are also employed as such: claims change, gross premium written, combined ratio, line of business concentration.

For the purposes of this thesis, this literature strand serves to distinguish particularities of the insurance firms, especially in Chapter 7 when selecting the control variables for modelling the

[18] Stock insurers refer to shareholder-owned while mutual insurers refer to policyholder-owned.
[19] “Pi” ratings refer to those based on the examination of published financial information and additional information in the public domain, sufficient to support a rating opinion.

effects of FSR actions on stock market. Table A 3.1 comprises the above papers on determinants and the expected relation to FSR.

3.4 Behaviour among CRAs

The second research question of this thesis proposed in Chapter 6 is focused on split ratings and rating migration. Before embarking on the research question, several studies were found as well as other dynamics across CRAs worth reviewing in this section. Among these are, competition effects of CRAs on ratings, lead & lags, herding behaviour, and split ratings.

3.4.1 Competition among CRAs

In the discussion around reputational concerns of CRAs and their competition effects on ratings, Becker and Milbourn (2011) stands out in the literature. Taking elements from reputational theories, their results advocate that the entrance of Fitch coincided with higher ratings, suggesting that increasing competition reduces industry rents, and thereby diminish incentives to invest in rating accuracy. Several extensions have flourished from these results such as: Bolton et al. (2012); Hirth (2014); Dimitrov et al. (2015); and Bae et al. (2015) (see key findings in Table A 3.3).[20]

Contributions of Bae et al. (2015) are also valuable for this thesis because they compile the two main views developed by the literature around the impact of competition among CRAs on rating quality. In summary, there is a line of argument that claims CRAs do not sacrifice their reputation by inflating firm ratings (supported by Xia, 2014), and another that suggests that competition among them arises from the conflict of interest inherent in their issuer-pay business model (consistent with Bolton et al., 2012; Hirth, 2014). Furthermore, Bae et al. (2015) address the impact of competition among CRAs on rating inflation using Ordinary Least Square (OLS) methods. Controlling for industry effects and firm characteristics, they conclude that Fitch's market share and credit ratings are driven by industry characteristics rather than competition among CRAs.

Specifically for insurers, Doherty et al. (2012) stands out. They tackle the effect of the entry of S&P versus the dominant CRA in insurer ratings (AM Best) and draw implications on the

[20] Higher ratings is not equivalent to the concept of ratings quality. The decrease in ratings quality occurs in three ways: (i) rating levels went up, (ii) correlation between market implied yields and ratings decreased and (iii) ratings ability to predict default decreased (Jones, 2019).

information content of ratings by using both OLS and discrete-time hazard regression models. Doherty et al. (2012) finds that new entrants have incentives to require higher standards relative to the incumbent CRAs for a firm to acquire a similar rating (Miao et al. 2014). Since Doherty et al. (2012) is the only paper on insurers' CRAs competition effects, opportunities to contribute towards this research area remain present.

The timing of rating revisions and/or the interdependence of actions among CRAs is another strand in the literature surrounding CRAs behaviour. How the actions of one CRA may influence the rating action of the other, can cause a phenomenon named herding behaviour (Lugo et al., 2015). Similarly, the tendency of a *CRA follower* incentivized to review their own ratings after the action of another *CRA leader* raises the concept of leads and lags (Güttler and Wahrenburg, 2007). On the other hand, a phenomenon called split ratings has been also an area of exploration as it occurs when the same firm is assigned different ratings by the CRAs (Ismail, et al., 2015). In the following sections, each phenomenon will be explained together with its literature available.

3.4.2 Leads and lags

In the group of papers which analyse when a lead CRA affects the actions of the other CRAs, Güttler and Wahrenburg (2007) for corporates; and Alsakka and ap Gwilym (2010b) and Alsakka and ap Gwilym (2012a) for sovereigns are highlighted (see in Table A 3.3). To study lead and lags, Güttler and Wahrenburg (2007) followed by Alsakka and ap Gwilym (2010b) and Matousek and Stewart (2015) set a trend by using a Granger-like method with ordered probit regression. Overall, through this technique, Güttler and Wahrenburg (2007) conclude that, for corporates, a given change by Moody's generates higher rating intensity adjustments by S&P. Meanwhile, Alsakka and ap Gwilym (2010b) for sovereigns, determine that Moody's tends to lead upgrade actions among the three, and that S&P tends to be the most independent CRA. No study exists on leads and lags among insurance ratings. Therefore, this literature offers methods and findings in other contexts that can be applied in the insurance setting.

In the context of U.S. insurance industry, Milidonis (2013) investigates the lead-lag relationship for changes in bond ratings and FSR using ratings assigned by S&P, Fitch and Egan Jones Ratings. They conclude that investor-paid rating agencies (Egan Jones) lead issuer-paid rating CRAs (S&P and Fitch) in the market for insurance bond ratings. The study also test the lead-lag relationship between changes in bond ratings and changes in FSRs, within the same CRA. On this regard, they find that information flows in both directions between the two types of ratings. This internal flow of information and the lead effect of investor-paid over issuer-paid CRA in changes in bond ratings, point to a link between investor-paid changes in bond ratings and issuer-paid changes in FSR. The author argue that this correspondence is important since FSR encourages market discipline, and are deemed as informative by investors as they are associated with significant cumulative abnormal returns.[21]

3.4.3 Herding behaviour

Turning to the literature about timing of rating actions, herding among CRAs is argued to arise from a reputation argument. Strong reputational concerns create incentives to herd (Lugo et al., 2015), and CRAs with lower reputational capital are more tempted to herd (Mathis et al., 2009). Mählmann (2011) determines that corporate rating inflation is linked with length of the business relationship between the CRA and rated firm and the rating fees.

Following that, Lugo et al. (2015) concludes that Fitch tends to apply more timely downgrades to converge toward Moody's and S&P ratings and not the opposite. Herding arguments also predict that CRAs assigning different ratings (split among CRAs) eventually converge towards the same evaluation. However, on this issue, there is a strong potential for differences among sovereign, corporate and insurance sectors, and for different time periods of investigation. Another limitation of this view is that herding can also come from irrational sources or explanations from behavioural finance where no paper is identified specifically on ratings.

3.4.4 Split ratings

Split ratings or rating disagreements refers to the situation when the same firm receives different rating from CRAs. To talk about split ratings, the concept of opacity also comes into place implying greater information asymmetry between firm insiders, such as managers, and outsiders, such as analysts, rating agents, regulators, and investors (Chen and Pottier, 2015). The more opaque a sector is, the more difficult is to evaluate the financial condition or prospects of a firm.

Ederington (1986) kicked off the discussion on split rating where CRAs disagreements have been attributed to random errors in the rating process. This means that split ratings are related to unsystematic errors in the rating process, which are later corrected by the CRAs rather than different credit assessment between CRAs or to divergences on the methodological approach and weights on the risk factors used by CRAs in their rating process.

[21] The issuer-pay business model implies that the issuer has to pay the CRA to rate its securities or its creditworthiness. Meanwhile, the subscriber-pay business model, o subscribers pay a fee to access the credit ratings and the report issued by the CRA.

A commonly cited paper for insurers in this issue is Pottier and Sommer (1999) who attempt to explain the level of CRAs' disagreement on insurers' creditworthiness. Compared to Ederington (1986) where only 13 percent of the corporate bonds rated by Moody's and S&P received different ratings, Pottier found that 56 percent of the insurers rated by these same two agencies received different FSR. Through ordered-probit models, the authors verified some differences between the agencies' determinants; AM Best focused mainly on capital, profitability, cash, reinsurance, and size measures; S&P focused on capital, profitability, net premium, and investment risk indicators; and Moody's used investment risk and size factors.

Several authors have linked the concept of opacity with split ratings supporting the notion that the insurance industry is relatively opaque. Morgan (2002) found consistent results compared to Pottier and Sommer (1999) and counter to this, Iannotta (2006) argued that banks carry the highest probability of a split rating. Interestingly, Purda (2007) found that one of the most informative variables to anticipate rating changes come from the rating agency itself and its competitors. In one hand, they show that Moody's release of rating watch actions indicate that a rating is under review. On the other hand, they find that disagreements in ratings between Moody's and S&P are both strong signals of upcoming rating changes.

For insurers, there is a gap in the literature for further analysis of insurer split ratings, especially covering a more recent time period and larger data samples. This is one area in which this thesis aims to contribute. Specifically, this thesis extends on Pottier and Sommer's (1999) work, but also adds new insights to the extant literature by proposing a more granular rating scale mapping and using a longer period of analysis. This will be presented in Chapter 4 with the proposed mapping of the rating scale among the four CRAs and in Chapter 6 by analysing split ratings and rating migrations for U.S P/C during 2003-2017.

3.5 Market impact

The third aim of this thesis is to provide a contribution regarding the information content of the FSR actions on the stock market. To do so, the dominant strands of the literature of efficient markets and information content of ratings will provide the theoretical background.

3.5.1 Efficient market hypothesis and information content of ratings

The theory of efficient markets (EMH) (see the seminal, Fama (1970)) holds the idea that the market prices fully reflect all available and relevant information. Due to the financial crisis, renewed attention was placed on the issue of whether financial markets fully exhibit the characteristics associated with EMH or whether behavioural approaches offer potential for more developments in the understanding of the market performance (Hundt et al., 2017). This debate is still ongoing and a vast number of studies have emerged on both strands tackling different issues.

Linking EMH with ratings, Halek and Eckles (2010) compiles the possible forms of market efficiency; strong, semi strong and weak form. First, in a strong-form efficient, there is no information asymmetry, and thus, CRAs' actions/announcements should have no effect on stock prices because any information should already be incorporated. Second, in a semi-strong form efficient market, all historical and present public information is immediately incorporated in stock prices. This implies that in a semi strong efficient market, CRAs' actions are instantly incorporated into prices. Third, in a weak-form efficient market, the capital markets are assumed to contain only the historical information of the firm. Here, valued information contained in rating actions will affect a change in the respective stock prices.

Interestingly, Brooks et al., (2004) add that if CRAs base their rating actions on publicly available information, the EMH predicts that stock prices will not adjust in response to the rating action. Hence, when stock prices are found to react to rating changes, this suggests either evidence against the semi-strong form EMH, or, private information available only to CRAs that has been released into the public domain within the rating action.

Another aspect linking EMH with ratings comes from Holthausen and Leftwich (1986)'s work, who have been widely cited and followed by numerous studies of rating announcements (e.g., Alsakka and ap Gwilym, 2012c; Drago and Gallo, 2016; Hundt et al., 2017; Wengner et al., 2015). Holthausen and Leftwich (1986) found no abnormal returns after the announcement of upgrades but evidence of abnormally low returns in the quarter following downgrades, constituting an asymmetric reaction of security returns to downgrade and upgrade announcements.

Other authors have extended Holthausen and Leftwich (1986)'s work by combining the information channel with the regulation channel that affects investors' demand (e.g., Bolton et al., 2012; Opp et al., 2013). In addressing these issues, the *information content hypothesis* has established the idea that a rating change transfers new information to investors, causing price adjustments immediately after the announcement.

Blending the previous elements, in a market that is not strong-form efficient, the information content hypothesis offers explanations on why a firm's stock price reacts to rating changes. The information content hypothesis suggests that a CRA possesses superior information relative to the public and that its ratings announcements add to the public information set (Halek and Eckles, 2010). Overall, this hypothesis predicts a symmetric reaction to ratings announcements. However, several studies have found that negative announcements affect equity and bond prices more significantly compared to upgrades (see Table A 3.4). Ederington and Goh (1998) suggest that asymmetric market reactions to rating changes may be influenced by the firm's investor relation policy. This implies that positive news are released by the firm itself whereas negative news are disclosed later. Hence, credit downgrades represent information that has not yet reached the market, whereas upgrades confirm information that is already reflected in market prices.

In this regard, Holthausen and Leftwich (1986) aim to explain this asymmetry for the bond market, arguing that *"…the loss function of the rating agency may not be symmetric. Consequently, upgrades may not be as "timely" as downgrades. Second, management's incentives to release information may not be symmetric."*. On the latter point, Halek and Eckles (2010) posit that a plausible choice by insurers' managers may be to delay disclosure of all bad news for as long as possible and reveal any form of good news as soon as possible. Thus, CRAs look as if to be solely the bearers of bad news, while any insurer good news has already been disseminated to the capital markets.

3.5.2 Market impact studies within the insurance industry

As identified in Section 3.2 of this Chapter, insurers' ratings can affect the willingness of consumers to purchase from insurers, brokers may base their decisions on where to domicile business on insurer ratings or changes in FSR can affect insurers' future cash flows.

Within the insurance industry, few authors inspect the influence of several events. For instance, Thomann (2013) examines the impact of the 10 most expensive catastrophes on insurers' stock volatility using daily return data from 1988 until 2006 on P/C insurance stocks from the U.S. Likewise, Park and Xie (2014) analyse the impact of reinsurer downgrades on primary insurers' risk of P/C insurance. Using a logit regression, they found that primary insurers' stock prices react negatively to the downgrade of reinsurers in the event study framework. These results provide evidence that there is presence of interconnectedness between P/C and reinsurers and the market has recognized it.

Related to FSR market effects, Singh and Power (1992) report the outcome of AM Best rating changes on insurance company stock prices from 1980 to 1988. They do not observe any significant impact of rating change announcements on stock prices and conclude that insurer ratings convey no new information to the markets. Singh and Power (1992) results imply that AM Best is most accurately described as a monitor of publicly available information, but it is not a CRA that reveals new information to the financial markets.

Table A 3.4 compiles relevant studies related to market impact of ratings. Uses and extensions of this literature can be also found in Chapter 7.

3.6 Conclusions

This thesis aims to contribute to literature blending insurance and credit rating industries. Prompted by failures of well rated big insurers (e.g., AIG) (Ciumaş et al., 2015), CRAs were blamed for imprecision and delayed actions that entrenched the global recession (Dimitrov et al., 2015; Lugo et al., 2015). Despite the critics, the relevant role that credit ratings have constituted as a key information channel among market participants (Becker and Milbourn, 2011; Alsakka and ap Gwilym 2010a) have become increasingly important, partly due to their riskier profile with the growing integration in financial markets (Caporale et al., 2017).

Respecting the theories and pertinent literature for this thesis, several theories are explored to build a robust basis for the three main research questions of this study. Supported by the notions from the *information theory* and the theory of *financial intermediation*, that information asymmetries exist in financial markets, CRAs' role gains relevance. Regarding the first research question, market discipline also acts as the theoretical background. The fact that updates in regulatory frameworks (e.g., SII in Europe, updates in U.S. RBC standards, and 2010 Dodd Frank Act.) were proposed to remedy the evidenced weaknesses during the financial crisis supports the notions of market discipline. A gap in the literature is revealed in issues such as determinants of FSR and likelihood of an insurance firm to be rated, which partially fall within the scope of this thesis (Chapter 5).

Regarding the impact of the financial crisis on the rating activity of insurers, authors such as Ciumaş et al., (2015) argue that due to over-publicized failures of several large life insurers, more attention by CRAs has been drawn to rate insurance companies. Therefore, alongside the first research question of this thesis, it is expected that the number of rating actions is greater during the financial crisis than during the rest of the period of analysis.

The second research question referred to the behaviour of CRAs can be investigated from several perspectives including leads & lags, herding behaviour and split ratings. In reviewing the literature on each of these phenomena, several gaps are discovered for the insurance sector literature. For instance, the timing of rating actions for insurers and a much more recent analysis of split ratings, represent clear potential contributions. The scope of this thesis is on the issue of split ratings where Chapter 6 examine the relationship between split ratings and rating migration, an aspect that is absent or scarcely studied by academics.

While prior studies have focused on explaining the determinants of split ratings, this chapter focuses on one of the hypotheses used by those studies; the opacity hypothesis. The asset opaqueness hypothesis is aligned with the idea that limited information quality and a high degree of uncertainty about the credit quality of an issuer may lead CRAs to disagree about its rating. Therefore, it is hypothesized that CRAs will disagree more frequently about the ratings of insurers within the speculative grade of the rating scale (a proxy for more opaque issuers) than for those with investment grade ratings.

Concerning the third research question, do FSR rating actions induce market impact?, a broad agreement is found in the literature on the information content of ratings, where downgrades affect prices more than upgrades. However, a gap still exists specifically in the case of insurance ratings whereby a very limited group of authors opines to the matter (e.g., Halek and Eckles, 2010; Miao et al., 2014; Singh and Power, 1992). Chapter 7 aims to contribute to this matter and uses an event study methodology to test it. Inferences about Cumulative Abnormal Returns (CARs) are drawn by testing the null hypothesis that the average excess return equals zero. If the null hypothesis is rejected, the study can support the claim that FSR actions (events) have a statistically significant effect on the insurer's stock price. In addition, a hypothesis can be drawn regarding to AM Best, as follows. As a specialized CRA, AM Best is the CRA that is commonly linked with the insurance industry. Thus, it is expected that AM Best FSR actions on P/C insurers induce a stronger impact on the stock market than the actions of other CRAs.

To conclude, despite all the related literature developments (in the context of each of the three research questions and hypothesis), the recent evolution of FSR across time and CRAs, behaviour of insurers' CRAs, and the market impact of FSR, the revealed gaps in the literature motivate and provide relevance for embarking upon these directions within this thesis.

Appendix 3.I – Supporting tables

Table A 3.1 Summary of literature on determinants of FSR

Ratio type	Ratio used	Relevant studies	Expected relation to FSR
Leverage	Equity/Assets	Gaver and Pottier (2005)	(+)
	Debt/Equity		(-)
	Property-liability loss reserves to assets		(?)
	Ratio of accumulated reserves to total assets	Adams et al., (2003)	(-)
	Net premiums written to capital	Pottier (1997)	
	Net technical provisions/Adjust liquid assets	Caporale et al., (2017)	
Profitability	The ratio of annual investment and underwriting income (net of expenses), plus unrealised capital gains, to statutory capital.	Adams et al., (2003)	(+)
	Income/Assets	Gaver and Pottier (2005)	(+)
	Investment income / Investments		(+)
	Losses & expenses / Premiums		(-)
	Dividends / Income		(+)
	ROE	Pottier (1997)	
	Under writing profit to total assets	Caporale et al., (2017)	(+)
Liquidity	Cash / Total assets	Caporale et al., (2017)	(+)
	Cash / Investments	Gaver and Pottier (2005)	(+)
	Ratio of liquid assets to deposits and short term funding	Adams et al., (2003)	(+)
Growth	Change in the natural logarithm of total admissible assets	Caporale et al., (2017)	(+)
Company Size	Natural logarithm of total admitted assets	Pottier (1997) Adams et al., (2003) Caporale et al., (2017)	(+)
	Log of assets	Gaver and Pottier (2005)	(+)
Organizational form	Mutual or non mutual	Pottier (1997) Adams et al., (2003) Caporale et al., (2017)	(?)
Reinsurance	Ratio of reinsurance premium	Adams et al., (2003)	(?)
	Premiums ceded to gross premium written	Caporale et al., (2017)	
Business activity	L/H or P/C insurer	Adams et al., (2003)	(?)

This table reports summary of studies investigating the most common determinants of FSR and the variables used. Gaver and Pottier (2005) refers to Capitalization instead of leverage. Also, they use "Asset risk" as a determinant measured by the ratio of stocks/investments and reinsurance/assets. Adams et al., (2003) refers to business activity as the distinction of the business line, long-term: life insurers and short-term: property-liability. The sign (?) means that no expected relation was defined in the cited study.

Table A 3.2 Relevant studies on market discipline notions

Theoretical approach	Representative studies	Regulation	Rating segment	Key findings
Market discipline	Cheng and Neamtiu (2009)	Sarbanes–Oxley Act (SOX), Credit Rating Agency Reform Act of 2006	Structured finance	CRAs respond by improving credit analysis when there is increased regulatory intervention and/or reputation concerns
	Ma and Pope (2019)		Insurers (U.S.)	They found that while publicly traded insurers have indeed experienced a significant reduction in loss reserve errors subsequent to SOX, the reduction is not attributable to SOX. These results hold true under a handful of robustness analyses.
Reputational theories	Opp et al. (2013)	Dodd Frank Act.	Banks	Remarks on the double use of ratings in an informative and regulatory role (e.g., the use of ratings in determining bank capital requirements)
	Dimitrov et al. (2015)		Corporate bonds	CRAs lower their ratings following Dodd Frank when their reputation is more valued.
Analysis of regulatory frameworks	Höring (2013)	SII	Insurers (Europe)	SII's capital requirements are less restrictive than conditions from an A rating of Standard and Poor's (S&P).
	Christiansen and Niemeyer (2014)		Insurers	Compare interpretations of SCR definition from the literature and generalizes
	Mezöfi et al. (2017)		Insurers	Supports the square-root formula used for the SCR calculation
	Bølviken and Guillen, (2017)		Insurers	Proposes SII enhancements by using a log-normal distribution in the calculations
Comparison between regulatory frameworks	Eling et al. (2008)	SST, SII and U.S. Risk-Based Capital standards	Insurers (Switzerland)	Discuss Swiss Solvency Test (SST) finding that the framework is based on a realistic economic model and its effects can be generalized to other approaches such as SII
	Holzmüller (2009)	SST, SII and U.S. Risk-Based Capital standards	Insurers (U.S., Europe and Switzerland)	Provides an analysis of risk-based capital requirements, with a focus on property/casualty insurance, as implemented in U.S., the European Union and Switzerland. They find various shortcomings of the standards used in the U.S. and indicates a need for reform in that country. SST and SII perform generally well.
	Gatzert and Wesker (2012)	Basel III vs SII	Insurers	Compare SII against Basel II/III in terms of SCR and MCR
	Laas and Siegel (2016)		Insurers and banks	Substantial discrepancies in the design of the frameworks involving different capital requirements (higher for banks)
	Dacorogna (2018)	SII vs SST	Insurers	Review of the changes experienced by insurers with the ascent of risk-based solvency comparing between SII and SST.

This table reports summary of studies on regulatory frameworks pertinent for the banking and insurance industries, and associate those into a theoretical approach. In this table, the Swiss Solvency Test (SST) is the regulatory solvency framework adopted in 2006 for Swiss insurance companies to implement risk-based capital standards with the same approach as Basel II and U.S. risk-based capital standards correspond to the framework in that country (Eling et al., 2008).

Table A 3.3 Relevant studies on behaviours among CRAs

Theoretical approach	Representative studies	Phenomenon among CRA	Rating segment	Key Findings
Reputational theories	Becker and Milbourn (2011)	Competition effect	Corporate bonds	Increased competition from Fitch coincides with lower quality ratings from the incumbents.
	Hirth (2014)		Across segments	Provide features about how CRAs' behaviour can be honest, concluding that rating inflation induces investors to be less trusting.
	Xia (2014)		Corporates	Significant improvement in S&P's ratings quality following the entrance of Egan-Jones Rating Company (EJR), an investor-paid rating agency.
	Bae et al. (2015)		Corporate bonds	Credit ratings are driven by industry heterogeneities rather than competition among CRAs.
	Doherty et al., (2012)		Insurers	The market entry of a new CRA in the insurance rating market (S&P) can improve ratings quality and precision.
	Bolton et al. (2012)	Upward bias in ratings	Across segments	Competition reduces efficiency as it enables rating shopping, and that ratings have an increased chance of being inflated in booms as investors are more trusting.
	Mathis et al. (2009)		Structured finance	Reputational concerns and asset complexity are stronger for CRAs with lower reputational capital.
	Opp et al. (2013)		Banks	Regulatory use of ratings.
	Güttler and Wahrenburg (2007)	Leads & Lags	Corporates	For corporates, a change by Moody's generates intense higher rating adjustments by S&P
	Alsakka and ap Gwilym (2010b)		Sovereigns	For sovereigns, Moody's is the first mover in upgrading sovereigns, while S&P rating changes are the most independent of other CRAs.
	Alsakka and ap Gwilym (2012b)		Sovereigns	For sovereigns, Moody's tends to be the first mover for positive outlook and watch signals, while S&P exhibits the least links with other CRAs' outlook or watch actions.
	Lugo et al. (2015)	Herding behaviour	Structured finance	Agents might decide to "hide in the herd", and reduce the likelihood of being punished in case of inaccuracy of rating action.
Information theory	Pottier and Sommer (1999)	Split ratings	Insurers	Provide evidence that different cut-offs can explain the high frequency of disagreement between Moody's and S&P.

This table provides a summary of studies related to phenomena among CRAs and associate those within a theoretical approach.

Table A 3.4 Relevant studies on market impact of credit ratings

Theoretical approach	Representative studies	Rating segment	Key findings	Findings related to CRAs
EMH	Halek and Eckles (2010)	Insurers	Significant negative abnormal returns are associated with any marginal downgrade of an insurer, but there is no consistent increase in returns associated with marginal rating upgrades	For AM Best and S&P rating upgrades, there is no significant corresponding change in returns. Slightly significant increase in returns after an upgrade from Moody's.
EMH	Alsakka and ap Gwilym (2012c)	Sovereigns and foreign exchange	Stronger market reactions to negative in contrast to positive credit signals on the foreign exchange spot market.	Fitch signals induce the most timely market responses, and the market also reacts strongly to S&P negative outlook signals.
Information theory	Miao et al., (2014)	Insurers	For insurers, downgrades have larger impact on bond prices than upgrades and stable ratings events.	Fitch elicits the largest price response. Results do not show that ratings changes from AM Best generally yield stronger results in terms of CARs.
EMH	Wengner et al. (2015)	Structured finance	Positive cumulative abnormal changes in Credit Default Swaps' spreads exist around the announcement date as well as downgrades.	It only uses credit rating data from S&P, finding evidence of asymmetric market reaction around credit upgrades and downgrades for the total sample and at the industry level.
Information discovery, monitoring and certification effect theories	Drago and Gallo (2016)	Sovereigns	Impact of a sovereign rating announcement on the credit default swaps (CDS) market. Rating changes (downgrades and upgrades) introduce "new" information, affecting investors' riskiness perception.	S&P outlooks and reviews are not relevant for investors. As robustness, data from Moody's and Fitch is used but they do not observe relevant differences for downgrade and rating warning announcements. Upgrades issued by Moody's do not have a significant impact on the CDS market, in contrast to upgrades issued by S&P and, to a lesser extent, by Fitch.
EMH	Hundt et al. (2017)	Structured finance	They analyse the Convertible Bonds price effects following the announcement of rating changes by using event study methodologies. They find that compared to downgrades, the non-significance of upgrades supports the asymmetric response of investors during upgrade and downgrade.	They expect that rating changes announced by S&P's would induce a stronger security price effect. However, coefficients of Fitch and S&P's indicate that there is no difference between rating changes announced by S&P's and Fitch compared to Moody's.

This table provides a summary of studies related to market impact of credit ratings and associate those within a theoretical approach. Halek and Eckles (2010) includes AM Best, S&P, Moody's, and Weiss. Alsakka and ap Gwilym (2012c) includes Fitch, Moody's and S&P during 1994– 2010. Wengner et al. (2015) only includes S&P. Drago and Gallo (2016) uses S&P as main results and robustness tests, they use Moody's and Fitch. Hundt et al. (2017) uses Fitch, Moody's, or S&P's between the years 2000 and 2010.

Chapter 4. Database construction

4.1 Introduction

In Chapter 3, empirical findings and theories surrounding insurers' credit ratings were reviewed. As noted, there is very little recent empirical literature on insurance companies' ratings published in academic journals, with a heavy focus instead on sovereigns, structured finance and corporate ratings after the global financial crisis of 2007-10. For this thesis to address any void in the literature in this research area, a crucial point is to ensure data quality as well as data coverage. This Chapter brings together common points that apply to the subsequent empirical Chapters 5, 6, and 7. It provides an overview of the dataset for insurers' ratings, and proceeds to discuss a series of steps undertaken to prepare adequate datasets for the research direction of this thesis. Indeed, the novelty of the research questions of this thesis is reinforced by the uniqueness of the data, which is built by combining information from the four most active major CRAs in the insurance industry, namely S&P, Moody's, Fitch, and AM Best. As explained in Chapter 2, each CRA has its own definitions, terminology, and rating scale. Therefore, there is a need for this chapter to underpin the subsequent three empirical chapters.

Prior literature have used insurers' ratings to investigate several issues discussed in this thesis, yet many studies focus on a shorter time period or examine data from only one or two CRAs (e.g., Florez-Lopez, 2007; Gaver and Pottier, 2005). For instance, Pottier and Sommer (1999) have a dataset of 1678 individual Property and Casualty (P/C) insurers involving AM Best, S&P and Moody's ratings, however the time period of analysis is a onetime snapshot i.e., July 1996 only. Similarly, Pottier and Sommer (2006) use a dataset of 161 insurers to address insurers' opacity, nonetheless, it employs one year of data only, for 1997. Doherty and Phillips (2002) provide a much wider time period of analysis from 1993-2000 and a sample of 13,989 firm-year observations but their work only focuses on AM Best rating data (See more detail in Table 4.7 in Section 4.4). More recently, the majority of researchers have continued to employ only AM Best data arguing that the traditional insurance literature commonly focuses on AM Best ratings alone (e.g., Chen et al., 2018) or that stronger results have been found with AM Best when reporting cumulative abnormal returns around announcements (e.g., Wade et al., 2015). Each of these approaches to datasets is unsatisfactory for a researcher seeking to present a comprehensive review of specific research questions, as is the case in this thesis.

This thesis employs a rich dataset of Long Term (LT) – Local currency (LC) Financial Strength Ratings (FSR) of U.S. Property/Casualty (P/C) insurers from the main four CRAs during the period from January 2000 to December 2017. The choice of the sample period reflects the most recent available data at the time of commencing the research for this thesis, while capturing the intersection across CRAs. Table 4.1 summarizes the key aspects considered when embarking on the data collection. The most substantive points arise from using FSR as the measure preferred for analysis, the stratification factors linked to FSR such as firm level, country of analysis, the CRA that assigns the rating, the long or short-term nature of the rating and the data sources used.

The remainder of this chapter is organised as follows. Section 4.2 describes the data sources, Section 4.3 provides details of the data selection by CRA, the matching process and the final sample, Section 4.4 expands on the comparisons with prior literature, Section 4.5 explains the numerical rating scale transformation adopted in this thesis, and Section 4.6 concludes.

Table 4.1 Data collection overview

Measures	Stratification factors	Sampling notes	Sources
Discrete categorical variable: FSR	By industry subsector By firm level By country By CRAs By long term (LT) By local currency (LC)	**Sample period**: Chapter 5: January 2000 to December 2017 Chapters 6 and 7: January 2003 to December 2017 **Sampling interval**: Chapters 5 and 6: Annual Chapter 7: Daily **Initial scope of dataset:** Global **Scope of dataset used in Chapters 5, 6 and 7 :** U.S. P/C **Main selection criteria**: Insurer must be FSR-rated by at least two of the four CRAs	**Data sources:** S&P Capital IQ® (Capital IQ) AM Best database Moody's and Fitch websites The ratings are transformed according to a 20-point numerical rating scale and 13-points rating scale in Chapters 5, 6 and 7.

This table provides an overall view of the data collection process portraying FSR as the main variable of analysis and the major factors involved in the decision-making for compiling the final data sample used in this thesis.

4.2 Data sources

The core database used for this thesis is S&P Capital IQ® Platform (hereafter "Capital IQ"), supplemented with Moody's Investors Service and Fitch websites, and a Bangor University subscription to AM Best database. Information at firm-level including insurers profile, major line of business (subsector), share prices, accounting and financial data used in Chapter 7 are mainly sourced from S&P Global Market Intelligence.[22]

Capital IQ is a powerful source of financial data, analytics and research with about 65,000 public companies and 15 million private companies profiled. It combines deep information on companies, markets and considers four big groups of industries: corporates, financial institutions, insurance, and governments. Within the platform, RatingsDirect is a component for credit analysis, which for insurers offers Issuer Credit Ratings (ICR), FSR, Financial enhancement, financial program, and resolution counterparty ratings on issuer and issue level. Likewise, the platform provides a distinction in terms of the rating categories review in Chapter 2 such as short/long term rating, local/foreign currency and global/national or regional scale credit ratings as factors to consider.

Moody's Investors Service provides information for corporates, financial institutions, funds and asset management, infrastructure and project finance, sovereign and supranational, structured finance, sub-sovereign, U.S. public finance and insurers. Within insurers, the website present ratings by industry subsector; financial guarantors, insurance brokerage, life & health, mortgage insurance, multiline, P/C, reinsurance and title insurer. By region, Moody's divides information from North America, Latin America & Caribbean, Africa, Europe, Middle east, Asia pacific, as well as political/economic groups such as Association of Southeast Asian Nations (ASEAN), Commonwealth of independent states, emerging markets, European union, Gulf cooperation council. Although Moody's assess less insurers than AM Best or S&P, it has acquired a solid reputation for reliability and expertise in its work in insurance rating (Ciumaş et al., 2015).

Fitch Ratings website also displays rating information by market sector (Autos, aviation, banks, chemicals and fertilizers, corporate finance, energy and natural resources, fund and asset managers, healthcare and pharma, insurance, among others), by region (North America,

[22] S&P Global Market Intelligence was renamed as S&P Capital IQ Pro in August 2021. The name change did not affect any of the content, features, and functionality within the platform.

Europe, Asia-Pacific, Latin America, Middle East and Africa), and information can be classified by report type, and language.

With regard to AM Best, as it is the only CRA specialized solely in rating insurers; the database provides information by ‘primary business type’ as follows; P/C, Life, Annuity and Accident, Health, Title, Composite, Healthcare Provider, Unknown/Unavailable, and Not Followed. Company name is associated with NAIC number, Federal employer number – FEIN, and type of rating is shown as FSR, long/short term ICR, issue credit ratings all linked with report dates. Compare to the other CRAs, apart from the country of Domicile, AM Best also disclose information detailing not only the country but also the states and provinces in Canada and U.S.

Finally, S&P Market intelligence platform digs deeper in a sector level focusing on financial institutions, insurance, energy, real state, metals and mining and technology, media and telecommunications. Market intelligence contains information of about 62,000 public institutions, including 47,000+ active with current financials. The platform was the main source to obtain the accounting information of the parent companies used in Chapter 7 as proxies of profitability, size, liquidity and leverage.[23]

[23] https://content.naic.org/

4.3 Data collection and selection

This section describes the ideal dataset for insurers, the route taken in the sample collection process and the criteria considered for the inclusion in the dataset. The first step consisted in determining the list of insurance companies to be included, and the subsectors and regions covered by each CRA. As mentioned, each CRA has its own terminology and entity identifier (ID) and at least two of the four largest CRAs (S&P, Moody's, Fitch, and AM Best) must rate an insurer in order to be included in the final sample. After collecting rating information by CRA, an intersection across datasets (hereafter "matching process") has proceeded to build a panel of credit ratings across firms and CRAs. Figure 4.1 illustrates the database construction adopted in this thesis and the research direction taken. The decision to focus on FSR and U.S. data will be derived as this section is develop.

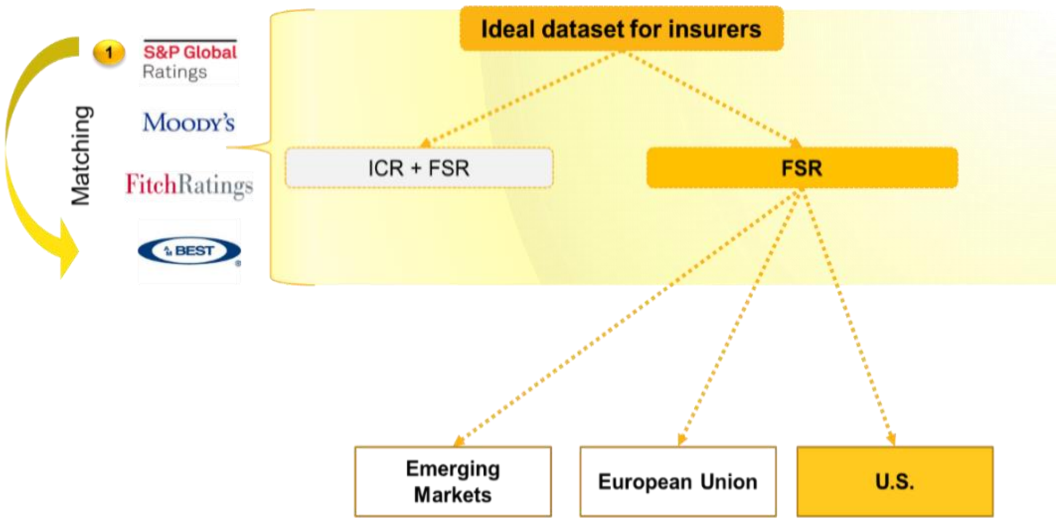

Figure 4.1 Ideal dataset for insurers

This figure represents the research direction taken choosing FSR from S&P, Moody's, Fitch, and AM Best as the focus, as well as the U.S. as the region of analysis. ICR in the figure refers to Issuer Credit Ratings.

4.3.1 S&P data collection process

S&P data is obtained from Capital IQ. The sample is formed by selecting the insurance industry as a filter, which corresponds to 10,738 companies in the database from 1990 up to 2017. The companies are geographically dispersed as follows, 74% corresponds to U.S. companies, 13.8% belongs to insurers from European Union, and 3.5% relates to countries considered as emerging markets. To identify "emerging" countries, the International Monetary Fund (IMF) country classification, is adopted. The choice of the sample as LT-LC is due to the fact that a major portion of ratings is available while Long term - Foreign Currency (LT-FC) ratings are assigned to a very limited number of companies. From the 10,738 insurers, some companies have to be removed as they have a non-rating designation (NR) or ratings are based on "national rating scales”. The remaining sample contains two types of companies. Companies with rating history from 2000 and NR designations at some point of the period, and companies with complete rating history available from 2000 to 2017. The sample shrinks to 5,114 companies, which will be the base sample to be intersected with the other CRAs rating data. The geographical distribution of the 5,114 companies is summarized in Table 4.2 were the U.S. dominates (65%) and where the biggest subsector is Property/Casualty (P/C) insurance.[24, 25]

Table 4.2 Number of sampled insurance companies rated by S&P during 2000 – 2017

Panel A. Region

Country/Region	**No**	**% of total**
United States	3313	65%
European Union	954	19%
Emerging markets	229	4%
Other countries	618	12%
Panel B. Insurance subsector		
Subsector	**No**	**% of total**
Property/Casualty	2923	57%
Life/Health	1581	31%
Reinsurance/Specialty	540	11%
Others	71	1%
Total	**5114**	**100%**

This table shows the number of insurance companies with LT-LC FSR available in S&P Capital IQ. The companies included have either complete rating history available from 2000 to 2017 or rating history from 2000 and NR designations at some point during the period. This table shows the distribution by country/region as well as the distribution by industry subsectors. The countries Bulgaria, Poland, Hungary, and Romania belong to both economic groups ‘Emerging markets’ and ‘European Union’, but are only reported in the ‘European Union’ group. Regarding the insurance subsectors, the category ‘others’ include bonds, title insurers, financial guarantors, multiline, composite insurers. ‘Other countries’ include Australia, Bermuda, Canada, Switzerland, Cuba, Curaçao, Guernsey, Gibraltar, Hong Kong, Israel, Isle of Man, Iceland, Jersey, Japan, South Korea, Cayman Island, Liechtenstein, Macao (SAR China), Monaco, Norway, New Zealand, Singapore, Taiwan.

[24] International Monetary Fund (2018) defines the European Union as composed of 28 countries: Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, Romania, and United Kingdom. All of the data in the thesis applies to the period prior to the withdrawal of the United Kingdom from the European Union on 31st January 2020.

[25] According to International Monetary Fund (2018), emerging market and developing economies are composed of 154 countries as follows. Afghanistan, Albania, Algeria, Angola, Antigua and Barbuda, Argentina, Armenia, Azerbaijan, The Bahamas, Bahrain, Bangladesh, Barbados, Belarus, Belize, Benin, Bhutan, Bolivia, Bosnia and Herzegovina, Botswana, Brazil, Brunei Darussalam, Bulgaria, Burkina Faso, Burundi, Cabo Verde, Cambodia, Cameroon, Central African Republic, Chad, Chile, China, Colombia, Comoros, Democratic Republic of the Congo, Republic of Congo, Costa Rica, Côte d'Ivoire, Croatia, Djibouti, Dominica, Dominican Republic, Ecuador, Egypt, El Salvador, Equatorial Guinea, Eritrea, Ethiopia, Fiji, Gabon, The Gambia, Georgia, Ghana, Grenada, Guatemala, Guinea, Guinea-Bissau, Guyana, Haiti, Honduras, Hungary, India, Indonesia, Iran, Iraq, Jamaica, Jordan, Kazakhstan, Kenya, Kiribati, Kosovo, Kuwait, Kyrgyz Republic, Lao P.D.R., Lebanon, Lesotho, Liberia, Libya, FYR Macedonia, Madagascar, Malawi, Malaysia, Maldives, Mali, Marshall Islands, Mauritania, Mauritius, Mexico, Micronesia, Moldova, Mongolia, Montenegro, Morocco, Mozambique, Myanmar, Namibia, Nauru, Nepal, Nicaragua, Niger, Nigeria, Oman, Pakistan, Palau, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Poland, Qatar, Romania, Russia, Rwanda, Samoa, São Tomé and Príncipe, Saudi Arabia, Senegal, Serbia, Seychelles, Sierra Leone, Solomon Islands, Somalia, South Africa, South Sudan, Sri Lanka, St. Kitts and Nevis, St. Lucia, St. Vincent and the Grenadines, Sudan, Suriname, Swaziland, Syria, Tajikistan, Tanzania, Thailand, Timor-Leste, Togo, Tonga, Trinidad and Tobago, Tunisia, Turkey, Turkmenistan, Tuvalu, Uganda, Ukraine, United Arab Emirates, Uruguay, Uzbekistan, Vanuatu, Venezuela, Vietnam, Yemen, Zambia, and Zimbabwe.

4.3.2 Moody's data collection process

Moody's rating data is retrieved from their official website using the section "coverage list" and this was compared to a list of insurers that was made available from an earlier dataset provided by my supervisor. A total of 4,375 insurers (including withdrawn ratings) appeared to have at least one type of rating available (i.e., long term issuer rating, senior unsecured rating). Once again, the selection is focused on LT-LC ratings ahead of LT-FC when available. From the initial sample of 4,375, only 966 companies have FSR available (both local and foreign currency) but only 897 are LT-LC FSR. Table 4.3 –Panel A shows the distribution by region where the U.S. represents 69% of the total, the European Union 10% and emerging markets 10%. Table 4.3 – Panel B, shows that most of rated companies belong to the P/C subsector (51%), follow by L/H (33%), reinsurers (12%), and others such as financial guarantors, multiline and title insurers add up to 4%.[26]

Using the 897 insurers, the matching process detailed in section 4.3.5 has proceeded in order to determine the companies that meet the main selection criteria: companies must be rated by at least two of the four CRAs.

Table 4.3 Number of sampled insurance companies rated by Moody's during 2000 – 2017

Panel A. Region		
Country/Region	**No**	**% of total**
United States	616	69%
European Union	93	10%
Emerging markets	95	10%
Other countries	93	11%
Panel B. Insurance subsectors		
Subsector	**No**	**% of total**
Property/Casualty	461	51%
Life/Health	293	33%
Reinsurance/Specialty	106	12%
Others	37	4%
Total	**897**	**100%**

This table shows the number of insurance companies with LT-LC FSR available from Moody's website. The companies included have either complete rating history available from 2000 to 2017 or rating history from 2000 and NR designations at some point during the period. This table shows the distribution by country/region as well as the distribution by industry subsectors. The countries Bulgaria, Poland, Hungary, and Romania belong to both economic groups 'Emerging markets' and 'European Union', but are only reported in the 'European Union' group. Regarding the insurance subsectors, the category 'others' include bonds, title insurers, financial guarantors, multiline, composite insurers. 'Other countries' include Australia, Bermuda, Canada, Switzerland, Hong Kong, Israel, Japan, South Korea, Norway, Singapore, and Taiwan.

4.3.3 Fitch data collection process

Fitch data is obtained from the 'coverage list' and the section "rating actions' headlines" on the Fitch website. To complement the data, rating history is also collected from the 'Dodd-

[26] https://www.moodys.com/researchandratings

Frank Rating Information Disclosure Form' that comprises the rating action commentary (RAC) and aspects such as the procedure/methodology used, assumptions/principles, limitations, information uncertainty, the use of third-party due diligence, conflicts of interest, ratings volatility, among others. The coverage list contains 1416 companies with the latest rating action commentary, while the headlines added to 10,056 titles. [27, 28]

Fitch provides both long term/short term ratings, national and international rating scales as well the category of interest, FSR. Within the universe of 1416 companies, only 831 firms have LT-LC FSR, and 242 have ICR available (which Fitch denominates LTR – Issuer). Table 4.4 shows the distribution by region as follows: U.S. relates to the 63% of the list, Europe 18%, and emerging markets represent 8% of the list. Panel B of Table 4.4 presents the subsectors within the insurance industry where 50% refers to P/C, 34% is classified as L/H whereas 9.9% are reinsurers, and others add to 5.5%. Using the 831 insurers, the next stage is to intersect the data with the other CRAs.

Table 4.4 Number of sampled insurance companies rated by Fitch during 2000 – 2017

Panel A. Region		
Country/Region	**No**	**% of total**
United States	521	63%
European Union	153	18%
Emerging markets	64	8%
Other countries	94	11%
Panel B. Insurance subsectors		
Subsector	**No**	**% of total**
Property/Casualty	416	50.1%
Life/Health	287	34.5%
Reinsurance/Specialty	82	9.9%
Others	46	5.5%
Total	831	100%

This table shows the number of insurance companies with LT-LC FSR available from Fitch's website. The companies included have either complete rating history available from the 2000 to 2017 or rating history from 2000 and NR designations at some point during the period. This table shows the distribution by country/region as well as the distribution by industry subsectors. The countries Bulgaria, Poland, Hungary, and Romania belong to both economic groups 'Emerging markets' and 'European Union', but are only reported in the 'European Union' group. Regarding the insurance subsectors, the category 'others' include bonds, title insurers, financial guarantors, multiline, composite insurers. 'Other countries' include Australia, Bermuda, Canada, Switzerland, Guernsey, Gibraltar, Hong Kong, Japan, South Korea, New Zealand, Singapore, and Taiwan.

[27] https://www.fitchratings.com

[28] The Dodd-Frank Act outlines a series of reforms and adds a number of requirements to the CRA market delegating the responsibility of developing specific rules to the SEC and other federal agencies (Dimitrov et al., 2015). The form was available in the previous Fitch website version prior to its update on 29th March 2020 when Fitch launched its new global website (www.fitchratings.com). The website was updated for the first time since 2015.

4.3.4 AM Best data collection process

Rating actions are sources from the AM Best database. During 1990 – 2018, AM Best has issued ratings for 20,478 companies spread in 155 countries. From the total, 13,869 companies have a NR designation, leaving 6,609 companies to intersect with the other CRAs rating data. By region, 71.7% are U.S. insurers, followed by 10.4% European countries, 4.7% are emerging countries, while 13% represents other countries. In terms of the major line of business, 61.7% corresponds to P/C, 34% to L/H, while others classified as multiline, composite and title corresponds to 4.3% of the sample. As mentioned, an intersection across datasets has proceeded in order to build a panel of credit ratings across firms and CRAs.

Table 4.5 Number of sampled insurance companies rated by AM Best during 2000 – 2017

Panel A. Region		
Country/Region	**No**	**% of total**
United States	4736	71.7%
European Union	688	10.4%
Emerging markets	309	4.7%
Other countries	877	13.3%
Panel B. Insurance subsectors		
Subsector	**No.**	**%**
Property/Casualty	4076	61.7%
Life/Health	2248	34.0%
Others	285	4.3%
Total	6609	100%

This table shows the number of insurance companies with LT-LC FSR available from AM Best database. The companies included have either complete rating history available from 2000 to 2017 or rating history from 2000 and NR designations at some point during the period. This table shows the distribution by country/region as well as the distribution by industry subsectors. The countries Bulgaria, Poland, Hungary, and Romania belong to both economic groups 'Emerging markets' and 'European Union', but only reported in the 'European Union' group. Regarding the insurance subsectors, the category 'others' include bonds, title insurers, financial guarantors, multiline, composite insurers. 'Other countries' include Anguilla, Australia, Bermuda, Canada, Switzerland, Cuba, Curaçao, Guernsey, Gibraltar, Hong Kong, Isle of Man, Iceland, Jersey, Japan, South Korea, Cayman Islands, Liechtenstein, Macao (SAR China), Monaco, Norway, New Zealand, Serbia, Singapore, Sint Maarten, Taiwan, and British Virgin Islands.

4.3.5 Results of the matching process

The next stage of the database construction involved combining information from the four CRAs detailed above. The process was done using companies' names, the Legal Entity Identifier (LEI), countries, and in some cases, states. The main challenge was the dissimilar names across CRAs due to abbreviations, characters, language, change of names due to mergers and acquisitions, and so on. For instance, Moody's rating service uses different characters compared to the other CRAs; they use "&" instead of "and" in the company name. For Fitch, all of the headlines - rating actions and company names are in the original language (German, Spanish, Chinese, etc.), thus, translations must be done in these cases. After matching the data across them, a total of 4,409 companies qualifies to be part of the study since they appear rated by at least two of the four CRAs. Figure 4.1 illustrates the intersection of the four datasets. For S&P, the initial 5114 shrinks to 4230 companies, for Moody's, 820/897 companies remain in the sample, for Fitch 731/831 companies meet the criteria, and finally for AM Best, 3036/6609 companies can be included. One can notice that AM Best and S&P rate most insurers compared to Moody's, and Fitch.

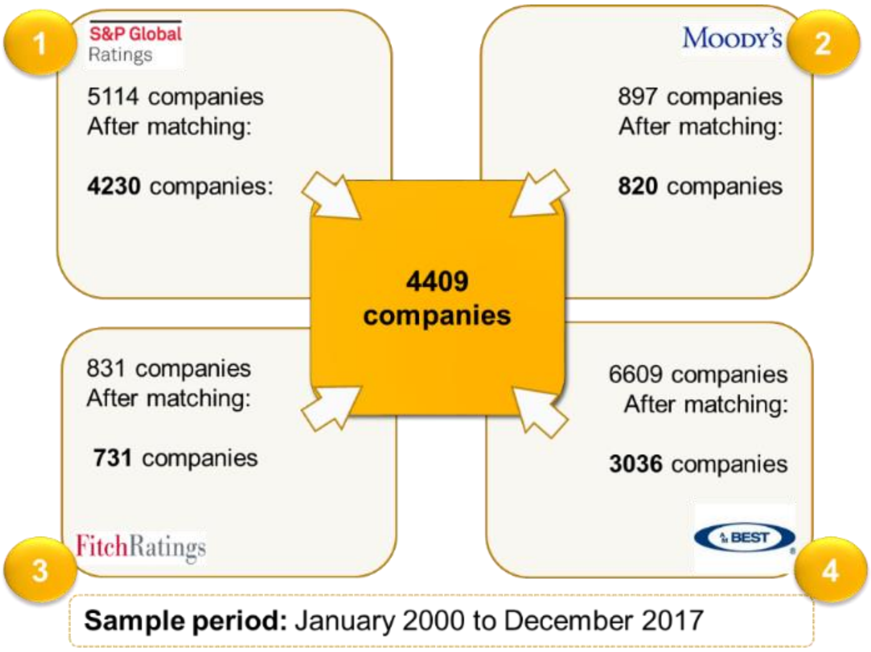

Figure 4.2 Intersection of data across firms and CRAs

This figure shows the global database of LT-LC FSR merge using information from the four main CRAs for insurers during January 2000 to December 2017. The number of companies obtained 4409 is the result of a matching process using companies' names, the Legal Entity Identifier (LEI), countries, and in some cases, states.

Table 4.6 presents the distribution by region and subsector of the 4409 companies worldwide. Consistent with the individual information by CRA, U.S. represents 65% of the global insurance market, and by subsector, P/C signifies the 57.3% of the total. In terms of the number of companies rated by CRAs pairs from the 4409, S&P and AM rate 2927, follow by S&P and Moodys, 713, Moody's and AM Best, 667, S&P and Fitch 642, Fitch and AM Best 601, while as expected, Moody's and Fitch only 380. There are further points of information by CRA pairs in Chapter 5 and 6 when only selecting U.S. P/C.

Table 4.6 Number of sampled insurance companies rated by at least two of the four CRAs during 2000 – 2017

Panel A. Region

Country/Region	**No**	**% of total**
United States	2864	65.0%
European Union	829	18.8%
Emerging markets	235	5.3%
Other countries	498	11.3%
Panel B. Insurance subsectors		
Subsector	**No**	**% of total**
Property/Casualty	2528	57.3%
Life/Health	1361	30.9%
Reinsurance/Specialty	451	10.2%
Others	69	1.6%
Total	**4409**	**100.0%**

This table shows the number of insurance companies with LT-LC FSR after the matching process across the four CRAs. The companies included have either complete rating history available from 2000 to 2017 or rating history from 2000 and NR designations at some point during the period. This table shows the distribution by country/region as well as the distribution by industry subsectors. The countries Bulgaria, Poland, Hungary, and Romania belong to both economic groups 'Emerging markets' and 'European Union', but are only reported in the 'European Union' group. Regarding the insurance subsectors, the category 'others' include bonds, title insurers, financial guarantors, multiline, composite insurers.

4.3.6 Final sample – Country selection

This section describes the final dataset used for the subsequent three empirical Chapters 5, 6, and 7. As mentioned earlier, this thesis employs a dataset of LT – LC FSR of U.S. P/C insurers from the four CRAs during the period from January 2000 to December 2017. The decision to narrow down the dataset to only one country and one subsector is due to several reasons. The choice of the country reflects the fact that about 65% of the global insurance market is in the U.S. and that institutional differences may affect empirical results when mixing different countries (Iannotta, 2006). The selection of P/C reveals the global importance of this subsector especially as a key pillar of the modern U.S. financial system with a 30% share of all financial intermediation in terms of value-added (Becker et al., 2020). Meanwhile, the choice of the sample period reflects the most recent available data that can be intersected across CRAs.

The delimitation of scope also exposes the complexity of the insurance industry. According to Caporale et al., (2017), non-life insurers offer products (i.e., property cover, liability policies) that are more vulnerable compared to those offered by life insurers (i.e., annuities, conventional life insurance). This vulnerability causes a big difference between both subsectors and makes it inappropriate to mix them together. Building upon the dataset of 4409 insurers detailed above, the procedure to follow is to take only U.S. companies and P/C insurers. Regarding each research question, the sample varies depending on additional criteria and methodology as follows.

For the first research question addressed in Chapter 5 which entails the difference in evolution across CRAs of the FSR using rating transitions; the selection procedure results in a final sample of 1384 U.S. P/C insurers rated between 2000 and 2017, where 1335 are rated by S&P, 330 by Moody's, 284 by Fitch and 1372 by AM Best.

The second research question developed in Chapter 6 explores the relationship between split rating insurers and the likelihood of rating migration in the next year. To operationalize the study, a subsample of the dataset used in Chapter 5 is taken. The final sample contains annual observations of FSR assigned by at least two of the four CRAs where the main criteria to qualify is that issuers from both CRAs (in the pair) must exist for at least one year prior to entering the sample for the split – migration calculation. The final sample corresponds then to 904 U.S. P/C insurers rated during 2003-2017. The choice of 2003 is because the number of insurers in the sample for S&P dropped dramatically in 2002 due to S&P announcing the withdrawal of its public information (pi) counterparty credit ratings and FSR on various insurance companies. This arose from their decision to refocus analytical research resources. Moreover, S&P asserts that this decision is mostly in those insurance sectors where S&P already provides significant coverage through its full, interactive rating process (S&P, 2003).

To unravel the meaning of 'pi ratings', S&P (2018) start its rating definitions stating that they use several rating features such as qualifiers, suffixes, identifiers, prefixes, or a combination of these. With qualifiers, S&P aims to limit the scope of a rating, while with identifiers S&P aims to meet regulations. S&P identifiers use words or symbols to provide additional information but do not change the definition of a rating or opinion about the issue's or issuer's creditworthiness. 'Pi ratings' is an inactive qualifier that was used to indicate ratings that were based on an analysis of an issuer's published financial information, as well as additional information in the public domain. However, such ratings did not include in-depth meetings with an issuer's organisation and could have been based on less comprehensive information.

Besides, pi ratings, S&P has another active or inactive identifiers. For instance, to indicate the solicitation status of a rating, S&P (2018) uses a 'u' identifier. For the other CRAs, Cole et al., 2017) state that CRAs have generally discontinued this practice or narrow the type of insurers to which they assign these ratings. This is the case of AM Best who currently does not issue unsolicited ratings (AM Best, 2019), Moody's indicates the unsolicited nature of the credit rating in Disclosure Forms as well as Fitch who disclose the solicitation status of the rating below each FSR action.

In this thesis, only S&P and Fitch offered unsolicited ratings for some part of the sample period. For S&P data, no observation had the 'u' identifier, while for Fitch about 20% of the data used in this thesis seem to have the status of unsolicited. Fitch (2019) clarifies that unsolicited ratings do not happen when public information is insufficient to support a rating, and that the solicitation status has no effect on the level of the credit ratings assigned.[29]

The third research question in Chapter 7 is focused on the market impact of FSR actions on the stock market, and two datasets are required. One from the FSR credit data and one from the stock market related to the parent companies. In general, operating insurers receive an ICR and FSR while the parent company listed in the stock market only receives ICR. To select the FSR actions, the baseline is the dataset used in Chapter 6, 904 U.S. P/C insurers. The sample shrink to 346 U.S. P/C insurers since the parent company related to those insurers must be listed in the U.S. stock market in order to be included in this Chapter. Considering the 346 U.S. P/C remaining, the credit dataset contains daily LT-LC FSR, Outlooks, and Watch actions by S&P, Moody's, Fitch, and AM Best from 1st January 2003 to 31st December 2017. The parent companies of those 346 insurers, they must be listed in the U.S stock market and have share prices available from January 2003 onwards. The final sample contains 30 parent companies.

Overall, the datasets used in Chapters 5, 6, and 7 are constructed in a format containing a time-series and cross-section dimensions using a unique ID per firm and transforming the FSR data using a numerical transformation given the discrete categorical nature of credit ratings. Concerning the three CRAs; S&P, Moody's and Fitch, any CRAs symbol has its counterpart in the other CRAs' rating scale. However, when it comes to transform AM best rating symbols to the other three CRA a challenge is faced. In Section 4.5, the proposed numerical transformation is explained in detail, as it will be use in the subsequent empirical chapters.

[29] In future research, authors should be conscious of unsolicited ratings when selecting the dataset of analysis.

4.4 Comparisons with prior literature

This section places the dataset used in this thesis in the context of previous research. The main purpose is to highlight the enhanced scope for contributions to knowledge by utilising a wider and more recent sample of insurers' ratings from the big four major CRAs. Moreover, there is a need to compare the numerical rating employed in this thesis with prior studies. In prior literature, several authors have used FSR data while applying different methodologies and proposing several ways to define mappings between ratings across CRAs including an alternative four-category system. Table 4.7 presents a summary of studies with their associated dataset compared to the current investigation within this thesis. Panel A details the sample characteristics while Panel B expands on the numerical transformations.

In the literature strand about the determinants of insurers' ratings review in Chapter 3, Adams et al. (2003) use a sample from S&P (40 companies) and AM Best (25 companies) FSR from 40 U.K. based insurers between 1993-1997. Regarding the industry subsector, Adams et al. (2003) focus on life and general insurance industries. Florez-Lopez (2007) take a sample of 257 European non-life insurers with S&P 'pi' ratings (discussed in Section 2.3.2 in Chapter 2) from 14 EU countries (UK, Germany, France, Italy, Netherlands, Spain, Austria, Denmark, Belgium, Sweden, Ireland, Finland, Portugal, and Greece) during the period from January 1999-August 2000. [30]

Regarding the first and second research questions addressed in Chapters 5 and 6. Pottier and Sommer (1999) stands out as one of the first papers to tackle rating determinants and address split ratings with a dataset of 1,678 individual property liability insurers that are rated by AM Best, S&P and Moody's. In terms of the rating scale, Pottier and Sommer (1999) use a 4-points levels to transform their ratings based on the verbal interpretation of the three CRAs, "Superior"/"Exceptional", "Excellent", "Very good/good", "adequate", and "uncertain claims paying ability" of the insurer (see explanations in Chapter 2). They highlight the difficulty to compare below the "adequate" level and that most insurers are place in the higher categories. Furthermore, Pottier and Sommer (2006) address whether some insurers are more difficult to evaluate than others using split ratings as a proxy of opacity. They employ 161 property and

[30] Public information ratings or 'Pi' ratings refer to those ratings with the suffix 'pi' which imply that the examination of published financial information and additional information in the public domain, is considered sufficient to support a rating opinion. The main difference with ratings without the suffix is that they not include in-depth meetings with an insurer's management team and other private information (Florez-Lopez, 2007; S&P, 2018)

liability insurers to focus on the FSR information provided by both Moody's and S&P. In this occasion, the correspondence of the scales between Moody's and S&P is widely accepted where each rating category was assigned a number, with the highest category (AAA, Aaa=1, the second highest as 2, and so on).

Table 4.7 Studies within the insurance industry using FSR rating data

Panel A. Sample characteristics

Research	Type of rating	Region	Subsector	CRAs	Sample size	Period
This thesis	FSR	U.S.	P/C	S&P Moody's Fitch AM Best	Chapter 5: 1384 Chapter 6: 904 Chapter 7: 346	Jan. 2003 – Dec. 2017
Wade et al., (2015)	FSR	U.S.	P/C= 89, L/H= 76	AM Best	165 publicly traded insurers	2005 and 2006
Florez-Lopez (2007)	FSR –Pi ratings	Europe	Non-life insurers	S&P	257	1997-1999
Pottier and Sommer (2006)	FSR	U.S.	P/L	S&P and Moody's	161	year-end 1997 data
Adams et al. (2003)	FSR	U.K.	Life and general insurance	S&P and AM Best	40 – AM Best 25 – S&P 28 – Not rated	1993- 1997
Doherty and Phillips (2002)	FSR	U.S.	P/L	AM Best	13,986 firm-year observations	1993-2000
Pottier and Sommer (1999)	FSR	U.S.	P/L	S&P, Moody's and AM Best	1678 1510 – AM Best 296 – S&P 170 – Moody's	July 1996

Panel B. Adopted methods and rating scale

Research	Method	Rating scale
This thesis	rating transitions matrix, probit models, event study	20-points 13-points
Wade et al., (2015)	short-selling event study panel data fixed effect models	No rating scale specified. Rating is an indicator variable equal to one on the downgrade, upgrade or affirm announcement day, and zero otherwise.
Florez-Lopez (2007)	feature selection; multivariate analyses, evaluation models	5-points AA = 1, A = 2, BBB = 3, BB = 4, B = 5
Pottier and Sommer (2006)	ordered probit model	AAA, Aaa = 1, = 2, etc.
Adams et al. (2003)	ordered probit model	3-points A+/A++ = 3, A = 2, A- = 1, B+ or less = 0
Doherty and Phillips (2002)	ordered probit model	4-points A++, A+ = 4, A=3, A- =2,B++,B+=1, B and lower = 0
Pottier and Sommer (1999)	ordered probit model	4-points AAA/Aaa/A++, A+ = 4 ….BBB+/Baa1/B and below = 1

This table contains relevant studies that have used sample insurers' ratings. Notice that Pottier and Sommer (1999) has a greater sample size compare to this thesis (1384 vs 1678). However, their study only considers one point in time while this thesis includes a much wider and recent time, 2000-2017. P/L is the term used by some researchers to refer to the non-life insurance sector.

In addition to the studies related in Table 4.9, other studies investigate about insurance companies. For instance, Gaver and Pottier (2005) employs 122 publicly traded property liability insurers (in this thesis equivalent to P/C). GAAP requirements reduce their sample to 80 publicly traded property liability insurers that received FSR of their consolidated insurance-operating subsidiaries from AM Best for the one-time year, December 31, 1997. Since FSR is the dependent variable in this study, this paper adopts a 5 points transformation of B or lower = 0; B++ or B+ = 1; A- = 2; A = 3; A+ = 4; A++ = 5. Similarly, Doherty et al., (2012) condense few categories to map S&P ratings into and AM Best. Their alternative is as follows: Superior/extremely strong = 3, Excellent/Very strong = 2, Good = 1, Marginal = 0.

With regard to the third research question in Chapter 7. Miao et al., (2014) is a main reference. They focus on the ratings announcements of a sample of 58 publicly traded insurance companies that are rated at least once by one of the four rating agencies during 2005–2010, by P/C and L/H types of insurance companies, each accounting for about 25 per cent of the sample. The dataset contains 260 from AM Best, 90 from Fitch Ratings, 104 from Moody’s and 167 from S&P. The approach of Miao et al. (2014) to map the ratings across the four CRAs consists of defining: DN: Bad news (downgrade ratings); NC: No news (stable ratings); UP: Good news (upgrade ratings).

Table 4.8 Studies using corporate and sovereign ratings

Research	Type of rating	CRAs	Dataset	Period	Methodology	Rating scale
Alsakka and ap Gwilym (2010a)	Sovereign ratings	S&P, Moody’s, Fitch	49 countries	Jan. 2000 – Jan 2008	Ordered probit model	20-points Aaa/AAA= 1 to C/SD−D=20
Livingston et al., (2008)	Bond issues and rating history	S&P and Moody's	9431 bond issues	1983–2000	Logistic regressions of rating changes	19-points. AAA=1 to C = 19
Iannotta (2006)	Bond ratings (Europe)	S&P and Moody 's	2,473 bonds 248 firms	1993–2003	Ordered logit models with and without fixed effects	Numerical scale not specify
Morgan (2002)	Bonds (U.S.)	S&P and Moody’s	7,862 new bonds	Jan. 1983–July 1993	Probit model	16-points AAA=Aaa =1,…B1 = B3 =16.

This table presents prominent studies useful when selecting the final dataset, data sources and methods use in the empirical chapters.

Table 4.8 presents relevant studies from the sovereign and corporate rating literature. In particular, Alsakka and ap Gwilym (2010a) and Livingston et al., (2008) serve as motivation for the research question in Chapter 6. Relative to insurers, sovereign literature uses a broader time period of analysis while bonds rating researchers such as Morgan (2002), Iannotta (2006), and Livingston et al., (2008), not only have a longer time period of analysis compare to insurers but also the rating scale transformation is much more standard and refined. These elements serve as a foundation for the next section where a numerical transformation is proposed.

4.5 Rating scale: numerical transformation

As mentioned in Chapter 1, there is lack of equivalence in the FSR rating scale use by the three major traditional CRAs and the CRA specialized in insurers, AM Best. Building upon the prior literature, this section outlines the alternative used in this thesis to map the 20-point numerical rating scale (AAA/Aaa = 1, AA+/Aa1 = 4, AA/Aa2 = 7… Caa3/CCC- = 19, Ca/CC/C/SD-D = 20) from S&P, Moody's and Fitch, with the 13-point points used by AM Best. Likewise, it presents how the process is reversed by mapping the 13-point numerical scale by AM Best towards the other three CRAs (Aaa/AAA =1, Aa1/AA+ =2, … Caa3/CCC- =11, Ca/CC to C/SD-D =13). To the best of my knowledge, no prior study has mapped directly each point in the big three CRAs scale with its counterparty AM Best rather the most common approach has been to condense few categories of the scale in a 5-point numerical scale. Table 4.9 presents the approach recommended by InteractiveData Credit Ratings (2016) which serves as the foundation to the numerical mapping proposed in this thesis. Notice that AM Best (FSR) has some gaps when mapping with other CRAs.

Table 4.9 Composite rating across different CRAs

Composite Rating	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Capital Intelligence	AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-
DBRS	AAA	AAH	AA	AAL	AH	A	AL	BBBH	BBB	BBBL
Fitch	AAA	AA+	AA	AA-	A=	A	A-	BBB+	BBB	BBB-
JCR	AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-
Moody's	Aaa	Aa1	Aa2	Aa3	A1	A2	A3	Baa1	Baa2	Baa3
S&P	AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-
AM Best (ICR)	aaa	aa+	aa	aa+	a+	a	a-	bbb+	bbb	bbb-
AM Best (FSR)	--	A++	--	A+	--	A	A-	--	B++	B+

This table shows the rating equivalence across CRAs proposed by InteractiveData Credit Ratings (2016). They define composite rating as the arithmetical average of the numerical scores assigned to each CRA' investment grade ratings. The highest long-term rating for each CRA is given by the score "1" and the lowest by the score "10".

On the other hand, Table 4.10 presents a section of AM Best (2017) methodology that states that ICR is the foundation to determine FSR and the holding company ICR. This table serves as evidence on how two categories in the ICR scale are equivalent to only one notch in the FSR scale.

Table 4.10 Translation AM Best ICR to FSR

Num. score	ICR	FSR
1	aaa aa+	A++
2	aa aa-	A+
3	a+ a	A
4	a-	A-
5	bbb+ bbb	B++
6	bbb-	B+
7	bb+ bb	B
8	bb-	B-
9	b+ b	C++
10	b-	C+
11	ccc+ ccc	C
12	ccc- cc	C-
13 13 13 13	c	D E F S

This table shows the rating translation table or equivalence presented in AM Best (2017) methodology. They state that the operating company ICR is the foundation for the operating company FSR and the Holding (parent) company ICR.

Considering both, Table 4.9 and Table 4.10, Table 4.11 presents the three alternatives designed to map the rating scales. Alternative 3 presents an average of the two categories, Alternative 2 opts for the upper value while the preferred, Alternative 1 is considered a more conservative approach. The choice of Alternative 1 is justified by the following arguments. Research has shown that insurers ratings have been criticised of being overly optimistic (Ciumaş et al., 2015) and other agencies -such as Fitch- argues that even with the NAIC classification system, the 'A–' category of AM Best should be aligned with 'BBB+'/'BBB' FSR ratings of Fitch, S&P and Moody's instead of being at the same level. [31]

[31] The National Association of Insurance Commissioners (NAIC) establish standards and best practices, conduct peer review, and coordinate their regulatory oversight.

Table 4.11 Alternatives to match AM Best rating scale with other CRAs

				Alternative 1.		*Alternative 2.*		*Alternative 3.*	
Num. score	**S&P**	**Moody's**	**Fitch**	**Num. score AM Best**	**AM Best**	**Num. score AM Best**	**AM Best**	**Num. score AM Best**	**AM Best**
1	AAA	Aaa	AAA			1	A++	1.5	A++
2	AA+	Aa1	AA+	2	A++				
3	AA	Aa2	AA			3	A+	3.5	A+
4	AA-	Aa3	AA-	4	A+				
5	A+	A1	A+			5	A	5.5	A
6	A	A2	A	6	A				
7	**A-**	**A3**	**A-**	**7**	**A-**	**7**	**A-**	**7**	**A-**
8	BBB+	Baa1	BBB+			8	B++	8.5	B++
9	BBB	Baa2	BBB	9	B++				
10	BBB-	Baa3	BBB-	10	B+	10	B+	10	B+
11	BB+	Ba1	BB+			11	B	11.5	B
12	BB	Ba2	BB	12	B				
13	**BB-**	**Ba3**	**BB-**	**13**	**B-**	**13**	**B-**	**13**	**B-**
14	B+	B1	B+			14	C++	14.5	C++
15	B	B2	B	15	C++				
16	B-	B3	B-	16	C+	16	C+	16	C+
17	CCC+	Caa1	CCC+			17	C	17.5	C
18	CCC	Caa2	CCC	18	C				
19	**CCC-**	**Caa3**	**CCC-**						
20	**CC**	**Ca**	**CC**	**20**	**C-**	**19**	**C-**	**19.5**	**C-**
20	C	C	C	20	D	19	D	19.5	D
20	R		D	20	E	19	E	19.5	E
20	SD			20	F	19	F	19.5	F
20	D			20	S	19	S	19.5	S

This table shows the three alternatives proposed in this thesis to match AM Best rating categories into the 20-point numerical scale of the other three CRAs. Alternative 3 is discarded since using averages; split ratings will always be present. Alternative 1 is chosen following a conservative approach. Notice that notches 7, 10, 13, are equivalent across all four CRAs. Following prior studies and the fact that very few insurers are rated in lower categories, CCC- to D are grouped into an entire numerical score, 20. (e.g., Alsakka, 2010; Alsakka and ap Gwilym, 2012c; Williams et al., 2013).

Building upon the above, Table 4.12 breaks down Alternative 1 as the preferred approach. Notice that the highlighted column starts from AAA/AA+/A++ = 2 rather than 1 as it is considered the closest to the reality of the correspondence among CRAs. Also, notice that notches 7, 10, 13, are equivalent across all four CRAs even following AM Best methodology. Furthermore, Panel B exhibit how the process is inversed and translates the scale of the three CRAs to AM Best 13-points rating scale. Observe that from CCC- to D categories, the decision is to group the entire category to 20 (rather than 21) given the low frequency of insurers rated in these categories and to keep the scale at the same level of points.

Table 4.12 Rating scale transformation: Alternative 1

Panel A. Rating scale transformation 20-point numerical scale

Num. score	**S&P**	**Moody's**	**Fitch**	**Num. score**	**AM Best**
1	AAA	Aaa	AAA		
2	AA+	Aa1	AA+	*2*	A++
3	AA	Aa2	AA		
4	AA-	Aa3	AA-	*4*	A+
5	A+	A1	A+		
6	A	A2	A	*6*	A
7	A-	A3	A-	*7*	A-
8	BBB+	Baa1	BBB+		
9	BBB	Baa2	BBB	*9*	B++
10	BBB-	Baa3	BBB-	*10*	B+
11	BB+	Ba1	BB+		
12	BB	Ba2	BB	*12*	B
13	BB-	Ba3	BB-	*13*	B-
14	B+	B1	B+		
15	B	B2	B	*15*	C++
16	B-	B3	B-	*16*	C+
17	CCC+	Caa1	CCC+		
18	CCC	Caa2	CCC	*18*	C
19	CCC-	Caa3	CCC-		
20	CC	Ca	CC	*20*	C-
20	C	C	C	*20*	D
20	R		D	*20*	E
20	SD			*20*	F
20	D			*20*	S

Panel B. Rating scale transformation based on 13-points numerical scale

Num. score	**AM Best**	**S&P**	**Moody's**	**Fitch**
		AAA	Aaa	AAA
1	A++	AA+	Aa1	AA+
		AA	Aa2	AA
2	A+	AA-	Aa3	AA-
		A+	A1	A+
3	A	A	A2	A
4	A-	A-	A3	A-
		BBB+	Baa1	BBB+
5	B++	BBB	Baa2	BBB
6	B+	BBB-	Baa3	BBB-
		BB+	Ba1	BB+
7	B	BB	Ba2	BB
8	B-	BB-	Ba3	BB-
		B+	B1	B+
9	C++	B	B2	B
10	C+	B-	B3	B-
		CCC+	Caa1	CCC+
11	C	CCC	Caa2	CCC
		CCC-	Caa3	CCC-
12	C-	CC	Ca	CC
13	D	C	C	C
13	E	R		D
13	F	SD		
13	S	D		

This table presents the alternative chosen to map rating symbols across CRAs with a numerical score. Panel A contains the approach used to match AM Best rating categories with the 20-point numerical rating scale of its peers S&P, Moody's and Fitch. Panel B contains the approach used to adapt the 13-points AM Best rating scale towards the other three CRAs.

4.6 Conclusion

The key aim of this Chapter is to provide a thorough explanation of common points that apply to the data employed in the subsequent empirical Chapters 5, 6 and 7. Relating to the database construction for this thesis, the chapter provides an overview of the ideal dataset for insurers' ratings, the data sources and a series of steps undertaken to prepare datasets that are suitable for the research direction taken in this thesis. Among the series of steps, the data collection is done individually using each CRAs' database and a matching process across the four CRAs was required. Each CRA has its own definitions, terminology, and rating scale. Therefore, there is a need for this chapter to underpin the subsequent three empirical chapters.

Considering that in terms of geography, the U.S. represents the vast majority of the data available across CRAs. Also, P/C is the subsector with about 60% of observations across the samples. A further step was to narrow down the dataset to this thesis choosing only LT – LC FSR of U.S. P/C insurers from the main four CRAs during the period from January 2000 to December 2017.

Comparing this dataset with the prior literature, one can notice that there is an opportunity for contributions to knowledge which are underpinned by data qualities in terms of sample size, extended time period, and a much more recent period of analysis. In terms of the numerical rating transformation, the literature contains several ways to define mappings between ratings across CRAs including an alternative four-category system proposed by Pottier and Sommer (1999) and a five-level system used by Doherty and Phillips (2002). Inspired by the sovereign, corporate, and bank rating literature, this chapter proposes a much more refined mapping of 20-point and 13-point rating scales which is then adopted in the subsequent empirical Chapters 5, 6 and 7.

Chapter 5. Rating transitions for U.S. P/C insurers: A unique comparative analysis

5.1 Introduction

As stated in Chapter 1, the financial crisis 2007-10 highlighted the pivotal role of corporate transparency, and the importance of proper monitoring of insurers' financial strength (Han et al., 2018). The bailout of American International Group (AIG), and the insolvency of Yamato Life Insurance, revealed several shortages in terms of risk management (Eling and Schmeiser, 2010). Meanwhile, the role of Credit Rating Agencies (CRAs) in assessing default risk has been subject to increased scrutiny. Conflicts of interest have been claimed to be inherent in the credit rating industry, and an overly positive rating attitude towards insurance companies has been pointed out (Ciumaş et al., 2015; Klein, 1992).[32]

Despite the criticism, insurers' ratings denote CRAs' opinions on the financial status of insurers and their ability to satisfy their obligations to policyholders (Ciumaş et al., 2015). Hence, ratings become critical because of the reliance that policyholders place on insurers being solvent when a claim arises (Bierth et al., 2015) and that investors place when taking decisions about insurers' bonds and other debt (Miao et al., 2014). Conversely, ratings can affect insurers' policy prices, rumours of downgrades could lead to loss of insurers' customers, or financial problems could be inflated (Ciumaş et al., 2015). Moreover, given that changes in insurers' ratings reflect changes in their financial strength, CRAs become a key contributor to monitoring solvency of insurance firms (Wang, 2010).

Prior research investigating insurers' ratings is very sparse. As reviewed in Chapter 3, Pottier and Sommer (1999) stands out as one of the first studies to address insurers ratings by focusing on disagreement among CRAs using a dataset of 1678 individual property-liability insurers. Their results demonstrate the variety in the models that CRAs use to assess companies via weights and factors but do not examine rating changes. Likewise, Adams et al., (2003) study, who focused on the likelihood to be rated and determinants of the financial strength of insurers in the U.K.

Adams et al., (2003) find that greater values of profitability, liquidity, growth, company size, and organisational form are link with higher ratings as well as lower values of leverage, and amount of reinsurance. Later developments in the literature address similar issues e.g., Pottier

[32] According to Eling and Schmeiser (2010), AIG, Swiss Re, and Japanese life insurer, Yamato Life Insurance are the most reported events of the crisis for the insurance industry. In particular, Yamato Life reflects the case when problems on asset management can produce a threatening economic situation. They experienced losses in the subprime area, and losses due to a high investment in stocks. However, no specific problems have been reported from the underwriting side.

and Sommer (2006) and Gaver and Pottier (2005) who focus on insurer rating determinants at a firm level and, Florez-Lopez (2007) that tackles rating determinants for European insurers (see more detail in Section 3.2 in Chapter 3).

Regarding credit rating changes, rating transitions matrices (RTM) are at the midpoint of credit risk management (Gavalas and Syriopoulos, 2014). RTM have become a valuable tool that regulators have included in trying to determine the financial condition of insurers (Pottier and Sommer, 2006), or that scholars have used to link bond price fluctuations to their credit changes (Wang, 2010). In practice, estimators of migration matrices are published by CRAs in developed countries, as well as, act as inputs to applications such as portfolio risk assessments and, pricing of credit derivatives and credit risk models (Alsakka and ap Gwilym, 2010a). For example, CreditMetrics™, an advanced risk management product offered by J.P. Morgan involves estimating the probability of shifting from one credit quality to another within a particular horizon (Livingston et al., 2008; Wang, 2010).

Relevant studies containing RTM for insurers are also limited. Almost all studies focus on corporate or sovereign ratings from a single agency only (usually Moody's or S&P) (Alsakka, 2010a), or use RTM as a complement of their main analysis. For instance, Hu and Cantor (2003) examine Moody's ratings for corporates and structured finance products finding higher levels of rating stability for structured finance products than corporate bonds in the years 1983-2002. Further, Hamilton and Cantor (2004) documents Moody's corporates' RTM and default rates during the 1995-2003 period, which, in addition, include rating outlooks and reviews. They conclude that recently downgraded issuers have a greater probability of future rating downgrades and default than do upgraded issuers. Moreover, they have also demonstrated the existence of non-Markovian behaviour, such as the effects of macroeconomic factors (Ayed et al., 2018).

In terms of estimation techniques, Hadad et al., (2009) construct RTMs for Indonesian companies and bond ratings using two approaches, the cohort method and the continuous method with time homogeneity concluding that the cohort method produce matrices with an uneven probability distribution concentrated around the diagonal whereas continuous methods provide a more spread probability. Likewise, Gavalas and Syriopoulos (2014) produce risk transition matrices of the loan portfolio of an Austrian bank comparing different estimation methods and macroeconomic states. They determined that default probabilities seem to be lower in the boom state and that maximum likelihood transition matrix capture better rating transition mobility relate to the more diagonal-dominant cohort estimated transition matrix.

A number of studies have documented the fact that RTM vary according to the economic cycle, industry, and the time span of the issuance of the bond (Ayed et al., 2018). In this sense, studies by Salvador et al., (2014) for Spanish banks and Salvador et al., (2018) for banks in the U.S., some European countries and Japan compare the effect of the financial crisis on rating performance. Overall, their matrices reveal that after the subprime crisis, ratings become less stable with average of 39.95% and 19.25% downward in Fitch and S&P, and an increased probability of being located in inferior rating categories. For insurers, a quite different picture emerges compared to the banking industry. Few authors argue that the impact of the crisis has been very uneven: for some parts of the insurance market relatively null effects, for others, they have been severe (Baluch et al., 2011; Jadi, 2015). In that respect, Wang (2010) examine AM Best's RTM of U.S. property-liability insurers for the period 1995-2006, and compared under different economic and industry conditions. Wang (2010) determines that initial ratings in the higher categories were more stable than those in the low categories and, when exogenous environment is favourable, insurer ratings are more stable and variations tend to be upgrades, and vice versa. However, this study does not cover the period of the crisis during 2007-2009.[33]

More recent, Jadi (2015) employ RTM and regression models in a sample of 57 U.K. insurers over the period of 2006 to 2010 to investigate the determinants of financial performance of insurance companies based on their FSR evolution. In a paper using the same sample by Jadi (2015), Sharma et al., (2018) focus on the effects of the credit crunch using AM Best's RTM matrices to analyse credit risk for the U.K. insurance industry. Their outcomes suggest that rating performance varies before and after the financial crisis; before the crisis with a more stable activity reflected in the chances of maintaining the current rating whereas, after the crisis, less stability, and more variations. Additionally, Chen and Pottier (2018) aim on determining whether rating changes, profit changes, and excess stock returns is a substitute for another in aiming to predict the future direction of firm financial performance. While attempting, they use a 18-year AM Best RTM of public insurers for the period 1996-2013, concluding that insurers that are rated 'A' or higher have a relatively higher frequency of rating downgrades than

[33] U.S. Property/Liability insurers are also known as general insurers and it is another term to refer to non-life insurers.

upgrades, and insurers that are rated 'B' to 'A-' have a relatively higher frequency of rating upgrades than downgrades.[34]

On the other hand, with the dramatic rise of economic costs of natural disasters over the last few decades (Bevere et al. 2015), an emerging literature stream has been focusing on the role of adverse effects of climate change on local economic conditions or institutions (see Strobl, 2011 and Schüwer et al., 2018). In this matter, insurers are at the frontline of calculating the impact of global warming (WSJ, 2018) but there is no agreement about how insurer's financial strength has been threatened. The discussion has been turned more about how the prices of the premiums are increasing and reflecting the risk (see, Michel-Kerjan et al., 2015), or how to control urbanization in exposed areas (see Grislain-Letrémy and Villeneuve, 2019).

Within this backdrop, this Chapter examines the financial strength rating (FSR) changes, upgrades and downgrades, of U.S. Property/Casualty (P/C) insurers for the period 2000-2017. Specifically, the research question is: 'what are the differences in rating trends for insurance companies among the big four CRAs?'. RTM are constructed and compared over different time spans seeking differences before and after the financial crisis across time and across agencies. The Chapter intents to offer insights into the effects of the financial turmoil on financial strength. Moreover, it considers the influence of three elements involved in the dynamic of insurers' ratings. First, factors that are driving differences across CRAs i.e., different rating scale. Second, additional drivers of rating changes such as natural or man-made catastrophes. Third, the frequency of natural disasters or regulatory particularities among states. Finally, the U.S. insurance market becomes a relevant case of analysis given its role in the economy; insurance spending accounted 11% of the GDP in 2017 (OECD, 2019). Thus, this research provides insights to regulators, customers, and scholars on the evolution of insurer's ratings and aid in the developing of risk management plans that are capable of coping with potential future crises.[35]

The remainder of the Chapter is structured as follows. Section 5.2 provides institutional background of the U.S. insurance market and natural disasters over the period. Section 5.3 explains the methodology used to calculate the transition matrices as well as the features of the

[34] Jadi (2015) discuss several definitions of the term financial performance, and concludes that it be defined as the robustness of the system, the efficiency of key economic functions and the absence of threats or harms that can impair financial performance.

[35] OECD (2019) defines insurance spending as the ratio of direct gross premiums to GDP, which represents the relative importance of the insurance industry in the domestic economy, and it is an indicator shown as a percentage of GDP.

sample. Section 5.4 includes the results and discussion, Section 5.5 comprise alternative specifications, and Section 5.6, concludes.

5.2 Institutional background in U.S. insurance market

5.2.1 Institutional background

In insurance, institutional differences are important as reinsurance, taxes, and premiums influence underwriting capacity and market strategies (Chang, 2019). According to Klein (2019), depending on how it is structured and managed, insurance regulation can improve market performance, have no impact, or cause significant problems in the market. In line with Chapters 2 and 3, there are several attributes of U.S. insurance industry to consider, namely: (1). U.S. has about 3000 P/C insurers that tend to form an utterly competitive market, whereas markets such U.K. (with around 150 insurers) tend to be an oligopoly (Chang, 2019); (2) U.S. states are the primary regulators, the market is recognized for its traditionally restrictive regulation where each state impose constraints in terms of defining an own set of laws and rules (Adams et al., 2019); and (3) U.S. federal government plays an important role by offering assistance and funding through a range of agencies and programs.[36]

Regarding the second point, state-based regulation has a large focus on solvency (Cummins et al., 2015). Each state counts with an insurance official who is charged with overseeing the solvency of insurers doing business in the state, as well as their rates, and other market practices (i.e., reinsurance; trades among affiliates; underwriting and claims handling, etc.) (IRI, 2019). For example, some states impose regulatory limits on premiums i.e., New York (Upreti and Adams, 2015) or impose higher capital maintenance requirements on foreign or 'alien' reinsurance companies than U.S.-owned reinsurers (Weiss and Chung, 2004). Moreover, the insurance official is elected in eleven states i.e., California, Washington, Montana, North Dakota, Kansas, Oklahoma, Louisiana, Mississippi, Florida, Georgia, North Caroline, and, is appointed in the others (Klein, 2005). In parallel, the National Association of Insurance Commissioners (NAIC) acts as a support organization created and governed by the chief

[36] Although U.S. and U.K have a different regulatory framework, common features can be also found between them. For instance, motor insurance is compulsory in both countries, at least for third party risks, with premiums based on measurable factors such as years of driving experience, or number and value of previous claims (Adams et al., 2019). For a detailed description of the U.K institutional background please refer to Upreti and Adams, (2015).

insurance regulators from the 50 states, the District of Columbia and five U.S. territories aiming to coordinate, strengthen and streamline their oversight of the insurance industry (NAIC, 2019).

Along with the states, the National Flood Insurance Program (NFIP) is a crucial protagonist among the programs supported by the federal government. The congress passed the National Flood Insurance Act (NFIA), 42 United States Code (U.S.C.) 4001 in 1968, creating the NFIP to manage residential flood insurance given that the standard multiperil homeowners policies (mandatory to obtain a mortgage) explicitly excludes coverage for flood damage resulting from rising water. Following that, in 1979, the Federal Emergency Management Agency (FEMA) was stablished to mitigate, take action, and recover from all domestic disasters, natural or man-made, including acts of terror (FEMA, 2017; Schüwer et al., 2018) and now it is in charge of the NFIP. During decades, the NFIP has earned more in premiums than it has paid out in claims. However, catastrophic losses, such as Hurricane Katrina in 2005 and Hurricane Sandy in 2012, required the NFIP to borrow an additional $1.6 billion from the US Department of the Treasury to pay claims. Even in January 2017, the NFIP had to cover losses from 2016, bringing its total debt to almost $25 billion (CIPR, 2017a). As a consequence, there is a current debate concerning of moving coverage from NFIP to the private sector (see Michel-Kerjan et al., 2015).

5.2.2 Potential drivers of rating changes: U.S. costly natural disasters on the rise

The fact that RTM only elucidates the changes but not the reason behind them (Jadi, 2015) raises the need to shed light on the drivers of rating changes. The insurance industry has generally been revamped after big disasters. For instance, natural-catastrophe modelling ascend after Hurricane Andrew hit Florida in 1992, where around thirteen insurers were liquidated (WSJ, 2018). More recent, 2004-2005 hurricane seasons triggered changes in terms of state legislation, insurance policy and coverage, catastrophe models, enhancements of the measure of risk NAIC RBC, and finally, rating agencies revised rating procedures by expanding the data required from insurers. In particular, Fitch moved to a tail value at risk (TVaR) from a single-point view analysis and AM Best asked insurers to include ancillary lines of business into account (CIPR, 2017b).

Although AM Best (2014) establishes that the main reasons why U.S. P/C insurers have failed during 1969-2013 are deficient loss reserves -inadequate pricing- (44.3%) and rapid growth companies (12.3%). The 7.1% corresponding to catastrophe losses led to believe that this amount could potentially increase with the pressure of global warming. Certainly, the number of storms, hurricanes, and floods strikingly increased to an annual average of 14 events the last

50 years of the century 1917-2016 compared with 1.6 events at the beginning of the same period (CIPR, 2017c). Likewise, from 1970 to 2008, 25 of the most costly insured losses, 14 happened since 2001, and 12 of which occurred in U.S. (Kunreuther and Michel-Kerjan, 2009). The remainder of causes for insurer's failure involves miscellaneous (8.4%), affiliate problems (7.8%), alleged fraud (7.1%), investment problems (6.6%), a significant change in business (3.4%), and reinsurance failure (3.0%). Aon Benfield (2019) adds that the rating trend of an insurer is influenced by their individual portfolios and policyholder guarantees, as well as on local regulations. The same, a sovereign default would cause financial market turmoil, therefore, would affect all insurers and reinsurers.

Regarding the major events, the terrorist attacks to the World Trade Center (WTC) in September 2001, caused 2976 deaths and an estimated $40 billion in insured losses (III, 2015). Next, in 2002, the bankruptcy of Enron, WorldCom accounting scandal, and natural catastrophes disturb the financial markets. In April 2002, there was a remarkable series of more than 30 tornadoes in the Midwest and the East of U.S. leaving insurers with a bill of US$ 1.6b. In November, the Midwest was hit again with extensive damage; 90 tornadoes, 35 fatal victims (Munich Re, 2003). During 2003, no major climate events happened whereas in 2004, Hurricane Charley, Ivan, and Frances, generated US$ 7.5bn, US$ 7.1 and US$4.6bn insured losses when happened (CIPR, 2017c). Concerning 2005, hurricane Katrina hit the Gulf Coast, causing $108 billion of destruction across seven states (largely Louisiana, Mississippi and Alabama) and generated $41.1 dollars -when occurred- in estimated insurance loss, and more than 1.7 million claims; making it the costliest U.S. hurricane (Bleemer and van der Klaauw, 2019; III, 2010). Along with Katrina, Hurricane Rita and Wilma took place generating unexpected losses and shaken asset quality of insurers, as a large part of the detriment suffered was not insured.

In the subsequent years, Hurricane Gustav and Ike took place and, after the financial crisis, 2011 had a very active tornado-hail season that surpassed insured losses by $25 billion, making it the deadliest thunderstorm season in over 75 years. Specifically, insured losses in U.S. reached $35.9 billion; above 2000 to 2010 average loss of $23.8 billion (in 2011 Dollars) (Munich Re, 2012). Additionally, Hurricane Irene and Tropical Storm Lee also occurred as well as the tsunami in Japan that affected some parts of U.S. and it is considered the deadliest natural disaster in 2011.

Respecting to 2012, Hurricane Sandy generated $19.9 billion of insured losses (CIPR, 2017a). Compared with Hurricane Katrina in 2005, those at risk from Sandy were better prepared for the disaster, with evacuation plans and risk-reduction measures investments in place (Michel-Kerjan et al., 2015). Finally, 2017 became the costliest year on record for weather disasters surpassing 2011, with landfalls of Hurricanes Harvey, Irma, and Maria that caused an estimated USD220 billion in damage and represented 62% of the annual economic loss (Aon Benfield, 2017). Nevertheless, the insurance industry was still able to meet the high volume of claims.

Building upon on the above, U.S. becomes a pertinent scenario to study insurers' ratings considering the potential lessons from the financial crisis and climate change –currently- adding pressure to the industry. Indeed, global warming is attaching tension on insurers to build models that aid estimate better the impact and define premiums that reflect the increasing underlying risk. As mentioned earlier, there is a growing number of insured losses during the last few years and the industry adaptation to the impacts will be major to both reinsurance and insurance companies (Herweijer et al., 2009; Michel-Kerjan and Kousky, 2010).

5.3 Data and methodology

5.3.1 Data

As mentioned in Chapter 4, the dataset for this study is the intersection of four datasets of Long Term (LT) – Local currency (LC) Financial Strength Ratings (FSR) of U.S. Property/Casualty (P/C) insurers acquired directly from the main CRAs: S&P, Moody's, Fitch and AM Best during 2000-2017. The data is obtained from Capital IQ for S&P ratings, the official website for Moody's and Fitch, while for AM Best; the data is obtained directly from AM Best. The U.S. is chosen as a country of analysis because it represents around 65% of the world insurance market, and P/C insurers embodies the biggest subsector. For the ratings, each CRAs has its specific policies and terminology on how they assign them. However, Trueck and Rachev (2009) argue that such variations are tolerable and acceptable by regulators. Concisely, FSR provides a forward-looking opinion of an insurer's financial strength and ability to meet ongoing obligations to policy-holders (AM Best, 2017a)

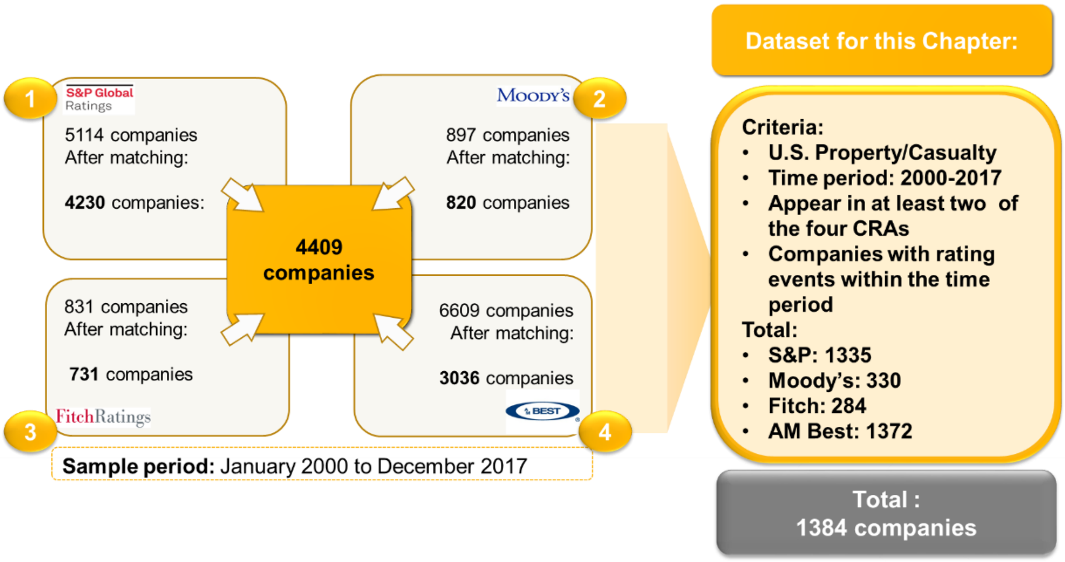

Figure 5.1 Dataset.

This figure presents the dataset of 1384 U.S. P/C insurers during the period Dec. 2000 to Dec. 2017 used in this Chapter taken from the 4409 insurance companies database constructed in Section 4.3.5 in Chapter 4. The criteria of companies with rating events within the time period refers to the fact that each company must have a minimum of one initial and terminal rating. If the company has rating activity for only one of those years, it has to be dropped from the sample.

To compare the rating trends among CRAs, only insurers that have FSRs available and, are rated by at least two of the four agencies during the observation period (December 2000-December 2017) are included in the data sample. Figure 5.1 shows the sample selection process, as follows: From the database constructed in Section 4.3.5 in Chapter 4, the initial sample for this chapter contains 1695 companies catalogued as U.S. P/C insurers. However, each company must have minimum of one initial and terminal rating. For example, an initial rating in year 2000 and a terminal rating in year 2001. If the company has rating activity for only one of those years, it has to be dropped from the sample. This condition forces the exclusion of some observations from some of the CRAs because a few companies will no longer be rated by at least two CRAs. Applying these criteria, as shown in Figure 5.1, the final sample comprises 1384 companies, where 1335 are rated by S&P, 330 by Moody's, 284 by Fitch, and 1372 by AM Best.

Table 5.1 Number of companies in sample

Panel A. Rated by two CRAs

CRAs	S&P Moody's	S&P Fitch	S&P AM Best	Moody's Fitch	Moody's AM Best	Fitch AM Best
No of insurers	298	256	1323	172	320	279

Panel B. Rated by three CRAs

CRAs	S&P Moody's Fitch	S&P Moody's AM Best	S&P Fitch AM Best	Moody's Fitch AM Best	S&P Moody's Fitch AM Best
No of insurers	161	288	252	170	159

This table presents the number of insurers included in the study rated by pairs and triplets during 2000-2017.

Table 5.1 shows the number of insurers rated by CRAs pairs and triplets. The numbers are consistent with the fact that AM Best is an insurers' specialized CRA, S&P is a growing market player, and Moody's and Fitch are gradually growing in the insurance rating market. Notice that comparing with prior studies rather than focusing on only one CRAs, the dataset covers the biggest four CRAs and covers the most recent time period at the time of starting this thesis.

Given the nature of ratings as an ordinal categorical variable, notches are used to identify rating changes and a numerical mapping is required. For the three CRAs, S&P, Moody's and Fitch, the process is straightforward while for AM Best, having a 13-points rating scale becomes a challenge because does not directly match to the 21-point and 19-point rating scales used by the other CRAs. This is addressed by taking *InteractiveData* Credit Ratings' approach and mapping the credit ratings to an 20-point rating scale (see details in Table 4.11 and Table 4.12 in Chapter 4).

In terms of the distribution of annual ratings, Figure 5.2 indicates that the four CRAs have a right-skewed distribution where ratings are grouping around the superior levels; AA/Aa2/AA (3) to A-/A3/A- (7) for S&P, Moody's, and Fitch and for AM Best from A++ (2) to A (6). The median rating one year is A (6), 22.4% of S&P ratings, 32.8% in Moody's and 38.6% in AM

Best. The majority of Fitch's ratings are in AA category (21.8%). One feature of S&P figure is that for the same period of analysis, 10% of companies appeared in default (20). Later on, the possible causes will be develop on why this may be occurring.

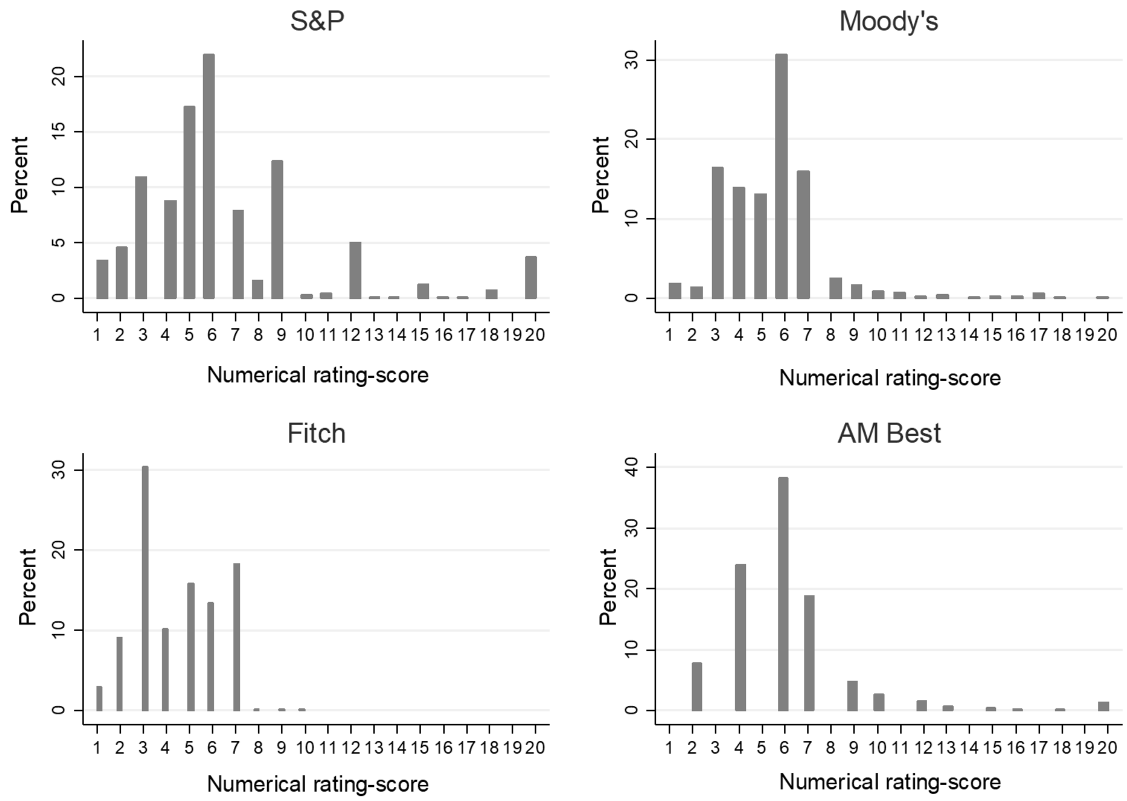

Figure 5.2 Distribution of annual ratings by rating score during Dec. 2000 – Dec. 2017

This figure displays the credit rating scale of each CRA transformed into a 20-point numerical scale (AAA=1, AA+=2 ….CCC=19, C-D=20).

5.3.2 Methodology

A rating transition matrix (RTM) summarizes the evolution in credit ratings over a given time horizon. Thus, it reflects the financial performance of an insurer by the changes in the rating grades (Sharma et al., 2018; Wang, 2010). The matrix presents the probability that a group of companies, are going to remain with the same rating in the next period, or the company exhibited a rating change up or down over a time lapse. Therefore, the diagonal of the matrix will denote the probability that an insurer persist at its original rating letter, and the off-diagonal elements of the matrix will indicate the probability that a company has suffered a downgrade (the area above the diagonal) or an upgrade (the area below the diagonal) (Livingston et al., 2008).

To calculate the transition probability, there are several methods used in the literature. The traditional multinomial/cohort method, that uses a discrete timescale, and duration/longitudinal techniques that can be either parametric (imposing time homogeneity) or non-parametric, such as Nelson-Aalen-Johansen estimator (Grzybowska et al., 2012). Although the latter procedures are renowned as more efficient (Hadad et al., 2009; Livingston et al., 2008), the cohort method is a technique widely accepted in rating transition analysis, it offers a simple estimation process, and its commonly used by CRAs to give a snapshot of the development of their rating activities (Wang, 2010).

In this Chapter, the cohort method is adopted following Hamilton and Cantor (2004) and Wang (2010). This method underlines two facts: i) the shortest time interval of estimation is one year (Grzybowska et al., 2012); and ii) transition matrices could be estimated for any desired time horizon (Hadad et al., 2009). In this case, cohorts of insurers are formed at one-year intervals between December 2000 and December 2017. The year 2000 is the first year employed to derive lagged rating actions for the whole sample, then for the subsamples by period, the years 2000, 2007, and 2010 are used to derive lagged rating actions corresponded to pre -crisis, crisis and post crisis periods, respectively. The choice of a specific breakpoint between these three periods needs to be justified clearly. From the overall 18-years (2000-2017), the pre-crisis period is specified as a five-year time frame, starting from 2000 to 2006. This seven year period is chosen in order to reflect the changes leading to the global financial crisis (GFC). The choice of the three-year period, 2007-2009, is done following Baluch et al., (2011) who describe the onset of the financial crisis in 2007 and assess the impact of the financial crisis on insurance markets and the role of the insurance industry in the crisis itself. Likewise, studies such as Billio et al., (2012) and Silva et al., (2017) who belong to the literature strand on systemic risk describe the GFC as the period 2007-2009. Additionally, Anginer et al., (2019) explore and summarize the evolution in bank capital regulations, and market discipline using the years 2007-2009 as well. Finally, the post-crisis period 2010-2017 includes the eight years remaining in the overall period of analysis.

Regarding the calculation of the transition rate, in Eq. (5.1), suppose there are N_i issuers, which are placed in the rating category i at the beginning of the year, and N_{ij} issuers move to category j over the year; then, the rate can be defined as:

$$\hat{P}_{ij} = \frac{N_{ij}}{N_i},\ i \neq j \tag{5.1}$$

Therefore, each element of the matrix will show the probability that the rating i in the period (t-1) is going to pass to the rating j in the subsequent period t or remain the same. However, any rating change that occurs within the period of analysis is ignored (Grzybowska et al., 2012).

5.4 Empirical results

The results discussion is based on the method explained in Section 5.3.2 and the data exposed in 5.3.1. For each CRA, four transition matrices are generated as follows:

i. 18-year RTM, 2000-2017: Overall transition
ii. Seven-year RTM, 2000 -2006: Pre-crisis
iii. Three-year RTM, 2007-2009: Financial crisis
iv. Eight-year RTM, 2010-2017: Post-crisis

The matrices are provided in the Appendix 5.1 condensing the degree and direction of rating changes for one-year horizon. As mentioned, each RTM compacts the average changes in credit quality providing insights about an insurers' ability to meet their obligations. Each cell of the matrices is the weighted average percentage of ratings at the start of each year in the sample that finishes up in each rating category at the end of that year (Hu and Cantor, 2003).

Table 5.2 summarizes the rating activity of the four CRAs derived from the RTMs. The table is constructed by adding the off-diagonal elements of the matrices and dividing them by the total number of actions over the period. Table 5.2 reveals some important features. AM Best appears to have the least amount of activity in the whole period, and FSR are more likely to be unchanged. Panel A reveals that the amount of upgrade and downgrade transitions over the total rating assessments within a year is superior for S&P (14.4%), followed by Moody's and Fitch with similar activity (11.6% - 11.2%) while AM best has the lowest amount, 9.8%. However, the fact that AM Best has fewer points in the rating scale (13-points) versus 21 and 19-points of its competitors brings a challenge to the fore. One could argue that fewer changes are due to fewer rating points. Thus, this shortcoming is addressed with the first alternative specification presented in Section 5.5. It is noteworthy that, Doherty et al., (2012) asserts that S&P entered the market by differentiating its rating scale from AM Best scale (thus being more informative), and AM best reacted to the entry by disclosing more information.

Table 5.2 Rating actions by period and by CRAs

Panel A. Rating actions by period

CRA	Full sample	Period 1: Pre-crisis 2000-2006	Period 2: Crisis 2007-2009	Period 3: Post-crisis 2010-2017
S&P	14.4%	15.8%	12.6%	13.7%
Moody's	11.6%	13.6%	18.0%	7.7%
Fitch	11.2%	14.7%	26.4%	4.6%
AM Best	9.8%	14.2%	8.3%	6.8%

Panel B. Rating actions by direction of the rating change

CRA	Action	Full sample	Period 1: Pre-crisis 2000-2006	Period 2: Crisis 2007-2009	Period 3: Post-crisis 2010-2017
S&P	**% Up**	4.6%	2.4%	5.5%	6.9%
	% Down	9.9%	13.3%	7.1%	6.8%
Moody's	**% Up**	5.1%	3.2%	9.7%	4.8%
	% Down	6.5%	10.4%	8.3%	2.9%
Fitch	**% Up**	3.8%	2.2%	10.1%	2.4%
	% Down	7.4%	12.5%	16.4%	2.2%
AM Best	**% Up**	4.4%	4.6%	4.6%	4.1%
	% Down	5.2%	9.1%	3.7%	2.6%

This table presents a summary of the rating activity of the four CRAs derived from the transition matrices. Panel A comprises all actions of CRAs over each respective time period pre-crisis, crisis, and post-crisis. Panel A was built by adding the off-diagonal elements of the matrices and dividing them by the total number of actions over the period. Panel B breaks down the actions by downgrades and upgrades corresponded to each CRA and time period.

Table 5.2 also provides rating activity divided into three sub-samples, pre-crisis, crisis, and post-crisis. In general, Panel B reveals that the number of downgrades during pre-crisis surpassed the amount during and even after the financial crisis. For example, in pre-crisis period, S&P downgrades correspond to 13.3% and upgrades to 2.4% whereas, during the crisis, 7.1% were downgrades and 5.5% upgrades. For 2010-2017, 6.9% were upgrades and 6.8% downgrades. Except for Fitch, the same trend seems to have happened for the other CRAs, that is, greater number of rating actions in the period before the crisis than during the actual turmoil. Further, comparing across CRAs, only for years before the crisis, AM Best has a similar amount of rating actions with its competitors (14.2%). During the crisis, Fitch has the most amount of activity (26.4%) followed by Moody's (18%) whereas in the period after the turmoil, S&P has greater number of actions again (13.7%).

Drawing upon prior academic research, the result about the less amount of rating activity during the crisis seems to be consistent with the evidence documented by Baluch et al., (2011): the impact of the U.S. subprime crisis on insurers have been uneven, with life insurers that seem to have suffered more than the non-life sector. Baluch et al., (2011) argues that the most affected insurers where those that extended operations into risky areas of structured finance. For instance, the renowned case of AIG, which created AIG Financial Products Corp. (AIGFP), to operate new financial products that were not under the regulatory terms of a traditional insurance company (Ciumaş et al., 2015).

Ciumaş et al., (2015) state that among CRAs, S&P and Moody's where especially placed under the spotlight in 2010 whereas, Fitch has mainly managed to escape the attention and AM Best has hardly been mentioned by the media. Considering these facts about the crisis, we still need to comprehend better conceivable reasons for rating transition. Therefore, we present some cases of companies aiming to identify the potential drivers of rating changes.

5.4.1 Transition matrices across CRAs

This section presents a summary of the findings of the matrices per each CRA:

5.4.1.1 S&P

Table A 5.1 presents 1-year RTM, 2000-2017. The results for whole period show that S&P ratings are relatively stable. For instance, for eight of the 20 categories, over 80% did not experience rating changes in one year. Specifically, there is an 81.36% probability that AAA- (1) ratings will remain same in the next period, an 86.93% probability of continuing A (6), and 2.62% likelihood to change from the rating category A- (7) to BBB+ (8). The diagonal is unbalanced for BB- (13) and B+ (14) categories as any company appears rated in those groups. Largely, it seems that S&P is more prompt to implement single-notch changes downwards within A- rated firms (the area in the corner above the diagonal) rather than upwards.

Breaking down in the sub-samples, Table A 5.2 indicates that there is a 52.54% probability of remaining at AA+ (2) but 27.9% of downgrading to AA (3) and 18.64% to AA- (4) during 2000-2006. In contrast, Table A 5.3 shows for 2007-2009 an 80.77% probability of staying at AA+ (2) but a 19.23% probability of migrating to A+ (5). Comparing Table A 5.2 and Table A 5.4, the probability of migrating, during the pre-crisis from A (6) to BBB (9) is 2.69% whereas during the crisis, there is probability of 0.69%. Likewise, there is 5.58% chance of transiting from A- (7) to BBB+ (8) before the crisis whereas during 0% and after 2.26%.

Further, Table A 5.3 S&P relates some cases of upgrades and downgrades during 2000-2006 most of them happening in 2002-2003. For example, there is a 1.52% probability of transiting from A- (7) to CC-D (20) that corresponds to three of 197 cases; Legion Indemnity Co., Legion Insurance Company, Villanova Insurance Company downgraded in 2002. By examining the cases during the financial crisis, most of them happened in 2008, e.g., AIG group (Audubon

Insurance Company, AIG Assurance Company), and companies of the group Farmers Insurance Group of Companies such as 21st Century Insurance Company.

Table A 5.5 depicts the rating evolution from 2010 to 2017; the probability of remaining on AAA (1) is 10.71%, much lower compared with the two previous periods where it was fluctuating from 80% to 100%. The probability of moving from AA (3) to BBB (9) is higher in this time-lapse with a value of 2.02% and from A (6) to BBB (9) is 2.84%. In terms of upgrades, the probability of passing from BBB (9) to AA (3) is higher than before with 1.05%. Finally, Table A 5.6 depicts cases off diagonal after the financial crisis where year 2011 is dominant in the number of downgrades, mostly attached to adversely impact by weather-related events, which disturbed the company's financial performance.

5.4.1.2 Moody's

Table A 5.7 reports that Moody's ratings are also relatively stable during the whole period of analysis. Similar to S&P, the probability of remaining Aaa (1) is 85.07% during 2000-2017, with no company terminating in the CC or below category. For six of the twenty categories, about 80% of companies did not experience rating changes in one year. Rating stability seems to be in a lower level for insurers compare to corporate and structure finance products reported by Hu and Cantor (2003) and Hamilton and Cantor (2004) where the likelihood of remainining in the same rating category was over 90%.

Table A 5.8 conveys consistent results with Table A 5.7; most of the rating activity is focused in the diagonal for the five-year period 2000-2006. In Panel B, two of 32 cases are highlighted, Legion Insurance Company and Villanova Insurance Company that transits from Baa2 (9) to Caa1 (17), and the case of Newark Insurance Co., that moves from B2 (15) to Caa2 (18) ratings in 2002. Apart from these two cases, examining other elements off diagonal most of them have happened during 2002 and 2005.

Further, Table A 5.9 reveals some particularities of the behaviour of Moody's ratings over one-year horizons during the financial crisis. All companies are rated between Aaa (1) to Ba1 (11) categories, and no company appears in the C or below column. Meanwhile, Table 5.10 displays the post-crisis period 2010-2017, the ratings are still concentrated on the diagonal but seem more stable given that nine of 11 categories have a probability to remain same of 90-100%. Therefore, for the pre-crisis period, the estimation results are spread around the whole range of categories whereas, after the crisis, ratings are concentrated on the upper categories.

5.4.1.3 Fitch

Table A 5.11 shows the average one-year transition rates for annual cohorts formed between 2000 and 2017, where each annual cohort is weighted by its size (the number of issuers). Overall, Fitch FSR ratings are concentrated in the top ten categories, where six of ten have a probability of 80%-90% to remain in the category. Moreover, Table A 5.11 reveals that superior rating categories have generally been less likely than lower ratings to be adjusted over a one- year period. For example, for AAA-rated insurers, the probability to remain with the same rating is within 80% - 90%, i.e., the ratings of 92.8% of AA-rated insurers did not change within one year. On the contrary, an issuer that began the year within the B rating category ended the year with that same rating only 40% -60 % of the time.

Dividing up the time period, Table A 5.12 shows rating activity before the crisis, which is quite consistent with the trend of the whole period with similar levels of rating stability (values on the diagonal), but still with more downgrades than upgrades. By contrast, during the financial crisis, Table A 5.13 evidence that Fitch's ratings were less stable with more cases of downgrades than upgrades. For instance, the probability of passing from A (6) to A- (7) is 25%, remaining same is 75%, and 0% chance of having an upgrade.

Nevertheless, companies that initiate with BBB (9) no longer have 100% probability of remaining with the same rating; compared to the previous years, it is reduced to 50%. On the other hand, Table A 5.14 show that for the post-crisis period, ratings oscillate in a range within the rating categories of AA+ (2) to A- (7); thus, no company terminates in categories equals or below B (15).

By examining rating changes over the whole period of analysis, it is noticeable that most rating changes happened during 2001 and 2004 before the crisis, in 2008 during the crisis, and after, in 2010 and 2015. There was a 24.87% probability to transit from AA (3) to AA- (4) for cases such as American States Insurance Company, SAFECO Insurance Company of America, The Travelers Indemnity Company and Travelers Casualty and Surety Company of America.

5.4.1.4 AM Best

Table A 5.15 reveals some important attributes of the behaviour of AM Best ratings over one-year horizons. For five of 12 categories, the probability of remaining with the same rating wavers from 80-90%. However, the higher values around the diagonal indicate that higher categories have generally been less likely than lower ratings to be revised over a one-year period. C-rated category have slightly less probability of remaining in the same rating. For the marginal and weak categories, C++, C+, C there is a probability of default of 20.75%, 11.11%, and 41.67%, respectively. Compare with S&P, AM Best ratings C-rated has a probability around 45%-50% to remain in the same rating, while S&P ranges between 70%-80%. This finding is consistent with Wang (2010) who argues that for AM Best, C-rated are more volatile than B-rated and A-rated. Regarding A- category, the probability of a downgrade is 3.03% whereas an upgrade is 5.53% during 2000-2006.

Some extreme cases draw upon the matrices terminate in the C-D column during five-year 2000-2006 period, most of them occurring in 2001, 2002. For instance, 15/254 cases migrate from B+ (10) to C-/S (20) forming a probability of 5.91% and others that initiate with B++ also end up in default (2.95% probability). Similarly, rating levels B++ (9) and B+ (10) have also higher probability of upgrade 14.25% and 14.57% compare with a downgrade 6.88% and 5.91%, respectively. Meanwhile, within A (6) category, there is higher probability of downgrades than upgrades.

Further, Table A 5.17 shows the rating evolution during the crisis 2007-2009. The highest values are still located over the diagonal with six of 10 elements with a probability of remaining of 80-98%. For the A- (7) level, the probability of upgrade is higher (8.58%) than downgrade (2.72%) whereas for categories such as A (6) and A+ (5) a downgrade is more likely than an upgrade to the top. Respecting to the results post-crisis, similar patterns appeared. Table A 5.18 has a symmetrical diagonal until the C (18) category where the probability of maintaining the same assessment is lower than for the other categories. Moreover, the values equal and below A- (7) have again more likelihood of upgrades than downgrades. For AM Best, it is pertinent to observe the transition of category A- (7) given that is one of the categories where AM Best matches with the other three CRAs. Additionally, academics and specialists argue that the A- rating level is critical for the longer-term viability of insurance firms (see Epermanis and Harrington, 2006).

5.4.2 Summary comparisons and interpretations

When comparing RTM among CRAs, several features can be highlighted. First, insurers' rating stability seems to exhibit slightly lower levels compared to corporates and structured finance products reported in prior studies (i.e., Hamilton and Cantor, 2004; Hu and Cantor, 2003). However, a different picture emerges when comparing more recent studies. The higher levels of rating stability reported by Hu and Cantor (2003) for the years 1983 to 2002 have changed dramatically in the following years. Studies such as Benmelech and Dlugosz (2010) assert that 31% of downgrades in the first three-quarters of 2008 involved negative developments for

AAA-rated structured finance products. They argue that the average downgrade for structured finance products was 4.7 and 5.6 notches in 2007 and 2008 respectively. Purda (2011) states that it is evident that initial ratings assigned to these products were too optimistic and corrected abruptly with the arrival of the financial crisis. This markedly contrasts with the results of this chapter since the financial strength of most P/C insurers in this sample is not severely affected at that time.

Certainly, most insurers are placed in the superior/strong categories and most of them remain in the rating in a one-year interval. AA/Aa2/AA (3) to A-/A3/A- (7) for S&P, Moody's, and Fitch and for AM Best from A++ (2) to A (6). Across CRAs, single and multi-notch rating changes are more common over one year than changes within a whole category, and the likelihood to remain with the same rating oscillates at 80% as the diagonal of the RTMs suggests.

Looking into the RTM's off-diagonal elements, and using the proposed 20-point rating scale, RTMs seem to indicate that AM Best is having less rating activity compared to the other three CRAs during 2000-2017. Thus, AM Best RTMs have greater values in diagonal compared to their peers, and ratings are concentrated in the strong categories. This implies that higher AM Best ratings have generally been less likely to be changed over a one-year period than lower ratings.

Comparing RTMs over different time periods (pre-crisis, crisis, and post-crisis) interesting outcomes were revealed. It was somewhat surprising that there was a large number of rating actions before the financial crisis. Therefore, this chapter digs into some of those cases to understand the underlying reasons. Some of the changes pointed to a more straightforward link of climate-related events and man-made disasters with the P/C insurance industry than the period of the financial crisis. Indeed, prior studies (e.g., Baluch et.al, 2011) have found that the financial crisis has had an uneven effect on the industry, with some insurers severely affected while others barely.

Considering the pressure of catastrophe events, all CRAs have tended to announce close monitoring of exposure, capital adequacy and assess the risk-management processes of affected insurers in the aftermath of a particular event. That is the case of AM Best (2005), who after Hurricane Katrina and Rita, announced the possibility for rating actions associated with the unprecedented catastrophic activity. Hurricane Katrina generated exorbitant losses, but insurers denied responsibility because most damages were flood-related and property policies did not cover it. As mentioned earlier, coverage is given in a separate policy from the NFIP and from a few private insurers (III, 2017).

Comparing 2005 vs 2004, hurricane losses were covered mostly by U.S. insurance companies in 2004, whereas losses from Hurricanes Katrina, Rita, and Wilma in 2005 did not disturb U.S. insurance companies to the same extent; the losses were mainly absorbed by the Bermuda insurance sector (Baluch et al., 2011). Nevertheless, Table A 5.19 shows some examples where the reason for rating actions is due to natural catastrophes threatening financial strength.

Regarding the changes before and after the financial crisis, all CRAs -except for Fitch- seem to have a slightly similar pattern of rating activity, with no clear decline in the performance of the ratings. In the following, some patterns of companies that suffered revision of rating:

5.4.2.1 Cases before the crisis

As expected, some similarities across CRAs appear in the extreme areas of the RTMs. For instance:

- American Growers Insurance Co.: In 2002, the company initiates with BBB- (10) and terminate with CC-D (20) in S&P ratings. Similarly, Moody's has also downgraded them to B2 from Ba1; justifying that the plans to sell some of its crop insurance assets were refused by regulators and the supervision order. For Moody's that reflected company has **limited financial flexibility and weak earnings prospects** (Moody's, 2002). Moreover, AM Best also downgraded this company assigning from B++ (11), a C-/S (20) mainly for the same reasons.
- Legion Insurance Company: Activity from S&P, Moody's and AM Best. In 2002, passed from Baa2 (9) to Caa1 (17) in Moody's, and in S&P initiated with A- (7) and terminated in default CC-D (20). Besides, AM Best has downgraded this company giving the fact that Pennsylvania State Court decided to place the companies **under regulatory control.**
- American Family Mutual Insurance Company: It exhibited rating activity from S&P and Fitch. In 2013 transit from BBB (9) to A (6) for S&P whereas for Fitch, the action was in 2015 passing from A (6) to A+ (5).

Future research could be conducted on the secondary actions as well as on the market conditions of the insurance industry. As explained in Chapter 2, CRAs can also provide Outlook and Watch list actions. In that sense, Hamilton and Cantor (2004) reported that at a one-year time horizon, issuers with negative outlooks are seven times more likely to be downgraded than upgraded; issuers with positive outlooks are nearly twice as likely to be upgraded as downgraded; and issuers with stable outlooks have the highest probability of no rating change.

In the same way, Insurance Journal (2005) reports that S&P's has placed several groups on CreditWatch with negative implications due to their possible "exposure to the catastrophic and unparalleled losses stemming from Hurricane Katrina". Some of them, ACE, Lloyd's, Montpelier Re, Oil Casualty, PXRE, Swiss Re. Likewise, AM Best stated that "the impact of Katrina and Rita was intense enough to lead Christopher Cox, chairman of the U.S. Securities and Exchange Commission, to announce the SEC would take several actions to ease the rules for insurers and reinsurers seeking additional capital" (AM Best, 2005).

5.4.2.2 Cases during the crisis 2007-2009

As mentioned, one remarkable case during the crisis is AIG group. The group exhibited rating downgrades from S&P, Moody's and AM Best. AIG Property Casualty Company, AIG Specialty Insurance Company, AIG Assurance Company, and Audubon Insurance Company migrate from AA+ (2) to A+ (5) in S&P. Likewise, in 2005, Moody's assigned to AIG Property Casualty Company, AIG Specialty Insurance Company with Aa2 (3) from Aaa (1). Besides, during 2007 -2009 rating changed again from Aa2 (3) to Aa3 (4). Nevertheless, the group is not rated at default by any CRAs.

5.4.2.3 Cases post-financial crisis

Especially during 2011, many insurers suffered with the tornado-hail season. For example, Table A 5.6 shows that most of the S&P downgrades were in 2011. AM Best justified some rating changes by saying "increase in the frequency and severity of weather-related and catastrophe events in its operating territories" or "wind and hailstorm losses, catastrophe exposure, tornado/hailstorms, and hurricane activity has dampened underwriting profitability and overall earnings". Respecting 2012, Hurricane Sandy generated $19.9 billion of insured losses (CIPR, 2017a). However, those at risk were better prepared for the disaster (compared with Hurricane Katrina in 2005), with evacuation plans and risk-reduction measures investments in place (Michel-Kerjan et al., 2015). Thus, financial strength rating levels did not seem to have been majorly affected.

Finally, 2017 became the costliest year on record for weather disasters surpassing 2011, with landfalls of Hurricanes Harvey, Irma, and Maria that caused. Again, the insurance industry was still able to meet the high volume of claims.

5.5 Alternative specifications

In the following, results of two alternative specifications are discussed. The first specification employs a different rating scale transformation and the second one assesses whether U.S. states that were affected with a higher frequency of catastrophes might have more stable or less stable FSR evolution. Regarding the first alternative specification, recall that AM Best uses a 13-points rating scale and it is mapped to a 20-points rating scale for equivalence with the other three CRAs. The alternative specification consists of taking AM Best rating scale as the base point and therefore the rating categories of S&P, Moody's, and Fitch are mapped to a 13-point scale as shown in Panel B of Table 4.12 in Chapter 4. The RTMs are then reconstructed for every period using the 13-point numerical transformation.

Table 5.3 Rating actions by period and by CRAs using AM Best rating scale approach

Panel A.

CRA	Full sample	Period		
		1	2	3
		Pre-crisis 2000-2006	Crisis 2007-2009	Post-crisis 2010-2017
S&P	9.7%	11.7%	8.9%	7.4%
Moody's	7.0%	9.2%	11.0%	3.9%
Fitch	6.1%	6.9%	19.3%	1.4%
AM Best	9.7%	13.8%	8.3%	6.7%

Panel B.

CRA	Action	Full sample	Period		
			1	2	3
			Pre-crisis 2000-2006	Crisis 2007-2009	Post-crisis 2010-2017
S&P	**% Up**	2.7%	2.2%	3.4%	3.1%
	% Down	6.9%	9.5%	5.5%	4.4%
Moody's	**% Up**	2.9%	1.9%	6.1%	2.5%
	% Down	4.1%	7.3%	4.9%	1.4%
Fitch	**% Up**	1.5%	1.3%	3.4%	1.0%
	% Down	4.6%	5.6%	15.8%	0.4%
AM Best	**% Up**	4.4%	4.6%	4.6%	4.1%
	% Down	5.3%	9.2%	3.7%	2.6%

This table presents a summary of the rating activity of the four CRAs derived from the transition matrices using AM Best rating scale (13-point scale). Panel A comprises all actions of CRAs over each respective time period pre-crisis, crisis, and post-crisis. Panel A was built by adding the off-diagonal elements of the matrices and dividing them by the total number of actions over the period. Panel B breaks down the actions by downgrades and upgrades corresponded to each CRA and time period.

Table 5.3 displays the level of activity using the 13-point scale. Analogous to Section 5.4, the table is built by adding the off-diagonal elements of the matrices and dividing them by the total number of actions over the period. The detail of these calculations can be found from the Tables A 5.20 to Table A 5.35 in Appendix 5.I. Overall, S&P and AM Best seem to have similar amount of rating activity over the whole period of analysis. In the pre-crisis, AM Best has more rating actions whereas during and after the crisis has the least amount. Similar to the main results, S&P, Moody's, and AM Best have more downgrades before the crisis. Only Fitch has more downgrades during the turmoil and again S&P appears to be the most active CRA.

Regarding to the second alternative specification based on natural hazards, floods accounted for the most property damage of all natural disasters. Floods can be classified with several types such as, regional floods, flash floods, ice jam floods, storm-surge, dam-and levee failure floods, debris landslide, and mudflow floods (Perry, 2000). The alternative specification consists on constructing RTM using storm surges, as it has happened often during this study's period of analysis. Thus, RTM are reconstructed considering the evolution of the 10 states at greatest risk of storm surge damage, which are Florida, Louisiana, Texas, New Jersey, Virginia, New York, North Carolina, South Carolina, Georgia, Massachusetts (CIPR, 2017a). For this subsample, results can be found in detail from Table A 5.36 to Table A 5.39 showing the variation among CRAs. For example, for S&P and Fitch, category 'AAA' (1) has a probability to remain the same with a probability of 70%-74% whereas for Moody's and AM Best ranges from 90-94%, both versus an 80% from the main results. However, rating activity patterns are consistent with the main findings; AM Best has relatively the least amount of rating activity and particularly so in the case of downgrades. During 2000-2017, S&P has 3.8% of upgrades and 10.9% of downgrades whereas AM Best has 4.2% of upgrades and 6.4% of downgrades. Respecting Moodys and Fitch, upgrades are placed in 4.4%, 3.4% and downgrades in 7.1% and 7.7%, respectively.

5.6 Conclusions

In this Chapter, rating transition matrices (RTM) are constructed using a sample of 1384 U.S. P/C insurers rated by at least two of the major CRAs for insurers, to compare and examine the evolution of FSR and capture the difference and similarities across time and CRAs. In addition, this Chapter shed light on the effects of the financial crisis 2007-9 on the evolution of insurer's financial strength. To this end, the study considers the fact that S&P has historically concentrated on rating individual debt issues, Moody's and Fitch are relatively growing players in insurance ratings market, while AM Best have always specialized in rating insurers. This feature adds an additional element to the insurance sector (compared with banks) given the lack of ratings comparability between AM Best rating scale and the three traditional CRAs. In terms of methods, the cohort method is use to estimate the matrices since is a widely accepted approach.

Overall, Chapter 5 reveals that numerous FSR actions occur before the crisis. Downgrades are more frequent than upgrades before and during the financial crisis, while after the crisis, upgrades and downgrades are quite balanced. Comparing among CRAs, using the proposed 20-point rating scale, AM Best has the least amount of rating activity during the whole period, S&P seems to be the most active agency, while Moody's and Fitch have quite similar amount of activity, with the latter assigning more downgrades during the crisis. Across CRAs, single (e.g., 'AA-' to 'AA') and multi-notch rating changes (e.g., 'AA-' to 'AA+') are more common over one year than changes across a whole category (e.g., 'AA-' to 'BBB+').

This Chapter conducts two alternative specifications. In the first one, RTM are re-constructed using an alternative numerical mapping based on AM Best 13-points rating scale (rather than 20-points), which confirms the main results of this Chapter. The second alternative specification consists of constructing RTM for the 10 states affected by storm surge. By doing so, diverse results are found among CRAs and a more spread probability. Thus, results of this chapter suggest a more straightforward relationship between FSR actions and climate-related events. From this baseline, a need is pointed for further analysis focusing on distinction between affected and unaffected states by weather related events, state legislative changes, and reasons behind most companies' downgrades is pointed. Likewise, to explore afterwards the relationship between RTM and split ratings.

Among the numerous FSR actions before, during, and after the financial crisis, the chapter highlights several climate-related and man-made events impacted the insurance industry.

Before the crisis, the terrorist attacks on the World Trade Center (WTC) in September 2001, the bankruptcy of Enron, the WorldCom accounting scandal and natural catastrophes in 2002. During 2004, Hurricanes Charley, Ivan, and Frances occurred, and in 2005, Hurricanes Katrina, Rita and Wilma generated unexpected losses and shook the asset quality of insurers. During the crisis 2007-2009, apart from the financial turmoil shaking the roots of the financial markets, Hurricane Gustav and Ike also took place.

A plausible explanation for the almost muted effect of the financial crisis over the financial strength of U.S. P/C insurers analysed in this study can draw upon what is found by the GAO (2013). They argue that actions by state and federal regulators and NAIC, among other factors, helped limit the effects of the crisis. They argue that state insurance regulators shared more information with each other to focus their oversight activities. GAO (2013) also found that since the crisis, NAIC and state regulators' efforts have included an increased focus on insurers' risks and capital adequacy, and oversight of noninsurance entities in the group holding company structures. Further, NAIC developed and implemented the Own Risk and Solvency Assessment in 2015, and amended its Insurance Holding Company System Regulatory Act to tackle the issues of transparency and oversight of holding company entities. Finally, with the 2010 Dodd Frank Act, the adherence of the Federal Insurance Office (FIO) has also impacted the regulatory oversight of the sector.

Regarding the period after the crisis 2010-2017, most rating changes occurred in 2011 where a very active tornado-hail season surpassed insured losses by $25 billion, making it the deadliest thunderstorm season in over 75 years. Additionally, Hurricane Irene and Tropical Storm Lee also occurred as well as the tsunami in Japan that affected some parts of U.S. and it is considered the deadliest natural disaster in 2011. Adding to those facts, in 2012, Hurricane Sandy generated $19.9 billion of insured losses (CIPR, 2017a), and 2017 became the costliest year on record for weather disasters, with landfalls of Hurricanes Harvey, Irma, and Maria that represented 62% of the annual economic loss (Aon Benfield, 2017). Nevertheless, the insurance industry was still able to meet the high volume of claims.

This Chapter contributes to expand the sparse previous literature on the role of insurer credit ratings, specifically as a measure of insurance company performance. It also provides rich findings that are consistent with those obtained by Wang (2010) and Chen and Pottier (2018). For instance, findings are in line with Chen and Pottier (2018) who state that 'A' or higher are downgraded more often than upgraded, while firms rated 'A-' to 'B' are upgraded more often than downgraded. For AM Best, outcomes from the matrices are aligned with Wang (2010) study in terms of the higher volatility of C-rated companies. Diversely, this results may seem inconsistent with Sharma et al., (2018) in the sense that they argue that before the crisis there is a more stable rating activity whereas, after the crisis, less stability, and more variations. However, their results could be different due to the different period consider as crisis (they use pre-financial crisis 2006-2007 and 2008-2010 as post-financial crisis), or the U.K. being affected by the crisis as reflected by the decline of insurance density and insurance penetration levels.

It is important to consider the different institutional background of the U.K. in comparison with the U.S. market. Jadi (2015) asserts that the U.S. insurance market is a very established market, with the largest percentage shares of the world market while the U.K., tends to have 5-10 insurers that dominate the market; in 2012, Aviva, Direct Line Group, AXA Insurance, RSA Group, and Ageas delivered about 47% of the total net written premium. Furthermore, as mentioned in Section 5.2.1, the U.S. has a state-based regulation where states can impose regulatory limits on premiums (e.g., New York) or impose higher capital maintenance requirements on so-called ‘alien’ reinsurance companies compared to U.S.-owned reinsurers. The focus of U.S. regulation also has a fundamental remit to protect American consumers. Meanwhile, the U.K. regulatory framework does not discriminate between reinsurance companies according to their origin, is defined as a unitary fiscal environment (Upreti and Adams, 2015), and it is subject to dual-regulation, aiming to protect both the players and the customers in the industry (Jadi, 2015).

From a credit ratings’ market perspective, the fact that AM Best has less rating activity compared to the other CRAs over the period 2000-2017 hints at potential dynamics among CRAs. Considering that obtaining an FSR is a voluntary practice, the cost of being assessed is a considerable important factor for the insurance company when choosing a CRA. AM Best have always specialised in the assessment of insurance firms, and as such, it is often the preferred choice for insurance companies (Pottier and Sommer, 1999). In terms of fees, AM Best charges annual fees that may range up to US$1,500,000 per organization/issuer (AM Best, n.d.). Moody’s fees range from $1,000 to approximately $2,700,000 (Moody’s, 2020). Fitch fees generally vary from US$1,000 to US$750,000 (or the currency equivalent) per issue (Fitch, 2021). For S&P (2022), U.S. ratings for corporates (including industrial and financial service companies fees have a minimum of $115,000 for most transactions. It is possible that

S&P, Moody’s and Fitch may be under-pricing their charges to undercut AM Best's market position of being an established CRA focused on the insurance market. This is an interesting angle of future research that did not fall in the scope of this thesis since fee negotiations are confidential and will tend to vary among insurers depending on the complexity of the task (Adams et al., 2003).

Finally, despite this chapter does not present definitive evidence that the climate-related events precede rating changes. This thesis agrees with CIPR (2017c) with the fact that if natural disasters continue to occur at this rate, it is largely expected the magnitude of insured losses will keep increasing, possible reaching a level that could, at some point, threaten the industry financial stability.

Appendix 5.I – Supporting tables

Table A 5.1 S&P: Rating transition matrix, 2000 – 2017

		Panel A. Ratings to (%)																	
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**17**	**18**	**20**
	From	**AAA**	**AA+**	**AA**	**AA-**	**A+**	**A**	**A-**	**BBB+**	**BBB**	**BBB-**	**BB+**	**BB**	**BB-**	**B+**	**B**	**CCC+**	**CCC**	**CC-D**
1	**AAA**	81.36	16.71	1.69	0.24	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	**AA+**	0	74.19	13.88	4.77	6.51	0.65	0	0	0	0	0	0	0	0	0	0	0	0
3	**AA**	0	0	89	5.93	2.07	1.86	0	0	1.14	0	0	0	0	0	0	0	0	0
4	**AA-**	0.41	0	5.7	71.79	16.29	4.99	0.31	0.41	0.1	0	0	0	0	0	0	0	0	0
5	**A+**	0	0.16	0	4.48	84.49	9.11	0.78	0.99	0	0	0	0	0	0	0	0	0	0
6	**A**	0.04	0	1.19	0.04	5.39	86.93	3.94	0.07	2.15	0.15	0	0	0	0	0.11	0	0	0
7	**A-**	0	0	0	0	0	10.14	85.71	2.62	0.44	0.44	0.11	0	0.11	0.11	0	0	0	0.33
8	**BBB+**	0	0	0	0	0.62	1.85	11.73	64.81	12.35	0.62	8.02	0	0	0	0	0	0	0
9	**BBB**	0	0	0.13	0	0	2.53	0.4	0.8	90.67	0.2	0.2	3.87	0.2	0	0.8	0	0.2	0
10	**BBB-**	0	0	0	0	0	0	6.67	0	20	66.67	0	0	0	0	0	0	0	6.67
11	**BB+**	0	0	0	0	0	0	0	0	0	0	94.74	0	2.63	0	0	2.63	0	0
12	**BB**	0	0	0.52	0	0	0	0	0	2.76	0.17	1.03	89.83	0	0.17	2.07	0	2.24	1.21
14	**B+**	0	0	0	0	0	0	0	0	0	0	0	0	0	100	0	0	0	0
15	**B**	0	0	0	0	0	0.65	0	0	0.65	0	0	5.84	0	0	84.42	0	3.9	4.55
17	**CCC+**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100	0	0
18	**CCC**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	81.82	18.18
20	**CC-D**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100

Table A 5.1 - Continued

	Panel B. Ratings to (frequency)																		
	From	**AAA**	**AA+**	**AA**	**AA-**	**A+**	**A**	**A-**	**BBB+**	**BBB**	**BBB-**	**BB+**	**BB**	**BB-**	**B+**	**B**	**CCC+**	**CCC**	**CC-D**	**Total**
1	**AAA**	336	69	7	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	413
2	**AA+**	0	342	64	22	30	3	0	0	0	0	0	0	0	0	0	0	0	0	461
3	**AA**	0	0	1,246	83	29	26	0	0	16	0	0	0	0	0	0	0	0	0	1400
4	**AA-**	4	0	56	705	160	49	3	4	1	0	0	0	0	0	0	0	0	0	982
5	**A+**	0	3	0	86	1,623	175	15	19	0	0	0	0	0	0	0	0	0	0	1921
6	**A**	1	0	32	1	145	2,341	106	2	58	4	0	0	0	0	3	0	0	0	2692
7	**A-**	0	0	0	0	0	93	786	24	4	4	1	0	1	1	0	0	0	3	917
8	**BBB+**	0	0	0	0	1	3	19	105	20	1	13	0	0	0	0	0	0	0	162
9	**BBB**	0	0	2	0	0	38	6	12	1,360	3	3	58	3	0	12	0	3	0	1500
10	**BBB-**	0	0	0	0	0	0	1	0	3	10	0	0	0	0	0	0	0	1	15
11	**BB+**	0	0	0	0	0	0	0	0	0	0	36	0	1	0	0	1	0	0	38
12	**BB**	0	0	3	0	0	0	0	0	16	1	6	521	0	1	12	0	13	7	580
14	**B+**	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	3
15	**B**	0	0	0	0	0	1	0	0	1	0	0	9	0	0	130	0	6	7	154
17	**CCC+**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0	0	5
18	**CCC**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	72	16	88
20	**CC-D**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	522	522
	Total	341	414	1410	898	1988	2729	936	166	1479	23	59	588	5	5	157	6	94	556	11854

This table presents rating transition matrices of U.S. P/C insurers rated by S&P from Dec. 2000- Dec. 2017.

Table A 5.2 S&P: Rating transition matrix, 2000 – 2006

Panel A. Ratings to (%)

From	**AAA**	**AA+**	**AA**	**AA-**	**A+**	**A**	**A-**	**BBB+**	**BBB**	**BBB-**	**BB+**	**BB**	**BB-**	**B+**	**B**	**CCC+**	**CCC**	**CC-D**
AAA	83.23	14.19	2.26	0.32	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AA+	0	52.54	27.97	18.64	0	0.85	0	0	0	0	0	0	0	0	0	0	0	0
AA	0	0	80.04	14.04	4.17	1.54	0	0	0.22	0	0	0	0	0	0	0	0	0
AA-	0.98	0	0	57.35	31.62	8.09	0.74	0.98	0.25	0	0	0	0	0	0	0	0	0
A+	0	0	0	5.92	78.79	11.83	1.01	2.45	0	0	0	0	0	0	0	0	0	0
A	0.09	0	0.61	0.09	0.7	93.14	1.91	0.17	2.69	0.35	0	0	0	0	0.26	0	0	0
A-	0	0	0	0	0	3.55	85.28	5.58	1.02	2.03	0	0	0.51	0.51	0	0	0	1.52
BBB+	0	0	0	0	1.3	3.9	9.09	44.16	24.68	1.3	15.58	0	0	0	0	0	0	0
BBB	0	0	0	0	0	2.52	0.47	0.47	90.01	0.09	0.28	4.48	0.28	0	1.12	0	0.28	0
BBB-	0	0	0	0	0	0	14.29	0	14.29	57.14	0	0	0	0	0	0	0	14.29
BB+	0	0	0	0	0	0	0	0	0	0	91.3	0	4.35	0	0	4.35	0	0
BB	0	0	0.77	0	0	0	0	0	1.29	0.26	0	89.72	0	0	2.83	0	3.34	1.8
B+	0	0	0	0	0	0.86	0	0	0.86	0	0	2.59	0	0	84.48	0	5.17	6.03
B	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100	0	0
CCC+	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	70.91	29.09
CCC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100

Panel B. Ratings to (frequency)

From	**AAA**	**AA+**	**AA**	**AA-**	**A+**	**A**	**A-**	**BBB+**	**BBB**	**BBB-**	**BB+**	**BB**	**BB-**	**B+**	**B**	**CCC+**	**CCC**	**CC-D**	**Total**
AAA	258	44	7	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	310
AA+	0	62	33	22	0	1	0	0	0	0	0	0	0	0	0	0	0	0	118
AA	0	0	365	64	19	7	0	0	1	0	0	0	0	0	0	0	0	0	456
AA-	4	0	0	234	129	33	3	4	1	0	0	0	0	0	0	0	0	0	408
A+	0	0	0	41	546	82	7	17	0	0	0	0	0	0	0	0	0	0	693
A	1	0	7	1	8	1,073	22	2	31	4	0	0	0	0	3	0	0	0	1151
A-	0	0	0	0	0	7	168	11	2	4	0	0	1	1	0	0	0	3	197
BBB+	0	0	0	0	1	3	7	34	19	1	12	0	0	0	0	0	0	0	77
BBB	0	0	0	0	0	27	5	5	964	1	3	48	3	0	12	0	3	0	1071
BBB-	0	0	0	0	0	0	1	0	1	4	0	0	0	0	0	0	0	1	7
BB+	0	0	0	0	0	0	0	0	0	0	21	0	1	0	0	1	0	0	23
BB	0	0	3	0	0	0	0	0	5	1	0	349	0	0	11	0	13	7	389
B+	0	0	0	0	0	1	0	0	1	0	0	3	0	0	98	0	6	7	116
B	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1
CCC+	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	39	16	55
CCC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	358	358
Total	263	106	415	363	703	1234	213	73	1025	15	36	400	5	1	124	2	61	392	5431

This table presents rating transition matrices of U.S. P/C insurers rated by S&P from Dec 2000- Dec 2006. No companies appeared into ratings B- (13), B+ (14), CCC- (19) in the initial rating and no companies in B- (16) and CCC- (19) in the terminal rating. Please refer to Table A 5.1 to see equivalence of rating symbols and numbers.

Table A 5.3 S&P: Cases off diagonal, 2000 – 2006

Company	Rating change From	Rating change To	Year of change	Cases Number cases / Total	Probability
i) Upgrades:					
21st Century Centennial Insurance Company	AA-	AAA	2003	4/408	0.98%
21st Century Indemnity Insurance Company	(4)	(1)	2003		
21st Century Preferred Insurance Company			2003		
21st Century Premier Insurance Company			2003		
America First Insurance Co.	BBB	A	2003	27/1071	2.52%
California Automobile Insurance Company	(9)	(6)	2006		
Citation Insurance Company Inc.			2003		
Consolidated Insurance Co.			2003		
Excelsior Insurance Company			2003		
Farmers Mutual Hail Insurance Comp. of Iowa			2005		
Florida Farm Bureau Casualty Insurance Comp.			2004		
Great American Casualty Insurance Company			2001		
Greater New York Mutual Insurance Company			2002		
Hallmark National Insurance Company			2003		
Hawkeye-Security Insurance Company			2003		
Home-Owners Insurance Co.			2004		
Indiana Insurance Company			2003		
Insurance Company of Greater New York			2002		
Midwestern Indemnity Company Inc.			2003		
MSI Preferred Insurance Co.			2004		
Netherlands Insurance Co.			2003		
Peerless Indemnity Insurance Co.			2003		
Peerless Insurance Company			2003		
Penn-Star Insurance Company			2005		
Property-Owners Insurance Co.			2004		
Shelter General Insurance Company			2005		
Shelter Mutual Insurance Company, Inc.			2005		
Southern-Owners Insurance Co.			2004		
The Commerce Insurance Company			2003		
Worldwide Direct Auto Insurance Company			2001		
Worldwide Insurance Company			2001		
ii) Downgrades					
American Healthcare Indemnity Company	A	B	2002	3/1151	0.26%
Kinsale Insurance Company	(6)	(15)	2002		
SCPIE Indemnity Company			2002		
Legion Indemnity Co.	A-	CC-D	2002	3/197	1.52%
Legion Insurance Company	(7)	(20)	2002		
Villanova Insurance Company			2002		
Casualty Reciprocal Exchange	BBB	CCC	2002	3/1071	0.28%
Equity Mutual Insurance Co.	(9)	(18)	2002		
Northwestern National Casualty Company			2001		
American Growers Insurance Co.	BBB- (10)	CC-D (20)	2002	1/7	14.3%
American & Foreign Insurance Co.	A+	BBB+	2002	17/693	2.45%
Arrowood Indemnity Company	(5)	(8)	2002		
Clarendon National Insurance Company			2006		
Connecticut Indemnity Company			2002		
Design Professional Insurance Co.			2002		
EBI Indemnity Company			2002		
Employee Benefits Insurance Company			2002		
Globe Indemnity Company			2002		
Guaranty National Insurance Co. Connecticut			2002		
Landmark American Insurance Company			2002		
Peak Property & Casualty Insurance Corp.			2002		
Royal Insurance Company of America			2002		
Safeguard Insurance Co.			2002		
Security Insurance Company of Hartford			2002		
The Fire & Casualty Ins. Co. of Connecticut			2002		
Viking County Mutual Insurance Co.			2002		
Viking Insurance Company of Wisconsin			2002		

This table shows examples of U.S. P/C insurers rated by S&P that are off the diagonal in the RTM during 2000-2006.

Table A 5.4 S&P: Rating transition matrix, 2007 – 2009

Panel A. Ratings to (%)

From	AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+	BB	B	CCC+	CCC	CC-D
AAA	100	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AA+	0	80.77	0	0	19.23	0	0	0	0	0	0	0	0	0	0	0
AA	0	0	89.6	5.45	4.95	0	0	0	0	0	0	0	0	0	0	0
AA-	0	0	1.74	88.7	3.04	6.52	0	0	0	0	0	0	0	0	0	0
A+	0	1.13	0	10.19	75.85	9.81	3.02	0	0	0	0	0	0	0	0	0
A	0	0	2.71	0	5.25	83.08	8.97	0	0	0	0	0	0	0	0	0
A-	0	0	0	0	0	4.83	94.48	0	0.69	0	0	0	0	0	0	0
BBB+	0	0	0	0	0	0	28	68	0	0	4	0	0	0	0	0
BBB	0	0	0	0	0	2.51	0.42	2.51	94.14	0	0	0.42	0	0	0	0
BBB-	0	0	0	0	0	0	0	0	25	75	0	0	0	0	0	0
BB+	0	0	0	0	0	0	0	0	0	0	100	0	0	0	0	0
BB	0	0	0	0	0	0	0	0	3.05	0	4.58	92.37	0	0	0	0
B	0	0	0	0	0	0	0	0	0	0	0	17.24	82.76	0	0	0
CCC+	0	0	0	0	0	0	0	0	0	0	0	0	0	100	0	0
CCC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100	0
CC-D	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100

Panel B. Ratings to (frequency)

From	AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+	BB	B	CCC+	CCC	CC-D	Total
AAA	75	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	75
AA+	0	126	0	0	30	0	0	0	0	0	0	0	0	0	0	0	156
AA	0	0	181	11	10	0	0	0	0	0	0	0	0	0	0	0	202
AA-	0	0	4	204	7	15	0	0	0	0	0	0	0	0	0	0	230
A+	0	3	0	27	201	26	8	0	0	0	0	0	0	0	0	0	265
A	0	0	16	0	31	491	53	0	0	0	0	0	0	0	0	0	591
A-	0	0	0	0	0	7	137	0	1	0	0	0	0	0	0	0	145
BBB+	0	0	0	0	0	0	7	17	0	0	1	0	0	0	0	0	25
BBB	0	0	0	0	0	6	1	6	225	0	0	1	0	0	0	0	239
BBB-	0	0	0	0	0	0	0	0	2	6	0	0	0	0	0	0	8
BB+	0	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0	5
BB	0	0	0	0	0	0	0	0	4	0	6	121	0	0	0	0	131
B	0	0	0	0	0	0	0	0	0	0	0	5	24	0	0	0	29
CCC+	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	3
CCC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	25	0	25
CC-D	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	164	164
Total	75	129	201	242	279	545	206	23	232	6	12	127	24	3	25	164	2293

This table presents rating transition matrices of U.S. P/C insurers rated by S&P from Dec. 2007- Dec. 2009. Please refer to Table A 5.1 to see the equivalence of rating symbols and numbers.

Table A 5.5 S&P: Rating transition matrix, 2010 – 2017

								Panel A. Ratings to (%)								
From	**AAA**	**AA+**	**AA**	**AA-**	**A+**	**A**	**A-**	**BBB+**	**BBB**	**BBB-**	**BB+**	**BB**	**B+**	**B**	**CCC+**	**CCC**
AAA	10.71	89.29	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AA+	0	82.35	16.58	0	0	1.07	0	0	0	0	0	0	0	0	0	0
AA	0	0	94.34	1.08	0	2.56	0	0	2.02	0	0	0	0	0	0	0
AA-	0	0	15.12	77.62	6.98	0.29	0	0	0	0	0	0	0	0	0	0
A+	0	0	0	1.87	90.97	6.96	0	0.21	0	0	0	0	0	0	0	0
A	0	0	0.95	0	11.16	81.79	3.26	0	2.84	0	0	0	0	0	0	0
A-	0	0	0	0	0	13.74	83.65	2.26	0.17	0	0.17	0	0	0	0	0
BBB+	0	0	0	0	0	0	8.33	90	1.67	0	0	0	0	0	0	0
BBB	0	0	1.05	0	0	2.63	0	0.53	90	1.05	0	4.74	0	0	0	0
BB+	0	0	0	0	0	0	0	0	0	0	100	0	0	0	0	0
BB	0	0	0	0	0	0	0	0	11.67	0	0	85	1.67	1.67	0	0
B+	0	0	0	0	0	0	0	0	0	0	0	0	100	0	0	0
B	0	0	0	0	0	0	0	0	0	0	0	11.11	0	88.89	0	0
CCC+	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100	0
CCC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100

								Panel B. Ratings to (frequency)									
From	**AAA**	**AA+**	**AA**	**AA-**	**A+**	**A**	**A-**	**BBB+**	**BBB**	**BBB-**	**BB+**	**BB**	**B+**	**B**	**CCC+**	**CCC**	**Total**
AAA	3	25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	28
AA+	0	154	31	0	0	2	0	0	0	0	0	0	0	0	0	0	187
AA	0	0	700	8	0	19	0	0	15	0	0	0	0	0	0	0	742
AA-	0	0	52	267	24	1	0	0	0	0	0	0	0	0	0	0	344
A+	0	0	0	18	876	67	0	2	0	0	0	0	0	0	0	0	963
A	0	0	9	0	106	777	31	0	27	0	0	0	0	0	0	0	950
A-	0	0	0	0	0	79	481	13	1	0	1	0	0	0	0	0	575
BBB+	0	0	0	0	0	0	5	54	1	0	0	0	0	0	0	0	60
BBB	0	0	2	0	0	5	0	1	171	2	0	9	0	0	0	0	190
BB+	0	0	0	0	0	0	0	0	0	0	10	0	0	0	0	0	10
BB	0	0	0	0	0	0	0	0	7	0	0	51	1	1	0	0	60
B+	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	3
B	0	0	0	0	0	0	0	0	0	0	0	1	0	8	0	0	9
CCC+	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1
CCC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8	8
Total	3	179	794	293	1,006	950	517	70	222	2	11	61	4	9	1	8	4130

This table presents rating transition matrices of U.S. P/C insurers rated by S&P from Dec. 2010- Dec. 2017. Please refer to Table A 5.1 to see the equivalence of rating symbols and numbers.

Table A 5.6 S&P: Cases off diagonal, 2010 – 2017

Company	Rating change		Year of change	Cases	Probability
	From	To		Number cases / Total	
i) Upgrades:					
Auto Club Family Insurance Company	BBB	AA	2011	2/190	1.05%
Automobile Club Inter-Insurance Exchange	(9)	(3)	2011		
American Family Mutual Insurance Company	BBB	A	2013	5/188	2.7%
Home-Owners Insurance Co.	(9)	(6)			
Owners Insurance Company					
Property-Owners Insurance Co.					
Southern-Owners Insurance Co.					
American Healthcare Indemnity Company	BB	BBB	2011	7/60	11.67%
Kentucky Farm Bureau Mutual Insurance Co.	(12)	(9)	2013		
SCPIE Indemnity Company			2011		
TDC Specialty Insurance Company			2011		
Tennessee Farmers Assurance Company			2013		
Tennessee Farmers Mutual Insurance Company			2013		
The Doctors' Co., An Interinsurance Exchange			2011		
ii) Downgrades					
Cotton States Mutual Insurance Company, Inc.	AA	BBB	2011	15 / 742	2.02%
Country Casualty Insurance Co.	(3)	(9)	2011		
Country Mutual Insurance Company			2011		
Country Preferred Insurance Co.			2011		
Home-Owners Insurance Co.			2011		
Kentucky Farm Bureau Mutual Insurance			2011		
Company			2011		
Middlesex Mutual Assurance Company			2011		
Modern Service Insurance Co.			2011		
MSI Preferred Insurance Co.			2011		
Owners Insurance Company			2011		
Property-Owners Insurance Co.			2011		
Shield Insurance Company			2011		
Southern-Owners Insurance Co.			2011		
Tennessee Farmers Assurance Company			2011		
Tennessee Farmers Mutual Insurance Company					
Auto Club Group Insurance Co.	A	BBB	2011	27/950	2.84%
Auto Club Insurance Association Co.	(6)	(9)	2011		
Dairyland Insurance Company			2013		
Florida Farm Bureau Casualty Insurance			2011		
Company			2011		
Grange Indemnity Insurance Company			2011		
Grange Mutual Casualty Company			2011		
Graphic Arts Mutual Insurance Company Inc.			2011		
Louisiana Farm Bureau Casualty Insurance			2011		
MemberSelect Insurance Co.			2011		
Mico Insurance Company			2013		
Middlesex Insurance Company, Inc.			2011		
Mississippi Farm Bureau Casualty Insurance			2011		
Motorists Commercial Mutual Insurance			2011		
Company			2012		
Motorists Mutual Insurance Company			2012		
New Jersey Manufacturers Insurance Company			2013		
New Jersey Re-Insurance Company			2011		
NGM Insurance Company, Inc.			2013		
Republic-Franklin Insurance Co.			2013		
Sentry Casualty Co. / Sentry Insurance A Mutual			2013		
Sentry Select Insurance Co.			2011		
Shelter General Insurance Company			2011		
Shelter Mutual Insurance Company, Inc.			2011		
Southern Farm Bureau Casualty Insurance Co			2011		
Utica Mutual Insurance Company, Inc.			2011		
Utica National Assurance Co.					
Utica National Insurance Co. of TX					

This table shows examples of U.S. P/C insurers rated by S&P that are off the diagonal in the RTM during 2010-2017.

Table A 5.7 Moody's: Rating transition matrix, 2000 – 2017

Panel A. Ratings to (%)

		1	2	3	4	5	6	7	8	9	10	11	12	13	15	17	18
	From	**Aaa**	**Aa1**	**Aa2**	**Aa3**	**A1**	**A2**	**A3**	**Baa1**	**Baa2**	**Baa3**	**Ba1**	**Ba2**	**Ba3**	**B2**	**Caa1**	**Caa2**
1	**Aaa**	85.07	2.99	11.94	0	0	0	0	0	0	0	0	0	0	0	0	0
2	**Aa1**	0	70	30	0	0	0	0	0	0	0	0	0	0	0	0	0
3	**Aa2**	0	0	92.9	6.69	0.4	0	0	0	0	0	0	0	0	0	0	0
4	**Aa3**	0	0	7.02	79.89	9.3	3.42	0.38	0	0	0	0	0	0	0	0	0
5	**A1**	0	0	0	3.46	84.42	9.31	0.87	0	1.73	0.22	0	0	0	0	0	0
6	**A2**	0	0	0.15	0.23	3.64	93.09	2.66	0	0	0.15	0.08	0	0	0	0	0
7	**A3**	0	0	0	0	0	11.82	86.97	0.61	0.3	0	0.3	0	0	0	0	0
8	**Baa1**	0	0	0	0	0	1.96	6.86	87.25	2.94	0.98	0	0	0	0	0	0
9	**Baa2**	0	0	0	0	0	0	1.72	5.17	72.41	3.45	5.17	0	8.62	0	3.45	0
10	**Baa3**	0	0	0	0	0	3.57	10.71	0	10.71	67.86	0	0	7.14	0	0	0
11	**Ba1**	0	0	0	0	0	0	0	0	0	16.67	83.33	0	0	0	0	0
12	**Ba2**	0	0	0	0	0	0	0	0	0	0	0	100	0	0	0	0
13	**Ba3**	0	0	0	0	0	0	0	0	0	0	0	0	100	0	0	0
15	**B2**	0	0	0	0	0	0	0	0	0	0	0	0	0	85.71	0	14.29
17	**Caa1**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100	0

Panel B. Ratings to (frequency)

	From	**Aaa**	**Aa1**	**Aa2**	**Aa3**	**A1**	**A2**	**A3**	**Baa1**	**Baa2**	**Baa3**	**Ba1**	**Ba2**	**Ba3**	**B2**	**Caa1**	**Caa2**	**Total**
1	**Aaa**	57	2	8	0	0	0	0	0	0	0	0	0	0	0	0	0	67
2	**Aa1**	0	28	12	0	0	0	0	0	0	0	0	0	0	0	0	0	40
3	**Aa2**	0	0	694	50	3	0	0	0	0	0	0	0	0	0	0	0	747
4	**Aa3**	0	0	37	421	49	18	2	0	0	0	0	0	0	0	0	0	527
5	**A1**	0	0	0	16	390	43	4	0	8	1	0	0	0	0	0	0	462
6	**A2**	0	0	2	3	48	1,226	35	0	0	2	1	0	0	0	0	0	1317
7	**A3**	0	0	0	0	0	78	574	4	2	0	2	0	0	0	0	0	660
8	**Baa1**	0	0	0	0	0	2	7	89	3	1	0	0	0	0	0	0	102
9	**Baa2**	0	0	0	0	0	0	1	3	42	2	3	0	5	0	2	0	58
10	**Baa3**	0	0	0	0	0	1	3	0	3	19	0	0	2	0	0	0	28
11	**Ba1**	0	0	0	0	0	0	0	0	0	3	15	0	0	0	0	0	18
12	**Ba2**	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	2
13	**Ba3**	0	0	0	0	0	0	0	0	0	0	0	0	5	0	0	0	5
15	**B2**	0	0	0	0	0	0	0	0	0	0	0	0	0	6	0	1	7
17	**Caa1**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	21	0	21
	Total	57	30	753	490	490	1,368	626	96	58	28	21	2	12	6	23	1	4070

This table presents rating transition matrices of U.S. P/C insurers rated by Moody's from Dec. 2000- Dec. 2017. Categories B3 (16) and Ca-C (20) have a 100% probability of remaining in the same category with frequencies B3= 6 and Ca-C = 3 that are part of the total shown in the table. No company started from Caa2 (18) and, no companies appeared in rating categories B1 (14) and Caa3 (19).

Table A 5.8 Moody's: Rating transition matrix, 2000 – 2006

Panel A. Ratings to (%)															
From	**Aaa**	**Aa1**	**Aa2**	**Aa3**	**A1**	**A2**	**A3**	**Baa1**	**Baa2**	**Baa3**	**Ba1**	**Ba3**	**B2**	**Caa1**	**Caa2**
Aaa	84.62	0	15.38	0	0	0	0	0	0	0	0	0	0	0	0
Aa1	0	50	50	0	0	0	0	0	0	0	0	0	0	0	0
Aa2	0	0	85.71	12.76	1.53	0	0	0	0	0	0	0	0	0	0
Aa3	0	0	4.04	88.82	6.52	0	0.62	0	0	0	0	0	0	0	0
A1	0	0	0	3.92	65.69	17.65	3.92	0	7.84	0.98	0	0	0	0	0
A2	0	0	0.67	1	1.34	87.92	8.05	0	0	0.67	0.34	0	0	0	0
A3	0	0	0	0	0	3.57	95.45	0	0.65	0	0.32	0	0	0	0
Baa1	0	0	0	0	0	0	4.17	87.5	6.25	2.08	0	0	0	0	0
Baa2	0	0	0	0	0	0	3.13	3.13	56.25	6.25	9.38	15.63	0	6.25	0
Baa3	0	0	0	0	0	7.14	0	0	7.14	71.43	0	14.29	0	0	0
Ba1	0	0	0	0	0	0	0	0	0	37.5	62.5	0	0	0	0
Ba3	0	0	0	0	0	0	0	0	0	0	0	100	0	0	0
B2	0	0	0	0	0	0	0	0	0	0	0	0	85.71	0	14.29
Caa1	0	0	0	0	0	0	0	0	0	0	0	0	0	100	0

Panel B. Ratings to (frequency)																
From	**Aaa**	**Aa1**	**Aa2**	**Aa3**	**A1**	**A2**	**A3**	**Baa1**	**Baa2**	**Baa3**	**Ba1**	**Ba3**	**B2**	**Caa1**	**Caa2**	**Total**
Aaa	44	0	8	0	0	0	0	0	0	0	0	0	0	0	0	52
Aa1	0	12	12	0	0	0	0	0	0	0	0	0	0	0	0	24
Aa2	0	0	168	25	3	0	0	0	0	0	0	0	0	0	0	196
Aa3	0	0	13	286	21	0	2	0	0	0	0	0	0	0	0	322
A1	0	0	0	4	67	18	4	0	8	1	0	0	0	0	0	102
A2	0	0	2	3	4	262	24	0	0	2	1	0	0	0	0	298
A3	0	0	0	0	0	11	294	0	2	0	1	0	0	0	0	308
Baa1	0	0	0	0	0	0	2	42	3	1	0	0	0	0	0	48
Baa2	0	0	0	0	0	0	1	1	18	2	3	5	0	2	0	32
Baa3	0	0	0	0	0	1	0	0	1	10	0	2	0	0	0	14
Ba1	0	0	0	0	0	0	0	0	0	3	5	0	0	0	0	8
Ba3	0	0	0	0	0	0	0	0	0	0	0	5	0	0	0	2
B2	0	0	0	0	0	0	0	0	0	0	0	0	6	0	1	5
Caa1	0	0	0	0	0	0	0	0	0	0	0	0	0	19	0	6
Total	44	12	203	318	95	292	327	43	32	19	10	12	6	21	1	1446

This table presents rating transition matrices of U.S. P/C insurers rated by Moody's from Dec. 2000- Dec. 2006. Categories B3 (16), Ba2 (12), Ca-C (20) have 100% probability of staying in the same category. Frequencies are B3= 6, Ba2= 2, Ca-C=3 and are part of the reported total (1446). Please refer to Table A 5.7 to check rating symbols and numerical equivalence.

Table A 5.9 Moody's: Rating transition matrix, 2007 – 2009

Panel A. Ratings to (%)											
From	**Aaa**	**Aa1**	**Aa2**	**Aa3**	**A1**	**A2**	**A3**	**Baa1**	**Baa2**	**Baa3**	**Ba1**
Aaa	71.43	28.57	0	0	0	0	0	0	0	0	0
Aa2	0	0	90	10	0	0	0	0	0	0	0
Aa3	0	0	16.55	60	11.03	12.41	0	0	0	0	0
A1	0	0	0	0	71.88	28.13	0	0	0	0	0
A2	0	0	0	0	0	99.57	0.43	0	0	0	0
A3	0	0	0	0	0	30.16	69.84	0	0	0	0
Baa1	0	0	0	0	0	0	30	70	0	0	0
Baa2	0	0	0	0	0	0	0	20	80	0	0
Baa3	0	0	0	0	0	0	0	0	18.18	81.82	0
Ba1	0	0	0	0	0	0	0	0	0	0	100

Panel B. Ratings to (frequency)												
From	**Aaa**	**Aa1**	**Aa2**	**Aa3**	**A1**	**A2**	**A3**	**Baa1**	**Baa2**	**Baa3**	**Ba1**	Total
Aaa	5	2	0	0	0	0	0	0	0	0	0	7
Aa2	0	0	117	13	0	0	0	0	0	0	0	130
Aa3	0	0	24	87	16	18	0	0	0	0	0	145
A1	0	0	0	0	23	9	0	0	0	0	0	32
A2	0	0	0	0	0	234	1	0	0	0	0	235
A3	0	0	0	0	0	38	88	0	0	0	0	126
Baa1	0	0	0	0	0	0	3	7	0	0	0	10
Baa2	0	0	0	0	0	0	0	2	8	0	0	10
Baa3	0	0	0	0	0	0	0	0	2	9	0	11
Ba1	0	0	0	0	0	0	0	0	0	0	4	4
Total	5	2	141	100	39	299	92	9	10	9	4	710

This table presents rating transition matrices of U.S. P/C insurers rated by Moody's from Dec 2007 – 2009. Any company has Aa1 (2), Ba2 (12) to Ca-C (20) as initial rating and none ends in a category lower than Ba1 (11). Please refer to Table A 5.7 to check rating symbols and numerical equivalence.

Table A 5.10 Moody's: Rating transition matrix, 2010 – 2017

Panel A. Ratings to (%)											
From	**Aaa**	**Aa1**	**Aa2**	**Aa3**	**A1**	**A2**	**A3**	**Baa1**	**Baa2**	**Baa3**	**Caa1**
Aaa	100	0	0	0	0	0	0	0	0	0	0
Aa1	0	100	0	0	0	0	0	0	0	0	0
Aa2	0	0	97.15	2.85	0	0	0	0	0	0	0
Aa3	0	0	0	80	20	0	0	0	0	0	0
A1	0	0	0	3.66	91.46	4.88	0	0	0	0	0
A2	0	0	0	0	5.61	93.11	1.28	0	0	0	0
A3	0	0	0	0	0	12.83	84.96	1.77	0	0.44	0
Baa1	0	0	0	0	0	4.55	4.55	90.91	0	0	0
Baa2	0	0	0	0	0	0	0	0	100	0	0
Baa3	0	0	0	0	0	0	100	0	0	0	0
Ba1	0	0	0	0	0	0	0	0	0	100	0
Caa1	0	0	0	0	0	0	0	0	0	0	100

Panel B. Ratings to (frequency)												
From	**Aaa**	**Aa1**	**Aa2**	**Aa3**	**A1**	**A2**	**A3**	**Baa1**	**Baa2**	**Baa3**	**Caa1**	Total
Aaa	8	0	0	0	0	0	0	0	0	0	0	8
Aa1	0	16	0	0	0	0	0	0	0	0	0	16
Aa2	0	0	409	12	0	0	0	0	0	0	0	421
Aa3	0	0	0	48	12	0	0	0	0	0	0	60
A1	0	0	0	12	300	16	0	0	0	0	0	328
A2	0	0	0	0	44	730	10	0	0	0	0	784
A3	0	0	0	0	0	29	192	4	0	1	0	226
Baa1	0	0	0	0	0	2	2	40	0	0	0	44
Baa2	0	0	0	0	0	0	0	0	16	0	0	16
Baa3	0	0	0	0	0	0	3	0	0	0	0	3
Ba1	0	0	0	0	0	0	0	0	0	6	0	6
Caa1	0	0	0	0	0	0	0	0	0	0	2	2
Total	8	16	409	72	356	777	207	44	16	7	2	1914

This table presents rating transition matrices of U.S. P/C insurers rated by Moody's from Dec. 2010 – Dec. 2017. No companies appear in categories Ba2 (12) to B3 (16) and Caa2 (18) to Ca-C (20). Please refer to Table A 5.7 to check rating symbols and numerical equivalence.

Table A 5.11 Fitch: Rating transition matrix, 2000 – 2017

		Panel A. Ratings to (%)									
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
		AAA	**AA+**	**AA**	**AA-**	**A+**	**A**	**A-**	**BBB+**	**BBB**	**BBB-**
1	**AAA**	80.41	13.51	6.08	0	0	0	0	0	0	0
2	**AA+**	0	86.03	10.68	3.29	0	0	0	0	0	0
3	**AA**	0	0.09	92.8	5.07	0.98	0	1.07	0	0	0
4	**AA-**	0	0	15.42	71.33	9.16	4.1	0	0	0	0
5	**A+**	0	0	0	1.99	90.89	5.13	1.99	0	0	0
6	**A**	0	0	0	0.88	5.07	88.99	5.07	0	0	0
7	**A-**	0	0.56	0	0	0	4.74	94.56	0.14	0	0
8	**BBB+**	0	0	0	0	0	0	40	40	0	20
9	**BBB**	0	0	0	0	0	33.33	0	0	66.67	0
10	**BBB-**	0	0	0	0	0	100	0	0	0	0

	Panel B. Ratings to (frequency)											
	From	**AAA**	**AA+**	**AA**	**AA-**	**A+**	**A**	**A-**	**BBB+**	**BBB**	**BBB-**	**Total**
1	**AAA**	119	20	9	0	0	0	0	0	0	0	148
2	**AA+**	0	314	39	12	0	0	0	0	0	0	365
3	**AA**	0	1	1044	57	11	0	12	0	0	0	1125
4	**AA-**	0	0	64	296	38	17	0	0	0	0	415
5	**A+**	0	0	0	12	549	31	12	0	0	0	604
6	**A**	0	0	0	4	23	404	23	0	0	0	454
7	**A-**	0	4	0	0	0	34	678	1	0	0	717
8	**BBB+**	0	0	0	0	0	0	2	2	0	1	5
9	**BBB**	0	0	0	0	0	1	0	0	2	0	3
10	**BBB-**	0	0	0	0	0	1	0	0	0	0	1
	Total	119	339	1156	381	621	488	727	3	2	1	3837

This table presents rating transition matrices of U.S. P/C insurers rated by Fitch from Dec. 2000 – Dec. 2017. No companies starts or ends on categories from BB+ (11) to CC-D (20).

Table A 5.12 Fitch: rating transition matrix, 2000 – 2006

Panel A. Rating to (%)										
From	**AAA**	**AA+**	**AA**	**AA-**	**A+**	**A**	**A-**	**BBB+**	**BBB**	**BBB-**
AAA	82.41	9.26	8.33	0	0	0	0	0	0	0
AA+	0	100	0	0	0	0	0	0	0	0
AA	0	0.53	74.6	24.87	0	0	0	0	0	0
AA-	0	0	1.52	87.88	7.58	3.03	0	0	0	0
A+	0	0	0	0	84.68	5.65	9.68	0	0	0
A	0	0	0	0	9.8	74.51	15.69	0	0	0
A-	0	4.55	0	0	0	4.55	89.77	1.14	0	0
BBB+	0	0	0	0	0	0	40	40	0	20
BBB	0	0	0	0	0	0	0	0	100	0
BBB-	0	0	0	0	0	100	0	0	0	0

Panel B. Ratings to (frequency)											
From	**AAA**	**AA+**	**AA**	**AA-**	**A+**	**A**	**A-**	**BBB+**	**BBB**	**BBB-**	Total
AAA	89	10	9	0	0	0	0	0	0	0	108
AA+	0	162	0	0	0	0	0	0	0	0	162
AA	0	1	141	47	0	0	0	0	0	0	189
AA-	0	0	3	174	15	6	0	0	0	0	198
A+	0	0	0	0	105	7	12	0	0	0	124
A	0	0	0	0	5	38	8	0	0	0	51
A-	0	4	0	0	0	4	79	1	0	0	88
BBB+	0	0	0	0	0	0	2	2	0	1	5
BBB	0	0	0	0	0	0	0	0	1	0	1
BBB-	0	0	0	0	0	1	0	0	0	0	1
Total	89	177	153	221	125	56	101	3	1	1	927

This table presents rating transition matrices of U.S. P/C insurers rated by Fitch from Dec. 2000 – Dec. 2006. No companies starts or ends on categories from BB+ (11) to CC-D (20). Please refer to Table A 5.11 to check rating symbols and numerical equivalence

Table A 5.13 Fitch: Rating transition matrix, 2007 – 2009

				Panel A. Ratings to (%)				
From	**AAA**	**AA+**	**AA**	**AA-**	**A+**	**A**	**A-**	**BBB**
AAA	100	0	0	0	0	0	0	0
AA+	0	61.36	29.55	9.09	0	0	0	0
AA	0	0	83.73	2.41	6.63	0	7.23	0
AA-	0	0	36.36	43.94	11.36	8.33	0	0
A+	0	0	0	18.33	81.67	0	0	0
A	0	0	0	0	0	75	25	0
A-	0	0	0	0	0	9.03	90.97	0
BBB	0	0	0	0	0	50	0	50

				Panel B. Ratings to (frequency)					
From	**AAA**	**AA+**	**AA**	**AA-**	**A+**	**A**	**A-**	**BBB**	Total
AAA	30	0	0	0	0	0	0	0	30
AA+	0	81	39	12	0	0	0	0	132
AA	0	0	139	4	11	0	12	0	166
AA-	0	0	48	58	15	11	0	0	132
A+	0	0	0	11	49	0	0	0	60
A	0	0	0	0	0	45	15	0	60
A-	0	0	0	0	0	13	131	0	144
BBB	0	0	0	0	0	1	0	1	2
Total	30	81	226	85	75	70	158	1	726

This table presents rating transition matrices of U.S. P/C insurers rated by Fitch from Dec. 2000 – Dec. 2006. No companies starts or ends on categories from BBB- (10) to CC-D (20). Please refer to Table A 5.11 to check rating symbols and numerical equivalence.

Table A 5.14 Fitch: Rating transition matrix, 2010 – 2017

			Panel A. Ratings to **(%)**			
From	**AA+**	**AA**	**AA-**	**A+**	**A**	**A-**
AAA	100	0	0	0	0	0
AA+	100	0	0	0	0	0
AA	0	99.22	0.78	0	0	0
AA-	0	15.29	75.29	9.41	0	0
A+	0	0	0.24	94.05	5.71	0
A	0	0	1.17	5.25	93.59	0
A-	0	0	0	0	3.51	96.49

			Panel B. Ratings to (frequency)				
From	**AA+**	**AA**	**AA-**	**A+**	**A**	**A-**	Total
AAA	10	0	0	0	0	0	10
AA+	71	0	0	0	0	0	71
AA	0	764	6	0	0	0	770
AA-	0	13	64	8	0	0	85
A+	0	0	1	395	24	0	420
A	0	0	4	18	321	0	343
A-	0	0	0	0	17	468	485
Total	81	777	75	421	362	468	2184

This table presents rating transition matrices of U.S. P/C insurers rated by Fitch from Dec. 2010 – Dec. 2017. No companies starts or ends on categories from BBB+ (8) to CC-D (20). Please refer to Table A 5.11 to check rating symbols and numerical equivalence.

Table A 5.15 AM Best: Rating transition matrix, 2000 – 2017

		Panel A. Ratings to (%)											
		2	**4**	**6**	**7**	**9**	**10**	**12**	**13**	**15**	**16**	**18**	**20**
	From	**A++**	**A+**	**A**	**A-**	**B++**	**B+**	**B**	**B-**	**C++**	**C+**	**C**	**C- / S**
2	**A++**	92.73	5.74	1.38	0.07	0.07	0	0	0	0	0	0	0
4	**A+**	1.61	92.06	5.74	0.57	0	0	0.02	0	0	0	0	0
6	**A**	0.01	2.65	94.06	2.77	0.34	0.12	0.03	0.01	0	0	0	0
7	**A-**	0	0.53	6.86	88.57	2.48	0.45	0.78	0.11	0.03	0	0	0.2
9	**B++**	0	0.11	0.99	13.85	76.04	5.93	0.77	0.33	0.44	0	0	1.54
10	**B+**	0.21	0.42	0.63	1.69	12.87	71.73	6.96	1.48	0.42	0	0.21	3.38
12	**B**	0	1.79	0.72	3.94	1.08	12.19	68.82	5.38	3.94	0.36	0.72	1.08
13	**B-**	0	0	0.85	1.71	0	2.56	7.69	68.38	6.84	3.42	0.85	7.69
15	**C++**	0	0	0	1.89	0	1.89	1.89	11.32	54.72	3.77	3.77	20.75
16	**C+**	0	0	0	0	0	0	5.56	11.11	0	61.11	11.11	11.11
18	**C**	0	0	0	0	0	0	0	0	16.67	0	41.67	41.67
20	**C- / S**	0	0	0	0	0	0.46	0	0	0.46	0	0.46	98.63

		Panel B. Ratings to (frequency)												
	From	**A++**	**A+**	**A**	**A-**	**B++**	**B+**	**B**	**B-**	**C++**	**C+**	**C**	**C- / S**	Total
2	**A++**	1276	79	19	1	1	0	0	0	0	0	0	0	1376
4	**A+**	74	4233	264	26	0	0	1	0	0	0	0	0	4598
6	**A**	1	195	6923	204	25	9	2	1	0	0	0	0	7360
7	**A-**	0	19	246	3177	89	16	28	4	1	0	0	7	3587
9	**B++**	0	1	9	126	692	54	7	3	4	0	0	14	910
10	**B+**	1	2	3	8	61	340	33	7	2	0	1	16	474
12	**B**	0	5	2	11	3	34	192	15	11	1	2	3	279
13	**B-**	0	0	1	2	0	3	9	80	8	4	1	9	117
15	**C++**	0	0	0	1	0	1	1	6	29	2	2	11	53
16	**C+**	0	0	0	0	0	0	1	2	0	11	2	2	18
18	**C**	0	0	0	0	0	0	0	0	2	0	5	5	12
20	**C- / S**	0	0	0	0	0	1	0	0	1	0	1	216	219
	Total	1352	4534	7467	3556	871	458	274	118	58	18	14	283	19003

This table presents rating transition matrices of U.S. P/C insurers rated by AM Best from Dec. 2000 – Dec. 2017.

Table A 5.16 AM Best: Rating transition matrix, 2000 – 2006

	Panel A. Ratings to **(%)**											
From	**A++**	**A+**	**A**	**A-**	**B++**	**B+**	**B**	**B-**	**C++**	**C+**	**C**	**C- / S**
A++	85.49	11.2	3	0.16	0.16	0	0	0	0	0	0	0
A+	0.5	88.18	9.65	1.62	0	0	0.06	0	0	0	0	0
A	0	2.91	91.15	4.73	0.81	0.36	0	0.04	0	0	0	0
A-	0	0.98	5.53	86.98	3.03	1.06	1.59	0.3	0.08	0	0	0.45
B++	0	0	1.23	14.25	72.24	6.88	0.74	0.74	0.98	0	0	2.95
B+	0	0.79	1.18	0.79	14.57	67.72	5.91	1.97	0.79	0	0.39	5.91
B	0	2.91	1.16	0.58	0.58	15.12	67.44	4.07	4.65	0.58	1.16	1.74
B-	0	0	0	1.69	0	3.39	10.17	59.32	10.17	0	1.69	13.56
C++	0	0	0	0	0	0	0	11.9	57.14	4.76	0	26.19
C+	0	0	0	0	0	0	11.11	22.22	0	55.56	0	11.11
C	0	0	0	0	0	0	0	0	18.18	0	45.45	36.36
C- / S	0	0	0	0	0	0.74	0	0	0.74	0	0.74	97.78

	Panel B. Ratings to (frequency)												
From	**A++**	**A+**	**A**	**A-**	**B++**	**B+**	**B**	**B-**	**C++**	**C+**	**C**	**C- / S**	**Total**
A++	542	71	19	1	1	0	0	0	0	0	0	0	634
A+	8	1417	155	26	0	0	1	0	0	0	0	0	1607
A	0	72	2256	117	20	9	0	1	0	0	0	0	2475
A-	0	13	73	1149	40	14	21	4	1	0	0	6	1321
B++	0	0	5	58	294	28	3	3	4	0	0	12	407
B+	0	2	3	2	37	172	15	5	2	0	1	15	254
B	0	5	2	1	1	26	116	7	8	1	2	3	172
B-	0	0	0	1	0	2	6	35	6	0	1	8	59
C++	0	0	0	0	0	0	0	5	24	2	0	11	42
C+	0	0	0	0	0	0	1	2	0	5	0	1	9
C	0	0	0	0	0	0	0	0	2	0	5	4	11
C- / S	0	0	0	0	0	1	0	0	1	0	1	132	135
Total	550	1,580	2,513	1,355	393	252	163	62	48	8	10	192	7126

This table presents rating transition matrices of U.S. P/C insurers rated by AM Best from Dec. 2000 – Dec. 2006. Please refer to Table A 5.15 to check rating symbols and numerical equivalence.

Table A 5.17 AM Best: Rating transition matrix, 2007 – 2009

Panel A. Ratings to (%)										
From	**A++**	**A+**	**A**	**A-**	**B++**	**B+**	**B**	**B-**	**C++**	**C-/S**
A++	98.15	1.85	0	0	0	0	0	0	0	0
A+	0	93.91	6.09	0	0	0	0	0	0	0
A	0	2.41	95	2.5	0.08	0	0	0	0	0
A-	0	0.27	8.58	88.28	2.72	0.14	0	0	0	0
B++	0	0.59	0.59	19.53	74.56	4.14	0.59	0	0	0
B+	0	0	0	2.47	14.81	76.54	4.94	1.23	0	0
B	0	0	0	0	2.94	8.82	85.29	2.94	0	0
B-	0	0	0	3.57	0	3.57	7.14	85.71	0	0
C++	0	0	0	0	0	12.5	12.5	12.5	62.5	0
C-/S	0	0	0	0	0	0	0	0	0	100

Panel B. Ratings to (frequency)											
From	**A++**	**A+**	**A**	**A-**	**B++**	**B+**	**B**	**B-**	**C++**	**C-/S**	**Total**
A++	159	3	0	0	0	0	0	0	0	0	162
A+	0	863	56	0	0	0	0	0	0	0	919
A	0	29	1141	30	1	0	0	0	0	0	1201
A-	0	2	63	648	20	1	0	0	0	0	734
B++	0	1	1	33	126	7	1	0	0	0	169
B+	0	0	0	2	12	62	4	1	0	0	81
B	0	0	0	0	1	3	29	1	0	0	34
B-	0	0	0	1	0	1	2	24	0	0	28
C++	0	0	0	0	0	1	1	1	5	0	8
C-/S	0	0	0	0	0	0	0	0	0	41	41
Total	159	898	1261	714	160	75	37	27	5	41	3377

This table presents rating transition matrices of U.S. P/C insurers rated by AM Best from Dec. 2007 – Dec. 2009. Please refer to Table A 5.15 to check rating symbols and numerical equivalence.

Table A 5.18 AM Best: Rating transition, 2010 – 2017

Panel A. Ratings to (%)

From	**A++**	**A+**	**A**	**A-**	**B++**	**B+**	**B**	**B-**	**C++**	**C+**	**C**	**C- / S**
A++	99.14	0.86	0	0	0	0	0	0	0	0	0	0
A+	3.19	94.26	2.56	0	0	0	0	0	0	0	0	0
A	0.03	2.55	95.71	1.55	0.11	0	0.05	0	0	0	0	0
A-	0	0.26	7.18	90.08	1.89	0.07	0.46	0	0	0	0	0.07
B++	0	0	0.9	10.48	81.44	5.69	0.9	0	0	0	0	0.6
B+	0.72	0	0	2.88	8.63	76.26	10.07	0.72	0	0	0	0.72
B	0	0	0	13.7	1.37	6.85	64.38	9.59	4.11	0	0	0
B-	0	0	3.33	0	0	0	3.33	70	6.67	13.33	0	3.33
C++	0	0	0	33.33	0	0	0	0	0	0	66.67	0
C+	0	0	0	0	0	0	0	0	0	66.67	22.22	11.11
C	0	0	0	0	0	0	0	0	0	0	0	100
C-/S	0	0	0	0	0	0	0	0	0	0	0	100

Panel B. Ratings to (%)

From	**A++**	**A+**	**A**	**A-**	**B++**	**B+**	**B**	**B-**	**C++**	**C+**	**C**	**C- / S**	Total
A++	575	5	0	0	0	0	0	0	0	0	0	0	580
A+	66	1953	53	0	0	0	0	0	0	0	0	0	2072
A	1	94	3526	57	4	0	2	0	0	0	0	0	3684
A-	0	4	110	1380	29	1	7	0	0	0	0	1	1532
B++	0	0	3	35	272	19	3	0	0	0	0	2	334
B+	1	0	0	4	12	106	14	1	0	0	0	1	139
B	0	0	0	10	1	5	47	7	3	0	0	0	73
B-	0	0	1	0	0	0	1	21	2	4	0	1	30
C++	0	0	0	1	0	0	0	0	0	0	2	0	3
C+	0	0	0	0	0	0	0	0	0	6	2	1	9
C	0	0	0	0	0	0	0	0	0	0	0	1	1
C-/S	0	0	0	0	0	0	0	0	0	0	0	43	43
Total	643	2056	3693	1487	318	131	74	29	5	10	4	50	8500

This table presents rating transition matrices of U.S. P/C insurers rated by AM Best from Dec. 2010 – Dec. 2017. Please refer to Table A 5.15 to check rating symbols and numerical equivalence.

Table A 5.19 Some examples of press releases by AM Best during 2011

Company	Date	Change	Reasons of change
Farmers Mutual Insurance Company of Nebraska	27/04/2011	Affirmed the financial strength rating of A (Excellent) Outlook to stable from positive	"Significant increase in the frequency and severity of wind and hailstorm losses in the past three years. Pre-tax operating returns and underwriting results over the next several years likely will lag the industry.
Farmers Insurance Group	31/05/2011	Affirmed the financial strength rating (FSR) of A (Excellent)	Moderately volatile operating performance due to **catastrophe exposure**, as well as elevated underwriting leverage.
State Auto Financial Corporation State Auto Insurance Companies and its members	01/06/2011	Downgraded FSR to A (Excellent) from A+ (Superior) Outlook stable from negative	Deterioration in underwriting and operating earnings in recent years, driven by an **increased frequency and severity of property catastrophe losses**. For instance, its exposure to localized tornado/hailstorms and hurricane activity has dampened underwriting profitability and overall earnings.
Pekin Insurance Group and Its Members	02/06/2011	Affirmed the FSR of A- (Excellent)	Solid risk-adjusted capitalization and conservative operating strategy with offsetting by Pekin's susceptibility to frequent and **severe weather-related** events as observed in recent years. However, these exposures are managed and mitigated through a comprehensive reinsurance program.
Tennessee Farmers Insurance Companies and its Members	03/06/2011	Outlook to **negative** from stable FSR affirmed of A++ (Superior) and ICR of "aa+"	**Severe weather and catastrophe events** have contributed to the deterioration in underwriting results. "..Ongoing competitive pressures have resulted in deterioration of core automobile book of business. Furthermore, the **severe spring storms** in April 2011 have resulted in significant underwriting losses"
Lititz Mutual Insurance Pool (Lititz)	14/06/2011	Outlook to **negative** from stable and affirmed FSR of A+ (Superior) and issuer credit rating of "aa-"	Underwriting losses over several years caused by an increase in the **frequency and severity of weather-related and catastrophe** events in its operating territories.
Farmers Mutual Fire Insurance Company	01/09/2011	Downgraded the FSR to B++ (Good) from A- (Excellent) and ICR to "bbb" from "a-".	Deterioration in underwriting results, coupled with losses to the company's surplus in recent years due to its geographic concentration of risks in Oklahoma. In addition, an unexpected rise in the company's probable maximum loss from a 100-year **tornado/hail event** is significantly elevated and represents a notable decline in Farmers' risk-adjusted capitalization.
Farmers Mutual of Tennessee	22/11/2011	Outlook to negative from stable	Poor underwriting results and recent surplus deterioration. Over the last two years, earnings have been strained due to **severe weather-related** events, which include winter storms, hailstorms and most recently, Hurricane Irene and Tropical Storm Lee.

This table shows cases of U.S. P/C insurers rated by AM Best that are off the diagonal in the RTM during 2000-2006.

Table A 5.20 S&P: Rating transition matrix, 2000 – 2017 (13-point scale)

		Panel A. Ratings to (%)										
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**11**	**13**
From		**AAA/AA+**	**AA/AA-**	**A+/A**	**A-**	**BBB+/BBB**	**BBB-/BB+**	**BB**	**BB-/B+**	**B**	**CCC+/CCC**	**C-D**
1	**AAA/AA+**	85.36	11.1	3.54	0	0	0	0	0	0	0	0
2	**AA/AA-**	0.17	87.75	11.08	0.12	0.87	0	0	0	0	0	0
3	**A+/A**	0.09	2.58	92.85	2.62	1.71	0.09	0	0	0.07	0	0
4	**A-**	0	0	10.14	85.71	3.05	0.44	0.11	0.11	0.11	0	0.33
5	**BBB+/BBB**	0	0.12	2.53	1.5	0.07	0.24	4.45	0.18	0.72	0.18	0
6	**BBB-/BB+**	0	0	0	6.67	0	66.67	0	0	0	0	6.67
7	**BB**	0	0.49	0	0	2.59	0.16	91.1	0.16	2.1	2.27	1.13
9	**B**	0	0	0.64	0	0.64	0	5.73	0	84.7	3.82	4.46
11	**CCC+/CCC**	0	0	0	0	0	0	0	0	0	2.8	17.2
13	**C-D**	0	0	0	0	0	0	0	0	0	0	100

		Panel B. Ratings to (frequency)											
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**11**	**13**	
From		**AAA/AA+**	**AA/AA-**	**A+/A**	**A-**	**BBB+/BBB**	**BBB-/BB+**	**BB**	**BB-/B+**	**B**	**CCC+/CCC**	**C-D**	**Total**
1	**AAA/AA+**	723	94	30	0	0	0	0	0	0	0	0	847
2	**AA/AA-**	4	2,114	267	3	21	0	0	0	0	0	0	2,409
3	**A+/A**	4	119	4,284	121	79	4	0	0	3	0	0	4,614
4	**A-**	0	0	93	786	28	4	1	1	1	0	3	917
5	**BBB+/BBB**	0	2	42	25	1,497	4	74	3	12	3	0	1,662
6	**BBB-/BB+**	0	0	0	1	3	10	0	0	0	0	1	15
7	**BB**	0	3	0	0	16	1	563	1	13	14	7	618
9	**B**	0	0	1	0	1	0	9	0	133	6	7	157
11	**CCC+/CCC**	0	0	0	0	0	0	0	0	0	77	16	93
13	**C-D**	0	0	0	0	0	0	0	0	0	0	522	522
	Total	731	2,332	4,717	936	1,645	23	647	5	162	100	556	11,854

This table presents rating transition matrices of U.S. P/C insurers rated by S&P from Dec 2000- Dec 2006 using the 13-point scale. No companies start from BB-/B+(8), or start and end on B-(10), and CCC-/CC (12) notches.

Table A 5.21 S&P: Rating transition matrix, 2000 – 2006 (13-point scale)

Panel A. Ratings to (%)											
From	**AAA/AA+**	**AA/AA-**	**A+/A**	**A-**	**BBB+/BBB**	**BBB-/BB+**	**BB**	**BB-/B+**	**B**	**CCC+/CCC**	**C-D**
AAA/AA+	84.75	15.25	0	0	0	0	0	0	0	0	0
AA/AA-	0.46	77.02	21.5	0.34	0.68	0	0	0	0	0	0
A+/A	0.05	2.66	92.63	1.57	2.71	0.22	0	0	0.16	0	0
A-	0	0	3.55	85.2	6.6	2.03	0	0.51	0.51	0	1.52
BBB+/BBB	0	0	2.7	1.05	9.02	0.17	5.49	0.26	1.05	0.26	0
BBB-/BB+	0	0	0	14.2	4.29	57.14	0	0	0	0	14.29
BB	0	0.73	0	0	1.21	0.24	89.81	0.24	2.67	3.4	1.7
B	0	0	0.86	0	0.86	0	2.59	0	84.4	5.17	6.03
CCC+/CCC	0	0	0	0	0	0	0	0	0	1.43	28.57
C-D	0	0	0	0	0	0	0	0	0	0	100

Panel B. Ratings to (frequency)												
From	**AAA/AA+**	**AA/AA-**	**A+/A**	**A-**	**BBB+/BBB**	**BBB-**	**BB+/BB**	**BB-**	**B+/B**	**CCC+/CCC**	**C-D**	**Total**
AAA/AA+	350	63	0	0	0	0	0	0	0	0	0	413
AA/AA-	4	677	189	3	6	0	0	0	0	0	0	879
A+/A	1	49	1,709	29	50	4	0	0	3	0	0	1,845
A-	0	0	7	168	13	4	0	1	1	0	3	197
BBB+/BBB	0	0	31	12	1,022	2	63	3	12	3	0	1,148
BBB-/BB+	0	0	0	1	1	4	0	0	0	0	1	7
BB	0	3	0	0	5	1	370	1	11	14	7	412
B	0	0	1	0	1	0	3	0	98	6	7	116
CCC+/CCC	0	0	0	0	0	0	0	0	0	40	16	56
C-D	0	0	0	0	0	0	0	0	0	0	358	358
Total	355	792	1,937	213	1,098	15	436	5	125	63	392	5,431

This table presents rating transition matrices of U.S. P/C insurers rated by S&P from Dec 2000- Dec 2006 using the 13-point rating scale. No companies start/end in BB-/B+ (8), and no companies end in B- (10) and CCC-/CC (12). Please refer to Table A 5.20 to check rating symbols and numerical equivalence.

Table A 5.22 S&P: Rating transition matrix, 2007 – 2009 (13-point scale)

Panel A. Ratings to (%)										
	AAA/AA+	**AA/AA-**	**A+/A**	**A-**	**BBB+/BBB**	**BBB-/BB+**	**BB**	**B**	**CCC+/CCC**	**C-D**
AAA/AA+	86.67	0	13.33	0	0	0	0	0	0	0
AA/AA-	0	92.69	7.31	0	0	0	0	0	0	0
A+/A	0.35	5.02	87.5	7.13	0	0	0	0	0	0
A-	0	0	4.83	94.48	0.69	0	0	0	0	0
BBB+/BBB	0	0	2.27	3.03	93.94	0	0.76	0	0	0
BBB-/BB+	0	0	0	0	25	75	0	0	0	0
BB	0	0	0	0	2.94	0	97.06	0	0	0
B	0	0	0	0	0	0	17.24	82.76	0	0
CCC+/CCC	0	0	0	0	0	0	0	0	100	0
C-D	0	0	0	0	0	0	0	0	0	0

Panel B. Ratings to (frequency)											
	AAA/AA+	**AA/AA-**	**A+/A**	**A-**	**BBB+/BBB**	**BBB-/BB+**	**BB**	**B**	**CCC+/CCC**	**C-D**	**Total**
AAA/AA+	195	0	30	0	0	0	0	0	0	0	225
AA/AA-	0	406	32	0	0	0	0	0	0	0	438
A+/A	3	43	749	61	0	0	0	0	0	0	856
A-	0	0	7	137	1	0	0	0	0	0	145
BBB+/BBB	0	0	6	8	248	0	2	0	0	0	264
BBB-/BB+	0	0	0	0	2	6	0	0	0	0	8
BB	0	0	0	0	4	0	132	0	0	0	136
B	0	0	0	0	0	0	5	24	0	0	29
CCC+/CCC	0	0	0	0	0	0	0	0	28	0	28
C-D	0	0	0	0	0	0	0	0	0	164	164
Total	198	449	824	206	255	6	139	24	28	164	2,293

This table presents rating transition matrices of U.S. P/C insurers rated by S&P from Dec 2007- Dec 2009 using the 13-point rating scale. No companies start/end in BB-/B+ (8), and no companies end in B- (10) and CCC-/CC (12). Please refer to Table A 5.20 to check rating symbols and numerical equivalence.

Table A 5.23 S&P: Rating transition matrix, 2010 – 2017 (13-point scale)

Panel A. Ratings to (%)									
	AAA/AA+	**AA/AA-**	**A+/A**	**A-**	**BBB+/BBB**	**BBB-/BB+**	**BB**	**B**	**CCC+/CCC**
AAA/AA+	85.17	14.83	0	0	0	0	0	0	0
AA/AA-	0	94.41	4.21	0	1.37	0	0	0	0
A+/A	0	1.41	95.45	1.62	1.52	0	0	0	0
A-	0	0	13.74	83.65	2.43	0	0.17	0	0
BBB+/BBB	0	0.8	2	2	90.8	0.8	3.6	0	0
BB	0	0	0	0	10	0	87.14	2.86	0
B	0	0	0	0	0	0	8.33	91.67	0
CCC+/CCC	0	0	0	0	0	0	0	0	100

Panel B. Ratings to (frequency)										
	AAA/AA+	**AA/AA-**	**A+/A**	**A-**	**BBB+/BBB**	**BBB-/BB+**	**BB**	**B**	**CCC+/CCC**	**Total**
AAA/AA+	178	31	0	0	0	0	0	0	0	209
AA/AA-	0	1,031	46	0	15	0	0	0	0	1,092
A+/A	0	27	1,826	31	29	0	0	0	0	1,913
A-	0	0	79	481	14	0	1	0	0	575
BBB+/BBB	0	2	5	5	227	2	9	0	0	250
BB	0	0	0	0	7	0	61	2	0	70
B	0	0	0	0	0	0	1	11	0	12
CCC+/CCC	0	0	0	0	0	0	0	0	9	9
Total	178	1,091	1,956	517	292	2	72	13	9	4,130

This table presents rating transition matrices of U.S. P/C insurers rated by S&P from Dec 2010- Dec 2017 using the 13-point rating scale. No companies start/end in BB-/B+ (8), B- (10) and CCC-/CC (12) and C-D (13). Please refer to Table A 5.20 to check rating symbols and numerical equivalence.

Table A 5.24 Moody's: Rating transition matrix, 2000 – 2017 (13-point scale)

		Panel A. Ratings to (%)											
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
	From	**Aaa/Aa1**	**Aa2/Aa3**	**A1/A2**	**A3**	**Baa1/Baa2**	**Baa3/Ba1**	**Ba2**	**Ba3/B1**	**B2**	**B3**	**Caa1/Caa2**	**Caa3/Ca**
1	**Aaa/Aa1**	81.31	18.69	0	0	0	0	0	0	0	0	0	0
2	**Aa2/Aa3**	0	94.35	5.49	0.16	0	0	0	0	0	0	0	0
3	**A1/A2**	0	1.18	95.95	2.19	0.45	0.17	0.06	0	0	0	0	0
4	**A3**	0	0	11.82	86.97	0.91	0	0.3	0	0	0	0	0
5	**Baa1/Baa2**	0	0	1.25	5	85.63	1.88	1.88	3.13	0	0	1.25	0
6	**Baa3/Ba1**	0	0	3.57	10.71	10.71	67.86	0	7.14	0	0	0	0
7	**Ba2**	0	0	0	0	0	15	85	0	0	0	0	0
8	**Ba3/B1**	0	0	0	0	0	0	0	100	0	0	0	0
9	**B2**	0	0	0	0	0	0	0	0	85.71	0	14.29	0
10	**B3**	0	0	0	0	0	0	0	0	0	100	0	0
11	**Caa1/Caa2**	0	0	0	0	0	0	0	0	0	0	100	0
12	**Caa3/Ca**	0	0	0	0	0	0	0	0	0	0	0	100

		Panel B. Ratings to (frequency)												
		Aaa/Aa1	**Aa2/Aa3**	**A1/A2**	**A3**	**Baa1/Baa2**	**Baa3/Ba1**	**Ba2**	**Ba3/B1**	**B2**	**B3**	**Caa1/Caa2**	**Caa3/Ca**	**Total**
1	**Aaa/Aa1**	87	20	0	0	0	0	0	0	0	0	0	0	107
2	**Aa2/Aa3**	0	1,202	70	2	0	0	0	0	0	0	0	0	1,274
3	**A1/A2**	0	21	1,707	39	8	3	1	0	0	0	0	0	1,779
4	**A3**	0	0	78	574	6	0	2	0	0	0	0	0	660
5	**Baa1/Baa2**	0	0	2	8	137	3	3	5	0	0	2	0	160
6	**Baa3/Ba1**	0	0	1	3	3	19	0	2	0	0	0	0	28
7	**Ba2**	0	0	0	0	0	3	17	0	0	0	0	0	20
8	**Ba3/B1**	0	0	0	0	0	0	0	5	0	0	0	0	5
9	**B2**	0	0	0	0	0	0	0	0	6	0	1	0	7
10	**B3**	0	0	0	0	0	0	0	0	0	6	0	0	6
11	**Caa1/Caa2**	0	0	0	0	0	0	0	0	0	0	21	0	21
12	**Caa3/Ca**	0	0	0	0	0	0	0	0	0	0	0	3	3
	Total	87	1,243	1,858	626	154	28	23	12	6	6	24	3	4,070

This table presents rating transition matrices of U.S. P/C insurers rated by Moody's from Dec 2000- Dec 2017 using the 13-point rating scale. No companies start/end in BB-/B+ (8), B- (10) and CCC-/CC (12) and C-D (13).

Table A 5.25 Moody's: Rating transition matrix, 2000 – 2006 (13-point scale)

Panel A. Ratings to (%)

From	**Aaa/Aa1**	**Aa2/Aa3**	**A1/A2**	**A3**	**Baa1/Baa2**	**Baa3/Ba1**	**Ba2**	**Ba3/B1**	**B2**	**B3**	**Caa1/Caa2**	**Caa3/Ca**
Aaa/Aa1	73.68	26.32	0	0	0	0	0	0	0	0	0	0
Aa2/Aa3	0	94.98	4.63	0.39	0	0	0	0	0	0	0	0
A1/A2	0	2.25	87.75	7	2	0.75	0.25	0	0	0	0	0
A3	0	0	3.57	95.45	0.65	0	0.32	0	0	0	0	0
Baa1/Baa2	0	0	0	3.75	80	3.75	3.75	6.25	0	0	2.5	0
Baa3/Ba1	0	0	7.14	0	7.14	71.43	0	14.29	0	0	0	0
Ba2	0	0	0	0	0	30	70	0	0	0	0	0
Ba3/B1	0	0	0	0	0	0	0	100	0	0	0	0
B2	0	0	0	0	0	0	0	0	85.71	0	14.29	0
B3	0	0	0	0	0	0	0	0	0	100	0	0
Caa1/Caa2	0	0	0	0	0	0	0	0	0	0	100	0
Caa3/Ca	0	0	0	0	0	0	0	0	0	0	0	100

Panel B. Ratings to (frequency)

From	**Aaa/Aa1**	**Aa2/Aa3**	**A1/A2**	**A3**	**Baa1/Baa2**	**Baa3/Ba1**	**Ba2**	**Ba3/B1**	**B2**	**B3**	**Caa1/Caa2**	**Caa3/Ca**	**Total**
Aaa/Aa1	56	20	0	0	0	0	0	0	0	0	0	0	76
Aa2/Aa3	0	492	24	2	0	0	0	0	0	0	0	0	518
A1/A2	0	9	351	28	8	3	1	0	0	0	0	0	400
A3	0	0	11	294	2	0	1	0	0	0	0	0	308
Baa1/Baa2	0	0	0	3	64	3	3	5	0	0	2	0	80
Baa3/Ba1	0	0	1	0	1	10	0	2	0	0	0	0	14
Ba2	0	0	0	0	0	3	7	0	0	0	0	0	10
Ba3/B1	0	0	0	0	0	0	0	5	0	0	0	0	5
B2	0	0	0	0	0	0	0	0	6	0	1	0	7
B3	0	0	0	0	0	0	0	0	0	6	0	0	6
Caa1/Caa2	0	0	0	0	0	0	0	0	0	0	19	0	19
Caa3/Ca	0	0	0	0	0	0	0	0	0	0	0	3	3
Total	56	521	387	327	75	19	12	12	6	6	22	3	1,446

This table presents rating transition matrices of U.S. P/C insurers rated by Moody's from Dec 2000- Dec 2006 using the 13-point rating scale. No companies start/end in BB-/B+ (8), B- (10) and CCC-/CC (12) and C-D (13). Please refer to Table A 5.24 to check rating symbols and numerical equivalence.

Table A 5.26 Moody's: Rating transition matrix, 2007 – 2009 (13-point scale)

	Panel A. Ratings to (%)						
From	**Aaa/Aa1**	**Aa2/Aa3**	**A1/A2**	**A3**	**Baa1/Baa2**	**Baa3/Ba1**	**Ba2**
Aaa/Aa1	100	0	0	0	0	0	0
Aa2/Aa3	0	87.64	12.36	0	0	0	0
A1/A2	0	0	99.63	0.37	0	0	0
A3	0	0	30.16	69.84	0	0	0
Baa1/Baa2	0	0	0	15	85	0	0
Baa3/Ba1	0	0	0	0	18.18	81.82	0
Ba2	0	0	0	0	0	0	100

	Panel B. Ratings to (frequency)							
From	**Aaa/Aa1**	**Aa2/Aa3**	**A1/A2**	**A3**	**Baa1/Baa2**	**Baa3/Ba1**	**Ba2**	**Total**
Aaa/Aa1	7	0	0	0	0	0	0	7
Aa2/Aa3	0	241	34	0	0	0	0	275
A1/A2	0	0	266	1	0	0	0	267
A3	0	0	38	88	0	0	0	126
Baa1/Baa2	0	0	0	3	17	0	0	20
Baa3/Ba1	0	0	0	0	2	9	0	11
Ba2	0	0	0	0	0	0	4	4
Total	7	241	338	92	19	9	4	710

This table presents rating transition matrices of U.S. P/C insurers rated by Moody's from Dec 2007 - Dec 2009 using the 13-point rating scale. No companies start/end in BB-/B+ (8) to B- (10), CCC-/CC (12) and C-D (13). Please refer to Table A 5.24 to check rating symbols and numerical equivalence.

Table A 5.27 Moody's: Rating transition matrix, 2010 – 2017 (13-point scale)

	Panel A. Ratings to (%)						
From	**Aaa/Aa1**	**Aa2/Aa3**	**A1/A2**	**A3**	**Baa1/Baa2**	**Ba2**	**Caa1/Caa2**
Aaa/Aa1	100	0	0	0	0	0	0
Aa2/Aa3	0	97.51	2.49	0	0	0	0
A1/A2	0	1.08	98.02	0.9	0	0	0
A3	0	0	12.83	84.96	1.77	0.44	0
Baa1/Baa2	0	0	3.33	3.33	93.33	0	0
Baa3/Ba1	0	0	0	100	0	0	0
Ba2	0	0	0	0	0	100	0
Caa1/Caa2	0	0	0	0	0	0	100

	Panel B. Ratings to (frequency)							
From	**Aaa/Aa1**	**Aa2/Aa3**	**A1/A2**	**A3**	**Baa1/Baa2**	**Ba2**	**Caa1/Caa2**	**Total**
Aaa/Aa1	24	0	0	0	0	0	0	24
Aa2/Aa3	0	469	12	0	0	0	0	481
A1/A2	0	12	1,090	10	0	0	0	1,112
A3	0	0	29	192	4	1	0	226
Baa1/Baa2	0	0	2	2	56	0	0	60
Baa3/Ba1	0	0	0	3	0	0	0	3
Ba2	0	0	0	0	0	6	0	6
Caa1/Caa2	0	0	0	0	0	0	2	2
Total	24	481	1,133	207	60	7	2	1,914

This table presents rating transition matrices of U.S. P/C insurers rated by Moody's from Dec 2007 - Dec 2009 using the 13-point rating scale. No companies start/end in BB-/B+ (8) to B- (10), CCC-/CC (12) and C-D (13). Please refer to Table A 5.24 to check rating symbols and numerical equivalence.

Table A 5.28 Fitch: Rating transition matrix, 2000 – 2017 (13-point scale)

		Panel A. Ratings to (%)					
		1	**2**	**3**	**4**	**5**	**6**
From		**AAA/AA+**	**AA/AA-**	**A+/A**	**A-**	**BBB+/BBB**	**BBB-/BB+**
1	**AAA/AA+**	88.3	11.7	0	0	0	0
2	**AA/AA-**	0.06	94.87	4.29	0.78	0	0
3	**A+/A**	0	1.51	95.18	3.31	0	0
4	**A-**	0.56	0	4.74	94.56	0.14	0
5	**BBB+/BBB**	0	0	12.5	25	50	12.5
6	**BBB-/BB+**	0	0	100	0	0	0

		Panel B. Ratings to (frequency)						
		1	**2**	**3**	**4**	**5**	**6**	**Total**
From		**AAA/AA+**	**AA/AA-**	**A+/A**	**A-**	**BBB+/BBB**	**BBB-/BB+**	
1	**AAA/AA+**	453	60	0	0	0	0	513
2	**AA/AA-**	1	1,461	66	12	0	0	1,540
3	**A+/A**	0	16	1,007	35	0	0	1,058
4	**A-**	4	0	34	678	1	0	717
5	**BBB+/BBB**	0	0	1	2	4	1	8
6	**BBB-/BB+**	0	0	1	0	0	0	1
	Total	458	1,537	1,109	727	5	1	3,837

This table presents rating transition matrices of U.S. P/C insurers rated by Fitch from Dec 2000 - Dec 2017 using the 13-point rating scale. No companies start/end in BB (7) to C-D (13) notches.

Table A 5.29 Fitch: Rating transition matrix, 2000 – 2006 (13-point scale)

	Panel A. Ratings to (%)					
From	**AAA/AA+**	**AA/AA-**	**A+/A**	**A-**	**BBB+/BBB**	**BBB-/BB+**
AAA/AA+	96.67	3.33	0	0	0	0
AA/AA-	0.26	94.32	5.43	0	0	0
A+/A	0	0	88.57	11.43	0	0
A-	4.55	0	4.55	89.77	1.14	0
BBB+/BBB	0	0	0	33.33	50	16.67
BBB-/BB+	0	0	100	0	0	0

	Panel B. Ratings to (frequency)						
From	**AAA/AA+**	**AA/AA-**	**A+/A**	**A-**	**BBB+/BBB**	**BBB-/BB+**	**Total**
AAA/AA+	261	9	0	0	0	0	270
AA/AA-	1	365	21	0	0	0	387
A+/A	0	0	155	20	0	0	175
A-	4	0	4	79	1	0	88
BBB+/BBB	0	0	0	2	3	1	6
BBB-/BB+	0	0	1	0	0	0	1
Total	266	374	181	101	4	1	927

This table presents rating transition matrices of U.S. P/C insurers rated by Fitch from Dec 2000 - Dec 2006 using the 13-point rating scale. No companies start/end in BB (7) to C-D (13) notches. Please refer to Table A 5.28 to check rating symbols and numerical equivalence

Table A 5.30 Fitch: Rating transition matrix, 2007 – 2009 (13-point scale)

Panel A. Ratings to (%)					
From	**AAA/AA+**	**AA/AA-**	**A+/A**	**A-**	**BBB+/BBB**
AAA/AA+	68.52	31.48	0	0	0
AA/AA-	0	83.56	12.42	4.03	0
A+/A	0	9.17	78.33	12.5	0
A-	0	0	9.03	90.97	0
BBB+/BBB	0	0	50	0	50

Panel B. Ratings to (frequency)						
From	**AAA/AA+**	**AA/AA-**	**A+/A**	**A-**	**BBB+/BBB**	**Total**
AAA/AA+	111	51	0	0	0	162
AA/AA-	0	249	37	12	0	298
A+/A	0	11	94	15	0	120
A-	0	0	13	131	0	144
BBB+/BBB	0	0	1	0	1	2
Total	111	311	145	158	1	726

This table presents rating transition matrices of U.S. P/C insurers rated by Fitch from Dec 2007 - Dec 2009 using the 13-point rating scale. No companies start/end in BBB-/BB+ (6) to C-D (13) notches. Please refer to Table A 5.28 to check rating symbols and numerical equivalence.

Table A 5.31 Fitch: Rating transition matrix, 2010 – 2017 (13-point scale)

Panel A. Ratings to (%)				
From	**AAA/AA+**	**AA/AA-**	**A+/A**	**A-**
AAA/AA+	100	0	0	0
AA/AA-	0	99.06	0.94	0
A+/A	0	0.66	99.34	0
A-	0	0	3.51	96.49

Panel B. Ratings to (frequency)					
	AAA/AA+	**AA/AA-**	**A+/A**	**A-**	**Total**
AAA/AA+	81	0	0	0	81
AA/AA-	0	847	8	0	855
A+/A	0	5	758	0	763
A-	0	0	17	468	485
Total	81	852	783	468	2,184

This table presents rating transition matrices of U.S. P/C insurers rated by Fitch from Dec 2007 - Dec 2009 using the 13-point rating scale. No companies start/end in BBB+/BBB (5) to C-D (13) notches. Please refer to Table A 5.28 to check rating symbols and numerical equivalence.

Table A 5.32 AM Best: Rating transition matrix, 2000 – 2017 (13-point scale)

		Panel A. Ratings to (%)												
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
From		**A++**	**A+**	**A**	**A-**	**B++**	**B+**	**B**	**B-**	**C++**	**C+**	**C**	**C-**	**D-S**
1	**A++**	92.73	5.74	1.38	0.07	0.07	0	0	0	0	0	0	0	0
2	**A+**	1.61	92.06	5.74	0.57	0	0	0.02	0	0	0	0	0	0
3	**A**	0.01	2.65	94.06	2.77	0.34	0.12	0.03	0.01	0	0	0	0	0
4	**A-**	0	0.53	6.86	88.57	2.48	0.45	0.78	0.11	0.03	0	0	0	0.2
5	**B++**	0	0.11	0.99	13.85	76.04	5.93	0.77	0.33	0.44	0	0	1.1	0.44
6	**B+**	0.21	0.42	0.63	1.69	12.87	71.73	6.96	1.48	0.42	0	0.21	0	3.38
7	**B**	0	1.79	0.72	3.94	1.08	12.19	68.82	5.38	3.94	0.36	0.72	0	1.08
8	**B-**	0	0	0.85	1.71	0	2.56	7.69	68.38	6.84	3.42	0.85	0	7.69
9	**C++**	0	0	0	1.89	0	1.89	1.89	11.32	54.72	3.77	3.77	1.89	18.87
10	**C+**	0	0	0	0	0	0	5.56	11.11	0	61.11	11.11	0	11.11
11	**C**	0	0	0	0	0	0	0	0	16.67	0	41.67	8.33	33.33
12	**C-**	0	0	0	0	0	0	0	0	0	0	0	28.57	71.43
13	**D/S**	0	0	0	0	0	0.47	0	0	0.47	0	0.47	0	98.58

		Panel B. Ratings to (frequency)													
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	
From		**A++**	**A+**	**A**	**A-**	**B++**	**B+**	**B**	**B-**	**C++**	**C+**	**C**	**C-**	**D-S**	**Total**
1	**A++**	1,276	79	19	1	1	0	0	0	0	0	0	0	0	1,376
2	**A+**	74	4,233	264	26	0	0	1	0	0	0	0	0	0	4,598
3	**A**	1	195	6,923	204	25	9	2	1	0	0	0	0	0	7,360
4	**A-**	0	19	246	3,177	89	16	28	4	1	0	0	0	7	3,587
5	**B++**	0	1	9	126	692	54	7	3	4	0	0	10	4	910
6	**B+**	1	2	3	8	61	340	33	7	2	0	1	0	16	474
7	**B**	0	5	2	11	3	34	192	15	11	1	2	0	3	279
8	**B-**	0	0	1	2	0	3	9	80	8	4	1	0	9	117
9	**C++**	0	0	0	1	0	1	1	6	**29**	2	2	1	10	53
10	**C+**	0	0	0	0	0	0	1	2	0	**11**	2	0	2	18
11	**C**	0	0	0	0	0	0	0	0	2	0	**5**	1	4	12
12	**C-**	0	0	0	0	0	0	0	0	0	0	0	**2**	5	7
13	**D/S**	0	0	0	0	0	1	0	0	1	0	1	0	**209**	212
Total		1,352	4,534	7,467	3,556	871	458	274	118	58	18	14	14	269	19,003

This table presents rating transition matrices of U.S. P/C insurers rated by AM Best from Dec 2000 - Dec 2017 using the 13-point rating scale.

Table A 5.33 AM Best: Rating transition matrix, 2000 – 2006 (13-point scale)

						Panel A. Ratings to (%)							
From	**A++**	**A+**	**A**	**A-**	**B++**	**B+**	**B**	**B-**	**C++**	**C+**	**C**	**C-**	**D-S**
A++	85.49	11.2	3	0.16	0.16	0	0	0	0	0	0	0	0
A+	0.5	88.18	9.65	1.62	0	0	0.06	0	0	0	0	0	0
A	0	2.91	91.15	4.73	0.81	0.36	0	0.04	0	0	0	0	0
A-	0	0.98	5.53	86.98	3.03	1.06	1.59	0.3	0.08	0	0	0	0.45
B++	0	0	1.23	14.25	72.24	6.88	0.74	0.74	0.98	0	0	2.21	0.74
B+	0	0.79	1.18	0.79	14.57	67.72	5.91	1.97	0.79	0	0.39	0	5.91
B	0	2.91	1.16	0.58	0.58	15.12	67.44	4.07	4.65	0.58	1.16	0	1.74
B-	0	0	0	1.69	0	3.39	10.17	59.32	10.17	0	1.69	0	13.56
C++	0	0	0	0	0	0	0	11.9	57.14	4.76	0	2.38	23.81
C+	0	0	0	0	0	0	11.11	22.22	0	55.56	0	0	11.11
C	0	0	0	0	0	0	0	0	18.18	0	45.45	0	36.36
C-	0	0	0	0	0	0	0	0	0	0	0	0	100
D/S	0	0	0	0	0	0.76	0	0	0.76	0	0.76	0	97.71

							Panel B. Ratings to (frequency)							
From	**A++**	**A+**	**A**	**A-**	**B++**	**B+**	**B**	**B-**	**C++**	**C+**	**C**	**C-**	**D-S**	Total
A++	542	71	19	1	1	0	0	0	0	0	0	0	0	634
A+	8	1,417	155	26	0	0	1	0	0	0	0	0	0	1,607
A	0	72	2,256	117	20	9	0	1	0	0	0	0	0	2,475
A-	0	13	73	1,149	40	14	21	4	1	0	0	0	6	1,321
B++	0	0	5	58	294	28	3	3	4	0	0	9	3	407
B+	0	2	3	2	37	172	15	5	2	0	1	0	15	254
B	0	5	2	1	1	26	**116**	7	8	1	2	0	3	172
B-	0	0	0	1	0	2	6	**35**	6	0	1	0	8	59
C++	0	0	0	0	0	0	0	5	**24**	2	0	1	10	42
C+	0	0	0	0	0	0	1	2	0	**5**	0	0	1	9
C	0	0	0	0	0	0	0	0	2	0	**5**	0	4	11
C-	0	0	0	0	0	0	0	0	0	0	0	**0**	4	4
D/S	0	0	0	0	0	1	0	0	1	0	1	0	**128**	131
Total	550	1,580	2,513	1,355	393	252	163	62	48	8	10	10	182	7,126

This table presents rating transition matrices of U.S. P/C insurers rated by AM Best from Dec 2000 - Dec 2006 using the 13-point rating scale. Please refer to Table A 5.32 to check rating symbols and numerical equivalence.

Table A 5.34 AM Best: Rating transition matrix, 2007 – 2009 (13-point scale)

					Panel A. Ratings to (%)					
From	**A++**	**A+**	**A**	**A-**	**B++**	**B+**	**B**	**B-**	**C++**	**D/S**
A++	98.15	1.85	0	0	0	0	0	0	0	0
A+	0	93.91	6.09	0	0	0	0	0	0	0
A	0	2.41	95	2.5	0.08	0	0	0	0	0
A-	0	0.27	8.58	88.28	2.72	0.14	0	0	0	0
B++	0	0.59	0.59	19.53	74.56	4.14	0.59	0	0	0
B+	0	0	0	2.47	14.81	76.54	4.94	1.23	0	0
B	0	0	0	0	2.94	8.82	85.29	2.94	0	0
B-	0	0	0	3.57	0	3.57	7.14	85.71	0	0
C++	0	0	0	0	0	12.5	12.5	12.5	62.5	0
D/S	0	0	0	0	0	0	0	0	0	100

					Panel B. Ratings to (frequency)						
From	**A++**	**A+**	**A**	**A-**	**B++**	**B+**	**B**	**B-**	**C++**	**D/S**	**Total**
A++	159	3	0	0	0	0	0	0	0	0	162
A+	0	863	56	0	0	0	0	0	0	0	919
A	0	29	1,141	30	1	0	0	0	0	0	1,201
A-	0	2	63	648	20	1	0	0	0	0	734
B++	0	1	1	33	126	7	1	0	0	0	169
B+	0	0	0	2	12	62	4	1	0	0	81
B	0	0	0	0	1	3	**29**	1	0	0	34
B-	0	0	0	1	0	1	2	**24**	0	0	28
C++	0	0	0	0	0	1	1	1	**5**	0	8
D/S	0	0	0	0	0	0	0	0	0	**41**	41
Total	159	898	1,261	714	160	75	37	27	5	41	3,377

This table presents rating transition matrices of U.S. P/C insurers rated by AM Best from Dec 2007 - Dec 2009 using the 13-point rating scale. Please refer to Table A 5.32 to check rating symbols and numerical equivalence

Table A 5.35 AM Best: Rating transition matrix, 2010 – 2017 (13-point scale)

Panel A. Ratings to (%)

From	A++	A+	A	A-	B++	B+	B	B-	C++	C+	C	C-	D-S
A++	99.14	0.86	0	0	0	0	0	0	0	0	0	0	0
A+	3.19	94.26	2.56	0	0	0	0	0	0	0	0	0	0
A	0.03	2.55	95.71	1.55	0.11	0	0.05	0	0	0	0	0	0
A-	0	0.26	7.18	90.08	1.89	0.07	0.46	0	0	0	0	0	0.07
B++	0	0	0.9	10.48	81.44	5.69	0.9	0	0	0	0	0.3	0.3
B+	0.72	0	0	2.88	8.63	76.26	10.07	0.72	0	0	0	0	0.72
B	0	0	0	13.7	1.37	6.85	64.38	9.59	4.11	0	0	0	0
B-	0	0	3.33	0	0	0	3.33	70	6.67	13.33	0	0	3.33
C++	0	0	0	33.33	0	0	0	0	0	0	66.67	0	0
C+	0	0	0	0	0	0	0	0	0	66.67	22.22	0	11.11
C	0	0	0	0	0	0	0	0	0	0	0	100	0
C-	0	0	0	0	0	0	0	0	0	0	0	66.67	33.33
D/S	0	0	0	0	0	0	0	0	0	0	0	0	100

Panel B. Ratings to (frequency)

From	A++	A+	A	A-	B++	B+	B	B-	C++	C+	C	C-	D-S	Total
A++	575	5	0	0	0	0	0	0	0	0	0	0	0	580
A+	66	1,953	53	0	0	0	0	0	0	0	0	0	0	2,072
A	1	94	3,526	57	4	0	2	0	0	0	0	0	0	3,684
A-	0	4	110	1,380	29	1	7	0	0	0	0	0	1	1,532
B++	0	0	3	35	272	19	3	0	0	0	0	1	1	334
B+	1	0	0	4	12	106	14	1	0	0	0	0	1	139
B	0	0	0	10	1	5	**47**	7	3	0	0	0	0	73
B-	0	0	1	0	0	0	1	**21**	2	4	0	0	1	30
C++	0	0	0	1	0	0	0	0	**0**	0	2	0	0	3
C+	0	0	0	0	0	0	0	0	0	**6**	2	0	1	9
C	0	0	0	0	0	0	0	0	0	0	**0**	1	0	1
C-	0	0	0	0	0	0	0	0	0	0	0	**2**	1	3
D/S	0	0	0	0	0	0	0	0	0	0	0	0	**40**	40
	643	2,056	3,693	1,487	318	131	74	29	5	10	4	4	46	8,500

This table presents rating transition matrices of U.S. P/C insurers rated by AM Best from Dec 2010 - Dec 2017 using the 13-point rating scale. Please refer to Table A 5.32 to check rating symbols and numerical equivalence.

Table A 5.36 S&P: Rating transition matrix, 2000 – 2017 (Subsample: storm surge)

Panel A. Ratings to (%)

		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**18**	**20**
From		**AAA**	**AA+**	**AA**	**AA-**	**A+**	**A**	**A-**	**BBB+**	**BBB**	**BBB-**	**BB+**	**BB**	**BB-**	**B+**	**B**	**CCC**	**CC/D**
1	**AAA**	75.68	20.27	2.7	1.35	0	0	0	0	0	0	0	0	0	0	0	0	0
2	**AA+**	0	63.51	21.6	5.41	9.46	0	0	0	0	0	0	0	0	0	0	0	0
3	**AA**	0	0	87.8	5.76	3.73	2.03	0	0	0.68	0	0	0	0	0	0	0	0
4	**AA-**	0	0	3.35	73.7	13.41	6.7	1.68	0.56	0.56	0	0	0	0	0	0	0	0
5	**A+**	0	0.36	0	6.18	79.27	13.09	0	1.09	0	0	0	0	0	0	0	0	0
6	**A**	0	0	0.75	0	5.25	87.05	4.32	0	2.63	0	0	0	0	0	0	0	0
7	**A-**	0	0	0	0	0	7.88	86.7	4.43	0	0.99	0	0	0	0	0	0	0
8	**BBB+**	0	0	0	0	0	5.88	11.76	58.82	20.59	0	2.94	0	0	0	0	0	0
9	**BBB**	0	0	0	0	0	1.52	0.3	0.3	89.7	0.3	0.61	4.85	0.91	0	1.21	0.3	0
10	**BBB-**	0	0	0	0	0	0	12.5	0	25	62.5	0	0	0	0	0	0	0
11	**BB+**	0	0	0	0	0	0	0	0	0	0	100	0	0	0	0	0	0
12	**BB**	0	0	0	0	0	0	0	0	1.91	0.48	0.48	89.95	0	0.48	2.87	2.39	1.44
14	**B+**	0	0	0	0	0	0	0	0	0	0	0	0	0	100	0	0	0
15	**B**	0	0	0	0	0	0	0	0	0	0	0	5.88	0	0	82.35	3.92	7.84
18	**CCC**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	75.68	24.32
20	**CC/D**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100

Panel B. Ratings to (frequency)

		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**18**	**20**	**Total**
From		**AAA**	**AA+**	**AA**	**AA-**	**A+**	**A**	**A-**	**BBB+**	**BBB**	**BBB-**	**BB+**	**BB**	**BB-**	**B+**	**B**	**CCC**	**CC/D**	
1	**AAA**	56	15	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	74
2	**AA+**	0	47	16	4	7	0	0	0	0	0	0	0	0	0	0	0	0	74
3	**AA**	0	0	259	17	11	6	0	0	2	0	0	0	0	0	0	0	0	295
4	**AA-**	0	0	6	132	24	12	3	1	1	0	0	0	0	0	0	0	0	179
5	**A+**	0	1	0	17	218	36	0	3	0	0	0	0	0	0	0	0	0	275
6	**A**	0	0	4	0	28	464	23	0	14	0	0	0	0	0	0	0	0	533
7	**A-**	0	0	0	0	0	16	176	9	0	2	0	0	0	0	0	0	0	203
8	**BBB+**	0	0	0	0	0	2	4	20	7	0	1	0	0	0	0	0	0	34
9	**BBB**	0	0	0	0	0	5	1	1	296	1	2	16	3	0	4	1	0	330
10	**BBB-**	0	0	0	0	0	0	1	0	2	5	0	0	0	0	0	0	0	8
11	**BB+**	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	3
12	**BB**	0	0	0	0	0	0	0	0	4	1	1	188	0	1	6	5	3	209
14	**B+**	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	3
15	**B**	0	0	0	0	0	0	0	0	0	0	0	3	0	0	42	2	4	51
18	**CCC**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	28	9	37
20	**CC/D**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	213	213
	Total	56	63	287	171	288	541	208	34	326	9	7	207	3	4	52	36	229	2521

This table presents rating transition matrices of U.S. P/C insurers from the 10 states with more risk of storm surge rated by S&P from Dec 2000 - Dec 2017 using the 20-point rating scale.

Table A 5.37 Moody's: Rating transition matrix, 2000 – 2017 (Subsample: storm surge)

		Panel A. Ratings to (%)														
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**13**	**15**	**16**	**17**	**18**
From		**Aaa**	**Aa1**	**Aa2**	**Aa3**	**A1**	**A2**	**A3**	**Baa1**	**Baa2**	**Baa3**	**Ba3**	**B2**	**B3**	**Caa1**	**Caa2**
1	**Aaa**	90.63	0	9.38	0	0	0	0	0	0	0	0	0	0	0	0
2	**Aa1**	0	50	50	0	0	0	0	0	0	0	0	0	0	0	0
3	**Aa2**	0	0	90.83	8.33	0.83	0	0	0	0	0	0	0	0	0	0
4	**Aa3**	0	0	4.76	78.57	9.52	4.76	2.38	0	0	0	0	0	0	0	0
5	**A1**	0	0	0	3.64	87.27	9.09	0	0	0	0	0	0	0	0	0
6	**A2**	0	0	0	0.43	2.56	93.59	2.56	0	0	0.85	0	0	0	0	0
7	**A3**	0	0	0	0	0	15.29	84.71	0	0	0	0	0	0	0	0
8	**Baa1**	0	0	0	0	0	0	5.26	89.47	0	5.26	0	0	0	0	0
9	**Baa2**	0	0	0	0	0	0	0	11.11	77.78	11.11	0	0	0	0	0
10	**Baa3**	0	0	0	0	0	11.11	0	0	11.11	55.56	22.22	0	0	0	0
15	**B2**	0	0	0	0	0	0	0	0	0	0	0	75	0	0	25
16	**B3**	0	0	0	0	0	0	0	0	0	0	0	0	100	0	0
17	**Caa1**	0	0	0	0	0	0	0	0	0	0	0	0	0	100	0

		Panel B. Ratings to (frequency)															
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**13**	**15**	**16**	**17**	**18**	
From		**Aaa**	**Aa1**	**Aa2**	**Aa3**	**A1**	**A2**	**A3**	**Baa1**	**Baa2**	**Baa3**	**Ba3**	**B2**	**B3**	**Caa1**	**Caa2**	**Total**
1	**Aaa**	29	0	3	0	0	0	0	0	0	0	0	0	0	0	0	32
2	**Aa1**	0	6	6	0	0	0	0	0	0	0	0	0	0	0	0	12
3	**Aa2**	0	0	109	10	1	0	0	0	0	0	0	0	0	0	0	120
4	**Aa3**	0	0	2	33	4	2	1	0	0	0	0	0	0	0	0	42
5	**A1**	0	0	0	2	48	5	0	0	0	0	0	0	0	0	0	55
6	**A2**	0	0	0	1	6	219	6	0	0	2	0	0	0	0	0	234
7	**A3**	0	0	0	0	0	13	72	0	0	0	0	0	0	0	0	85
8	**Baa1**	0	0	0	0	0	0	1	17	0	1	0	0	0	0	0	19
9	**Baa2**	0	0	0	0	0	0	0	1	7	1	0	0	0	0	0	9
10	**Baa3**	0	0	0	0	0	1	0	0	1	5	2	0	0	0	0	9
15	**B2**	0	0	0	0	0	0	0	0	0	0	0	3	0	0	1	4
16	**B3**	0	0	0	0	0	0	0	0	0	0	0	0	6	0	0	6
17	**Caa1**	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	3
	Total	29	6	120	46	59	240	80	18	8	9	2	3	6	3	1	630

This table presents rating transition matrices of U.S. P/C insurers from the 10 states with more risk of storm surge rated by Moody's from Dec 2000 - Dec 2017 using the 20-point rating scale.

Table A 5.38 Fitch: Rating transition matrix, 2000 – 2017 (Subsample: storm surge)

		1	2	3	4	5	6	7	8	10
		Panel A. Ratings to (%)								
From		**AAA**	**AA+**	**AA**	**AA-**	**A+**	**A**	**A-**	**BBB+**	**BBB-**
1	**AAA**	71.43	14.29	14.29	0	0	0	0	0	0
2	**AA+**	0	77.5	15	7.5	0	0	0	0	0
3	**AA**	0	0.53	91.58	4.74	2.11	0	1.05	0	0
4	**AA-**	0	0	11.54	75.64	11.54	1.28	0	0	0
5	**A+**	0	0	0	1.27	92.36	4.46	1.91	0	0
6	**A**	0	0	0	2.41	6.02	89.16	2.41	0	0
7	**A-**	0	0.77	0	0	0	2.31	96.15	0.77	0
8	**BBB+**	0	0	0	0	0	0	0	0	100
10	**BBB-**	0	0	0	0	0	100	0	0	0

		1	2	3	4	5	6	7	8	10	
		Panel B. Ratings to (frequency)									
From		**AAA**	**AA+**	**AA**	**AA-**	**A+**	**A**	**A-**	**BBB+**	**BBB-**	**Total**
1	**AAA**	15	3	3	0	0	0	0	0	0	21
2	**AA+**	0	31	6	3	0	0	0	0	0	40
3	**AA**	0	1	174	9	4	0	2	0	0	190
4	**AA-**	0	0	9	59	9	1	0	0	0	78
5	**A+**	0	0	0	2	145	7	3	0	0	157
6	**A**	0	0	0	2	5	74	2	0	0	83
7	**A-**	0	1	0	0	0	3	125	1	0	130
8	**BBB+**	0	0	0	0	0	0	0	0	1	1
10	**BBB-**	0	0	0	0	0	1	0	0	0	1
	Total	15	36	192	75	163	86	132	1	1	701

This table presents rating transition matrices of U.S. P/C insurers from the 10 states with more risk of storm surge rated by Fitch from Dec 2000 - Dec 2017 using the 20-point rating scale.

Table A 5.39 AM Best: Rating transition matrix, 2000 – 2017 (Subsample: storm surge)

Panel A. Ratings to (%)													
		2	**4**	**6**	**7**	**9**	**10**	**12**	**13**	**15**	**16**	**18**	**20**
From		**A++**	**A+**	**A**	**A-**	**B++**	**B+**	**B**	**B-**	**C++**	**C+**	**C**	**C-/D**
2	**A++**	94.02	5.32	0.66	0	0	0	0	0	0	0	0	0
4	**A+**	1.31	91.47	6.89	0.33	0	0	0	0	0	0	0	0
6	**A**	0	1.92	93.98	3.59	0.38	0	0.06	0.06	0	0	0	0
7	**A-**	0	0.31	4.94	89.51	3.4	0.82	0.93	0.1	0	0	0	0
9	**B++**	0	0.36	1.08	14.44	73.65	6.86	0.72	0.36	0.36	0	0	2.17
10	**B+**	0	0	0	0.72	13.77	69.57	7.25	2.17	1.45	0	0.72	4.35
12	**B**	0	3.03	2.02	7.07	1.01	9.09	68.69	3.03	5.05	0	0	1.01
13	**B-**	0	0	0	0	0	0	9.76	63.41	12.2	4.88	2.44	7.32
15	**C++**	0	0	0	0	0	0	0	4.76	42.86	9.52	4.76	38.1
16	**C+**	0	0	0	0	0	0	6.25	12.5	0	68.75	0	12.5
18	**C**	0	0	0	0	0	0	0	0	0	0	0	100
20	**C-/D**	0	0	0	0	0	0	0	0	0.9	0	0	99.1

Panel B. Ratings to (frequency)														
		2	**4**	**6**	**7**	**9**	**10**	**12**	**13**	**15**	**16**	**18**	**20**	
From		**A++**	**A+**	**A**	**A-**	**B++**	**B+**	**B**	**B-**	**C++**	**C+**	**C**	**C-/D**	**Total**
2	**A++**	283	16	2	0	0	0	0	0	0	0	0	0	301
4	**A+**	12	836	63	3	0	0	0	0	0	0	0	0	914
6	**A**	0	30	1468	56	6	0	1	1	0	0	0	0	1,562
7	**A-**	0	3	48	870	33	8	9	1	0	0	0	0	972
9	**B++**	0	1	3	40	204	19	2	1	1	0	0	6	277
10	**B+**	0	0	0	1	19	96	10	3	2	0	1	6	138
12	**B**	0	3	2	7	1	9	68	3	5	0	0	1	99
13	**B-**	0	0	0	0	0	0	4	26	5	2	1	3	41
15	**C++**	0	0	0	0	0	0	0	1	9	2	1	8	21
16	**C+**	0	0	0	0	0	0	1	2	0	11	0	2	16
18	**C**	0	0	0	0	0	0	0	0	0	0	0	2	2
20	**C-/D**	0	0	0	0	0	0	0	0	1	0	0	110	111
	Total	295	889	1,586	977	263	132	95	38	23	15	3	138	4,454

This table presents rating transition matrices of U.S. P/C insurers from the 10 states with more risk of storm surge rated by AM Best from Dec 2000 - Dec 2017 using the 20-point rating scale.

Chapter 6. Split ratings and rating migration: Evidence from U.S. P/C insurers

6.1 Introduction

How insurance ratings fluctuate over time and how Credit Rating Agencies (CRAs) react to rating decisions by rival agencies is an important issue, since information about financial strength is crucial for investment decisions and policyholders, who rely on insurers being solvent when a claim arises (Adams et al., 2003; Bierth et al., 2015). As stated in Chapters 2 and 4, each CRA has different rating methodology and labelling system (Caporale et al., 2017), presenting major challenges in defining points of comparability that have long been confusing to market participants (Fitch, 2016). Moreover, disagreement on the rating for a particular insurer may occur, resulting in the so-called phenomenon, split ratings. While most academic efforts have been centre in determining the root causes of split ratings, the influence of rating disagreement on subsequent rating changes is an unexplored area for insurance companies.

The aim of this thesis Chapter is to address this shortcoming by empirically analysing how rating disagreement can affect later rating changes. Specifically, the main research question consists of 'Is there any relationship between split ratings and subsequent rating migration for U.S. Property/Casualty (P/C) insurers' ratings?'. Certainly, the *sui generis* nature of the insurance industry provides an original case study for this analysis. This is because adding to the fact that four major CRAs exist; as mentioned in Chapter 5, the insurance sector is on the front lines shaking its roots with concerns about the potential negative impact of climate change on its costs and availability (S&P, 2015). In addition, the P/C industry has an investment portfolio that amounted to $1,529 ($1,586) billion in 2015, and 2016, respectively (FIO, 2016, 2017). Thus, it is considered one of the largest institutional investors.

Likewise, -despite critics of CRAs-, financial strength ratings (FSR) are heavily relied upon by market participants i.e., policyholders, regulators, investors, and lenders (Doherty and Phillips, 2002; Miao et al., 2014; Pottier and Sommer, 1999). Traditionally, insurance firms use ratings in their advertising, regulators use them as tools to measure insurer risk and many academics use them as measurers of insolvency risk (Pottier and Sommer, 1999). Indeed, U.S. insurance companies explicitly rely on NRSRO ratings in defining risk-based capital, and bonds held by insurers are allocated capital charges based upon their credit ratings (Bongaerts et al., 2012). Regarding rating migrations, numerous applications in risk management, such as credit portfolio models (e.g., JP Morgan's CreditMetrics, CreditRisk+, and McKinsey's

CreditPortfolioView), bond pricing models, pricing of credit derivatives and modelling credit risk premium (Frydman and Schuermann, 2008) also use ratings as a key input. [37]

Three former papers motivate the development of this chapter. Livingston et al., (2007, 2008) and Alsakka and ap Gwilym (2010a) argue that split ratings convey additional information that can influence subsequent rating changes. Livingston et al., (2008) found that initial split ratings of corporate bonds during 1983-2000 tend to exhibit upcoming rating migrations. Likewise, Alsakka and ap Gwilym (2010a) show that split rated emerging sovereigns are likely to be upgraded by the rating agency from whom a lower rating exist and prone to be downgraded by the rating agency from whom a higher rating exist within a 1 year interval. For insurers, the lack of discussion about rating migration is evident. The only studies to depart from are Pottier and Sommer (1999, 2006) who indicate that CRAs exhibit systematic differences in the relative importance given to the different factors they consider. Further, Pottier and Sommer (2006) claim that property liability insurers are not transparent, where small size ones, stock insurers, insurers with a history of reserving errors, greater levels of investment in stocks and low grade in bonds and geographically diversified insurers, are more difficult to assess.

The majority of former studies have used disagreement among CRAs as a proxy for the opacity of an industry, which is a relevant issue and a major obstacle for obtaining outside funding (Hauck and Neyer, 2014). The dominant view advocates that a higher number of rating splits should be observed if a sector is more opaque (Hauck and Neyer, 2008). Among all industries studied, Morgan (2002) states that U.S. insurance firms tend to generate more recurrent split ratings; becoming the most opaque among non-banking firms. Iannotta (2006) claims that, for European companies, ordered logit regression results indicate that the probability of a split rating rises by more than 20% when the issuer is a bank followed by the insurance sector who has a close percentage (Williams et al., 2013).

To the best of my knowledge, there is no study that relates split ratings and future rating changes, exclusively for insurers. The main literature strings for insurance companies are the determinants of financial strength (e.g., Adams et al., 2003, Florez-Lopez, 2007), causes of split ratings (e.g., Pottier and Sommer, 1999, 2006), and competition effects (e.g., Doherty et

[37] As mentioned in Chapter 2, nine agencies qualify as Nationally Recognized Statistical Rating Organizations (NRSROs): A.M. Best Company, DBRS Inc., Fitch Ratings Inc., Egan-Jones Rating Co, Japan Credit Rating Agency Ltd, HR Ratings de México S.A. de C.V, Kroll Bond Rating Agency, Inc. (formerly known as Lace Financial Corp.), Moody's Investors Service, and S&P Global Ratings (formerly known as Standard & Poor's Ratings Services).

al., 2012). As mentioned in Chapter 3, Doherty et al., (2012) highlights how the differences in rating standards across CRAs are likely to create confusion about the meaning of ratings. Recently, attention has been drawn onto systemic risk (Asimit et al., 2016; Bierth et al., 2015), insolvency risk of insurance companies (Caporale et al., 2017) and effects of regulatory frameworks such as Solvency II in Europe (e.g., Höring, 2013; Laas and Siegel, 2016; Mezöfi et al., 2017) or regulatory changes in U.S. (e.g. Dimitrov et al., 2015).

This research offers key contributions to the existing literature. The Chapter makes a significant contribution by identifying a split rating as a valuable factor affecting the probabilities of insurers' rating changes. Second, implications of the results can affect decisions of market participants as they have more information on the correspondence between the different agencies' categories for insurer' ratings (enhancing market transparency). Third, this chapter focuses on FSR from four CRAs rather than only one and covers the most recent data. The sample includes ratings from the largest four CRAs (S&P, Moody's, Fitch and AM Best) for 904 U.S. P/C insurers during the period December 2003 to December 2017. Moreover, it contributes to the studies about reputational issues since, up to date, there is no study apart from Doherty et al. (2012) looking at the competition effects for insurers' CRAs.

To find possible explanations on the link between split ratings and subsequent rating changes, this chapter borrows foundation in the broader literature on herding behaviour. A theoretical literature area foresees that analysts with stronger reputational concerns have more severe incentives to herd (Scharfstein and Stein, 1990), and reputational concerns are enlarged for those CRAs with lower reputational capital (Mathis et al., 2009). In the insurance setting, AM Best would be considered the CRA with highest reputation while Fitch is sensibly considered to be of lower reputation than either Moody's or S&P (Lugo et al., 2015). It is expected that the three main CRAs are strongly influenced by AM Best than by one the others. Similarly, it could be expected that S&P, Moody's, and AM Best are more influenced by each other than by Fitch and that they influence the latter more than the other way around.

The key findings of this Chapter can be summarized as follows. Split ratings among the four CRAs are influential on each other's future rating migrations. Although, the interaction between them has different particularities. Primary, the relationship among the four CRAs, AM Best, S&P, Moody's and Fitch seems to point that Moody's is the agency that is influenced by all the other three CRAs in both directions, upgrades, and downgrades. When S&P/Fitch/AM Best had one, two or more notches higher (lower) in the previous year, Moody's is more likely to upgrade (downgrade). Second, the magnitude of the split influences future S&P rating changes more strongly in the case of upgrades than downgrades. Third, S&P and Moody’s have a stronger relationship by including their assessments into their ratings, while for Fitch, Moody’s/S&P ratings have no significant effect on Fitch’s future rating changes, especially when deciding an upgrade.

Regarding the interaction between the three CRAs contrasted with AM Best as the industry expert; S&P and Moody's equations results, imply that split rated insurers with higher (lower) AM Best ratings are more likely to be upgraded (downgraded) by S&P and Moody's in the following year than non-split rated issuers. However, for Fitch, AM Best actions have a significant effect on Fitch’s future rating changes only when deciding a downgrade. Conversely, AM Best seems to be strongly influenced by all three (S&P/Moody’s/Fitch) when deciding an upgrade, but for downgrades, the degree of influence is lower and only comes from S&P and Moody’s. On the other hand, the dummy for the years 2007-2011 is exhibiting “unexpected” results for some of the CRA pairs. Consistent with our previous finding that the crisis has had an uneven effect over the P/C insurance industry; other factors seem to have more influence in the rating changes of insurers.

The rest of the Chapter is structured as follows. Section 6.2 contains a brief review of the literature on split ratings connected with rating migration. Section 6.3 specifies the sample used and analyses the principal descriptive statistics that allow the behaviour of ratings to be analysed. Section 6.4 presents the empirical expression with which we model the probability of obtaining an upgrade/downgrade given a split rating in the previous year. Section 6.5 sets out the empirical results for each pair of CRAs. In Section 6.6, supplementary results are presented. Finally, Section 6.7 sets out the conclusions.

6.2 Literature review

The main goal of this chapter is to examine the influence of split rated insurers with their upcoming rating changes. Thus, key themes that are further associated with this empirical research are develop, as follows.

6.2.1 Determinants of split ratings and concept of opacity

As briefly mentioned in Chapter 3, there is a broad literature addressing the causes of rating disagreement. Explanation starts from Ederington (1986) who argued that differences of opinion are unsystematic or random (Random error hypothesis), continuing with Cantor and Packer (1997), who emphasize the use of different rating models by CRAs. Subsequently, Morgan (2002) -followed by Iannotta (2006)- suggested the asset opaqueness hypothesis stating that discrepancies can be guided by accounting variables, such as assets that principally form the banks' balance sheets. Other authors have extended this idea on other factors such as analysts' opinions, market dynamics (Livingston et al., 2007), opacity index (Livingston and Zhou, 2016) and opacity measures (Dahiya et al., 2017). Furthermore, it has been advocated that CRAs are lopsided where several conclusions have arisen; Moody's is more conservative than S&P (Morgan, 2002), S&P is more conservative than Moody's (Iannotta, 2006), and S&P sovereign ratings tend to be more conservative (Alsakka et al., 2017).[38]

An extensive literature has provided evidence about the noted concept of opacity, which refers to the difficulty in assessing the value of an item on the balance sheet of a company due to lack of information disclosure (Park et al., 2016). Information opaqueness is considered one of the main driving forces behind CRAs assessing issuers differently to each other (Williams et al., 2013) and it has been argued that the recent turmoil on financial markets was amplified by the opacity of financial products (Borio and Zhu, 2008; Turnbull et al., 2007). Starting from Morgan (2002), the discussion about opacity has increased but with no definitive agreement. On one side, Morgan (2002) uses splits as a proxy of opacity by analysing ratings assigned by Moody's and S&P across different U.S. industries to determine whether there are more split ratings in the banking sector than in others. He finds that the proportion of split ratings is much higher in the banking and insurance sectors compared to non-financial firms (Adamson et al., 2014; Williams et al., 2013) and discrepancies are due to the opaqueness of bank balance

[38] The random error hypothesis proposed by Ederington (1986) claims that split ratings are related to unsystematic errors in the rating process, which are later corrected by the CRAs. This is contrary to the idea that split ratings arise from differences in credit assessment or weights allocated to different factors during the rating process among CRAs.

sheets. On the other side, authors such as Hauck and Neyer (2008) claim that splits may occur if an industry is rather opaque but that they may also happen if an industry is rather transparent.

Despite the absence of a unique view about opaqueness, following Morgan (2002) contribution, several empirical studies have used split ratings, as a proxy for opacity. Specifically, Iannotta (2006) uses split ratings to test whether banks are relatively more opaque than other industries. For European data on firms rated by Moody's and S&P, Iannotta (2006) concludes that the opaqueness of bank balance sheets causes the differences between agencies and that this opaqueness increases with size and capital, but it decreases with fixed assets (Salvador, 2018).

While studies about opaqueness and split ratings have kept slowly growing, there is also literature examining motives for obtaining an additional rating. Among the reasons issuers shop for a supplementary rating are, the hope of improving their rating (see Poon and Firth, 2005), meet regulatory purposes (Bongaerts et al., 2012), or addressing information gaps across CRAs (Alsakka et al., 2017). Livingston and Zhou (2016) assert that an extra rating is considered valuable -by fund managers- since for a one-time fee, CRAs assign the rating category and provide additional detailed reports. Alternatively, investors that are averse to uncertainty can reduce it by additional ratings, as they would obtain a better perspective of the creditworthiness of the securities or financial institutions (Fabozzi and Vink, 2015).

Closest to this Chapter within the insurance sector, Pottier and Sommer (1999, 2006) is again high-pointed. Pottier and Sommer (1999) indicate that insurers' rating agencies exhibit systematic differences in the relative importance given to the different factors they consider. More recently, other studies have extended on opaqueness. Adamson et al., (2014) considers insurer opacity with respect to ownership, whereas Park et al., (2016) study opaqueness by analysing information asymmetry inherent in life and non-life U.S. insurers' assets. They conclude that the effect of information asymmetry was more significant with life insurers than with non-life insurers.

6.2.2 Rating migration and reputational theories

Limited empirical literature exists that investigates rating migration, especially for insurance companies. For corporates, Hu and Cantor (2003) and Hamilton and Cantor (2004) suggested that the direction of the prior rating change affects the migration probability. For sovereigns, Fuertes and Kalotychou (2007) study sovereign Moody's rating migration by examining rating momentum and duration effects on sovereign rating upgrades and downgrades.

The papers that motivate this research, Alsakka and ap Gwilym, 2010a and Livingston et al., (2008) argue that since asset opacity is the main driver of split ratings, further information on the issuer would reduce information asymmetry, leading to upcoming rating changes. In the insurance setting, Wang and Carson (2014) is the only research focus on insurers' rating migration. They test for three main rating drift phenomena: initial rating effect, time dependence, and momentum drift. Based on a sample of FSR ratings during 1995 to 2006 and using cox model, they find evidence of an initial rating effect and momentum drift for insurer rating migrations. [39]

Table 6.1 Relevant literature about split ratings

	Current chapter	Livingston and Zhou (2016)	Livingston et al., (2008)	Alsakka and ap Gwilym (2010a)	Pottier and Sommer (2006)	Iannotta (2006)	Morgan (2002)	Pottier and Sommer (1999)
Type of rating	FSR U.S. P/C insurers	U.S. corporates	Bonds	Emerging sovereigns	FSR P/L	European vs. non-banks	U.S. vs. non-U.S banks	FSR P/L
Sample size	904	6,655 U.S. domestic bonds	9431 bond issues	49 countries	125	2,473 bonds 248 firms	7,862 bonds	1678
Period	2003-2017	2000-2014	1983-2000	2000-2008	year-end 1997	1993-2003	Jan. 1983 - July 1993	July 1996
CRAs	S&P Moody's Fitch, AM Best	S&P Moody's	S&P Moody's	S&P, Moody's, Fitch, CI, JCR, R&I	S&P Moody's	S&P Moody's	S&P Moody's	S&P, Moody's and Best

This table presents relevant studies investigating split ratings within several settings. JCR refers to Japan Credit Rating Agency, R&I refers to Japan Rating and Investment Information and CI refers to Capital Intelligence. Pottier and Sommer (2006) uses the terminology Property/Liability (P/L) to refer to non-life insurers.

Table 6.1 summarizes research of split ratings with some of the noted studies (i.e., Alsakka and ap Gwilym, 2010a). Nevertheless, other studies on split ratings can be highlighted. For sovereigns, Vu et al., (2015) and Alsakka et al., (2017); and for corporates, Ismail et al., (2015) and Jiang and Packer (2019). Vu et al., (2015) focuses on identifying the extent to which split ratings affect the bond market reaction to CRAs' sovereign credit events. They find that only the splits between S&P and Moody's entail an impact on sovereign credit spreads' sensitivity to credit events. Alsakka et al., (2017) analyse split ratings in sovereign credit signals and their

[39] In their paper, Wang and Carson (2014) define an 'initial rating effect' as the effect when future rating transitions depend on the insurer's current rating. 'Time dependence' refers to the longer an insurer's rating remains in a given level, the lower the likelihood that the rating will change and 'momentum drift' means that future downgrades and upgrades are related with the insurer's past rating changes.

influence on European stock markets. They also conclude that split ratings have a significant association with subsequent negative credit actions by each CRA, but the links among Moody's/Fitch actions and their split ratings with other CRAs have weakened post-EU regulatory reforms in July 2011. On the other hand, Jiang and Packer (2019) examine the risk assessments of Chinese (non-financial) companies assesses by the major Chinese rating agencies and the three largest global CRAs. They find an impact of the ratings of both in the market prices despite having significant differences in the rating scales. Moreover, Ismail et al., (2015) add in the field by saying that firms in emerging markets have higher degrees of split ratings than firms in advanced markets.

Another field on which this thesis Chapter borrows foundation is the broader literature on herding behaviour or predictions of others. Scharfstein and Stein (1990) stand that analysts with stronger reputational concerns have more acute incentives to herd, and that reputational concerns are enlarged for those CRAs with lower reputational capital (Mathis et al., 2009). Therefore, a CRA with a lower reputation is expected to be more influenced by the behaviour of other agencies. Likewise, Mariano (2012) concludes that a CRA with lower reputational capital is expected to exercise a weaker influence over other rating agencies. In addition, Lugo et al., (2015) found that Fitch is on average the first mover and that Moody's and S&P also influence Fitch more than they are influenced by it. Several theoretical and empirical studies raise the drawbacks of the issuer-pay model suggesting that greater competition might motivate CRAs to provide biased high ratings to increase or maintain their market share (e.g., Becker and Milbourn, 2011; Bolton et al., 2012; Opp et al., 2013).

6.3 Data

6.3.1 Data

To operationalize the analysis, a dataset is carefully construct by merging four data sources that comprise Long Term (LT) – Local currency (LC) Financial Strength Ratings (FSR) of U.S. Property/Casualty (P/C) insurers. First, S&P Capital IQ platform is used to obtain S&P ratings. Next, Moody's and Fitch's website is used to obtain rating history of Moody's and Fitch respectively. Lastly, AM Best ratings are obtained from AM Best rating database. The sample contains annual observations (31st of December) of FSR assigned by at least two of the four CRAs, S&P, Moody's, Fitch and AM Best. The most prevalent rule for classifying rated insurers was as follows: To be part of the sample, the issuers from both CRAs (in the pair) must exist for at least one year prior to entering the sample for the split – migration calculation. The split is calculated with the value on December 31st. Some issuers (in this case, insurers) are rated by two agencies but on different dates so, it is not possible to calculate the split. Therefore, the preliminary sample consists of 1364 insurers rated by at least two of the four CRAs. However, the sample must leave out insurers that are assessed "R/SD/D" categories in the first year that they enter the dataset, since very few will recover from those categories in the following year. This reduces the sample to 904 U.S. P/C insurers.

Table 6.2 Insurers in sample

Panel A. Rated by two CRAs – 2003-2017

CRAs	**S&P Moody's**	**S&P Fitch**	**Fitch Moody's**	**AM Best S&P**	**AM Best Moody's**	**AM Best Fitch**
No. of insurers	261	240	171	833	292	279

Panel B. Rated by three and all CRAs – 2003-2017

	S&P/Moody's Fitch	**S&P/Moody's AM Best**	**S&P/ Fitch AM Best**	**S&P/ Moody's Fitch/ AM Best**
No. of insurers	152	254	230	147

This table displays the distribution of the whole sample by CRA pairs and triplets.

The sample period is from 2003 to 2017. It starts in 2003 because the number of insurers in the sample for S&P dropped dramatically in 2002; S&P's Ratings Services announced withdrew its public information (pi) counterparty credit and FSR on various insurance companies because of a decision to refocus analytical research resources" (S&P, 2003). Data is stopped in 2017 as it was the most recent available data at the time of commencing the research for this thesis. Table 6.2 exhibits the number of insurers rated by CRA pairs and triplets. Similar to Chapter 5 of this thesis, the table is consistent with the fact that AM Best is the industry expert, S&P is a fast-growing market player, and Moody's and Fitch are gradually growing in the insurance rating market, with Fitch appearing as the smaller.

Further, two mapped numerical rating scales are used: **(I)** a 20-point numerical scale (Aaa/AAA=1, Aa1/AA+=2…Caa3/CCC−=19, Ca/CC to C/SD−D=20) which it will be used in the main results section (see e.g., Alsakka et al., 2017; Alsakka and ap Gwilym, 2009, 2010a). **(II)** a 13-point numerical scale based on AM Best rating points, which it will be referred in the supplementary results section (A++ =1, A+=2…C−=12, D to S =13). In order to conduct such transformations, labelling system differences are considered: First, S&P FSR rating scale has a 21-category scale (ranging from 'AAA' to 'D'). Second, Fitch uses a 19-category scale with similar symbols as S&P, from 'AAA' to 'C'. Third, Moody's uses the same scale but modifies its symbols (from 'Aaa' instead of 'AAA', 'Aa1' instead of 'AA+'), while AM Best uses a 13-point rating scale ranging from 'A++' to 'S'. Despite the differences, for the first three CRAs, it is straightforward to find its counterpart in the other agency rating scale. The challenge comes when mapping AM Best 13-points rating scale with the 20-points rating scale of the other CRAs. Since no prior studies were found mapping AM Best directly with its peers' scales, a conservative approach is proposed to map them as explained in Section 4.5 in Chapter 4.

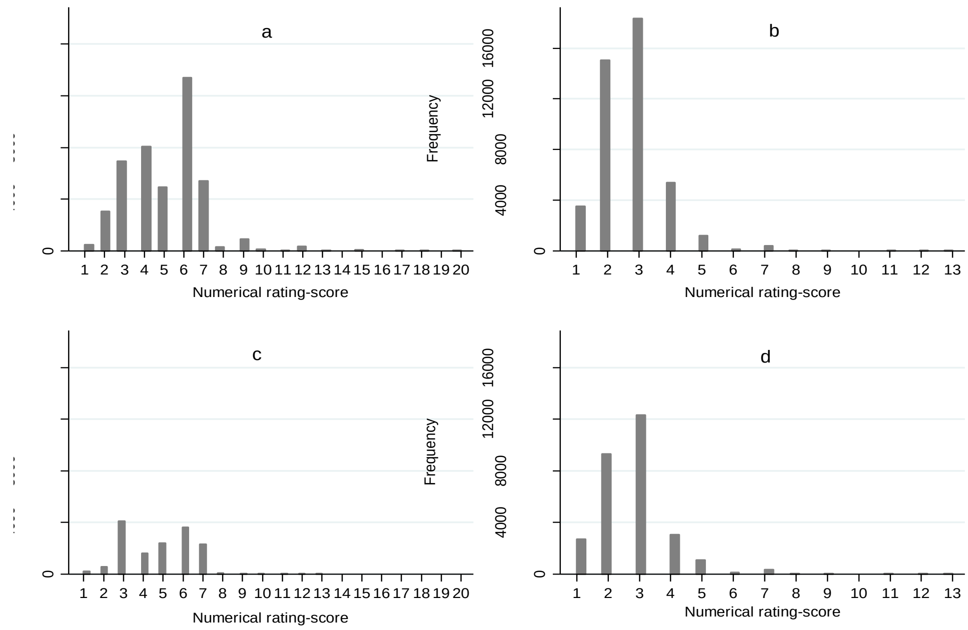

Figure 6.1 Distribution of insurance companies by rating scale, Dec. 2003 – Dec. 2017.

This figure presents the distribution of yearly financial strength ratings (FSR) during the period of analysis 2003-2017, using the 20-point or 13-point numerical scales. Figure 6.1(a) includes all agencies, the credit ratings scale is transformed into a 20-point numerical scale (Aaa/AAA=1, Aa1/AA+=2…Caa3/CCC−=19, Ca/CC to C/SD−D=20). Figure 6.1 (b) represents all agencies, the credit ratings scale is transformed into a 13-point numerical scale based on AM Best methodology (A++/AAA/AA+ =1, A+ / AA/ AA-= 2 to C/SD−D=13). Figure 6.1(c) depicts S&P, Moody's, and Fitch pairs, with the credit rating scale transformed into a 20-point numerical scale. Figure 6.1(d) includes AM Best, S&P, Moody's, and Fitch pairs, but the credit rating scale is transformed into a 13-point numerical scale.

Figure 6.1 (a) presents the distribution of annual 20-points ratings for whole sample-all agencies, while Figure 6.1 (b) illustrates the distribution of annual 13-points ratings, whole sample-all agencies. Overall, both scales reflect that there is a high concentration of ratings at the extremely strong to strong ability categories; most insurers are rated AA/Aa2 and A/A2 (3 and 6) and a very small proportion of ratings at the bottom of the scale. Less than 1% of observations are at Caa1/CCC+ or below. Figure 6.1(c) and Figure 6.1(d) illustrate subsamples that exclude and include AM Best in the sample, respectively.

6.3.2 Descriptive statistics

Table 6.3 presents the distribution of annual rating changes by CRA pairs for the whole sample. The changes are calculated by comparing the rating on December 31st of a determined year with the rating of December 31st of the previous year. The first three columns refer to upgrades (UP), downgrades (DOWNS) and "No change" in the rating. The fourth column reports collectively the frequency and percentage of insurers with at least one rating change for the whole period. The table reveals that most insurers maintain the same rating within a one-year horizon, however, across CRA pairs, the percentage of upgrades tend to be slightly higher than downgrades. Further, the sample has been break down by three subsamples: 2003-2006, 2007-2011, 2012-2017; the period 2007-2011 relates to the dummy of the financial crisis according to the World Bank (n.d.) (see details in Table A 6.1 and Table A 6.2 in Appendix 6.I). By doing so, it can be observed that the trend varies during the financial turmoil with downgrades higher than upgrades. Moreover, there are a few noticeable differences between CRA pairs as follows.[40]

For the first CRAs pair, S&P and Moody's, about 9.3% (12.9%) of insurers experienced a change in Moody's (S&P) rating within one year in the whole period. By looking at the sample by periods, during 2003-2006, the percentage of changes is 4.5% (13.0%) whereas during the financial crisis the percentage increases to about 14.1% (16.8%) and in the final period, the percentage decrease to 7.5% (9.5%). For the next pair, S&P and Fitch, the pattern seems similar. About 10.5% (14.3%) of insurers experienced a change in Fitch (S&P) rating within one year during the whole period 2003-2017 (in Fitch with more downgrades than upgrades). Decomposing the sample by periods, it is noticeable that most of those changes occur either during 2003-2006 with 12.4% (21.1%) in Fitch (S&P), and during the financial crisis 2007-11

[40] Notice that since annual data is used, some rating changes that occur within a year but were later upgrade or downgrade are not capture.

where the changes are similar between the two CRAs, 18.1% (18.16%). In the last period of analysis, the activity decreases to about 3.2% (8.8%). Regarding Moody's and Fitch, about 11.1% (8.3%) insurers have changed in Fitch (Moody's) during the whole period of analysis. Separating the sample, during 2003-06, 12.8% (5.4%) changes, during the crisis 12.0% (7.6%) and after 3.3% (4.7%).

Table 6.3 Annual insurers rating changes, Whole sample: Dec. 2003 – Dec. 2017

CRAs	UP	DW	No change	Changes	1n-up	>1n-up	1n-dw	>1n-dw
1. S&P and Moody's (total no of obs. 2874)								
Moody's no.	148	120	2606	268	146	2	93	27
S&P no.	205	166	2503	371	205	0	130	36
Moody's % of obs.	5.1%	4.2%	90.7%	9.3%	5.1%	0.1%	3.2%	0.9%
S&P % of obs.	7.1%	5.8%	87.1%	12.9%	7.1%	0.0%	4.5%	1.3%
2. S&P and Fitch (total no of obs. 2763)								
Fitch no	117	174	2472	291	117	0	140	34
S&P no	201	193	2369	394	194	7	172	21
Fitch % of obs.	4.2%	6.3%	89.5%	10.5%	4.2%	0.0%	5.1%	1.2%
S&P % of obs.	7.3%	7.0%	85.7%	14.3%	7.0%	0.3%	6.2%	0.8%
3. Fitch and Moody's (total no of obs. 1898)								
Fitch no.	97	113	1688	210	92	5	91	23
Moody's no.	78	79	1741	157	77	1	67	12
Fitch % of obs.	5.1%	6.0%	88.9%	11.1%	4.8%	0.3%	4.8%	1.2%
Moody's % of obs.	4.1%	4.2%	91.7%	8.3%	4.1%	0.1%	3.5%	0.6%
4. AM Best and S&P (total no of obs. 8017)								
AM Best no.	322	208	7487	530	81	241	38	170
S&P no.	476	563	6978	1039	393	83	376	187
AM Best % of obs.	4.0%	2.6%	93.4%	6.6%	1.0%	3.0%	0.5%	2.1%
S&P % of obs.	5.9%	7.0%	87.0%	13.0%	4.9%	1.0%	4.7%	2.3%
5. AM Best and Moody's (total no of obs. 3205)								
AM Best no.	138	91	2976	229	32	106	14	77
Moody's no.	171	136	2898	307	163	8	105	31
AM Best % of obs.	4.3%	2.8%	92.9%	7.1%	1.0%	3.3%	0.4%	2.4%
Moody's % of obs.	5.3%	4.2%	90.4%	9.6%	5.1%	0.2%	3.3%	1.0%
6. AM Best and Fitch (total no of obs. 3339)								
AM Best no.	111	62	3166	173	17	94	4	58
Fitch no.	137	204	2998	341	130	7	160	44
AM Best % of obs.	3.3%	1.9%	94.8%	5.2%	0.5%	2.8%	0.1%	1.7%
Fitch % of obs.	4.1%	6.1%	89.8%	10.2%	3.9%	0.2%	4.8%	1.3%

This table presents summary statistics for the dataset, which comprises four main CRAs for insurers. The sample consists of annual long-term local-currency ratings of U.S. during the period December 2003 to December 2017. Rating changes are measured by notches based on a 20-point rating scale. Notice that in pairs S&P and Moody's, S&P and Fitch, Fitch and Moody's, very low or zero observations are display in >1n-up.

Considering AM Best relative to its peers, Table 6.3 documents similar pattern as the previous CRA pairs. For instance, between S&P and AM Best, about 6.6% (13.0%) of insurers experienced a change in AM Best (S&P) rating within one year in the whole period. During 2003-06, about 8.7 (11.0%), during the crisis 6.6% (16.6%) and the last years 2012-17, the changes were less 5.1% (10.2%) in AM Best (S&P). Similarly, for Moody's and AM Best, about 7.1% (9.6%) of insurers experienced a change in AM Best (Moody's) rating within one year in the whole period. During 2003-06, the percentage of change represented 11.0% (6.4%), during the crisis, 5.8% (13.9%) and after 6.3% (7.7%). Finally, for Fitch and AM Best, around 5.2% (10.2%) of insurers experienced a change in AM Best (Fitch) rating within one year in the whole period. During 2003-06, the percentage varied to 10.5% (11.1%), during the crisis fluctuate to 3.4 (17.9%) and in the last years, activity has shirked to 4.9% (4.1%).

To provide some context about the insurance industry, a range of causes may have fuelled rating changes during 2003-2017. During 2003-06, several events threatened the U.S. P/C industry bringing unexpected losses and weakening asset quality of some financial institutions (Schüwer et al., 2018). For instance, U.S./Caribbean hurricanes, Japanese typhoons, U.S. legacy liabilities during 2004-05, while in 2006, catastrophe model inflation suffered several updates (Aon Benfield, 2019). Specifically, in 2005, Hurricane Katrina became the costliest natural disasters in U.S. history, with estimated property damages ranging from $100 billion to over $200 billion (CIPR, 2017b; Schüwer et al., 2018). From 2007 to 2017, the remarkable boom and bust of the subprime mortgage-backed securities placed CRAs into the spotlight (Lugo et al., 2015) and severe climate-related events took place (e.g., Chile and New Zealand earthquakes, Japan and New Zealand earthquakes, as well as Australia and Thailand floods) (Aon Benfield, 2019). Moreover, Hurricane Sandy in 2012 caused an estimated US$72 billion in damage (Michel-Kerjan et al., 2015) and 2017 have now become the costliest year on record for weather disasters (Aon, 2018). Despite the severity of this events, Baluch et al., (2011) argues that relative to the banking sector, the only significant deviation between insurance and banking performance before the crisis was in 2004 thanks to the hurricane losses largely covered by U.S. insurance companies. They state that losses from Hurricanes Katrina, Rita and Wilma did not affect U.S. insurance companies, as the Bermuda insurance firms covered these fatalities.

Table 6.4 documents the frequencies of agreement and disagreement across rating agencies for each agency pair. The split rating across agencies represents more than half of all observations except for S&P and Moody’s (39.8%); and, S&P and Fitch (36.2%) who have the lowest frequency of split ratings between agencies. AM Best and Fitch have different ratings in 78.7% of the cases, followed by AM Best and S&P with 69.9% of cases, AM Best and Moody's with 58.6%, and Moody’s and Fitch with 53.4% cases. Fitch seems to be the harsher among the six agencies as it has mostly lower Fitch ratings compared with the FRS rating compared with the other five. Meanwhile, AM Best seems to be the most generous agency as it has mostly higher ratings compared with the other ratings of the larger three. Nevertheless, this is a wary conclusion since the greater number of issuers in AM Best pairs could be pushing this behaviour.[41]

Table 6.4 Annual rating (Dis) agreement among CRAs in U.S. P/C insurers, 2003 – 2017

CRAs	No. of insurers	Whole sample	Non-split	Split	Split % of whole sample	1-n higher from first agency t-1	More than 1-n higher from first agency t-1	1-n lower from first agency t-1	More than 1-n lower from first agency t-1
S&P and Moody's	261	2874	1729	1145	39.8%	626	71	454	18
S&P and Fitch	237	2763	1764	999	36.2%	365	0	478	306
Moody's and Fitch	170	1898	884	1014	53.4%	551	114	362	0
AM Best and S&P	833	8017	2413	5604	69.9%	1773	1606	1807	445
AM Best and Moody's	292	3205	1328	1878	58.6%	930	375	531	52
AM Best and Fitch	279	3339	710	2629	78.7%	1329	39	909	351

This table presents frequencies of agreement and disagreement across rating agencies for each agency pair based on a 20-point rating scale during December 2003-December 2017. The second column refers to the number of insurers in the pair taken from the whole sample of 904 issuers. The third column includes the number of observations in the pair. From Column 4 to 6, we separate the number and percentage of observations between split and non-split ratings. The rest of the table exhibits the number of observations where the first agency is one-notch or more-than-one-notch higher (lower) in the previous year.

[41] In their thesis, Cattellion and Matthys (2016) argue that split ratings in the insurance sector appear to exist effectively between Best and S&P as well as Best and Moody's. For AM Best and S&P, split ratings generally occur in 60% of the cases while AM Best with Moody's, a split rating occurs in 68% of the cases.

6.4 Methodology

To draw inference in how CRAs react to rating decisions by rival agencies considering the split/non-split rating in the previous year, a probit modelling approach is employed. The major reason to adopt this method comes from the discrete ordinal nature of credit ratings and its implementation in prior studies reporting robust results (e.g., Alsakka et al., 2017; Alsakka and ap Gwilym, 2010a). The methodology employed is closely related to Alsakka and ap Gwilym (2009, 2010a) work adapted to the insurance setting in the following manner. A probit model is selected rather than ordered probit models, as the distribution of rating changes reflects that more-than-one notch have happened less than 3% in most of the CRAs pairs within a one-year horizon. In addition, standard errors clustered are used by issuer to correct for heteroscedasticity following explanations from Petersen (2008), and applications by former researchers such as Fabozzi and Vink (2015); Michel-Kerjan and Kousky (2010) and Schüwer et al., (2018). Likewise, a control variable is included to capture the effect of the financial crisis. Therefore, the econometric specification is defined as follows: [42]

$$y_{it} = \beta_1 1N\_H\_A_{it-1} + \beta_2 2N\_H\_A_{it-1} + \beta_3 1N\_L\_A_{it-1} + \beta_4 2N\_L\_A_{it-1} + \propto_1 RatingH_{A_{it-1}} + \propto_2 RatingL_{A_{it-1}} + \lambda Y07\_11 + \varepsilon_{it}; \qquad \varepsilon_{it} \sim N(0,1) \qquad (6.1)$$

i is the number of issuers , $t = 2,..., 14$ years. It starts with two as it compares within the year, 2 means the second year of the sample because of the lag.

y is a dummy variable equal to either UP or DOWN , UP(DOWN) = 1 if an issuer was upgraded by agency A by one or more than one notch, respectively in year *t, 0* otherwise.

1N_H_A$_{it-1}$ is a dummy taking the value of 1 if an issuer *i* has one notch higher rating from given agency A than from agency b at year t-1, zero otherwise It was upgraded by agency A than from agency b at year t-1, zero otherwise.

2N_H_A$_{it-1}$ is a dummy taking the value of 1 if an issuer *i* has more than one notch higher rating from given agency A than from agency b at year t-1, zero otherwise.

1N_L_A$_{it-1}$ is a dummy taking the value of 1 if an issuer *i* has one notch lower by agency A than from agency b at year t-1, zero otherwise.

[42] In this chapter, it is preferred to report the estimated probit models rather than ordered probit models since in the majority of pairs, the distribution of changes in notches is less than 3% for more than 2 notches. However, in some pairs, estimations were done, obtaining consistent and significant results.

$2N\_L\_A_{it-1}$ is a dummy taking the value of 1 if an issuer *i* has more than one notch lower rating from given agency A than from agency b at year t-1, zero otherwise.

$RatingH\_A_{it-1}$ and **$RatingL\_A_{it-1}$** are dummy variables created to control for differences in credit quality as done by previous studies (e.g., Livingston and Zhou, 2016, Alsakka and ap Gwilym, 2010a; Livingston et al., 2008). **$RatingH\_A_{it-1}$** is equal to 1 when rating ranges from 'AAA' (1) to 'A-' (5) for superior categories, and zero otherwise, while **$RatingL\_A_{it-1}$** is equal to 1 when rating ranges from 'A-' (7) to 'C/D' (20), and zero for otherwise. A (6) is the base case since most insurers are rated in this category.

$\lambda \boldsymbol{Y07\_11}$ is a control variable that considers the financial crisis period defined by World Bank (2019) as the period from 2007 to 2011. In this model, there is no need to control for industry or country because this model only includes U.S. P/C insurers.

For any probit model, marginal effects can be an informative measure for summarizing how a change in response is related to change in a covariate. A collection of terms exists when calculating marginal effects depending on the characteristics of the variables i.e., continuous, categorical of the econometric model. Average Marginal Effects (AME), Marginal Effect at the Mean (MEM) and Marginal Effects at Representative Values (MER) are some of the main modes that can be computed (Coca Perraillon, 2019). In this setting, both dependent and independent variables are categorical, thus, the effects of discrete changes are calculated to show how predicted probabilities change as the binary independent variable (*X)* changes from 0 to 1 holding all other *Xs* equal (Williams, 2012).

Furthermore, the main purpose of obtaining marginal effects is to quantify the economic impact of the four split rating dummies, the financial crisis and the rating category dummy variables on the probabilities of annual rating upgrades and downgrades (following Alsakka and ap Gwilym, 2010a). In other words, they reflect the partial derivative of the predicted probability of the dependent variable that results when the independent dummy variable takes the value of one while the other variables are held at their mean.

6.5 Empirical results

6.5.1 Overview

Section 6.5.1 to Section 6.5.5 discuss the impact of split ratings (or rating disagreement) between CRA pairs on each other's rating actions. Section 6.5.2 discusses the results for S&P and Moody's; Section 6.5.3 discusses S&P and Fitch results, Section 6.5.4 analyses the results for Moody's and Fitch, while Section 6.5.5, examines the impact of split ratings between AM Best and the other larger three CRAs. Briefly, the main findings are as follows:

- Moody's is always affected by its split rating with the other CRAs.
- S&P is always influenced by its split rating with the other three CRAs when deciding an upgrade the next year. It has been strongly influenced by AM Best, Fitch, and partially influenced by Moody's when upgrading. For downgrade, results vary by CRA pair. Some inconclusive results are found. However, split ratings between S&P and AM Best have a significant effect on downgrade decisions made by S&P.
- AM Best is always affected by its split rating with other CRAs when deciding an upgrade the next year. For downgrade, AM Best is influenced by S&P and Moody's but not by prior split ratings with Fitch.
- Fitch is the CRA with less likelihood to emit upgrade rating actions following prior split rating with one of its peers. However, results indicate a slight influence when deciding a downgrade, especially from AM Best.

Summary of results can also be found from Figure A 6.1 to Figure A 6.4 in Appendix 6.II.

6.5.2 Moody's and S&P

Table 6.5 reports the estimation results of Eq. (6.1) for insurers jointly rated by Moody's and S&P. In Moody's upgrades regression, coefficients for the first two split rating dummy variables are significant at 1% level (0.54, 1.86), meaning that when S&P is higher than Moody's by one or more-than-one-notch in the previous year, Moody's is more likely to upgrade the next year. It is interesting to notice that none of the 148 upgrades reported in Table 6.3, occurred when S&P had one or more-than-one notches lower than Moody's. This hints that there is a very low or absent likelihood of a Moody's upgrade in the following period when S&P has had notches lower than Moody's. Further, as explained above, marginal effects express an absolute change in the probability of an outcome while holding all other variables constant. If margins are negative, it represents a decrease in probability and an increase if the opposite. In Table 6.5**,** issuers having one and more-than-one-notch higher S&P, ratings increase the probability of an annual upgrade by 5% and 16%, respectively. Regarding the control variables, highly rated insurers are less likely to have rating changes compared to ‘A’ rated insurers while insurers below ‘A-’ (7) behave similarly compared to ‘A’ (6) rated firms.

Table 6.5 also reveals that Moody’s is less likely to downgrade the next year (-0.76) when S&P is higher than Moody’s by one or more-than-one-notch in the preceding year. Indeed, issuers having one and more-than-one-notch higher (lower) S&P, have decreased (increased) the probability of an annual downgraded by 4% (1% and 9%, respectively). Meanwhile, highly rated insurers are more likely to have downgrades compared to ‘A’ rated insurers, whereas insurers rated below ‘A-’ (7) behave similarly. Finally, for both, Moody’s upgrades and downgrades equation, year control is positive and significant indicating that during 2007-11 a Moody’s upgrade or downgrade was more likely, compared to the rest of the years within the whole period. This outcome could be explained by the fact that financial crisis had relatively null effects for some parts of the insurance market, and for others, they have been severe (Baluch et al., 2011; Jadi, 2015).

On the other hand, results on the impact of split ratings between Moody’s and S&P on S&P’s rating actions are also reported in Table 6.5. The equation for S&P upgrades partially suggests that, split rated insurers are more likely to be upgraded by S&P the following year than non-split insurers. Issuers with one notch or more-than-one notch higher by Moody’s (in table, more-than-one-notch-lower-S&P) have increased S&P annual upgrade probability by 11% and 12%, respectively. However, results when Moody’s has had one-notch or more-than-one-notch lower are positive, as not expected, but statistically insignificant. Relative to the control variables, coefficients indicate that insurers assessed between ‘AAA’ and ‘A+’ are less likely to have rating changes, and insurers previously placed below ‘A-’ do not have more or less likelihood of an upgrade compared to ‘A’ insurers.

Regarding S&P downgrades, Table 6.5 shows that results are not conclusive about Moody’s influence over S&P decisions. Despite S&P is less likely to downgrade when Moody's had two or more notches higher in the previous year (-0.34), coefficient of one-notch and more-than-one-notch lower is negative and not significant indicating that when Moody’s had two or more notches lower in the previous year, S&P is not likely to downgrade and 0% increased probability. Moreover, year control dummy in S&P upgrades (downgrades) equation reveals that during the financial crisis upgrades (downgrades) were less (more) likely to happen than in the rest of the period which, compared with Moody’s results have the expected sign.

Table 6.5 Rating migration and (Dis) agreements between Moody's and S&P

VARIABLES	Coef.	z-value	ME	Coef.	z-value	ME
	Moody's upgrades		1	Moody's down.		1
1N-H-S&P	0.54***	5.32	0.05***	-0.76***	-6.38	-0.04***
2N-H-S&P	1.86***	7.90	0.16***	Merged with 1N-H-S&P		
N-L-S&P¥	NA	NA	NA	0.22**	2.34	0.01**
2N-L-S&P¥	NA	NA	NA	1.71***	6.54	0.09***
AAA-A+	-0.44***	-4.84	-0.04***	1.16***	5.90	0.06***
A- C	-0.10	-1.09	-0.01	0.28	1.17	0.01
Y07-11	0.37***	4.59	0.03***	0.53***	6.15	0.03***
Constant	-1.81***	-19.44		-2.80***	-13.62	
Observations	2,754			2,726		
Pseudo R^2	12.79%			16.05%		
VARIABLES	Coef.	z-value	ME	Coef.	z-value	ME
	S&P upgrades		1	S&P down.		1
1N-H-S&P	0.04	0.33	0.00	-0.13	-1.36	-0.01
2N-H-S&P	Merged with 1N-H-S&P			-0.49	-1.44	-0.05
1N-L-S&P	0.96***	9.60	0.11***	-0.34**	-2.45	-0.03**
2N-L-S&P	1.01***	3.18	0.12***	Merged with 1N-L-S&P		
AAA-A+	-0.40***	-4.47	-0.05***	0.40***	4.20	0.04***
A- C	0.01	0.08	0.00	-0.50***	-2.62	-0.05***
Y07-11	-0.20***	-2.91	-0.02***	0.79***	9.55	0.07***
Constant	-1.47***	-19.23		-2.073***	-20.34	
Observations	2,708			2,669		
Pseudo R^2	12.02%			10.30%		

This table reports the main regression results using Eq. (6.1). The dependent variable is y is a dummy variable equal to either UP or DOWN, UP(DOWN) = 1 if an issuer was upgraded by agency A by one or more than one notch, respectively in year t, 0 otherwise. Rating upgrades/downgrades are identified by notches (one and more than one notch) using a 20-point rating scale and on the basis of 1-year intervals during the period of December 2003-December 2017. In S&P upgrades and downgrades equations, coefficient 1N-L-S&P (1N-H-S&P) is equivalent to one notch higher (lower) of Moody's in the previous year. The same logic applies to 2N-L-S&P (2N-H-S&P). ¥ Due to the small numbers of one or two notches lower from S&P in the sample of jointly rated by S&P and Moody's, the Moody's upgrade regression has a 'NA' in this estimation.
*The variables named as 'Merged' reflect the fact that in some cases there might be not enough variation for some of the independent variables so the dummy does not have enough observations to be included in the estimation. Therefore, combining all notches enables us to include them in the regression. For example, 1N-H-S&P + 2N-H-S&P = Merged with 1N-H-S&P, and 1N-L-S&P + 2N-L-S&P = Merged with 1N-L-S&P. *** Significant at 1% level, ** Significant at 5% level, *Significant at 10% level.*

6.5.3 Fitch and S&P

Table 6.6 documents estimation results between S&P and Fitch. For this CRA pair, there is a relatively small number of insurers to be imbibed in the models. As shown in Table 6.3, 201 S&P upgrade changes took place; with none of them occurring when Fitch had one or more-than-one notch lower in the previous year. Similarly, from the 174 reported Fitch downgrades, none of them has happened when S&P has had one or more-than-one notch higher in the previous year. Looking into Fitch upgrades equation, the four split dummy coefficients indicate that S&P and Fitch split rated insurers have no significant influence on Fitch rating upgrade dynamics (coefficients have the expected sign but are not significant). In contrast, issuers with one-notch or more-than-one-notch lower S&P, have greater likelihood to be downgraded by Fitch. Certainly, issuers having one and more-than-one-notch lower, have increased the probability of an annual downgrade by 3% and 8%, respectively.

Table 6.6 also exhibits results for S&P rating actions. Overall, opposite to Fitch's outcome, split ratings between Fitch and S&P have a significant influence on rating change's decisions made by S&P. Marginal effects reveal that issuers having one and more-than-one-notch higher Fitch, have increased the probability of an annual S&P upgrade by 13% and 4%, correspondingly. Similarly, S&P downgrades are more likely to happen when Fitch had one or more-than-one notches lower in the earlier year. However, this is not consistent with the coefficient of one or more-than-one-notch higher Fitch (in table one and more-than-one-notch lower S&P) as it is positive and not significant.

Table 6.6 Rating migration and (Dis) agreements between Fitch and S&P

VARIABLES	Coef. Fitch upgrades	z-value	ME 1	Coef. Fitch downgrades	z-value	ME 1
1N-H-S&P	0.11	0.70	0.01	NA	NA	NA
2N-H-S&P	Merged with 1N-H-S&P			NA	NA	NA
1N-L-S&P	-0.27	-1.64	-0.02	0.36***	3.77	0.03***
2N-L-S&P	0.11	0.67	0.01	0.85***	4.88	0.08***
AAA-A+	0.30*	1.90	0.03*	0.56***	3.26	0.05***
A- C	0.52***	2.94	0.04***	-0.09	-0.53	-0.01
Y07-11	0.36***	4.56	0.03***	0.74***	11.14	0.07***
Constant	-2.12***	-12.77		-2.46***	-14.57	
Observations	2,589			2,646		
Pseudo R^2	3.53%			12.24%		
VARIABLES	Coef. S&P upgrades	z-value	ME 1	Coef. S&P downgrades	z-value	ME 1
1N-H-S&P	NA	NA	NA	0.93***	6.40	0.10***
2N-H-S&P	NA	NA	NA	Merged with 1N-H-S&P		
1N-L-S&P	1.50***	12.15	0.13***	0.10	0.64	0.01
2N-L-S&P	0.41***	3.16	0.04***	1.05***	6.52	0.11***
AAA-A+	-0.12	-0.98	-0.01	0.46***	4.75	0.05***
A- C	0.99***	7.20	0.09***	NA	NA	NA
Y07-11	-0.56***	-7.31	-0.05***	0.75***	9.90	0.08***
Constant	-1.93***	-15.76		-2.45***	-19.28	
Observations	2,570			2,562		
Pseudo R^2	22.09%			13.25%		

*This table reports the main regression results using Eq. (6.1). The dependent variable is y is a dummy variable equal to either UP or DOWN, UP(DOWN) = 1 if an issuer was upgraded by agency A by one or more than one notch, respectively in year t, 0 otherwise. Rating upgrades/downgrades are identified by notches (one and more-than-one notch) using a 20-point rating scale and on the basis of 1-year intervals during the period of December 2003-December 2017. The variables named as 'Merged' reflect the fact that in some cases there might be not enough variation for some of the independent variables so the dummy does not have enough observations to be included in the estimation. Therefore, combining all notches enables us to include them in the regression. For example, 1N-H-S&P + 2N-H-S&P = Merged with 1N-H-S&P, and 1N-L-S&P + 2N-L-S&P = Merged with 1N-L-S&P. *** Significant at 1% level, ** Significant at 5% level, *Significant at 10% level.*

A further two remarkable results emerge from this analysis. First, the coefficients of one and more-than-one notch higher Fitch suggest a higher probability of an annual S&P upgrade when

S&P has had a lower rating than Fitch in the prior year, but also, there is more probability of a Fitch downgrade if there is lower S&P rating (probability increased by 3% and 8%). This highlights important features that require further examination. As a start, some examples of split-rated insurers that experienced rating changes during the following year were extracted (See Table A 6.3 in Appendix 6.I). It can be observed that in most cases, there is some convergence whereby most of the time Fitch changes their ratings toward S&Ps rating, resulting in rating convergence, except with few cases where they had opposite rating actions. It is plausible that an economic shock such as catastrophe events or the financial crisis may influence CRA's actions, making upgrades less (more) likely to happen during (out-of) such period, while downgrades more likely to happen.

The second remarkable result focuses on the S&P downgrade equation. Coefficients of one and more-than-one notches lower (or one or two notches higher Fitch) have unexpected signs 0.10 and 1.05, respectively. A possible explanation for these findings may be the role of the reputation of CRAs. Fitch is reasonably considered to be of lower reputation than either Moody's or S&P (Lugo et al., 2015). Therefore, further investigation is needed in this area within the insurance ratings market.

On the other hand, the control variables also exhibit major outcomes. Primary, issuers rated above and below 'A' are more likely to have a Fitch upgrade. For downgrades, as expected, issuers placed in top categories are more likely to have a Fitch downgrade while insurers below 'A-' are not significantly less likely than 'A' ones. Second, S&P outcomes appear to be the opposite. The control variables indicate that insurers rated below 'A-' are more likely to have S&P upgrades (but not downgrades) than 'A' insurers and insurers in the top categories are significantly more likely to have an S&P downgrades. Finally, year control for both agencies confirms that during the crisis 2007-11, S&P upgrades were less likely to occur (but not from Fitch) while downgrade were more likely to happen from both CRAs, compared to the rest of the period.[43]

6.5.4 Moody's and Fitch

Table 6.7 provides the results for insurers jointly rated by Moody's and Fitch. Moody's upgrades equation reveals that disagreements with Fitch have a significant effect in Moody's likelihood to upgrade the next year (coefficients equal to 2.83, 3.56). Issuers having one and

[43] For S&P downgrades, there are not enough insurers placed below 'A-', therefore the variable is omitted from the estimation.

more-than-one-notch higher Fitch has increased the probability of a Moody's annual upgrade by slight positive 2%. The coefficients of one or more-than-one-notch lower Fitch were not possible to estimate since there are zero observations that had a subsequent Moody's upgrade (see Table 6.3). The control variables about credit quality indicate that insurers rated on the top categories are less likely to have rating changes, whereas insurers rated below 'A-' are more likely to have variations, both compared to 'A' category. Similarly, Moody's downgrade equation reveals that disagreements with Fitch have a significant effect in Moody's likelihood to downgrade the next year. The coefficient of one-notch and more-than-one notch lower Fitch (merged) is significant at 1% level (1.10), and coefficient of one-notch higher Fitch (-0.24) exposes that Moody's is significantly less likely to downgrade.

Table 6.7 also shows that the impact of split ratings between Moody's and Fitch has a significant but frail effect on Fitch rating decisions about upgrades. For instance, the coefficient linked to the case when Moody's had one or more-than-one notch lower in the previous year, a weak positive influence seems to be happening on Fitch probability to upgrade the next year (different than expected). Meanwhile, when Moody's had more-than-one-notch higher in the previous year, observations were not enough to estimate the effect. Results are also **not significant** in terms of different categories; insurers below 'A-' have not a significant impact in rating changes compared to 'A' rated insurers. However, issuers placed on the top categories are less likely to have rating changes as expected.

Contrariwise, results on the effect of split ratings seem to have a slight influence in terms of Fitch downgrades. Both coefficients of one-notch and more-than-one-notch lower Moody's (see coefficient 1N-H-Fitch and 2N-H-Fitch in Table 6.7) are significant at the 5% and 1% level, suggesting that split rated insurers are more likely to have a downgrade than non-split rated ones with a probability at 6%- 4%. Yet, when there is one or more-than-one notch higher from Moody's in the previous year, Fitch downgrades are not necessarily more likely to happen.

Finally, across all equations, an unexpected outcome comes from the year control, which suggests that during the financial crisis both, Moody's and Fitch's activity, upgrades and downgrades were **more** likely to happen than in the rest of the period. This could be in line with Baluch et al., (2011) who affirms that the sectors least affected during the crisis were Asia-Pacific, U.K. insurers, and U.S. P/C insurance companies, while European insurance companies were the worst performers.

Table 6.7 Rating migration and (Dis) agreements between Moody's and Fitch

	Coef.	z-value	ME	Coef.	z-value	ME
VARIABLES	Moody's upgrades		1	Moody's downgrades		1
1N-H-Fitch	2.83***	9.76	0.02*	-0.24**	-2.02	-0.01*
2N-H-Fitch	3.56***	11.04	0.02*	0.27	1.22	0.02
1N-L-Fitch	NA	NA	NA	1.10***	6.36	0.06***
2N-L-Fitch	NA	NA	NA	Merged with 1N-L-Fitch		
AAA-A+	-0.76***	-5.11	0.00	0.24	1.51	0.01
A- C	0.78***	7.86	0.00	-1.95***	-5.72	-0.11***
Y07-11	0.49***	4.28	0.00 *	0.30***	3.79	0.02***
Constant	-3.81***	-11.34		-2.00***	-13.51	
Observations	1,820			1,821		
Pseudo R^2	32.03%			12.81%		
	Coef.	z-value	ME	Coef.	z-value	ME
VARIABLES	Fitch upgrades		1	Fitch downgrades		1
1N-H-Fitch	0.19*	1.70	0.02	0.86***	6.01	0.06***
2N-H-Fitch	Merged with 1N-H-Fitch			0.57**	2.36	0.04**
1N-L-Fitch	NA	NA	NA	0.20	1.42	0.01
2N-L-Fitch	NA	NA	NA	Merged with 1N-L-Fitch		
AAA-A+	-0.24**	-2.11	-0.03**	0.63***	3.99	0.05***
A- C	0.04	0.20	0.00	NA	NA	NA
Y07-11	0.41***	5.15	0.05***	0.80***	9.55	0.06***
Constant	-1.70***	-14.12		-2.83***	-24.63	
Observations	1785			1802		
Pseudo R^2	2.85%			17.57%		

*This table reports the main probit regression results using Eq. (6.1). The dependent variable is y is a dummy variable equal to either UP or DOWN, UP(DOWN) = 1 if an issuer was upgraded by agency A by one or more than one notch, respectively in year t, 0 otherwise. Rating upgrades/downgrades are identified by notches (one and more-than-one notch) using a 20-point rating scale and on the basis of 1-year intervals during the period of December 2003-December 2017. In equations for Fitch upgrades/downgrades, the coefficients 1N-H-Fitch and 2N-H-Fitch are equivalent to 1N-L-Moody's and 2N-L-Moody's, respectively. Likewise, 1N-L-Fitch is equivalent to 1N-H-Moody's. *** Significant at 1% level, ** Significant at 5% level, *Significant at 10% level.*

6.5.5 AM Best and the other three agencies: S&P, Moody's and Fitch

This subsection aims to disentangle the different interactions between AM Best and its peers considering it is the only CRA specialized in insurance ratings. Moreover, recall that AM Best uses a 13-points rating scale which does not map directly to the 20-point rating scale of the other three CRAs. To match them, Table 4.12 in Section 4.5 - Chapter 4 shows the proposed and used numerical mapping.

Table 6.8 and Table 6.9 report the effects of split ratings between AM Best and the other three larger CRAs regarding the probability of an upgrade and downgrade, respectively. For S&P and AM Best, results reveal S&P and AM Best split rated issuers have significant influence on both S&P and AM Best rating dynamics. In the upgrade equations (see Panel A-Table 6.8), all coefficients on the four split rating dummy variables are significant with the expected sign, suggesting that one or more-than-one notch higher (lower) AM Best is more (less) likely to be upgraded by S&P in the following year compared to non-split insurers. Issuers having one-notch higher (lower) AM Best ratings increase (decrease) the probabilities of one-notch and more-than-one-notch annual rating upgrades by S&P by 1% (5%) and 2% (1%). Similarly, issuers with one-notch lower (higher) AM best have decreased (increased) the probability of more-than-one notch annual upgrade by 7% (3%) by S&P (AM Best).

Meanwhile, in the downgrade equations (see Table 6.9), the coefficient for one-notch lower AM Best dummy variable is positive and significant for S&P rating downgrade, indicating that split rated issuers are more likely to be downgraded by S&P than non-split insurers within a one-year interval. However, only when S&P is more-than-one notch lower in the previous year, AM Best is more likely to downgrade (coefficient one-notch is not significant). The rest of the coefficients such as one or more-than-one notch higher S&P (or one or more-than-one notch lower AM Best) exhibit different sign as expected.

For Moody's and AM Best, split ratings between them have significant effect on rating change decisions made by both CRAs, but the influence is stronger for Moody's rather than the other way around. In the upgrade Moody's equation (see Table 6.8), the coefficients on the one and more-than-one notch higher (lower) AM Best dummy variables are positive (negative) and significant for the Moody's rating change, implying that split rated insurers with higher (lower) AM Best's rating are more (less) likely to be upgraded by Moody's than non-split rated issuers. In contrast, results in AM Best's upgrade equation indicate that split ratings between Moody's and AM Best have a weak effect on rating change decisions made by AM Best. Only when Moody's had one-notch higher, AM Best is more likely to perform a rating upgrade. Also, issuers with one-notch higher Moody's ratings increase the probability of an AM Best annual upgrade by 4% and decrease by 2% when there is more-than-one notch lower Moody's.

With respect to downgrading changes, the same pattern is captured. In Moody's downgrade equation, all four split dummy coefficients are significant with the expected sign while for AM Best downgrade rating equation, only when Moody's has had more-than-one notch lower, AM Best decisions are more likely to react to rating disagreements with its CRA rival. The results between these two CRAs may be an indication of reputational factors, but again these aspects require further investigation. [44]

[44] In Table 6.8, refer to the coefficient: one and more-than-one notch lower AM Best.

Table 6.8 Rating migration and split ratings between AM Best and the other CRAs: upgrades

	Coef.	z-value	ME 1	Coef.	z-value	ME 1
VARIABLES	S&P upgrades			AM Best upgrades		
Panel A – S&P vs AM						
1N-H-AM Best	0.11**	2.37	0.01**	-0.95***	-5.38	-0.05***
2N-H-AM Best	0.18***	2.61	0.02***	-0.23**	-2.57	-0.01**
1N-L-AM Best	-0.60***	-7.06	-0.07***	0.40***	5.37	0.02***
2N-L-AM Best	-0.61***	-3.77	-0.07***	0.55***	5.29	0.03***
AAA-A+	-0.21***	-4.24	-0.02***	-0.29***	-4.83	-0.02***
A- C	-0.33***	-3.49	-0.04***	0.70***	8.92	0.04***
Y07-11	0.07	1.47	0.01	-0.23***	-4.13	-0.01***
Constant	-1.39***	-35.08		-1.76***	-29.71	
Observations	7454			7,809		
Pseudo R^2	3.89%			12.79%		
	Moody's upgrades			AM Best upgrades		
Panel B – Moody's vs AM						
1N-H-AM Best	0.31***	3.61	0.03***	-0.18	-1.58	-0.01
2N-H-AM Best	0.74***	6.01	0.07***	-0.40***	-3.44	-0.02***
1N-L-AM Best	-0.41***	-2.64	-0.04***	0.64***	4.73	0.04***
2N-L-AM Best	Merged with 1N-L-AM Best			-0.21	-0.46	-0.01
AAA-A+	-0.52***	-5.93	-0.05***	-0.36***	-3.77	-0.02***
A- C	0.06	0.47	0.01	1.03***	7.87	0.06***
Y07-11	0.33***	4.98	0.03***	-0.58***	-6.74	-0.04***
Constant	-1.71***	-22.64		-1.65***	-21.10	
Observations	3,069			3,114		
Pseudo R^2	7.58%			14.09%		
	Fitch's upgrades			AM Best upgrades		
Panel C – Fitch vs AM						
1N-H-AM Best	-0.77***	-6.26	-0.04***	NA	NA	NA
2N-H-AM Best	0.38	1.45	0.02	NA	NA	NA
1N-L-AM Best	-1.20***	-9.12	-0.07***	1.16***	9.25	0.04***
2N-L-AM Best	Merged with 1N-L-AM Best			0.66***	3.63	0.02***
AAA-A+	-0.10	-1.11	-0.01	-0.10	-0.98	0.00
A- C	0.49***	3.83	0.03***	1.17***	5.68	0.04***
Y07-11	0.50***	5.74	0.03***	-0.74***	-6.28	-0.03***
Constant	-1.36***	-23.61		-2.33***	-20.83	
Observations	3,135			3,277		
Pseudo R^2	15.90%			21.55%		

*This table reports the main probit regression results using Eq. (6.1). The dependent variable is y is a dummy variable equal to either UP or DOWN, UP(DOWN) = 1 if an issuer was upgraded by agency A by one or more than one notch, respectively in year t, 0 otherwise. Rating upgrades/downgrades are identified by notches (one and more-than-one notch) using a 20-point rating scale and on the basis of 1-year intervals during the period of December 2003-December 2017. *** Significant at 1% level, ** Significant at 5% level, *Significant at 10% level.*

Regarding Fitch and AM Best, split ratings between them have a slight significant impact on rating changes' decisions made by Fitch. For instance, in the upgrade Fitch's equation (see Table 6.8), from the four split rating dummy variables, only one coefficient is significant with the expected sign. Only when AM Best is one or more-than-one notch lower in the previous year, Fitch is less likely to do an upgrade in the next year, but not necessarily is more likely to do it when AM Best have had one or more-than-one notch higher. Regarding AM Best's upgrade equation, there are not enough observations to determine the likelihood when Fitch is one or more-than-one notch lower in the previous year. However, it can be observed that one or more-than-one notch higher Fitch increase the annual probability of an AM Best upgrade by 4% and 2%, respectively.

Other interesting outcome emerges from the downgrade equations. It seems that when is about a downgrade decision; split ratings between Fitch and AM Best have a significant impact on rating changes' decisions made by Fitch but not the other way around. Fitch is influenced by AM Best downgrade rating actions but AM Best is not. In downgrade Fitch's equation, all four split dummy variables have the expected sign and are significant, suggesting that when AM Best have had one or more-than-one notch lower (higher), Fitch is more (less) likely to downgrade. In terms of economic significance, the impact of the split rating dummies on the probability of rating changes indicates that probability will increase (decrease) by 2% (2%) when AM Best have had one or more-than-one notch lower (higher) in the prior year. On the other hand, AM Best downgrade equation, none of the four split dummy coefficients is statistically significant. Again, the results between AM Best and Fitch can be explained by the mentioned reputational theories in section 6.2.2, but as stated above, these aspects require further investigation.

Examining the year control coefficients, results indicate that highly rated insurers (AAA to A+) are less likely to have rating changes than 'A' rated insurers, but there is no clear pattern in rating changes for the bottom categories. Further, the financial crisis dummy is negative and significant for AM Best upgrades equation across all pairs while it is positive and significant in the Moody's and Fitch regressions. This suggests that during 2007-2011, issuers were more likely to have rating changes up than the rest of the period. Nevertheless, for downgrade equations, the year control is positive and significant for S&P/Moody's/Fitch, whereas for AM Best results vary across pairs and are not significant. The unclear direction of rating changes could be linked with the fact that insurers that were significantly negatively affected tended to be sizable insurers that wrote a large volume of annuity business in the years prior to the crisis, rather than P/C insurers (e.g., American International Group-AIG) (Niehaus and Chiang, 2017).

Table 6.9 Rating migration and split ratings between AM Best and the other CRAs: downgrades

VARIABLES	Coef.	z-value	ME 1	Coef.	z-value	ME 1
	S&P down.			AM Best down.		
Panel A – S&P vs AM						
1N-H-AM Best	-0.47***	-6.62	-0.06***	-0.02	-0.19	0.00
2N-H-AM Best	0.05	0.57	0.01	0.62***	5.98	0.03***
1N-L-AM Best	0.42***	7.24	0.05***	0.12	1.15	0.01
2N-L-AM Best	0.69***	9.30	0.08***	0.67***	5.75	0.03***
AAA-A+	0.12**	2.36	0.01**	0.53***	6.22	0.02***
A- C	-0.19**	-2.31	-0.02**	0.19	1.57	0.01
Y07-11	0.43***	10.34	0.05***	0.16***	2.68	0.01***
Constant	-1.80***	-38.95		-2.58***	-30.69	
Observations	7,541			7,695		
Pseudo R^2	8.50%			9.04%		
	Moody's down.			AM Best down.		
Panel B – Moody's vs AM						
1N-H-AM Best	-0.49***	-4.56	-0.04***	-0.69***	-4.00	-0.03***
2N-H-AM Best	-0.59***	-3.43	-0.05***	0.27**	2.04	0.01*
1N-L-AM Best	0.28**	2.31	0.02**	-0.26*	-1.66	-0.01*
2N-L-AM Best	0.78	3.21	0.06***	Merged with 1N-L-AM Best		
AAA-A+	0.27***	3.06	0.02***	0.68***	5.40	0.03***
A- C	-0.08	-0.39	-0.01	0.13	0.50	0.01
Y07-11	0.29***	4.23	0.02***	0.11	1.17	0.00
Constant	-1.91***	-24.44		-2.24***	-18.11	
Observations	3,034			3,067		
Pseudo R^2	8.09%			10.97%		
	Fitch down.			AM Best down.		
Panel C – Fitch vs AM						
1N-H-AM Best	-0.18*	-1.72	-0.02*	0.20	1.27	0.01
2N-H-AM Best	Merged with 1N-H-AM Best			Merged with 1N-H-AM Best		
1N-L-AM Best	0.21*	1.78	0.02*	0.01	0.05	0.00
2N-L-AM Best	0.93***	9.05	0.08***	Merged with 1N-L-AM Best		
AAA-A+	0.20**	2.41	0.02**	0.88***	5.05	0.03***
A- C	0.11	0.53	0.01	NA	NA	NA
Y07-11	0.64***	9.67	0.06***	-0.03	-0.29	0.00
Constant	-2.17***	-25.51		-2.840***	-12.55	
Observations	3,202			3228		
Pseudo R^2	15.67%			6.96%		

This table reports the main probit regression results using Eq. (6.1). The dependent variable is y is a dummy variable equal to either UP or DOWN, UP(DOWN) = 1 if an issuer was upgraded by agency A by one or more than one notch, respectively in year t, 0 otherwise. Rating upgrades/downgrades are identified by notches (one and more-than-one notch) using a 20-point rating scale and on the basis of 1-year intervals during the period of December 2003-December 2017. 'Down' abbreviates downgrades. **** Significant at 1% level, ** Significant at 5% level, *Significant at 10% level.*

6.6 Supplementary empirical results

As discussed in Chapter 4, one of the challenges of this thesis is the lack of comparability across CRAs rating scales. The purpose of this section is to discuss a supplementary set of results using the 13-points numerical mapping used by AM Best. Specifically, two alternative results are performed as follows: (**i)** Re-estimate Eq. (6.1) using the 20-point rating scale for the independent variables, but when defining AM Best rating changes; the dependent variable 'AM Best upgrades' and 'AM Best downgrades' use directly the notch change on the 13-points AM Best rating scale, and not the 20-point numerical scale. (**ii)** Re-estimate Eq. (6.1) but the mapping across CRAs is all based on 13-points rating scale, where S&P/Moody's and Fitch are translated to AM Best's rating points.

A summary of the estimations is reported in Table A 6.4 in Appendix 6.I for upgrade equations of all pairs of CRAs while, Table A. 6.5 shows the coefficients for downgrades. The second column refers to the first supplementary test where estimation is done varying the rating scale of the dependent variable with 13-points and keeping the independent variables with a 20-points rating scale. The first and third column contains the estimation of rating changes using AM Best 13-points rating scale in both sides of the equation for the respective CRAs equation. Overall, supplementary outcomes are consistent with prior findings; split ratings among the larger four CRAs are influential on each other's future rating migrations. Results may be even stronger in some cases with the rating scale variations.

Panel A of Table A 6.4 shows the results for the first pair of CRAs, S&P and AM Best. In the third column, marginal effect analysis suggests that issuers with one and more-than-one notch lower S&P; ratings decrease the probability of an annual AM Best upgrade by 5% and 2% (compared to 5% and 1% in results section). Further, AM Best seems to be *only* more likely to upgrade when there is more-than-one notch higher S&P (significant at 10%), whereas in the results section both, one and more-than-one notch higher were significant at 1% level.

In addition, the alternative estimation for S&P upgrades is in line with the previous findings: S&P is more likely to upgrade when AM Best had one or more-than-one notch higher in the previous year. However, the magnitude of the marginal effects increases at 5% (compared to 1% and 2% in main results). Moreover, coefficients of one-notch, more-than-notch lower and the dummy of the financial crisis exhibit opposite sign compared to the section 6.5 results but this time with no statistically significance.

Panel B of Table A 6.4 shows results for Moody's and AM Best. The second column reveals that regardless of the choice of numerical rank-ordering, the binary dependent variable 'AM Best upgrades' has captured the same effect. In the third column, most coefficients also remain unaffected relative to the main results, except the coefficient of one or more-than-one notch higher Moody's which is negative and no longer significant (-0.25). This suggests that split ratings between Moody's and AM Best have a weaker significant effect on rating change upgrades made by AM Best. AM Best is still less likely to upgrade when one or more-than-one notch difference lower but it is no longer more likely to happen when S&P had one or more-than-one notch higher in the previous year. Similar to S&P, supplementary results for Moody's equations corroborates that split ratings between AM Best and Moody's have a significant effect on rating change decisions made by Moody's. Indeed, the magnitude of the coefficients of one and more-than-one notch higher is greater and significant compared to main results section (1.29 and 2.28 versus 0.31 and 0.74). The coefficients of one and more-than-one notch lower change sign but they are not showing statistical significance.

Panel C of Table A 6.4 shows Fitch and AM Best interaction. Compared to Section 6.5, the supplementary results exhibit few shifts. With the rating scale variation, AM Best is more likely to upgrade only when Fitch had one-notch higher (but not more-than-one), and issuers rated between 'AAA' and 'A+' seem to be significantly more likely to be upgraded by AM Best compared to 'A'. From Fitch's point of view, split ratings between Fitch and AM Best seem to have a significant effect on upgrade decisions made by Fitch. In contrast to the main results, the coefficients of one and more-than-one notch higher AM Best are positive and significant using the 13-point rating scale.

Table A 6.5 in Appendix 6.I document the supplementary results for all CRAs' pairs regarding downgrade actions. Panel A reveals that AM Best is only significantly more likely to downgrade when S&P had more-than-one notch lower (same to the section 6.5). Unexpectedly, AM Best seems to also be more likely to do it when S&P had one-notch higher (0.62 is positive and significant at 1% level). For S&P downgrade rating changes, coefficients remain with the same sign and significance, suggesting no change to prior findings.

Panel B of Table A 6.5 shows Moody's and AM Best downgrades. For AM Best downgrades, there are some differences relative to Section 6.5. First, the coefficient of one and more-than-one notch lower Moody's remains negative but now is not significant. Second, an impact of changing the scale to 13-points is that as most variables are dummies, there might be not enough variation for some of them. This is the case of the coefficients of one and more-than-one notches higher, which appear as NA in Table A 6.5 (Appendix 6.I). Blending these two facts, a definitive conclusion cannot be drawn about AM downgrades. On the other hand, for Moody's downgrades, coefficients of the four split dummy variables remain unchanged leading to the same conclusions as in the result section. Even, issuers with one or more-than-one notch lower probability of an annual Moody's downgrade has increased by 4% compared to 2% in the main results section.

Panel C of Table A 6.5 shows the results for Fitch and AM Best. For AM Best downgrade equation, results are even stronger paralleled to the main results section 6.5. In the first column, the coefficients of one and more-than-one notch lower Fitch are positive and significant indicating that AM Best is significantly more likely to upgrade. However, AM Best seems to be also more likely to downgrade when Fitch had one and more-than-one notch higher the year before, which is unexpected. Panel C also reveals an even stronger effect in Fitch downgrades' equation; coefficients of one and more-than-one notch lower AM Best are greater than in Section 6.5 (1.525 versus 0.21). Further, marginal effects suggest that issuers with one or more-than-one notch lower AM Best, probability of an annual Fitch downgrade increases by 7% (compared to 2% in the main results section).

To end, considering results in Section 6.5 and results in Table A.6.4 and Table A. 6.5, findings are in line with Alsakka and ap Gwilym (2010a), Livingston et al., (2008), and Martin-Merizalde (2020). Split ratings among CRAs are influential on each other's future rating migrations. From another perspective, results across CRAs may be an indication that reputation is playing a role in insurers' credit rating market. Mariano (2012) and Lugo et al., (2015) argue that CRAs have herding incentives to protect their reputational capital. CRAs may "hide in the herd" to reduce their likelihood of being penalized in case their decision proves to be inaccurate later (Scharfstein and Stein, 1990). Furthermore, Mariano (2012) states that once CRAs reveal their rating decisions, rivals might decide to incorporate this information in their assessments, especially in sectors such as insurance, which have been shown by Iannotta (2006) and Morgan (2002) to be opaque. Indeed, results in this chapter support that split rating influence between S&P and Moody's is stronger than with Fitch (a CRA considered to be of lower reputation) than either the other three CRAs, especially AM Best, the insurance industry expert. Nevertheless, aspects regarding CRAs' reputation and herding behaviour require further investigation.

6.7 Conclusions

The current chapter is the first study that investigates whether split ratings have led to detectable financial strength rating changes for U.S. Property/Casualty (P/C) insurers in approximately 13 years. The main research question addressed consists of 'Is there any relationship between split ratings and subsequent rating migration for U.S. P/C insurers' ratings'. To embark on the investigation, this chapter takes advantage of the presence of a particular setting –four main CRAs rather than three- and considers a sample of 904 U.S. P/C insurers rated by at least two of the four CRAs. By taking annual ratings on 31st of December during the period from 2003 to 2017, split ratings and rating changes are computed, using one-notch and more-than-one-notch with a 20-point numerical rating scale and a 13-points rating scale as supplementary results. Certainly, the lack of comparability across CRAs rating scales presents fundamental challenges in defining the adequate numerical mapping between them within the need to provide insights about the correspondence amongst the different agencies' categories for insurer' ratings. [45]

Consistent with the rating transitions presented in Chapter 5, the descriptive analysis in this chapter shows that most insurers remain with the same rating within a one-year interval and those that have changed are mostly with a one-notch variation. The disagreement across agencies represents more than half of all observations except for S&P and Moody's with 39.8% and, S&P and Fitch (36.2%) who have the lowest frequency of split ratings between CRAs. Regarding AM Best versus the other three CRAs, the disagreement ranges from 58.6% to 78.7%. For the analysis of the influence of split ratings on rating changes, a probit modelling approach is employed, where the dependent variable refers to both, one-notch and/or more-than-one-notch upgrade/downgrade. For the independent variables, the model has four dummy variables defining split ratings (one and more-than-one notch higher, and one and more-than-one notch lower).

Overall, results suggest that split ratings among the larger four CRAs (AM Best, Moody's, S&P, and Fitch) are influential on each other's future rating migrations. This is in line with prior work from Alsakka and ap Gwilym (2010a), Livingston et al., (2008) and Martin-Merizalde (2020), who motivate this research. Results indicate that the interaction between them has different particularities. Primary, the relationship among the four CRAs, AM Best,

[45] For rating changes, one-notch and more-than-one-notch is merged

S&P, Moody's and Fitch seems to point that Moody's is the agency that is influenced by all the other three CRA in both directions, upgrades, and downgrades. When S&P/Fitch/AM Best had one, two or more notches higher (lower) in the previous year, Moody's is more likely to upgrade (downgrade). Second, the magnitude of the split influences future S&P rating changes is stronger on upgrades than downgrades. Third, S&P and Moody's have a stronger relationship by including their assessments into their ratings, while for Fitch, Moody's/S&P ratings have no significant effect on Fitch's future rating changes, especially when deciding an upgrade.

Regarding the interaction between the three CRAs versus AM Best as the insurers' specialised CRA; S&P and Moody's equations results, imply that split rated insurers with higher (lower) AM Best ratings are more likely to be upgraded (downgraded) by S&P and Moody's in the following year than non-split rated issuers. However, for Fitch, AM Best actions have a significant effect on Fitch's future rating changes only when deciding a downgrade. Conversely, AM Best seems to be strongly influenced by all three (S&P/Moody's/Fitch) when deciding an upgrade, but for downgrades, the degree of influence is lower and only comes from S&P and Moody's. Moreover, the component about the financial crisis continues to indicate an uneven effect over the insurance industry; other factors seem to be influencing the rating changes of insurers.

Possible explanations for the interactions among CRAs in this chapter can be found in the literature on reputation and herding behaviour. However, these topics require further investigation. For instance, future research can be focus on herding incentives. CRAs herding incentives to protect their reputational capital and the phenomenon "hide in the herd" gives chance to reduce a CRA likelihood of being penalized in case their decision proves to be inaccurate later (Scharfstein and Stein, 1990). Mariano (2012) states, once CRAs reveal their rating decisions, rivals might decide to incorporate this information in their assessments, especially in sectors such as insurance, which has been shown by Iannotta (2006) and Morgan (2002) to be complex and opaque.

Results of this Chapter grab attention to the fact that Moody's, instead of Fitch, is the CRA that is influenced by all the other three CRAs in both directions, upgrades, and downgrades. Plausible explanations can be drawn by utilising comparisons with the sovereign and corporate credit rating literature. For instance, Brooks et al., (2004) find that of all CRAs in their analysis (i.e., S&P, Moody's, Fitch and Thomson), S&P tends to "lead" the other CRAs while Moody's tend to be a "follower". In their lead and lag analysis, Alsakka and ap Gwilym (2010b) conclude that among Moody's, S&P, Fitch, and Japanese agencies, JCR and R&I; the Japanese agencies are influenced by the rating dynamics of S&P and Fitch, but not vice versa. Meanwhile, Moody’s can lag rating downgrades by JCR/R&I, but to a lesser extent than the other way around. In the corporate segment, Livingston et al., (2010) report a tendency for Moody’s to be more conservative and more likely to assign a lower rating to corporate bond issues in the event of a split. They named this view as the Moody’s conservatism hypothesis. For banks, Morgan (2002) reveals that Moody’s consistently assign more conservative (inferior) ratings than S&P.

From a market competition perspective (see Section 3.4.1 in Chapter 3), Becker and Milbourn (2011) uncover evidence of rating inflation by both Moody’s and S&P in response to the market entry of a competitor agency, Fitch. In the case of insurers, Doherty et al., (2012) investigate the effect of the entry of S&P in the insurance rating market initially dominated by AM Best. They suggest that, for a given rating by an incumbent CRA, new rating companies often need to demonstrate higher standards. Hence, this may be linked to the fact that Fitch (not AM Best) seems to be the leading CRA. Likewise, the solicitation status of a small portion of the sample by Fitch may have an influence on the results of this chapter. In the sample, about 20% of insurers are unsolicited ratings and in general, approximately 17% of U.S. insurance groups with public FSR are rated by Fitch on an unsolicited basis (Fitch, 2016). Perhaps, this could be diminishing Fitch’s interdependence with its rivals and point to the need for further exploration in this regard.

Closer to this chapter, Alsakka and ap Gwilym (2010a) find that the split ratings between S&P/Fitch and the smaller CRAs tend not to influence the future actions of S&P/Fitch sovereign ratings. Conversely, Moody’s upgrade decisions are influenced by rating disagreements between Moody’s and both CI and R&I ratings. Hence, it is likely that Moody’s follow and lead rating changes made by the smaller CRAs, while smaller CRAs are affected by the rating adjustments of S&P and Fitch, but not vice versa. Adding to their main findings, Livingston et al., (2008) also observe interesting differences between Moody’s and S&P rating changes by industry. Industrial issues seem to have fewer rating changes by Moody’s than financial issues within one year of initial issuance.

To sum up, implications of the results of this chapter can affect decisions of market participants as they have more information on the correspondence between the different agencies’ categories for insurer’ ratings. It is evident that the lack of transparency has led to confusion and a false sense of comfort (Fitch, 2016). Additionally, the few papers on rating migration mostly use data from one rating agency (Moody's or S&P) to determine the probability of future rating migrations. Thus, this study increases the spectrum by incorporating the four CRAs and provides evidence suggesting that estimation of insurers' rating migrations can be improved by considering the effect of split ratings with rival agencies.

Appendix 6.I – Supporting tables

Table A 6.1 Annual insurers rating changes, subsample 2003 – 2006 & 2007 – 2011

Panel A. Sub-sample: December 2003 – December 2006

CRAs	**UP**	**DW**	**No change**	**Changes**	**1n-up**	**>1n-up**	**1n-dw**	**>1n-dw**
1. S&P and Moody's (total no of obs. 575)								
Moody's no.	14	12	549	26	12	2	4	8
S&P no	38	37	500	75	38	0	37	0
Moody's % of obs.	2.4%	2.1%	95.5%	4.5%	2.1%	0.3%	0.7%	1.4%
S&P % of obs.	6.6%	6.4%	87.0%	13.0%	6.6%	0.0%	6.4%	0.0%
2. S&P and Fitch (total no of obs. 418)								
Fitch no	14	38	366	52	14	0	38	0
S&P no	44	44	330	88	43	1	44	0
Fitch % of obs.	3.3%	9.1%	87.6%	12.4%	3.3%	0.0%	9.1%	0.0%
S&P % of obs.	10.5%	10.5%	78.9%	21.1%	10.3%	0.2%	10.5%	0.0%
3. Fitch and Moody's (total no of obs. 338)								
Fitch no.	12	31	293	43	11	1	31	0
Moody's no.	6	12	318	18	5	1	4	8
Fitch % of obs.	3.6%	9.2%	87.2%	12.8%	3.3%	0.3%	9.2%	0.0%
Moody's % of obs.	1.8%	3.6%	94.6%	5.4%	1.5%	0.3%	1.2%	2.4%
4. AM Best and S&P (total no of obs. 1994)								
AM Best no.	93	81	1820	174	15	78	11	70
S&P no.	86	134	1774	220	59	27	89	45
AM Best % of obs.	4.7%	4.1%	91.3%	8.7%	0.8%	3.9%	0.6%	3.5%
S&P % of obs.	4.3%	6.7%	89.0%	11.0%	3.0%	1.4%	4.5%	2.3%
5. AM Best and Moody's (total no of obs. 691)								
AM Best no.	33	43	615	76	3	30	12	31
Moody's no.	19	25	647	44	16	3	13	12
AM Best % of obs.	4.8%	6.2%	89.0%	11.0%	0.4%	4.3%	1.7%	4.5%
Moody's % of obs.	2.7%	3.6%	93.6%	6.4%	2.3%	0.4%	1.9%	1.7%
6. AM Best and Fitch (total no of obs. 514)								
AM Best no.	23	31	460	54	19	4	1	30
Fitch no.	17	40	457	57	14	3	40	0
AM Best % of obs.	4.5%	6.0%	89.5%	10.5%	3.7%	0.8%	0.2%	5.8%
Fitch % of obs.	3.3%	7.8%	88.9%	11.1%	2.7%	0.6%	7.8%	0.0%

Panel B. Sub-sample: December 2007 – Dec 2011

CRAs	UP	DW	No change	Changes	1n-up	>1n-up	1n-dw	>1n-dw
1. S&P and Moody's (total no of obs. 1052)								
Moody's no.	75	73	904	148	75	0	54	19
S&P no	63	114	875	177	63	0	78	36
Moody's % of obs.	7.1%	6.9%	85.9%	14.1%	7.1%	0.0%	5.1%	1.8%
S&P % of obs.	6.0%	10.8%	83.2%	16.8%	6.0%	0.0%	7.4%	3.4%
2. S&P and Fitch (total no of obs. 1050)								
Fitch no	63	127	860	190	63	0	93	34
S&P no	62	134	854	196	57	5	113	21
Fitch % of obs.	6.0%	12.1%	81.7%	18.1%	6.0%	0.0%	8.8%	3.2%
S&P % of obs.	5.9%	12.7%	81.2%	18.6%	5.4%	0.5%	10.7%	2.0%
3. Fitch and Moody's (total no of obs. 651)								
Fitch no.	49	77	525	126	49	0	54	23
Moody's no.	43	37	571	80	43	0	33	4
Fitch % of obs.	4.7%	7.3%	49.9%	12.0%	4.7%	0.0%	5.1%	2.2%
Moody's % of obs.	4.1%	3.5%	54.3%	7.6%	4.1%	0.0%	3.1%	0.4%
4. AM Best and S&P (total no of obs. 3237)								
AM Best no.	105	109	3023	214	54	51	22	87
S&P no.	198	338	2701	536	159	39	221	117
AM Best % of obs.	3.2%	3.4%	93.4%	6.6%	1.7%	1.6%	0.7%	2.7%
S&P % of obs.	6.1%	10.4%	83.4%	16.6%	4.9%	1.2%	6.8%	3.6%
5. AM Best and Moody's (total no of obs. 1131)								
AM Best no.	25	41	1065	66	24	1	2	39
Moody's no.	84	73	974	157	81	3	54	19
AM Best % of obs.	2.2%	3.6%	94.2%	5.8%	2.1%	0.1%	0.2%	3.4%
Moody's % of obs.	7.4%	6.5%	86.1%	13.9%	7.2%	0.3%	4.8%	1.7%
6. AM Best and Fitch (total no of obs. 1217)								
AM Best no.	19	22	1176	41	13	6	1	21
Fitch no.	72	146	999	218	71	1	102	44
AM Best % of obs.	1.6%	1.8%	96.6%	3.4%	1.1%	0.5%	0.1%	1.7%
Fitch % of obs.	5.9%	12.0%	82.1%	17.9%	5.8%	0.1%	8.4%	3.6%

This table presents the distribution of annual rating changes for CRA pairs (i.e., the insurer at 31st December of each year is compared with its rating at the 31st December of the previous year). This table is showing the distribution by sub-samples before (2003-2006), and during the financial crisis (2007-2011).

Table A 6.2 Annual insurers rating changes, subsample: 2012 – 2017

CRAs	**UP**	**DW**	**No change**	**Changes**	**1n-up**	**>1n-up**	**1n-dw**	**>1n-dw**
1. S&P and Moody's (total no of obs. 1247)								
Moody's no.	59	35	1153	94	59	0	35	0
S&P no	104	15	1128	119	104	0	15	0
Moody's % of obs.	4.7%	2.8%	92.5%	7.5%	4.7%	0.0%	2.8%	0.0%
S&P % of obs.	8.3%	1.2%	90.5%	9.5%	8.3%	0.0%	1.2%	0.0%
2. S&P and Fitch (total no of obs. 1295)								
Fitch no	40	9	1246	40	40	0	9	0
S&P no	95	15	1185	110	94	1	15	0
Fitch % of obs.	3.2%	0.7%	99.9%	3.2%	3.2%	0.0%	0.7%	0.0%
S&P % of obs.	7.6%	1.2%	95.0%	8.8%	7.5%	0.1%	1.2%	0.0%
3. Fitch and Moody's (total no of obs. 911)								
Fitch no.	36	5	870	41	32	4	5	0
Moody's no.	29	30	852	59	29	0	30	0
Fitch % of obs.	2.9%	0.4%	69.8%	3.3%	2.6%	0.3%	0.4%	0.0%
Moody's % of obs.	2.3%	2.4%	68.3%	4.7%	2.3%	0.0%	2.4%	0.0%
4. AM Best and S&P (total no of obs. 2786)								
AM Best no.	124	18	2644	142	12	112	5	13
S&P no.	192	91	2503	283	175	17	66	25
AM Best % of obs.	4.5%	0.6%	94.9%	5.1%	0.4%	4.0%	0.2%	0.5%
S&P % of obs.	6.9%	3.3%	89.8%	10.2%	6.3%	0.6%	2.4%	0.9%
5. AM Best and Moody's (total no of obs. 1383)								
AM Best no.	80	7	1296	87	5	75	0	7
Moody's no.	38	68	1277	106	66	2	38	0
AM Best % of obs.	5.8%	0.5%	93.7%	6.3%	0.4%	5.4%	0.0%	0.5%
Moody's % of obs.	2.7%	4.9%	92.3%	7.7%	4.8%	0.1%	2.7%	0.0%
6. AM Best and Fitch (total no of obs. 1608)								
AM Best no.	69	9	1530	78	4	65	2	7
Fitch no.	48	18	1542	66	45	3	18	0
AM Best % of obs.	4.3%	0.6%	95.1%	4.9%	0.2%	4.0%	0.1%	0.4%
Fitch % of obs.	3.0%	1.1%	95.9%	4.1%	2.8%	0.2%	1.1%	0.0%

This table presents the distribution of annual rating changes for CRA pairs (i.e., the insurer at 31st December of each year is compared with its rating at the 31st December of the previous year). This table is showing the distribution of the sub-sample during 2012-2017, period after the financial crisis.

Table A 6.3 Some examples of split rated insurers that experienced rating changes during the following year

Date	Insurer	S&P	Fitch	Rating action next year
2008	AIG Assurance Company	A+	AA-	Downgrade by Fitch to A+
2008	AIG Property Casualty Company	A+	AA-	Downgrade by Fitch to A+
2008	AIG Specialty Insurance Company	A+	AA-	Downgrade by Fitch to A+
2008	AIU Insurance Company	A+	AA-	Downgrade by Fitch to A+
2016	Allied World Assurance Company (U.S.), Inc.	A	A+	Downgrade by S&P to A-
2016	Allied World Assurance Company (U.S.), Inc.			Downgrade by Fitch to A
2016	Allied World Insurance Company	A	A+	Downgrade by S&P to A-
2016	Allied World Insurance Company			Downgrade by Fitch to A
2016	Allied World National Assurance Company	A	A+	Downgrade by S&P to A-
2016	Allied World National Assurance Company			Downgrade by Fitch to A
2007	Allstate County Mutual Insurance Company	AA	AA+	Downgrade by Fitch to AA
2007	Allstate Indemnity Company	AA	AA+	Downgrade by Fitch to AA
2007	Allstate Insurance Company	AA	AA+	Downgrade by Fitch to AA
2007	Allstate Property and Casualty Insurance Company	AA	AA+	Downgrade by Fitch to AA
2007	Allstate Texas Lloyd's	AA	AA+	Downgrade by Fitch to AA
2007	Allstate Vehicle and Property Insurance Company	AA	AA+	Downgrade by Fitch to AA
2008	American Casualty Company of Reading, Pennsylvania, Inc.	A-	A	Downgrade by Fitch to A-
2005	**American Fire & Casualty Company**	**BBB+**	**A-**	**Upgrade by S&P to A-** **Upgrade by Fitch to A**
2006	**American Fire & Casualty Company**	**A-**	**A**	**Upgrade by S&P to A** **Downgrade by Fitch to A-**
2008	American Home Assurance Company, Inc.	A+	AA-	Downgrade by Fitch to A+
2009	**California Automobile Insurance Company**	**A+**	**AA-**	**Downgrade by S&P to A** **Downgrade by Fitch to A+**
2008	Columbia Casualty Company	A-	A	Downgrade by Fitch to A-
2008	Commerce and Industry Insurance Company, Inc.	A+	AA-	Downgrade by Fitch to A+
2008	Continental Casualty Company, Inc.	A-	A	Downgrade by Fitch to A-
2008	Continental Insurance Company Of New Jersey	A-	A	Downgrade by Fitch to A-
2008	Granite State Insurance Company	A+	AA-	Downgrade by Fitch to A+
2004	Greenwich Insurance Company	AA-	AA	Downgrade by S&P to A+
2004	Greenwich Insurance Company			Downgrade by Fitch to AA-
2007	Greenwich Insurance Company	A+	AA-	Downgrade by S&P to A
2007	Greenwich Insurance Company			Downgrade by Fitch to A

Table A 6.3 Continued

Date	Insurer	S&P	Fitch	Rating action next year
2004	Horace Mann Insurance Company	A	A+	Downgrade by Fitch to A
2004	Horace Mann Property & Casualty Insurance Company	A	A+	Downgrade by Fitch to A
2008	Illinois National Insurance Company	A+	AA-	Downgrade by Fitch to A+
2004	Indian Harbor Insurance Company	AA-	AA	Downgrade by Fitch to AA-
2007	Indian Harbor Insurance Company	A+	AA-	Downgrade by S&P to A Downgrade by Fitch to A
2008	Lexington Insurance Company	A+	AA-	Downgrade by Fitch to A+
2008	National Fire Insurance Company Of Hartford	A-	A	Downgrade by Fitch to A-
2008	National Union Fire Insurance Company of Pittsburgh, Pa.	A+	AA-	Downgrade by Fitch to A+
2008	Nationwide Mutual Insurance Company	A+	AA-	Downgrade by Fitch to A
2008	New Hampshire Insurance Company	A+	AA-	Downgrade by Fitch to A+
2005	**Ohio Security Insurance Company Inc.**	**BBB+**	**A-**	**Upgrade by S&P to A-** **Downgrade by Fitch to A**
2006	**Ohio Security Insurance Company Inc.**	**A-**	**A**	**Upgrade by S&P to A** **Downgrade by Fitch to A-**
2004	Teachers Insurance Company	A	A+	Downgrade by Fitch to A
2008	The Cincinnati Casualty Company	A+	AA-	Downgrade by Fitch to A+
2008	The Cincinnati Indemnity Company	A+	AA-	Downgrade by Fitch to A+
2008	The Cincinnati Insurance Company, Inc.	A+	AA-	Downgrade by Fitch to A+
2008	The Continental Insurance Company	A-	A	Downgrade by Fitch to A-
2008	The Insurance Company of the State of Pennsylvania	A+	AA-	Downgrade by Fitch to A+
2006	**The Ohio Casualty Insurance Company**	**A-**	**A**	**Upgrade by S&P to A** **Downgrade by Fitch to A-**
2008	Transportation Insurance Company Inc.	A-	A	Downgrade by Fitch to A-
2008	Valley Forge Insurance Company	A-	A	Downgrade by Fitch to A-
2006	**West American Insurance Co.**	**A-**	**A**	**Upgrade by S&P to A** **Downgrade by Fitch to A-**
2004	XL Insurance America, Inc.	AA-	AA	Downgrade by Fitch to AA-
2004	XL Insurance Company of New York, Inc.	AA-	AA	Downgrade by Fitch to AA-
2004	XL Select Insurance Company	AA-	AA	Downgrade by Fitch to AA-
2004	XL Specialty Insurance Company	AA-	AA	Downgrade by Fitch to AA-

This table exhibits some examples of split rated insurers between S&P and Fitch that experienced rating changes during the following year. Period of analysis 2003-2017. Except for the cases in bold, there is rating convergence in the following year.

Table A 6.4 Supplementary results between AM Best and the other CRAs: upgrades

	Coef.	z-value	ME 1	Coef.	z-value	ME 1	Coef.	z-value	ME 1
VARIABLES	**S&P upgrades***			**AM Best upgrades (1)**			**AM Best upgrades (2)**		
Panel A– S&P vs AM									
1N-H-AM Best	1.01***	15.33	**0.05*** **	-0.95***	-5.38	-0.05***	-0.82***	-9.20	**-0.05*** **
2N-H-AM Best	1.02***	9.36	**0.05*** **	-0.24***	-2.58	-0.01**	-0.32***	-3.19	**-0.02*** **
1N-L-AM Best	-0.28	-0.80	-0.01	0.40***	5.37	0.02***	**0.20**	1.61	0.01
2N-L-AM Best	0.47	1.07	0.03	0.56***	5.33	0.03***	**0.45***	1.79	**0.03***
AAA-A+	-0.38***	-6.58	-0.02***	-0.29***	-4.83	-0.02***	-0.26***	-4.35	-0.02***
A- C	-0.32***	-3.10	-0.02***	0.71***	8.94	0.04***	0.75***	8.08	0.04***
Y07-11	**-0.08**	-1.26	-0.00	-0.23***	-4.15	-0.01***	-0.31***	-5.39	-0.02***
Constant	-2.19***	-35.66		-1.76***	**-29.71**		-1.51***	-30.41	
Observations	6,861			7,808			7,021		
Pseudo R^2	11.17%			12.82%			12.03%		
	Moody's upgrades*			**AM Best upgrades (1)**			**AM Best upgrades (2)**		
Panel B – Moodys vs AM									
1N-H-AM Best	1.29***	9.43	0.03***	-0.18	-1.58	-0.01	**-0.45*** **	-3.96	-0.03***
2N-H-AM Best	2.28***	7.37	0.06***	-0.40***	-3.44	-0.02***	-0.56***	-2.61	-0.04**
1N-L-AM Best	0.60	1.52	0.02	0.64***	4.73	0.04***	**-0.25**	-0.64	-0.02
2N-L-AM Best	Merged with 1N-L-AM Best			-0.21	-0.46	-0.01	Merged with 1N-L-AM Best		
AAA-A+	-1.05***	-8.43	-0.03***	-0.36***	-3.77	-0.02***	**-0.10**	-1.16	-0.01
A- C	0.25	1.42	0.01	1.03***	7.87	0.06***	0.99***	7.00	0.07***
Y07-11	0.23**	2.05	0.01	-0.58***	-6.74	-0.04***	-0.67***	-7.37	-0.05***
Constant	-2.51***	-18.42	0.01**	-1.65***	-21.10		-1.47***	-20.11	
Observations	2,845			3,114			2,852		
Pseudo R^2	28.80%			14.08			11.31%		

Table A 6.4 Continued

	Coef.	z-value	ME 1	Coef.	z-value	ME 1	Coef.	z-value	ME 1
	Fitch's upgrades*			**AM Best upgrades (1)**			**AM Best upgrades (2)**		
Panel C – Fitch vs AM									
1N-H-AM Best	0.97***	4.33	**0.01*** **	NA	NA	NA	NA	NA	NA
2N-H-AM Best	Merged with 1N-H-AM Best			NA	NA	NA	NA	NA	NA
1N-L-AM Best	NA	NA	NA	1.16***	9.25	0.04***	0.34***	2.75	0.02**
2N-L-AM Best	NA	NA	NA	0.66***	3.63	0.02***	**-0.19**	-0.38	-0.01
AAA-A+	-0.47***	-2.93	-0.01**	-0.10	-0.98	0.00	**0.20*** *	2.25	0.01**
A- C	1.63***	6.97	0.02***	1.17***	5.68	0.04***	1.23***	6.71	0.07***
Y07-11	0.23**	2.22	0.00*	-0.74***	-6.28	-0.03***	-0.66***	-6.65	-0.04***
Constant	-2.85***	-11.83		-2.33***	-20.83		-1.94***	-21.95	
Observations	3,219			3,277			3,277		
Pseudo R^2	20.58%			21.55%			10.09%		

This table reports the supplementary estimation results of the probit regression in Eq. (6.1). The dependent variable is y is a dummy variable equal to UP, UP = 1 if an issuer was upgraded by agency A by one or more than one notch, respectively in year t, 0 otherwise. Rating upgrades/downgrades are identified by notches (one and more-than-one notch) using a numerical transformation of the rating scale and based on 1-year intervals during the period of December 2003-December 2017. ***S&P/Moody's/Fitch upgrades**** *uses a 13-point rating scale for all the econometric expression.* ***AM Best upgrades (1)*** *uses a 13-point rating scale for the dependent variable and a 20-point rating scale for the independent variables.* ***AM Best upgrades (2)*** *uses a 13-point rating scale for all the econometric expression. *** Significant at 1% level, ** Significant at 5% level, *Significant at 10% level.*

Table A 6.5 Supplementary results between AM Best and the other CRAs: downgrades

VARIABLES	**Coef.**	**z-value**	**ME 1**	**Coef.**	**z-value**	**ME 1**	**Coef.**	**z-value**	**ME 1**
	S&P downgrades*			**AM Best downgrades (1)**			**AM Best downgrades (2)**		
Panel A – S&P vs AM									
1N-H-AM Best	-0.39***	-5.31	-0.03	-0.02	-0.08	0.00	**0.09**	1.04	0.00
2N-H-AM Best	-0.04	-0.32	0.00	0.61***	5.94	0.02***	**0.62*** **	5.04	0.02***
1N-L-AM Best	0.76***	10.92	0.06	0.12	1.24	0.02***	**0.62*** **	7.39	0.02***
2N-L-AM Best	0.82***	2.60	0.06	0.69***	5.79	0.02	0.41	0.85	0.02
AAA-A+	0.17***	2.62	0.01	0.53***	6.18	0.03***	0.67***	6.83	0.03***
A- C	-0.12	-1.19	-0.01	0.20*	2.17	0.01*	0.28*	1.93	0.01*
Y07-11	0.61***	-33.70	0.04	0.15**	2.11	0.01***	0.30***	4.60	0.01***
Constant	-2.09***			-2.58***			-2.74***	-34.47	
Observations	6,930			7,695			6,889		
Pseudo R^2	12.18%			9.06%			9.26%		
	Moody's downgrades*			**AM Best downgrades (1)**			**AM Best downgrades (2)**		
Panel B – Moody's vs AM									
1N-H-AM Best	-0.70***	-4.41	-0.02***	-0.69***	-4.00	-0.03***	-0.15	-1.07	0.00
2N-H-AM Best	Merged with 1N-H-AM Best			0.27**	2.04	0.01*	Merged with 1N-H-AM Best		
1N-L-AM Best	1.14***	**4.63**	**0.04*** **	-0.26*	-1.66	-0.01*	NA	NA	NA
2N-L-AM Best	Merged with 1N-L-AM Best			Merged with 1N-L-AM Best			NA	NA	NA
AAA-A+	0.67***	4.70	0.02***	0.68***	5.40	0.03***	1.28***	5.30	0.03***
A- C	0.02	0.05	0.00	0.13	0.50	0.01	0.81***	3.03	0.02***
Y07-1	0.49***	4.51	0.02***	0.11	1.17	0.00	0.49***	4.63	0.01***
Constant	-2.50***	-16.34		-2.24***	-18.11		-3.19***	-14.69	
Observations	2,811			3,067			2,786		
Pseudo R^2	14.76%			10.97%			13.88%		

Table A 6.5 Continued

VARIABLES	Coef.	z-value	ME 1	Coef.	z-value	ME 1	Coef.	z-value	ME 1
	Fitch's downgrades*			**AM Best downgrades (1)**			**AM Best downgrades (2)**		
Panel C – Fitch vs AM									
1N-H-AM Best	NA	NA	NA	0.20	1.27	0.01	**0.34*** **	2.65	0.01***
2N-H-AM Best	NA	NA	NA	Merged with 1N-H-AM Best			Merged with 1N-H-AM Best		
1N-L-AM Best	**1.525*** **	19.75	**0.07*** **	0.01	0.05	0.00	**0.54*** **	4.39	0.02***
2N-L-AM Best	Merged with 1N-L-AM Best			Merged with 1N-L-AM Best			Merged with 1N-L-AM Best		
AAA-A+	0.167**	2.02	0.01**	0.88***	5.05	0.03***	0.91***	4.98	0.03***
A- C	-0.459**	-2.31	-0.02**	NA	-0.29	NA	NA	-0.86	NA
Y07-11	NA	-30.72	NA	-0.03	-12.55	0.00	-0.08	-14.65	0.00
Constant	-2.349***			-2.84***			-2.98***		
Observations	3,286			3,228			3,228		
Pseudo R^2	23.81%			6.96%			8.67%		

This table reports the supplementary estimation results of the probit regression in Eq. (6.1). The dependent variable is y is a dummy variable equal to DOWN, DOWN = 1 if an issuer was upgraded by agency A by one or more than one notch, respectively in year t, 0 otherwise. Rating upgrades/downgrades are identified by notches (one and more-than-one notch) using a numerical transformation of the rating scale and based on 1-year intervals during the period of December 2003-December 2017. ***S&P/Moody's/Fitch downgrades**** *uses a 13-point rating scale for all the econometric expression.* ***AM Best downgrades (1)*** *uses a 13-point rating scale for the dependent variable and a 20-point rating scale for the independent variables.* ***AM Best downgrades (2)*** *uses a 13-point rating scale for all the econometric expression. *** Significant at 1% level, ** Significant at 5% level, *Significant at 10% level.*

Appendix 6.II – Supporting figures

Figure A 6.1 Summary of results between Moody's and the other CRAs

Split in t-1 / Moody's in t	S&P Global	FitchRatings	AM Best
UPS	When **S&P** had one, two or more notches higher in the previous year, Moody's **is more likely** to upgrade	When Fitch had two or more notches higher in the previous year, **Moody's** is **more likely** to upgrade	When AM Best had one or more notches higher in the previous year **Moody's** is **more likely** to upgrade. When AM Best had one, two or more notches lower in the previous year, **Moody's less likely** to upgrade
DOWNS	When S&P had two or more notches higher in the previous year, **Moody's is less likely** to downgrade When S&P had two or more notches lower in the previous year, **Moody's is more likely** to downgrade.	When Fitch had two or more notches higher in the previous year, **Moody's is less likely** to downgrade When Fitch had two or more notches lower in the previous year, **Moody's is more likely** to downgrade	When AM Best had two or more notches higher in the previous year, **Moody's is less likely** to downgrade When AM Best had two or more notches lower in the previous year, **Moody's is more likely** to downgrade

This figure provides an overview of the estimation results of Moody's rating actions in time t when there was split rating (rating disagreement) in the prior year.

Figure A 6.2 Summary of results between S&P's and the other CRAs

Split in t-1 / S&P in t	Moody's	FitchRatings	AM Best
UPS	When Moody's had one or more notches higher (lower) in the previous year * **S&P** is **more (less)** likely to upgrade	When Fitch had two or more notches higher in the previous year **S&P** is **more likely** to upgrade. 1N-L-Fitch does not apply (not enough observations **)	When AM Best had one or more notches higher (lower) in the previous year **S&P** is **more (less)** likely to upgrade
DOWNS	When Moody's had two or more notches lower in the previous year, **S&P** is **not more** likely to downgrade. When Moody's had one or two notches higher in the previous year, **S&P** is **less** likely to downgrade	When Fitch had two or more notches lower in the previous year, **S&P** is **more likely** to downgrade. If Fitch had two or more notches higher in the previous year, **S&P** is **more likely** to downgrade but it is not significant	When AM Best had one or more notches lower in the previous year **S&P** is **more likely** to downgrade Consistently, 2N-H-AB is negative and significant meaning **S&P is less likely** to downgrade. However, 1N-H-AB is positive not significant

This figure provides an overview of the estimation results of S&P's rating actions in time t when there was split rating (rating disagreement) in the prior year. UPS refers to upgrades, DOWNS, refers to downgrades.

Figure A 6.3 Summary of results between Fitch and the other CRAs

Split in t-1 / Fitch in t	S&P Global	Moody's	BEST
UPS FitchRatings	When **S&P** had one, two or more notches higher in the previous year, **Fitch** is **not** necessarily more likely to upgrade	When Moody's had more-than-one-notch higher in the previous year, observations were not enough to estimate the effect When Moody's had two or more notches lower in the previous year, **Fitch** is **not less** likely to upgrade	When AM Best had one notch higher in the previous year, **Fitch is not more likely** to upgrade When AM Best had one, two or more notches lower in the previous year, **Fitch** is **less likely** to upgrade
DOWNS FitchRatings	When S&P had two or more notches lower in the previous year, **Fitch** is **more likely** to downgrade. Coefficient 1N-H-S&P and 2N-H-S&P does not apply	When Moody's had one or two notches lower in the previous year, **Fitch** is **more** likely to downgrade Coefficient 1N-L-Fitch is expected to be negative. The result is positive but not significant	When AM Best had one or two notches lower in the previous year, **Fitch** is **more** likely to downgrade

This figure provides an overview of the estimation results of Fitch's rating actions in time t when there was split rating (rating disagreement) in the prior year. UPS refers to upgrades, DOWNS, refers to downgrades.

Figure A 6.4 Summary of results between AM Best and the other CRAs

Split in t-1 / AM Best in t	S&P Global	Moody's	FitchRatings
UPS BEST	When S&P had two or more notches higher in the previous year **AM Best** is **more likely** to upgrade	When Moody's **had two or more** (but not one) notches higher in the previous year **AM Best** is **more likely** to upgrade	When Fitch had one or more notches higher in the previous year **AM Best** is **more likely** to upgrade.
DOWNS BEST	When S&P had two or more (but not one) notches lower in the previous year **AM Best** is **more likely** to downgrade 1N-L-AB and 2N-L-AB are expected to be positive but the results are negative	When Moody's had two or more notches higher in the previous year **AM Best** is **less likely** to downgrade. However, when Moody's had two or more notches lower in the previous year, **AM Best** is **not more likely** to downgrade.	When Fitch had two or more notches lower in the previous year, **AM Best** is not significantly more likely to downgrade When Fitch had two or more notches higher in the previous year, **AM Best** is **not less likely** to downgrade

This figure provides an overview of the estimation results of AM Best's rating actions in time t when there was split rating (rating disagreement) in the prior year. UPS refers to upgrades, DOWNS, refers to downgrades.

Chapter 7. Do financial strength rating actions induce stock market reactions?

7.1 Introduction

Prior empirical studies have examined heavily the market impact of credit ratings actions of corporate bonds, banks, and sovereigns, and agreed upon the influential role of Credit Rating Agencies (CRAs) as key providers of information (Miao et al., 2014). In the case of insurers, however, research associated with the market impact of the CRA's opinion of the insurer's ability to meet its policyholder obligations has enticed limited attention. The motivation of the Chapter arises from this gap in the literature, added to the potential importance of Financial Strength Ratings (FSR), and the unique setting of the insurance industry. As stated in Chapter 6, insurance is one of the most opaque industries (Morgan, 2002), with levels of risk that vary widely across industry subsectors, informational uncertainty, and technicality of products that lead to face particularly acute information asymmetries (Adams et al., 2003, 2019). Likewise, the fact that insurers are the only sector assessed by four major CRAs: S&P, Moody's, Fitch, and AM Best creates a unique case study for this analysis. This potentially will allow establishing whether market impact differs across CRAs, especially when S&P has historically focused on rating individual debt issues, Moody's and Fitch are relatively minor players in insurance ratings market, while AM Best have always specialized in insurers' ratings. [46]

As in Chapter 5, rating transitions showed the variability across time and CRAs, and revealed that most insurers remained in the same rating level from one year to the other. In this Chapter, secondary rating actions from the four CRAs are included to help elucidate other features in the insurance setting. Likewise, as in Chapter 6 where opacity was studied through split ratings and its influential role on each other's future rating migrations, the opacity of the insurance sector will be studied in this Chapter via market impact.

The relevance of analysing this matter comes from two reasons. First, rating actions are recurrently pointed as lacking market movements and public information (e.g., Sy, 2004). Second, the Property/Casualty (P/C) subsector comprises a much wider range of insurance product-types than life insurance (Adams et al., 2019), and in the U.S., the P/C sector contributes to more than 4% of the GDP, becoming a source of capital to financial markets (Ben Ammar et al., 2018). Indeed, the sector is a key pillar of the modern U.S. financial system with a 30% share of all financial intermediation in terms of value-added (Becker et al., 2020;

[46] For example, brokers that will use credit ratings to allocate (particularly corporate) business to primary underwriters or when insurance users are determining how much they are willing to pay for insurance from a particular company (Berger et al., 1992). Likewise, corporate consumers may require an insurer to have a minimum rating before acquiring commercial coverage (Pottier and Sommer, 1999).

Greenwood and Scharfstein, 2013), and despite such facts, insurance sector event studies related specifically to credit ratings have received little attention in academic literature.[47]

This Chapter investigates whether FSR actions affect the U.S. stock market. Specifically, the study focuses on the relative influence of FSR actions by S&P, Moody's, Fitch and AM Best. In general, operating insurers tend to be private companies that receive a FSR and Issuer Credit Ratings (ICR) whereas the parent company, which is the publicly listed, receives an ICR. The sample period is January 2003 to December 2017, and the data includes daily FSR actions associated to U.S. P/C insurers (subsidiaries) including Outlook and Watch actions. There is a total of 527 qualifying FSR actions spanning 2003 to 2017. The research question can be expressed then as ''Do financial strength rating actions induce stock market reactions?'.

Prior studies have provided evidence that Outlook and Watch actions are at least as important as rating changes in their market impact (e.g., Hill and Faff, 2010; Sy, 2004), and renowned for carrying predictive power in the direction of future rating migrations by the same CRA (rating momentum; Alsakka and ap Gwilym, 2012a). This Chapter examines how the share prices of 30 parent companies react to FSR actions associated to 346 U.S. P/C insurers. Prior literature shows that all four CRAs play different and significant roles in the markets (e.g., Hill and Faff, 2010), yet most studies focus on only one CRA (e.g., Halek and Eckles, 2010). This Chapter examines the individual and the joint impact of the four CRAs, which can potentially highlight that market participants make use of FSR provided by all four CRAs.

The main findings are summarised as follows. The univariate analysis suggests that negative FSR actions provide a stronger impact on the parent companies' stock price compared to positive FSR actions. Overall, the strongest market reaction is to negative FSR actions by Fitch, where the largest negative Cumulative Abnormal Returns (CARs) are found. For S&P, the market reaction is to negative Outlook. For Moody's, results indicate that market reacts to negative Watch actions, and for AM Best, there is somewhat muted evidence that market reacts to negative FSR actions. For positive FSR actions, the stock market have a slight significant reaction to AM Best's FSR actions specifically upgrades, whilst there is weak evidence that the market reacts to these FSR actions by S&P, Moody's, and Fitch. The results are in favour of the information content hypothesis; CRAs play a relevant role in the market and information asymmetry seems to be present.

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[47] In the U.S. context, the composition of the P/C sector's invested assets reach $1,586 billion in 2016 (FIO, 2017) placing insurers as one of the major institutional investors.

The results from the multivariate analysis shows that the market impact of positive FSR actions is stronger for parent companies that have higher profitability and those more diversified. It suggests that after allowing the reaction on stock markets based on parent companies' characteristics, positive average CARs may be enlarged collectively by parent companies' characteristics especially by profitability and diversification whereas CARs arising from negative FSR actions, only individual variables appear to enlarge the effect of the negative sign. More specifically, in the regression for the entire set of negative FSR actions, leverage, and to some extent, the magnitude of the rating actions is detected to be significant.

In summary, this Chapter makes three contributions to the literature. First, it studies FSR that is important to several stakeholders but has received scarce academic attention. In this regard, the Chapter adds to both, the discussion about the information content of ratings, the literature strand on the role of FSR in addressing opacity in the insurance industry as well as referring to the parent-subsidiary relationship. Indeed, this Chapter builds on from Chapter 6 where the focus was on the relationship between split ratings and subsequent rating changes between the four CRAs. Implications of the results from Chapter 6 are relevant since FSR can affect decisions of market participants as they have more information of the correspondence between the different agencies' categories for FSR. Second, this study contains a unique set of FSR actions in which the major CRAs assess a set of U.S. P/C insurers, a sector that is a key pillar of the modern U.S. financial system and a major institutional investor. This distinctive setting allows examining the importance of FSR for shareholders, and other agents in the marketplace. Finally, findings support the idea that FSR actions provide pertinent information for policyholders, stockholders, and insights about the CRAs industry as well.

The Chapter is organised as follows: Section 7.2 presents relevant literature; Section 7.3 describes the sample selection from FSR actions and stock market. Section 7.4 explains the empirical methodology. Section 7.5 presents the empirical results of the univariate analysis and multivariate analysis, and Section 7.6 concludes the Chapter.

7.2 Literature review

This section progresses the main literature strands that serve as a foundation for this Chapter: 1) impact of rating actions on financial markets, 2) research surrounding FSR actions and 3) parent – subsidiary relationship, 4) Event study methodology.

7.2.1 Market impact of rating actions on financial markets

In addition to the EMH issues cited in Section 3.5 in Chapter 3, the financial crisis questioned the reliability of CRAs, reviving the discussion about their role in the financial markets. So far, the evidence supports that, despite the criticism, credit ratings are still relevant in economic activity (Cornaggia et al., 2017). This is consistent with the *information theory* which claims that CRAs reveal new information about firm's performance (Miao et al., 2014), and have an overall effect on the welfare of market participants (Bae et al., 2015).

Specific to the analysis of market impact to rating changes, two main theories have been derived: (1) Information asymmetry and signalling hypothesis (IASH) often called information content of ratings; and (2) Wealth redistribution hypothesis (Abad-Romero and Robles-Fernandez, 2006). Generally, IASH advocates that CRAs have access to considerable non-public information about a certain company and thus a rating action may impart additional information to the market about total firm value. Hence, a positive (negative) rating change is expected to increase (decrease) the stock market price. In the second group, the focus is on the conflict of interest between bondholders and stockholders. This theory predicts that only rating changes that are related to changes in financial outlook, without influencing cash flow variance, affects the stock market in the same direction (negative for downgrades and positive for upgrades).

Literature has continued to flourish, testing both hypothesis as well as spillover effects after certain rating events by means of an event study. In the sovereign rating literature, related work focus on the impact of sovereign credit rating news from individual CRAs on the price of financial assets (e.g., Gande and Parsley, 2005; Ferreira and Gama, 2007). Gande and Parsley (2005) study the effect of a sovereign rating change of one country on the sovereign credit spreads of other countries from 1991 to 2000, finding that a rating change in one country has a significant effect on sovereign credit spreads of others, therefore indicating that rating changes convey new information that is relevant across markets. They consider a set of 34 countries supporting the hypothesis that positive rating events abroad have no apparent impact on sovereign spreads, whereas negative rating events are related to an increase in spreads.

Ferreira and Gama (2007) extends this investigation by looking at the spillover of credit rating actions (rating changes and Outlook) of one country (the event country) to the stock market return spreads of all other countries (the non-event countries). Their findings corroborate that negative sovereign rating news does spill over, consistent with the hypothesis that rating changes in one country incorporate valuable information for the stock market returns of other countries. Hill and Faff (2010) examine the market impact of rating actions (rating changes, Watch, and Outlook), over countries and carry out a separate analysis of crisis periods. They confirm that a significant negative reaction to negative events is robust to the exclusion of crisis periods, albeit that during crisis periods the impact in the 12-day (−10, +1) window is more than three times as great. Their research uncover evidence that the event window response to downgrades in crisis periods is positively related to the pre-event window return. In addition, they concludes that S&P tend to be more active, provide more timely rating assessments and offer more new information than either Fitch or Moody's. Finally, they show evidence of specialisation among CRAs, and highlight the effect of split ratings on sovereign rating assessments.

Furthermore, Alsakka and ap Gwilym, (2012c) analyse the reaction of the foreign exchange spot market to sovereign credit signals by Fitch, Moody's, and S&P during 1994–2010. Aligned with prior studies, stronger reactions in the cases of negative news are reported when larger rating adjustments and outlook and watch events occur. Moreover, there are uneven responses to the three CRAs' signals. For instance, Fitch signals induce the timeliest reactions, particularly in developed countries, and S&P offers informative negative outlook signals, especially in emerging economies. Meanwhile, Moody's demonstrates an information lead for upgrades in developed economies and for downgrades in emerging economies, whereas the opposite is true for S&P.

In the banking literature, Williams et al., (2013) focus on the possible links between sovereign rating actions and bank share prices across Europe during the sovereign debt crisis. The investigation turns around the relative effects of sovereign credit rating actions by S&P, Moody's and Fitch on the share prices of European banks during the 2007-2011 financial crisis. Pancotto et al., (2020) explores how the implementation of the Banking Union (BU) in Europe impact on financial market. Pancotto et al., (2020) find that the BU announcements had a broadly consistent reaction in banks' stock prices as well as in the CDS market, leading to a surge in bank CDS spreads, while having a detrimental effect on stock prices. Moreover, the stock futures market does not evidence any systemic pattern of reactions.

King et al., (2020) analyse how disclosed information is valuable to bank shareholders by investigating the impact of Fitch's rating announcement of replacing the existing 9-point standalone ratings with 21-point Viability Ratings. This enabled the CRA to provide more granular detail on the relative ranking of banks that formerly were grouped in the same rating category. King et al., (2020) obtain interesting outcomes. First, they find a significant negative relationship between banks' share price reaction and their share of Fitch securitization business. Second, bank size is positively associated with rating surprises. Third, the transition to a more granular rating scale tends to deliver higher than expected bank standalone ratings, i.e., rating inflation, but results are not sufficient to conclude that CRAs' clients are exerting pressure on the CRAs to get better ratings, a phenomenon known as 'ratings catering' (Griffin et al., 2013).

At the corporate level, Goh and Ederington (1993) examine the redistribution hypothesis by exploring whether all downgrades are bad news for equity-holders and whether all downgrades are a surprise, arguing that it is inappropriate to assume that a downgrade has negative implications for stockholders. From their view, it is unlikely that all downgrades are a surprise since many follow news of an increase in the firm's riskiness and while a surprised downgrade is bad news for bondholders, it is not for stockholders. Therefore, downgrades due to changes in financial leverage reflect transfers of wealth from bondholders to shareholders. Overall, they conclude that the market reacts negatively to downgrades caused by the deterioration or revaluation of the firm's or industry's financial outlook, but there is no significant reaction to rating actions for other reasons.

Dichev and Piotroski (2001) examine abnormal stock returns following bond ratings actions rated by Moody's during 1970 to 1997. They find substantial negative abnormal returns following downgrades but no reliable abnormal returns for stocks receiving upgrades. Most of the underperformance of downgrades occurs in the first year after the announcement, with negative abnormal returns on the magnitude of -10% to -14% a year. They argue a possible underreaction to the information content of downgrades because the poor returns have limited duration, and are most pronounced for small and low-credit-quality firms. Besides, it seems that the market does not fully anticipate the negative implications of downgrades for future profitability.

Abad-Romero and Robles-Fernandez (2006) study corporate bond rating actions by Moody's, S&P and Fitch on stock prices in the Spanish stock market during January 1990 to February 2003. Contrary to the information content hypothesis, they document significant negative excess returns for upgraded firms and no significant excess returns for downgraded firms. For upgrades, the estimated impact on abnormal return seems to be transitory since they do not find significant effects on abnormal returns in the pre- and post- event windows in all groups. Their results are in favour of the wealth redistribution hypothesis in the case of rating upgrades in the financial sector firms, and this effect dominates when the whole sample is analysed.

Lastly, Purda (2007) find the well-known asymmetry of statistically significant negative returns at the time of downgrade but no reaction to upgrades regardless of whether they are anticipated. Purda (2007) developed a model of rating change anticipation that provides the probability of a downgrade, constant rating, or upgrade at the beginning of each firm-quarter. They utilised a sample of issuer credit ratings of firms that maintained Moody's ratings at any point between 1991 and 2002. They find that the stock market reacts negatively to downgrades that are largely predictable and to those that are a surprise, and there is no evidence that the level of anticipation has any effect on the stock price reaction to downgrades.

7.2.2 Research surrounding insurers' FSR actions

Turning to the literature about insurers' credit ratings, the main emphasis has been towards the determinants of credit ratings rather than market impact. Some literature related to market impact within the industry is compile in Section 3.5.1 in Chapter 3 (e.g., Singh and Power, 1992). The literature about determinants (also reviewed in Section 3.2 in Chapter 3) serves to distinguish particularities of the insurance sector, and it is informative when selecting the control variables for modelling the influence of parent companies' characteristics on CARs. As previously cited, the papers to highlight are Pottier and Sommer, 1999, Adams et al., 2003, 2019; Caporale et al., 2017; Doherty et al., 2012. Most of these authors agree that size, profitability, liquidity, and reinsurance are all factors that influence the CRAs assessment. In particular, Pottier and Sommer (1999) concludes that insurers obtain ratings mainly to reduce uncertainty concerning insolvency risk that may be vital to consumers, regulators, insurance brokers, and investors. Caporale et al. (2017) find that such insolvency risk varies depending on the business line, reinsurance levels, and clusters within them.

Closer in spirit to the research question of this Chapter are Halek and Eckles (2010), Miao et al., (2014), Wade et al., (2015), and Chen et al., (2018). Halek and Eckles (2010) examine the effects of rating actions on stock prices of insurance companies utilizing an event study approach. Using 232 unique publicly-traded insurers by AM Best, S&P, Moody's, and Weiss between 1993 and 2003, Halek and Eckles (2010) support the information content hypothesis by showing that the stock price of insurers tend to move in the direction of rating actions. For unfavourable changes, they confirm that CRAs possess superior information relative to the public and those rating actions add to the public information related to an insurer. Moreover, the event study results vary across CRAs with AM Best yielding stronger results compared to S&P and Moody's.[48]

Miao et al. (2014) focus on insurers' bond market response to credit rating actions. They report that downgrades have a stronger impact on bond prices than upgrades and stable rating events, and find that the impact of downgrade events on abnormal returns is negative and statistically significant. Besides, downgraded insurers experience significant negative bond price reactions across all event windows. Further, when they break down the overall sample into single, multiple, and sequential events, they find that isolated rating changes by any of the four CRAs do not have a clear impact on excess returns.

Wade et al., (2015) examine FSR market reaction using a sample of 165 AM Best ratings announcements between 2005 and 2006, testing whether short selling is unusually high in the period directly former to FSR action. Their results are in line with Halek and Eckles (2010) by providing new evidence of informed trading in the days preceding ratings changes. Specifically, a decrease 2 days prior to downgrades in insurers' stock prices have been observed, suggesting that informed trading occurs during the pre-downgrade period.

Building upon Halek and Eckles (2010) findings, Chen et al., (2018) investigate in what contexts FSR provide information that is relevant to equity valuation, as well as the timing of the market response stock returns move in the direction of the rating action (either upgrade or downgrade) prior to the announcement. Using only AM Best ratings, abnormal performance is evident 12 months before the action is announced and continues into the days leading up to the event. They conclude that investors and CRAs are responding to publicly available information, and there is an additional stock price response following the announcement of a downgrade, but no response to upgrade announcements. Nevertheless, the market reaction to downgrades is short-lived, distinct only in the month when the downgrade occurs and the following few days. This provides contrary results relative to bond rating actions, where negative abnormal performance can persist for up to a year as documented by Dichev and Piotroski, (2001).

Milidonis (2013) find that rating actions published by investor-paid CRAs are not only predictive in the market for bond ratings, but they can also predict changes in FSRs, which

[48] Halek and Eckles (2010) use the "group" rating for an insurer provided by AM Best, which enables them to a one-to-one correspondence between the insurance security and its affiliated companies.

serve as a mechanism for market discipline in the insurance industry. In line with Halek and Eckles (2010), Milidonis (2013) confirm the presence of significant CARs associated with the announcement of changes in FSRs by issuer-paid agencies with results larger in magnitude for downgrades than upgrades. Meanwhile, Ben Ammar et al., (2018) argue that anomalies typically considered in the (non-financial, U.S.) equity market are either not present in P/C insurance stocks or different in magnitude and/or direction from other industries.

7.2.3 Parent-subsidiary transmission channels

Despite the evidence provided by the above studies, no prior research in the insurance literature has covered the four major CRAs together and a more recent time period after the financial crisis. Overall, the key contributions of this Chapter to the literature lie in the structure of the rating data, the timing of analysis, and the chosen event study model and statistical tests. Firstly, this study focuses on U.S. P/C insurers' FSR actions rather than insurers' bond ratings from both P/C and life insurers such as Miao et al., (2014). Second, this study is utilises data from S&P, Moody's, Fitch, and AM Best which is not the case in Singh and Power (1992), Chen et al., (2018), Wade et al., (2015), and Halek and Eckles (2010). Third, it classifies positive and negative FSR actions following a wider approach (detail provided in Table 7.3 in Section 7.3.1) rather than considering downgrades and upgrades only. Likewise, it extends Miao et al., (2014) by adding a multivariate analysis with the relationship of CARs and their relationship with parent companies' characteristics.

Finally, this Chapter extends on the literature about the channels through FSR actions could permeate into parent companies' stock price. To the best of my knowledge, hardly any study analyse potential links or transmission channels between subsidiaries' FSR actions and effects on the parent company's share price. Gaver and Pottier (2005) is the only prior study to address the influence of parent company characteristics on the AM Best FSR of a subsidiary group. Their results suggest that parent-level data is collectively useful in the ratings decision, especially aspects of parent-level financing and dividend policy. However, their data does not allow them to identify the specific ratios that are important. In addition, Gaver and Pottier (2005) leave the debate open about how individual P/C ratings are related to aspects of the group and parent company in which the subsidiary is embedded.

Considering the above, this Chapter grasp elements from two major areas reviewed in Chapter 2, in the effort to comprehend better the relationship between parent-subsidiary: i) CRAs methodologies, and ii) academic and regulators' discussions about insurers' systemic risk. Examining CRAs' methodologies, the overall statement across CRAs is that there is no mechanical formula for combining the factors in assessing each parent-subsidiary relationship. Few particularities can be highlighted by CRA. For instance, AM Best (2017) argues that, in one side, parent company provide subsidiaries with a degree of financial flexibility through capital infusions, access to capital markets, and in some cases additional cash flow from other operations. Conversely, parent companies' debt and other securities can diminish the subsidiary financial flexibility, strain future earnings, and inhibit subsidiary surplus growth. In particular, AM Best reviews the financial flexibility, liquidity, financial leverage, interest coverage, dividend requirements, and cash sources and uses to determine the effect on the lead rating unit, which contains the rating of the parent company and subsidiaries define as part of such unit.

Regarding the other CRAs, in a report, S&P (2006) address 'Parent/Subsidiary Rating Links' focusing on the structural subordination norm that applies for banks and insurance operating companies, where there are no fixed limits governing the gaps between corporate credit ratings of the parent and its subsidiaries. Factors that can affect the evaluation are potential mitigating factors, such as guarantees, operating assets at the parent, parent company diversification, concentration of debt in certain subsidiaries, downstream loans. Certainly, S&P determines a stand-alone credit profile (SACP) that together with the support framework (i.e., Group or Government influence), they determine the ICR on an insurer. For most companies, the FSR and financial enhancement rating (FER), if any, are identical to the ICR (S&P, 2019).

About the literature on systemic risk, after the financial crisis 2007-2009, a debate has flourished questioning whether the systemic risk is created or amplified by the insurance sector. Few authors refer back to the case of American International Group (AIG) bailout as an illustration of how its subsidiary AIG Financial Products Unit (AIGFP), managed to escape insurance regulation but threaten the systemic risk. Other authors claim that transmission channels that apply in the banking industry differ from those that apply in the insurance industry but also find commonalities in their role as financial intermediaries between savers and investors as well as large-scale investors (e.g., Thimann, 2015).[49]

[49] The four differences between banks and insurers stated by Thimann (2015) are as follows: i) banks are institutionally connected, insurers are stand-alone operators, ii) maturity transformation and leverage is inherent in banking while insurers match asset and liabilities; leverage is quasi-absent. iii) Banks face inherent liquidity risk while insurers are liquidity-rich and, iv) banks create money, credit and constitute the payment system whereas insurers do not create money, they use the payment system.

Within the same debate, EIOPA (2017) identifies four main transmission channels in which the sources of systemic risk may affect financial stability and/or the real economy, as follows i) Exposure channel; ii) Asset liquidation channel; iii) lack of supply of insurance products; iv) bank-like channel; v) expectations and information asymmetries. Likewise, EIOPA (2017) establishes three main sources of systemic risk. i) entity-based related sources, ii) activity-based related sources, and iv) behaviour-based sources. It is mainly in the entity approach where the role of the subsidiary becomes key.

Briefly, the exposure channel consists of the direct and indirect linkages whereby a shock in one or more insurance companies could spill over to other agents and/or markets that are exposed to them. The asset liquidation refers to a company is forced to liquidate assets quickly and on a scale that aggravates market movements and asset price volatility (e.g., fire sales or herding). The third channel refers to the impact in case certain products or services are no longer provided (i.e., lack of substitutability), the fourth consists of insurers that deviate from traditional activities to get involved in banking-type activities, and the fifth is linked to issues such as irrational panics and re-evaluation of expectations as well as reputational issues.

Relative to the sources of the risk, the entity-based approach comprises the failure of a systemically important company or the collective failure of non-systemically important insurers as a result of exposures to common shocks. It is in this scenario where the additional information via FSR assigned by CRAs would play a key role as providers of information to the stock market as well as in the effort to contribute to the control of the systemic risk.

7.2.4 Event study methodology

Different methodologies are used in the literature to gauge the information content of rating actions. The most accepted methods for modelling the normal/expected returns are the mean-adjusted returns method (used by Hill and Faff, 2010; Williams et al., 2013), and the market model (used by Gande and Parsley, 2005). These models serve to model a security's expected price performance, and by comparing to the raw return, the "abnormal" return can be calculated. Table 7.1 displays several studies that use either one or both models. For instance, Hill and Faff (2010) choose the mean-adjusted returns to calculate the abnormal returns, but they also use a market model and index model for robustness, and their outcomes do not change. Hill and Faff (2010) calculate the mean daily return for each issuer prior to each event using 200 daily observations for the period -230 to -30 days. The mean represents the expected daily return (ER), which is subtracted from the raw return for each day in the event windows under consideration to give the daily abnormal return (AR). Abnormal returns are cumulated over consecutive days to give cumulative abnormal returns (CARs). Williams et al., (2015) also use the mean daily return for each bank prior to a sovereign rating event calculated using 200 daily observations for the period t = -230 to t = -30, where t = 0 is the event day. There is no standard convention in the literature for selecting a particular expected returns model in event study methodology, nor is there a standard convention in the choice of estimation window (Miao et al., 2014). Most authors choose a range between 230 and 260 days in the estimation period (e.g., Pancotto et al., 2020; Alsakka et al., 2015), which roughly corresponds to the number of trading days in a calendar year.

In this thesis, a 250-day estimation period is chosen. Following Williams et al., (2013) and Hill and Faff (2010), the windows adopted are a [-10, -1] pre-event window, a short event-window [0, +1] to reduce contamination from other credit events, and a post-event [+2, +11] window that will capture any delayed market impact from the FSR actions.

Table 7.1 Summary of literature on market impact of rating actions

Research	Event of analysis	Dataset	Period	Methodology	Event window	Estimation period	Rating scale
This Chapter	Equity market reaction to FSR actions	346 U.S. P/C insurers associated to 30 parent companies (527 FSR)	Jan. 2003 – Dec. 2017	Market model	Pre-event [-10, -1] Events [0, +1] Post-event [+2, +11]	-300 to day -50	20-points 13-points
Gande and Parsley, (2005)	Equity market reaction to sovereign credit events	Daily market-closing observations of interest rate spread and S&P ratings changes	Jan. 1991 – Dec. 2000	Market model	Two-day [0, +1] Pre-event [-10, -1] Post-event [+2, +11]	Six or 12 months	16-points. Add +1 (-1) to positive outlook (negative). Add +0.5 (-0.5) to positive (negative) watch
Ferreira and Gama, (2007)	Cross-country stock market reaction to S&P news of a sovereign credit rating or credit outlook change	S&P history of sovereign rating for the countries	July 1989 – Dec. 2003	Market model	Two-day [0, +1]	CAR estimated monthly over a centered window of 35 months	20-points. Add +1 (-1) to positive outlook (negative). Add +0.5 (-0.5) to positive (negative) watch
Hill and Faff, (2010)	Market impact of sovereign rating actions	101 countries	1990–2006	Mean-adjusted returns and market model	Pre-event [-10, -1] Event [0, +1]	-230 to -30 days 200 daily return observation	21-points. AAA (= 21) to C (= 1)
Halek and Eckles, (2010)	Effect of rating changes on stock prices	Daily returns of publicly traded U.S. insurance companies	1992–2005	Market model	21-day trading period centered in day 0	255-day trading period following the end of the event window	Not specific about rating scale used.
Alsakka and ap Gwilym, (2012c)	Sovereign ratings on U.S. exchange rate	LT Foreign currency ratings, outlooks and watch from S&P, Moody's, Fitch	Aug. 1994– July 2010	Market risk-adjusted expected return	[-1, +1], [-1, +3] [-1, +7], [-1, +14] [-1, +30]	-	20-points 58-points LCCR

Table 7.1 Continued

Research	Event of analysis	Dataset	Period	Methodology	Event window	Estimation period	Rating scale
Williams et al., (2013)	Sovereign credit signals from S&P, Moody's, Fitch to effect over bank's abnormal stock returns	European banks	2007 –2011	Mean-adjusted return Ordered probit modelling approach	Pre-event [-10, -1] Event [0, +1] and post-event [+2, +11]	t = -230 to t = -30.	20-points: 1 to 20 58-points LCCR numerical rating
Miao et al., (2014)	Insurer ratings changes on bond prices	Ratings announcements by S&P, Moody's, Fitch and AM Best for insurance companies' stocks	2005 –2010	Market risk-adjusted expected return	[-5,-2], [-2,+2], [-1,+1], [-1,-1], [0,0], [+1,+1], [+2,+5]	t = −300,…., −46 days (estimation period)	Not specific about rating scale used. It divide events by good news, bad news, and no news.
Wade et al., (2015)	FSR ratings announcements	165 publicly traded insurers (89-P/C, 76-LH) rated by A.M. Best and short-sale data	Jan. 2005 – Dec. 2006	Market-adjusted returns	8-day window	Not specific	Not specific about rating scale used.
Williams et al., (2015)	Reaction of bank share prices to their home country's sovereign rating	19 emerging market countries.154, 122 and 128 sovereign rating actions for S&P, Moody's and Fitch	Jan. 2001 to Sep. 2011	Mean-adjusted returns method	pre-event [-10, -1], event [0, +1], post-event [+2, +11] windows	t = -230 to t = -30,	20-notch, 58-point CCR and LCCR numerical rating scales
Chen et al., (2018)	Immediate and longer term stock market response to FSR events using insurer stock returns	267 rating changes announced by AM Best for a sample of 238 insurers: 126 P/C, 70 LH firms, and 42 multiline insurers.	1996–2013	Benchmark portfolio approach	[-12m,-1m], [-6m,-1m], [-3m,-1], [+1m,+3m], [+1m,+6m], [+1m,+12m]	25-month period	Not specific

This table reports summary of studies investigating the effect of a particular event, the sample, period of study and method used. Some papers use a LCCR rating scale which is based on a logit-type transformation to the 58-point CCR, whereby LCCR = ln [CCR/(59-CCR)]. This scale is used to address possible rating scale non-linearity.

7.3 Data

7.3.1 FSR actions data

The credit dataset is based on the sample used in Chapter 6: 904 U.S. P/C insurers with FSR available and rated by at least two of the four major CRAs. The sample shrink to 346 U.S. P/C insurers since the parent company related to the insurers must be listed in the U.S. stock market in order to be included in this Chapter. Using the 346 U.S. P/C insurers remaining, the credit dataset contains daily LT-LC FSR, Outlooks, and Watch actions by S&P, Moody's, Fitch, and AM Best from 1st January 2003 to 31st December 2017. Building upon the rating definitions and differences across CRAs in their rating actions (see Section 2.3.1 in Chapter 2), Table 7.2 presents on detail the classification of negative and positive FSR actions. *Negative Watch actions* include placing issuer *i* on Watch for possible downgrade, and the action of confirming the rating of issuer *i* after being on Watch for possible upgrade. *Positive Watch* actions include placing issuer *i* on Watch for possible upgrade, and the action of confirming the FSR of issuer *i* after being on Watch for possible downgrade. *Negative Outlook* actions include changes to negative Outlook from stable/positive Outlook, and changes to stable Outlook from positive outlook. *Positive Outlook* actions include changes to positive Outlook from stable/negative outlook, and changes to stable outlook from negative Outlook. *Upgrade (downgrade) actions* are defined as an upward (downward) move in the 20-notch numerical scale (AAA/Aaa = 1, AA+/Aa1 = 4, AA/Aa2 = 7… Caa3/CCC- = 19, Ca/CC/C/SD-D = 20). Table A 7.1 in Appendix illustrates the 20-point numerical scale; and to be consistent with Chapter 5 and 6, it also includes the 13-point numerical scale (AAA/Aaa = 1, AA+/Aa1 = 4, AA/Aa2 = 7… Caa3/CCC- = 11, Ca/CC/C/SD-D = 13) by AM Best in full.

'Positive FSR actions' in this Chapter include positive Watch, positive Outlook, upgrade actions, and positive combined actions which refers to those insurers that are upgraded and simultaneously placed on positive Outlook or positive Watch, as well as upgrades that are preceded by positive Outlook or positive Watch. 'Negative FSR actions' include negative Watch, negative Outlook, downgrade actions, and negative combined actions, i.e., an insurer can be downgraded and simultaneously placed on negative Outlook or Watch, as well as downgrades that are preceded by negative Outlook or negative Watch.

Table 7.2 FSR actions classification

Types of FSR actions	Negative FSR actions	Positive FSR actions
Watch actions	• On watch for possible downgrade, • Rating confirmation of insurer after being on watch for possible upgrade	• On watch for possible upgrade, and • Rating confirmation after being on watch for possible downgrade • Rating confirmation after being on watch for possible downgrade. • Actions which involve moving to negative outlook from negative watch (with no rating change) are regarded as a positive FSR action
Outlook actions	• Changes to negative outlook from stable/positive outlook, and • Changes to stable outlook from positive outlook.	• Changes to positive outlook from stable/negative outlook, and • Changes to stable outlook from negative outlook
Downgrade/Upgrade	• Downgrades are defined as an downward in the 20-notch numerical scale	• Rating upgrades move as an upward in the 20-notch numerical scale (AAA=1 through C-D=20)
Combined actions	• Downgrade and stable outlook (from neg. outlook or neg. watch to stable outlook) • Downgrade and simultaneously placed on negative outlook or negative watch	• Upgrade and stable Outlook (from pos. outlook or pos. watch to stable outlook) • Upgrade and simultaneously placed on positive outlook or positive watch
Under review	• Under review with negative implications (for AM Best)	• Under review with positive implications (for AM Best)

This table presents the list of possible FSR actions and it is the main guideline to decide whether a particular date associated with a rating action is classified as a positive or negative FSR action.

Table 7.3 presents summary statistics on the S&P, Moody's, Fitch and AM Best FSR actions for the 346 U.S. P/C insurers (subsidiaries) based on the 20-point numerical rating scale. There are 527 qualifying FSR actions spanning 2003-2017, as follows: 200 FSR actions by S&P, 112 FSR actions by Moody's, 75 FSR actions by Fitch, and 140 FSR actions by AM Best. Analysis of the FSR data of the 346 subsidiaries shows that about 90% of the subsidiaries associated to one parent company have the exact same FSR action on the same date. Thus, a rule of thumb is implemented when selecting the FSR actions, if 80-90% of the subsidiaries associated to one parent company have the same FSR action, this is the observation considered in this study. [50]

[50] Some observations did not qualify to be part of the FSR actions dataset for several reasons. One, some subsidiaries contain a 'q', 'pi' rating or 'NR' in S&P ratings (21 U.S P/C subsidiaries). Second, some subsidiaries had a different parent company during the study. Third, some FSR actions were 21 days close with the other and cannot be considered 'independent'. On the other hand, some subsidiaries were only rated once and had rating affirmation over time. This reduced dramatically the number of FSR actions and corroborates how insurance ratings are a somewhat particular compared to corporates, sovereigns and banks, which seem to have more rating actions.

The final dataset comprises 20 (28), 19 (11), 5 (10), and 0 positive (negative) Watch actions announced in isolation i.e., with no simultaneous upgrade or downgrade; by S&P, Moody's, Fitch and AM Best, respectively; and 57 (36), 31 (16), 19 (14), and 34 (18) isolated positive (negative) Outlook actions by S&P, Moody's, Fitch and AM Best, respectively. Table 7.4 also presents summary data on upgrades and downgrades. There are 6 (7), 6 (5), 8 (4), and 26 (16) upgrades (downgrades) by S&P, Moody's, Fitch ad AM Best, respectively. Most of the upgrades in S&P, Moody's and Fitch are by one-notch, while for AM Best, the majority of upgrades are by two-notches and for downgrades it's similar. Finally, some upgrade and downgrade actions are combined actions (see Table 7.3). There are 19 (27), 16 (8), 4 (11), and 15(7) combined FSR actions by S&P, Moody's, Fitch and AM Best, respectively (see Rows 31 and 44, in Table 7.3). Overall, AM Best has the highest number of positive combined actions 41 (26+14+1), followed by S&P with 25, Moody's with 22 and Fitch with 12.

The proportion of positive (negative) FSR actions as a percentage of the total FSR actions by S&P, Moody's, Fitch and AM Best is 51% (49%), 64% (36%), 48% (52%), and 59% (41%) respectively. These figures give insight about the policies of the four CRAs. S&P is the most active among the four CRAs with 200 total FSR actions (102 positive and 98 negative FSR actions) followed by AM Best with 140 FSR actions (82 positive and 58 negative), compared to 112 (72 positive and 40 negative), and 75 (36 positive and 39 negative) from Moody's and Fitch, respectively. Although S&P is the most active, Moody's is the only CRA that make equal use of Watch for possible upgrades and downgrades, while Fitch and S&P opt not to assign Watch for possible upgrades; AM Best does not have this type of action in their methodology. As a whole, S&P execute negative Watch actions most frequently while Moody's and Fitch have similar numbers. Interestingly, these findings seem to be partially in line with Williams et al., (2013) who find that for sovereigns, S&P tend not to perform any positive Watch actions to sovereigns, but perform negative Watch actions regularly whereas Moody's execute negative Watch actions most often.[51]

For AM Best, it is noteworthy that the number of under review actions with negative implications is greater than the positive ones. This suggest that AM Best may be quite conservative, it seems that when there is positive news about issuers, they are more likely to

[51] The 140 FSR actions from AM Best are classified as 82 positive and 58 negative. From the 82 positive FSR actions, 7 are under review actions with positive implications and from the 58 negative FSR actions, 17 are under review with negative implications.

perform upgrade actions while with negative FSR actions about issuers, they are more cautious and use under review actions as signal before executing a downgrade action.

Table 7.3 Descriptive statistics of the FSR actions

Row	Types of FSR actions	S&P	Moody's	Fitch	AM$
1	Watch for possible upgrade	0	11	0	
2	From stable outlook to pos. watch with no rating change	1	0	0	
3	Confirm rating after being placed on watch for downgrade	0	3	2	
4	From neg. watch to neg. outlook with no rating change	12	3	2	
5	From neg. watch to Stable outlook with no rating change	7	1	1	
4	From pos. outlook to pos. watch with no rating change	0	1	0	
5	From neg. outlook to pos. watch with no rating change	0	0	0	
6	Positive Watch actions (rows 1 to 5)	20	19	5	0
7	Watch for possible downgrade	10	10	10	
8	From stable outlook to negative watch with no rating change	13	0	0	
9	Confirm rating after being placed on watch for upgrade	0	1	0	
10	From pos. watch to pos. outlook with no rating change	0	0	0	
11	From pos. watch to stable outlook with no rating change	0	0	0	
12	From neg. outlook to neg. watch with no rating change	5	0	0	
13	From pos. outlook to neg. watch with no rating change	0	0	0	
14	Negative Watch actions (rows 7 to 13)	28	11	10	0
15	Total Watch actions (row 6 + 14)	48	30	15	0
16	To pos. outlook from stable/negative outlook	22	13	9	18
17	To stable outlook from neg. outlook	35	18	10	16
18	Positive Outlook actions (row 16+17)	57	31	19	34
19	To neg. outlook from stable/positive outlook	31	12	11	17
20	To stable outlook from pos. outlook	5	4	3	1
21	Negative Outlook actions (row 19+20)	36	16	14	18
22	Total outlook actions	93	47	33	52
23	Total outlook / watch actions (1+25)	141	77	48	52

Table 7.3 Continued

Row	Types of FSR actions	S&P	Moody's	Fitch	AM$
24	Upgrade and stable Outlook (from stable to stable outlook)*	6	6	8	26
	Number of 1-notch upgrade	5	5	8	5
	Number of 2-notch upgrade	1	1	0	16
	Number of more than 2 -notch upgrade	0	0	0	5
25	Upgrade and stable outlook (from pos. to stable outlook)	14	9	4	14
26	Upgrade and stable outlook (from pos. watch to stable outlook)	3	5	0	0
27	Upgrades and pos. outlook (from pos. outlook to pos. outlook)	0	0	0	0
28	Upgrades and pos. watch (from pos. outlook to pos. watch)	0	0	0	0
29	Upgrades and pos. watch (from no previous action)	2	1	0	0
30	Upgrade and neg. outlook**	0	1	0	1
31	Combined positive actions (rows 25 to 30)	19	16	4	15
32	Downgrade and stable outlook (from stable to stable)	7	5	4	16
	Number of 1-notch downgrade	5	5	4	8
	Number of 2-notch downgrade	1	0	0	6
	Number of more than 2 -notch downgrade	1	0	0	2
33	Downgrade and stable outlook (from neg. to stable outlook)	8	2	2	3
34	Downgrade and stable outlook (from neg. watch to stable out.)	6	0	2	0
35	Downgrade and neg. outlook (from neg. outlook to neg. outlook)	5	0	3	4
36	Downgrade and neg. watch (from neg. outlook to neg. watch)	0	0	0	0
37	Downgrade and neg. watch (from no previous action)	0	1	2	0
38	Downgrade and pos. outlook***	0	0	0	0
39	Downgrade and stable outlook (from positive to stable outlook)	1	0	0	0
40	Downgrade and neg. outlook (from stable to neg. outlook)	0	3	1	0
41	Downgrade and neg. outlook (from neg. watch to neg. outlook)	5	1	1	0
42	Downgrade and neg. watch (from neg. watch to neg. watch)	1	1	0	0
43	Downgrade and neg. watch (from neg. outlook to neg. watch)	1	0	0	0
44	Combined negative actions (rows 33 to 43)	27	8	11	7
45	Additional rating actions				
	Under review (specific to AM Best)	0	0	0	24
	with pos. implications				7
	with neg. implications				17
	Total FSR actions	200	112	75	140

This table presents summary statistics for the FSR actions dataset, which consists of daily information on LT-LC, outlooks and watch for 346 U.S. P/C insurers rated by S&P, Moody's, Fitch and AM Best during the period 1st January 2003 to 31st December 2017. ***Notes:*** *$ AM abbreviates AM Best.*

** Upgrades from stable to stable outlook: For AM Best, it includes two cases of companies that were upgraded with stable outlook after being under review.*

*** Unusual rating actions: For Moody's, this was the case of Gulf Insurance Company and members of the legacy St. Paul, United States Fidelity & Guaranty (USF&G) pools upgraded to Aa3 following the completion of the re-pooling of these companies with the legacy Travelers Indemnity Company pool (whose pooled companies were already rated Aa3 for FSR) and the dissolution of the legacy pooling agreements. However, Moody's changed previously the outlook for the debt ratings and for the FSR of members the Travelers Indemnity pool to negative from stable. Moody's stated that the resolution of the negative outlook will focus on capital adequacy of the operating companies (Moody's, 2005). For AM Best, the case is Mesa Underwriters Specialty Insurance Company in 2012. These rating actions follow the acquisition of Montpelier US Insurance Company (MUSIC) by Selective Insurance Group, Inc. [NASDAQ: SIGI], effective December 31, 2011, as well as the execution of an updated pooling agreement under which MUSIC has become a member of the pool led by Selective Insurance Company of America (SICA).The negative outlook was previously assigned* (AM Best, 2012).

**** Row 38 is only included to match row 30.*

An important point to consider is that actions by CRAs are included in the dataset only if they are 'independent'. This is done following prior studies such as Hill and Faff, (2010). An FSR action is defined as 'independent' when at least one of the subsidiaries associated with the same parent company has not received another FSR action within 21 trading days (of day t = 0) by any of the other three CRAs. This ensures that all FSR actions are not contaminated by others within the (−10, +11) window. Moreover, the bankruptcy filing of Lehman Brothers Holdings Inc. on September 15, 2008, was one of the most extreme events of the financial crisis (FDIC, 2011). Thus, to avoid introducing any bias in the results, all FSR actions during the week of 15th September 2008 are excluded to avoid obvious interconnection amongst actions by different CRAs that could influence the overall inferences from the investigation.

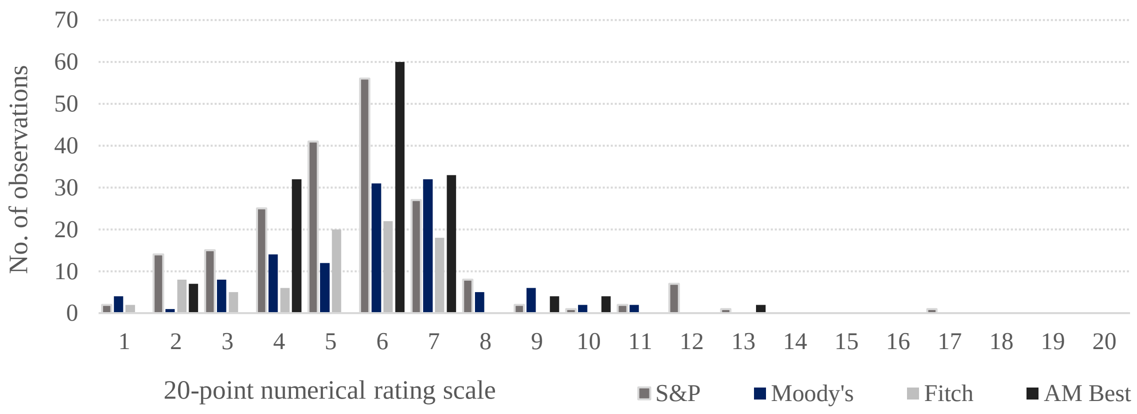

Figure 7.1 Distribution of daily FSR insurer's ratings

This figure presents the distribution of daily FSR actions from 1st of January 2003 to 31 December 2017 for S&P, Moody's, Fitch and AM Best. The credit ratings scale is transformed into a 20-point numerical scale (AAA/Aaa = 1, AA+/Aa1 = 4, AA/Aa2 = 7… Caa3/CCC- = 19, Ca/CC/C/SD-D = 20) (see Table A 7.1).

Figure 7.1 presents the distribution of daily 20-point ratings. A/A2 and A-/A3 represent 50.9% of the total number of daily observations while speculative-grade ratings represent only 4.2% of the total. Drawing from Figure 7.1 (and Figure A 7.1 in Appendix 7.I), one can notice that a different picture emerges on comparing the distribution of FSR with other markets either on a different or similar period (e.g., banking, corporate bonds, sovereigns). For instance, Alsakka et al., (2017) documented that for EU countries, 34% of the total number of daily observations corresponds to AAA/Aaa ratings and only 8.6% represent speculative-grade ratings. In other scenario, Alsakka and ap Gwilym (2012a) show a reasonable spread of observations across categories, with 15% of observations that placed in AAA/Aaa-rated sustained the rating during the period of analysis (1994-2010) and with less than 3% of observations place in Caa1/CCC or below because defaults are also very rare.

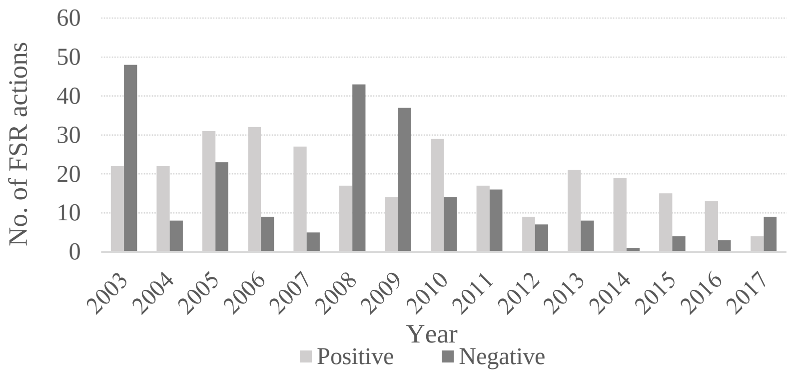

Figure 7.2 Distribution of negative and positive FSR actions over time

This figure presents the number of rating/dates (including rating change, outlook and watch actions) by the four largest CRAs for US P/C insurers from January 2003 to December 2017.

The dissimilar distribution of FSR may cause a completely different outcome when analysing the market impact to FSR. Some authors claim that not all insurance firms are rated, and the ratings normally stay the same for many years (Caporale et al., 2017). Other authors claim that insurance stocks are different (Ben Ammar et al., 2018). This is because they are highly leveraged, complex and opaque because of policyholder liabilities, exposure to specific risks, based on reputational capital (e.g., ratings; Milidonis, 2013), and market discipline mechanism (Epermanis and Harrington, 2006).

Figure 7.2 presents the distribution of all FSR actions from all CRAs over time. Overall, positive FSR actions occur more often than negative FSR actions. However, these are spread over the period while negative actions are concentrated in certain years. In 2003, negative FSR actions outnumber positive actions, possibly as a consequence of natural disasters such as the series of tornadoes in the Midwest and the East of U.S. leaving insurers with a bill of US$ 1.6b; or the fact that in November, the Midwest was hit again with wide-ranging loss (Munich Re, 2003). The trend is reverted to a weak positive pattern in 2004, but in 2005, negative FSR actions are more recurrent. In the following years, positive FSR actions are dominant mainly by S&P in 2006 and 2007, but during 2008-2009, a dramatic increase of unfavourable FSR actions across all CRAs occurs since the financial crisis hit worldwide. In the subsequent years, a weak positive trend is observed in 2013 and 2016.

Table A 7.2 in Appendix 7.I presents the FSR actions by year and CRA. S&P has executed the highest number of negative rating actions in 2008 while Fitch performed more in 2009. Moody's and AM Best have relatively the same amount in the crisis period. About positive FSR actions, in 2006, all CRAs conduct more positive FSR actions relative to negative ones, especially S&P, followed in order by Moody's, AM Best, and Fitch.

7.3.2 Parent companies' stock prices

As mentioned, the initial sampling is based on the dataset used in Chapter 6. The parent company of associated to those 904 U.S. P/C insurers must be listed in U.S. stock market in order to be selected, making the sample shrink to 346 subsidiaries, which are related to 30 parent companies. Using Capital IQ, the share prices are gathered for all the parent companies listed in the U.S. stock market and have share prices available from January 2003 onwards. The final sample consists of 30 parent companies as shown in Table 7.4.

Table 7.4 List of parent companies

No	Symbol	Parent company	No. of subsidiaries	Date	Last trade
1	NYSE:AET	Aetna Inc.	1	13/12/2000	28/11/2018
2	NYSE:Y	Alleghany Corporation	3	26/12/1986	Currently
3	NYSE:AFG	American Financial Group, Inc.	20	14/11/1978	Currently
4	NYSE:AIG	American International Group, Inc.	17	02/01/1969	Currently
5	NasdaqGS:ANAT	American National Group Inc.	2	20/11/2000	Currently
6	NasdaqGM:AFSI	AmTrust Financial Services, Inc.	3	13/11/2006	28/11/2018
7	NYSE:AIZ	Assurant, Inc.	1	05/02/2004	Currently
8	NYSE:BRK.A	Berkshire Hathaway Inc.	24	16/04/1985	Currently
9	NYSE:CB	Chubb Limited	32	25/03/1993	Currently
10	NasdaqGS:CINF	Cincinnati Financial Corporation	3	22/01/1985	Currently
11	NasdaqGS:ESGR	Enstar Group Limited	2	01/02/2007	Currently
12	NYSE:GE	General Electric Company	1	02/01/1968	Currently
13	NYSE:HIG	Hartford Financial Services Group Inc.	14	15/12/1995	Currently
14	NYSE:HMN	Horace Mann Educators Corporation	3	15/11/1991	Currently
15	NYSE:KMPR	Kemper Corporation	24	23/04/1990	Currently
16	NYSE:L	Loews Corporation	22	02/01/1968	Currently
17	NYSE:MKL	Markel Corporation	12	07/04/1987	Currently
18	NYSE:MCY	Mercury General Corporation	8	20/11/2000	Currently
19	NYSE:ORI	Old Republic International Corp.	11	20/12/1983	Currently
20	NYSE:PRA	ProAssurance Corporation	7	04/09/1991	Currently
21	NYSE:PGR	Progressive Corporation	32	19/10/1983	Currently
22	NYSE:RLI	RLI Corp.	2	19/02/1985	Currently
23	NasdaqGS:SIGI	Selective Insurance Group, Inc.	10	08/02/1983	Currently
24	NYSE:ALL	The Allstate Corporation	15	03/06/1993	Currently
25	NYSE:THG	The Hanover Insurance Group, Inc.	4	11/10/1995	Currently
26	NasdaqGM:NAVG	The Navigators Group, Inc.	2	02/06/1987	22/05/2019
27	NYSE:TRV	The Travelers Companies, Inc.	46	02/04/2004	Currently
28	NasdaqCM:TIPT	Tiptree Inc.	1	22/06/2007	Currently
29	NasdaqGS:UFCS	United Fire Group, Inc.	5	15/07/1986	Currently
30	NYSE:WRB	W. R. Berkley Corporation	19	18/12/1984	Currently
		Total of subsidiaries	346		

This table shows the list of parent companies included in the sample as well as the number of U.S. P/C insurers associated to them. It reports their ticker-symbol and their first and last date of trading. Note that for General Electric, 'Electric Insurance Company' is the only subsidiary included and only have actions in AM Best. S&P also gave a rating but it is an affirmation of the same rating over time with a stable outlook. Aetna stopped trading in 2018. Now is part of CVS Health Corp.

Data is available for a total of 30 qualifying parent companies where about 80% can be classified as insurers (SIC code: 6331 = Fire, Marine, and Casualty Insurance). Prior studies support the view that insurance firms are stable and their business is not very diverse (Caporale et al., 2017). However, as it will be seen, this is not always the case. More details of the parent companies can be found in Appendix 7.I.

Table 7.5 reveals that most of the maximum and minimum levels of stock returns are surrounding the period of the financial crisis. For instance, The Hartford Financial Services Group, Inc. had the maximum return in December 2008 bouncing back from the minimum level reach in October of the same year. According to the 'Share Pricing – Annotations' provided in Capital IQ database, the maximum return corresponds to the analyst/investor day and the minimum return is linked with several events such as Executive/Board Changes – Other, Earnings Calls, Announcements of Earnings, SEC Filing (8K and 10Q). However, in early November news are about Discontinued Operations/Downsizings, Executive/Board Changes – Other. Regarding AIG, the maximum return in March 2009 is due to the business expansions planned from January to April 2009 while the minimum is surrounded by news about product-related announcements.

Table 7.5 Top six insurers by max returns - Log returns

Company	Obs.	Mean	Std. Dev.	Min	Max	Date Min	Date max
The Hartford Fin. Services G., Inc.	4027	0.00	3.68	-72.49	70.49	30/10/2008	05/12/2008
American International Group, Inc.	4027	-0.08	4.09	-93.63	50.68	15/09/2008	16/03/2009
The Hanover Insurance Group, Inc.	4027	0.02	2.08	-35.38	41.49	03/10/2002	09/01/2003
American Financial Group, Inc.	4027	0.05	1.87	-15.53	37.41	08/10/2008	13/10/2008
Old Republic International Corp.	4027	0.01	2.10	-29.21	31.98	22/09/2008	18/09/2008
Horace Mann Educators Corp.	4027	0.02	2.40	-51.47	24.04	09/10/2008	13/10/2008

This table reports the descriptive statistics of 6 of the 30 parent companies that exhibit the highest and lowest levels of market returns. Obs. refers to the number of observations in the period of analysis from Jan. 2003 – Dec. 2017. Std. Dev. stands for standard deviation of such returns. Min. and Max. correspond to the minimum and maximum log return obtained and the dates associated to them. Returns are shown in percentage (%). Corp. refers to Corporation.

Figure 7.3 illustrates the three steps involved in the selection of the FSR actions and the interrelation between both datasets, the FSR credit data and the parent companies' stock prices.

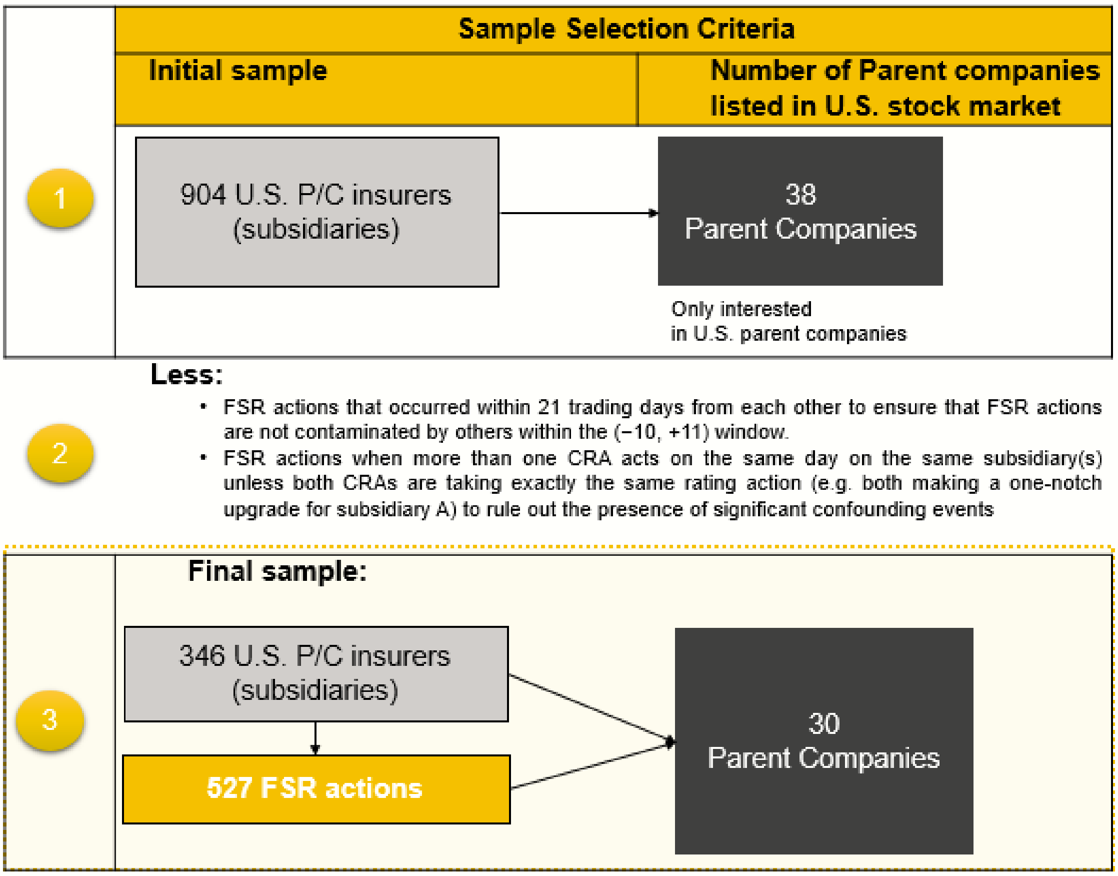

Figure 7.3 Sample selection criteria

This figure presents the link between the two datasets, credit rating data and stock market as well as the steps to obtain the final sample.

7.4 Methodology

The event study approach is well-designed to investigate the effect of FSR actions on the stock market. This methodology has been widely employed either to investigate the valuation effects of regulatory reforms or rating changes in other scenarios (see Section 7.2). Following the approaches of Halek and Eckles (2010) and Miao et al., (2014) within the insurance industry, this chapter applies the market model to calculate abnormal returns (AR) and the cumulative abnormal returns (CAR). Halek and Eckles (2010) argues that market model is the more appropriate model given that the research is focus on one particular industry of the entire market, i.e., P/C insurance. Starting from the expression:

$$R_{k,t} = \propto_k + \beta_k R_{m,t} + \varepsilon_{i,t} \tag{7.2}$$

$$E[\varepsilon_{k,t}] = 0 \qquad VAR[\varepsilon_{k,t}] = \sigma^2$$

$R_{k,t}$ is the daily asset return of the parent company k at time t, $R_{m,t}$ is the market return and $\varepsilon_{k,t}$ is the zero mean error term. Market model parameters, i.e., $\propto_k$, β_k and σ^2, are estimated by OLS regression over a 200-day estimation period ending 50 days before the announcement date (t = -250 to -50). A 50-day count is preferred following Miao et al., (2014) and Alsakka et al., (2015) who choose 46, 50 days respectively. The 50-day count roughly corresponds to the number of trading days in two months and a half, which is selected to avoid any possible effects of rating anticipation (Alsakka et al., 2015). Regarding the benchmark, the market indices are all are sourced from Capital IQ database, as follows:[52]

1) **S&P 500 P/C Insurance (S&P 500 P/C).** The S&P Select Industry Indices measure the performance of stocks comprising specific Global Industry Classification Standard (GICS®) sub-industries or groups of sub-industries (S&P, 2020b). Thus, this sub index contains those companies that are classified as members of P/C insures within the GICS® framework.[53]
2) **Dow Jones U.S. P/C Insurance Index (DJUSIP).** The Dow Jones U.S. index (DJUS) aims to provide 95% market capitalization coverage of U.S. trade stocks. The 16.4% of

[52] Other index that could have been used is the Dow Jones Insurance Titans 30 Index designed to measure leading companies in the global insurance sector.

this index corresponds to financials and some of these is what constitutes the sub index DJUSIP.

3) **NASDAQ Insurance Index (INSR)** contains securities of NASDAQ-listed companies classified according to the Industry Classification Benchmark as Insurance. They include full line insurance, insurance brokers, property and casualty insurance, reinsurance, and life insurance. On February 5, 1971, the INSR began with a base of 100.
4) **S&P Composite 1500 Insurance-Industry (S&P 1500).** The S&P Composite 1500 is a combination of the S&P 500, S&P MidCap 400, and S&P SmallCap 600 and measures the performance of all three-market size segments. S&P 1500-4030 comprises those companies included in in the S&P Composite 1500 that are classified as members of the GICS® insurance sub-industry.[54]

Taking into account the selected benchmark, the ARs are obtained as the difference between the actual returns and the estimated values, unconditional on the events, predicted by the market model:

$$AR_{k,t} = R_{k,t} - E\left[R_{k,t}\right]$$

$$AR_{k,t} = R_{k,t} - \left(\widehat{\alpha}_k - \hat{\beta}_k R_{m,t}\right) \quad (7.3)$$

In Eq. (7.3), negative ARs imply 'abnormal' drops following a FSR action, while positive ones reflect the inverse. Once the AR is obtained, the relevant event window is aggregated around the announcement date t = 0, in order to obtain the cumulative abnormal returns (CARs), as follows:

$$CAR(t_1, t_2) = \frac{1}{N}\sum_{i=1}^{N} AR_k(t_1, t_2) \quad (7.4)$$

Once abnormal returns are computed, it is necessary to evaluate their statistical significance. To assume economic relevance, CARs must be statistically significant. Considering that, the literature offers two types of tests, parametric and non-parametric ones. Parametric tests assumes that ARs, and CARs, are normally distributed with mean 0 and variance σ^2, while non-parametric tests are not attached to any a-priori assumption.

For **parametric tests**, literature has developed alternative methods starting from a basic t-test. For this setting, a cross-sectional parametric test is applied first as the event study considers a

[54] According to S&P (2020a), changes to index composition of the S&P 1500 Composite are made on an as-needed basis with no scheduled reconstitution, additions and deletions are announced with at least three business days advance notice.

sample of multiple FSR actions affecting one parent company. The test for AR: $H_0: AR = 0$ vs. $H_a: AR \neq 0$, $t_{AAR} = AR_t / (\sigma(AR_{it})/\sqrt{N})$. Similarly, for the CAR, the null hypothesis $H_0: CAR = 0$, $H_a: CAR \neq 0$, $t_{CAR} = CAR_t / (\sigma(CAR_{it})/\sqrt{N})$ is tested. The cross-sectional parametric test has showed to be prone to event-induced volatility which can result in low power (Brown and Warner, 1985). Therefore, a Boehmer et al., (1991) known as BMP test is applied since it is considered more robust as it controls for event induced variance (Williams et al. 2015).[55]

It is worth mentioning that a major problem in statistical tests of abnormal returns is that stock prices are not normally distributed. Thus, nonparametric tests tend to be adopted in conjunction with parametric tests as tend to be superior and can provide a check of the robustness of conclusions based on the standard significance tests. Relative to non-parametric tests, several alternatives are also available. In this Chapter, the sign test by Cowan (1992) is used.

7.4.1 Multivariate analysis

Beyond the analysis of how share prices of the parent companies reacted to FSR actions of their subsidiaries, this Chapter tests whether parent company-specific factors could potentially intensify or lessen the responses. The variables included are based on the literature review about determinants in Chapter 3 and prior literature on event studies. The multivariate regression is estimated using robust standard errors, separating positive and negative FSR actions. This is done first, by taking the full set of FSR actions by all CRAs, followed by the estimation of the regression by each CRA in both directions using in the form:

$$CAR_{[T1,T2]} = \alpha + \beta_1 ASSET_{k,t-1} + \beta_2 PROFIT_{k,t-1} + \beta_3 LEV_{k,t-1} + \beta_4 LIQ_{k,t-1} + \beta_5 DIVER_k + \beta_6 LARGE_k + FED_{t-1} + \varepsilon_{k,t} \quad (7.5)$$

where **CAR[*T*1,*T*2]** denotes the CAR of parent company *k* within the event window [*0,+1*] calculated using S&P500 P/C index. The indexes DJUSIP, INSR, S&P 1500 are used for robustness. Gande and Parsley, (2005) and Williams et al., (2015) suggest this short two-day event window to limit the possibility of contamination from other events in the event window.

---

[55] The most popular parametric tests are Normal, Patell (1976) and Boehmer et al., (1991). These three tests suffer from the cross-sectional correlation of abnormal returns that heavily affects their outcome in case of event day clustering that verifies when a single event simultaneously affects all securities included in the analysis. More recent, Kolari and Pynnönen (2010) modifies both Patell and BMP tests, introducing a correction for the cross-correlation and hence proposing the adjusted Patell (AdjPatell) and Kolari and Pynnönen (2010) (KP) tests. For the current setting, KP test is not adequate as this study is dealing with a sample of events that affect one entity, the parent company.

ASSET conveys the parent company size measured by the natural logarithm of total assets deflated using the consumer price index (CPI). Doherty et al., (2012) use this approach as a control variable to test the impact of S&P entry in the insurance rating market -dominated by AM Best- on the information content of ratings. Total Assets is the preferred proxy and Admitted Assets (ADM) are used for robustness. In terms of the expected sign of this variable within the model, literature suggest that for larger firms, abnormal returns should respond less negatively to negative actions (and less positively).

PROFIT of the parent company is measured using two variables, a traditional one, Return on average equity (ROAE) equal to net profit as a percent of average and a more insurance focus one; Loss ratio (LR), equal to the ratio of annual incurred claims and loss adjustment costs to total annual gross premiums earned. Hundt et al., (2017) argues that for investors, a high profitability reduces the negative effects of negative rating actions. Therefore, ROAE should exhibit a positive sign when there is a negative FSR action (LR negative sign) while ROAE should have negative sign when a positive FSR action occurs (LR positive sign).[56]

LEV denotes the leverage of the parent company, calculated using traditional variables such as the relationship between equity as a percent of assets (TE-TA) and, total debt divided by total equity (TD-TE). In general, higher TE-TA ratios reflect how effectively a company fund asset requirements without using debt (the higher the ratio, the less leveraged is the company), whereas higher TD-TE hint companies or stocks with higher risk to shareholders. Adrian et al., (2015) highlight that leverage can be used by P/C insurers as a tool to expand their balance sheet with less strict underwriting guidelines which also rises the risk. Likewise, Hundt et al., (2017) stated that a higher leverage can drive stock prices upward. Thus, it is expected that leverage-based negative FSR actions to cause stronger negative price effects for stocks prices.

LIQ is liquidity measured with the relationship between cash and investments divided by assets as a percentage. Aon Benfield, (2019) includes liquid assets as a percentage (%) of the total assets as one of the possible measures of liquidity, where liquid assets constitute non-affiliated shares, bonds, and cash and readily realizable investments. The financial turmoil in 2008 highlighted the relevance of liquidity suggesting that a stronger exposure to market illiquidity requires a risk premium and thus higher returns (Adrian et al., 2015). In this setting, a parent

[56] Loss ratio is equal to incurred claims divided by net premiums earned. Typically, LR ranges from 60% to 70%. The lower the ratio, the greater potential of profitability.

company with higher liquidity should be in a position to absorb and face negative rating FSR actions events relative to less liquid ones.

DIVER is a variable designed to capture the level of diversification of the parent company. The idea is to determine whether a more diversified parent company will have or not more influence on the CAR. The variable is designed using information from the profile of the parent company obtained on S&P Market Intelligence. To define it, the starting point is the SIC code "6331" (similar to Ben Ammar et al., 2018) where all companies are assumed to be focused on the insurance sector. However, "Industry details" reveal that some parent companies have the same SIC code but some have more than one industry line. Therefore, DIVER is equal to:

- 2 when Industry details → Financials → Insurance
- 1 when the Industry details → Financials → Insurance + 1 additional industry line
- 0 when the Industry details → Financials → Insurance + 2 or more industry lines

For example, Alleghany Corporation has SIC code 6331 as Kemper Corporation. However, it also has real estate, energy and utilities, healthcare, industrials and consumer businesses. More details of the parents can be found in Appendix 7.I.

LARGE is a dummy variable built on an indicator that is constructed by combining changes in notches (up and downs) based on the 20-point numerical scale, and Outlook and Watch assignations (positive and negative) as shown in Table 7.6. Once the indicator is calculated, the dummy is equal to 1 if the absolute value of the indicator is greater or equal to 3, 0 otherwise.

Table 7.6 Magnitude of the change

Indicator of the action	Magnitude of the change
2 notch or more up	+6
2 notch or more up - outlook negative	+5
1 notch up + positive outlook	+4
1 notch up	+3
Positive Watch +	+2
Positive Outlook +	1
Stable or No Watch	0
To stable from positive	0
From negative watch to negative outlook	-1
Negative Outlook -	-1
Negative Watch -	-2
1 notch down	-3
1 notch down – negative outlook	-4
1 notch down – watch outlook	-5
2 notch or more down	-6
2 notch or more down + negative outlook	-7
2 notch or more down + watch negative	-8

This table presents the adjustments that are added (+/-) to the 20-point numerical scale to capture the magnitude of the rating considering the secondary rating actions.

FED funds rate is used as a proxy of a U.S. economic environment. The federal funds rate is the central interest rate in the U.S. financial market influencing other interest rates and, indirectly controlling longer-term interest rates such as mortgages, loans, and savings (Board of Governors of the Federal Reserve System (U.S.)). There is no clear relationship between CARs and the federal fund rate. However, the interest rate can affect the economic environment of the insurance subsidiaries and parents in terms of their investments, liquidity, and leverage position making a company riskier, therefore, impacting the stock market. Indeed, most insurers take premiums from customers and invest them to generate income (especially life insurers) which under a high or low interest rate environment can have a different outcome.

Table 7.7 Variables used in multivariate analysis

Label	Indicator	Details variable	Reference study*
CAR	CAR (dependent) = Average Cumulative Abnormal Return	Cumulative abnormal return of the issuer *k* within the event window [0,+1] using the S&P 500 as a benchmark	Gande and Parsley, (2005), Ferreira and Gama, 2007)
LNTA	Asset = Firm Size	Natural logarithm of Total assets deflated using the consumer price index (CPI)) 2010	Adams et al., (2019), Doherty et al., (2012)
ROAE	Profit = Profitability	ROAE (%): Return on average equity; net profit as a percent of average equity	King et al., (2020) Ben Ammar et al., (2018)
LR		LR = incurred claims / net premiums earned The loss ratio (LR) is defined as the ratio of annual incurred claims and loss adjustment costs to total annual gross premiums earned, so a higher loss ratio results in lower underwriting profits. The lower the ratio, the more profitable the insurance company	Aon Benfield, (2019) Chang (2019)
TE-TA	LEV = Leverage	Total Equity / Total Assets (%) Equity as a percent of assets	King et al., (2020)
TD-TE		Total Debt / Total Equity: All debt, senior and subordinated, as a multiple of equity	Hundt et al., (2017)
LIQ	Liquidity = LIQ	Cash and Investments / Assets (%): Cash and investments as a percent of GAAP assets	King et al., (2020) Aon Benfield, (2019)
FED	Macroeconomic	The federal funds rate is the interest rate at which depository institutions trade federal funds (balances held at Federal Reserve Banks) with each other overnight.	Bae et al., (2015); Caporale et al., (2017)
DIVER	Level of diversification	Variable equal to 2 when industry details of the parent companies is only "Insurance" Variable equal to 1 if parent company has different SIC code and or at least ONE Industry Detail is different than Insurance Variable equal to 0 if parent company has different SIC code or MORE than one additional industry line	Own criteria
LARGE	Large rating actions (magnitude)	Dummy equal to 1 when the absolute value of the Indicator is equal to 3 or more, 0 otherwise	Own criteria

This table presents the entire set of parent company explanatory variables considered in the multivariate analysis, as well as the dependent variable (CARs computed over a [0,+1] event window around each FSR action).

Table 7.7 summarizes the set of explanatory variables considered in the multivariate analysis, as well as the dependent variable represented over a [0,+1] event window (Table A 7.17 in Appendix 7.I adds more prior studies that motivate the selection of each variable). All variables are constructed from parent companies' balance sheet information, on an annual basis, obtained from the S&P Market intelligence database, for the period from 2002 to 2017. Table 7.8 presents the correlation coefficients between the variables employed in the multivariate analysis of negative and positive FSR actions in panel A and B, respectively. No evidence of high and significant correlations is found for any parent company specific variables not hinting potential multicollinearity among explanatory variables. The variables ADM and COMB refer to admitted assets and combined ratio added for robustness to compared with the behaviour of the chosen variables but neither are used in the estimation included in the multivariate analysis.

Table 7.8 Correlation matrix

Panel A. Negative FSR actions – All CRAs

	CAR	LNTA	ADM	ROAE	TETA	TDTE	LIQ	COMB	LR	DIVER	LARGE	FED
CAR	1											
LNTA	0.01	1										
ADM	0.06	0.86	1									
ROAE	0.02	-0.14	-0.08	1								
TETA	0.13	-0.27	-0.11	0.17	1							
TDTE	-0.07	0.54	0.40	-0.38	-0.43	1						
LIQ	-0.08	-0.32	-0.26	0.03	0.12	0.06	1					
COMB	0.04	0.03	-0.17	-0.20	-0.02	-0.01	-0.10	1				
LR	-0.05	0.22	-0.01	-0.03	-0.19	0.18	-0.02	0.56	1			
DIVER	-0.06	-0.21	-0.11	-0.07	-0.38	0.19	0.24	-0.09	0.06	1		
LARGE	0.09	-0.02	0.02	-0.06	0.07	0.03	0.11	0.01	-0.06	0.00	1	
FED	-0.04	0.02	0.10	0.16	-0.11	0.18	0.14	-0.33	-0.13	0.14	-0.02	1

Panel B. Positive FSR actions – All CRAs

	CAR	LNTA	ADM	ROAE	TETA	TDTE	LIQ	COMB	LR	DIVER	LARGE	FED
CAR	1											
LNTA	0.05	1										
ADM	-0.02	0.87	1									
ROAE	-0.31	-0.24	-0.12	1								
TETA	-0.07	-0.25	0.02	0.22	1							
TDTE	0.20	0.39	0.21	-0.60	-0.35	1						
LIQ	-0.12	-0.29	-0.24	0.09	0.29	0.01	1					
COMB	0.05	0.21	0.03	-0.22	-0.30	0.23	-0.25	1				
LR	0.07	0.24	0.01	-0.20	-0.37	0.24	-0.23	0.73	1			
DIVER	0.06	-0.18	-0.13	0.01	-0.30	0.07	0.05	-0.24	-0.02	1		
LARGE	0.04	-0.03	0.08	0.10	0.22	-0.18	0.00	-0.18	-0.17	0.04	1	
FED	0.02	-0.12	-0.06	0.15	0.00	0.04	0.02	-0.11	-0.10	0.09	0.02	1

This table shows the simple pairwise correlation coefficients between the variables for the stock market. Sample period: Jan. 2003- Dec. 2017.

Table 7.9 reports the descriptive statistics on the variables for negative and positive FSR actions, respectively

Table 7.9 Descriptive statistics

Panel A – Negative FSR actions					
Variable	Obs.	Mean	Std. Dev.	Min	Max
CAR	223	-1.28	5.39	-50.5	19.8
CAR2	223	-1.20	5.23	-49.1	17.9
CAR3	223	-1.10	5.24	-47	13.52
CAR4	223	-1.13	5.07	-48.8	17.34
LNTA	223	17.46	1.82	14.2535	21.01
ADM	116	16.56	1.60	13.72	19.23
ROAE	223	7.40	12.75	-130.68	31.53
TETA	223	23.11	12.09	3.25	62.24
TDTE	223	0.42	0.44	0.00	3.26
LIQ	223	65.51	13.31	29.36	88.31
LR	218	72.01	15.51	24	117.99
COMB	195	98.43	10.65	30.23	128.87
DIVER	223	1.35	0.80	0	2
LARGE	223	0.37	0.48	0	1
FED	223	2.02	1.72	0.09	5.02

Panel B – Positive FSR actions					
Variable	Obs.	Mean	Std. Dev.	Min	Max
CAR	277	0.41	3.80	-8.00	47.80
CAR2	277	0.39	3.83	-8.00	48.10
CAR3	277	0.48	3.96	-6.67	48.20
CAR4	277	0.47	3.98	-8.30	47.49
LNTA	277	17.32	1.53	14.59	20.81
ADM	251	16.25	2.67	13.77	19.62
ROAE	277	9.17	14.17	-130.68	31.53
TETA	277	22.08	9.98	0.00	62.24
TDTE	277	0.35	0.37	0.00	3.26
LIQ	277	66.81	12.89	0.00	88.31
LR	273	69.42	15.84	18.13	129.20
COMB	248	96.24	10.57	52.50	150.50
DIVER	277	1.43	0.79	0.00	2.00
LARGE	277	0.35	0.48	0.00	1.00
FED	277	1.58	1.71	0.09	5.02

This table presents the summary statistics of the financial variables associated to the parent companies associated to the 527 FSR actions for the period January 2003 to December 2017. Notice that the total number of observations (positive and negative) is less than 527 due to availability of the accounting data. For the definition of the variables see Section 7.4. Obs. stands for observations, Std. Dev. is standard deviation. CAR refers to the average cumulative abnormal return calculated using S&P 500 P/C as a benchmark. CAR2 uses Dow Jones U.S. P/C (DJUSIP). CAR3 uses NASDAQ Insurance Index (INSR) as a benchmark and CAR4 use the S&P 1500-4030 index as a market reference.

7.5 Empirical results

This section uses the event study methodology to measure and test the parent companies' stock price reaction to FSR actions of U.S. P/C subsidiaries. The benchmark for a normal market return presented here is the S&P 500 P/C; however, the analysis also includes the three additional benchmarks mentioned in section 7.3.3 (see Appendix for results using the other indexes in detail). Results do not vary largely considering a different market reference.

To draw meaningful insights from the results, the event study is run in two steps. In the first step, the effect of negative and positive FSR actions are analysed, while in the second stage, the event study is conducted by subsamples: positive (negative) Watch actions, positive (negative) Outlook, upgrades (downgrades), and combined positive (negative) actions as shown in Table 7.3 of Section 7.3.

7.5.1 Univariate analysis

Table 7.10 presents the average CARs around negative FSR actions, while Table 7.11 around positive FSR actions. CARs are evaluated over the pre-event [-10, -1], event [0, +1] and the post-event [+2, +11] windows. Likewise, standard errors are calculated following the traditional cross-sectional t-test, Boehmer et al.'s (1991) (BMP) standardized cross-sectional test, and the proportion of the sign of the CAR as a non-parametric method to check significance of the CARs.

7.5.1.1 Impact of the negative FSR actions

Table 7.10 shows that the impact of negative FSR actions on abnormal returns is negative and statistically significant in the event window [0,+1] for S&P, Moody's, and Fitch at -1.1%, -1.2% and -1.9%, respectively, but not significant for AM Best (CAR at -1% for all FSR actions). In terms of anticipation/leakage of FSR actions, the results show (alongside Figure 7.4(a)) that there is anticipation of negative FSR actions from Moody's and Fitch as the CARs in the pre-event window are significant and negative. These findings seem to be aligned with Hill and Faff (2010) as well as with Milidonis (2013). The latter conclude that the major CRAs are usually slow to downgrade stocks, but when they do, the market drops before the announcement and reverses in the few days after the announcement. Moreover, they also concur with Wade et al., (2015) who noticed that at least for short sellers, a decrease 2 days prior to downgrades, suggesting that informed trading occurs during the pre-downgrade period. By type of FSR actions, negative Outlooks are driving S&P overall results. The two-day event window CAR is -3% for negative Outlook actions, and statistically significant at the 10% level.

The impact of downgrades, negative Watch and negative combined actions are weaker and statistically insignificant, although the CARs are all negative in the two-day event window. There is also evidence of a delayed reaction to negative Outlook actions by S&P, with a post-event window CAR of -3.7% that is statistically significant at the 5% level.

For Moody's, negative Watch, negative Outlook and downgrade actions have a very similar impact with event window CARs of -2.3%, -1.6% and -1.6%, respectively. However, these coefficients are not statistically significant. There is evidence that there is more anticipation to Moody's downgrade actions, with a pre-event window CAR of -3.6%, compared to -1.1% and -1.2% for negative Watch and negative Outlook, respectively. But again, these coefficients are not supported by statistical significance. Following negative Watch actions by Moody's there appears to be a reversal in the share prices, with a statistically significant post-event window CAR of +3.3%. The finding of a significant pre-event and post-event CAR relate to similar results in Hill and Faff (2010). They suggested that Watch actions might be more timely thus invoking a greater reaction to the leaked news, the significance of the pre-event window may be indicating that CRAs are reacting to the stock market rather than vice versa, and contrary to ours, their post-event CAR is insignificant. The insignificance suggests that the causality is from rating actions to the stock market.

Regarding Fitch, an event window CAR of -4.1% (significant at 1%) suggests that negative Watch actions have the strongest market impact from any FSR action type by any CRA. Negative Outlook actions by Fitch are associated with an event window CAR of -2.2% which is significant. In the pre-event window, the CAR is -3.3% for negative Watch actions and -5.1% for negative Outlook actions, and statistically significant only for the negative Outlook. This is evidence of either anticipation of these types of negative rating actions or that these actions happen during a time of other negative news. But the pre-event window CARs does not detract from the negative actions themselves having an immediate and significant impact during the two-day event window. The insignificant post-event CARs for negative Watch and negative Outlook, suggests that the market is reacting to the actual FSR actions. For downgrade and combined actions, there is no evidence of significant market impact in the event CARs. The pre-event window CAR coefficients are more negative than the event CARs at -3.9% and -3.2%, for downgrade and combined actions, respectively, however they are not statistically significant.

For AM Best the event window CARs of -1.4%, -0.2% and -4.4%, are in the expected direction with for negative Outlook, downgrade and combined actions, respectively, although they are not significant. It is for the negative combined actions that the CAR is close to the 10% significant level with the BMP test. The pre-event CARs of +0.1% and +0.2% for negative Outlook and downgrade actions is evidence that there is no market anticipation of these types of AM Best negative rating actions. The pre-event CAR of -5.7% is found for negative combined actions, suggesting that these actions are either anticipated or happed during a time of other negative news for the parent, but this coefficient is statistically insignificant. The event window CAR is positive and insignificant for negative UR actions. The results indicate that FSR actions from AM Best generally do not yield significant market reactions in terms of CARs. This seems to be aligned with what is found from Singh and Power (1992) who concludes that AM Best fulfils a certification role for insurers while rating changes are a non-event in terms of new information transferred to the market. More recent, Miao et al., (2014) also finds no stronger AM Best results within the bond insurance market whereas Halek and Eckles (2010) do find ratings actions from AM Best yielding stronger results in terms of CARs than those of S&P or Moody's. The difference in results may be due to the fact on the definition of good and bad news relative to the definitions of positive and negative FSR used in this Chapter.[57]

7.5.1.2 Impact of the positive FSR actions

Table 7.11 displays the market reaction for all positive FSR actions. Across CRAs, no significant positive CARs are found for the pre- [−10, -1], and event windows [0, +1] for positive actions by Moody's and AM Best. However, there are significant CARs in the pre-event window for S&P and in the post-event window [+2, +11] for Fitch.

For S&P, the whole sample of positive FSR actions provide a negative CAR at -1% in the pre-event but a positive and not insignificant CAR of 0.2% in the event window. By type of action, the strongest market reaction is found in the pre-event window to positive Outlook actions with a negative and significant CAR at -1.5%. Although positive Watch action have no significant CARs, it has the highest values across windows (0.9% in the event window). Peculiarly, upgrades have positive CARs in the pre-event and event windows but negative ones in the following 10 days after the event. For both, Outlook and Watch actions, CARs in the post-

[57] Halek and Eckles (2010) classifies events as "no news," "good news," or "bad news." For AM Best, they utilize "A−" ("excellent") as threshold to determine if an event is classified as such, for S&P, they use "AA−" ("very strong") and for Moody's they use "Aa3" ("excellent"). For example, if an insurers' AM Best rating drops from a prior rating of "A−" to a current rating of "B+" on a reported effective date, this is categorized as a bad-news event.

event window are still positive and not significant, suggesting a weak but persisting effect. A possible explanation to higher CARs in the pre-event window may be as Holthausen and Leftwich(1986) suggest that firms may have an incentive to leak positive information to the market prior to an upgrade, but no incentive to do so for a downgrade.

For Moody's, results for all sample are similar to S&P, the t-value, and BMP test exhibit a negative CAR at -0.4% in the pre-event window and a higher positive CAR at 0.9% in the event window. Post-event window CAR (0.8%) is lower than S&P; however, they are all insignificant. This suggests that investors receive the positive news but not necessarily have an impact on the marketplace. Similar to S&P, Watch actions seem to be driving the market reaction with CAR at 0.11% and combined actions at 2.3% but again both are insignificant. For upgrade actions, odd results are found since negative CARs are found in all event windows, which may be an insight of delayed market reactions.

Fitch's results differ from Moody's and S&P. For all positive FSR actions, unexpected signs are obtained because negative CARs are found in the pre-event and event windows denoting that FSR actions by Fitch may have a delayed positive effect on parent companies' share prices. Collectively, the CAR in the post-event window is positive and significant. By subsample, positive Watch, Outlook and combined actions have positive CARs but not significant in the event window with CARs at 0.1%, 0% and 1%, respectively. On the contrary, upgrades are showing a negative sign in the event window and a positive few days after the positive FSR action. For AM Best, the event window CARs are positive for all types of positive rating actions, and most noteworthy is the event CAR of +0.6%, which is significant at the 1% level, is found for upgrade actions. This is evidence that upgrade actions by AM Best provide timely and new information to the stock market. For the pre- and post-event window CARs, no significant results are found for positive FSR actions by AM Best.

Figure 7.4 plots the CARs (in percentage) over the entire event window for FSR actions from all four CRAs. Panel a (Panel b) shows the CARs associated with negative (positive) FSR actions for S&P, Moody's, Fitch and AM Best. Figure 7.4 illustrates that the strongest market reaction is to negative FSR actions by Fitch, where the largest negative CARs are found, follow by Moody's and AM Best (when includes under review actions). Furthermore, Figure A 7.2 in Appendix 7.II exhibits the CARs by Watch, Outlook, downgrade/upgrade, and combined actions where important results arise by type of rating action. Figure A 7.2 confirms that negative Watch actions, as well as negative Outlook actions by Fitch, have the strongest market impact compared to the other three CRAs. However, it also highlights the fact that downgrade actions by Moody's and Fitch generate the most negative CARs, while for AM Best is the negative combined actions that generate the most negative CARs. Interesting, Figure A 7.2 suggests that positive Outlook and positive combined actions by Moody's and Fitch unveil higher CARs than the other CRAs. Only with upgrade actions, S&P and AM Best display higher percentages

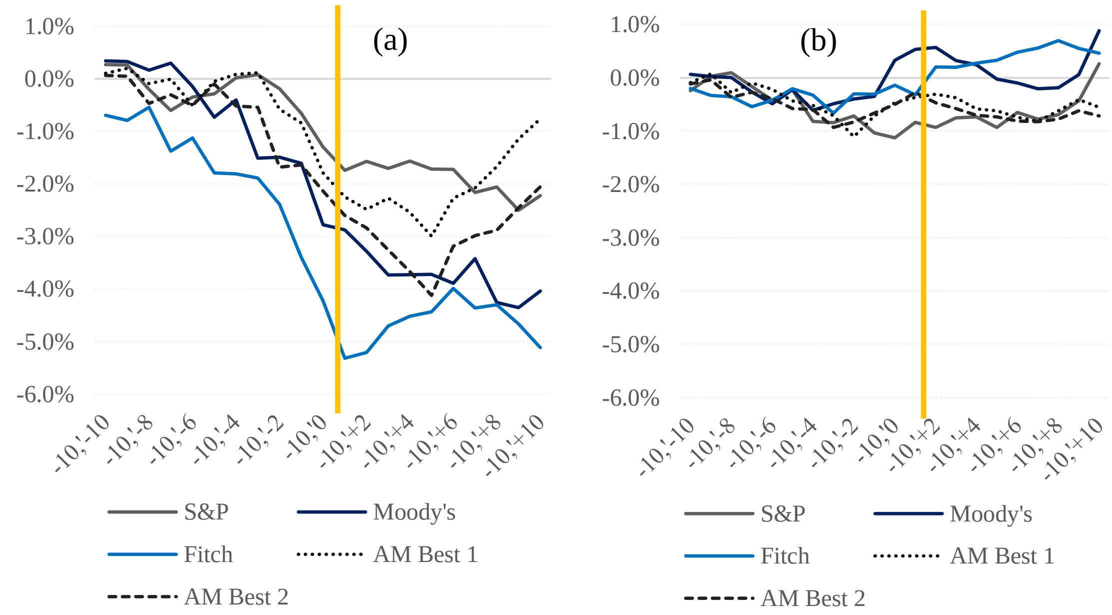

Figure 7.4 Cumulative abnormal return for all negative and positive actions

This figure shows the average cumulative abnormal returns (CARs) based on market-model abnormal returns for S&P, Moody's, Fitch and AM Best in the event window [-10,+10] for the 30 parent companies associated to 346 U.S. P/C insurers. 'AM Best 1' does not consider the under review (UR) FSR actions and 'AM Best 2' includes them. Business days around the event are shown on the horizontal axis and the average CARs in percent on the vertical axis.

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Table 7.10 Market impact of negative FSR actions

	CARs around S&P's actions				CARs around Moody's actions				CARs around Fitch's actions				CARs around AM Best's actions			
	N	[-10,-1]	[0,+1]	[+2,+11]	N	[-10,-1]	[0,+1]	[+2,+11]	N	[-10,-1]	[0,+1]	[+2,+11]	N	[-10,-1]	[0,+1]	[+2,+11]
All	98				40				39							
CAR		-0.007	-0.011	-0.005		-0.015	-0.012	-0.013		-0.034	-0.019	-0.010		-0.016	-0.010	0.005
t-test		-0.741	-1.726*	-0.620		-1.072	-1.780*	-0.734		-1.527	-3.256***	-0.647	58	-1.105	-1.389	0.525
BMP		-0.011	-1.904*	-0.818		-1.941*	-1.465	-0.353		-2.292***	-2.531**	-0.747		-0.718	-1.261	-0.272
Sign		45/98	47/98	48/98		24/40	21/40	19/40		26/39	29/39	25/39		29/58	38/58	30/58
Watch	28															
CAR		-0.010	-0.002	-0.018	11	-0.011	-0.023	0.033		-0.033	-0.041	-0.012		NA	NA	NA
t-test		-0.862	-0.202	-0.966		-0.494	-1.480	2.164*	10	-1.212	-3.293***	-0.330	NA	NA	NA	NA
BMP		-1.136	-0.624	-0.077		-0.891	-1.147	2.008*		-1.002	-3.291***	-1.600		NA	NA	NA
Sign		15/28	12/28	13/28		7/11	6/11	2/11		7/10	9/10	6/10		NA	NA	NA
Outlook																
CAR		-0.031	-0.030	-0.037		-0.012	-0.016	-0.002		-0.051	-0.022	-0.014		0.001	-0.014	-0.001
t-test	36	-1.034	-1.963*	-1.393	16	-1.126	-1.413	-0.328	14	-1.908*	-2.494*	-0.793	18	0.070	-1.206	-0.085
BMP		-0.687	-1.796*	-2.053**		-0.581	-1.258	0.271		-2.537**	-1.791*	-0.037		-0.016	-1.179	-0.295
Sign		17/36	17/36	24/36		10/16	9/16	7/16		10/14	12/14	8/14		11/18	12/18	9/18
Downgrades																
CAR		0.029	-0.001	-0.009		-0.036	-0.016	-0.108		-0.039	-0.010	0.030		0.002	-0.002	0.016
t-test	7	1.082	-0.200	-1.109	5	-0.972	-1.252	-1.545	4	-0.195	-0.794	0.301	16	0.306	-0.345	1.241
BMP		1.042	-0.139	-1.426		-0.922	-0.993	-1.604		-0.876	-0.850	0.616		0.089	0.017	0.768
Sign		3/7	4/7	4/7		3/5	3/5	3/5		3/4	2/4	3/4		8/16	10/16	6/16
Combined																
CAR		-0.024	-0.005	0.019		-0.005	0.010	-0.033		-0.032	-0.002	-0.013		-0.057	-0.044	0.053
t-test	27	-0.910	-0.881	0.956	8	-0.082	0.743	-0.439	11	-1.273	-0.161	-0.783	7	-0.899	-1.209	1.489
BMP		0.296	-1.527	0.308		-0.927	0.960	-0.442		-1.082	-0.551	-0.609		-0.330	-1.911	1.516
Sign		13/27	15/27	7/27		4/8	4/8	4/8		4/11	5/11	4/11		3/7	5/7	2/7
Under R.													17			
CAR														-0.036	0.001	-0.019
t-test														-0.922	0.083	-1.225
BMP														-0.773	-0.037	-1.391
Sign														7/17	11/17	13/17

*This table presents the results of the cumulative abnormal returns (CARs) around the time of subsidiaries negative FSR actions by S&P, Moody's, Fitch and AM Best to 30 parent companies in the period 1st January 2003 to 31st December 2017. See list of parent companies in Table 7.4. This table reports the 10-day pre-event [−10, −1], the two-day event [0, +1] and the 10-day post-event [+2, +11] window CARs. Parametric tests are the cross-sectional t-test (t-test) and the Boehmer et al. (1991) (BMP), reported beneath each CAR coefficient. As a non-parametric test, 'Sign' refers to the proportion of CARs with positive (negative) sign, respectively. *** Significant at 1% level, ** Significant at the 5% level, * Significant at the 10%.*

Table 7.11 Market impact of positive FSR actions

	CARs around S&P's actions				CARs around Moody's actions				CARs around Fitch's actions				CARs around AM Best's actions			
	N	[-10,-1]	[0,+1]	[+2,+11]	N	[-10,-1]	[0,+1]	[+2,+11]	N	[-10,-1]	[0,+1]	[+2,+11]	N	[-10,-1]	[0,+1]	[+2,+11]
All	102				72				36							
CAR		-0.010	0.002	0.013		-0.004	0.009	0.008		-0.003	-0.0001	0.010		-0.007	0.004	-0.005
t-test		-1.783*	0.809	1.558		-0.544	1.194	0.703		-0.447	-0.041	2.020**	82	-1.575	1.123	-1.285
BMP		-1.698*	0.876	0.962		-0.130	1.067	-0.489		-0.381	-0.426	1.645		-0.942	1.055	-1.288
Sign		49/102	51/102	60/102		35/72	39/72	36/72		14/36	17/36	21/36		36/82	45/82	37/82
Watch	20															
CAR		-0.023	0.009	0.051	19	-0.024	0.011	0.035		-0.021	0.001	0.018		NA	NA	NA
t-test		-1.047	1.202	1.324		-1.071	1.295	0.863	5	-0.619	0.099	1.063	NA	NA	NA	NA
BMP		-1.208	0.979	1.454		-0.375	0.927	-0.120		-1.753	-0.384	-0.111		NA	NA	NA
Sign		10/20	11/20	12/20		7/19	11/19	8/19		1/5	2/5	3/5		NA	NA	NA
Outlook																
CAR		-0.015	0.002	0.008		0.006	0.002	0.000		-0.004	0.000	0.009		-0.013	0.001	-0.004
t-test	57	-2.499**	0.651	1.262	31	0.837	0.879	0.017	19	-0.441	-0.116	1.426	34	-1.392	0.150	-0.676
BMP		-2.238**	0.718	0.828		0.622	0.848	-0.185		-0.457	-0.074	1.703		-1.345	-0.007	-0.637
Sign		23/57	28/57	30/57		15/31	20/31	18/31		6/19	11/19	12/19		15/34	14/34	13/34
Upgrades																
CAR		0.016	0.001	-0.004		-0.005	-0.001	-0.007		0.005	-0.004	0.012		0.005	0.006	0.000
t-test	6	0.627	0.187	-0.443	6	-0.721	-0.542	-1.085	8	0.422	-1.515	1.048	26	0.994	3.042***	0.023
BMP		0.198	0.522	-0.375		-0.473	-0.341	-1.051		0.527	-1.546	1.004		1.132	2.903***	-0.151
Sign		3/6	5/6	4/6		3/6	2/6	1/6		4/8	3/8	4/8		14/26	18/26	15/26
Combined																
CAR		0.000	-0.005	-0.003		0.001	0.023	-0.005		0.006	0.010	0.007		-0.009	0.009	-0.011
t-test	19	0.064	-0.844	-0.401	16	0.140	0.762	-0.678	4	0.879	1.772	0.809	15	-1.406	1.104	-1.667
BMP		-0.130	-0.276	-1.000		-0.497	0.542	-0.357		1.087	1.606	0.821		-0.559	1.190	-1.415
Sign		7/19	10/19	8/19		9/16	7/16	8/16		2/4	4/4	3/4		4/15	10/15	6/15
Under R.													7			
CAR														-0.023	0.001	-0.007
t-test														-1.618	0.108	-0.469
BMP														-1.206	-0.129	-0.523
Sign														2/7	3/7	4/7

*This table presents the results of the cumulative abnormal returns (CARs) around the time of subsidiaries positive FSR actions by S&P, Moody's, Fitch and AM Best to 30 parent companies in the period 1st January 2003 to 31st December 2017. See list of parent companies in Table 7.4. This table reports the 10-day pre-event [−10, −1], the two-day event [0, +1] and the 10-day post-event [+2, +11] window CARs. Parametric tests are the cross-sectional t-test (t-test) and the Boehmer et al. (1991) (BMP), reported beneath each CAR coefficient. As a non-parametric test, 'Sign' refers to the proportion of CARs with positive (negative) sign, respectively. *** Significant at 1% level, ** Significant at the 5% level, * Significant at the 10%.*

7.5.1.3 Overview of the univariate results:

Results are summarised in Table 7.12 varying across CRAs and event windows. There is mixed evidence about the impact of FSR actions on the parent companies' share prices. Consistent with prior literature, results from negative FSR actions confirm that CRAs are pertinent in providing new and relevant information to the stock market while the impact of positive FSR actions is not as strong. Indeed, the average CAR from positive FSR actions is significantly smaller (ranging from -0.0001 to 0.009) than the average CAR of negative ones (ranging from -0.19 to 0.010) in the event window.

In reference to the significance of the CARs, the traditional parametric statistical tests (t-test and BMP) versus the non-parametric ones (sign test) suggest that significance seems to be arising from the magnitude of the reaction rather than the sign of the CARs, which the non-parametric method does not capture. By CRA, the strongest market reaction is to negative FSR actions by Fitch, where the largest negative CARs are found. For S&P, the market reaction is to negative Outlook while for Moody's the market reacts to negative Watch actions. For AM Best, there is somewhat muted evidence that markets react to negative FSR actions. For positive FSR actions, there is a slight significant reaction to AM Best's FSR actions, specifically to upgrades, whilst there is again somewhat muted evidence that the market reacts to these FSR actions by S&P, Moody's and Fitch.

Table 7.12 Summary of univariate analysis

CRA	Negative FSR actions	Positive FSR actions
S&P	The average CAR is negative pre [-10,-1], during [0,+1] and post-event [+2,+11] but only significant in the event window (both tests)	The average CAR is negative and significant (T-test and BMP) in the [-10,-1] pre-event window possibly driven by outlook actions. CARs are positive yet no significant for the event and post-event windows [0,+1], [+2,+11]
Moody's	The average CAR is negative and significant pre-, event and post-event but only significant in the event window (T-test*)* and pre-event window (BMP) at 10% level. This suggests some information leaking and the effect of negative FSR actions remain.	The average CARs values are negative and not significant for the [-10,-1] pre-event window of the all FSR actions sample but positive for outlook and combined actions. This possibly indicates a leak of information for this type of rating action.
Fitch	The average CARs are negative and significant pre-, event, and post-event window (T-test*)* and pre-event window (BMP) at 1% level with a stronger negative -3.4%. This indicates some information leaking and the effect of negative FSR actions remain.	The average CARs values are negative but not significant in the pre-event [-10,-1] and event window but positive in the post-event window, suggesting delayed market reaction
AM Best	The average CARs are negative and significant pre-, event and post-event window but none is significant. The value of the CAR pre-event is -1.6% when under review actions are included	The average CARs values are negative but not significant (T-test and BMP) in the pre-event window. It seems to be a reversal effect in the post-event window. Upgrades are the only type of action with positive and significant CARs.

This table reports the main findings of the univariate analysis developed in this section.

7.5.2 Multivariate analysis

This section discusses the results of the regression model in Eq. (7.4). Table 7.13 and 7.14 compile the reaction towards the full set of negative and positive FSR actions by all CRAs. From Table 7.15 to Table 7.22, regression results are CRA specific, i.e., S&P, Moody's, Fitch, and AM Best. The dependent variable is the average CAR calculated over a 2-day event window using robust standard errors to control for clustering at the company level.

For all multivariate regressions, the impact of FSR actions on CARs, ceteris paribus, is captured by the constant (C), the magnitude of the FSR action is captured by the dummy LARGE, and the level of diversification of the parent company is captured through the dummy, DIVER. All regressions use specific parent company characteristics (size, profitability, liquidity, and leverage) varying the proxy or measure employed. These explanatory variables may have been known months ahead of the FSR action, but the stock market could have considered some of these as drivers. In Tables 7.14 to 7.23, the coefficients in columns 1 and 2 include traditional firm variables (ASSET, ROAE, LIQ, TE-TA, TD-TE). Column 1 omits macroeconomic conditions (FED) while column 2 includes them. For multivariate regressions in columns 3 and 4, instead of using ROAE as a profitability measure, it uses an insurer-specific variable, LR (since the majority of the parent companies are insurers), and to measure leverage, columns alternate between TD-TE and TE-TA, respectively. For regressions in columns 5 and 6, both ROAE and LR are included as a proxy of profitability but column 5 uses TD-TE whereas column 6 uses TE-TA as a proxy for leverage.

7.5.2.1 Regression results for negative and positive FSR actions – all CRAs

On the multivariate regressions of all negative FSR actions, TE-TA (proxy of leverage) yields positive and significant coefficients at a 10% level in all columns while TD-TE (also a proxy of leverage) is negative and not significant. If higher leverage is associated with driving stock prices upwards, then negative FSR actions are expected to have stronger negative price effects in firms with higher leverage. Thus, for the multivariate regressions in columns 1, 2, 4, and 6; TE-TA exhibits the expected positive sign in the scenario of negative FSR actions since the greater the ratio, the less leveraged is the company. TD-TE in columns 3 and 5 also has the envisaged negative sign as the greater the ratio, the more aggressive is the company in financing its growth with debt. This means that, in a scenario of negative FSR actions combined with high leveraged parent companies, investors tend to react more sensitively to negative FSR actions. Furthermore, parent company size (LNTA) is positive as expected but insignificant while the magnitude of the actions (LARGE) is showing conflicting results. Contrary to what is expected, coefficient LARGE is positive, and significant in columns 3, 4, and 5. This indicates that negative FSR actions with greater magnitude have a weaker impact (less negative) relative to FSR actions with smaller notch changes according to the 20-point numerical scale.

Connecting these results with the parent – subsidiary transmission channels (see section 7.2.3), the results highlight how FSR actions are providers of information to the stock market, especially via the entity-based related source, and market impact can be enlarged by parent company characteristics such as leverage. The exposure channel plays a modest role on the basis of this evidence, where the direct and indirect linkages by one or more insurance subsidiary, could spillover to other agents that they are exposed to them.

Table 7.13 Determinants of CARs for negative FSR actions – all CRAs

Negative	Exp. sign	(1) CAR	(2) CAR	(3) CAR	(4) CAR	(5) CAR	(6) CAR
C		-2.163	-2.203	-0.969	-2.406	-1.043	-2.408
		(5.490)	(5.621)	(4.858)	(5.466)	(4.728)	(5.398)
LNTA	+	0.0887	0.0923	0.166	0.147	0.171	0.147
		(0.215)	(0.225)	(0.257)	(0.271)	(0.261)	(0.236)
ROAE	+	0.00278	0.00384			-0.00398	0.000112
		(0.026)	(0.025)			(0.028)	(0.030)
LR	-			-0.0136	-0.00958	-0.0134	-0.00959
				(0.043)	(0.042)	(0.043)	(0.025)
TE-TA	+	0.0673*	0.0667*		0.0702*		0.0702**
		(0.037)	(0.034)		(0.036)		(0.037)
TD-TE	-			-1.058		-1.120	
				(0.938)		(0.924)	
LIQ	-	-0.0436	-0.0428	-0.0328	-0.0487	-0.0326	-0.0487
		(0.030)	(0.031)	(0.033)	(0.031)	(0.033)	(0.031)
DIVER	-	0.182	0.190	-0.0759	0.266	-0.0747	0.266
		(0.415)	(0.425)	(0.362)	(0.420)	(0.363)	(0.548)
LARGE	-	1.006	1.003	1.169*	1.086*	1.165*	1.086
		(0.648)	(0.644)	(0.640)	(0.632)	(0.635)	(0.772)
FED	-		-0.0402	-0.0167	-0.00490	-0.00885	-0.00509
			(0.284)	(0.343)	(0.322)	(0.351)	(0.229)
Obs.		223	223	218	218	218	218
R^2		0.035	0.035	0.027	0.040	0.027	0.040
Adj. R^2		0.008	0.004	-0.005	0.008	-0.010	0.003

*This table presents the coefficient estimates of Eq. (7.4). Coefficients are based on all CRAs FSR actions from 2003 to 2017. The model estimates the relationship between the CAR [0, +1] and parent companies' characteristics. The values in parentheses are robust standard errors. *** Significant at 1% level, ** Significant at 5% level, *Significant at 10% level.*

The rest of the coefficients in Table 7.13 do not provide any evidence of significant price impact. First, ROAE (a proxy for profitability) yields a positive coefficient in a range of a range of 0.000112 to 0.00384 (except -0.00398 in column 3), LR (insurer-specific proxy) is negative in columns 4 to 6, ranging from -0.00959 to -0.0134, but none are significant. Despite not being significant, the sign of these coefficients supports the view that the higher the profitability the less response is caused by negative FSR actions. Second, LNTA (proxy for company size) in all columns is positive as expected but does not provide statistically significant evidence that the market impact of negative FSR actions is stronger in larger firms. LIQ (a proxy for liquidity) exhibits an expected negative sign but is not significant. Third, diversification and macroeconomic conditions seem extraneous in the scenario of negative FSR actions, implying that no matter how tight the FED monetary policy; the information diffuses in the stock prices progressively when FSR actions are announced.

Table 7.14 Determinants of CARs for positive FSR actions – all CRAs

Positive	Exp.	(1)	(2)	(3)	(4)	(5)	(6)
	sign	CAR	CAR	CAR	CAR	CAR	CAR
C		4.370	3.984	5.601	0.521	5.345	3.807
		(5.196)	(5.141)	(3.490)	(4.678)	(3.243)	(4.477)
LNTA	-	-0.105	-0.0933	-0.229*	0.0284	-0.174	-0.111
		(0.160)	(0.160)	(0.128)	(0.191)	(0.110)	(0.172)
ROAE	-	-0.0863***	-0.0885***			-0.0791**	-0.0885***
		(0.022)	(0.022)			(0.039)	(0.021)
LR	+			0.00401	0.0128	0.00211	0.00561
				(0.022)	(0.018)	(0.020)	(0.017)
TE-TA	-	0.0132	0.0136		-0.00343		0.0146
		(0.019)	(0.019)		(0.020)		(0.016)
TD-TE	+			2.539**		0.593	
				(1.078)		(1.439)	
LIQ	+	-0.0345	-0.0343	-0.0429	-0.0311	-0.0341	-0.0336
		(0.034)	(0.034)	(0.035)	(0.034)	(0.031)	(0.033)
DIVER	+	0.348**	0.327**	0.162	0.305*	0.219	0.315*
		(0.169)	(0.164)	(0.205)	(0.176)	(0.219)	(0.167)
LARGE	+	0.469	0.475	0.639	0.361	0.588	0.484
		(0.639)	(0.640)	(0.606)	(0.687)	(0.565)	(0.686)
FED	+		0.134	0.0215	0.0722	0.141	0.163
			(0.114)	(0.102)	(0.111)	(0.113)	(0.115)
Obs.		277	277	273	273	273	273
R^2		0.116	0.120	0.070	0.024	0.122	0.121
Adj. R^2		0.097	0.097	0.045	-0.002	0.095	0.094

This table presents the coefficient estimates of Eq. (7.4). Coefficients are based on sub-sample of all CRAs positive FSR actions from 2003 to 2017. The model estimates the relationship between the CAR [0, +1] and parent companies' characteristics. The values in parentheses are robust standard errors. ∗ Significant at 10%, ∗∗ Significant at 5%, ∗∗∗ Significant at 1%.

Turning to the joint results for all CRAs positive FSR actions, Table 7.14 shows that ROAE yields a negative coefficient oscillating from -0.0791 to -0.0885 that is statistically significant at the 1% level in all columns, while LR is positive (as expected) but does not appear significant. This is suggesting that when positive FSR actions land in the market, the impact is weaker (stronger) on the share price of parent companies with comparatively higher (lower) profitability. Likewise, leverage is exhibiting the expected sign, but only in column 3, TD-TE has a positive coefficient (+2.539) significant at 5%. Further, the dummy for diversification DIVER suggests that parent companies exclusively engaged in the P/C market (less diversified) have a greater reaction to positive FSR actions (significant at 1% level) relative to parent companies with additional business activities outside the P/C industry (such as healthcare, real state, energy, etc.).

These results highlight some evidence of the parent-subsidiary transmission channels explained in section 7.2.3. For instance, one of the indirect systemic risk sources comes from activity-based related aspects. The fact that there is less reaction to positive FSR actions from parent companies with more diversification, seems to be indicate that the market is aware that insurers may be engaging in certain activities or products with greater potential to pose systemic risk. Thus, the information via FSR assigned by CRAs plays a key role as providers of information to the stock market as well as in the effort to contribute to the control of the systemic risk.

Analogous to the effect of negative FSR actions, liquidity, and macroeconomic conditions do not seem to enlarge the market impact of positive FSR actions. Lastly, the magnitude of the positive FSR actions (LARGE) does not seem to have a significant effect and, despite the coefficient LNTA is negative as expected, there is only weak evidence that it has an effect. In column 3, the coefficient on LNTA is negative and significant at the 10% level, suggesting the market impact of positive FSR actions is weaker for larger firms. In the remaining five columns (columns 1-4 + 6) there is no statistically significant evidence that size has any influence, although the sign of the coefficient is negative in all but column 4.

Surprisingly, no significant price effect is detected during periods of high or low-interest rate. Including the variable FED does not alter the sign of the coefficient-comparing columns 1 and 2. While the outcome of interest rate changes may be uncertain, historical investigations have revealed that the overall trend is for the profitability of the insurance sector to increase in an environment of rising interest rates. During 2003-2017, the trend of FED interest rate was initially rising but it has a sudden drop since 2008, as a response to the financial crisis, keeping levels from 0.12-0.16 (see Figure A 7.3).

The outcome relative to the FED is coherent with Hundt et al., (2017) findings. They did not detect any significant price effect of rating actions announced during either of the economic downturns for the bond market. Furthermore, this is agreeing with the findings in Chapter 5, where the impact of the 2008-2009 crisis on P/C insurers shown to be relatively muted, compared to other sectors where they have been severe (Baluch et al., 2011). Likewise, Ben

Ammar et al., (2018) states that the most significant aspect that affects the profitability of P/C insurers might be incurred disaster losses and other non-projected losses and that stock returns should not be affected by disasters if those were perfectly diversifiable by the insurer.

7.5.2.2 S&P

Table 7.15 provides details about the market impact of negative FSR actions by S&P. To some extent, S&P seems to be driving the joint results, as most coefficients signs are similar to the 'All CRAs' sample, except for profitability where one of its measures have the opposite expected sign.

Table 7.15 Determinants of CARs for negative FSR actions by S&P

	Exp. sign	(1) CAR	(2) CAR	(3) CAR	(4) CAR	(5) CAR	(6) CAR
C		1.993	2.094	10.70	4.935	11.05	5.495
		(10.74)	(10.654)	(7.668)	(8.967)	(7.674)	(9.007)
LNTA	+	-0.00649	0.00201	0.00549	0.292	0.0119	0.262
		(0.447)	(0.453)	(0.482)	(0.550)	(0.480)	(0.549)
ROAE	+	-0.114	-0.0840			-0.0692	-0.0927
		(0.078)	(0.070)			(0.054)	(0.059)
LR	-			-0.101*	-0.0976*	-0.103*	-0.0976*
				(0.060)	(0.058)	(0.061)	(0.058)
TE-TA	+	0.0703	0.0583		0.0135		0.0310
		(0.063)	(0.053)		(0.041)		(0.043)
TD-TE	-			2.153		1.804	
				(1.828)		(1.792)	
LIQ	-	-0.0570*	-0.0461	-0.0558	-0.0500	-0.0544	-0.0514
		(0.033)	(0.038)	(0.038)	(-1.33)	(-1.45)	(-1.36)
DIVER	-	-0.245	-0.216	-0.542	-0.226	-0.508	-0.129
		(0.551)	(0.553)		(0.564)	(0.532)	(0.570)
LARGE	-	0.933	0.884	1.139	1.048	1.116	0.991
		(1.063)	(1.037)	(1.138)	(1.088)	(1.147)	(1.092)
FED	-		-0.458	-0.783	-0.669	-0.680	-0.539
			(0.537)	(0.632)	(0.580)	(0.635)	(0.565)
Obs.		90	90	89	89	89	89
R-sq.		0.062	0.076	0.131	0.123	0.137	0.134
Adj. R^2		-0.006	-0.003	0.056	0.048	0.051	0.047

*This table presents the coefficient estimates of Eq. (7.4). Coefficients are based on S&P negative FSR actions from 2003 to 2017. The model estimates the relationship between the CAR [0, +1] and parent companies' characteristics. The values in parentheses in the table are robust standard errors. *** Significant at 1% level, ** Significant at 5% level, *Significant at 10% level.*

The coefficient ROAE is unexpectedly negative and insignificant while the coefficient LR is negative and significant at 10%. This suggests that negative FSR actions by S&P have a stronger impact on the share prices of parent companies that have relatively higher loss ratios (less profitable parent companies). Regarding to leverage, both proxies appear to be positively associated with the parent company stock price reactions, except the relationship is not significant. About the magnitude of the actions, although LARGE is positive does not exhibit any relevance. Liquidity on the other hand is exhibiting the expected negative sign (only significant in column 1, implying that negative FSR actions will have relatively stronger impact on parent companies with more liquidity.

Table 7.16 Determinants of CARs for positive FSR actions by S&P

Pos.	Exp. sign	(1) CAR	(2) CAR	(3) CAR	(4) CAR	(5) CAR	(6) CAR
C		-3.628	-3.633	2.972	-7.177	0.637	-3.349
		(3.262)	(3.467)	(4.354)	(7.234)	(4.257)	(3.956)
LNTA	-	0.106	0.106	-0.181	0.247	-0.0760	0.0721
		(0.153)	(0.162)	(0.189)	(0.322)	(0.188)	(0.171)
ROAE	-	-0.0672**	-0.0672***			-0.0468*	-0.0666***
		(0.023)	(0.023)			(0.028)	(0.014)
LR	+			-0.00809	0.00885	-0.00389	0.00404
				(0.014)	(0.009)	(0.013)	(0.012)
TE-TA	-	0.0319*	0.0319*		0.00801		0.0291
		(0.019)	(0.019)		(0.022)		(0.026)
TD-TE	+			2.975**		1.211	
				(1.481)		(1.280)	
LIQ	+	0.0201	0.0201	-0.000936	0.0273	0.0144	0.0216
		(0.018)	(0.019)	(0.019)	(0.026)	(0.020)	(0.018)
DIVER	+	0.431*	0.432*	0.0671	0.363	0.142	0.360
		(0.250)	(0.255)	(0.241)	(0.333)	(0.232)	(0.267)
LARGE	+	-0.481	-0.481	-0.237	-0.533	-0.235	-0.400
		(0.505)	(0.510)	(0.577)	(0.570)	(0.562)	(0.541)
FED	+		0.000747	0.00532	0.0691	0.0367	0.0551
			(0.123)	(0.127)	(0.148)	(0.129)	(0.131)
Obs.		90	90	88	88	88	88
R-sq.		0.280	0.280	0.223	0.052	0.275	0.273
Adj. R^2		0.228	0.218	0.156	-0.031	0.202	0.200

*This table presents the coefficient estimates of Eq. (7.4). Coefficients are based on S&P positive FSR actions from 2003 to 2017. The model estimates the relationship between the CAR [0, +1] and parent companies' characteristics. The values in parentheses in the table are robust standard errors. *** Significant at 1% level, ** Significant at 5% level, *Significant at 10% level.*

Table 7.16 presents the parent companies' characteristics influence on CARs when there are positive FSR actions on the subsidiary level. Results ratifies that profitability is relevant, the coefficient ROAE ranges from -0.0468 to -0.0672 and significant at 1% (LR with mixed results), which means that positive FSR actions by S&P have a stronger (weaker) impact on the share prices of parent companies with relatively lower (higher) profitability. This is indication that market participants are valuing ROAE surrounding S&P positive FSR actions, whilst they value LR during S&P negative FSR actions. Regarding leverage, one of the measures used have opposite expected sign and therefore leverage effect is unclear for S&P. In columns, 1 and 2, TE-TA coefficient is equal to +0.0319 and it is significant at 10% while TD-TE in column 3 is positive as expected equal to +2.975 significant at 5%. A possible explanation to this result is the capital structure differences between parent company and subsidiary. As a determinant of FSR, Gaver and Pottier (2005) find that parent companies are financed in general with 30% equity, 35% property liability reserves and 35% other liabilities;

while at the subsidiary level, other liabilities only represents 25%. This extra borrowing on the balance sheet of the parent company vs the subsidiary as well as the nature of each ratio (TE-TA and TD-TE) may be influencing the unclear results. Moreover, as outline in section 7.2.3 about the parent – subsidiary relationship, there are no fixed limits governing the gaps between credit ratings of the parent and its subsidiaries. One of the factors that can affect S&P evaluation is concentration of debt in certain subsidiaries or downstream loans. On the other hand, the degree of diversification is positive and significant as reflected in the 'All CRAs' sample. The positive and significant TD-TE disappears when ROAE is controlled for.

7.5.2.3 Moody's

Table 7.17 displays results for the parent companies' factors that may be enlarging or reducing the market impact of negative FSR actions by Moody's. Consistent with the joint effect of all CRAs, TE-TA yields positive coefficients ranging from 0.175 to 0.180 significant at 5% unravelling that parent companies with higher leverage ratios react more strongly (more negative CARs) to negative FSR actions. Contrary to the 'All CRAs' sample, liquidity and diversification are relevant. LIQ has negative and significant coefficients at the 1% or 5% level in four out of six columns implying that the higher (lower) the liquidity, the stronger (weaker) is the reaction to negative rating events. Regarding diversification, the coefficient DIVER is positive and significant at a 5% level contrary to what was concluded for the total sample and for S&P. It seems that less (more) diversified insurers will have a weaker (stronger) reaction to negative actions.

The estimation results for the positive FSR actions by Moody's are reported in Table 7.18. The profitability measure ROAE is negative and significant at 1% confirming that parent companies that are more (less) profitable have a weaker (stronger) reaction to positive FSR actions. This is similar to the results found for S&P positive FSR actions. Unlike the whole sample, the degree of diversification is not relevant, and the rest of the parent characteristics do not seem to magnify the information content of positive FSR actions by Moody's. Nevertheless, the coefficients of DIVER, TE-TA, TD-TE, LARGE, SIZE have the expected sign. Unexpectedly, LIQ has a negative coefficient in all columns, but they are not significant.

Table 7.17 Determinants of CARs for negative FSR actions by Moody's

Neg.	Exp. sign	(1)	(2)	(3)	(4)	(5)	(6)
		CAR	CAR	CAR	CAR	CAR	CAR
C		-9.311	-9.007	5.969	-9.379	8.960	-8.506
		(10.81)	(11.392)	(14.960)	(11.078)	(15.320)	(9.772)
LNTA	+	0.469	0.451	-0.237	0.500	-0.364	0.466
		(0.508)	(0.544)	(0.756)	(0.547)	(0.780)	(0.452)
ROAE	+	0.0203	0.0194			0.0629	0.0216
		(0.044)	(0.043)			(0.050)	(0.068)
LR	-			-0.0206	-0.0157	-0.0255	-0.0169
				(0.052)	(0.040)	(0.050)	(0.044)
TE-TA	+	0.177**	0.176**		0.180**		0.175*
		(0.076)	(0.079)		(0.077)		(0.071)
TD-TE	-			0.496		0.909	
				(2.797)		(2.879)	
LIQ	-	-0.136***	-0.137***	-0.0764	-0.126**	-0.0934	-0.129**
		(0.046)	(0.047)	(0.060)	(0.051)	(0.065)	(0.059)
DIVER	-	2.823**	2.767**	1.533	2.808**	1.574	2.801***
		(1.094)	(1.197)	(0.995)	(1.194)	(1.012)	(0.992)
LARGE	-	1.864	1.881	2.180	1.666	2.435	1.786
		(1.210)	(1.214)	(1.409)	(1.228)	(1.464)	(1.445)
FED	-		0.0880	0.149	0.0674	0.106	0.0569
			(0.476)	(0.502)	(0.464)	(0.502)	(0.419)
Obs.		40	40	40	40	40	40
R-sq.		0.327	0.328	0.184	0.329	0.203	0.331
Adj. R^2		0.205	0.181	0.005	0.182	-0.003	0.159

*This table presents the coefficient estimates of Eq. (7.4). Coefficients are based on Moody's negative FSR actions from 2003 to 2017. The model estimates the relationship between the CAR [0, +1] and parent companies' characteristics. The values in parentheses in the table are robust standard errors. *** Significant at 1% level, ** Significant at 5% level, *Significant at 10% level.*

Table 7.18 Determinants of CARs for positive FSR actions by Moody's

Pos.	Exp. sign	(1) CAR	(2) CAR	(3) CAR	(4) CAR	(5) CAR	(6) CAR
C		11.54	11.74	3.210	-0.896	2.082	7.116
		(16.313)	(16.636)	(6.305)	(12.874)	(6.029)	(12.620)
LNTA	-	-0.338	-0.343	-0.388	-0.152	-0.125	-0.427
		(0.604)	(0.613)	(0.398)	(0.704)	(0.315)	(0.685)
ROAE	-	-0.123***	-0.122***			-0.144**	-0.114***
		(0.045)	(0.045)			(0.071)	(0.037)
LR	+			0.0836	0.0868	0.0604	0.0603
				(0.079)	(0.071)	(0.064)	(0.061)
TE-TA	-	-0.0251	-0.0258		-0.0178		-0.00845
		(0.073)	(0.074)		(0.065)		(0.062)
TD-TE	+			1.777		-2.122	
				(1.977)		(2.604)	
LIQ	+	-0.0612	-0.0613	-0.0489	-0.0352	-0.0356	-0.0441
		(0.075)	(0.076)	(0.068)	(0.062)	(0.059)	(0.061)
DIVER	+	0.162	0.185	0.478	0.513	0.423	0.314
		(0.397)	(0.424)	(0.738)	(0.538)	(0.702)	(0.498)
LARGE	+	1.432	1.427	1.772	1.527	1.207	1.588
		(2.341)	(2.353)	(2.274)	(2.551)	(1.912)	(2.476)
FED	+		-0.0631	-0.0854	-0.0420	0.124	0.0398
			(0.180)	(0.185)	(0.168)	(0.237)	(0.181)
Obs.		72	72	72	72	72	72
R-sq.		0.173	0.173	0.098	0.086	0.200	0.189
Adj. R^2		0.096	0.083	-0.001	-0.014	0.098	0.086

*This table presents the coefficient estimates of Eq. (7.4). Coefficients are based on Moody's positive FSR actions from 2003 to 2017. The model estimates the relationship between the CAR [0, +1] and parent companies' characteristics. The values in parentheses in the table are robust standard errors. *** Significant at 1% level, ** Significant at 5% level, *Significant at 10% level.*

7.5.2.4 Fitch

The multivariate estimation results for negative FSR actions by Fitch are reported in Table 7.19. In line with the 'All CRAs' regression, the coefficient TE-TA for the proxy of leverage is positive as expected (but not significant) and TD-TE is negative and significant at 5% in column 5 equal to -4.244. This reveals that neither Fitch nor S&P is the source of the significant coefficient of leverage in the 'All CRAs' sample. For the magnitude of actions, LARGE coefficient is positive and significant which means that large rating actions have a weaker impact (less negative CARs) on parent share prices compared to rating actions that are smaller in size. This is evidence that it is the LARGE FSR actions by Fitch that's driving the results found in Table 7.13. Furthermore, the two measures of profitability have mixed results, LR is negative as expected but insignificant while ROAE have unexpected negative sign across all columns. This may indicate that ROAE is counterbalancing the effect of negative FSR actions since all coefficients are negative (ranging -0.0662 to -0.0111) and significant at 10% in column 5.

Table 7.19 Determinants of CARs for negative FSR actions by Fitch

Neg.	Exp. sign	(1) CAR	(2) CAR	(3) CAR	(4) CAR	(5) CAR	(6) CAR
C		-1.873	-1.752	-4.280	-2.468	-10.56	-1.830
		(9.536)	(9.882)	(9.933)	(9.577)	(8.332)	(9.453)
LNTA	+	-0.137	-0.140	0.184	-0.100	0.482	-0.143
		(0.372)	(0.387)	(0.412)	(0.362)	(0.352)	(0.367)
ROAE	+	-0.0111	-0.0121			-0.0662*	-0.0122
		(0.015)	(0.015)			(0.037)	(0.028)
LR	-			-0.0149	-0.00114	-0.00380	0.00132
				(0.046)	(0.039)	(0.042)	(0.052)
TE-TA	+	0.0796	0.0805		0.0765		0.0810
		(0.051)	(0.052)		(0.047)		(0.064)
TD-TE	-			-1.697		-4.244**	
				(1.633)		(1.792)	
LIQ	-	-0.00473	-0.00957	-0.00325	-0.00747	0.0136	-0.00918
		(0.062)	(0.065)	(0.059)	(0.062)	(0.058)	(0.078)
DIVER	-	0.00114	0.0315	0.185	0.0756	0.368	0.0263
		(0.978)	(0.958)	(1.012)	(1.006)	(0.951)	(0.883)
LARGE	-	2.654**	2.685**	2.706*	2.690*	2.597*	2.675*
		(1.239)	(1.263)	(1.389)	(1.370)	(1.313)	(1.310)
FED	-		0.0800	0.0492	0.0498	0.271	0.0817
			(0.441)	(0.461)	(0.452)	(0.490)	(0.383)
Obs.		39	39	39	39	39	39
R^2		0.175	0.176	0.169	0.171	0.242	0.177
Adj. R^2		0.021	-0.009	-0.019	-0.016	0.040	-0.043

*This table presents the coefficient estimates of Eq. (7.4). Coefficients are based on Fitch negative FSR actions from 2003 to 2017. The model estimates the relationship between the CAR [0, +1] and firm characteristics. The values in parentheses in the table are robust standard errors. *** Significant at 1% level, ** Significant at 5% level, *Significant at 10% level.*

Table 7.20 displays the multivariate regression results for Fitch's positive FSR actions. Opposite to the 'All CRAs' sample, the constant is significant, meaning that allowing for parent company characteristics, positive FSR actions by Fitch have a significant effect on CARs in the event window. For profitability, one of the two proxies has an opposite sign and therefore profitability the influence of profitability is unclear. The traditional proxy ROAE has the expected sign but is only significant in column 6 with a coefficient of -0.0810, whereas the LR (insurance-specific proxy) has the opposite expected sign and shows significance at 10% in columns 3 (-0.0322) and column 5 (-0.0286), respectively. The negative coefficients for LR means that parent companies with higher LR (lower profitability) will have a weaker reaction (less positive) to positive FSR actions by Fitch. The conflicting results for both profitability proxies can possibly be explained by the fact that not all parent companies are perceived as strong insurance players or deal with other business activities may be reducing the influence of profitability and its links with CARs. For the remaining independent variables, the magnitude and the interest rate have the expected signs but are not significant, and liquidity and diversification, contrary to a priori expectations, have unexpected signs but they are not significant.

Table 7.20 Determinants of CARs for positive FSR actions by Fitch

Pos.	Exp. sign	(1) CAR	(2) CAR	(3) CAR	(4) CAR	(5) CAR	(6) CAR
C		6.926	7.064	8.804*	6.943	9.508**	9.532**
		(4.844)	(5.065)	(4.687)	(4.572)	(4.366)	(4.631)
LNTA	-	-0.176	-0.182	-0.151	-0.0728	-0.166	-0.170
		(0.174)	(0.178)	(0.193)	(0.169)	(0.183)	(0.165)
ROAE	-	-0.0711	-0.0750			-0.0843	-0.0810*
		(0.051)	(0.063)			(0.059)	(0.044)
LR	+			-0.0322*	-0.0256	-0.0286*	-0.0289
				(0.017)	(0.018)	(0.016)	(0.019)
TE-TA	-	0.0272	0.0279		0.00393		0.00134
		(0.031)	(0.031)		(0.035)		(0.041)
TD-TE	+			0.991		-0.119	
				(1.054)		(1.061)	
LIQ	+	-0.0533	-0.0538	-0.0578	-0.0525	-0.0534	-0.0539
		(0.032)	(0.033)	(0.037)	(0.035)	(0.035)	(0.032)
DIVER	+	-0.127	-0.129	-0.130	-0.108	-0.123	-0.122
		(0.239)	(0.244)	(0.240)	(0.251)	(0.241)	(0.258)
LARGE	+	0.249	0.212	0.377	0.113	0.213	0.233
		(0.457)	(0.479)	(0.640)	(0.548)	(0.625)	(0.569)
FED	+		0.0308	-0.142	-0.115	0.0538	0.0447
			(0.141)	(0.126)	(0.122)	(0.143)	(0.171)
Obs.		36	36	36	36	36	36
R^2		0.222	0.223	0.218	0.190	0.282	0.282
Adj. R^2		0.061	0.029	0.023	-0.012	0.070	0.070

*This table presents the coefficient estimates of Eq. (7.4). Coefficients are based on Fitch positive FSR actions from 2003 to 2017. The model estimates the relationship between the CAR [0, +1] and parent companies' characteristics. The values in parentheses in the table are robust standard errors. *** Significant at 1% level, ** Significant at 5% level, *Significant at 10% level.*

7.5.2.5 AM Best

The results for the multivariate regression analysis for negative FSR actions by AM Best are presented in Table 7.21. The constant is negative in all columns, significant in columns 3, and 5. This partially suggests that negative FSR actions by AM Best in the event window notwithstanding for parent company characteristics have a significant effect at 10% and 5%, respectively. Profitability, measured by ROAE, is not significant in all estimations whereas LR, contrary to the 'All CRAs' sample as well as for negative rating actions by S&P, Moody's, and Fitch samples, is positive and significant. This means that parent companies with higher LR (lower profitability) have a weaker (less negative) share price reaction to negative FSR actions by AM Best relative to parent companies with lower LR (higher profitability). This is in contrast to what we see for negative FSR actions by S&P (Section 7.5.2.2), where the coefficient on LR is negative and significant, so the effect is the opposite. The two leverage measures have mixed but relevant results. When using TE-TA ratio, the sign is consistent with the 'All CRAs' sample, but statistically insignificant while using the proxy TD-TE, coefficients are negative and significant in columns 3 and 5. The results in TD-TE hint that the impact of negative FSR actions by AM Best is stronger (weaker) in more (less) leveraged firms. This finding agrees with Thimann's (2015) argument that for insurers, a leverage ratio would be better defined as equity over debt, or the inverse, the gearing ratio TD-TE, rather than equity over assets (TE-TA). About the influence of macroeconomics conditions, FED coefficients are equal to +1.141, +1.127 in columns 3 and 4, respectively, significant at a 5% level with a positive sign. This denotes that the policy of the FED and the macroeconomic environment may dampen the market impact of negative FSR actions by AM Best, contrary to the 'All CRAs' sample where the sign of FED coefficients is negative not significant.

Table 7.21 Determinants of CARs for negative FSR actions by AM Best

Neg.	Exp.	(1)	(2)	(3)	(4)	(5)	(6)
	sign	CAR	CAR	CAR	CAR	CAR	CAR
C		-4.766	-2.607	-16.32*	-8.816	-18.83**	-10.99
		(9.395)	(10.749)	(8.920)	(9.468)	(8.536)	(9.653)
LNTA	+	-0.0702	-0.195	-0.161	-0.577	-0.0726	-0.503
		(0.292)	(0.298)	(0.382)	(0.375)	(0.331)	(0.335)
ROAE	+	0.236	0.203			0.147	0.145
		(0.161)	(0.181)			(0.108)	(0.119)
LR	-			0.216**	0.212**	0.202**	0.197**
				(0.097)	(0.103)	(0.077)	(0.081)
TE-TA	+	-0.0115	-0.0236		-0.00302		-0.00626
		(0.067)	(0.078)		(0.072)		(0.065)
TD-TE	-			-4.287**		-4.329**	
				(1.877)		(1.703)	
LIQ	-	0.0636	0.0660	0.0418	0.0331	0.0545	0.0463
		(0.078)	(0.077)	(0.069)	(0.069)	(0.070)	(0.069)
DIVER	-	-0.762	-1.105	-1.139	-1.670*	-0.870	-1.437
		(1.005)	(1.272)	(0.767)	(0.960)	(0.808)	(1.039)
LARGE	-	-0.726	-0.944	0.828	0.527	0.945	0.625
		(1.241)	(1.294)	(1.167)	(1.192)	(1.064)	(1.144)
FED	-		0.537	1.141**	1.127**	0.880	0.870
			(0.604)	(0.519)	(0.551)	(0.584)	(0.625)
Obs.		54	54	50	50	50	50
R^2.		0.158	0.183	0.384	0.330	0.420	0.366
Adj. R^2		0.051	0.059	0.281	0.219	0.307	0.242

*This table presents the coefficient estimates of Eq. (7.4). Coefficients are based on AM Best positive events from 2003 to 2017. The model estimates the relationship between the CAR [0, +1] and firm characteristics. The values in parentheses in the table are robust standard errors. *** Significant at 1% level, ** Significant at 5% level, *Significant at 10% level.*

Finally, Table 7.22 reports the multivariate results for positive FSR actions by AM Best. None of the coefficients are evidence of being a significant factor that enlarge or reduce the market impact of positive FSR actions. In particular, company size (LNTA) has ambiguous results, as well as the two measures for profitability which have mixed signs and therefore their effect is unclear. Both ROAE and LR are insignificant suggesting that if any FSR positive action by AM Best has an effect on the market, it is unrelated to profitability. Moreover, it is worth noting that Pottier (1997) has also obtained unclear results in terms of profitability when analysing AM Best FSR determinants for life insurers.

Table 7.22 Determinants of CARs for positive FSR actions by AM Best

Pos.	Exp. sign	(1)	(2)	(3)	(4)	(5)	(6)
		CAR	CAR	CAR	CAR	CAR	CAR
C		2.992	2.218	1.680	3.407	1.617	3.312
		(5.347)	(5.153)	(5.624)	(6.170)	(5.429)	(6.185)
LNTA	-	-0.0256	0.00366	0.0367	0.129	0.0742	0.147
		(0.194)	(0.206)	(0.247)	(0.280)	(0.254)	(0.285)
ROAE	-	0.0244	-0.0247			-0.116	-0.0494
		(0.068)	(0.070)			(0.101)	(0.082)
LR	+			-0.0413	-0.0375	-0.0503	-0.0395
				(0.040)	(0.051)	(0.045)	(0.052)
TE-TA	-	0.00794	0.00846		-0.0136		-0.00811
		(0.021)	(0.022)		(0.041)		(0.040)
TD-TE	+			5.974		6.739	
				(4.465)		(4.644)	
LIQ	+	-0.0480	-0.0450	-0.0269	-0.0514	-0.0187	-0.0503
		(0.042)	(0.039)	(0.032)	(0.043)	(0.028)	(0.042)
DIVER	+	0.381	0.407	0.317	0.302	0.527	0.419
		(0.366)	(0.407)	(0.317)	(0.351)	(0.444)	(0.419)
LARGE	+	0.303	0.449	0.451	0.256	0.506	0.250
		(0.781)	(0.695)	(0.645)	(0.795)	(0.635)	(0.799)
FED	+		0.354	0.252	0.351	0.429	0.430
			(0.338)	(0.231)	(0.341)	(0.346)	(0.401)
Obs.		79	79	77	77	77	77
R^2		0.046	0.077	0.219	0.096	0.249	0.102
Adj. R^2		-0.034	-0.014	0.140	0.004	0.161	-0.004

*This table presents the coefficient estimates of Eq. (7.4). Coefficients are based on AM Best positive events from 2003 to 2017. The model estimates the relationship between the CAR [0, +1] and firm characteristics. The values in parentheses in the table are robust standard errors. *** Significant at 1% level, ** Significant at 5% level, *Significant at 10% level.*

7.5.2.6 Overview of the multivariate results:

Table 7.23 presents a summary of the findings, and the takeaways depend on the sample. In the regression for 'All CRAs' negative FSR actions (Table 7.13), leverage and to some extent, the magnitude of the rating actions is detected to be significant, while for the entire set of positive FSR actions (Table 7.14), profitability and diversification seem to be the factors enlarging the market impact. The CRAs-specific regressions in Tables 7.15 to 7.22 are mostly in line with the joint result but few of them have particularities to highlight.

Table 7.23 Summary of multivariate results

Reg.	Negative	Positive
All CRAs	Leverage and magnitude of the action: TE-TA ranges from 0.0667 to 0.0702 and significant at 10% whereas magnitude (LARGE) has an unexpected positive sign in all columns	Profitability, diversification and leverage exhibit interesting results: ROAE is negative and significant (-0.0792 to -0.0886) at 1% while LR is positive as expected yet not significant Leverage: TD-TE is significant at 5% but TETA mixed results (not conclusive) DIVER is positive and significant results at 5% Size has the expected sign but only significant in column 3 (-0.229)
S&P	Profitability measured by LR is significant at 10% while using ROAE has negative sign (inconclusive) Liquidity is negative as expected (only significant in column 1) LARGE coefficient is positive but not significant	Profitability, diversification and leverage: ROAE negative and significant at 1% but LR with mixed results across columns TE-TA with unexpected sign but TD-TE with significant and expected one DIVER is positive as expected and significant at 1%
Moody's	Leverage, liquidity and diversification: TE-TA is positive (as expected) and significant at 5% whereas TD-TE is also positive but not significant LIQ is negative and significant at 1% DIVER is significant but with unexpected sign LARGE coefficient is positive but not significant	ROAE values are negative as expected, and significant at 1% level Magnitude is positive as expected but not significant
Fitch	Leverage, magnitude and profitability: ROAE only significant in column 5 but unexpected sign TD-TE is negative and significant in column 5 LARGE is positive and significant (conflicting results). Thus, this is reflected in the whole sample	Profitability and constant have mixed results: Constant is significant LR is negative (unexpected sign) and significant but ROAE is negative and significant in column 6. Thus, inconclusive result
AM Best	Leverage, profitability, constant, FED with mixed results: Constant is negative and significant at 5% LR is significant but with unexpected sign while ROAE is with the expected sign but not significant TD-TE and TETA have the expected signs but only TDTE is significant at 5% LARGE coefficient has mixed signs across columns but not significant FED is significant at 5% but with unexpected sign	Any variable is significant but most variables have the expected signs (c, TETA, TD-TE, LIQ, DIVER M LARGE, FED)

This table contains a brief summary of the regressions' findings developed in Sections 7.5.2.1 to 7.5.2.5.

7.6 Conclusions

Previous studies have provided evidence that CRAs play an important role in providing valuable credit and default-related information to investors, and other stakeholders. For insurers, FSR are relevant, as they provide a forward-looking opinion about their ability to meet policyholder obligations. These ratings have attracted scarce attention among academics, even though they encompass useful information to stakeholders. The objective of this thesis Chapter is to contribute towards the literature in the field of market impact, addressing the research question: 'Do financial strength rating actions induce stock market reactions?'. Using a unique set of Long-Term Local-Currency (LT-LC) Financial strength rating (FSR) actions of 346 U.S. P/C insurers from January 2003 to December 2017, the goal is to examine whether the disclosed information on FSR actions affected the returns of the 30 parent companies associated to them.

The analysis is undertaken in two parts, focusing on (a) positive and negative FSR actions impact on stock-market returns, aggregating and breaking down by type of action and CRA, and (b) a multivariate analysis to determine if parent companies' characteristics enlarge the effects on CARs in the event window. Key features of the findings can be summarised as follows. Consistent with former studies (e.g., Chen et al., 2018; Halek and Eckles, 2010; Miao et al., 2014), negative FSR actions seem to provide a greater impact in the stock market compared to positive FSR actions favouring the information content hypothesis and asymmetric reaction of the stock markets. Indeed, the average CAR of positive FSR actions is smaller than the average CAR of negative ones. Across CRAs, negative FSR actions by Fitch have the strongest market reaction, based on the highest average CARs. S&P's strongest market reactions arise from negative Outlook actions while for Moody's, Watch actions seem to have the strongest reaction, be anticipated and generate interesting results in the post-event window. For AM Best, results do not indicate that negative FSR actions generally yield stronger market impact.

Regarding positive FSR actions, no significant positive CARs are found in the whole set of FSR actions across CRAs. Results by CRA indicate that there is only a slightly significant increase in returns for insurers that receive an upgrade in ratings from AM Best, whilst there is somewhat muted evidence that the market reacts to these FSR actions by S&P, Moody's and Fitch. Such a modest market response to AM Best upgrades may be explained by the fact that AM Best has been historically associated with the insurance industry; Singh and Power (1992) claim that AM Best fulfils a certification role for the insurance product market. Moreover, since companies usually leak positive news, i.e. anticipated actions; an insurance company may decide to reveal any form of good news as soon as possible (Halek and Eckles, 2010) and take advantage of AM Best's role.

Overall, possible explanations for the asymmetric response of positive FSR actions versus negative FSR actions can be draw upon Holthausen and Leftwich (1986)'s research (see in Section 3.5.1 in Chapter 3). They elaborate on the asymmetric response to upgrades versus downgrades of bond ratings. First, by referring to the loss function of the CRA not being symmetric, thus causing upgrades not to be as "timely" as downgrades. Second, management's incentives to release information may not be symmetric. Therefore, an insurer's strategy may be to delay disclosure of all bad news for as long as possible and reveal any form of good news as soon as possible. Thus, CRAs appear to be the carriers of bad news, while good news have already been disseminated to the capital markets.

The findings of this Chapter are in line with Miao et al., (2014). These authors also find that rating actions from Fitch elicit the largest market response, rather than AM Best which is the CRA that is most commonly associated with insurers. Possible explanations provided by Miao et al., (2014) arise from Doherty et al., (2012)'s work. Doherty et al., (2012) look at the effect of competition between CRAs within the insurance rating market. They posit that, for a given rating by an incumbent CRA, new rating companies often require higher standards. Hence, it is possible that the larger market reaction to Fitch (a relatively late entrant to the insurer rating market) is a reflection of the market's recognition of these differences. Besides, Miao et al., (2014) conclude that downgrades are the action that causes insurers to experience significant negative bond price reactions. In this investigation, as secondary actions are included, negative Outlook and negative Watch actions appear to have a stronger effect compared to downgrades.

Drawing comparisons with other segments such as sovereign and corporate ratings, the unequal reactions to signals across CRAs are common. For instance, Brooks et al., (2004) reveals that of the four CRAs examined, S&P and Fitch sovereign rating downgrades result in significant market falls. Similarly, Alsakka and ap Gwilym (2012b) find that S&P has more emphasis on short-term accuracy than other CRAs, while Moody's policy places more weight on stability. This may explain the strongest market reaction arising on S&P negative outlook actions and for Moody's watch actions. Furthermore, market reactions to negative FSR actions can also be linked with the results of Chapter 6. Chapter 6 shows Fitch (AM Best) actions are the least (most) dependant on other CRAs, which is coherent with the most (least) significant market reactions to Fitch (AM Best) actions.

In the second part of the analysis to dig deeper into the impact of FSR actions on stock market prices, the takeaways of the multivariate regressions depend on the sample. In the regression for the entire set of negative FSR actions, leverage, and to some extent, the magnitude of the rating actions is found to be significant, while for the entire set of positive FSR actions, profitability and diversification seem to be the factors that influence the market impact. By CRA, liquidity is relevant for the impact of negative FSR actions by S&P while profitability and diversification for the positive ones. For Moody's, leverage is significant on the impact of negative FSR actions whereas profitability is for positive ones; and concerning Fitch, it is the magnitude of negative FSR actions that is driving the results found in the entire set of negative actions, while no variable is relevant on the impact of positive FSR actions. Turning to AM Best regressions, leverage and macroeconomic conditions are relevant on the impact of negative FSR actions, while for positive actions, no parent company characteristic seems to influence the market impact.

Connecting these results with the parent-subsidiary transmission channels, it is on the entity-based approach and exposure channel explained by EIOPA (2017) where FSR actions and parents' characteristics such as leverage and profitability can have implications. Likewise, the activity-based related source, when engaging in certain activities or products with greater potential than insurance to pose systemic risk. The entity-based approach within the exposure transmission channel comprises the failure of a systemically important company or the collective failure of non-systemically important insurers because of exposures to common shocks. Thus, it is in this scenario where the additional information via FSR assigned by CRAs would play a key role as providers of information to the stock market as well as in the effort to contribute to the control of the systemic risk.

Considering the above, this Chapter makes three contributions to the literature. First, it studies FSR, which are important to stakeholders but have so far received minimal academic attention. It contributes to the existing literature on the role of FSR in addressing the insurer's opacity, literature about the information content of ratings and literature about the parent-subsidiary relationship. Second, this analysis uses a unique set of FSR actions by the four major CRAs, allowing the detection of whether market impact varies across CRA making the FSR action, especially by AM Best who is a CRA specialized on rating insurers.

Third, this Chapter provides pertinent information for policyholders, stockholders, and insights about the CRAs industry as well. Policyholders and stockholders can know that the information surrounding the firm of interest is a valuable source of information. In particular, for stockholders, negative FSR actions (especially Outlook and Watch actions) by CRA can reveal and help in their decision making process since FSR actions seem to be releasing some information that was thus undiscovered. Finally, CRAs can see the degree to which their FSR actions are valued by the market, and can parallel the reactions of one CRAs versus the other.

To conclude, while this Chapter provides insight into a much more recent time period (2003-2017) than prior studies, additional research will further help to elucidate the future of market efficiency and the understanding of the role CRA plays. Future research in this area can make additional contributions by using more insurance-specific variables in the multivariate analysis (e.g., log of admitted assets, combined ratio, the ratio of net premiums written and equity plus reserves, among others). In this thesis, the choice of traditional proxies as independent variables was driven by data availability considerations for the majority of the parent companies as well as supported by prior studies to ensure that they were a suitable choice (e.g., Gande and Parsley, (2005), Ferreira and Gama, 2007).

Another possible improvement of this research can arise from what is found in Chapter 5, where climate related events seem to be a discernible factor for the industry. Therefore, an introduction of a variable that captures climate-related events (at least big catastrophe events) into the multivariate analysis may highpoint the influence of specific risk factors of the industry. Moreover, the role of split ratings in the impact of CARs can be also an extension of this analysis. As seen in Chapter 6, actions of one CRA affect each other's actions and in other scenarios, it has been proved that split ratings enlarge the market reaction to negative FSR actions.

Appendix 7.I – Supporting tables

Table A 7.1 Credit rating numerical scale

Rating symbols	Outlook / Watch	20-point scale	20-point scale for AM	13-point scale	58-Point	58-Point CCR
AAA/Aaa	Stable watch/ outlook	1	2	1	1	1
AAA/Aaa	Negative outlook	1	2	1		2
AAA/Aaa	Negative watch	1	2	1		3
AA+/Aa1/A++	Pos. watch	2	2	1		2
AA+/Aa1/A++	Pos. outlook	2	2	1		3
AA+/Aa1/A++	Stable	2	2	1	4	4
AA+/Aa1/A++	Negative outlook	2	2	1		5
AA+/Aa1/A++	Negative watch	2	2	1		6
AA/Aa2	Pos. watch	3	4	2		5
AA/Aa2	Pos. outlook	3	4	2		6
AA/Aa2	Stable	3	4	2	7	7
AA/Aa2	Negative outlook	3	4	2		8
AA/Aa2	Negative watch	3	4	2		9
AA-/Aa3	Pos. watch	4	4	2		8
AA-/Aa3	Pos. outlook	4	4	2		9
AA-/Aa3	Stable	4	4	2	10	10
AA-/Aa3	Negative outlook	4	4	2		11
AA-/Aa3	Negative watch	4	4	2		12
A+/A1	Pos. watch	5	6	3		11
A+/A1	Pos. outlook	5	6	3		12
A+/A1	Stable	5	6	3	13	13
A+/A1	Negative outlook	5	6	3		14
A+/A1	Negative watch	5	6	3		15
A/A2	Pos. watch	6	6	3		14
A/A2	Pos. outlook	6	6	3		15
A/A2	Stable	6	6	3	16	16
A/A2	Negative outlook	6	6	3		17
A/A2	Negative watch	6	6	3		18
A-/A3	Pos. watch	7	7	4		17
A-/A3	Pos. outlook	7	7	4		18
A-/A3	Stable	7	7	4	19	19
A-/A3	Negative outlook	7	7	4		20
A-/A3	Negative watch	7	7	4		21
BBB+/Baa1	Pos. watch	8	9	5		20
BBB+/Baa1	Pos. outlook	8	9	5		21
BBB+/Baa1	Stable	8	9	5	22	22
BBB+/Baa1	Negative outlook	8	9	5		23
BBB+/Baa1	Negative watch	8	9	5		24
BBB/Baa2	Pos. watch	9	9	5		23
BBB/Baa2	Pos. outlook	9	9	5		24
BBB/Baa2	Stable	9	9	5	25	25
BBB/Baa2	Negative outlook	9	9	5		26
BBB/Baa2	Negative watch	9	9	5		27

Table A 7.1- Continued

Rating symbols	Outlook / Watch	20-point scale	20-point scale for AM	13-point scale	58-Point	58-Point CCR
BBB-/Baa3	Pos. watch	10	10	6		26
BBB-/Baa3	Pos. outlook	10	10	6		27
BBB-/Baa3	Stable	10	10	6	28	28
BBB-/Baa3	Negative outlook	10	10	6		29
BBB-/Baa3	Negative watch	10	10	6		30
BB+/Ba1	Pos. watch	11	12	6		29
BB+/Ba1	Pos. outlook	11	12	6		30
BB+/Ba1	Stable	11	12	6	31	31
BB+/Ba1	Negative outlook	11	12	6		32
BB+/Ba1	Negative watch	11	12	6		33
BB/Ba2	Pos. watch	12	12	7		32
BB/Ba2	Pos. outlook	12	12	7		33
BB/Ba2	Stable	12	12	7	34	34
BB/Ba2	Negative outlook	12	12	7		35
BB/Ba2	Negative watch	12	12	7		36
BB-/Ba3	Pos. watch	13	13	8		35
BB-/Ba3	Pos. outlook	13	13	8		36
BB-/Ba3	Stable	13	13	8	37	37
BB-/Ba3	Negative outlook	13	13	8		38
BB-/Ba3	Negative watch	13	13	8		39
B+/B1	Pos. watch	14	13	8		38
B+/B1	Pos. outlook	14	13	8		39
B+/B1	Stable	14	13	8	40	40
B+/B1	Negative outlook	14	13	8		41
B+/B1	Negative watch	14	13	8		42
B/B2	Pos. watch	15	15	9		41
B/B2	Pos. outlook	15	15	9		42
B/B2	Stable	15	15	9	43	43
B/B2	Negative outlook	15	15	9		44
B/B2	Negative watch	15	15	9		45
B-/B3	Pos. watch	16	16	10		44
B-/B3	Pos. outlook	16	16	10		45
B-/B3	Stable	16	16	10	46	46
B-/B3	Negative outlook	16	16	10		47
B-/B3	Negative watch	16	16	10		48
CCC+/Caa1	Pos. watch	17	18	11		47
CCC+/Caa1	Pos. outlook	17	18	11		48
CCC+/Caa1	Stable	17	18	11	49	49
CCC+/Caa1	Negative outlook	17	18	11		50
CCC+/Caa1	Negative watch	17	18	11		51
CCC/Caa2	Pos. watch	18	18	11		50
CCC/Caa2	Pos. outlook	18	18	11		51
CCC/Caa2	Stable	18	18	11	52	52
CCC/Caa2	Negative outlook	18	18	11		53
CCC/Caa2	Negative watch	18	18	11		54
CCC-/Caa3	Pos. watch	19	20	12		53
CCC-/Caa3	Pos. outlook	19	20	12		54
CCC-/Caa3	Stable	19	20	12	55	55
CCC-/Caa3	Negative outlook	19	20	12		56
CCC-/Caa3	Negative watch	19	20	12		57
CC/C/R/SD/D		20	20	13	58	58

This table presents the transformation of the alphabetical rating symbols to a 20-point numerical scale. The process is straightforward for S&P, Moody's and Fitch. For AM Best, the mapping of the 20-point numerical. The process is also reverted by mapping the 13-point rating scale by AM Best to the other three CRAs.

Table A 7.2 Rating actions by year

CRAs	S&P			Moody's			Fitch			AM Best				
Year	**Pos.**	**Neg.**	**Total**	**Pos.**	**Neg.**	**Total**	**Pos.**	**Neg.**	**Total**	**Pos.**	**Neg.**	**UR (+)**	**UR (-)**	**Total**
2003	11	25	36	7	10	17	1	3	4	3	10			13
2004	8	5	13	6	2	8	1	0	1	7	1			8
2005	14	9	23	7	3	10	4	4	8	6	3		4	9
2006	12	7	19	10	0	10	3	0	3	6	1	1	1	7
2007	6	2	8	8	0	8	5	1	6	8	1		1	9
2008	6	18	24	5	8	13	0	9	9	6	6		2	12
2009	7	7	14	3	7	10	1	14	15	3	7		2	10
2010	7	7	14	3	1	4	9	3	12	6	2	4	1	8
2011	6	6	12	4	4	8	1	2	3	4	4	2		8
2012	0	3	3	3	2	5	2	0	2	4	1		1	5
2013	9	3	12	5	2	7	2	1	3	5	1		1	6
2014	6	0	6	2	0	2	3	0	3	8	1			9
2015	4	3	7	3	0	3	3	0	3	5	0		1	5
2016	6	0	6	5	0	5	1	0	1	1	2		1	3
2017	0	3	3	1	1	2	0	2	2	3	1		2	4
Total	102	98	200	72	40	112	36	39	75	75	41	7	17	116
Percent	51.0%	49.0%		64.3%	35.7%		48.0%	52.0%		64.7%	35%			

This table reports the number of FSR actions included in the event study by each CRA from 1st Jan. 2003 to December 2017. In this table, Pos. refers to positive, Neg. to negative. UR refers to under review actions. See Table 7.3 for classification of what is considered a positive or negative FSR action.

Table A 7.3 Parent companies characteristics

Parent company name	SIC code	LEI	DIVER	Industry details
Aetna Inc.	6324	549300QKBENKLBXQ8968	1	Financials -> Insurance, Healthcare
Alleghany Corporation	6331	549300DCJE6AYX159479	0	Financials -> Insurance, Real Estate, Energy and Utilities, Healthcare, Industrials, Consumer
American Financial Group, Inc.	6331	549300AFOM7IVKIU1G39	2	Financials -> Insurance
AIG	6331	ODVCVCQG2BP6VHV36M30	2	Financials -> Insurance
American National Group, Inc.	6311	549300I1RRC5M591MY93	1	Financials -> Insurance
AmTrust Financial Services, Inc.	7374		2	Financials -> Insurance
Assurant, Inc.	6399	H3F39CAXWQRVWURFXL38	2	Financials -> Insurance
Berkshire Hathaway Inc.	6331	5493000C01ZX7D35SD85	0	Financials -> Insurance, Real Estate, Energy and Utilities, Materials, Industrials, Consumer Technology, Media & Telecommunications
Chubb Limited	6331	E0JAN6VLUDI1HITHT809	2	Financials -> Insurance
Cincinnati Financial Corporation	6331	254900Q4WEDMZBOZ0002	2	Financials -> Insurance
Enstar Group Limited	6331	213800AMAL5QFXVUCN04	1	Financials -> Insurance, Industrials
General Electric Company	9997		0	Financials -> Insurance, Healthcare, Industrials
Hartford Financial Services Group Inc.	6331	IU7C3FTM7Y3BQM112U94	1	Financials -> Insurance, Industrials
Horace Mann Educators Corporation	6331	254900G5YAV3A2YK8T32	2	Financials -> Insurance
Kemper Corporation	6331	549300FNI1JKTRY2PV09	2	Financials -> Insurance
Loews Corporation	6331	R8V1FN4M5ITGZOG7BS19	0	Financials -> Insurance, Energy and Utilities, Materials, Consumer
Markel Corporation	6331	549300SCNO12JLWIK605	0	Financials -> Insurance Healthcare, Industrials Consumer
Mercury General Corporation	6331	5493001Q9EXPCEL4W527	2	Financials -> Insurance

Table A 7.3 Continued

Parent company name	SIC code	LEI	DIVER	Industry details
Old Republic International Corporation	6331	549300IV6O2YY2A1KH37	1	Financials -> Insurance, Real state
ProAssurance Corporation	6331	54930015E5J57R675E89	2	Financials -> Insurance
Progressive Corporation	6331	529900TACNVLY9DCR586	2	Financials -> Insurance
RLI Corp.	6331	529900AMTJE5ECN9PS55	2	Financials -> Insurance
Selective Insurance Group, Inc.	6331	549300R3WGJWLE40R258	2	Financials -> Insurance
The Allstate Corporation	6331	OBT0W1ED8G0NWVOLOJ77	1	Financials -> Insurance Industrials
The Hanover Insurance Group, Inc.	6331	JJYR6MFKFF6CF8DBZ078	2	Financials -> Insurance
The Navigators Group, Inc.	6331		2	Financials -> Insurance
The Travelers Companies, Inc.	6331	549300Y650407RU8B149	2	Financials -> Insurance
Tiptree Inc.	6331		1	Financials -> Insurance Industrials
United Fire Group, Inc.	6331		2	Financials -> Insurance
W. R. Berkley Corporation	6331	SQOAGCLKBDWNVYV1OV80	2	Financials -> Insurance

This table presents details of the parent companies included in the event study. Standard industrial classification (SIC) code describes the primary business activity of the company and it is taken from S&P Market Intelligence. The codes are 6331: Fire, Marine, and Casualty Insurance; 6311: Life Insurance; 7374: Computer Processing and Data Preparation and Processing Services; 6399: Insurance Carriers, not elsewhere classified; 6324: Hospital and Medical Service Plans; 9997 – Conglomerates. Legal entity identifier (LEI) is a 20-characters, alphanumeric code that enables a clear identification of legal entities. DIVER is a dummy variable assigned to the parent company to capture the level of diversification. To define DIVER, SIC code "6331" and "Industry details" were considered. DIVER is equal to: 2 when Industry details → Financials → Insurance; 1 when the Industry details → Financials → Insurance + 1 additional industry line, 0 when the Industry details → Financials → Insurance + 2 or more industry lines. An exception of this rule was done with American National Group, Inc. Despite, it has only one industry line, the SIC code is different from 6331 focusing more in life insurers rather than P/C. Therefore, I have decided to place it in-group 1.

Table A 7.4 Market impact of negative FSR actions – DJUSIP

	CARs around S&P's actions				CARs around Moody's actions				CARs around Fitch's actions				CARs around AM Best's actions[+]			
	N	[-10,-1]	[0,+1]	[+2,+11]	N	[-10,-1]	[0,+1]	[+2,+11]	N	[-10,-1]	[0,+1]	[+2,+11]	N	[-10,-1]	[0,+1]	[+2,+11]
All	98				40				39							
CAR		-0.007	-0.011	-0.005		-0.015	-0.011	-0.011		-0.029	-0.017	-0.008		-0.016	-0.009	0.006
t-test		-0.798	-1.746	-0.610		-1.055	-1.658	-0.617		-1.308	-3.028***	-0.553	58	-1.114	-1.360	0.719
BMP		-0.104	-1.889	-0.942		-1.983*	-1.447	-0.246		-2.089*	-2.445	-0.752		-0.704	-1.060	-0.114
Sign		44/98	51/98	50/98		26/40	20/40	18/40		23/39	26/39	24/39		31/58	36/58	30/58
Watch	28															
CAR		-0.010	-0.003	-0.013	11	-0.015	-0.020	0.028		-0.030	-0.037	-0.014		NA	NA	NA
t-test		-0.936	-0.272	-0.681		-0.627	-1.278	1.760	10	-1.037	-3.190**	-0.433	NA	NA	NA	NA
BMP		-1.183	-0.716	0.269		-1.051	-1.007	1.610		-1.010	-2.885	-1.698		NA	NA	NA
Sign		15/28	12/28	13/28		4/11	6/11	8/11		6/10	9/10	6/10		NA	NA	NA
Outlook																
CAR		-0.033	-0.029	-0.039		-0.015	-0.017	-0.001		-0.042	-0.020	-0.009		0.003	-0.012	0.002
t-test	36	-1.111	-1.949*	-1.488	16	-1.542	-1.583	-0.204	14	-1.643	-2.672**	-0.544	18	0.176	-1.095	0.144
BMP		-0.896	-1.687	-2.339		-0.798	-1.390	0.576		-2.151*	-1.960*	0.170		0.095	-1.022	-0.148
Sign		16/36	20/36	23/36		6/16	8/16	9/16		9/14	11/14	7/14		11/18	12/18	9/18
Downgrades																
CAR		0.025	-0.002	-0.007		-0.037	-0.010	-0.096		-0.033	-0.008	0.030		-0.001	-0.001	0.015
t-test	7	0.880	-0.403	-0.890	5	-0.950	-0.993	-1.386	4	-0.170	-0.596	0.329	16	-0.112	-0.309	1.202
BMP		0.923	-0.239	-1.210		-0.947	-0.685	-1.489		-0.871	-0.617	0.575		-0.108	0.463	0.793
Sign		3/7	4/7	4/7		2/5	3/5	2/5		3/4	2/4	3/4		9/16	9/16	6/16
Combined																
CAR		-0.020	-0.005	0.016		-0.001	0.010	-0.029		-0.028	0.000	-0.010		-0.048	-0.042	0.054
t-test	27	-0.828	-1.079	0.807	8	-0.009	0.728	-0.418	11	-1.202	0.036	-0.725	7	-0.806	-1.224	1.383
BMP		0.552	-1.799*	0.060		-0.882	0.883	-0.465		-1.014	-0.599	-0.703		0.077	-2.023	1.377
Sign		12/27	18/27	9/27		4/8	4/8	4/8		6/11	5/11	7/11		3/7	5/7	2/7
Under R.													17			
CAR														-0.036	0.001	-0.017
t-test														-0.972	0.074	-1.159
BMP														-0.860	-0.002	-1.330
Sign														8/17	10/17	13/17

*This table presents the results of the CARs around the time of subsidiaries negative FSR actions by S&P, Moody's, Fitch and AM Best in the period 1st January 2003 to 31st December 2017. The benchmark used to calculate the CARs is Dow Jones U.S. P/C Insurance Index (DJUSIP). This table reports the 10-day pre-event [−10, −1], [0, +1] and [+2, +11] window CARs. Parametric tests are the cross-sectional t-test and the Boehmer et al. (1991) (BMP), reported beneath each CAR coefficient. As a non-parametric test, 'Sign' refers to the proportion of CARs with positive (negative) sign, respectively. *** Significant at 1% level, ** Significant at the 5% level, * Significant at the 10%.*

Table A 7.5 Market impact of positive FSR actions – DJUSIP

	CARs around S&P's actions				CARs around Moody's actions				CARs around Fitch's actions				CARs around AM Best's actions			
	N	[-10,-1]	[0,+1]	[+2,+11]	N	[-10,-1]	[0,+1]	[+2,+11]	N	[-10,-1]	[0,+1]	[+2,+11]	N	[-10,-1]	[0,+1]	[+2,+11]
All	102				72				36							
CAR		-0.009	0.002	0.011		-0.003	0.009	0.008		0.000	-0.001	0.007		-0.005	0.004	-0.004
t-test		-1.606	0.700	1.328		-0.491	1.175	0.708		-0.050	-0.300	1.696*	82	-1.148	1.151	-1.221
BMP		-1.365	0.773	0.643		-0.136	1.040	-0.557		-0.155	-0.715	1.523		-0.416	1.135	-1.145
Sign		51/102	50/102	50/102		34/72	39/72	33/72		15/36	17/36	20/36		38/82	44/82	32/82
Watch	20															
CAR		-0.021	0.009	0.050	19	-0.018	0.011	0.036		-0.013	-0.003	0.014		NA	NA	NA
t-test		-1.011	1.098	1.300		-0.895	1.221	0.906	5	-0.422	-0.231	1.015	NA	NA	NA	NA
BMP		-1.061	0.848	1.376		-0.042	0.892	-0.047		-1.464	-0.538	-0.032		NA	NA	NA
Sign		10/20	10/20	12/20		8/19	10/19	9/19		1/5	2/5	3/5				
Outlook																
CAR		-0.014	0.001	0.005		0.003	0.001	0.001		-0.003	0.000	0.005		-0.011	0.002	-0.004
t-test	57	-2.355**	0.551	0.938	31	0.499	0.800	0.134	19	-0.373	-0.026	0.918	34	-1.274	0.254	-0.660
BMP		-2.133**	0.695	0.658		0.148	0.816	-0.082		-0.438	-0.162	1.334		-1.095	0.162	-0.599
Sign		24/57	26/57	31/57		14/31	19/31	16/31		6/19	10/19	11/19		16/34	14/34	13/34
Upgrades																
CAR		0.021	-0.002	-0.007		-0.004	0.000	-0.004		0.003	-0.005	0.014		0.006	0.004	-0.001
t-test	6	0.813	-0.383	-0.641	6	-0.711	-0.210	-0.757	8	0.257	-1.609	1.177	26	1.533	2.015*	-0.148
BMP		0.417	-0.172	-0.822		-0.554	-0.010	-0.680		0.339	-1.621	1.198		1.597	2.046*	-0.247
Sign		4/6	4/6	2/6		2/6	3/6	1/6		5/8	3/8	5/8		14/26	17/26	13/26
Combined																
CAR		0.001	-0.004	-0.006		0.002	0.024	-0.008		0.021	0.009	0.005		-0.006	0.010	-0.009
t-test	19	0.242	-0.765	-0.664	16	0.199	0.759	-1.306	4	1.668	1.685	0.698	15	-1.106	1.360	-1.742
BMP		0.053	-0.176	-1.348		-0.386	0.535	-1.064		2.105	2.160	0.253		-0.216	1.609	-1.320
Sign		8/19	10/19	6/19		9/16	8/16	6/16		3/4	3/4	2/4		4/15	10/15	5/15
Under R.													7			
CAR														-0.019	0.002	-0.002
t-test														-1.403	0.350	-0.201
BMP														-1.142	0.195	-0.117
Sign														3/7	3/7	2/7

*This table presents the results of the CARs around the time of subsidiaries negative FSR actions by S&P, Moody's, Fitch and AM Best to 30 parent companies in the period 1st January 2003 to 31st December 2017. The benchmark used to calculate the CARs is Dow Jones U.S. P/C Insurance Index (DJUSIP). This table reports the 10-day pre-event [−10, −1], the two-day event [0, +1] and the 10-day post-event [+2, +11] window CARs. Parametric tests are the cross-sectional t-test (t-test) and the Boehmer et al. (1991) (BMP), reported beneath each CAR coefficient. As a non-parametric test, 'Sign' refers to the proportion of CARs with positive (negative) sign, respectively. *** Significant at 1% level, ** Significant at the 5% level, * Significant at the 10%.*

Table A 7.6 Market impact of negative FSR actions – INSR

	CARs around S&P's actions				CARs around Moody's actions				CARs around Fitch's actions				CARs around AM Best's actions+			
	N	[-10,-1]	[0,+1]	[+2,+11]	N	[-10,-1]	[0,+1]	[+2,+11]	N	[-10,-1]	[0,+1]	[+2,+11]	N	[-10,-1]	[0,+1]	[+2,+11]
All	98				40				39							
CAR		-0.009	-0.010	-0.002		-0.015	-0.011	-0.008		-0.018	-0.015	-0.007		-0.014	-0.008	0.009
t-test		-1.116	-1.573	-0.267		-1.019	-1.595	-0.512		-0.873	-2.480**	-0.575		-0.944	-1.284	0.927
BMP		-0.595	-1.646	-0.469		-1.637	-1.307	-0.121		-1.778*	-1.876*	-0.732		-0.589	-0.735	-0.004
Sign		48/98	47/98	47/98		22/40	19/40	16/40		19/39	27/39	20/39		31/58	32/58	32/58
Watch	28															
CAR		-0.007	-0.006	-0.007	11	-0.016	-0.022	0.020		-0.031	-0.031	-0.014		NA	NA	NA
t-test		-0.625	-0.588	-0.421		-0.712	-1.268	1.281	10	-1.032	-2.710**	-0.484	NA	NA	NA	NA
BMP		-0.992	-0.925	0.698		-0.933	-0.948	1.289		-1.079	-2.266**	-1.410		NA	NA	NA
Sign		16/28	12/28	13/28		7/11	5/11	3/11		4/10	9/10	5/10		NA	NA	NA
Outlook																
CAR		-0.038	-0.026	-0.033		-0.014	-0.017	0.005		-0.040	-0.014	-0.002		0.005	-0.010	0.009
t-test	36	-1.306	-1.826*	-1.266	16	-1.131	-1.701	0.766	14	-1.596	-1.417	-0.108	18	0.309	-0.922	0.566
BMP		-1.297	-1.534	-1.419		-0.160	-1.389	0.952		-2.162**	-1.251	0.495		0.369	-0.937	0.332
Sign		18/36	20/36	21/36		8/16	9/16	10/16		9/14	8/14	6/14		11/18	8/18	8/18
Downgrades																
CAR		0.013	-0.002	-0.007		-0.034	-0.009	-0.080		0.013	-0.007	0.031		-0.003	0.002	0.015
t-test	7	0.462	-0.366	-0.739	5	-0.944	-1.061	-1.160	4	0.071	-1.283	0.385	16	-0.305	0.560	1.021
BMP		0.750	-0.162	-0.938		-0.961	-0.851	-1.312		-0.691	-0.622	0.656		-0.286	1.195	0.190
Sign		3/7	3/7	3/7		1/5	4/5	2/5		2/4	4/4	2/4		9/16	8/16	8/16
Combined																
CAR		-0.019	-0.001	0.015		-0.002	0.014	-0.030		-0.012	-0.006	-0.019		-0.047	-0.048	0.054
t-test	27	-0.837	-0.209	0.717	8	-0.027	1.056	-0.445	11	-0.643	-0.453	-1.245		-0.840	-1.299	1.367
BMP		0.126	-1.013	-0.032		-1.050	1.191	-0.427		-0.436	-0.909	-1.244		-0.060	-2.351*	1.268
Sign		12/27	15/27	10/27		5/8	4/8	4/8		6/11	5/11	7/11		3/7	6/7	4/7
Under R.													17			
CAR														-0.030	0.000	-0.017
t-test														-0.748	-0.015	-1.164
BMP														-0.739	-0.033	-1.379
Sign														8/17	10/17	12/17

*This table presents the results of the CARs around the time of subsidiaries rating actions by S&P, Moody's, Fitch and AM Best to 30 parent companies in the period 1st January 2003 to 31st December 2017. The benchmark used to calculate the CARs is NASDAQ Insurance Index (INSR). This table reports the pre-, event, and post [−10, −1], [0, +1], [+2, +11] window CARs. Parametric tests are the cross-sectional t-test (t-test) and the Boehmer et al. (1991) (BMP), reported beneath each CAR coefficient. As a non-parametric test, 'Sign' refers to the proportion of CARs with positive (negative) sign, respectively. *** Significant at 1% level, ** Significant at the 5% level, * Significant at the 10%.*

Table A 7.7 Market impact of positive FSR actions – INSR

	CARs around S&P's actions				CARs around Moody's actions				CARs around Fitch's actions				CARs around AM Best's actions			
	N	[-10,-1]	[0,+1]	[+2,+11]	N	[-10,-1]	[0,+1]	[+2,+11]	N	[-10,-1]	[0,+1]	[+2,+11]	N	[-10,-1]	[0,+1]	[+2,+11]
All	102				72				36							
CAR		-0.012	0.003	0.008		0.000	0.009	0.007		0.003	0.0004	0.004		-0.005	0.004	-0.005
t-test		-2.274**	1.173	1.020		-0.078	1.179	0.657		0.361	0.161	0.985	82	-1.271	1.261	-1.527
BMP		-2.225**	1.483	0.053		0.424	0.798	-0.529		0.189	-0.552	1.062		-0.520	1.399	-1.803*
Sign		41/102	55/102	49/102		36/72	37/72	32/72		16/36	17/36	23/36		38/82	44/82	34/82
Watch	20															
CAR		-0.029	0.012	-0.116	19	-0.017	0.010	0.037		0.003	0.001	0.012		NA	NA	NA
t-test		-1.619	1.130	-0.663		-0.954	0.852	0.964	5	0.083	0.114	1.201	NA	NA	NA	NA
BMP		-1.646	0.995	1.474		-0.117	0.062	0.210		-1.056	-0.416	1.409		NA	NA	NA
Sign		7/20	10/20	12/20		8/19	6/19	8/19		1/5	2/5	3/5		NA	NA	NA
Outlook																
CAR		-0.015	0.002	0.000		0.006	0.001	0.000		0.001	0.001	0.001		-0.013	0.002	-0.005
t-test	57	-2.623**	0.730	-0.057	31	1.034	0.553	0.080	19	0.120	0.474	0.174	34	-1.431	0.278	-0.833
BMP		-2.691	1.008	-0.460		0.787	0.409	-0.241		0.035	0.077	0.382		-1.265	0.245	-1.171
Sign		18/57	29/57	27/57		18/31	20/31	15/31		9/19	8/19	11/19		14/34	13/34	13/34
Upgrades																
CAR		0.020	0.004	-0.002		0.000	0.001	0.002		0.000	-0.006	0.010		0.002	0.005	-0.001
t-test	6	0.843	1.022	-0.282	6	0.068	0.625	0.368	8	-0.011	-1.353	0.993	26	0.571	2.799***	-0.152
BMP		0.465	1.418	-0.421		-0.024	0.823	0.740		0.170	-1.325	0.925		0.912	2.672**	-0.502
Sign		2/6	5/6	4/6		3/6	4/6	2/6		4/8	4/8	5/8		13/26	18/26	14/26
Combined																
CAR		0.000	-0.003	-0.004		0.005	0.027	-0.015		0.014	0.010	0.004		0.005	-0.010	0.009
t-test	19	-0.062	-0.599	-0.553	16	0.456	0.864	-1.766*	4	1.168	1.517	0.523	15	-0.211	1.572	-1.640
BMP		-0.552	0.041	-1.347		-0.007	0.825	-1.667		1.104	1.869	0.084		0.337	2.022*	-0.989
Sign		9/19	10/19	6/19		8/16	8/16	6/16		3/4	3/4	3/4		8/15	10/15	6/15
Under R.													7			
CAR														-0.012	0.001	-0.011
t-test														-1.032	0.122	-0.908
BMP														-0.715	0.064	-0.619
Sign														2/7	4/7	2/7

*This table presents the results of the cumulative abnormal returns (CARs) around the time of subsidiaries rating actions by S&P, Moody's, Fitch and AM Best to 30 parent companies in the period 1st January 2003 to 31st December 2017. The benchmark used to calculate the CARs is NASDAQ Insurance Index (INSR). This table reports the 10-day pre-event [−10, −1], the two-day event [0, +1] and the 10-day post-event [+2, +11] window CARs. Parametric tests are the cross-sectional t-test (t-test) and the Boehmer et al. (1991) (BMP), reported beneath each CAR coefficient. As a non-parametric test, 'Sign' refers to the proportion of CARs with positive (negative) sign, respectively. *** Significant at 1% level, ** Significant at the 5% level, * Significant at the 10%.*

Table A 7.8 Market impact of reaction FSR actions – S&P 1500

	CARs around S&P's actions				CARs around Moody's actions				CARs around Fitch's actions				CARs around AM Best's actions[+]			
	N	[-10,-1]	[0,+1]	[+2,+11]	N	[-10,-1]	[0,+1]	[+2,+11]	N	[-10,-1]	[0,+1]	[+2,+11]	N	[-10,-1]	[0,+1]	[+2,+11]
All	98				40				39							
CAR		-0.006	-0.009	0.003		-0.011	-0.012	-0.0103		-0.030	-0.019	-0.006		-0.018	-0.007	0.004
t-test		-0.793	-1.448	0.245		-0.877	-1.805*	-0.650		-1.595	-3.385***	-0.436		-1.307	-1.311	0.476
BMP		-0.087	-1.599	0.301		-1.439	-1.504	-0.268		-2.295**	-2.594**	-0.385		-0.574	-0.874	0.071
Sign		48/98	52/98	48/98		26/40	19/40	18/40		25/39	29/39	22/39		34/58	34/58	27/58
Watch	28															
CAR		-0.015	0.002	0.011	11	-0.008	-0.020	0.023		-0.025	-0.033	-0.014		NA	NA	NA
t-test		-1.326	0.192	0.549		-0.392	-1.276	1.648	10	-0.895	-3.156**	-0.437	NA	NA	NA	NA
BMP		-1.400	-0.377	1.825*		-0.912	-1.007	1.509		-1.103	-3.520***	-1.408		NA	NA	NA
Sign		16/28	12/28	12/28		8/11	5/11	3/11		5/10	9/10	5/10		NA	NA	NA
Outlook																
CAR		-0.034	-0.027	-0.032		-0.015	-0.018	0.005		-0.048	-0.024	-0.008		0.001	-0.012	0.002
t-test	36	-1.119	-1.866	-1.202	16	-1.576	-1.716	0.551	14	-2.325**	-2.274*	-0.401	18	0.064	-1.106	0.136
BMP		-0.800	-1.631	-1.394		-0.794	-1.449	1.021		-2.757**	-1.758*	0.251		0.361	-0.974	0.043
Sign		18/36	20/36	22/36		11/16	8/16	6/16		11/14	11/14	7/14		11/18	11/18	8/18
Downgrades																
CAR		0.029	-0.005	-0.009		-0.020	-0.009	-0.098		-0.046	-0.015	0.018		-0.009	-0.006	0.010
t-test	7	0.997	-0.726	-1.142		-0.649	-0.965	-1.411		-0.285	-1.793	0.186		-0.786	-1.352	1.100
BMP		1.004	-0.474	-1.296		-0.746	-0.875	-1.524		-0.931	-0.123	0.450		-0.440	-0.108	0.831
Sign		4/7	4/7	4/7		2/5	2/5	2/5		3/4	3/4	3/4		9/16	8/16	6/16
Combined																
CAR		-0.012	-0.003	0.008		-0.001	0.007	-0.033		-0.025	-0.006	-0.004		-0.043	-0.029	0.036
t-test	27	-0.581	-0.647	0.509	8	-0.014	0.488	-0.562	11	-1.100	-0.535	-0.242	7	-0.745	-1.307	1.313
BMP		0.957	-1.380	0.004		-0.453	0.803	-0.845		-0.911	-1.303	-0.364		0.313	-1.982*	1.036
Sign		12/27	17/27	9/27		4/8	4/8	4/8		6/11	5/11	7/11		4/7	5/7	1/7
Under R.																
CAR														-0.036	0.005	-0.014
t-test														-1.027	0.440	-0.943
BMP														-0.841	0.381	-1.117
Sign														10/17	10/17	12/17

*This table presents the results of the CARs around the time of FSR actions by S&P, Moody's, Fitch and AM Best to 30 parent companies in the period 1st January 2003 to 31st December 2017. The benchmark used to calculate the CARs is S&P1500. This table reports the 10-day pre-event [−10, −1], the two-day event [0, +1] and the 10-day post-event [+2, +11] window CARs. Parametric tests are the cross-sectional t-test (t-test) and the Boehmer et al. (1991) (BMP), reported beneath each CAR coefficient. As a non-parametric test, 'Sign' refers to the proportion of CARs with positive (negative) sign, respectively. *** Significant at 1% level, ** Significant at the 5% level, * Significant at the 10%.*

Table A 7.9 Market impact of positive FSR actions – S&P1500

	CARs around S&P's actions				CARs around Moody's actions				CARs around Fitch's actions				CARs around AM Best's actions[+]			
	N	[-10,-1]	[0,+1]	[+2,+11]	N	[-10,-1]	[0,+1]	[+2,+11]	N	[-10,-1]	[0,+1]	[+2,+11]	N	[-10,-1]	[0,+1]	[+2,+11]
All	102				72				36							
CAR		-0.011	0.003	0.007		-0.003	0.009	0.005		-0.0020	0.0005	0.0069		-0.006	0.003	-0.004
t-test		-2.334**	1.024	0.968		-0.548	1.233	0.598		-0.335	0.235	1.419	82	-1.491	1.090	-1.280
BMP		-2.186	1.221	0.067		-0.295	0.989	-0.610		-0.482	-0.157	1.240		-0.574	-0.874	0.071
Sign		41/102	55/102	46/102		38/72	37/72	33/72		17/36	17/36	20/36		39/82	41/82	36/82
Watch	20															
CAR		-0.029	0.012	0.040	19	-0.012	0.014	0.026		-0.017	0.002	0.015		NA	NA	NA
t-test		-1.760*	1.063	1.300		-0.793	1.100	0.821	5	-0.659	0.201	1.233	NA	NA	NA	NA
BMP		-1.584	1.232	1.254		-0.014	0.641	-0.173		-1.895	-0.192	0.436		NA	NA	NA
Sign		7/20	11/20	11/20		10/19	8/19	7/19		1/5	2/5	3/5		NA	NA	NA
Outlook																
CAR		-0.016	0.002	0.003		0.001	0.001	0.001		-0.002	-0.001	0.003		-0.011	0.001	-0.005
t-test	57	-2.778***	0.754	0.521	31	0.175	0.716	0.157	19	-0.287	-0.215	0.536	34	-1.442	0.143	-0.861
BMP		-2.815***	0.870	0.224		0.050	0.757	-0.166		-0.349	-0.268	0.932		-1.257	0.029	-0.968
Sign		20/57	31/57	27/57		15/31	20/31	17/31		9/19	8/19	11/19		16/34	12/34	14/34
Upgrades																
CAR		0.0192	0.000	-0.010		0.000	0.001	0.004		-0.002	-0.002	0.013		0.006	0.004	0.000
t-test	6	1.079	0.1121	-0.781	6	0.049	0.442	0.785	8	-0.243	-0.532	0.779	26	1.144	2.504**	-0.037
BMP		0.854	0.210	-0.788		0.013	0.365	1.095		-0.119	-0.684	0.729		1.392	2.637**	-0.145
Sign		4/6	3/6	2/6		4/6	4/6	3/6		4/8	4/8	4/8		15/26	18/26	13/26
Combined																
CAR		0.004	-0.004	-0.009		-0.001	0.024	-0.011		0.015	0.012	0.013		-0.013	0.008	-0.008
t-test	19	0.790	-0.640	-1.129	16	-0.109	0.778	-1.504	4	0.675	2.037	1.169	15	-1.610	1.155	-1.239
BMP		-0.055	0.009	-1.795*		-0.801	0.582	-1.452		0.339	3.022*	0.892		-0.520	1.193	-0.697
Sign		9/19	10/19	6/19		9/16	6/16	5/16		2/4	4/4	3/4		5/15	8/15	5/15
Under R.													7			
CAR														-0.017	0.004	-0.004
t-test														-1.275	0.777	-0.390
BMP														-0.956	0.721	-0.281
Sign														2/7	3/7	4/7

*This table presents the results of the CARs around the time of positive FSR actions by S&P, Moody's, Fitch and AM Best to 30 parent companies in the period 1st January 2003 to 31st December 2017. The benchmark used to calculate the CARs is S&P1500. This table reports the 10-day pre-event [−10, −1], the two-day event [0, +1] and the 10-day post-event [+2, +11] window CARs. Parametric tests are the cross-sectional t-test (t-test) and the Boehmer et al. (1991) (BMP), reported beneath each CAR coefficient. As a non-parametric test, 'Sign' refers to the proportion of CARs with positive (negative) sign, respectively. *** Significant at 1% level, ** Significant at the 5% level, * Significant at the 10%.*

Table A 7.10 Correlation matrix – all CRAs / all negative FSR actions – DJUSIP

	CAR2	LNTA	ADM	ROAE	TETA	TDTE	LIQ	COMB	LR	DIVER	LARGE	FED
CAR2	1											
LNTA	0.0116	1										
ADM	0.0516	0.859	1									
ROAE	0.0125	-0.1371	-0.0831	1								
TETA	0.1432	-0.2697	-0.1102	0.1698	1							
TDTE	-0.0837	0.5446	0.3963	-0.3828	-0.4258	1						
LIQ	-0.0815	-0.3189	-0.2639	0.0255	0.115	0.0557	1					
COMB	0.0396	0.0322	-0.1683	-0.1987	-0.0161	-0.0082	-0.1044	1				
LR	-0.0619	0.2184	-0.0099	-0.0292	-0.1874	0.1825	-0.0228	0.5583	1			
DIVER	-0.0611	-0.2133	-0.1128	-0.065	-0.3828	0.1875	0.2435	-0.0903	0.0602	1		
LARGE	0.0887	-0.0232	0.0209	-0.0647	0.0675	0.0292	0.1098	0.0077	-0.0599	-0.0037	1	
FED	-0.0646	0.0219	0.0988	0.1638	-0.1099	0.1756	0.1438	-0.3325	-0.1333	0.1422	-0.0245	1

This table presents the correlation matrix for the insurer variables listed in Table 7.9 using the benchmark DJUSIP to calculate the CARs corresponding to negative FSR actions.

Table A 7.11 Correlation matrix – all CRAs / all negative FSR actions – INSR

	CAR3	LNTA	ADM	ROAE	TETA	TDTE	LIQ	COMB	LR	DIVER	LARGE	FED
CAR3	1											
LNTA	-0.001	1										
ADM	0.0474	0.859	1									
ROAE	0.0106	-0.1371	-0.0831	1								
TETA	0.1522	-0.2697	-0.1102	0.1698	1							
TDTE	-0.085	0.5446	0.3963	-0.3828	-0.4258	1						
LIQ	-0.0561	-0.3189	-0.2639	0.0255	0.115	0.0557	1					
COMB	0.0199	0.0322	-0.1683	-0.1987	-0.0161	-0.0082	-0.1044	1				
LR	-0.0721	0.2184	-0.0099	-0.0292	-0.1874	0.1825	-0.0228	0.5583	1			
DIVER	-0.0389	-0.2133	-0.1128	-0.065	-0.3828	0.1875	0.2435	-0.0903	0.0602	1		
LARGE	0.0873	-0.0232	0.0209	-0.0647	0.0675	0.0292	0.1098	0.0077	-0.0599	-0.0037	1	
FED	-0.0484	0.0219	0.0988	0.1638	-0.1099	0.1756	0.1438	-0.3325	-0.1333	0.1422	-0.0245	1

This table presents the correlation matrix for the insurer variables listed in Table 7.9 using the benchmark NASDAQ to calculate the CARs corresponding to negative FSR actions.

Table A 7.12 Correlation matrix – all CRAs / all negative FSR actions – S&P 1500

	CAR4	LNTA	ADM	ROAE	TETA	TDTE	LIQ	COMB	LR	DIVER	LARGE	FED
CAR4	1											
LNTA	0.0344	1										
ADM	0.0998	0.859	1									
ROAA	0.0248	-0.1371	-0.0831	1								
ROAE	0.1346	-0.2697	-0.1102	0.1698	1							
TETA	-0.0811	0.5446	0.3963	-0.3828	-0.4258	1						
TDTE	-0.0938	-0.3189	-0.2639	0.0255	0.115	0.0557	1					
LIQ	0.0181	0.0322	-0.1683	-0.1987	-0.0161	-0.0082	-0.1044	1				
COMB	-0.073	0.2184	-0.0099	-0.0292	-0.1874	0.1825	-0.0228	0.5583	1			
LR	-0.0635	-0.2133	-0.1128	-0.065	-0.3828	0.1875	0.2435	-0.0903	0.0602	1		
DIVER	0.0703	-0.0232	0.0209	-0.0647	0.0675	0.0292	0.1098	0.0077	-0.0599	-0.0037	1	
LARGE	-0.045	0.0219	0.0988	0.1638	-0.1099	0.1756	0.1438	-0.3325	-0.1333	0.1422	-0.0245	1

This table presents the correlation matrix for the insurer variables listed in Table 7.9 using the benchmark S&P 1500 to calculate the CARs corresponding to negative FSR actions.

Table A 7.13 Correlation matrix – all CRAs / all positive FSR actions – DJUSIP

	CAR2	LNTA	ADM	ROAE	TETA	TDTE	LIQ	COMB	LR	DIVER	LARGE	FED
CAR2	1											
LNTA	0.0455	1										
ADM	-0.0269	0.8724	1									
ROAA	-0.2285	-0.2581	-0.0414	1								
ROAE	-0.3404	-0.2409	-0.1178	0.7644	1							
TETA	-0.0677	-0.248	0.0193	0.5788	0.2216	1						
TDTE	0.227	0.3893	0.2059	-0.4672	-0.6023	-0.3527	1					
LIQ	-0.109	-0.2853	-0.2376	0.2253	0.0921	0.2873	0.0083	1				
COMB	0.0496	0.2109	0.034	-0.5107	-0.2176	-0.2993	0.2319	-0.2543	1			
LR	0.0677	0.2428	0.0078	-0.4072	-0.198	-0.3747	0.2358	-0.2317	0.732	1		
DIVER	0.0608	-0.176	-0.1283	-0.0013	0.0056	-0.2983	0.0659	0.052	-0.2434	-0.0223	1	
LARGE	0.0321	-0.0268	0.082	0.2035	0.1038	0.2187	-0.1807	-0.0024	-0.1835	-0.1685	0.0372	1

This table presents the correlation matrix for the insurer variables listed in Table 7.9 using the benchmark DJUSIP to calculate the CARs corresponding to positive FSR actions.

Table A 7.14 Correlation matrix – all CRAs / all positive FSR actions – INSR

	CAR3	LNTA	ADM	ROAE	TETA	TDTE	LIQ	COMB	LR	DIVER	LARGE	FED
CAR3												
LNTA	0.0754	1										
ADM	0.0061	0.8724	1									
ROAA	-0.2758	-0.2581	-0.0414	1								
ROAE	-0.4164	-0.2409	-0.1178	0.7644	1							
TETA	-0.0794	-0.248	0.0193	0.5788	0.2216	1						
TDTE	0.2815	0.3893	0.2059	-0.4672	-0.6023	-0.3527	1					
LIQ	-0.1034	-0.2853	-0.2376	0.2253	0.0921	0.2873	0.0083	1				
COMB	0.0521	0.2109	0.034	-0.5107	-0.2176	-0.2993	0.2319	-0.2543	1			
LR	0.0773	0.2428	0.0078	-0.4072	-0.198	-0.3747	0.2358	-0.2317	0.732	1		
DIVER	0.0749	-0.176	-0.1283	-0.0013	0.0056	-0.2983	0.0659	0.052	-0.2434	-0.0223	1	
LARGE	0.0377	-0.0268	0.082	0.2035	0.1038	0.2187	-0.1807	-0.0024	-0.1835	-0.1685	0.0372	1

This table presents the correlation matrix for the insurer variables listed in Table 7.9 using the benchmark INSR to calculate the CARs corresponding to positive FSR actions.

Table A 7. 15 Correlation matrix – all CRAs / all positive FSR actions – S&P 1500

	CAR4	LNTA	ADM	ROAE	TETA	TDTE	LIQ	COMB	LR	DIVER	LARGE	FED
CAR4	1											
LNTA	0.0847	1										
ADM	0.0172	0.8724	1									
ROAA	-0.4342	-0.2409	-0.1178	1								
ROAE	-0.0704	-0.248	0.0193	0.2216	1							
TETA	0.2962	0.3893	0.2059	-0.6023	-0.3527	1						
TDTE	-0.0874	-0.2853	-0.2376	0.0921	0.2873	0.0083	1					
LIQ	0.0509	0.2109	0.034	-0.2176	-0.2993	0.2319	-0.2543	1				
COMB	0.0718	0.2428	0.0078	-0.198	-0.3747	0.2358	-0.2317	0.732	1			
LR	0.0648	-0.176	-0.1283	0.0056	-0.2983	0.0659	0.052	-0.2434	-0.0223	1		
DIVER	0.0273	-0.0268	0.082	0.1038	0.2187	-0.1807	-0.0024	-0.1835	-0.1685	0.0372	1	
LARGE	0.0134	-0.1166	-0.0562	0.1489	0.0031	0.0415	0.0237	-0.1128	-0.0954	0.0937	0.0167	1

This table presents the correlation matrix for the insurer variables listed in Table 7.9 using the benchmark S&P 1500 to calculate the CARs corresponding to positive FSR actions.

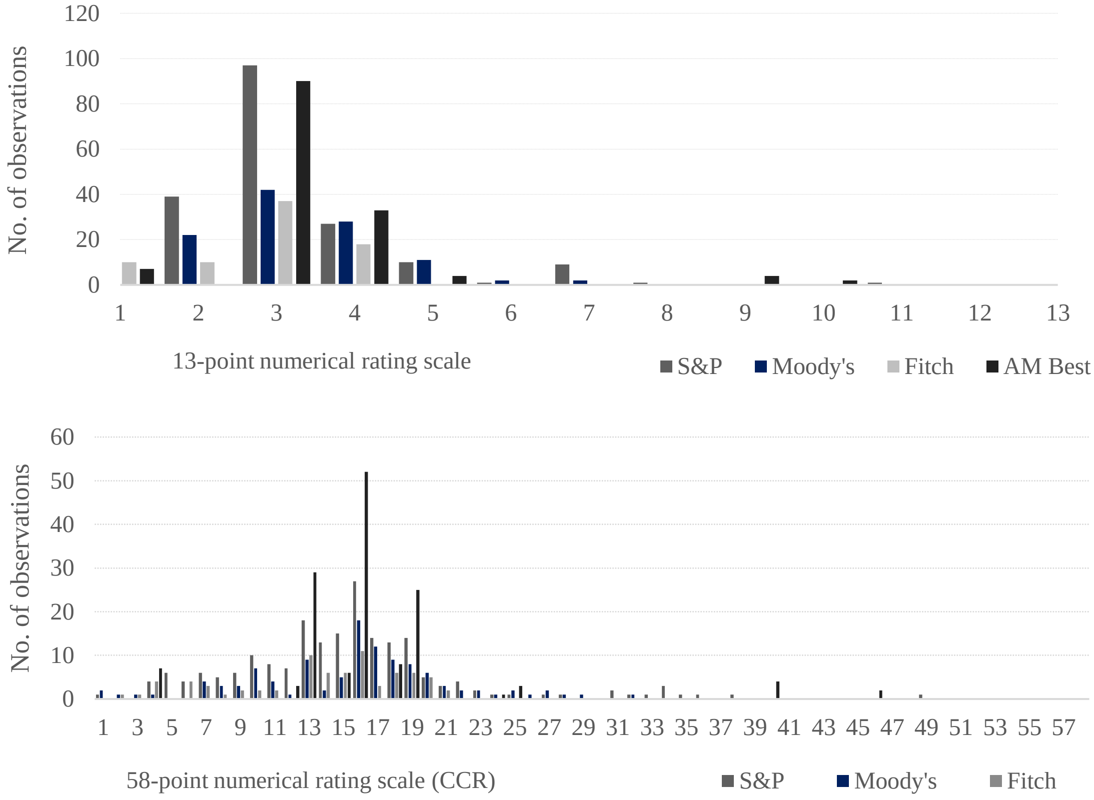
Table A 7.16 Variables used in multivariate analysis

Label	Indicator	Prior studies that motivate to select variable
LNTA	Asset = Firm Size	Doherty et al., (2012) use natural logarithm of total assets deflated using the consumer price index (CPI) as a control variable to test the impact of S&P entry in the insurance rating market on the information content of ratings. Adams et al., (2019) use it as a control variable to determine whether U.K. large insurers are likely to have better underwriting performance than small ones. Other studies have used the logarithm of admitted assets (e.g., Adams et al., 2003; Caporale et al., 2017) as proxy for firm size instead of total assets arguing that there is highly skewed distribution of total assets among firms operating in the insurance industry (Pottier and Sommer, 1997).
ROAE, LR	Profit = Profitability	Prior studies within general insurance literature have used the following variable to capture profitability. Adams et al., (2003) delimits profitability as the ratio of annual investment and underwriting income (net of expenses), plus unrealised capital gains, to statutory capital. Meanwhile, Caporale et al., (2017) use under writing profit to total assets, and Aon Benfield (2019) highlights the superiority of combined ratio as a key profitability variable.
TE-TA, TD-TE	LEV = Leverage	On the other hand, prior research have used alternative measures to leverage such as: the ratio of accumulated reserves to total assets (Adams et al., 2003), the annual ratio of net total liabilities or difference between total assets and policyholders' surplus (Upreti and Adams, 2015) Net technical provisions to adjust liquid assets (Caporale, 2017) and the ratio of net premiums written and equity plus reserves (Adams et al., 2019).
LIQ	Liquidity	The most popular measures for liquidity are also liquid assets as a percentage of total net technical provisions, liquid assets as a percentage of total liabilities. Compared to former papers, liquidity has been also measured using the ratio of current assets to current liabilities (Adams et al., 2003; Pottier and Sommer, 1999).
FED	Macroeconomic	Bae et al., (2015); Caporale et al., (2017)
DIVER	Level of diversification	Own criteria
LARGE	Large rating actions (magnitude)	Own criteria

This table provides additional detail about the variables chosen in the multivariate section of the methodology, specifically prior literature that motivate the selection of it.

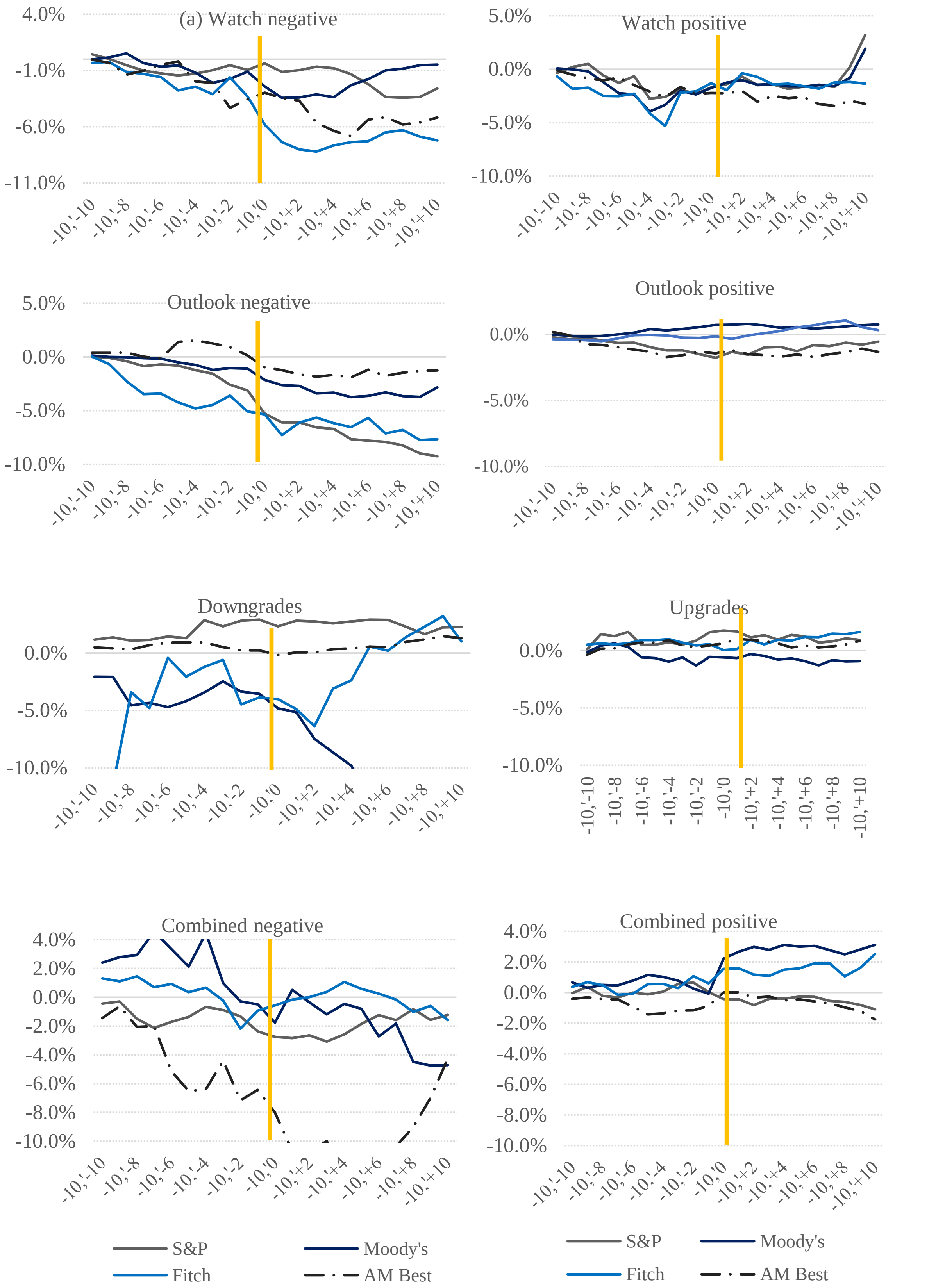
Appendix 7.II – Figures

Figure A 7.1 Distribution of daily FSR insurer's ratings



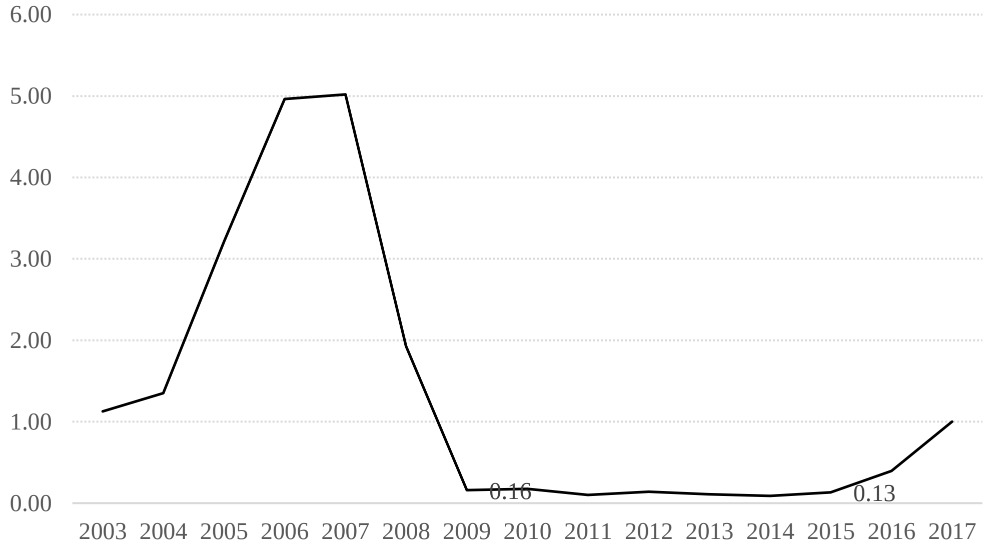
This figure presents the distribution of the 527 FSR actions included in this study from 1st of January 2003 to 31 December 2017 by S&P, Moody's, Fitch and AM Best. To be consistent with Chapter 5 and 6, the credit ratings scale is also transformed into the 13-point numerical from AM Best towards the other three CRAs (A++/AAA/AA+ =1, A+ / AA/ AA-= 2 to C/SD−D=13). Likewise, to compare with prior literature, the credit rating scale is also transformed into 58-point numerical scale (AAA/Aaa =1 , AA+/Aa1 =3, AA/Aa2 = 7…CCC-/Caa3 = , CC/Ca, SD-D/C = 58). By means of the 13-points AM Best rating scale, 96% of the total observations are included in superior, excellent and good categories while only 4% are classified as fair, marginal and below. Alternatively, using the 58-point scale, the majority of insurers are placed in the 16 category (which corresponds to A/A2 with stable outlook) and disaggregating by CRA and their respective totals, this corresponds to 14% in S&P, 16% in Moody's, 15% in Fitch. AM Best is not included in this graph.

Figure A 7.2 Cumulative abnormal return by subsamples of negative and positive type of FSR actions



This figure shows the cumulative abnormal returns (CARs) based on market-model abnormal returns for S&P, Moody's, Fitch and AM Best by type of activity (watch, outlook, up-downgrade) in the event windows [−10,+10].

Figure A 7.3 Effective Federal Funds Rate



This figure displays the federal funds rate during the period from January 2003 to December 2017. The federal funds rate is the interest rate at which depository institutions trade federal funds with each other overnight. For instance, a bank with excess cash will lend to another bank that needs to quickly raise liquidity, and the rate that the borrowing institution pays to the lending institution is determined between the two banks. However, the weighted average rate for all of these types of negotiations is called the effective federal funds rate. The Federal Open Market Committee (FOMC) determines the target rate. If they believe the economy is growing too fast and inflation pressures affect the main goal of the Federal reserve, the Committee may set a higher federal funds rate target to alleviate economic activity. On the contrary, the FOMC may set a lower federal funds rate target to incentive greater economic activity. Source: Board of Governors of the Federal Reserve System (US).

Chapter 8. Conclusions

8.1 Conclusions

This thesis aims to provide empirical contributions on the intersection between the insurance sector and Credit Rating Agencies (CRAs) literature. The fact that insurers are the only sector assessed by four major CRAs, namely S&P, Moody's, Fitch, and AM Best, creates a unique case study for this analysis. S&P has historically focused on rating debt issues, Moody's and Fitch have been growing gradually in the insurance rating market, while AM Best is the established CRA that has always specialized in insurers' ratings. Considering the *sui generis* nature of the insurance industry, this thesis explores three different dimensions of insurers' financial strength ratings (FSR). The first aspect investigates the evolution of FSR and differences across the four major CRAs. The second aspect examines the effect of split ratings on subsequent rating migrations. The third aspect analyses whether FSR actions induce a stock market reaction. Each of these aspects imparts highly original insights and thereby provides valuable contributions to the academic literature.

CRAs continue to act as key contributors to financial markets despite criticism during the financial turmoil of 2007-2010. Especially in an opaque industry such as insurance, CRAs gain relevance since they aid in the monitoring of the solvency of insurance firms. By assigning FSRs, CRAs install a market discipline mechanism in the insurance market. Insurers use FSR as a marketing tool to promote trust from their existing and potential clients, while customers and investors use them in their policy buying and investing process, respectively.

Studies on insurers' ratings have been relatively scarce. Despite an explosive growth in the academic literature on CRAs during the last ten years, it is striking that the insurance sector has barely received any attention. After the financial crisis, research attention has been placed on structured finance, sovereigns, and bank ratings. Likewise, prior literature on insurers' ratings has been mostly focused on AM Best since it is the CRA with the longest track record (see Section 2.2 in Chapter 2).

Furthermore, research attention has been drawn to the root causes of the failures and potential remedies within the financial system. On one side, crystalized weaknesses in terms of regulatory oversight highlighted the need for harmonization and regulatory updates (e.g., Solvency II, risk-based requirements). Likewise, concerns have arisen from the business ties between the insurance and banking industries. A debate has been reignited on whether the insurance sector creates or enlarges systemic risk (see Section 2.4.3 in Chapter 2). Moreover, an increasing pressure to respond to climate change has led to calls for action by insurers.

Nevertheless, considering the importance of the potential research questions relative to insurers' ratings, the literature is still very limited. This is especially apparent in the lack of studies using data from the last 10 years and with most studies based on only one CRA or a very short time period. The few existing studies show that, despite being voluntary, FSRs are heavily relied upon by market participants i.e., policyholders, regulators, investors, and lenders (e.g., Doherty and Phillips, 2002; Halek and Eckles, 2010; Miao et al., 2014; Milidonis, 2013; Pottier and Sommer, 1999).

Regarding regulatory developments or updates for the insurance sector (e.g., Solvency II, SST, and U.S. Risk-based Capital), some of the gaps in the literature are revealed in the latent effects of Solvency II (SII) on European rating levels, as well as further research in other issues such as determinants of FSR and the likelihood of an insurance firm to be rated. These items did not ultimately fall within the scope of this thesis but provided the foundation and inspired its overarching goals. Indeed, FSRs have linked with SII in the sense that insurers manage their level of capitalization and capital structure following regulatory capital requirements, CRAs' requirements, as well as their own management view. On the other hand, CRAs assess insurance companies using various quantitative and qualitative criteria to allocate FSRs and other credit ratings, and one of those criteria is the assessment of the capital adequacy of the insurer using risk-based capital models (Höring, 2013). Considering this, potential avenues of future research can be focused on determining the impact of European FSR levels, the evolution of insurers' investment strategies, and levels of premiums before and after SII's implementation.

Furthermore, the credit rating industry has gone from being largely unregulated to being subject to regulatory reforms (SEC, 2020b). This is evident by the enactment of the 2010 Dodd Frank Act in the U.S. and the establishment of ESMA in 2011 in the EU. Although this thesis did not consider these explicitly in the empirical analysis, it is relevant to point out the need for future studies in this regard. For instance, within the U.S. context, the state-based regulations have played a historical role and new additions from Dodd-Frank such as the Federal Insurance Office (FIO) have added another dimension. Some argue that thanks to the actions of the states and the presence of the NAIC, the Property/Casualty (P/C) industry did not suffer major effects in the global financial crisis. Others argue that the state-based regulation has become overly complex, anticompetitive and requires modernization (III, n.d.).

Investigating FSR is highly relevant, considering that the insurance industry fulfils an essential role as a provider of coverage of diverse types of risks in exchange for a premium. In particular, the P/C industry, which is the main subsector of analysis of this thesis, is a main pillar in the U.S. economy. The P/C sector contributes to more than 4% of the GDP (Ben Ammar et al., 2018), its investment portfolio amounted to $1,529 ($1,586) billion in 2015, and 2016, respectively (FIO, 2016, 2017) and therefore is considered one of U.S. largest institutional investors. This is particularly pertinent because information asymmetries between issuers and investors are more significant in an industry that has been found to be one of the most opaque as well as the banking industry.

Regarding the development of this thesis, Chapter 4 explains the data sources and the series of steps undertaken to prepare datasets that are suitable for the research directions taken with the empirical chapters of this thesis. Each CRA has its own definitions, terminology, and rating scale. Therefore, there is a need for Chapter 4 to underpin the subsequent three empirical chapters. The chapter highlights the lack of ratings equivalence across S&P, Moody's and Fitch versus AM Best. It also identifies several opportunities for contributions to knowledge, which are reinforced by data qualities in terms of sample size, extended time period, and a much more recent period of analysis (compared to pre-existing literature). In terms of the numerical rating transformation, prior studies contain several ways to define mappings between ratings across CRAs (e.g., Pottier and Sommer, 1999, Doherty and Phillips, 2002). However, they neglect granularity in such equivalence. Thus, taking insights from the sovereign, corporate, and bank rating literature, this thesis proposes much more refined mappings of 20-point and 13-point rating scales which are then adopted in the subsequent empirical Chapters 5, 6, and 7.

Given the above motivations to embark on this research, the specific aims of each of the empirical chapters of the thesis are as follows. Chapter 5 studies the evolution of FSR actions assigned by the major four CRAs to find differences or patterns in rating trends but also to offer insights into the effects of the financial crisis on financial strength. Chapter 6 analyses the effect of split ratings upon future rating changes, which is an unexplored area by prior insurance credit rating literature. Chapter 7 investigates whether FSR actions induce stock market reactions to test the information content of FSR actions, and to better understand the parent company-subsidiary transmission channels.

Chapter 5 considers the research question: 'What are the differences in rating trends for insurance companies among the big four CRAs?'. To address the investigation, the chapter employs an approach based on rating transition matrices (RTM). The sample comprises 1384 U.S. P/C insurers with long-term (LT) local-currency (LC) FSR assigned by at least two of the four CRAs; S&P, Moody's, Fitch, and AM Best during the period of 2000-2017. From the sample, 1335 insurers are rated by S&P, 330 by Moody's, 284 by Fitch, and 1372 by AM Best.

The uniqueness of the study is its focus on a sample that considers insurers rated by at least two of the four CRAs to aim for comparability as well as considering issues surrounding rating scales and a recent time period. The results of Chapter 5 show that a number of FSR actions occur before the crisis, downgrades are more frequent than upgrades before and during the financial crisis, while after the crisis, upgrades and downgrades are balanced. Using a proposed 20-point rating scale, RTMs indicate that AM Best has the least amount of FSR actions during the whole period. S&P seems to be the most active CRA, while Moody's and Fitch have a similar amount of FSR actions, with the latter assigning more downgrades during the crisis. Across CRAs, single (AA- to AA) and multi-notch rating changes (e.g., 'AA-' to 'AA+') are more common over one year than changes across a whole category (e.g., 'AA-' to 'BBB+').

The results in Chapter 5 also provide insights into the effect of the financial crisis on rating levels of the P/C industry. Results reveal a more straightforward link with climate-related events rather than with the financial crisis. Indeed, prior literature asserts the uneven effect of the financial crisis on the insurance industry (see Baluch et al., 2011), with life/health (L/H) insurers probably more affected than P/C insurers. On the other hand, CRAs argue that P/C insurers have been resilient enough to meet their obligations after natural catastrophes, thus not affecting FSR levels majorly. Nevertheless, the frequency and severity of catastrophe events are raising, urging the sector to keep monitoring its financial strength and anticipating future impacts of climate change.

Alternative specifications are also developed in Chapter 5 to construct the RTMs. One alternative consists of using AM Best 13-point rating scale to map the other three CRAs and, a second specification consists of reconstructing RTMs considering the evolution of the 10 states at greatest risk of storm surge damage. From the first alternative, rating activity patterns are consistent with the main finding of the chapter; AM Best has relatively the least amount of rating activity. Supplemental findings from the second alternative using only the most affected states by storm surge do not show a particular pattern. Instead, results agree with the argument that insurers seem to have been resilient enough to keep their FSR almost intact. Again, this thesis insists on the fact that the alarm is set for the FSR future trend considering the increased frequency and severity of climate-related events.

Chapter 6 investigates the research question: 'Is there any relationship between split ratings and subsequent rating migration for U.S. P/C insurers' ratings?'. This research area has been unexplored for insurance companies. Thus, Chapter 6 addresses the shortcoming in the literature and takes an original and unique direction by analysing the dynamic of the four CRAs and a much more recent and extensive-time period. The research question is addressed by employing a probit approach using a sample of 904 U.S. P/C with FSR assigned by at least two of the four major CRAs during the period from 2003 to 2017.

The results of Chapter 6 suggest that insurers' split ratings between the four CRAs influence future rating changes. In particular, results indicate that Moody's is the CRA that is influenced by all the other three CRA in both directions, upgrades, and downgrades. For S&P, the magnitude of the split influences future S&P rating changes more strongly in the case of upgrades than downgrades. For Fitch, surprisingly, Moody's/S&P ratings have no significant effect on its future rating changes, especially when implementing an upgrade. Regarding the interaction between the three CRAs contrasted with AM Best as the insurers' specialized CRA; S&P and Moody's results imply that split rated insurers with higher (lower) AM Best ratings are more likely to be upgraded (downgraded) by S&P and Moody's in the following year than non-split rated issuers. However, for Fitch, AM Best actions have a significant effect on Fitch's future rating changes only when assigning a downgrade. In contrast, AM Best seems to be strongly influenced by all three (S&P/Moody's/Fitch) when deciding on an upgrade, but for downgrades, the degree of influence is lower and only comes from S&P and Moody's.

Results in Chapter 6 are in line with prior work from Alsakka and ap Gwilym (2010a), Livingston et al., (2008), and Martin-Merizalde (2020), whose work on other rating segments motivates this research. The insurance literature is limited to Morgan (2002), Pottier and Sommer (2006) and Iannotta (2006) who study insurers' split ratings amongst other industries for the EU and U.S., respectively. This chapter takes an original and unique direction by analysing the dynamic of the four CRAs and a much more recent and extensive time period.

Up to this point, Chapter 5 has shown FSR variability across time and CRAs, revealed via RTMs, that most insurers remain in the same rating level from one year to the other. Likewise, with Chapter 6, opacity is studied through split ratings and their influential role on each CRA's future rating migrations. Building upon those findings, Chapter 7 aims to contribute to the discussion by adding secondary rating actions to help elucidate other features in the insurance setting, as well as adding another perspective of opacity within insurers through studying market reaction.

Chapter 7 examines the research question: 'Do FSR actions induce stock market reactions?'. To do so, a set of FSR actions from 346 U.S. P/C subsidiaries is selected to capture the effect on the share prices of the 30 parent companies associated with them. Relating to these 346 subsidiaries, there is a total of 527 FSR rating events spanning 2003 to 2017. To examine the effect of the FSR actions, the analysis is undertaken in two parts. The first part involved using event study methodology focusing on positive and negative FSR actions that affect stock-market returns collectively, by type of action, and CRA. The second part involved a multivariate analysis to determine if parent companies' characteristics (e.g., size, profitability, liquidity) are associated with the effects on Cumulative Abnormal Returns (CARs) in the event windows.

The results from Chapter 7 suggest that negative FSR actions seem to provide a greater impact in the stock market compared to positive FSR actions, thus favouring the information content hypothesis and asymmetric reaction of the stock markets. In particular, negative FSR actions by Fitch drive the largest average CARs across CRAs. S&P's strongest market reactions arise from negative Outlook actions while for Moody's, Watch actions seem to have the strongest reaction. Finally, for AM Best, results do not show that negative FSR actions generally yield strong market impact. However, the market reveals a slight significant reaction to AM Best's positive FSR actions, whilst there is somewhat muted evidence that the market reacts to these FSR actions by S&P, Moody's, and Fitch.

Results from the multivariate regression analysis in Chapter 7 also provide new insights. Using the entire set of negative FSR actions from all CRAs, leverage, and the magnitude of the rating actions are found to be significantly influential in the market reaction, while for the entire set of positive FSR actions, profitability and diversification seem to influence the most. By CRA, liquidity is relevant for the impact of negative FSR actions by S&P while profitability and diversification for the positive ones. For Moody's, leverage seems a significant driver on the impact of negative FSR actions whereas profitability is relevant when the market receives FSR positive actions. Concerning Fitch, the magnitude of negative FSR actions is what seems to be influencing the most when negative FSR actions land in the market, while no parent company characteristic is relevant to the impact of positive FSR actions. Turning to AM Best results, leverage and macroeconomic conditions have a relevant influence on the impact of negative FSR actions, while for positive actions, no parent company characteristic seems to enlarge or diminish the market reaction.

Connecting these results with the parent-subsidiary transmission channels, it is on the entity-based risk source explained by EIOPA (2017) where FSR actions and parents' characteristics such as leverage and profitability can have repercussions. This entity-based risk source within the different transmission channels (i.e., exposure channel, asset liquidation channel, expectations and information asymmetries), comprises the failure of a systemically important company or the collective failure of non-systemically important insurers because of exposures to common shocks. Thus, it is in this scenario where the additional information via FSR assigned by CRAs would play a key role as providers of information to the stock market as well as in the effort to contribute to the control of the systemic risk.

Overall, this thesis contributes new insights to the credit rating literature in several ways. Chapter 5 reveals the variability of FSR evolution across time and CRAs and draws attention to the fact that the financial crisis had an uneven effect on the insurance sector. In contrast, climate-related events show a much more straightforward link with P/C insurers. From this finding, future research can point to the literature strand of Environmental, Social, and Governance (ESG) factors. Future studies can be taken to how ESG factors are included in methodologies and how this can create more split insurer ratings among CRAs. Indeed, agencies such as AM Best anticipate that *factors related to climate risk and governance will have the highest impact on financial strength over the near term, while environmental liability and certain transition risks are likely to become more relevant over time* (AM Best, 2021).

This thesis benefits substantially from the construction of a unique dataset with a much longer and recent time period and bringing together the four major CRAs for insurers. Likewise, in Chapter 7 when the rating data is matched with financial and accounting variables from the parent company. Chapter 6 is the first study on the insurers' rating industry based on the effect of split ratings on subsequent rating migrations among the four major CRAs. These topics were both unexplored in the prior split rating literature and have economic relevance due to the important role of the P/C insurance sector in the U.S. with the aforementioned weight in the U.S. GDP. It is clear that this study addresses an important omission in the literature about players in the U.S insurance market. In future research, it will be of interest to see how the CRAs' reputational role lines up with insurers' split rating results, and investigate herding behaviour within the insurers' credit rating industry. Prior studies such as Lugo et al., (2015) have determined the reputational role in a credit rating market combining arguments from the market share, the weakness or strength of market impact of the CRA in the studied market, and the rating accuracy (accuracy ratio performance) of the CRAs. Therefore, elements can be taken from there and new insights could be gleaned from herding/reputational protection perspectives and research approaches could involve interviews and/or survey evidence.

Further, the research design used in Chapter 7 enables the study of the drivers of parent company characteristics, which is unique in the literature. In other words, Chapter 7 takes a novel perspective on the market reaction of FSR by examining the effect of FSR actions of U.S. P/C insurers on the share price effect of their respective parent company. It also adds components in terms of the parent-subsidiary transmission channels in a broader context.

While this thesis limits itself to empirically examine the FSR of U.S. P/C insurers, the regulatory environment also encompasses the wider context of the industry overall. There is potential for further investigation to consider whether similar behaviours are found in the Life and Health (L/H) sector, the reinsurance sector, especially in the split rating and rating migration component. Within the U.S. context, a direction of future research can be focused on more information on the U.S. state-based regulatory environment and its links with CRAs' ratings. In addition, comparisons can be undertaken with other active insurance markets such as the U.K. or the European region as they have different institutional settings, which would underpin the value of comparisons on a geographical basis. Nevertheless, institutional differences should be tempered as they might affect the effective comparison of ratings between say the U.S. and U.K./Europe.

As for any research, it is important to recognise some limitations, which remain at the end of the process. One limitation arises from the method by which the RTM is constructed. In this thesis, the traditional cohort method is applied following previous studies such as Hu and Cantor (2003), Jadi (2015) and Wang (2010). However, continuous methods would have been an alternative to extend the analysis. Hadad et al., (2009) have found that continuous methods provide more efficient results and estimations using transition matrices with a more dispersed probability distribution. On the other hand, the choice of the years representing the global financial crisis (GFC) was following prior studies (i.e., Baluch et al., 2011) but it would be beneficial to run the matrices modifying the years to be able to compare with more studies.

Some other limitations arise in Chapter 6. The challenge for the analysis is the lack of rating comparability in the numerical conversion of the rating scale to calculate the split; specifically, the fact that the FSR scale used by AM Best does not directly portray the rating scales used by the other CRAs. Moreover, one can argue that limitations in Chapter 7 can arise from the conventional event study design. An alternative for future research is to consider the issuer credit rating (ICR) from the parent company, and use more insurer-specific variables in the multivariate analysis.

To conclude, the implications of the results of this thesis are as follows. The findings may affect the decisions of market participants as they have more information on the evolution of FSR in the last decade, the correspondence between the different CRAs' categories for insurers' ratings, and the market reaction of FSR actions. On one side, it is evident that the lack of transparency has led to potential confusion and with this study, the spectrum increases by incorporating the four CRAs and a more recent reflection of the insurers' rating market. Policyholder-customers, who rely on insurers when a claim arises, want to continue buying safe insurance products and should be aware of the lack of equivalence of FSR across CRAs. Furthermore, investors can benefit from an improved understanding of the influence of FSR actions and then stock price changes, Furthermore, investors can benefit from an improved understanding of the influence of FSR actions and then stock price changes, and regulatory implications could be also drawn upon considering the states' roles in the U.S. and variables such as leverage or profitability within the insurers' parent companies.

Regarding CRAs' lack of transparency, a distinction needs to be made between CRAs' transparency and standardization of the credit rating methodologies. As mentioned earlier, regulatory changes (i.e., the 2010 Dodd-Frank Act and ESMA in the EU) have been enacted and CRAs have become more transparent over time. Meanwhile, the desirability of standardization is a matter of opinion. Regulators have required CRAs to be transparent, not standardized. Standardization will mean there is no benefit of having more than one CRA. Also, as the definition suggests, a credit rating and more specifically an FSR is a forward-looking opinion about the ability of the insurer to meet their claims and each CRA reflects such opinion in the ratings they assign. Each CRA bases its assessment on quantitative and qualitative information and competes for clients by seeking the most successful methodologies. Merging these elements, the debate about the future of the insurers' credit rating industry needs to continue with the efforts focussed on transparency and competition. There is an opportunity for enhancement in terms of the clarity for the rating users in terms of the equivalence of the rating scale from AM Best with their peers and the regulatory use of ratings.

References

Abad-Romero, P. and Robles-Fernandez, M.D. (2006), 'Risk and return around bond rating changes: new evidence from the Spanish stock market', Journal of Business Finance & Accounting, 33 (5-6), pp. 885–908.

Adams, M., Burton, B. and Hardwick, P. (2003), 'The determinants of credit ratings in the United Kingdom insurance industry', Journal of Business Finance and Accounting, 30 (3–4), pp. 539–572.

Adams, M., Upreti, V. and Chen, J. (2019), 'Product-market strategy and underwriting performance in the United Kingdom's property–casualty insurance market', European Journal of Finance, 25 (11), pp. 1012–1031.

Adamson, S.R., Eckles, D.L. and Haggard, K.S. (2014), 'Insurer opacity and ownership structure', Journal of Insurance Issues, 37 (2), pp. 93–134.

Adrian, T., Evan, F. and Muir, T. (2015), The cost of capital of the financial sector. Federal Reserve Bank of New York Staff reports, 755, New York, available at: https://ideas.repec.org/p/fip/fednsr/755.html.

Agarwal, S., Chen, V.Y.S. and Zhang, W. (2016), The information value of credit rating action reports: a textual analysis", Management Science, 62 (8), pp. 2218–2240.

Ahern, K. and Painter, G. (2016), 'S&P Global Ratings: Insurance ratings history, methodology and process', NAIC/CIPR Webinar, p. 17.

Alsakka, R. (2010), 'Sovereign credit ratings in emerging countries', PhD thesis, Aberystwyth University.

Alsakka, R. and ap Gwilym, O. (2009), 'Heterogeneity of sovereign rating migrations in emerging countries', Emerging Markets Review, 10 (2), pp. 151–165.

Alsakka, R. and ap Gwilym, O. (2010a), 'Split sovereign ratings and rating migrations in emerging economies', Emerging Markets Review, 11 (2), pp. 79–97.

Alsakka, R. and ap Gwilym, O. (2010b), 'Leads and lags in sovereign credit ratings', Journal of Banking & Finance, 34(11), pp. 2614–2626.

Alsakka, R. and ap Gwilym, O. (2012a), 'The causes and extent of split sovereign credit ratings in emerging markets', Emerging Markets Finance and Trade, 48 (1), pp. 4–24.

Alsakka, R. and ap Gwilym, O. (2012b), 'Rating agencies' credit signals: an analysis of sovereign watch and outlook', International Review of Financial Analysis, 21 (Supplement C), pp. 45–55.

Alsakka, R. and ap Gwilym, O. (2012c), 'Foreign exchange market reactions to sovereign credit news', Journal of International Money and Finance, 31 (4), pp. 845–864.

Alsakka, R., ap Gwilym, O. and Vu, H. (2017), 'Differences of opinion in sovereign credit signals during the European crisis', European Journal of Finance, 23 (10), pp. 859–884.

Alsakka, R., ap Gwilym, O, Klusak, P. and Tran, V. (2015), 'Market impact under a new regulatory regime: Credit rating agencies in Europe', Economic Notes, 44 (2), pp. 275–308.

AM Best (2005), BestWeek: Battered by hurricanes, Bermuda reinsurers seek boost from capital markets, Best's insurance news & analysis. available at: https://news.ambest.com/presscontent.aspx?altsrc=108&refnum=9802

AM Best (2014), U.S. P/C Impairments down sharply in 2013; alternative risk players faltered. available at: http://www3.ambest.com/bestweekpdfs/sr745011714541dfull.pdf.

AM Best (2017a), Best's credit rating methodology. available at: http://www3.ambest.com/ambv/ratingmethodology/.

AM Best (2017b), Rating Takaful (Shari'a Compliant) companies. available at: https://www3.ambest.com/ambv/ratingmethodology/OpenPDF.aspx?rc=197661

AM Best (2019), Understanding Best's credit ratings. available at: http://www3.ambest.com/ambv/ratingmethodology/OpenPDF.aspx?rc=238151.

AM Best (2021), AM Best historical highlights. available at: https://www.ambest.com/about/historical_highlights.html

AM Best (n.d.). Compensation disclosure, available at: https://www.ambest.com/regulatory/compensationdisclosure_AMBRS.pdf.

Angell, K., Archer-Lock, P., Harris, S., Moss, G., Patfield, S. and Sayers, J. (2000), 'Assessing the financial strength of insurers', General insurance convention, actuaries.org.uk, p. 29.

Anginer, D., Bertay, A.C., Cull, R., Demirgüç-Kunt, A. and Mare, D.S. (2019), Bank regulation and supervision ten years after the global financial crisis. available at: https://openknowledge.worldbank.org/bitstream/handle/10986/32589/WPS9044.pdf?sequence=4&isAllowed=y.

Aon (2018), Weather, climate & catastrophe insight - 2017 Annual report. available at: https://www.aon.com/home/solutions/reinsurance.html

Aon Benfield (2017), Weather, climate & catastrophe insight, New York. available at: http://thoughtleadership.aonbenfield.com/Documents/20180124-ab-if-annual-report-weather-climate-2017.pdf.

Aon Benfield (2019), financial analysis workshop: 'Market security & analysis approach to (Re)insurance counterpart risk', lecture notes, delivered 2019.

Asimit, A. V, Badescu, A.M., Haberman, S. and Kim, E.-S. (2016), 'Efficient risk allocation within a non-life insurance group under Solvency II regime', Insurance: Mathematics and Economics, 66 (Supplement C), pp. 69–76.

Ayed, M. Ben, Karaa, A. and Prigent, J. (2018), 'Duration models for credit rating migration: Evidence from the financial crisis', Economic Inquiry, 56 (3), pp. 1870–1886.

Bae, K.-H., Kang, J.-K. and Wang, J. (2015), 'Does increased competition affect credit ratings? A reexamination of the effect of Fitch's market share on credit ratings in the corporate bond market', Journal of Financial and Quantitative Analysis, 50 (05), pp. 1011–1035.

Baluch, F., Mutenga, S. and Parsons, C. (2011), 'Insurance, systemic risk and the financial crisis', Geneva Papers on Risk and Insurance - Issues and Practice, 36 (1), pp. 126–163.

Becker, B. and Ivashina, V. (2015), 'Reaching for yield in the bond market', Journal of Finance, 5, pp. 1863–1902.

Becker, B. and Milbourn, T. (2011), 'How did increased competition affect credit ratings?', Journal of Financial Economics, 101 (3), pp. 493–514.

Becker, B., Opp, M. and Saidi, F. (2020), ‘Regulatory forbearance in the U.S. insurance industry: The effects of eliminating capital requirements’, Swedish House of Finance Research Paper, 20 (6).

Ben Ammar, S., Eling, M. and Milidonis, A. (2018), ‘The cross-section of expected stock returns in the property/liability insurance industry’, Journal of Banking & Finance, 96, pp. 292–321.

Benmelech, E. and Dlugosz, J. (2010), ‘The credit rating crisis’, National Bureau of Economic Research, Inc, pp. 161-207 in BT-NBER Macroeconomics Annual 2009.

Berger, L.A., Cummins, J. and Tennyson, S. (1992), ‘Reinsurance and the liability insurance crisis’, Journal of Risk and Uncertainty, 5 (3), pp. 253–272.

Bernal, O., Gnabo, J.-Y. and Guilmin, G. (2014), ‘Assessing the contribution of banks, insurance and other financial services to systemic risk’, Journal of Banking & Finance, 47, pp. 270–287.

Bevere, L., Orwin, K. and Sharan, R. (2015), Natural catastrophes and man-made disasters in 2014: convective and winter storms generate most losses. Swiss Re Sigma, 2, pp. 52. available at: https://www.swissre.com/institute/research/sigma-research/sigma-2015-02.html.

Bierth, C., Irresberger, F. and Weiß, G.N.F. (2015), ‘Systemic risk of insurers around the globe’, Journal of Banking & Finance, 55 (Supplement C), pp. 232–245.

Billio, M., Getmansky, M., Lo, A.W. and Pelizzon, L. (2012), ‘Econometric measures of connectedness and systemic risk in the finance and insurance sectors’, Journal of Financial Economics, 104 (3), pp. 535–559.

Bisani, B. (2011), Takaful and its business models, Master's thesis, University of Vienna. available at: http://othes.univie.ac.at/15997.

Bleemer, Z. and van der Klaauw, W. (2019), ‘Long-run net distributionary effects of federal disaster insurance: The case of Hurricane Katrina’, Journal of Urban Economics, 110, pp. 70–88.

Bliss, R. (2014), Market discipline in financial markets, edited by Berger, A.N., Molyneux, P. and Wilson, J.O.S., Oxford University Press. available at: https://doi.org/10.1093/oxfordhb/9780199688500.013.0024.

Board of Governors of the Federal Reserve System (US), Effective Federal Funds Rate [FEDFUNDS], retrieved from FRED, Federal Reserve Bank of St. Louis, available at: https://fred.stlouisfed.org/series/fedfunds (accessed 14 December 2020).

Boehmer, E., Masumeci, J. and Poulsen, A.B. (1991), ‘Event-study methodology under conditions of event-induced variance’, Journal of Financial Economics, 30 (2), pp. 253–272.

Bolton, P., Freixas, X. and Shapiro, J. (2012), ‘The credit ratings game’, Journal of Finance, 67 (1), pp. 85–111.

Bølviken, E. and Guillen, M. (2017), ‘Risk aggregation in Solvency II through recursive log-normals’, Insurance: Mathematics and Economics, 73, pp. 20–26.

Bongaerts, D., Cremers, K.J.M. And Goetzmann, W.N. (2012), ‘Tiebreaker: Certification and multiple credit ratings’, Journal of Finance, 67 (1), pp. 113–152.

Borio, C. and Zhu, H. (2008), Capital regulation, risk-taking and monetary policy: a missing link in the transmission mechanism?, available at: https://econpapers.repec.org/RePEc:bis:biswps:268.

Bryce, C., Webb, R., Cheevers, C., Ring, P. and Clark, G. (2016), 'Should the insurance industry be banking on risk escalation for Solvency II?', International Review of Financial Analysis, 46 (Supplement C), pp. 131–139.

Brown, S.J. and Warner, J. (1985), 'Using daily stock returns. The case of event studies', Journal of Financial Economics, 14, pp. 3–31.

Cantor, R. and Packer, F. (1997), 'Differences of opinion and selection bias in the credit rating industry', Journal of Banking & Finance, 21 (10), pp. 1395–1417.

Caporale, G.M., Cerrato, M. and Zhang, X. (2017), 'Analysing the determinants of insolvency risk for general insurance firms in the UK', Journal of Banking and Finance, 84, pp. 107–122.

Cattellion, L. and Matthys, C. (2016), Split ratings binnen de verzekeringssector, Master's thesis, Universiteit Gent. available at: https://libstore.ugent.be/fulltxt/RUG01/002/273/498/RUG01-002273498_2016_0001_AC.pdf.

Chang, V.Y. (2019), 'Does reinsurance purchasing enhance insurers' competitiveness? Evidence from the U.S. property-liability insurance industry', Geneva Papers on Risk and Insurance - Issues and Practice. available at: https://doi.org/10.1057/s41288-019-00124-y.

Chen, L., Gaver, J.J. and Pottier, S.W. (2018), 'An investigation of the short-run and long-run stock returns surrounding insurer rating changes', Journal of Risk and Insurance, 85 (1), pp. 35–67.

Chen, L. and Pottier, S.W. (2018), 'Rating changes and competing information: evidence on publicly traded insurance firms', Journal of Risk and Insurance, 85 (3), pp. 811–842.

Cheng, M. and Neamtiu, M. (2009), 'An empirical analysis of changes in credit rating properties: Timeliness, accuracy and volatility', Journal of Accounting and Economics, 47(1), pp. 108–130.

Christiansen, M.C. and Niemeyer, A. (2014), 'Fundamental definition of the solvency capital requirement in Solvency II', ASTIN Bulletin, 44(3), pp. 501–533.

Chorafas, D.N. (2004a), '12 - Role of rating agencies in the creditworthiness of insurance firms', in Chorafas, D.N. (Ed.), Operational risk control with Basel II, Butterworth-Heinemann, Oxford, pp. 251–273.

Chorafas, D.N. (2004b), '10 - The science of insurance and the notion of technical risk', in Chorafas, D.N. (Ed.), Operational risk control with Basel II, Butterworth-Heinemann, Oxford, pp. 209–229.

CIPR (2017a), Flood risk and insurance, Kansas, available at: https://www.naic.org/documents/cipr_study_1704_flood_risk.pdf?26.

CIPR (2017b), NAIC enhances P/C formula for catastrophe risk charges, Kansas City. available at: https://www.naic.org/cipr_newsletter_archive/vol22_rbc_formula.pdf

CIPR (2017c), Natural catastrophes, insurance and alternative risk transfer, Kansas City. available at: https://www.naic.org/cipr_newsletter_archive/vol23_alt_risk_transfer.pdf

Ciumaş, C., Oniga, A. and Popa, I. (2015), 'The rating of insurance companies during the financial crisis', Procedia Economics and Finance, 32 (Supplement C), pp. 1494–1504.

Coca Perraillon, M. (2019), 'Week 13: Interpreting model results: Marginal effects and the margins command', lecture notes, University of Colorado, Colorado. available at: https://clas.ucdenver.edu/marcelo-perraillon/sites/default/files/attached-files/week_13_margins.pdf

Cole, C.R., He, E. and McCullough, K.A. (2017), 'A comprehensive examination of insurer financial strength ratings', Journal of Financial Perspectives: Insurance, 4 (1), p. 14.

Cornaggia, J.N., Cornaggia, K.J. and Hund, J.E. (2017), 'Credit ratings across asset classes: a long-term perspective', Review of Finance, 21 (2), pp. 465–509.

Cowan, A.R. (1992), 'Nonparametric event study tests', Review of Quantitative Finance and Accounting, 2 (4), pp. 343–358.

Cummins, J.D., Klumpes, P. and Weiss, M.A. (2015), 'Mergers and acquisitions in the global insurance industry: Valuation effects', Geneva Papers on Risk and Insurance - Issues and Practice, 40 (3), pp. 444–473.

Cummins, J.D. and Weiss, M.A. (2014), "Systemic risk and the u.s. insurance sector", Journal of Risk and Insurance, 81(3), pp. 489–528.

Dacorogna, M. (2018), 'A change of paradigm for the insurance industry', Annals of Actuarial Science, 12 (2), pp. 211–232.

Dahiya, S., Iannotta, G. and Navone, M. (2017), 'Firm opacity lies in the eye of the beholder', Financial Management, 46 (3), pp. 553–592.

DBRS (2013), Claims paying ability rating scale. available at: https://www.dbrsmorningstar.com/document/236747.pdf.

Dichev, I.D. and Piotroski, J.D. (2001), 'The long-run stock returns following bond ratings Changes', Journal of Finance, 56 (1), pp. 173–203.

Dilly, M. and Mählmann, T. (2016), 'Is there a 'boom bias' in agency ratings?', Review of Finance, 20 (3), pp. 979–1011.

Dimitrov, V., Palia, D. and Tang, L. (2015), 'Impact of the Dodd-Frank Act on credit ratings', Journal of Financial Economics, 115 (3), pp. 505–520.

Doherty, N.A., Kartasheva, A. V and Phillips, R.D. (2012), 'Information effect of entry into credit ratings market: The case of insurers' ratings', Journal of Financial Economics, 106 (2), pp. 308–330.

Doherty, N.A. and Phillips, R.D. (2002), 'Keeping up with the Joneses: changing rating standards and the buildup of capital by U.S. property-liability insurers', Journal of Financial Services Research, 21 (1), pp. 55–78.

Doherty, N.A. and Tinic, S. (1981), 'Reinsurance under conditions of capital market equilibrium: A note', Journal of Finance, 36 (4), pp. 949–953.

Drago, D. and Gallo, R. (2016), 'The impact and the spillover effect of a sovereign rating announcement on the euro area CDS marke', Journal of International Money and Finance, 67 (Supplement C), pp. 264–286.

Ederington, L.H. (1986), 'Why split ratings occur', Financial Management, 15 (1), pp. 37–47.

EIOPA (2017), Systemic risk and macroprudential policy in insurance. available at: https://www.eiopa.europa.eu/sites/default/files/publications/pdfs/003systemic_risk_and_macroprudential_policy_in_insurance.pdf.

EIOPA (2021), About EIOPA. available at: https://www.eiopa.europa.eu/about_en

Eling, M., Gatzert, N. and Schmeiser, H. (2008), 'The Swiss Solvency Test and its market implications', Geneva Papers on Risk and Insurance - Issues and Practice, 33 (3), pp. 418–439.

Eling, M. and Jia, R. (2018), 'Business failure, efficiency, and volatility: Evidence from the European insurance industry', International Review of Financial Analysis, 59, pp. 58–76.

Eling, M. and Schmeiser, H. (2010), 'Insurance and the credit crisis: impact and ten consequences for risk management and supervision', Geneva Papers on Risk and Insurance - Issues and Practice, 35 (1), pp. 9–34.

Eling, M. and Schmit, J.T. (2012), "Is there market discipline in the european insurance industry? an analysis of the german insurance market", Geneva Risk and Insurance Review, 37 (2), pp. 180–207.

Epermanis, K. and Harrington, S.E. (2006), 'Market discipline in property/casualty insurance: evidence from premium growth surrounding changes in financial strength ratings', Journal of Money, Credit and Banking, 38 (6), pp. 1515–1544.

Fabozzi, F.J. and Vink, D. (2015), 'The information content of three credit ratings: the case of European residential mortgage-backed securities', European Journal of Finance, 21 (3), pp. 172–194.

Fama, E.F. (1970), 'Efficient capital markets: a review of theory and empirical work', Journal of Finance, 25(2), pp. 383–417.

FDIC (2011), The orderly liquidation of Lehman Brothers holdings Inc. under the Dodd-Frank Act, FDIC Quaterly, 5(2), pp. 31–49. available at: https://www.fdic.gov/analysis/quarterly-banking-profile/fdic-quarterly/2011-vol5-2/lehman.pdf.

Feldblum, S. (2011), Rating agencies. available at: https://www.casact.org/sites/default/files/2021-03/Feldblum_Rating_Agencies.pdf.

FEMA (2017), Emergency Manangement Institute (EMI) overview, EMI'S History. available at: https://training.fema.gov/history.aspx

Ferreira, M.A. and Gama, P.M. (2007), 'Does sovereign debt ratings news spill over to international stock markets?', Journal of Banking & Finance, 31 (10), pp. 3162–3182.

Ferriero, A. (2016), 'Solvency capital estimation, reserving cycle and ultimate risk', Insurance: Mathematics and Economics, 68 (Supplement C), pp. 162–168.

Financial Times (2021), UK regulator warns insurers on Solvency II capital reforms, *Financial Times*, London, 16 March. available at: https://www.ft.com/content/bf4bd008-ebf4-49c5-a475-5a04b8ac7d79.

FIO (2016), Annual report on the insurance industry. available at: https://home.treasury.gov/system/files/311/2016_Annual_Report_FINAL.pdf.

FIO (2017), Annual report of the insurance industry. available at: https://www.treasury.gov/initiatives/fio/reports-and-notices/Documents/2017_FIO_Annual_Report.pdf.

FIO (2020), Annual report on the insurance industry. available at: https://home.treasury.gov/system/files/311/2020-FIO-Annual-Report.pdf.

Fitch (2009), Fitch updates market on Q-IFS scores. available at: https://www.fitchratings.com/research/insurance/fitch-updates-market-on-q-ifs-scores-23-03-2009.

Fitch (2016), Not all insurer financial strength ratings are created equal. available at: https://www.fitchratings.com/site/insurance/ifsratings.

Fitch (2018), Rating definitions. available at: https://www.fitchratings.com/products/rating-definitions

Fitch (2019), The ratings process. available at: https://www.fitchratings.com/research/structured-finance/the-ratings-process-22-05-2019.

Fitch (2021), Terms of use. available at: https://www.fitch.group/terms-of-use.

Florez-Lopez, R. (2007), 'Modelling of insurers' rating determinants. An application of machine learning techniques and statistical models', European Journal of Operational Research, 183 (3), pp. 1488–1512.

Frydman, H. and Schuermann, T. (2008), 'Credit rating dynamics and Markov mixture models', Journal of Banking & Finance, 32 (6), pp. 1062–1075.

Fuertes, A.-M. and Kalotychou, E. (2007), 'Optimal design of early warning systems for sovereign debt crises', International Journal of Forecasting, 23 (1), pp. 85–100.

Gande, A. and Parsley, D.C. (2005), 'News spillovers in the sovereign debt market', Journal of Financial Economics, 75 (3), pp. 691–734.

GAO (2013), Impacts of and regulatory response to the 2007-2009: Financial crisis. available at: https://www.gao.gov/products/gao-13-583.

Gavalas, D. and Syriopoulos, T. (2014), 'Bank credit risk management and rating migration analysis on the business cycle', International Journal of Financial Studies, 2, pp. 122–143.

Gaver, J.J. and Pottier, S.W. (2005), 'The role of holding company financial information in the insurer-rating process: evidence from the property-liability industry', Journal of Risk and Insurance, 72 (1), pp. 77–103.

Gatzert, N. and Martin, M. (2012), 'Quantifying credit and market risk under Solvency II: standard approach versus internal model', Insurance: Mathematics and Economics, 51 (3), pp. 649–666.

Gatzert, N. and Wesker, H. (2012), 'A comparative assessment of Basel II/III and Solvency II', Geneva Papers on Risk and Insurance - Issues and Practice, 37 (3), pp. 539–570.

Geneva Association. (2010), Special report of the geneva association systemic risk working group. systemic risk in insurance. an analysis of insurance and financial stability, available at: https://www.genevaassociation.org/sites/default/files/research-topics-document-type/pdf_public/ga2010-systemic_risk_in_insurance_1.pdf.

Goh, J.C. and Ederington, L.H. (1993), ‘Is a bond rating downgrade bad news, good news, or no news for stockholders?’, Journal of Finance, 48 (5), pp. 2001–2008.

Gonzalez, F., Haas, F., Johannes, R., Persson, M., Toledo, L., Violi, R., Wieland, M., et al. (2004), ‘Market dynamics associated with credit ratings a literature review’. available at: https://www.ecb.europa.eu/pub/pdf/scpops/ecbocp16.pdf

Greenwood, R. and Scharfstein, D. (2013), ‘The Growth of Finance’, Journal of Economic Perspectives, 27(2), pp. 3–28.

Griffin, J.M., Nickerson, J. and Tang, D.Y. (2013), ‘Rating shopping or catering? An examination of the response to competitive pressure for CDO credit ratings’, Review of Financial Studies, 26 (9), pp. 2270–2310.

Grislain-Letrémy, C. and Villeneuve, B. (2019), ‘Natural disasters, land-use, and insurance’, Geneva Risk and Insurance Review, 44 (1), pp. 54–86.

Grzybowska, U., Karwanski, M. and Orłowski, A. (2012), ‘Examples of migration matrices models and their performance in credit risk analysis’, Acta Physica Polonica A, 121, available at:https://doi.org/10.12693/APhysPolA.121.B-40.

Güttler, A. and Wahrenburg, M. (2007), ‘The adjustment of credit ratings in advance of defaults’, Journal of Banking & Finance, 31(3), pp. 751–767.

Hadad, M.D., Santoso, W., Santoso, B., Besar, D. and Rulina, I. (2009), Rating migration matrices: empirical evidence in Indonesia, available at: https://www.bis.org/ifc/publ/ifcb31u.pdf.

Halek, M. and Eckles, D.L. (2010), ‘Effects of analysts’ ratings on insurer stock returns: evidence of asymmetric responses’, Journal of Risk and Insurance, 77 (4), pp. 801–827.

Hamilton, D.T. and Cantor, R.M. (2004), ‘Rating transition and default rates conditioned on outlooks’, Journal of Fixed Income, available at: https://ssrn.com/abstract=971135.

Han, S., Lai, G.C. and Ho, C.-L. (2018), ‘Corporate transparency and reserve management: Evidence from US property-liability insurance companies’, Journal of Banking & Finance, 96, pp. 379–392.

Hauck, A. and Neyer, U. (2008), ‘Are rating splits a useful indicator for the opacity of an industry?’, SSRN Electronic Journal, available at: https://doi.org/10.2139/ssrn.1304146.

Hauck, A. and Neyer, U. (2014), ‘Disagreement between rating agencies and bond opacity: a theoretical perspective’, Economics Letters, 123 (1), pp. 82–85.

Herweijer, C., Ranger, N. and Ward, R.E.T. (2009), ‘Adaptation to climate change: threats and opportunities for the insurance industry’, Geneva Papers on Risk and Insurance - Issues and Practice, 34 (3), pp. 360–380.

Hill, P. and Faff, R. (2010), ‘The market impact of relative agency activity in the sovereign ratings market’, Journal of Business Finance & Accounting, 37 (9-10), pp. 1309–1347.

Hirth, S. (2014), ‘Credit rating dynamics and competition’, Journal of Banking & Finance, 49 (Supplement C), pp. 100–112.

Holthausen, R.W. and Leftwich, R.W. (1986), ‘The effect of bond rating changes on common stock prices’, Journal of Financial Economics, 17 (1), pp. 57–89.

Holzmüller, I. (2009), ‘The United States RBC Standards, Solvency II and the Swiss Solvency Test: A comparative assessment’, Geneva Papers on Risk and Insurance - Issues and Practice, 34 (1), pp. 56–77.

Höring, D. (2013), ‘Will Solvency II market risk requirements bite? The impact of Solvency II on insurers’ asset allocation’, Geneva Papers on Risk and Insurance - Issues and Practice, 38 (2), pp. 250–273.

Hu, J. and Cantor, R. (2003), ‘Structured finance rating transitions’, Journal of Fixed Income, 13 (1), pp. 7 LP – 27.

Hundt, S., Sprungk, B. and Horsch, A. (2017), ‘The information content of credit ratings: evidence from European convertible bond markets’, European Journal of Finance, 23 (14), pp. 1414–1445.

Iannotta, G. (2006), ‘Testing for opaqueness in the European banking industry: Evidence from bond credit ratings’, Journal of Financial Services Research, 30 (3), pp. 287–309.

III (2010), Hurricane Katrina fact file, New York, NY. available at: https://www.iii.org/sites/default/files/docs/pdf/HurricaneKatrinaFactFile-0320101.pdf.

III (2015), ‘Brief history’, Insurance handbook. available at: https://www.iii.org/publications/insurance-handbook/brief-history

III (2017), ‘Spotlight on: Flood insurance’. available at: https://www.iii.org/publications/insurance-handbook/insurance-and-disasters/spotlight-on-flood-insurance (accessed 18 April 2019).

III (n.d.), Regulation, commercial insurance - How it functions. available at: https://www.iii.org/publications/commercial-insurance/how-it-functions/regulation

Insurance journal (2005), ‘S&P puts 10 insurers on ‘Katrina’ creditwatch/negative’. available at: https://www.insurancejournal.com/news/international/2005/09/12/59361.htm (accessed 18 April 2019)

InteractiveData Credit Ratings (2016), InteractiveData Credit Ratings International, ISSN UK Centre, United Kingdom. available at: https://portal.issn.org/resource/ISSN/1753-7444.

International Monetary Fund (2018), ‘Country groups infomation’, Country groups. available at: https://www.imf.org/external/pubs/ft/weo/2018/01/weodata/weoselagr.aspx (accessed 1 June 2018).

IRI (2019), ‘Insurance regulation & state guaranty associations questions and answers with IRI CEO Cathy Weatherford’. available at: https://www.irionline.org/government-affairs/annuities-regulation-industry-information/insurance-regulation-state-guaranty-associations (accessed 5 September 2020).

Ismail, A., Oh, S. and Arsyad, N. (2015), ‘Split ratings and debt-signaling in bond markets: A note’, Review of Financial Economics, 24, pp. 36–41.

Jadi, D.M. (2015), ‘An empirical analysis of determinants of financial performance of insurance companies in the United Kingdom’, PhD thesis, University of Bradford, available at: https://bradscholars.brad.ac.uk/bitstream/handle/10454/14383/PhD Final Submission DiaraMDJADI.pdf?sequence=1&isAllowed=y.

Jiang, X. and Packer, F. (2019), ‘Credit ratings of Chinese firms by domestic and global agencies: Assessing the determinants and impact’, Journal of Banking & Finance, 105, pp. 178–193.

Jones, L. (2019), ‘The credit rating industry under new regulatory regimes: the case of financial institutions’, PhD thesis, Bangor University. available at: https://research.bangor.ac.uk/portal/en/theses/the-credit-rating-industry-under-new-regulatory-regimes(86afd105-d094-431e-b345-1e9db149cb46).html.

Kassim, Z.A.M. (2005). Takaful: The Islamic way of insurance. available at: https://ribh.files.wordpress.com/2008/05/takaful-the-islamic-way-of-insurance-by-zainal-abidin-mohd-kassim.pdf.

King, M.R., Ongena, S. and Tarashev, N. (2020), 'Bank standalone credit ratings', International Journal of Central Banking, 63, p. 44.

Klein, R.W. (1992), Insurance company rating agencies: A description of their methods and procedures. available at:https://www.naic.org/documents/prod_serv_special_rat_ob.pdf.

Klein, R.W. (2005), A regulator's introduction to the insurance industry, Kansas City, available at: https://www.naic.org/documents/prod_serv_marketreg_rii_zb.pdf.

Klein, R.W. (2019), 'The regulation of insurance markets subject to catastrophics risks', in Kunreuther, H. and Meyer, R.J. (Eds.), The Future of Risk Management (Critical Studies in Risk and Disaster), University of Pennsylvania Press, Inc., p. 448.

Koijen, R.S.J. and Yogo, M. (2016), 'Shadow insurance', Econometrica, 84 (3), pp. 1265–1287.

Kolari, J.W. and Pynnönen, S. (2010), 'Event study testing with cross-sectional correlation of abnormal returns', Review of Financial Studies, 23 (11), pp. 3996–4025.

Kunreuther, H.C. and Michel-Kerjan, E.O. (2009), 'A new era of catastrophes', At war with the weather managing large-scale risks in a new era of catastrophes, The MIT Press, Cambridge, Massachusetts - London, England, p. 23.

Laas, D. and Siegel, C.F. (2016), 'Basel III versus Solvency II: an analysis of regulatory consistency under the new capital standards', Journal of Risk and Insurance, pp. 1–37.

Livingston, M., Naranjo, A. and Zhou, L. (2007), 'Asset opaqueness and split bond ratings', Financial Management, 3, pp. 49–62.

Livingston, M., Naranjo, A. and Zhou, L. (2008), 'Split bond ratings and rating migration', Journal of Banking & Finance, 32 (8), pp. 1613–1624.

Livingston, M., Wei, J. (Diana) and Zhou, L. (2010), 'Moody's and S&P ratings: Are they equivalent? Conservative ratings and split rated bond yields', Journal of Money, Credit and Banking, 42(7), pp. 1267–1293.

Livingston, M. and Zhou, L. (2016), 'Information opacity and Fitch bond ratings', Journal of Financial Research, 39 (4), pp. 329–357.

Lugo, S., Croce, A. and Faff, R. (2015), 'Herding behavior and rating convergence among credit rating agencies: evidence from the subprime crisis', Review of Finance, 19 (4), pp. 1703–1731.

Ma, YL. and Pope, N. (2019), 'The impact of Sarbanes-Oxley on property-casualty insurer loss reserve estimates', Geneva Papers on Risk and Insurance - Issues and Practice, 45, pp. 313–334.

Mählmann, T. (2011), 'Is there a relationship benefit in credit ratings?', Review of Finance, 15 (3), pp. 475–510.

Mariano, B. (2012), 'Market power and reputational concerns in the ratings industry', Journal of Banking & Finance, 36 (6), pp. 1616–1626.

Martin-Merizalde, A. (2020), 'Credit rating divergence and the role of opacity in emerging market banks', PhD thesis, Bangor University, available at: https://research.bangor.ac.uk/portal/files/28680524/2020MartinAphd.pdf

Mathis, J., McAndrews, J. and Rochet, J.-C. (2009), 'Rating the raters: are reputation concerns powerful enough to discipline rating agencies?', Journal of Monetary Economics, 56 (5), pp. 657–674.

Matousek, R. and Stewart, C. (2015), Is there a lead-lag relationship for country ratings?, Kent Business School Working Paper No. 310, University of Kent. available at: http://eprints.kingston.ac.uk/id/eprint/32142.

Mezöfi, B., Niedermayer, A., Niedermayer, D. and Süli, B.M. (2017), 'Solvency II reporting: how to interpret funds' aggregate solvency capital requirement figures', Insurance: Mathematics and Economics, 76, pp. 164–171.

Miao, H., Ramchander, S. and Wang, T. (2014), 'The response of bond prices to insurer ratings changes', Geneva Papers on Risk and Insurance - Issues and Practice, 39 (2), pp. 389–413.

Millon, M.H. and Thakor, A. V. (1985), 'Moral hazard and information sharing: A model of financial information gathering agencies', Journal of Finance, 40(5), pp. 1403–1422.

Michel-Kerjan, E., Czajkowski, J. and Kunreuther, H. (2015), 'Could flood insurance be privatised in the United States? A primer', Geneva Papers on Risk and Insurance - Issues and Practice, 40 (2), pp. 179–208.

Michel-Kerjan, E.O. and Kousky, C. (2010), 'Come rain or shine: Evidence on flood insurance purchases in Florida', Journal of Risk and Insurance, 77 (2), pp. 369–397.

Milidonis, A. (2013), 'Compensation incentives of credit rating agencies and predictability of changes in bond ratings and financial strength ratings', Journal of Banking & Finance, 37 (9), pp. 3716–3732.

Moody's (2002), Rating action: Moody's lowers ratings of acceptance insurance companies inc. and subsidiaries. available at: https://www.moodys.com/research/moodys-lowers-ratings-of-acceptance-insurance-companies-inc-and-subsidiaries--pr_55377.

Moody's (2019), Rating symbols and definitions. available at: https://www.moodys.com/researchdocumentcontentpage.aspx?docid=PBC_79004.

Moody's (2020), Policy for fee discussions. available at: https://www.moodys.com/uploadpage/McoDocuments/SP13355_Policy_for_Fee_Discussions_KSA.pdf.

Morgan, D.P. (2002), 'Rating Banks: Risk and uncertainty in an opaque industry', American Economic Review, 92 (4), pp. 874–888.

Munich Re (2003), Annual review: natural catastrophes 2002, München. https://reliefweb.int/report/world/munich-res-analysis-natural-catastrophes-2002

Munich Re (2012), 2011 natural catastrophe year in review. available at: https://www.iii.org/sites/default/files/docs/pdf/MunichRe-010412.pdf.

NAIC (2019), About the NAIC. available at: https://www.naic.org/index_about.htm.

NAIC (2020), Risk-based capital. available at: https://content.naic.org/cipr_topics/topic_riskbased_capital.htm (accessed 21 July 2021).

NAIC (2021a), Rating agencies. available at: https://content.naic.org/cipr_topics/topic_rating_agencies.htm.

NAIC (2021b), Glossary of insurance terms. available at: https://content.naic.org/consumer_glossary#C.

NAIC (2021c), Group capital calculation. available at: https://content.naic.org/cipr_topics/topic_group_capital_calculation.htm.

Niehaus, G. and Chiang, C.-C. (2017), 'U.S. life insurers' responses to the financial crisis: a review of the research', Journal of Financial Perspectives: Insurance, 4 (1), p. 120.

OECD (2019), 'Insurance spending', OECD insurance statistics. available at: https://data.oecd.org/insurance/insurance-spending.htm#indicator-chart

Opp, C.C., Opp, M.M. and Harris, M. (2013), 'Rating agencies in the face of regulation', Journal of Financial Economics, 108 (1), pp. 46–61.

Pancotto, L., ap Gwilym, O. and Williams, J. (2020), 'Market reactions to the implementation of the Banking Union in Europe', European Journal of Finance, 26 (7–8), pp. 640–665.

Park, S.C., Lemaire, J. and Xie, X. (2016), 'The opaqueness of structured bonds: Evidence from the U.S. insurance industry', Geneva Papers on Risk and Insurance - Issues and Practice, 41 (4), pp. 650–676.

Park, S.C. and Xie, X. (2014), 'Reinsurance and systemic risk: The impact of reinsurer downgrading on property–casualty insurers', Journal of Risk and Insurance, 81 (3), pp. 587–621.

Patell, J.M. (1976), 'Corporate forecasts of earnings per share and stock price behavior: Empirical test', Journal of Accounting Research, 14 (2), pp. 246–276.

Perry, C. (2000), Significant floods in the united states during the 20th century USGS measures a century of floods. available at: https://pubs.usgs.gov/fs/2000/0024/report.pdf.

Petersen, M.A. (2008), 'Estimating standard errors in finance panel data sets: comparing approaches', Review of Financial Studies, 22 (1), p. 46.

Poon, W.P.H. and Firth, M. (2005), 'Are unsolicited credit ratings lower? International evidence from bank ratings', Journal of Business Finance & Accounting, 32 (9-10), pp. 1741–1771.

Pottier, S.W. (1997), 'Life insurer risk characteristics and the rating process', Journal of Insurance Issues, 20 (2), pp. 111–130.

Pottier, S.W. and Sommer, D.W. (1999), 'Property-liability insurer financial strength ratings: differences across rating agencies', Journal of Risk and Insurance, 66 (4), pp. 621–642.

Pottier, S.W. and Sommer, D.W. (2006), 'Opaqueness in the insurance industry: Why are some insurers harder to evaluate than others?', Risk Management and Insurance Review, 9 (2), pp. 149–163.

Purda, L.D. (2007), 'Stock market reaction to anticipated versus surprise rating changes', Journal of Financial Research, 30 (2), pp. 301–320.

Purda, L.D. (2011), 'Assessing credit or determining quantity? The evolving role of rating agencies', Journal of Applied Finance, 21 (2), pp. 1–17.

S&P (2003), Various public information ratings affirmed then withdrawn, New York. available at: www.standardandpoors.com/ratingsdirect.

S&P (2006), Corporate ratings criteria. available at: http://sbufaculty.tcu.edu/mann/_Inv%20II%20F09/S&P%20Ratings%20criteria%20-%202006.pdf.

S&P (2015), How environmental and climate risks factor into global corporate ratings. available at: www.spglobal.com/ratingsdirect.

S&P (2018), S&P Global Ratings definitions. available at: https://www.spratings.com/documents/20184/774196/SPGlobalRatingsDefinition_Oct-31-2018.pdf/e38d629a-94f1-8930-4180-e9812725adc4.

S&P (2019), How we rate insurers, Canada, APAC, United States of America, EMEA, Latin America. available at: https://www.spglobal.com/ratings/en/research/articles/190830-how-we-rate-insurers-8412641.

S&P (2020a), S&P U.S. indices methodology. available at: https://www.spglobal.com/spdji/en/documents/methodologies/methodology-sp-us-indices.pdf

S&P (2020b), S&P Select Industry Indices methodology. available at: https://www.spglobal.com/spdji/en/documents/methodologies/methodology-sp-select-industry-indices.pdf

S&P (2022), S&P Global ratings U.S. ratings fees disclosure. available at: https://disclosure.spglobal.com/ratings/en/regulatory/delegate/getpdf?articleid=2775964&type=comments&subtype=regulatory.

Salvador, C., de Guevara, J.F. and Pastor, J.M. (2018), 'The adjustment of bank ratings in the financial crisis: International evidence', North American Journal of Economics and Finance, 44, pp. 289–313.

Salvador, C., Pastor, J.M. and Fernández de Guevara, J. (2014), 'Impact of the subprime crisis on bank ratings: The effect of the hardening of rating policies and worsening of solvency', Journal of Financial Stability, 11, pp. 13–31.

Scharfstein, D. and Stein, J. (1990), 'Herd behavior and investment', American Economic Review, 80 (3), pp. 465–479.

Schüwer, U., Lambert, C. and Noth, F. (2018), 'How do banks react to catastrophic events? Evidence from Hurricane Katrina', Review of Finance, 23 (1), pp. 75–116.

SEC (2018), Annual report on nationally recognized statistical rating organizations. available at: https://www.sec.gov/2018-annual-report-on-nrsros.pdf.

SEC (2020), Annual report on nationally recognized statistical rating organizations. available at: https://www.sec.gov/files/2020-annual-report-on-nrsros.pdf.

Sharma, A., Jadi, D.M. and Ward, D. (2018), 'Evaluating financial performance of insurance companies using rating transition matrices', Journal of Economic Asymmetries, 18, p. e00102.

Silva, W., Kimura, H. and Sobreiro, V.A. (2017), 'An analysis of the literature on systemic financial risk: A survey', Journal of Financial Stability, 28, pp. 91–114.

Singh, A.K. and Power, M.L. (1992), 'The effects of Best's rating changes on insurance company stock prices', Journal of Risk and Insurance, 59 (2), pp. 310–317.

Strobl, E. (2011), 'The economic growth impact of hurricanes: Evidence from U.S. coastal counties', Review of Economics and Statistics, 93 (2), pp. 575–589.

Swiss Re (2018), 'At USD 144 billion, global insured losses from disaster events in 2017 were the highest ever, sigma study says', news releases. available at: https://www.swissre.com/media/news-releases/2018/nr20180410_sigma_global_insured_loses_highest_ever.html.

Sy, A.N.R. (2004), 'Rating the rating agencies: Anticipating currency crises or debt crises?', Journal of Banking & Finance, 28 (11), pp. 2845–2867.

Thimann, C. (2015), 'Systemic features of insurance and banking, and the role of leverage, capital and loss absorption', Geneva Papers on Risk and Insurance - Issues and Practice, 40 (3), pp. 359–384.

Tran, V. (2015), 'Sovereign credit ratings and financial market volatility: Bi-directional relationships and heterogeneous Impact', PhD thesis, Bangor University. available at: http://e.bangor.ac.uk/4737/2/Final PhD Thesis.pdf.

Thomann, C. (2013), 'The impact of catastrophes on insurer stock volatility', Journal of Risk and Insurance, 80 (1), pp. 65–94.

Trueck, S. and Rachev, S.T. (2009), Rating based modeling of credit risk - Theory and application of migration matrices, Academic Press. available at: https://doi.org/10.1016/B978-0-12-373683-3.X0001-2.

Turnbull, S.M., Crouhy, M. and Jarrow, R.A. (2007), The subprime credit crisis of 07 (July 9, 2008). available at: https://ssrn.com/abstract=1112467

Upreti, V. (2014), 'Reinsurance and the Cost of Equity in the United Kingdom's Non-Life Insurance Market', PhD thesis, University of Bath. available at: https://researchportal.bath.ac.uk/en/studentTheses/reinsurance-and-the-cost-of-equity-in-the-united-kingdoms-non-lif.

Upreti, V. and Adams, M. (2015), 'The strategic role of reinsurance in the United Kingdom's (UK) non-life insurance market', Journal of Banking and Finance, 61, pp. 206–219.

van Bragt, D., Steehouwer, H. and Waalwijk, B. (2010), 'Market consistent ALM for life insurers-Steps toward Solvency II', Geneva Papers on Risk and Insurance - Issues and Practice, 3 5(1), pp. 92–109.

Vu, H., Alsakka, R. and ap Gwilym, O. (2015), 'The credit signals that matter most for sovereign bond spreads with split rating', Journal of International Money and Finance, 53, pp. 174–191.

Vu, H., Alsakka, R. and ap Gwilym, O. (2021), 'Does competition improve sovereign credit rating quality? ', Journal of International Financial Markets, Institutions and Money, 76, pp. 101-478.

Wade, C., Liebenberg, A. and Benjamin, M., B. (2015), 'Information and insurer financial strength ratings: do short sellers anticipate ratings changes?', Journal of Risk and Insurance, 83 (2), pp. 475–500.

Wang, Y. (2010), 'Analysing insurer rating transitions with different economic and industry cycles', Geneva Papers on Risk and Insurance - Issues and Practice, 35 (3), pp. 435–451.

Wang, Y. and Carson, J.M. (2014), 'Rating drift in property-liability insurer rating transitions', Journal of Insurance Issues, 37 (1), pp. 59–76.

Wengner, A., Burghof, H.-P. and Schneider, J. (2015), 'The impact of credit rating announcements on corporate CDS markets—Are intra-industry effects observable?', Journal of Economics and Business, 78 (Supplement C), pp. 79–91.

Weiss, M.A. and Chung, J.-H. (2004), 'U.S. reinsurance prices, financial quality, and global capacity', Journal of Risk and Insurance, 71 (3), pp. 437–467.

Williams, G., Alsakka, R. and ap Gwilym, O. (2013), 'The impact of sovereign rating actions on bank ratings in emerging markets', Journal of Banking & Finance, 37 (2), pp. 563–577.

Williams, G., Alsakka, R. and ap Gwilym, O. (2015), 'Does sovereign creditworthiness affect bank valuations in emerging markets?', Journal of International Financial Markets, Institutions and Money, 36, pp. 113–129.

Williams, R. (2012), 'Using Stata's margins command to estimate and interpret adjusted predictions and marginal effects', Stata Journal, 12 (2), pp. 308–331.

Winter, R.A. (1991), 'The liability insurance market', Journal of Economic Perspectives, 5 (3), pp. 115–136.

World Bank (2019). Global financial development, electronic dataset, World Bank. available at: https://databank.worldbank.org/source/global-financial-development.

WSJ (2018), 'Climate change is forcing the insurance industry to recalculate'. available at: https://www.wsj.com/graphics/climate-change-forcing-insurance-industry-recalculate/.

Xia, H. (2014), 'Can investor-paid credit rating agencies improve the information quality of issuer-paid rating agencies?', Journal of Financial Economics, 111 (2), pp. 450–468.