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Sovereign credit ratings and financial market volatility
bi-directional relationships and heterogeneous impact

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Sovereign credit ratings and financial market volatility:

Bi-directional relationships and heterogeneous impact

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Abstract

This thesis examines the bi-directional relationship between sovereign credit ratings and financial market volatility. Prior literature focuses on one aspect of the relationship which is the impact of credit rating actions on financial assets' returns, whereas the links between rating actions and market volatility have attracted little attention. Based on a comprehensive dataset of rating events from the three largest credit rating agencies (CRAs) i.e. S&P, Moody's, and Fitch, this thesis presents unique evidence of (i) inter-relationships between sovereign rating information and equity market volatility dynamics; (ii) heterogeneous effects of sovereign rating actions on equity and foreign exchange market volatilities; (iii) volatility spill-over effects of rating actions. Several methodologies are employed in order to confirm the robustness of the findings, including event study, multivariate regressions, non-parametric tests, Vector Autoregressive models, probit analyses, and Monte Carlo experiments.

The findings reveal that certain types of rating news play an important "confirmation role" whereby rating actions can reduce market ex-post volatility and ex-ante uncertainty. Also, there is evidence of differences in rating policies and timeliness across CRAs which provides some explanation for the heterogeneous effects of rating actions. Rating news which incorporates new information, either negative or positive, is associated with elevated ex-ante market uncertainty and ex-post volatility, while additional rating news which is not new to the public can lead to reduced market uncertainty and volatility.

The contribution of this thesis is threefold. First, the findings contribute significantly to the debate on the information content of rating news and highlight the importance of multiple ratings in coordinating investors' heterogeneous beliefs. Second, the thesis provides valuable insights for the debate on the role and regulation of CRAs since the global financial crisis. Third, the findings offer practical implications for option traders, international investors, financial institutions, and portfolio managers.

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Abbreviations

BIS	Bank for International Settlements
Basel Committee	Basel Committee on Banking Supervision
CDS	Credit default swap
CRA (s)	Credit rating agency (ies)
EC	European Commission
ESMA	European Securities and Markets Authority
Fitch	Fitch Ratings, Ltd
FX	Foreign exchange
GDP	Gross Domestic Products
IMF	International Monetary Fund
IOSCO	International Organization of Securities Commissions
IV	Option-implied volatility
NRSRO(s)	Nationally Recognized Statistical Rating Organization(s)
OLS	Ordinary Least Square
MLE	Maximum Likelihood Estimation
Moody's	Moody's Investors Service
RV	Realised volatility
S&P	Standard and Poor's Ratings Services
SEC	US Securities and Exchange Commission
VAR	Vector Auto Regressive

Chapter 1: Introduction

During recent financial crises, credit rating agencies (CRAs) have been under close scrutiny. Recent downgrades on European countries such as Greece, Italy, Portugal, Spain, have led to angry critique. CRAs have been accused of exacerbating and/or precipitating investors' pessimistic sentiments, hence, provoking global financial stability. However, much of these accusations lack scientific evidence. Prior literature focuses on the impact of rating actions on financial assets' returns, but largely ignores market volatility. This dimension of financial markets is directly related to the heart of the above accusations and the debate on global financial stability. An investigation on this matter needs to consider the lead-lag relationship between credit rating dynamics and market movements. In other words, it is plausible that a bi-directional relationship exists between credit rating actions and information incorporated in financial markets. This thesis addresses the void in prior literature by investigating the inter-relation between sovereign credit rating and market volatility dynamics.

Credit ratings represent subjective opinions about the ability and willingness of an obligor to honour its financial obligations in full and in a timely manner. Although CRAs are generally seen to have performed reasonably well in the traditional segment of debt markets, especially before recent financial crises (e.g. Bank of England, 2011), recent experience has placed them under heavy criticism. Initially, critique arose from structured finance ratings which are widely viewed as having been methodologically flawed (e.g. Smith, 2009).

The issuer-pays business model in the rating industry has also been a heightened concern (e.g. IMF 2010a). There are obvious incentives for debt issuers seeking more favourable ratings which determine the marketability of their debts. Consequently, there are two issues arising in a business model where debt issuers pay for credit ratings. Firstly, debt issuers could shop around for the most favourable ratings because most CRAs provide privately known shadow ratings before debt issuers agree to pay for publicised ratings (Skreta and Veldkamp, 2009). The second is conflict of interest which arguably incentivises CRAs to inflate their ratings in order to attract high revenues (e.g. Mathis et al., 2009; Bolton et al., 2012).

Moreover, rating actions are repeatedly accused of lagging market movements and public information (e.g. Sy, 2004; Vernazza et al., 2014). Thus, a vigorous debate on the information content of rating news arises (e.g. Vernazza et al., 2014). There is also criticism on CRAs of being irresponsible by casting credit ratings as opinions, thus, bearing no direct liability for their errors (e.g. Partnoy, 2006). Ironically, after all, credit ratings are still highly regarded and embedded in investment guidelines and regulation (e.g. SEC, 2011c, 2013; Bongaerts et al., 2012). For instance, the numbers of outstanding credit ratings except for those on asset-backed securities is still rising (author's calculation based on SEC 2011c, 2013). There is obviously a clear rationale for the rating industry to exist for over a century and for investors who are generally perceived as rational, at least in the long term, to use credit ratings as a measurement of creditworthiness.

The main theme of this thesis is to investigate the bi-directional relationship between sovereign credit ratings and market dynamics. Specifically, I examine the lead-lag relationship and the impact of sovereign credit rating actions on ex-ante uncertainty and ex-post realised volatility of financial markets. Three specific empirical topics will be investigated as follows.

The first topic (in Chapter 4) examines the inter-relationship between sovereign credit ratings and stock market volatility. In this chapter, the volatilities of stock markets are captured by stock indices' option-implied volatility. The lead-lag relationship between stock indices option-implied volatility and sovereign rating dynamics is plausible given two facts:

(i) the leading role of derivatives markets in the price (credit information) discovery process (e.g. Acharya and Johnson, 2007); (ii) CRAs often publish market-implied ratings (e.g. Moody's KMV^{TM}) and probably consult with financial markets prior to rating actions.

The second topic (in Chapter 5) investigates the impact of sovereign rating actions on foreign exchange (FX) market ex-ante uncertainty and ex-post volatility. FX market ex-ante uncertainty is measured by FX option-implied volatility, while the market ex-post volatility is captured by realised volatility based on intraday data (e.g. Andersen et al., 2003a). Given the enormous size of the FX market (e.g. BIS, 2013), this chapter aims at contributing to the debate on the information content of rating news. The matter has been a long lasting concern for market participants, policy makers, and academic circles. The topic is also closely relevant to the debate on global financial stability.

The third empirical investigation (in Chapter 6) is on the question of volatility spill-overs. Specifically, the chapter considers whether and to what extent volatility spill-over effects of sovereign rating news exists in the context of global FX markets. In other words, I investigate whether sovereign rating actions on one country increase or reduce volatility of other countries' exchange rates against the U.S. dollar. The topic is compelling and has been ignored by prior literature. This is also directly related to the above debate on whether sovereign rating news provokes global financial instability.

The dataset for this thesis is comprehensive and covers the largest possible sample of national economies at the time of writing. For instance, the dataset for Topic 1 (in Chapter 4) covers all countries with liquid option markets on national stock indices. Datasets for Topic 2 and Topic 3 (in Chapters 5 and 6) cover all main currencies using in global trades, i.e. listed in the last survey by Bank for International Settlements (BIS) in 2013. Sovereign ratings data is generally supplied from my supervisors' dataset, and also collected directly from CRAs' publications. The three largest global CRAs are considered, namely: Moody's, S&P, and

Fitch. Option-implied volatility data is collected via Data Stream. The primary sources are stock exchanges for Chapter 4, and Thomson Reuters for Chapters 5 and 6. Realised volatility based on intraday data is retrieved via Bloomberg. Financial data is retrieved via Data Stream. The sample period for Chapter 4 is from 2000 to 2012, while it is from 2007 to 2013 in Chapters 5 and 6.

Methodologies used in this thesis include an event study, non-parametric tests, multivariate regressions, Vector Autoregressive (VAR) models, probit models, and Monte Carlo experiments. Specifically, Chapter 4 employs an event study and non-parametric tests for preliminary investigations on the impact of sovereign rating actions on equity market volatility while multivariate regressions control for other factors that possibly impact market volatility. In addition, the probit model is used for robustness checks on potential market anticipation of rating actions while VAR models and log-likelihood ratio tests are employed to examine the lead-lag relationship between market volatility dynamics and sovereign rating actions. Chapters 5 and 6 use an event study and multivariate regression analyses to examine the impact and spillover effect of sovereign credit rating news on FX market volatility. In addition, Monte Carlo experiments are employed as robustness checks of the findings.

The structure of the thesis is as follows: Chapter 2 provides background knowledge of the credit rating industry. Key concepts related to the core of this thesis and recent developments in the area are also discussed in this chapter. These are crucial in understanding the rating industry as well as topical issues that have arisen recently and which motivate investigations in the subsequent chapters.

Chapter 3 critically reviews the existing literature and methodological frameworks used in sovereign credit rating research. The main aim is to identify the gaps in prior literature which will be subject for empirical investigations in the subsequent chapters. The chapter also provides insights on the types of data, variables, and methodology that have been used in prior papers on credit ratings.

Chapter 4 starts the empirical investigations in this thesis by examining the inter-relationship between sovereign rating and equity market volatility dynamics. Heterogeneous effects of sovereign rating news are also analysed. Interestingly, the findings reveal a lead-lag relationship between market volatility dynamics and rating actions. Moreover, an important "confirmation role" of credit rating news which is unnoticed in prior literature is recorded. Certain types of (even negative) credit rating news reduce market volatility. Numerous significant contributions to the literature arise. For instance, the findings shed light on the price (credit information) discovery process and raise a caveat on the debate whether CRAs exacerbate and/or precipitate financial crises.

Chapter 5 investigates the impact of sovereign rating actions on FX market volatility. The main approach is similar, but the context is now the FX market which is gigantic (e.g. BIS, 2013). Moreover, the chapter utilises realised volatility based on intraday data which is much richer (in addition to option-implied volatility). Monetary policy and persistence in the volatility measurements are also considered. Consistent with the previous chapter, the findings present concrete evidence of the heterogeneous effects and the "confirmation role" of sovereign credit rating news. The "confirmation role" is attributed to the rationale whereby CRAs co-ordinate heterogeneous beliefs and expectations among market participants.

Chapter 6 investigates the volatility spillover effects of sovereign rating news in the context of global FX markets. The main motivation is the discussion on mechanisms underlying well-known spillover phenomena in international finance (e.g. Andersen et al., 2003b; Dornbusch et al., 2000; Kaminsky et al., 2003; Li and Muzere, 2010). Specifically, negative news on one economy (and its currency) is not necessarily negative for others (e.g. Dornbusch et al., 2000; Kaminsky et al., 2003). A very logical connection to sovereign credit rating research arises. This chapter presents striking results that some types of (even negative) rating news could be beneficial for global financial stability.

Finally, Chapter 7 summarises and concludes the thesis. Discussion of limitations and directions for future research is also included.

The thesis contributes to literature in a number of aspects. Academically, contribution to the information content of rating news is significant by investigating the void in prior literature, relating to the impact of rating news on financial market volatility. In addition, the volatility spillover effect of rating news is another important contribution. For policy makers and regulators, the result is of particular interest as it raises a caveat on the debates surrounding CRAs which directly motivate recent regulatory developments. The findings also have important practical implications for option traders, multinational banks and financial institutions, CRAs, international portfolio managers, and other investors.

Chapter 2: Background of the credit rating industry

2.1. Introduction

Credit risk research and management are perhaps the most challenging and crucial areas in the investment and financial world. CRAs provide valuable functions in managing credit risk and in developing financial markets (Bank of England, 2011; Basel Committee, 2009; IMF, 2010a). CRAs are commercial firms that receive payments for issuing assessments on the creditworthiness of debt issuers and/or debt issues. Along with the increasing global integration and CRAs' growing prestige, credit ratings are critically influential in financial markets. Mr Towns Edolphus - Chairman of the US House of Oversight and Government Reform Committee – the US House of Representatives, in the beginning of the Committee's gathering in 30th September 2010, claimed that CRAs were at the heart of the last financial collapse, and will be at the heart of the next financial collapse (US Government Printing Office, 2010). This stresses the importance of the credit rating industry and also the criticism over its failures in the 2007- financial crisis.

Current public debt crises highlight the so called 'hard-wiring'[1] and 'cliff effect'[2] of sovereign credit ratings (Bank of England, 2011; Financial Stability Board, 2010). Moreover, sovereign rating downgrades could spill-over to other sovereign entities not directly due to these sovereigns' creditworthiness (Arezki et al., 2011). In 2011-2012, series of European countries, including Greece, Portugal, Spain, Italy were downgraded by Fitch, S&P, and Moody's. Financial markets in Europe and the US had tumbled as investors have been overwhelmed by the fear that sovereign debt crisis could spread over the EU zone and threaten the fragile recovery of the global economy. On 5th August 2011, S&P downgraded

[1] Credit ratings are embedded into regulations and private investment mandates, making them more influential. See section 2.4 for more detail.
[2] Sudden illiquidity of debt instruments having been downgraded. See section 2.5 for more detail.

the US sovereign credit rating from AAA to AA+. On 28th November 2011, Fitch put the US sovereign credit rating on a negative outlook. On 24th August 2011, Moody's has downgraded Japan sovereign debts from Aa2 to Aa3. On 22nd May 2012, Fitch downgraded Japan sovereign credit rating to A+ and remained a negative outlook. The threat of higher US and Japan bond yields and the associated rises in the refinancing interest could restrict further fiscal policies in attempts to back up the shaky growths of the two largest economies which are prime motivation of the global economic growth. Moreover, this negative scenario could spill-over to global financial markets and cause renewed financial and debt crisis (European Central Bank, 2011). Credit rating understanding and proper regulation have emerged among the top concerns of not only researchers but also investors, regulators, public authorities, and other market participants.

Derivative market is the largest and critical segment of the global financial market. By December 2010, the global over the counter (OTC) derivatives amounted to $601 trillion in terms of notional amount outstanding.[3] By this measure, the OTC derivative market is more than four times larger than the combination of the equity and bond markets, measured by the global stock markets capitalisation plus bond and public debts outstanding which in total is about $148 trillion (McKinsey Global Institute, 2011). Furthermore, majority of the derivative market participants are institutional investors who are usually attributed by informational advantages as well as by economies of scale. Over 90% of derivative market participants are financial institutions and corporates (Deutsche Borse Group, 2008). In addition, empirical studies point out that the derivative market plays a leading role in the price discovery process (Blanco et al., 2005; Acharya and Johnson, 2007; Forte and Pena, 2009; Avino et al., 2013). Therefore, movements in the derivative market may provide timely indication of the underlying issuer financial health and creditworthiness.

[3] The figure continues to rise and amounted at $710 by the end of 2013 (source: BIS available at: http://www.bis.org/statistics/derstats.htm).

The main goal of this thesis is to investigate the interaction between the derivative markets and sovereign credit ratings, a very essential core of global credit risk management as sovereign credit rating is a robust determinant of all other types of credit ratings including corporate and financial institutions (Duggar et al., 2009; Borensztein et al., 2013). This chapter aims at providing a background of the industry, recent developments as well as definitions and explanations of the key concepts relevant to subsequent chapters of the dissertation. The chapter is organised as follows. The main CRAs, rating methodologies and rating philosophy are discussed in section 2.2. Section 2.3 briefly discusses basic definitions related to credit ratings. Section 2.4 highlights the credit rating industry's functions and its importance to financial markets. Criticism over CRAs and recent developments in regulation are summarised in section 2.5. Section 2.6 concludes the chapter.

2.2. Main rating agencies, methodologies and philosophy

2.2.1. Main rating agencies

The credit rating industry has long played an essential role in financial markets, and credit ratings have been widely used since before the First World War initially in the US, then gradually spreading over the industrialised countries. Nowadays, there are numerous CRAs over the world. In the hearing on 30/9/2009 before the US 111th Congress, Dr Richard Cantor, Chief Risk Official and also Chief Credit Official - Moody's Investors Service, said that "there are currently perhaps a hundred CRAs around the world" (US Government Printing Office, 2010). However, rating market is actually dominated by three global agencies, namely S&P, Moody's, and Fitch who respectively accounts for 42.2%, 36.9%, and 17.9% of the market in terms of total credit ratings outstanding (SEC, 2011c). Other CRAs' shares, including Japan Credit Rating Agency, Egan Jones, Rating and Investment Information, AM Best Company, Morningstar Credit Ratings, Kroll Bond Rating Agency, DBRS Inc, are marginal, ranging from 0.03% to 1.51% (SEC, 2011c). They either focus on specific industries or certain geographical regions. On the other hand, the big three CRAs together account for 99% (91%) of the rating market on sovereign (corporate) debts (SEC, 2011c, 2012, 2013). Table 2.1 presents a list of main CRAs.

Table 2.1: Main rating agencies

Rating agency	Focus
Moody's Investors Service	Global
Standard and Poor's	Global
Fitch	Global
Dominion Bond Rating Service Inc	North America
Egan-Jones Rating Company	North America
Japan Credit Rating Agency, Ltd	Japan
Rating and Investment Information Inc	Japan
Capital Intelligence	Middle East, Central and Eastern Europe, South Asia
Kroll Bond Rating Agency (acquired LACE Financial Corp in August 2010)	Financial and Insurance
A.M. Best Company Inc	Financial and Insurance
Morningstar Credit Ratings LLC (acquired Realpoint LLC in May 2010)	Asset-backed finance

Source: SEC, 2011c, 2012, 2013.

2.2.2. Rating philosophy

Market participants appreciate both rating accuracy and rating stability. The desire for the "accuracy" is intuitive. Since investors consider credit ratings as measures of credit risks, no investor would prefer a rating system giving a misleading proxy to the risks. Besides, a stable rating system is also desirable by many market participants, especially bond funds, pension funds, mutual funds, and other investors who follow passive investment strategies.

The worst thing that a CRA can do is to downgrade an issuer today and to reverse in a near future. For instance, a security is downgraded into the speculative-grade in order to spontaneously capture a recent deterioration relating to the issuer's creditworthiness. This downgrade forces many fund managers to sell their holdings since rating-based mandates are widely used by the funds' trustees to govern the managers avoiding speculative investments. If good news regarding the issuer's creditworthiness comes in the following day(s), the security would be upgraded so as to ensure the precise rating accuracy. The managers might have to repurchase the same security, hence, incur unnecessary transaction costs. Therefore, a wildly volatile rating system imposes the great frequency of transactions in accordance to frequent rating reversals, hence, high transaction costs. In accordance to rating users' preferences, CRAs seek to balance the trade-off between rating accuracy and rating stability as two primary objectives (Löffler, 2005; Cantor and Mann, 2007).

In order to aim at the balance between rating accuracy and rating stability, CRAs follow a "through the business cycle" rating philosophy. CRAs strive to capture long-term permanent rather than temporary credit risks. CRAs, thus, emphasize structural rather than cyclical changes. There is no need upgrading (downgrading) an issuer which has temporary prosperity (difficulty) if that is not anticipated to be permanent. This philosophy considers increased volatility as increased risk. An issuer who is heavily influenced by the business cycle, hence, typically is assigned a lower rating if all other elements are equal (S&P, 2011). Empirical studies generally support the view that CRAs pursue a 'through the cycle' philosophy (Altman and Rijken, 2004; Amato and Furfine, 2004; Bangia et al., 2002). Nevertheless, some market participants might be more interested in rating accuracy rather than stability. Aiming at mitigating the tension between rating accuracy and stability, CRAs introduced rating outlook and watch procedures in early 1990s which provide supplemental indicators of the rated issuers'/ issues' creditworthiness (Hamilton and Cantor, 2004).

Outlook and watch procedure allow CRAs to buy time for an eventual rating decision while signalling immediate rating activity (Altman and Rijken, 2004). Generally, outlook and watch procedure informs market participants that actual rating levels are under considerations and are likely to be changed within medium- or short-term (see section 2.3.5 for more details).

2.2.3. Rating methodologies

In terms of methodology, CRAs base their judgments on both quantitative and qualitative elements related to an obligor's creditworthiness (S&P, 2003; Moody's, 2008; Fitch, 2011b; S&P, 2011). They generally agree on the major quantitative determinants of credit ratings, yet the weights assigned to these determinants can vary across CRAs (Cantor and Packer, 1996; Bennell et al., 2006; Afonso et al., 2007). In addition, qualitative information varies to a greater extent across CRAs. For example, a corporate rating often takes into account the firm's management, franchise value, competition, operating and/or regulatory environment, sector attributes, etc; a sovereign rating usually takes into consideration political elements, governments' willingness to fulfil their financial obligations, or social, political costs of default versus paying debts. These qualitative considerations are ultimately subjective judgements of credit risk analysts from each CRA (IMF, 2010a; House of Lords, 2011), hence, might be very different between CRAs. Moreover, issuers might channel private information to some certain CRAs in many cases of solicited ratings, thus enable them to become super informed against others. Furthermore, CRAs' rating approaches are also different. S&P's approach only bases on probability of default (S&P, 2009), while Moody's includes loss given default assessments (Moody's, 2011a). Fitch takes into account both probability of default and recovery given default, which equals to total due amount less loss given default (Fitch, 2011a). Therefore, rating methodologies vary across CRAs.

In summary, the rating industry is highly concentrated, and is dominated by the three global CRAs, namely Moody's, S&P, and Fitch. While rating through the business cycle is widely accepted, CRAs disagree to a large extent about rating methodology not only in terms of the importance of each information segment, qualitative information judgements, private sources of information, but also in terms of the general approach of credit rating methods.

2.3. Definitions

2.3.1. What is a credit rating?

In general, a credit rating is an independent, subjective opinion provided by a CRA which specialises in assessing the creditworthiness to the public. In other words, a credit rating is an opinion about the ability of an obligor to repay its financial obligations in full, including principal and interest, and on time.

Table 2.2: Definition of credit ratings from S&P, Moody's, and Fitch

S&P's	Moody's	Fitch
Credit ratings express forward-looking opinions about the creditworthiness of issuers and obligations. S&P's credit ratings express a relative ranking of creditworthiness. Issuers and obligations with higher ratings are judged by us to be more creditworthy.	Credit ratings are opinions of the relative credit risk of financial obligations/issuers. They address the possibility that a financial obligation will not be honored as promised. Such ratings reflect both the likelihood of default and any financial loss suffered in the event of default.	Credit ratings are forward-looking opinions on credit quality of issuers or obligations. Credit ratings are relative measures of credit risk. Credit ratings do not constitute recommendations to buy/sell/ hold any security.

Sources: S&P, 2009*;* Moody's, 2011a*;* Fitch, 2011a.

Table 2.2 summarises definitions of credit ratings by S&P, Moody's and Fitch. According to CRAs, credit ratings are opinions, not recommendations to sell, buy, or hold any security. Importantly, credit ratings are entirely forward looking, reflecting the CRAs' assessment of the creditworthiness of debt issuers/ issues. From this aspect, credit ratings are not the same as accounting ratios, which are contemporaneous or backward-looking indicators. In addition, CRAs explicitly express that credit ratings are not aimed at absolute measures of credit worthiness but ordinal rankings or relative measures of these creditworthiness.

2.3.2. Types of credit ratings

There are numerous ratings provided by CRAs. However, these can be categorised as follows:

- **Issue versus issuer ratings**

An issuer credit rating is the opinion of a CRA about the overall ability of an obligor to honour its financial obligations and contracts on time (Fitch, 2011a; Moody's, 2011a; S&P, 2009). CRAs provide credit ratings on a range of issuers, including non-financial firms, financial institutions, managed funds, sovereign and supra-national entities. While assigning credit ratings on commercial firms, known as corporate credit ratings, is traditional business, giving credit ratings on governments' debts, known as sovereign credit ratings, is rather new segment which is fast developing recently due to the integration of financial markets and investors' need of international diversification.

An issue credit rating is the opinion of a CRA about the creditworthiness of an obligor regarding a particular financial obligation. Issue credit ratings address the possibility that a financial obligation will not be honoured as promised (Fitch, 2011a; Moody's, 2011a). There are several types of issue credit ratings including bonds, commercial papers, preferred stock, bank loans, and structured securities.

- **Foreign currency and local currency ratings**

Both sovereigns and firms may receive local and/or foreign currency ratings depending on the currency of debt issuance. A local currency corporate credit rating is an opinion about a firm's capacity to generate sufficient local currency resources to honour its financial obligation(s) in absence of the risk that its government may impose intervention on foreign currency market or constrain foreign currency debt payments. In contrast, a foreign currency corporate credit rating takes into consideration the risks concerning governments' actions that may directly impact access to the foreign exchange needed for timely honouring the rated obligation(s) (S&P, 2003).

Sovereign credit ratings take into account local and foreign currency obligation(s) in a different aspect. Local currency sovereign ratings are supported by the unique powers that governments possess within their own borders, including issuance of their own currency and regulatory control of the domestic financial system. The risk that a government defaults on its local currency debts, hence, is lower than on foreign currency commitments. Therefore, local currency sovereign ratings are usually no lower than foreign currency ratings (see Moody's, 2008, 2013; Fitch, 2011a; S&P, 2011). The key question in assigning local currency sovereign credit ratings is to what extent a government is able and willing to adjust its balance sheet in order to generate sufficient resources to repay the debt on time. While local currency sovereign credit ratings rest exclusively upon the government's capacity and willingness to raise resources in its own currency, foreign currency sovereign credit ratings may be affected by private sectors' capacities in repaying debts since there is only one balance of payment for the whole economy, including the government and other players. Foreign currency sovereign credit ratings, hence, take external elements, such as balance of payments, external debts, external liquidity, into greater consideration than local currency ratings (see e.g. Moody's, 2013).

- **Long-term versus short-term ratings**

Both long-term and short-term debts are rated by CRAs. Short-term ratings are opinions of the ability of issuers to honour short-term financial obligations with an original maturity not exceeding 13 months (Fitch, 2011a; Moody's, 2011a; S&P, 2009). These ratings may be assigned to issuers, short-term programs or to other short-term debt instruments. On other hand, long-term ratings are opinions of the relative credit risk of financial obligations with an original maturity of one year or more (Fitch, 2011a; Moody's, 2011a; S&P, 2009).

Similarly, long-term ratings could be assigned to issuers, long-term bonds, programme and projects.

- **Solicited versus unsolicited ratings**

Solicited ratings are initiated by issuers' requests whereas unsolicited ratings are not. CRAs are typically paid by issuers for assigning solicited ratings. However, issuers do not pay for unsolicited ratings and their involvement in the rating process are often expected to be less diligence than those in solicited credit ratings. Although assumed to be based on public information only, Byoun and Shin (2002) and Behr and Guttler (2008) find that unsolicited credit ratings still convey new information to the public and trigger significant market reactions.

Generally, CRAs assign unsolicited ratings due to the interest of building reputation and improving market coverage (Duff and Einig, 2007). There is a prevailing phenomenon that unsolicited ratings are downward biased (Poon, 2003; Gan, 2004; Poon and Firth, 2005; Bannier and Tyrell, 2006). Basing on a sample of US firms, Gan (2004) finds that Moody's and S&P unsolicited credit ratings tend to be lower than solicited ones after controlling for publicly available information. Basing on data sets of S&P credit ratings on firms and banks domiciled in a number of countries, Poon (2003) and Poon and Firth (2005) agree that unsolicited credit ratings are downward biased compare to solicited ratings after controlling for differences in sovereign risk and key financial characteristics. Gan (2004) and Bannier and Tyrell (2006) clarify that the gap between unsolicited and solicited ratings is a result of a self-selection process. Firms with better private information would self-select to request solicited ratings and disclose the private positive information to CRAs, hence, can receive higher credit ratings. In contrast, firms without positive private information stick to their unsolicited ratings. Bannier et al. (2010) provide empirical evidence that 'conservatism' of CRAs also play a significant role in explaining the downward bias against unsolicited credit ratings, especially in cases of opaque issuers. In other words, a conservative CRA often concerns about overrating more than underrating, an effect that should be magnified by a weak information basis to judge upon which is assumed in unsolicited rating processes. As a result, the lack of supplement information in unsolicited ratings could lead to a significant difference compare to solicited ratings. Especially, the downward bias of unsolicited ratings should be highest for opaque issuers. Banks and insurance companies are often mentioned as the most opaque firms due to their complex asset and liability structures. Therefore, downward bias against unsolicited ratings is found robust in bank ratings and increases along with banks' opaqueness.

In summary, CRAs typically provide both long-term and short-term ratings on a wide range of types of issuers, including corporate, financial institution, managed fund, sovereign and supra-national entities, also on several types of issues, such as commercial paper, preferred stock, bonds, bank loans, and structured financing. An issuer/issue may receive both foreign currency and/or local currency depending on the currency of the issued debts.

2.3.3. Rating scales

In order to express their opinions, CRAs distil multiple credit information to a single letter on a rating scale. For example, S&P employs a scale from "AAA", representing highest creditworthiness and very low probability of default, through "AA", "A", "BBB", and so on to "D", indicating that a bankruptcy petition has been filed in. Table 2.3 briefly presents the scales for long-term senior debt ratings using by S&P, Moody's and Fitch.

The ratings scale is divided into two broad categories: Investment grade and Speculative grade. The investment-speculative boundary is very important as many market participants choose to allocate and reallocate their portfolios in reference to this credit threshold. Investment grade indicates that the issuers or issues have good or adequate payment capacity, while speculative grade issuers either have a high degree of uncertainty about whether they will make their payments or not, or are already in default. For instance, issuers rated Baa3 or BBB- and above by Moody’s or S&P and Fitch are investment-grade, while those of BB+/ Ba1 and below are speculative grade.

Table 2.3: Ratings scales using by three leading agencies

S&P	Moody’s	Fitch	Interpretation	
AAA	Aaa	AAA	highest quality, with minimal credit risk	Investment grade
AA+\AA\AA-	Aa1\Aa2 \Aa3	AA+\AA\AA-	high quality, with very low credit risk	
A+\ A \ A-	A1\ A2\ A3	A+\ A \ A-	upper-medium grade, with low credit risk	
BBB+\BBB\ BBB-	Baa1\Baa2\ Baa3	BBB+\BBB\ BBB-	medium grade, with moderate credit risk, may possess certain speculative characteristics	
BB+\BB\BB-	Ba1\ Ba2\Ba3	BB+\BB\BB-	have speculative elements, substantial credit risk	Speculative grade
B+\B\B-	B1\B2\B3	B+\B\B-	speculative, with high credit risk	
CCC+\CCC\ CCC-	Caa1\Caa2\ Caa3	CCC+\CCC\ CCC-	poor standing, with very high credit risk	
CC\ C	Ca\ C	CC\ C	highly speculative; likely to default, with some prospect of recovery of principal and interest	
R\ SD\ D	D	RD\ D	lowest rated class; typically in default, with very little prospect for recovery of principal and interest	

Sources: S&P, 2009*;* Moody's, 2011a*;* Fitch, 2011a

2.3.4. Rating migration

Once a credit rating is released, the CRA continuously monitor the issuer’s creditworthiness due to the fact that the CRA has a vital interest in maintaining rating accuracy and its prestige in financial markets. In the case of an increase in the issuer’s credit quality, an upgrade might be announced. If the creditworthiness of the issuer deteriorates, a rating downgrade would be issued. These rating changes are known as rating migrations.

Credit rating migrations attract substantial attention from investors as well as academic circles due to its importance in the real dynamic world. Rating dynamics are key inputs to many applications in modern risk management, such as portfolio risk assessments and models, for example, J.P. Morgan's CreditMetrics, CreditRisk+ by Credit Suisse Financial Products, and McKinsey's CreditPortfolioView, bond pricing models, pricing of credit derivatives and modelling credit risk premia (Frydman and Schuermann, 2008).

2.3.5. Watch and outlook notifications

CRAs employ outlooks and review or watch notifications as supplemental tools to reflect the creditworthiness of an issuer or issue and to signal in advance their intention to consider actual rating changes. Specifically, CRAs often place an issuer/ issue under watch/ outlook procedure prior an actual credit rating change. During this procedure credit analysts collect additional information from senior executives in cases of corporate ratings or key policymakers and senior representatives of public sector institutions in cases of sovereign ratings. For instance, Moody’s, S&P, Fitch use negative (positive) review or watch notification to signal that a negative (positive) rating action is likely to happen in a short-term period. An “uncertain”/ “developing”/ “evolving” watch is respectively used by Moody’s, S&P, and Fitch indicating unknown direction change in a credit rating in short-term. In medium-term, they use a negative, positive, or developing outlook notification to respectively indicate the potential for a rating downgrade, upgrade, or unknown direction change in one- to two-year period (Moody's, 2011a; Fitch, 2011a).

Boot et al. (2006) highlight the importance of watch/ outlook review procedures in a theoretic model of the interactions between investors, issuers and CRAs. They argue that without watch/ outlook review procedure, credit rating changes are not informative because the credit qualities of the issuers are observable to all market participants. Only through contracting interactions with issuers, CRAs gather additional information and are at an informational advantage to the public. Moreover, watch procedure presence incentivises all issuers whose probabilities of recovery are higher than a certain threshold to undertake recovery effort, hence, resolves the multiple equilibrium which exists otherwise. Prior empirical studies show a mixture in supporting Boot et al. (2006) implication upon the role of outlook, watch procedure. Chan et al. (2011) present empirical evidence that rating downgrades which follow watch procedures are neither more nor less informative than downgrades with no prior watch procedure. In contrast, IMF (2010a) states that most of informational value which is added to the public by credit ratings is delivered through rating outlook and watch procedures rather than actual rating changes (IMF, 2010a). Bannier and Hirsch (2010) argue that the economic function of the outlook/watch procedure depends on creditworthiness of the rated issuers. For the high quality borrowers, the outlook/ watch procedure is employed primarily in order to improve the delivery of imformation. In other words, outlook/watch procedure is used as a supplement to balance the accuracy-stability tradeoff and provide market participants with more timely indicators in order to compensate for the slow reactions in actual rating changes due to the ‘through the cycle’ rating philosophy, which are widely followed by CRAs. For low quality borrowers, outlook/watch procedure, in contrast, is likely to aim at contracting monitoring role which is initiated by Boot et al. (2006).

2.3.6. Split ratings

Split rating is the phenomena when CRAs disagree on specific rating assignments. In other words, a split rating is defined as different rating levels given to an issuer/obligation by two or more CRAs. As credit ratings can be assigned by several CRAs to a given issue/issuer, split ratings are inevitable given the fact that CRAs disagree to a large extent about rating methodology with respect to the importance of each quantitative indicator, the judgements on qualitative information, private sources of information, and general approaches (see section 2.2.3. for more details). Split ratings occur in about 20% of US corporate and municipal bonds (Livingston et al., 2008). Splits happen even more frequently in sovereign ratings than in corporate ratings (Cantor and Packer, 1995; Alsakka and ap Gwilym, 2012b).

There are a number of studies in prior literature attempting to explain the main reasons why CRAs disagree on credit rating assignments. Generally, they can be either one or some of following reasons: (i) non-systematic, random errors happen due to the complexity and subjectivity inherent in rating processes, hence, credit ratings from a CRA might differ to others (Ederington, 1986); (ii) methodological differences (Cantor and Packer, 1995; Alsakka and ap Gwilym, 2010b); (iii) differences in sources of information, especially in cases of solicited versus unsolicited ratings (Cantor et al., 1997; Jewell and Livingston, 1999); (iv) Differences in rating scales and credit worthiness thresholds using by CRAs (Dandapani and Lawrence, 2007); (v) Opaqueness: CRAs disagree to a greater extent in cases of opaque issuers (Morgan, 2002; Livingston and Zhou 2010); (vi) Home bias: CRAs are more favourable issuers in same nationalities or geographic regions (Alsakka and ap Gwilym, 2012b).

In cases of split credit ratings, the measure of the credit risk of an issuer/issue is intuitively questioned. Therefore, split ratings attract substantial interest. Empirical studies show that split ratings convey valuable information and affect future rating changes (Livingston et al., 2008; Alsakka and ap Gwilym, 2010b).

2.4. The rating industry: Its rationale and importance

Langohr (2006) claims that the rating industry offers a gate-keeping function to access international capital markets. von Schweinitz (2007) estimates that roughly 80% of international capital flows are influenced by credit ratings. Issuers seek ratings in order to access international capital markets, where international investors are likely to prefer rated securities over unrated securities of similar credit risk.

Besides, credit ratings have been "hard-wired" into regulation giving them wide influence. Regulators use credit ratings assigned by recognized CRAs to restrict public managed funds to invest in debts below certain levels of credit ratings. The motivations are: (i) aiming at financial soundness via establishing prudential minimum credit quality for portfolio holdings, (ii) incorporating a minimum credit quality of securities issuance to protect investors, and (iii) enhancing market efficiency through raised awareness of the risk characteristics of securities (Dale and Thomas, 1991). A well-known example of regulatory hard-wiring is the so-called "Nationally Recognized Statistical Rating Organizations" (NRSROs) mechanism in the US. The NRSROs concept was first adopted in 1975 when the SEC incorporated credit ratings assigned by at least two NRSROs in computing net capital for broker-dealers' proprietary positions in financial instruments under Rule 15c3-1 of the Securities Exchange Act of 1934. Rule 15c3-1 requires broker-dealers to deduct from net worth certain percentages of the market value ("haircuts") of their proprietary securities positions (SEC, 1994, 1997). Over time, the NRSROs concept and the use of NRSROs' ratings have extended to other aspects of the US regulatory framework. For instance, rule 2a–7 of the U.S. Investment Company Act of 1940 restricts the investments of money market funds to AAA assets rated by NRSROs, and pension funds and municipalities are restricted to invest in investment-grade assets (US Securites and Exchange Commission, 2011a).

Furthermore, the Basel II Accord allows banks and financial institutions using credit ratings assigned by recognised CRAs in calculating adequate capital to cover their credit risk exposures in its so-called "standardised approach". Under this approach, the credit risk weight of each asset is decided based on credit ratings in order to form the total credit risk exposure of the institution that equals to sum of each asset credit risk weight multiplying by value of the asset (Basel Committee, 2003). In response to recent crises, the new Basel III Accord has been issued in December 2010. This Accord will be discussed in details in section 2.5.2. In general, the new Basel Accord appeals banks to have methodologies that enable them to assess the credit risk involved in exposures to individual borrowers or counterparties as well as at the portfolio level regardless of whether they are rated or unrated. In addition, new leverage ratio is introduced to serve as a backstop to the risk-based requirements. However, credit ratings are still at the heart of the "standardised approach" which is widely used by banks in determining the credit risk-weights of banks' assets and calculating their capital adequacy (Basel Committee, 2011).

Moreover, rating-based practical guidelines instruct (either explicitly or implicitly) fund managers to allocate and reallocate the fund portfolios in debts in references to credit ratings. Cantor et al. (2007) present survey evidence that about 75% of plan sponsors and fund managers use credit ratings in setting minimum credit quality guidelines for bond purchases; around 50% of plan sponsors and fund managers use credit ratings to set maximum portfolio proportions by rating class, maximum single security exposures by rating category, and guidelines for downgraded securities that longer meet the guidelines. They also explain that ratings-based governance rules mitigate the problems that arise due to the different interests and incentives of clients and the portfolio managers, and rating follow-ups help to resolve the moral hazard problem to creditors. As a result, credit ratings have been "hard-wired" into not only regulation but also private investment guidelines and mandates by bondholders, pension funds' trustees, and other fiduciary agents.

Overall, credit ratings provide three essential economic functions: **information**, **monitoring**, and **certification** (Boot et al., 2006; IMF, 2010a; Bank of England, 2011).

Firstly, CRAs initially arise to mitigate the fundamental adverse selection problem between borrowers and investors. The adverse selection problem exists due to the informational asymmetry which means that borrowers possess more information over the true condition of their businesses than lenders do. Risk-averse investors, hence, might opt to stay out of the financial market due to fear of the 'lemon' investments. Alternatively, they might demand higher risk premia in compensation for the inferior position which is, in many cases, undesirable by debt issuers themselves who in turn are not able or do not choose to issue debts at such risk premium. In these circumstances, there are market failures. Given the economies of scale, a CRA, a trusted and independent third party, through the gathering and analysis of data relating to creditworthiness mitigates the informational asymmetry, adverse selection problem, decreases the risk premium of a debt issue, and hence increases liquidity of assets which otherwise are illiquid without credit ratings in the financial markets (IMF, 2010b; Bank of England, 2011).

Secondly, rating-based guidelines and rules perform a monitoring role and mitigate principal-agent problems. Besides, by signalling a potential downgrade via negative outlooks and/or reviews or watch lists, CRAs also encourage an issuer to improve its creditworthiness (Boot et al., 2006). To the extent that investors respond to rating changes by adjusting their portfolios, such negative rating announcements impose the implicit threat on issuers that failure to act will degrade their ability to refinance their projects and businesses in the future.

Finally, given the reliance of the public on ratings, CRAs provide a certification function for fund managers, regulators, central banks, and other market participants in distinguishing between securities with different risk characteristics, and specifying terms and conditions in financial contracts (IMF, 2010a). One example of credit ratings' certification function is that a fund's trustees set an investment mandate restricted to investment-grade securities. Another pervasive example can be found in determining regulatory capital requirements for banks, insurance companies, and other financial firms which are allowed by the Basel Accord (II and III) to using its so-called 'standardised approach' in measuring credit exposure (Basel Committee, 2003, 2011). The SEC's regulatory references to credit ratings in calculating the 'hair cut' for brokers and/or dealers under the Securities Exchange Act of 1934 and restricting money market fund to invest in below AAA assets under the Investment Company Act of 1940 are also prevailing examples of the certification function (SEC, 2011b).

2.5. Criticisms during the recent crises and regulatory responses

2.5.1. Criticisms

- Methodological flaws: CRAs have been extensively under fire for fuelling the unsustainable growth of the asset-backed securities market, one root cause of the 2007-2010 crisis. Unlike normal debt, asset-backed structured financing is generally unlimited in supply. CRAs failed to capture actual risk elements involved in these types of securities and usually assigned very strong rating categories to them. The high-level group of experts chaired by Jacques de Larosiere, former President of the European Bank of Reconstruction and Development, argued that there were flaws in CRAs' methodologies of evaluating the credit risk associated with CDOs (Smith, 2009). Given the low transparency and great complexity of structured finance, a heavy reliance by market participants on CRAs along with the over-confidence of CRAs led to the dramatic growth of this market. While generous credit ratings fuelled the growth, subsequent downgrades accelerated the market's collapse and imposed disastrous consequences on the global financial market. From 1984 to 2006, almost 99% of structured finance issues rated Aaa by Moody's had remained Aaa. However, only 62% of Aaa-rated structured finance issues remained in the highest category during the crisis period between September 2008 and August 2009 (Bank of England, 2011). A similar deterioration in performance was also observed for S&P and Fitch. For instance, almost 40% of all structured finance ratings were downgraded by Fitch during the similar period (Bank of

England, 2011). CRAs, from the beginning, provide a convenient measure of credit risk and serve to mitigate the adverse selection problem, decrease the risk premiums of debt issues, and deepen the financial markets. Over the time, credit ratings, along with the growing prestige of CRAs, became very convenient and cost-effective measures of credit risk appetite and discouraged other market participants from conducting their own investigations and due diligence. When CRAs fail to perform their job properly, the collective fallibility during the credit expansion causes destructive consequences.

- Inherent conflict of interest: Rating structured securities was far more profitable than traditional rating (Partnoy, 2006). The structured financing market, hence, increased the revenue streams and marginal profitability of CRAs with their issuer-pay business model. For example, rating structured finance made up 44% of Moody's revenues in 2006 (Mathis et al., 2009). This fact accentuates the criticism upon the inherent conflicts of interest within the credit rating business model. A CRA, at the end of day, is a company, and it is under the pressure of gaining or keeping its business. Since CRAs' revenues are dominated by rating fees collected from issuers, a CRA might be upward biased in order to meet its customers' expectations, and thereby obtain a reasonable compromise between maintaining long-term reputation and short-term targeted market share.

In response to the accusation, CRAs argue that they cannot afford such a dangerous attitude as their reputation, the most important asset, is at stake (e.g. Bolton et al., 2012). S&P claimed that the ongoing value of S&P's business is wholly dependent on continued market confidence in the credibility and reliability of its credit ratings (S&P, 2002). In testing the reputation argument, Mathis et al. (2009) theorically claim that a CRA would always inflate its clients' ratings on complex products if majority of its income comes from this segment. In a recent report based on examinations of 10 NRSROs, SEC has indentified that conflict of interest may also arise due to some rating analysts' ownership of rated securities or rated issuers’ ownership of NRSROs’ shares or CRAs may provide rated issuers with ancillary bussiness, such as investment advice. However, the report determined that no issue constitutes a ‘material regulatory deficiency’ (SEC, 2011c) despite the fact that managing the conflict of interest inherent within rating business has been heavily concerned.

- “Hard-wiring” and “cliff-effect”:

The recent crises have highlighted the “hard-wiring” and “cliff effect” of credit ratings. Credit ratings hard-wiring generates public reliance in numerous aspects of the investment world (see section 2.4 about “hardwiring” of credit ratings for more details). Moreover, hard-wiring into regulations creates some sense that CRAs’ judgements are true and officially confirmed by public authorities, hence, might bring about a more broad-based overreliance on credit ratings. The overreliance on credit ratings in turn creates the “cliff-effect”.

The term of “cliff effect” is used to describe the phenomena of a sudden loss of signals in digital telecommunication. As credit ratings are increasingly embedded in both regulatory and private contractual rules, many market participants are forced to sell-off simultaneously securities those are abruptly downgraded lower than certain credit rating thresholds, usually the investment-speculative threshold. Therefore, rating downgrades could impose grave effects on the liquidity of the rated securities and press the rated issuers deeper into the pre-existed stresses. In other words, rating downgrades could amplify cyclicality and cause herding behaviour in financial markets (Financial Stability Board, 2010). Besides, banking organisations also encounter “cliff effects” in calculating regulatory capital requirements. When securities held by banking organisations are downgraded below the speculative-grade threshold, an excessively severe capital charge is imposed and risk weights could jump up from 100% to 1250% causing the banks harsh distress (American Bankers Association, 2010).

- Spill-over effect:

Rating downgrades could spill-over to other entities not directly due to their own creditworthiness. For example, the downgrade on Greece from A- to BBB+ by Fitch on December 8, 2009 spilled over to European countries (Arezki et al., 2011). In the 2010–2012 period, a series of European countries, including Greece, Ireland, Portugal, and Spain, were downgraded by Fitch, S&P, and Moody's. The premium on Greece's, Portugal's, Spain's 5-year bonds in the CDS market had reached about 900, 300, and 260 basis points at the end of June 2010 (Source: DataStream and Bloomberg). This rating trigger leads to possible illiquidity, distress of rated sovereigns and even others who are performing rationally well, hence worsen the sovereign debt crisis. Furthermore, the sovereign crisis can spill-over to other private sectors of the economies via increased institutional, political uncertainty (Duggar et al., 2009). Moreover, the total exposure of the global banking system to these sovereign debts (Greece, Portugal, Spain, Ireland, Italy) has reached $2 trillion (Patrick, 2011) raising the concern over the sustainability of the global banking system. Subsequently, financial markets in Europe and the US had tumbled as investors have been overwhelmed by the fear that sovereign debt crisis could spread over the EU zone and threaten the fragile recovery of the global economy. Therefore, CRAs have been heavily criticised for the unjustified timing of the rating downgrades, hence, precipitating the sovereign debt crisis.

In response to the accusation, CRAs argue credit ratings are more stable and tend to lag behind other market participants' movements and rating downgrades for example in the case of Greece simply are in response to sudden revision of its statistics concerning the national debt and deficit (House of Lords, 2011). Open Europe stated that the series of downgrades which many countries have faced are ultimately due to the poor health of these economies. The Association of British Insurers argued that "symptoms should not be confused with cause" and "there was no point shooting the messenger" (House of Lords, 2011).

2.5.2. Recent developments

Academicians and governmental authorities have proposed a range of regulatory resolutions in response to the criticism over the credit rating industry during the current crises. In general, the resolutions are aiming at dealing with the problematic issues which have been vigorously criticised, namely methodological flaws, lack of transparency in rating procedure and process; inherent conflict of interest and business model; overreliance on credit ratings and their hard-wiring effect. Table 2.4 seeks to summarise main recent developments in a chronological order.

In 2008, International Organization of Securities Commissions (IOSCO) revised the Code of Conduct Fundamentals for Credit Rating Agencies by strengthening the quality of the rating process, subsequent monitoring; preventing analysts' involvement in the design of structured securities; promoting of public disclosures and periodic review of compensation policies (International Organisation of Securities Commissions, 2009). In the April 2009 Declaration on Strengthening the Financial System, the G-20 leaders came to a consensus that all CRAs should be subject to a prudent surveillance regime which includes registration and is consistent with IOSCO's Code of Conduct (Katz et al., 2010).

In addition, they agreed that national authorities shall enforce compliance, with the IOSCO playing a coordinating role, and that CRAs should distinguish credit ratings for structured products and increase disclosures, and the Basel Committee should review the role of external credit ratings in prudential regulation and identify any adverse incentives that need to be addressed. Moreover, the European Commission (EC) has already issued regulations that require all credit ratings agencies operating in Europe to register with

European Union (EU) regulators and to observe demanding rules of conduct. Regulations on vis-à-vis CRAs would require closer transatlantic coordination, given the fact that many of these are based in the US (The Policy Network, 2010). By September 2014, 23 CRAs have registered with European Securities and Markets Authority (ESMA) which is authorised by the EC to exclusively supervise CRAs operating in Europe (ESMA, 2014).

Table 2.4: Main recent developments

Time	Event	Current status
May 2008	IOSCO revised the Code of Conduct Fundamentals for CRAs	
April 2009	G20 summit appeals a prudent surveillance on CRAs based on IOSCO's Code of Conduct	
April 2009	Solvency II rules were passed by EC aiming at more prudential regulations	
December 2009	SEC required issuers to channel any private information to all NRSROs	
2009 -2010	Some alternative business models have been proposed, eg. Investor-pay model, platform model, state CRA, non-profit CRA	
July 2010	Dodd-Frank Act was passed requiring a reform throughout the US financial system. A major content relates to CRAs.	
December 2010	Basel III Accord was issued	25 countries have started/ completed regulatory amendments toward Basel III
April 2011	SEC proposed removing references to credit ratings in the Investment Company Act of 1940 and the Securities Exchange Act of 1934	Most proposed contents are still under considerations
July 2011	EC proposed reducing reliance on ratings in regulations. CRA regulation has been handled to EMSA which requires CRAs to register and observe its rules	23 CRAs (at a group level) has been registered.
November 2011	ESMA proposed amendments to Regulation on CRAs operating in Europe	The amended Regulation (CRA III regulation) became in force since June 2013

In an attempt to mitigate public overreliance, rating-based rules and guidelines have been under consideration to be dismissed. For instance, SEC revised the regulatory reliance on external credit ratings as the Dodd-Frank Act requires federal agencies to review how their existing regulations rely on credit ratings. In particular, in April 2011, SEC proposed amendments removing references to credit ratings in the Investment Company Act of 1940 and the Securities Exchange Act of 1934, legal backbone of the US financial system (US Securites and Exchange Commission, 2011a, b).

Regarding the Investment Company Act of 1940, the role of credit ratings in Rules 2a-7, 5b-3, 6a-5 and Forms N-1A, N-2, N-3 was replaced with alternatives as assessments of creditworthiness (US Securites and Exchange Commission, 2011a). With respect to rule 2a-7, a money market fund is required to make its own independent evaluations over the credit quality of a security which previously rested entirely upon a credit rating assigned by an NRSRO. A money market fund is still able to use credit ratings as measures of credit quality but the fund advisers are required to understand the method for determining the ratings and make an independent judgment of credit risks, and to consider an outside source's record with respect to evaluating the types of securities in which the fund invests. Rule 5b-3 authorises repurchase agreements for securities and their attendant collateralization of a fund basing on its board of directors assessments over the securities' credit risk and liquidity. Rule 6a-5 regulates Business and Industrial Development Companies which operate under state statue to invest in debt securities that the board of directors or members of the companies determine that the debt securities are subject to no greater than moderate credit risk and sufficiently liquid which means the securities can be sold at or near their carrying value within a reasonably short period of time. Currently, Forms N-1A, N-2, N-3 require shareholder reports using credit ratings assigned by a single NRSRO to depict portfolio holdings by credit quality categories. The new proposed amendment is to eliminate the required use of NRSRO's credit ratings.

Instead, funds can choose to use credit quality categorisations in the required table, chart or graph of portfolio holdings. If a fund chooses to use NRSRO credit ratings to depict credit quality of portfolio holdings, it would be required to use the credit ratings of a single NRSRO.

Regarding the Securities Exchange Act of 1934, Rules 15c3-1, 101 and 102 of Regulation M, 10b-10, and Appendices A, E, G, F were proposed to changed (SEC, 2011b). Rule 15c3-1 and the Appendices are related to minimum net capital requirements for broker-dealers. A broker-dealer has to deduct percentages "hair cut" of the value of securities owned by the broker-dealer in calculating his net capital. Under the current Rule, the hair cuts are lower for securities which are rated in higher rating categories by at least two NRSROs. SEC proposed removing references to credit ratings and substituting by other alternatives of creditworthiness measurements. Under this proposal, a broker-dealer takes a 15% haircut on its proprietary positions in commercial paper, nonconvertible debt, and preferred stock unless the broker-dealer has a process for determining creditworthiness that satisfies the criteria described below. Nonetheless, commercial paper, nonconvertible debt, and preferred stock without a ready market would remain subject to a 100% haircut. Regulation M is designed to preserve the integrity of the securities trading market as an independent pricing mechanism by prohibiting activities which could artificially influence the market for an offered security. Rules 101 and 102 of Regulation M specifically prohibit issuers, selling security holders, distribution participants, and any of their affiliated purchasers, from directly or indirectly bidding for, purchasing, or attempting to induce another person to bid for or purchase a "covered security" until the applicable restricted period has ended. Rules 101c2 and 102d2 currently except investment-grade nonconvertible and asset-backed securities, rated by at least one NRSRO, from these prohibitions. SEC proposed removing the references to credit ratings in Rules 101c2 and 102d2 and replacing them with new standards relating to the trading characteristics of covered securities. Specifically, SEC proposed to except nonconvertible debt securities, nonconvertible preferred securities, and asset-backed securities from Rules 101 and 102 if they: (1) are liquid relative to the market for that asset class; (2) trade in relation to general market interest rates and yield spreads; and (3) are relatively fungible with securities of similar characteristics and interest rate yield spreads. Rule 10b-10 under the Exchange Act requires broker-dealers to provide customers with a written notification disclosing certain information about the terms of the transaction. One term that broker-dealers have to inform customers is if a debt security, other than a government security, is unrated by an NRSRO. SEC proposed removing this point. Up to the time of doing this thesis, these proposals, related to both the Investment Company Act and the Securities Exchange Act, are still under considerations and have not been legally approved.

Under Solvency II rules, proposed by the Omnibus directive – the EC, insurance companies operating in Europe have to estimate two capital requirements, namely Solvency Capital Requirement and Minimum Capital Requirement. While the former, a risk-based capital requirement, could use credit ratings in its calculation, the latter is an absolute floor and is not based on external credit ratings in order to reduce rating overreliance (Basel Committee, 2009). In addition, Financial Stability Board (2010) proposes that market participants, especially sophisticated institutional investors, should have their own credit assessments, and not rely solely or mechanistically adjust their portfolios based on external credit ratings. Regulators should offer incentives to market participants avoiding relying extensively on rating-based guidelines and fund managers should be encouraged to ensure adequate public disclosure of how credit ratings are employed in the fund's risk assessment processes.

The Basel III Accord, issued in December 2010, requests banks to have methodologies that enable them to assess the credit risk involved in exposures to individual borrowers or counterparties as well as at the portfolio level regardless of whether they are rated or unrated. In estimating capital adequacy, they are appealed to assess credit risk exposures and determining whether the risk-weights applied to such exposures under the standardised approach are appropriate for their inherent risk. However, credit ratings still can be used in determining the risk-weights of banks' assets. In supplement, new leverage ratio is introduced to serve as a backstop the risk-based requirements. The leverage ratio is "a simple, transparent, non risk-based measure" which restricts the absolute level of indebtedness of a bank given an amount of tier 1 capital. Therefore, the ratio aims at a safeguard role against any attempt to game the risk-based capital requirements and also mitigate discrepancies and/or mis-judgments in risk attribution to assets (Basel Committee, 2011). Incorporation of the IOSCO's Code of Conduct, the Basel III Accord appeals national credit rating regulators to supervise CRAs on a continuous basis, and responsible for determining whether a CRA meets the regulatory criterions which seek to enhance objectivity, independence, transparency, public disclosure, credibility of the agency. Besides, the supervisory process for recognising CRAs should be publicly transparent, and avoid unnecessary barriers to entry (Basel Committee, 2010).

In July 2011, the EC proposed new banking regulations related to capital requirements in implementation of Basel III Accord (EC, 2011). Regarding to the role of credit ratings, the new proposal seeks to reduce to the mechanic and over-reliance by credit institutions on external credit ratings. Banks are required to make investment decisions not only based on credit ratings but also on their own internal credit opinion. Besides, banks with a material number of exposures in a given portfolio are required to develop internal ratings for that portfolio instead of relying on external credit ratings for the calculation of their capital requirements.

In an attempt to mitigate the conflict of interest stimulated within the prevalent issuer-pay model in the rating industry, structural reform has been proposed considering investor-pay model, platform-pay model, and public CRAs. In principle, a business model in which CRAs compete for investor subscriptions might be more likely to yield unbiased, reliable credit ratings than a model in which CRAs compete for issuer mandates. An investor-pays model, hence, alleviates the existing conflict of interest in the ratings industry. However, implementing the investor-pay model in fact is problematic due to the free-riding issue. In the past, credit rating business relied mainly on investors' subscriptions. Since the development of photocopying machines in the early 1970s, this model was prone to free-riding (e.g. Mathis et al., 2009; IMF, 2010a; Bank of England, 2011). Once a credit rating was made available to the public, numerous free-riders enjoyed it without paying to the CRA. Moreover, investor-pay model could generate "information leakage" when uninformed investors, who do not buy credit ratings, condition their decisions on the price that informed investors, who purchased ratings, realised (Skreta and Veldkamp, 2009). This leakage reduces the motivation for buying ratings. Therefore, CRAs would be left with insufficient resources to devote for credit risk research and analyses. Consequently, credit ratings, even unbiased, could not capture sufficiently credit risk elements. Alternatively, a platform-pay model has been proposed to resolve the conflict of interest in the ratings industry (Mathis et al., 2009). Under this proposal, each issuer would first approach the "centre platform", which could be a ratings clearing house, an exchange, or a central depository. The centre platform would in turn select one or several CRAs to rate the security. The issuer would still pay for the rating(s), but the CRAs would be paid by the centre platform. However, a concern with this model is that criterions used by the centre platform to match CRAs to issuers could distort market resources. Another solution is replacing private CRAs by a public/ non-profit CRA. Again, the public agency is likely to artificially introduce subjective intervention into the free market and distort resources inefficiently. Moreover, a public authority would be extensively exposed to private lobbying and cause moral hazard. It could also exaggerate the problems of overreliance on ratings and the hard-wiring effect as credit ratings, assigned by a public authority, could create the sense of being officially trustworthy (Bank of England, 2011).

Measures lowering barriers to entry and enhancing competitiveness in the credit rating market are also taken into consideration. Together with efforts to reduce overreliance on ratings, lowering barriers to entry and promoting competiveness in the ratings industry could mitigate the hardwiring effect. In late 2009, SEC required all issuers to ensure that any private information made available to its appointed CRAs is also made available to all other NRSROs in an attempt to assists CRAs with smaller market shares to overcome informational barriers associated with the reputation and name recognition enjoyed by larger incumbents (SEC, 2009). A similar provision was taken into consideration in Europe, but will not now proceed (Bank of England, 2011). On the other hand, increased competition in the rating business might have unwanted side effect of worsening the conflict of interest within the issuer-pay model given the fact that "ratings shopping"[4] is a controversial feature in the field (Skreta and Veldkamp, 2009; Bolton et al., 2012). If each CRA has to struggle for a reduced share of an increasingly competitive market, they might have greater motivation to keep and gain its market share rather than to maintain a reputation for accurate ratings. Becker and Milbourn (2011) present an empirical evidence of deterioration in bond rating quality after the entry of a competitor, Fitch, into the market previously dominated by Moody's and S&P. Even CRAs are assumed to tell the truths, increasing competition among

[4] Issuers can approach CRAs for privately known 'shadow' credit ratings, then only pay a CRA if it asks the CRA to publicise the rating. If an issuer is unhappy with a rating, it may solicit another one. In other words, issuers can shop for favourable rating(s).

CRAs would encourage ratings shopping behaviour and create a systematic bias in publicised credit ratings on complex products (Skreta and Veldkamp, 2009).

In summary, the measures announced primarily aimed at introducing direct governmental involvement in credit rating industry; improving the accuracy and the integrity of the rating process; promoting competition in the credit rating industry; revising the issuer-pays model; reducing the hardwiring and cliff effect of credit ratings. However, no common consensus on a single set of reforms has been agreed.

2.6. Conclusions

Recent financial and debt crises have drawn a huge interest upon CRAs. Researchers, investors, regulators, policy makers, public authorities, politicians and other market participants have been concerning over credit rating industry more than ever.

CRAs have long played an essential role in global financial markets. Accessing international capital markets is the main reason for issuers seeking credit ratings from CRAs. Credit ratings help to mitigate fundamental adverse selection problem, reduce information asymmetry between investors and borrowers, thus, decrease costs of capital. Rating-based guidelines offer a solution for the principal-agent problem.

However, CRAs have failed to properly capture elements associated with asset-backed assets that imposed one of grave consequences to global financial markets and contribute significantly to the 2007- global crisis. This has placed the credit rating industry under fire. Among heated issues, methodological flaws, conflict of interest, public overreliance, hardwiring and cliff effects have been concerned vigorously. In response, a range of measures has been taken in consideration but no common consensus on a single set of reforms has been agreed.

Given the public awareness over the CRAs' failures, the importance and market impact of credit ratings post-crisis has been questioned. This thesis seeks to address such questions and investigates the interaction between derivative markets and sovereign credit ratings. This is at the core of global credit risk management because sovereign credit rating is a robust determinant of other issuers' creditworthiness. The next chapter will discuss in detail the role and market impact as well as prior literature on sovereign credit ratings.

Chapter 3: Literature review on sovereign ratings

3.1. Introduction

Sovereign risk awareness and research are of key importance given the rapidly increasing demand of international diversified investments and the huge size of sovereign debt markets (House of Lords, 2011; IMF, 2011; McKinsey Global Institute, 2011). Sovereign credit ratings strive to measure long-term structural default risk of national governments, hence, directly pertinent for investors whose interest is in sovereign debts market, the largest single segment of the global debt market (e.g. IMF, 2011). In addition, sovereign credit ratings also are interest of others because of their relevance to international diversification considerations. It is very essential for investors who are going to participate in either direct or indirect investments in a certain country (ies) to be conscious of the country's (ies') sovereign risk. Among the country's (ies') sovereign risk measures, the sovereign credit rating(s) is a very cost-effective and convenient proxy, especially when the investors may participate in a number of countries. Although country risk and sovereign default risk are distinctive concepts, there is a positive association between the two (Fitch, 2011b). Sovereign bond yields usually act as benchmarks for sovereign risk (Dittmar and Yuan, 2008). Meanwhile, sovereign credit ratings determine sovereign bond yields. Besides, sovereign credit ratings generally play a core role in determining creditworthiness of a huge number of other economic players (e.g. Cantor and Packer, 1995; Fitch, 2011c; Moody's, 2011a; Borensztein et al., 2013; Williams et al., 2013). Sovereign crises can spill-over into the corporate sector via institutional and political factors (e.g. Duggar et al., 2009; Bedendo and Colla, 2013; Gennaioli et al., 2014). Moreover, sovereign credit ratings actions could spill-over to the financial markets not only of the rated sovereigns but also others (see Kaminsky and Schmukler 2002; Brooks et al., 2004; Martell, 2005; Ferreira and Gama, 2007; Arezki et al., 2011). Furthermore, sovereign credit ratings affect cross-border bank lending and capital flows into emerging economies (Kim and Wu, 2008, 2011). The European sovereign debt crisis, which is of investors', regulators', politicians' and other market participants' concerns continuously in recent years, has drawn a huge demand of further research related to sovereign credit ratings. In a nutshell, sovereign credit rating is a critical research domain which is of key relevance of not only researchers but also investors, regulators, and other market participants.

This chapter aims at providing an overview of prior literature on sovereign credit ratings and highlighting the important gaps which shall be fulfilled in my empirical researches in the following chapters. Prior literature on sovereign credit ratings primarily seeks to dealing with the following main issues: the determinants and methods of sovereign credit ratings, migration behaviour of sovereign credit ratings, sovereign split ratings, sovereign credit ratings' market impact and informational content. The remaining of this chapter is organised as followings. Section 3.2 briefly presents the definition of a sovereign credit rating. The rationale of sovereign credit ratings is highlighted in section 3.3. Reviews of prior literature on determinants of sovereign credit ratings, split sovereign ratings, rating migrations are discussed in section 3.4, 3.5, 3.6, respectively. Section 3.7 shall analyse in depth prior researches on market impacts of sovereign credit ratings. Section 3.8 concludes the chapter.

3.2. What is a sovereign credit rating?

A sovereign rating is the credit rating of a national central government. In other words, a sovereign credit rating is an opinion regarding the capacity and willingness of a central government to service its debt obligations in full and on time. Similar to a corporate, a sovereign (central government) may receive foreign currency and/or local currency, long-term and/or short-term ratings depending on currency of the issued debts.

While corporate credit rating has been traditionally used and researched for over a century, sovereign credit rating is a rather new area mainly due to the blossom of the sovereign debts market from 1990s. Different to a corporate, that cannot opt not to repay its due debts, a sovereign may refuse to fulfil its financial obligations after comparing socio-economic and political costs of their alternatives. Therefore, CRAs also consider a sovereign's willingness to pay its debts when assigning a sovereign credit rating. Table 3.1 briefly summarises the sovereign credit rating definition from three leading CRAs, S&P's, Moody's, and Fitch. A sovereign rating is a forward-looking over the creditworthiness of a country, but it is not a country rating. This is an important and often misunderstood distinction by market participants.

3.3. Underlying rationale of sovereign credit ratings

Sovereign ratings are the credit ratings of national governments, hence, provide all functions for sovereign debt market participants as do corporate credit ratings for the corporate debt market participants. Moreover, sovereign ratings offer investors who may not participate in the sovereign debt market with valuable implications for the international diversification strategies.

Firstly, sovereign credit ratings strive to measure long-term structural default risk of national governments, hence, directly pertinent for players whose interest is in the sovereign debts market. It is worth to imagine how huge the sovereign debt market. The sovereign debt market is the largest single segment of the global debt market, accounting for more than 60% of debt issued (House of Lords, 2011). According to a report by the McKinsey Global Institute, the amount of governments' debts reached $41 trillion and accounted for nearly 80% of global net borrowing and 69% of global GDP by the end of 2010 (McKinsey Global

Institute, 2011). According to an IMF projection, despite many governments' recent efforts in cutting their budget deficits, the financing needs of governments over the world are increasing considerably. By the end of 2012, many countries need substantial resources just to balance their budget deficits and to repay due debts, only a part of their outstanding public debts. For instance, Japan demands 58.6% of its GDP to finance budget deficit and repaying due debts while the equivalent figures for US, Pakistan, Italy, Portugal, Belgium, France, Spain, Greece are respectively 30.4%, 26.5%, 23.5%, 22.3%, 22.2%, 20.8%, 20.6%, 16.5% (IMF, 2011). These add up to governmental gross debts which will reach 76.3% of the global GDP by the end of 2012. In longer terms, IMF estimates the governmental debts will stabilise around 76% of GDP (IMF, 2011). Given these huge figures of sovereign borrowings, the sovereign debt market has been playing and is going to be a very essential segment of the global capital markets.

Sovereign credit ratings play a critical role in developing the sovereign debt market due to the contribution in addressing the fundamental problem of adverse selection, informational asymmetry, fears of lemon investments. Sovereign credit ratings provide all functions for the sovereign debt market participants as do corporate credit ratings for the corporate debt market players. These functions include information, monitoring, and certification (see Section 2.4 for more details about rationale and importance of corporate credit ratings). In general, governments seek credit ratings in order to mitigate hurdles and expenses when accessing to international capital markets while investors prefer sovereign credit ratings due to the need of cost effective, convenient proxies of the credit risk of the borrowers.

In addition, sovereign credit ratings also are interest of other markets' participants, including non-sovereign debts, equity markets as well as cross-border bank lending, cross-border direct investments, due to the relevance of sovereign ratings to international diversification considerations. Along with the globalisation of financial markets, investors, particularly managed funds, increasingly focus on international diversification which reduces their portfolios' risk by eliminating country specific risk. A well internationally diversified portfolio only bears the global systematic risk and is on the global efficient frontier which induces better trade-off between risk and return. It is requisite for investors who are considering participate in either direct or indirect investments in a certain country to be conscious of the country's sovereign risk. Among the country's sovereign risk measures, the sovereign credit rating is a very cost effective and convenient proxy, especially when the investors may participate in a number of countries. Although country risk and sovereign default risk are distinctive concepts, there is a positive association between the two (Fitch, 2011b).

Moreover, Dittmar and Yuan (2008) claim that a sovereign bond acts as a benchmark to the country's systematic risk. They show that an emerging sovereign bond plays a significant role in developing the country's corporate bond market which is usually under-developed. Therefore, the presence of a sovereign bond is significantly beneficial for the country's corporations to raise capital via the bond market, hence, also beneficial for the development of the country. Importantly, the study clarifies the contribution of sovereign bonds in three mechanisms. Firstly, sovereign bonds improve the price discovery of corporate bonds to the extent related to country-systematic risk. Dittmar and Yuan (2008) provide evidence that over one-fifth of the information in corporate yield spreads is traced to innovations in sovereign bond yields. Secondly, sovereign bonds improve investors' opportunities of inclusion of the sovereign bonds in their portfolios and hedging against the country risks. Finally, in presence of informational asymmetry, sovereign bonds' issuances help to mitigate adverse selection, hence, improve the liquidity of the secondary corporate bond market. These results all come up to a final conclusion that sovereign bond yields act as benchmarks to country-systematic risk.

In the meantime, a sovereign credit rating addresses a sovereign default risk and is directly linked to the sovereign's bonds. Furthermore, sovereign credit ratings generally impose "ceiling effect" and play a determining role of the creditworthiness of a huge number of other entities of the same nationality (Cantor and Packer, 1995; Fitch, 2011c; Moody's, 2011a; Borensztein et al., 2013). For example, numbers of European banks during the period of 2011-2013 have been downgraded by CRAs who later explicitly explained these downgrades not directly due to the banks' financial health but deteriorations in their governments' financial capacities and willingness to bailout these 'too big to fail' players in case of catastrophe. Duggar et al. (2009) shows episodes of large-scale corporate defaults generally coincide with episodes of sovereign crises; in the period from 1995 to 2008, 71% of emerging market defaults occurred during sovereign crises. They also suggest that sovereign crises can spill-over into corporate sector via institutional and political factors. Kim and Wu (2008, 2011) reveal that sovereign credit ratings are important in encouraging financial sector development and attracting capital flows, including foreign direct investment and portfolio flows, into emerging markets after controlling for various economic and corporate governance factors. In other words, sovereign credit ratings play a significant role not only in the debt markets, including the sovereign debt and corporate debt markets, but also in international bank lending channels into emerging economies.

Furthermore, sovereign credit ratings news could spill-over to financial markets, including debt market, equity market, foreign exchange market ect., not only of the rated countries but also others (see Kaminsky and Schmukler 2002; Brooks et al., 2004; Martell, 2005; Ferreira and Gama, 2007). Arezki et al., (2011) assert that the sovereign rating downgrades on certain countries, eg. Greece, Ireland, Iceland etc., during the period from

2007 to 2010, significantly spill-over to other European countries' financial markets, including stock market, CDS market, banking, and insurance markets.

Therefore, demand for sovereign credit ratings has intensively increased due the appropriateness in international diversifications and numerous aspects of investments. Accordingly, sovereign credit ratings have been surged vastly. In 1994, just over 40 sovereigns were rated by Moody's. A similar number were rated by S&P's while Fitch covered about 20 sovereigns (Alsakka and ap Gwilym, 2010a). As of 30 July 2010, S&P's, Moody's, and Fitch respectively rated 125, 110, 107 sovereigns (IMF, 2010a). By the end of 2013, SEC reported that the three CRAs assigned 1,907,750 credit ratings on governments' securities (SEC, 2013).

In a nutshell, sovereign credit ratings are of vital interest of both governments who issue debts into international capital markets and investors who either participate in the sovereign debt market or non-sovereign debt market or international diversifications or cross-border lending and investments as well as are pertinent to researchers, policymakers who seek to promote the countries' sound financial development.

3.4. Determinants of sovereign credit ratings

Sovereign credit ratings represent CRAs' opinions regarding the likelihoods at which the given governments will default on their financial obligations. Unlike corporate credit ratings, credit ratings on sovereign debts involve complexities as a national government poses a unique ability of choosing defaulting state even it has enough resources to repay debts in full and on time. Therefore, CRAs distil both the assessments concerning the government's capacity to pay and willingness to pay its debt obligations in a sovereign credit rating. In assessing a government's capacity and willingness to repay its debts, CRAs generally base on sets of quantitative and qualitative indicators of the country's economic, financial fundamentals as well as political and legal risks, institutional environment (Fitch, 2011b; IMF, 2010a; Moody's, 2008; S&P, 2011). Economic and financial fundamentals of a country are usually linked to the sovereign's ability to repay its debts in full and on time, while and political, legal risks, institutional environment are more likely to be related to the sovereign's willingness to fulfil its obligations (Butler and Fauver, 2006). Nevertheless, CRAs do not reveal the details of their methodology for rating assessments (Bennell et al., 2006). Recent regulatory developments have promoted more transparency in rating process and rating methodologies. However, the credit rating is a lucrative industry, and CRAs surely lack of motivation to make it completely clear to the public how their sovereign rating analyses are conducted. Therefore, many of prior empirical literature seek to answer the critical question which factors determine sovereign credit ratings. Overall, these determinants can be categorised into two broad groups of criterions respectively estimating a government's capacity and willingness to fulfil its obligations.

In gauging the capacity, CRAs usually base their judgements on economic and financial fundamentals. Many empirical studies have investigated this relationship between sovereign credit ratings and economic and financial indicators. Some claims that current economic and financial indicators alone do not determine sovereign credit ratings (Bissoondoyal-Bheenick, 2005), yet majority suggests that sovereign ratings are mainly driven by economic fundamentals.

Cantor and Packer (1996) is a very first study attempting the question over the determinants of sovereign credit ratings. They examine the relationship between sovereign credit ratings, by Moody's and S&P, and economic variables, including per capita income, Gross Domestic Product (GDP) growth, inflation, fiscal balance, current account deficit, foreign debt to exports, dummy variables representing economic development status and history of default. Based on a cross-sectional data of 49 sovereigns in 1995, Cantor and

Packer (1996) find that sets of economic fundamentals are highly significant in explaining variation in sovereign ratings. In my opinion, Cantor and Packer (1996) approach to the issue is great, but their method of estimation is problematic. Cantor and Packer (1996) transform sovereign credit ratings into numerical scores and then try to explain variations in sovereign ratings by the economic fundamentals, based on OLS estimations which assume a linear relationship between the rating categories' probabilities and the economic fundamentals. Many later studies criticise this assumption and employ probit, logistic estimations which base on non-linear functions in describing the relationship between sovereign credit rating probabilities and explanatory variables (e.g. Mellios and Paget-Blanc, 2006; Bennell et al., 2006; Afonso et al., 2007; Alsakka and ap Gwilym, 2010b). Additionally, Cantor and Packer (1996) do not contemplate the discrete nature of credit ratings. In other words, the variation in continuous numerical scores cannot fit the changing in credit ratings which have no value other than integers. For example, there is no rating which takes 0.33, 1.41 etc. Moreover, the OLS assumes that the differences between credit rating levels are the same. For example, a downgrade from AAA to AA+ is assumed the same as a downgrade from AA+ to AA (because the numerical values of the differences are one in both cases). Indeed, this is not true. All the information can be inferred from a rating change is that as the score decreases/increases, there is a monotonic deterioration/improvement in the credit quality. In addition, Cantor and Packer (1996) take average values between Moody's and S&P's ratings. This is not advisable given the large degree of disagreements between the CRAs. Besides, the data set which only covers 49 countries in 1995 is very weak compare to recent studies.

Bissoondoyal-Bheenick (2005) using an ordered response model on a panel data of 95 sovereigns in the period from 1995 to 1999 examines the relationship between sovereign ratings by the two leading CRAs, namely Moody's and S&P, and economic variables. She divided the total data into 2 sub-samples, namely high-rated sample which consist 25 high-rated countries and low-rated sample of the remaining countries. In high-rated sample, the study finds that the economic variables do not play an important role in explaining ratings' variation. On the other hand, some economic indicators such as GNP per capita and inflation, current account balance and foreign reserves do play an important role in the determination of sovereign ratings in the low-rated sample. I suppose that this finding can be explained by the lack of variability in the ratings assigned to high-rated countries.

In contrast to the finding of Bissoondoyal-Bheenick (2005), empirical researches by Mulder and Perrelli (2001); Mellios and Paget-Blanc (2005); Bennell et al. (2006); Afonso et al. (2007, 2011); Powell and Martínez (2008); Hill et al. (2010) confirm that ratings can be explained well by economic and financial fundamentals.

Mulder and Perrelli (2001) employ Least Square estimations on a panel data of 25 sovereigns in the period from 1992 to 1999. They show that sovereign credit ratings are influenced by the ratios of investment to GDP, debt to exports, short-term debt to reserves, and the rescheduling history. Again, Mulder and Perrelli (2001) have a major methodological limit. Discrete, ordinal nature of the dependent variable, sovereign credit ratings, makes the Least Square technique no longer appropriate. Besides, Least Square techniques have to rely on the assumption of a linear relationship between sovereign credit rating probabilities and the explanatory variables which have been criticised in Cantor and Packer (1996) above.

Using ordered probit regression on a panel data set of 70 sovereigns during the period from 1989 to 1999, Bennell et al. (2006) examines the relationship between sovereign ratings and a set of macro-economic variables, including one-year lagged foreign debt to exports, fiscal deficit/surplus to GDP for the previous three years, average current deficit/surplus to GDP for the previous three years, average rate of inflation for the previous three years, average GDP growth in previous three years, GDP per capita for the previous three years, and development indicator. They take the average values of macroeconomic indicators into account in order to reflect the CRAs' philosophy of rating through the cycle. The study shows that all economic variables are highly significant in explaining rating variation, and all variables have anticipated signs except for external balance, which is also found to be unexpected negative by Cantor and Packer (1996). Furthermore, using likelihood ratio test which tests the hypothesis that all coefficients except for the intercept are zero, Bennell et al. (2006) finds that all the economic variables are collectively meaningful in explaining sovereign credit ratings variation. However, the paper had pooled all credit ratings from 11 CRAs into a dependent variable and compensated by including agency indicator dummy variable into their model. From my perspective, this is not a really advisable approach because the coefficients of their model would be the same for all 11 CRAs. This is not true given the split ratings and obvious independence in each CRA's methodology and its weighted economic factors. Besides, larger datasets in cross-sectional and time-series dimensions are now available. Additionally, role of qualitative, political factors which have been disclosed to be crucial in CRAs' sovereign credit rating assignments (Moody's, 2008; Fitch, 2011b; S&P, 2011) has been ignored. Furthermore, the study has ignored individual effects, country by country characteristics, which could be nonzero distributed.

Based on an unbalance panel data of 78 countries during the period from 1995-2005, Afonso et al. (2007) using random effects ordered probit detect a set of core variables relevant for the determination of sovereign credit ratings, including per capita GDP, GDP real growth rate, government effectiveness, government debt, external debt and external reserves, default indicators. Their models do provide high predictive power. On average, 70 percent of all observations on sovereign credit ratings are correctly predicted. The percentage increases to more than 95% when within one notch errors are allowed. Afonso et al. (2007) improve the issue which was criticised in Bennell et al. (2006) about pooling credit ratings from different agencies into one dependent variable by modelling each CRA's ratings via separated equations. The results show the coefficients of sovereign credit ratings from the CRAs are different to each other, hence, reassert the methodological differences between the CRAs. However, Afonso et al. (2007) do not materialise the effects of qualitative, political factors that play an important role in determining sovereign credit ratings (Moody's, 2008; Fitch, 2011b; S&P, 2011). Although they can argue that the individual effects can mop up social, political factors, this implicitly assumes that the social, political elements of a country stay constant over the 10-year period which could be hardly true in reality. Moreover, the random effects models have to be based on an assumption that the individual effects, country characteristics, are uncorrelated with the independent variable, economic fundamentals. This is also hardly true in reality.

Using a cumulative probit regression on a data set of sovereign credit ratings assigned by Moody's, S&P, and Fitch on 129 sovereigns during the period from 1990 to 2006, Hill et al. (2010) revise the question over determinants of sovereign credit ratings and reassert significance of economic fundamentals in rating sovereigns. These economic fundamentals include per capita GDP, GDP growth, inflation, fiscal balance, external balance, external debt, dummy variable representing history of default. In addition, Hill et al. (2010) find that Institutional Investor rating (country risk rating) and market risk premium are significant in determining sovereign credit ratings. Hill et al. (2010) improve the issue which was criticised in Afonso et al. (2007) and seek to materialise the effects of qualitative, political factors in determining sovereign credit ratings by including Institutional Investor rating (country risk rating) and market risk premium. In my views, this is, however, not really advisable. Country risk and sovereign credit risk which is proxied by sovereign credit ratings are expected to be highly correlated (Fitch, 2011b). Nevertheless, correlation and causality are distinctive concepts. It is not sensible to claim that country risk determines sovereign credit risk.

Similarly, the market risk premium cannot be included in the right hand side of Hill et al. (2010) models without theoretical justifications.

In supplement to quantitative economic and financial indicators; institutional strength, governance quality, political risk are substantial elements that CRAs take into consideration when assigning sovereign ratings (S&P, 2006; Moody's, 2008; Fitch, 2011b; S&P, 2011). The rule of laws, separations of powers, quality of policy making process, institutional power, public participation in politics, whether military threats or potential conflict exist, relations with neighbouring countries are core aspects that a CRA look at when analysing political risk of a sovereign. The separation of powers between legislative, executive and judicial is an essential factor in the development of civil institutions, especially the independence of press. The stability, predictability, and transparency of a country's political institutions are significant considerations in analysing the parameters for policymaking, including how quickly policy errors are identified and corrected. CRAs also examine the extent to which politics is adversarial and the frequency of changes in government, as well as any public security concerns. Relations with neighbouring countries are studied with an eye toward. National security and potential external security risk are concerned when military threats place a significant burden on fiscal policy, reduce the flow of potential investment, and put the balance of payments under stress. Empirical literature also confirms the importance of institutional strength, governance quality, and political stability (risk) in determining sovereign credit ratings (Mellios and Paget-Blanc, 2006; Butler and Fauver, 2006; Afonso et al., 2012).

In summary, both prior literature and disclosures from major CRAs confirm that sovereign credit ratings are determined by the sovereign’s economic fundamentals as well as political stability, and governance quality indicators.

3.5. Split ratings

Split rating is the phenomena when CRAs disagree on specific sovereign rating assignments. Sovereign credit ratings are CRAs' assessments of a country's capacity and willingness to repay its debts in full and on time based on both quantitative and qualitative inputs. While CRAs generally agree on the major quantitative inputs, yet the weights assigned to these inputs can vary across the agencies (e.g. Bennell et al., 2006; Afonso et al., 2007). In addition, qualitative considerations, very crucial in assigning a sovereign credit rating, vary to a greater extent across CRAs as the qualitative considerations are ultimately subjective judgements by credit risk analysts from each CRA (IMF, 2010a; House of Lords, 2011). Furthermore, CRAs' general approaches in assigning credit ratings are different as well (see section 2.2.3 for more details about methodological differences between major CRAs).

As sovereign credit ratings are assigned by several CRAs, sovereign split ratings are inevitable due to the methodological differences as well as the subjectivity of these agencies. Jewell and Livingston (1999) show that split rating in sovereign is more frequent than for corporate rating leaving investors uncertain about the credit risk of the governments in question.

There are a number of studies in prior literature attempting to explain the main reasons why CRAs disagree over sovereign credit rating assignments. Prior researchers generally consider that some of reasons of corporate split ratings are less significant in the case of sovereign split ratings (see section 2.3.6 for more details about main reasons why agencies disagree on corporate rating assignments). Cantor and Packer (1995) argue that the split sovereign ratings between Moody's and S&P are due to the CRAs' lack of experience in rating sovereign credits and different in weighting of qualitative risk factors. CRAs also do not agree on the importance of each quantitative macroeconomic elements. For example, fiscal balance is significant in Moody's and Fitch's sovereign credit ratings while inflation rate and external balance are important in S&P's ratings (Hill et al., 2010). Overall, prior literature identifies main reasons of sovereigns split ratings as follows: (i) CRAs employ different economic factors and different weights on these factors (e.g. Cantor and Packer, 1995, Hill et al., 2010); (ii) CRAs disagree to a greater extent about more "opaque" issuers (e.g. Alsakka and ap Gwilym, 2012b); (iii) "home bias": CRAs tend to be more in favour of issuers in their home region (Alsakka and ap Gwilym, 2012b).

Sovereign split ratings might affect the probability of future rating changes. Alsakka and ap Gwilym (2010b) find strong evidence in support of the hypothesis in cases of emerging countries. Split rated sovereigns tend to be upgraded by the CRA awarding the lower ratings and tend to be downgraded by the CRA assigning the higher ratings within a 1-year period. In addition, the study also shows that the harsher are the split ratings, the greater the effect on future potential rating changes.

3.6. Rating migrations

As a sovereign's creditworthiness barely stay constant all time in a real dynamic world, CRAs continuously update their information regarding the sovereign's creditworthiness due to the vital interest in maintaining their reputation in financial markets. Hence, there is always a probability(ies) that the current credit rating on a sovereign shall change in the next period(s). Rating migration is a sub-field exploring the probabilities at which sovereign credit ratings shall stay the same or be altered. Rating migration is a key input to many applications in modern risk management, such as portfolio risk assessments and models, bond pricing models, pricing of credit derivatives (Frydman and Schuermann, 2008). These applications all require migration matrices which consist of probabilities of transition from each rating category to another category and probabilities of default of each rating category. Different estimators of the transition matrices have been proposed in literature. The popular approach for modelling rating migration is a discrete multi-nominal time-homogeneous Markov process (Bangia et al., 2002). However, Fuertes and Kalotychou (2007) suggests that (i) discrete transition matrices might misleadingly imply a high degree of rating stability or low migration risk; and (ii) heterogeneous continuous estimators appears less biased and to be more appropriate in modelling rating migration. Alsakka and ap Gwilym (2010c) suggest that the estimation of sovereign rating migrations can be improved by considering rating history, rating duration and rating outlook/watch status, and country-specific characteristics.

3.7. Market impact

3.7.1. Impact on bond markets

Numerous prior empirical studies show that sovereign ratings are a key element influencing the movement of sovereign bond yield spreads (Cantor and Packer, 1995, 1996; Sy, 2002; Kaminsky and Schmukler, 2002; Gande and Parsley, 2005; Andritzky et al., 2007; Gaillard, 2009; Arezki et al., 2011; Afonso et al., 2012).

Using Moody's and S&P's sovereign credit ratings, Cantor and Packer (1995) find that the market generally requires much larger risk premia for sovereign than for similar rated corporate bonds, and the rank-orderings of sovereign risks implied by market yields differ from the rankings assigned by the CRAs. They conclude that the influence of sovereign ratings on market yields appears limited, particularly, for non-investment grade countries.

Based on a cross-sectional data of sovereign ratings by Moody's and S&P on 49 sovereigns in 1995, Cantor and Packer (1996) examine the relationship between sovereign credit ratings and bond yield spreads. They show that sovereign yields tend to rise as ratings decline and suppose that although financial markets generally agree with the CRAs' relative ranking of sovereign credits, market participants are more pessimistic than Moody's and S&P about sovereign credit risks below the A level. In addition, they found that within 2 days after rating change announcements, yield spreads rise 0.9 percentage points for negative announcements and fall 1.3 percentage points for positive announcements. Because this is the very first paper researching sovereign credit ratings, a number of aspects can be criticised, especially problematic methodology and very weak data set (see section 3.4 for details). Overall, Cantor and Packer (1996) employ OLS estimations in researching credit ratings, yet this approach is inappropriate. Dealing with a multiple discrete and ordinal dependent variable like credit ratings, OLS cannot be applied, and the ordered response approaches, which bases on MLE, are employed. The ordered probit approach has been widely accepted in recent literature in credit rating (see Bennell et al., 2006; Afonso et al., 2007; Alsakka and ap Gwilym, 2010a). In addition, Cantor and Packer (1996) take average values, between Moody's and S&P's ratings, which are also not advisable approach given the large degree of split ratings between CRAs.

Sy (2002) uses uni-variate and multi-variate models of sovereign bond yield spreads, sovereign credit ratings assigned by Moody's and S&P, and several variables in order to detect significant differences between CRAs' and market views. The study uses an unbalanced panel of 17 sovereigns for the period from January 1994 to April 2001. The study finds a negative relationship between sovereign bond yield spreads and emerging sovereign credit ratings and that a one-notch upgrade by CRAs on average decreases the yield spread by 14%. There are some points that could be improved. In terms of methodology, multi-variate regression should be employed in fixed effects given different characteristics by country to country. The fact that individual (country) effects present and are correlated with the regressor was actually shown in the univariate regression of the paper. However, Sy (2002) does not control for that in the multi-variate version. Moreover, the study did not differentiate between upgrades and downgrades in the regressions given the fact that by nature, financial investors might be more sensitive to negative rating news or different informative content of rating news. Furthermore, Sy (2002) takes averages of Moody's and S&P’s sovereign credit ratings, hence, cannot highlight differences across the two agencies’ influence. Besides, the data set only covers 17 sovereigns which is very small compare to recent studies.

Employing a GARCH (1,1) model on a panel data for 12 emerging countries in the period 1998 to 2004, Andritzky et al. (2007) claim that emerging sovereign bond spreads respond mainly to announcements about rating migrations either upgrades or downgrades rather than macro-economic and policy announcements. In addition, the study finds important differences between announcement impacts in emerging and mature markets. Spreads in emerging markets tend to be mainly driven by sovereign rating changes, whilst domestic policy announcements are insignificant in explaining spread variation. Unlike emerging markets, domestic policy announcements in mature markets are proven to be significant in explaining spread variation. Furthermore, the authors clarify their findings that in emerging sovereign bond market, investors often considered the domestic policy announcements as noisy and difficult to interpret, given the national economies’ on-going structural changes and the role of political factors. Rating-based guidelines of institutional investors also help to explain the market reactions against rating changes due to the reallocation of large funds’ portfolios based on rating changes rather than domestic policy announcements. In contrast, domestic policy releases in mature markets, which are usually characterised by greater informational transparency, have high information content, prompting investors to change their portfolio allocations. However, the study bases on a very few number of economies making its robustness questionable.

Gaillard (2009) re-visits this relationship between sovereign credit ratings and bond yield spreads based on a panel data of sovereign ratings on 32 countries by Moody’s, S&P,

Fitch and JP Morgan EMBI spreads during the period December 1993 to February 2007. Using univariate regression explaining yield spreads by the three CRAs' sovereign ratings separately, the study reasserts the negative relationship sovereign bond yield spreads and sovereign credit ratings for emerging economies, although the market behaviours slightly different to each CRA. Using multivariate regressions explaining immediate changes in yield spreads by number of variables including the three CRAs' upgrade (downgrade) dummies, Gaillard (2009) finds that upgrades and downgrades by Fitch do not have an immediate impact on the spreads, while Moody's upgrades (not downgrades) and S&P's downgrades (not upgrades) have significant influence on bond yield spreads within the two days following the rating changes. Generally, S&P's downgrades impose the most significant impact on the market. This study has fixed the problems in Sy (2002) by highlighting the asymmetric effect of upgrades versus downgrades as well as across the CRAs. However, it can be made better as some following points would be improved. Firstly, the multivariate regressions should be taken in fixed effects model. Secondly, one-notch and multiple-notch upgrades (downgrades) data can be included in the regressions. Finally, outlook and watch status should be studied and would explain further about investors' behaviour toward sovereign credit rating changes.

Using a panel data of daily bond yields and rating announcements, including ratings and outlooks, made by Moody's, S&P, and Fitch on 24 EU countries from 1995 to 2010, Afonso et al. (2012) analyse how sovereign yield spreads respond to sovereign credit rating news. In terms of methodology, they use event study method to investigate whether adjusted measures of sovereign yield spreads around rating events are different to those without rating events. The sovereign yield spreads equal to sovereign yields minus German sovereign yields. The adjusted measures of sovereign yield spreads are estimated by the sovereign yield spreads minus the average spreads of all the countries in the sample in order to control for high correlation between the countries' yield spreads. Afonso et al. (2012) find that the adjusted sovereign yield spreads react significantly to negative rating events while the reaction to positive events is much more muted.

Based on a database of daily sovereign yield spreads and rating announcements made by Moody's, S&P, and Fitch on 16 emerging countries during the period January 1990 to June 2000, Kaminsky and Schmukler (2002) find that sovereign rating changes affect rated country's bond yield and spill-over to other countries' bonds. The effects are stronger during crisis and for non-transparent economies. Moreover, the study provides evidence that outlook news is more influential than announcements on actual rating changes. Spill-over effect and impact of outlook announcements are the important contribution of Kaminsky and Schmukler (2002) to literature. However, this study also encounters some weakness in my views. The regressions should take into account countries' different characteristics by fixed effects, and upgrades and downgrades should be differentiated. In addition, one-notch and multiple-notch upgrades (downgrades) can be included and would explain further about investors' behaviour toward sovereign credit rating changes. Moreover, the transparency criteria used in this paper is not very clear and probably reflected in the sovereign credit ratings themselves. Besides, splitting the sample into sub-samples and then comparing the coefficients causes unequal sample sizes, hence, could affect the significance of the tests and imply misleading conclusions. Furthermore, splitting of the small sample of 16 economies makes the sub-samples very small and the robustness of the inferences weak.

Based on a panel data of sovereign credit rating changes by S&P on 34 countries during the period from January 1991 to December 2000, Gande and Parsley (2005) re-affirm that spill-over effect of sovereign credit ratings exists. Moreover, the spill-over effect was found to be asymmetric. Negative sovereign rating announcements are associated with an increase in bond spreads, whereas positive rating changes have no discernable impact on bond yield spreads. In terms of methodology, they regress changes in bond yield spreads within two days following rating events to a rating event dummy and a set of controlling variables, including current comprehensive credit ratings (CCR), maturity, year and country dummies. In addition, Gande and Parsley (2005) clarify transmission channels via which spill-over effects take place. In terms of methodology, they employ a probit estimation and a VAR model based on Monte Carlo simulations in order to test (using Log-likelihood ratio and Granger-causality tests) a null hypothesis that lagged rating events on abroad countries do not collectively affect probabilities that credit ratings of domestic countries change. None of the tests can reject the null hypothesis suggesting that the first magnitude of spill-over effects does not channel via credit ratings themselves. Furthermore, the study tests whether spill-over effects transmit via capital and/or trade linkages. In terms of methodology, dummies indicating a highly positive or negative correlation between two countries' gross capital flows (gross trade flows) to the US are included in the initial regression, explaining changes in yield spreads within two days following rating events. The US, here, is a proxy for the rest of the world. The coefficients of the dummies indicating a highly negative correlation between two countries' gross capital flows (gross trade flows) are significantly negative. No significance is found in highly positive correlations. This implies that negative correlation in capital (trade) flows lessens the spill-over effects of rating downgrades. Besides, the coefficient of capital flows is significantly greater than that of trade flows suggesting the spill-over effects transmit via capital channels to a greater extent rather than trade linkages. In order to check the robustness of the finding, other dummies indicating adjacent status, distance, cultural similarities, same language, same trade bloc, common law, rule of law are included in the right hand side of the model. None of newly included dummies is even weakly significant confirming the dominance of capital channels. Asymmetric impact and spill-over effects of sovereign rating news and clarifications on transmission channels are valuable contributions in Gande and Parsley (2005). Besides, the study has improved some main methodological weakness in Kaminsky and Schmukler (2002) and prior studies. Firstly, upgrades and downgrades are distinguished. This is a prerequisite to evidence the asymmetry of the spill-over effects. Secondly, the countries' characteristics are taken into account by country dummy as one of explanatory variables of the regressions. Thirdly, year dummy is included in order to control for the business cycle. Another improvement is CCR, introduced to test whether spill-over effects differ to a great extent between sovereigns with different creditworthiness levels. In fact, the coefficient of own country's CCR is significant suggesting that the higher the credit quality of a country is, the less spill-over effect it suffers from downgrades on aboard sovereigns. Therefore, it is important to control for CCR in the regressions explaining yield spreads. However, one-notch and multiple-notch rating events could be included and would explain further about investors' behaviour toward sovereign credit rating changes.

Besides, sovereign credit ratings are not only shown to be a core factor in sovereign bond valuation but also a powerful determinant of credit ratings on other types of issuers, such as corporate, financial firms. CRAs generally do not assign public or private sector issuers with credit ratings which are higher than their home country's sovereign ratings (Cantor and Packer, 1995). Recently, CRAs have officially moved away from the "ceiling effect", yet sovereign ratings play a "ceiling lite" role in determining corporate credit ratings (Borensztein et al., 2013). Williams et al., (2013) show that emerging sovereign rating changes strongly impact credit ratings of banks in same directions. This means if a sovereign is upgraded (downgraded), there is a very high probability for banks domiciled in the country to be upgraded (downgraded) simultaneously or soon afterwards. Corporate and bank credit ratings in turn are critical in driving the yields on the firms' projects or businesses.

In summary, sovereign credit ratings are critically influential to debt markets. They strongly drive not only rated sovereign yields, but also spill-over to other sovereigns' yields. Generally, the effect of sovereign rating events is asymmetric. Moreover, sovereign credit ratings powerfully influence non-sovereign issuers in the international debt market.

3.7.2. Impact on equity markets

The equity market also appears to be affected by sovereign rating news in prior empirical investigations (Kaminsky and Schmukler, 2002; Brooks et al., 2004; Martell, 2005; Ferreira and Gama, 2007; Gande and Parsley, 2010; Arezki et al., 2011).

Kaminsky and Schmukler (2002) analyse the effect of sovereign rating changes on emerging economies' stock indices. Basing on daily log returns of national stock indices and rating announcements issued by Moody's, S&P, and Fitch on 16 emerging countries during the period January 1990 to June 2000, the study finds that sovereign rating changes affect rated country's stock index and spill-over to other countries' indices. The effects are stronger during crisis and for non-transparent economies. Additionally, the study provides evidence that outlook news is more influential than announcements on actual rating changes. However, this study also encounters some weakness (discussed in the section 3.7.1). Country characteristics, distinguishing between rating upgrades and downgrades, between one-notch and multiple-notch rating events, transparency criteria, unequal sub-samples are main points for potential improvement in my views.

Brooks et al. (2004) examine impacts of sovereign rating changes on abnormal returns of rated-national equity markets based on data set of all rating changes by 4 CRAs, namely Moody's, S&P, Fitch and Thomson in the period from 1st January 1973 to 31st July 2001. However they actually focus their analysis on rating announcements made by S&P rather than those of the remaining CRAs. In terms of methodologies, Brooks et al. (2004) employs event study method examining abnormal return of a market which is calculated based on the market beta multiplying by the return of MSCI world market index. In addition, the study conducts a regression explaining market abnormal return by emerging status, rating dummy, and other dummies. Finally, they find that i) sovereign rating downgrades have a negative impact on national stock market return, but upgrades generally do not trigger abnormal returns; ii) stock market does not anticipate rating changes; iii) Emerging markets are not more sensitive to rating changes than mature ones; iv) Multiple rating changes do not impose more severe market reaction.

Based on a panel data of sovereign rating changes issued by Moody’s and S&P on 32 countries during the period from 1986 to 2003, Martell (2005) examines the effect of sovereign credit rating changes on emerging stock markets. Using event study method, this paper shows that the stock indices only response to sovereign rating downgrades while sovereign rating upgrades have no significant impact on the stock market. In addition, S&P are found more influential than Moody’s. Martell (2005) also analyses effect of sovereign rating events on stock prices, and finds that i) sovereign rating downgrades affect more strongly in poorer economies than in richer ones; ii) larger firms were also found to be more strongly affected compared to smaller firms.

Ferreira and Gama (2007) analyse spill-over effect of sovereign rating changes of one country on stock indices of other countries. Based on a panel data of S&P's rating announcements on 29 countries during the period from July 1989 to December 2003, the study finds that sovereign credit rating changes of one country impose asymmetric impact on the stock markets in other countries. Specifically, sovereign rating downgrades cause negative reaction, whereas upgrades have no significant impact on stock indices. In addition, geographic proximity and country status as an emerging market are shown to amplify the spill-over effect. In terms of methodology, regressions explaining stock market returns during a two-day window [0,1] by a rating dummy (takes -1 or 0 or 1) are run. In addition, other dummies indicating emerging status, geographic proximity and a set of control variables, including CCR, year and country dummies are included in order to clarify the spill-over effects.

Arezki et al. (2011) examine the spillover effect of sovereign rating announcements, including rating changes and outlook revisions, on 9 European countries and 4 financial markets, namely sovereign CDS, banking equity, issurance equity, and national stock markets, during the period from 2007 to 2010 (the data set, methodology will be discussed in details in section 3.7.4 because this paper also examines behaviour of the CDS market, one of derivative markets). Generally, the study finds that sovereign rating downgrades have significant spillover effects both across countries and financial markets.

Sovereign rating signals contribute significantly to capital flights (Gande and Parsley, 2010). Using monthly data from 85 countries and S&P's rating announcements on the countries during the period from 1996 - 2002, Gande and Parsley (2010) find that sovereign credit rating changes are associated with significant changes in contemporaneous net equity portfolio-investment flows into (out of) event countries. The effect is asymmetric. Rating downgrades are strongly associated with equity outflows while upgrades do not trigger discernable changes in equity flows. In terms of methodology, they apply similar methods in Gande and Parsley (2005) (see section 3.7.1 for details). In short, regressions explaining net equity flows by a rating event dummy and a set of control variables are used. Interestingly, rating downgrades augment capital flights to quality. In other words, transparent non-event countries receive net equity inflows which were triggered by abroad rating downgrades. The transparency is measured by the corruption index, released by Transparency International. The more transparent a country is, the higher amount of net equity inflows it receives. The effect does not appear to be sensitive to country size, market liquidity, rule of law, legal traditions, or crisis versus non-crisis periods.

In summary, most of empirical works find that sovereign credit rating downgrades generate negative reactions from the equity market while rating upgrades generally do not trigger the significant market's response.

3.7.3. Impact on the foreign exchange (FX) market

Brooks et al. (2004) examines impacts of sovereign rating changes on abnormal returns of rated-national currencies against the US dollar (USD) based on data set of all rating changes by 4 CRAs, namely Moody's, S&P, Fitch and Thomson in the period from 1st January 1973 to 31st July 2001. Although the main aim of this paper is the equity market which has been discussed in section 3.7.2 above, some analyses related to the FX market have been presented. Besides, Brooks et al. (2004) only present results of the FX market reactions to S&P's rating announcements not to the remaining CRAs' announcements. In terms of methodology, Brooks et al. (2004) employs the event study method examining abnormal return of a currency which is calculated by a ratio between the exchange rate of the currency against the USD minus a benchmark and standard deviation of the exchange rate. The benchmark is the mean value of the exchange rate in a 100-day period beginning from 120 days ahead of a rating event. Brooks et al. (2004) find that both sovereign rating downgrades and upgrades significantly affect the rated country's exchange rate. However, the effect of rating downgrades is more extended than upgrades where positive effects are found within only 2 days since rating news are disclosed.

Using daily data of 42 countries' exchange rates against the USD during the period 1995-2003, Hooper et al. (2008) examine how sovereign rating changes from Moody's, S&P's, and Fitch affect rated-countries' exchange rates. In terms of methodology, they employ regression models explaining changes in the exchange rates in a 3-day window around rating events by rating news, including both actual rating and outlook announcements, and control variables. In addition, supplemental regressions which differentiate between rating upgrades and downgrades, between foreign currency and local currency rating news, between actual rating changes and outlook announcements, ect. are run in order to detect any difference of market behaviour in response to rating news. Hooper et al. (2008) conclude that rating announcements significantly affect rated-country's exchange rate. On average, a one-notch upgrade (downgrade) results in a 0.28% appreciation (depreciation) of the rated-country's currency against the USD. In the later regressions, they find that market reaction is asymmetric. Specifically, downgrades, actual rating changes, and foreign currency rating news are significantly influential while upgrades, outlook announcements, local currency rating news trigger no discernable market reaction. In my opinion, there are some points which could be improved. Firstly, the authors examine market reaction to rating changes regardless these changes are made by different CRAs. This implicitly assumes that investors would consider all CRAs' announcements the same which is found not true in many papers. Secondly, control variables including in the regressions explaining exchange rate changes are more relevant to the global stock trend rather than the trend in the FX market. Therefore, important variables might be ignored causing bias and inconsistency in estimations. Thirdly, the estimations do not consider current levels of creditworthiness of countries upon whom rating news is disclosed. Fourthly, some countries in the dataset are in the EU which shares one currency from 2002, the Euro. Market behaviour in response to rating announcements upon these countries would be expected differently to others. Finally, watch procedure is ignored and could be included in order to investigate further market behaviour in response to rating news.

Using a daily database of 32 emerging countries' exchange rates against the USD during the period spanning from 1/1/1998 to 25/4/2007, Cavallo et al. (2008) examine the informational content of sovereign rating changes made by Moody's, S&P's, and Fitch in the FX market. In terms of methodology, they employ an OLS model explaining exchange rate changes in a 21-day window, centered on the day of a rating event, by the rated sovereign bond spreads, credit ratings which are transformed into numerical scores spanning from 1 (D) to 21 (AAA), and the Volatility Index (VIX) which bases on implied volatilities of a wide range of S&P 500 index options. The rated sovereign bond spreads and ratings are included in a 'horse race' in order to investigate credit ratings' informational content beyond which is already conveyed in sovereign bond spreads. The VIX is employed to control for the effect of global factors. Cavallo et al. (2008) find asymmetric effects of rating news made by different CRAs. S&P's ratings are significant in explaining exchange rate changes only in cases of upgrades, while those from Moody's and Fitch are significant in both upgrades and downgrades cases. From my point of views, robustness of the findings is limited because of some following issues. Firtsly, many papers present evidence that sovereign credit ratings play core role in driving sovereign bond spreads (e.g. Cantor and Packer, 1996; Sy, 2002; Kaminsky and Schmukler, 2002; Gande and Parsley, 2005; Gaillard, 2009; Arezki et al., 2011). Therefore, including both sovereign credit ratings and bond spreads in the right hand side of the regression explaining exchange rate changes might result in severe colinearity. Secondly, rating **levels** not rating changes, which should be used, are employed to explain exchange rate changes around rating events. The model, hence, cannot infer if a rating change is significant or insignificant in explaining an exchange rate change.

Alsakka and ap Gwilym (2012a, 2013) analyse the reaction of the FX market to sovereign credit announcements from Moody's, S&P and Fitch spanning from 1994-2010 in Alsakka and ap Gwilym (2012a) and from 2000-2010 in Alsakka and ap Gwilym (2013). The data set in the former study covers 112 countries worldwide among whom 104 are rated by Moody's, 112 are rated by S&P, 101 are rated by Fitch. The equivalent figures for the later study are 41, 42, 40 European and Central Asian countries, the focus of Alsakka and ap Gwilym (2013), hence, is on the current European sovereign debt crisis. The both studies agree that both positive and negative credit news affects not only the rated country exchange rate but also spills-over to other countries' exchange rates. In addition, the studies provide evidence that outlook and watch signals trigger stronger reactions from the FX market. Besides, the market is shown to response differently to the three CRAs. Fitch signals trigger strongest immediate reactions, while the market behaviour to S&P and Moody's rating news varies depending on geographic regions. The methodological framework in the both studies is based on Sy (2004), Gande and Parsley (2005), and Ferreira and Gama (2007) with some modifications. Firstly, a log-transformation of comprehensive credit ratings scale is constructed which aims at incorporating information in ratings and outlook, watch notifications and controlling for possible non-linearity. Models explaining log-changes in exchange rates by variation in the scale and a set of control variables show evidence that rating signals significantly affect exchange rates of not only event countries but also non-event countries. In addition, dummies indicating various types of rating news are employed to clarify the market behaviour in response to rating upgrades/downgrades, outlook, watch, multiple-notches credit signals by each CRA. The results show that outlook, watch, and multiple-notches credit signals trigger stronger reactions than one-notch credit rating changes. In my view, some points can be considered for possible improvements. A country's foreign exchange rates can be significantly affected by the country's foreign exchange mechanism and dollarization. In other words, fixed or non-freely float exchange rate regimes could hamper the variation in the dependent variable. States of dollarization could also impact movements of the exchange rate of a country even its government's creditworthiness does not change. The International Fisher Effects of interest and inflation rates could play a role in determining exchange rates. Alsakka and ap Gwilym (2012a, 2013) include country and year dummies in order to mop up these factors. Since the data sets of the studies consist of daily changes over long periods (16 years in Alsakka and ap Gwilym (2012a); 10 years in Alsakka and ap Gwilym (2013)), there is still element that could not fully controlled.

3.7.4. Impact on derivative markets

Prior literature mainly focuses on examining the response of the Credit Default Swap (CDS) market to rating announcements. Credit default swap (CDS) are the rapid-growing segment and the largest segment of the credit derivative market as many investors, particularly managed funds, rely on this instrument to efficiently manage the portfolio's credit risk. The British Bankers Association's survey (2002) suggests that CDS accounts for about 50% of the global credit derivatives market, while Patel (2003) finds the figure is 72%. The International Swaps and Derivatives Association's survey (2010) reveals that by the end of 2009, the outstanding notional amount of CDS market was US$30.43 trillions.

CDS is a contract (usually over-the-counter contract), which is similar to an insurance contract, that provides protection against a default of a bond issuer, which is called credit event. The buyer of the protection pays periodic amount of money to the seller, who acts similarly to an insurance company, until the occurrence of a credit event or the maturity of the contract whatever happens first. In return, the buyer shall be compensated for the loss if a credit event occurs. The rate of the payments made per year by the buyer is called as the CDS spread or CDS premium.

Recently, CRAs has been criticised intensively by European politicians for precipitating and exacerbating the sovereign debt crisis which in turn threatens the unstable recovery of the global economy, just edged out the bottom of the financial crisis. Especially, sovereign credit rating downgrades and movements in the CDS market have been heavily concerned on the mass media. This urges huge demand on researching thoroughly the impact of sovereign credit ratings in the CDS market. Hull et al. (2004) and Norden and Weber (2004) are among first papers investigating the relationship between credit ratings and CDS market, but their subject were corporate credit ratings. Ismailescu and Kazemi (2010) and Arezki et al. (2011) investigate sovereign credit ratings' influence on CDS spreads.

Hull et al. (2004) analyses the dynamic relationship between 5-year CDS and Moody's rating on corporations during the period from October 1998 to May 2002, and find that significant increase in adjusted CDS spread leads negative rating events, including rating downgrades, reviews of downgrade, negative outlooks. This result can be explained by the implication that the CDS market anticipates negative rating events. In contrast, the results for positive rating events were much less significant than those for negative rating events. This finding highlights evidence that the derivative market is different to bond and equity markets which are found to be more likely to lag negative credit rating changes (Ederington and Goh, 1998; Brooks et al., 2004; Gande and Parsley, 2005; Ferreira and Gama, 2007). In other words, bond and equity markets anticipate positive rating announcements so that positive information is already contained in the prices of bonds and/or stocks prior the rating announcements whereas CDS market anticipates negative rating changes. This might reflect the lead role of CDS premium in price discovery procedure or simply is due to the difference in subject of the researches. In other words, Hull et al. (2004) study corporate credit ratings whereas Brooks et al. (2004), Gande and Parsley (2005) and Ferreira and Gama (2007) research sovereign credit ratings. However, the later possibility is addressed by Afonso et al. (2012) who present empirical evidence that the sovereign CDS market anticipates sovereign rating downgrades (this study shall be discussed later in this section).

Norden and Weber (2004) examine whether and how strongly the corporate CDS market responds to credit rating events, including rating migrations, reviews of rating migrations. The study's data set consists of 5-year maturity CDS spreads and rating announcements, made by Moody's, S&P, Fitch, on 90 companies during the period between 2000 and 2002. In terms of methodology, the adjusted CDS change is calculated by daily change in CDS spreads less corresponding changes in CDS index, then event study method is applied. Using t-tests (and Wilcoxon rank tests) over null hypotheses that mean values (median values) of adjusted CDS changes within announcements' windows equal to zero, Norden and Weber (2004) find that means (medians) of adjusted CDS changes are significantly greater than zero prior downgrades and reviews of downgrades by all three agencies, and are insignificantly different to zero after rating events. Although the CDS market reaction to rating upgrades and reviews for rating upgrades is insignificant, the study do not consider this result as robust evidence of asymmetric response to rating changes due to the small number of upgrade observations. In general, Norden and Weber (2004) agree with Hull et al. (2004) that the CDS market anticipates rating downgrades and reviews for downgrade.

Micu et al. (2006) examine impact of multiple corporate rating announcements on CDS spreads. They find that all types of rating announcements, including changes in outlook, have a significant impact on CDS spreads. Even rating news preceded by similar news has an impact. The price impact is the greatest for firms with split ratings, small cap firms and firms rated near the threshold of investment-speculative grade.

Ismailescu and Kazemi (2010) investigates the relationship of sovereign credit rating announcements and CDS market basing on a sample of S&P's rating changes and daily 5-year maturity CDS premiums on 22 sovereigns during the period from 2001 to 2009. In terms of methodology, they use event study method to test adjusted CDS spread changes in different windows and find that positive events have greater impact on CDS market in 2 day window and are more likely to spill-over to other emerging countries. While the informational content of negative rating announcements is anticipated and already reflected in CDS premiums by the time of credit rating change is announced. In addition, logit regression explaining changes in CDS premiums in previous month by this month credit rating announcements is run and confirms the robustness of the conclusion. From my point of views, there are some issues for possible improvements. Firstly, the sample size is small making the adjusted CDS spread changes which base on average value of the 22 sovereign CDS spreads not capturing the abnormal segment of each sovereign CDS spread change. Therefore, t-tests, wilcoxon rank tests, and chi-square tests in the paper might infer misleading conclusion. Secondly, there is a confliction between constructing data and using, regressing the data. When transferring comprehensive credit ratings to numerical scale, Ismailescu and Kazemi (2010), consistent with prior literature, create a system reflecting rating level, outlook, and watch status. However, they only used rating level and outlook in their regressions explaining adjusted CDS spread changes by next month rating events. The result of unanticipated positive rating events is likely due to no positive sovereign watch in the sample. Thirdly, time windows up to 90 days before rating events are employed and CDS changes in one month after rating announcements are used in the logit regression. The long time window and CDS spread changes after rating events are likely to suffer from informational contamination, results, hence, might be questionable. Finally, the study only bases on S&P's rating announcements, thus, cannot highlight obvious split across CRAs.

Cathcart et al. (2010) questions whether there is informational deterioration of credit rating announcements subsequent to the 2007-2010 financial crisis. The study bases on event study over Moody's rating announcements on 298 US based corporate and CDS premiums during the period from 9/2004 to 12/2009. By splitting the sample to prior and post the crisis

2007, they find that impact of Moody's rating announcements on the CDS market has diminished significantly after the crisis. However, robustness of this finding might be weak because the significance of the tests in the paper could be affected by unequal sample sizes. Moreover, the CDS market is barely developing in period 2004 – 2007 compared with 2007 - 12/2009. In addition, CRAs consider rating stability as a primary objective. As a result, credit ratings often lag behind other market-based risk indicators, such as CDS spreads, especially, during the period of turbulence, 2007 – 12/2009 when uncertainty remains high throughout and CDS spreads fluctuate wildly.

Based on a daily data of CDS spreads, stock market indices and 71 rating announcements by Moody's, S&P's, and Fitch's on 20 EU countries during the period from 1/1/2007 to 12/4/2010, Arezki et al. (2011) examine the spillover effect of sovereign rating news across European countries and financial markets. In terms of methodology, they use a Vector Auto Regressive (VAR) model explaining returns of 4 financial markets, namely CDS, banking equity, insurance equity, national equity, by lagged values of the returns and dummies indicating rating announcements. Generally, they find that sovereign rating downgrades have significant spillover effects both across countries and financial markets. The sign and magnitude of the effects depend on the type of rating news, the country experiencing downgrades, and the CRA. In my views, there are some problems with this paper. Firstly, the data set is weak. The VAR model only covers 9 EU countries making the number of observations involving a rating announcement few. Secondly, the study only uses rating changes and outlook revisions. Watch reviews should be included as they are critical in examining markets' response. Thirdly, the dummies representing rating announcements are problematic. Arezki et al. (2011) construct step dummies which equal accumulations of impulse dummies. Each impulse dummy is 1 as a rating news is released and 0 otherwise. These step dummies cannot differentiate between positive and negative news, hence, offer misleading meanings in cases of rating reversals. For example, a sovereign rating is put on outlook negative in day 1 then put on outlook stable in day 100. The step dummy series representing the sovereign shall equal to 1 in the first 100 values and 2 from time 101. In fact, the later rating signal is interpreted as cancelling the former one then the step dummy should be 0 (not 2) from time=101. Therefore, the step dummies in Arezki et al. (2011) reprenst something other than rating news. Moreover, the study employs sovereign CDS spreads, banking, insurance sub-indices, and whole national stock indices in 4 equations of the VAR model while the banking, insurance sub-indices are components of the national stock indices. This means obvious correlations between the banking, insurance sub-indices, and the national stock indices. In fact, the estimations from bi-variate VAR, excluding the banking, insurance sub-indices, in the paper infer qualitatively different results. Finally, Arezki et al. (2011) do not consider countries' current levels of credit worthiness in examining spill-over effects of rating signals which was proved to be significant (Gande and Parsley, 2005). In other words, magnitude of the spill-over effects to countries in the top of rating scale is likely to be less than ones in the bottom.

Using a panel data set of daily CDS spreads and rating announcements, including ratings and outlooks, made by Moody's, S&P, and Fitch on 24 EU countries during the period from 1995 to 2010, Afonso et al. (2012) analyse how sovereign CDS spreads respond to sovereign credit rating news. In terms of methodology, they use event study and supplement fixed effects regressions. Event time window is defined [-1,+1] in order to mitigate information contamination. Afonso et al. (2012) calculate a sovereign CDS spread by a sovereign CDS premium minus German CDS premium. Adjusted measures of CDS spreads are estimated by the sovereign CDS spreads minus the average spreads of all the countries in the sample. Afonso et al. (2012) find that there is a significant reaction of adjusted sovereign CDS spreads to negative rating events while the reaction to positive events is much more muted. They claim that this result is consistent with previous studies by Norden and Weber (2004), Hull et al. (2004). However, I find that it is not true to a large extent. Norden and Weber (2004) and Hull et al. (2004) state that the (corporate) CDS market anticipates negative rating events and CDS spreads are insignificantly different to zero after rating events. The only similarity between Afonso et al. (2012) and Norden and Weber (2004), Hull et al. (2004) is the market behaviour at rating events, [-1, 1]. In order to cope with the specification problem which might have arisen due to pattern of the CDS spreads evolution, Afonso et al. (2012) employ fixed effects regressions explaining variation in the adjusted sovereign CDS spread by its lagged one values and a rating dummy. The regressions generally agree with the event study results that negative rating events pose more significant impact to sovereign CDS spreads. In addition, [-60,-1] and [-30, -1] time windows are employed in order to clarify whether the CDS market anticipates rating events. The study claims that rating outlooks are not anticipated by the market while there is weak evidence that rating downgrades seem to be anticipated by the CDS market. In my views, this weak evidence of anticipation might arise due to the misspecification of CDS spreads. A CDS spread is already a credit spread and captures the default risk of the reference entity. A CDS spread does not need to be deducted a risk-free benchmark, such as German CDS spread. In testing the impact or anticipation of the CDS market, CDS spreads should be employed instead of the CDS spreads over the German CDS spreads (see Norden and Weber (2004), Hull et al. (2004), Blanco et al. (2005)). As Afonso et al. (2012) use the CDS spreads over the German CDS spreads, the abnormal changes in the CDS spreads in prior rating events windows might reduce considerably. Moreover, [-60,-1] and [-30,-1] time windows are likely to encounter information contamination. Shorter-time windows, such as [-7,-2], [-2,-1] and [0,+1], [+1,+7], could improve results of testing whether sovereign CDS market responses or anticipates rating announcements.

Departing from the CDS market, Alsakka and ap Gwilym (2011) examine the impact of sovereign rating changes on the forward FX market. The study bases on a data set of Moody's, S&P, Fitch sovereign rating announcements during the period from 10/8/1994 to 31/10/2010 and 1-week, 1-month, 3-month, 6-month, and 12-month forward exchange rates of 20 currencies against USD. In terms of methodologies, Alsakka and ap Gwilym (2011) employs event study approach using three time windows [-1,+1], [-1, +3], and [-1, +7] and then using a benchmark regression explaining forward FX changes by changes in Comprehensive Credit Ratings (CCR), current level of CCR, an US business cycle proxy, and dummies representing country and year. Finally, the study finds that both positive and negative sovereign rating news affects rated country's forward FX rate and spills over to other countries' forward FX rates. In addition, the market reacts more strongly to negative news and watch events. Among the terms of forward rates, 1-week and 3-month forwards react strongest. This can be explained by the short term of 1-week forward and by the coincidence of watch signal target term of 90 days.

In summary, prior literature on the relationship between derivative markets and sovereign credit ratings mainly focuses on examining the response of the sovereign CDS spreads to rating announcements. Impacts of sovereign credit ratings on other derivative markets have not yet been investigated. Furthermore, prior researchers examine how the CDS market response to sovereign credit rating changes, but no one has asked whether the relationship is in another way around. In other words, it is worth to wonder whether or not CRAs consult with movements in derivative markets. This might be plausible given two following facts: (i) CRAs usually publish ratings implied by markets. For example, Moody's KMV™ bases on market signals integrated in Merton's (1970) contingent claims analysis to calculate Distance to Default and Expected Default Frequency (Moody's KMV, 2003). (ii) derivative markets play a lead in the price discovery process (Blanco et al., 2005; Acharya and Johnson, 2007; Forte and Pena, 2009; Avino et al., 2013).

3.7.5. Impact on market volatility

Although the relationship between numerous factors including corporate news, macroeconomic news, credit spreads, CDS premiums and option-implied volatility has been researched for long time, prior literature is silent about the impact of credit ratings, including corporate and sovereign credit ratings, on implied volatility.

Based on a data of scheduled news released by 23 firms, which were listed and traded on the Amsterdam Stock Exchange and options on these stocks were listed on the European Options Exchange during the period from June 1991 to December 1992, Donders and Vorst (1996) analyse impact of 'scheduled news' on implied volatility of call options. In terms of methodology, they regress excess implied volatility to dummies representing whether it is belong to before, after or on the day of the scheduled news announced. The paper finds that coefficient of pre-event dummy is the only significantly positive inferring that implied volatilities increase in pre-event period and reach a maximum on the eve of the news announcement.

Using a sample of 25 large mergers during the period from 1996 to 2004, Geppert and Kamerschen (2008) examine the effect of mergers on implied volatilities of stock options. The study compares the post-announcement implied volatility of firms doing actiquistion to the prior-announcement implied volatility calculated by a weighted average portfolio of the underlying stocks of the pre-merger firms. They find that the post-announcement implied volatility is significant larger than that of the prior-announcement implied volatility infering that mergers cause an increase in implied volatilities of equity options.

Vrugt (2009) investigates whether US and Japanese macroeconomic news affects implied volatilities of Japanese, Hong Kong, South Korean, Australian stock markets. Basing on data of option premiums and US and Japanese macroeconomic announcements during the period 1996 to 2007, a multivariate regression explaining implied volatility by number of variables including lagged values and surprise by the US and Japanese news dummies provides evidence that the impact of international macroeconomic announcements on implied volatilities is very weak.

Beber and Brandt (2006, 2009) reveal that scheduled macroeconomic news always reduces financial market uncertainty regardless of whether the news is more negative or more positive compared to prior expectations. While Beber and Brandt (2006) employ the second moment of option-implied state-price-densities to proxy the (US Treasury) market uncertainty, Beber and Brandt (2009) use (US T-bonds, S&P 500 index, Eurodollar, stocks) options-implied volatilities. The higher is the ex-ante uncertainty over the content of the macroeconomic news, the larger the drop in the market uncertainty when the news is released.

Bisoondoyal-Bheenick et al. (2011) examining the impact of rating actions on FX realised volatility. The study is based on a small number of rating downgrades/upgrades on four countries only (i.e. Indonesia, South Korea, Thailand, Philippines) in 1997 which overlaps the Asian crisis. They do not consider information on outlook or watch procedures. Moreover, the paper encounters severe methodological shortcomings. Bisoondoyal-Bheenick et al. (2011) compare arithmetic average values of realised volatility of each country's exchange rate during event- to non-event days without any statistical testing basis, and then draw conclusions based on the simple comparisons. In other words, the paper presents very weak scientific evidence.

3.8. Review of methodologies in credit ratings research

3.8.1. Least Square models

- Introduction

The Ordinary Least Square (OLS) is a basic, simple method of estimation. Mathematically, the OLS estimates a relationship between an independent variable and explanatory variables basing on minimising sum square of errors of the estimation. In other words, the sum square of all deviations of observed data away from the estimated model shall be minimised subject to a constraint that the sum of all these deviations equals to zero. Minimising a function subject to one condition is a classic optimising quest that can be solved easily. The vector of estimated coefficients is as follows:

$$\hat{\beta} = (X'X)^{-1} X'Y$$

Where X is the matrix of explanatory variables' values; X' is the transposed matrix of X; X^{-1} is inverted matrix of X; Y is the vector of independent variable's values (see Greene, 2012 for details).

Because estimated coefficients ($\hat{\beta}$) are functions of random variables, X and Y, they are thus also random variables with their own expected values and variances. The OLS method has to base on several assumptions in order to ensure that probability distributions of estimated coefficients collapse on to true values of parameters of population that a researcher seeks to estimate. Firstly, the relationship between the independent and the explanatory variables is assumed to be linear. This assumption is implicit by specifications of the OLS estimated equation where an error of the estimation equals to a linear function of the independent and explanatory variables. Secondly, the variation of all the error terms should remain constant throughout. The errors then are said to be homoscedastic. In contrast, if heteroscedasticity presents, variations of the coefficients will be over-estimated, hence, inferences from t-tests and F-test testing significance of the coefficients will be misleading.

Thirdly, the errors are uncorrelated with one another. In presence of autocorrelation, the coefficients derived using OLS are still unbiased, but the standard error of the OLS estimation could be wrong. In the case of positive autocorrelation, the estimated standard error shall be downward biased compare to the true standard error. This would lead to an increase in the probability of type I error of t-tests and F-test. In other words, there is a high tendency to reject the null hypothesis when it is actually correct. In case of negative autocorrelation, the opposite situation happens. There is an increase in the probability of type II error of t-test and F-test from the OLS estimation. Another assumption is that explanatory variables are not perfectly (or highly) correlated with each other. If an exact relationship between two or more of explanatory variables happens, the product of transposed matrix and matrix of explanatory variables, (X'X), will be not full rank. Therefore, the determinant of (X'X) will be zero and inverted matrix, $(X'X)^{-1}$, cannot be estimated. Moreover, explanatory variables and error terms are assumed to have no relation. This is exogeneity assumption which ensures the estimated coefficients unbiased, efficient and consistent. Finally, errors are assumed to be normally distributed in order to ensure that OLS estimators are the best possible estimators.

Panel data: Since a panel data set includes both cross-sectional and time-series observations, the increased size of the data probably allows richer findings than equivalent pure cross-sectional or time-series data. However, complications arise when applying the OLS to a panel data set. There are three alternatives dealing with a panel data set, namely Pooled model, fixed effects and random effects models. The Pooled model totally ignores the structure of a panel data. This means that cross-sectional and time-series variation is considered the same. In other words, no individual effect plays a role in determining the dependent variable of the model. If this assumption does not hold, individual effects will be mopped up into the residuals of the pooled model, hence, cause exogeneity. Therefore, coefficients of the models appear to be inefficient and inconsistent. The random effects and fixed effects models recognise individual effects and in different manners. While a random effects model assumes that there is no relation between error terms of individual effects and regressors, a fixed effects model does not require such assumption.

- Applications in prior literature

The Least Square technique is really popular in researching sovereign credit ratings. Prior papers, including Cantor and Packer (1996), Mulder and Perrelli (2001), Kaminsky and Schmukler (2002), Sy (2002), Brooks et al. (2004), Gande and Parsley (2005), Cavallo et al. (2008), Hooper et al. (2008), Gaillard (2009), Afonso et al. (2012) and many others, employ OLS in order to investigate both (either) determinants and (or) market impacts of credit ratings.

Cantor and Packer (1996) and Mulder and Perrelli (2001) apply OLS models on cross-sectional data of 49 sovereigns in 1995 to investigate both the determinants and the impact of sovereign credit ratings in the sovereign debt. Criticism of the OLS methodology in the paper is discussed in details in section 3.5.

Kaminsky and Schmukler (2002) run four Least Square regressions explaining daily changes in rated sovereign bond yield spreads and rated national stock indices by their own lagged values and dummies representing rating news, including upgrades and downgrades either in actual rating levels or in outlooks on either own sovereigns or others. This study also encounters some weakness in my views. The regressions should take into account countries' different characteristics by fixed effects in order to mop up these characteristics, and upgrades and downgrades should be differentiated. In addition, one-notch and multiple-notch upgrades (downgrades) can be included and would explain further about investors' behaviour toward sovereign credit rating changes.

Brooks et al. (2004), Gande and Parsley (2005), Hooper et al. (2008), Gaillard (2009) employ Least Square estimations in their models explaining abnormal changes in either sovereign bond spreads or national stock indices or exchange rates of rated countries by rating event dummies and controlling variables. In general, the controlling variables are used to control for emerging country status (Brooks et al. (2004)); or current status of the global business cycle (Hooper et al. (2008), Gaillard (2009)). Noticeably, Gande and Parsley (2005) introduce Comprehensive Credit Rating (CCR) and country fixed effects in the right hand side of their models in order to control for current creditworthiness levels and country characteristics which were ignored by Brooks et al. (2004), Hooper et al. (2008), Gaillard (2009) and above mentioned papers.

In summary, Least Square technique is popular in researching determinants and market impacts of sovereign credit ratings. This is, however, more relevant in examining the market impacts from my point of views given the discrete, ordinal nature of credit ratings as well as the non-linear relationship between credit rating probabilities and explanatory variables. In modelling the market impacts, sovereign credit ratings levels or dummies representing rating news and sets of controlling variables are included in the right hand side of a model to explain variation in sovereign bond yield spreads, abnormal returns of national stock indices, or exchange rates. Besides, assumptions of OLS technique need to be ensured in order to archive unbiased, efficient, consistent estimated coefficients and robust inferences. Among the assumptions, heteroscedasticity, multicolinearity could be troublematic in some prior papers. In addition, country fixed effects should be taken into consideration when modelling the market impacts of sovereign credit ratings. In my empirical investigations, comprehensive credit ratings (CCR) would be used so as to convey all information that CRAs provide to markets including rating levels, outlooks and watch status.

3.8.2. Ordered response models

- Introduction

In reality, many subjects of researching are discrete, limited by nature. Results from Yes/No questionnaires, surveys cannot be other than 'Yes' or 'No', coded as 0 or 1. Multiple questionnaires can extend the possibility of answers to more, for example 'Yes', 'No', 'Not Appropriate'. Categorical variables, such as credit ratings, rating migrations, political polls, are popular examples in which the possible values can get up to 50 or more. Nonetheless, the possible values of this kind of variables cannot be continuous and the number of the values is limited. In other words, it cannot be infinite. This type of variables is known as limited variables. In modelling limited variables, multinomial linear probability, multinomial logit/ probit, ordered logit/ probit can be employed. While a linear probability model employs OLS estimation, logit and probit models are based on MLE technique which allows non-linear relationship between probability of dependent and independent variables. In researching credit ratings, the non-linear relationship and the ordinal nature of credit ratings can make the multinomial approaches no longer appropriate and offer biased, inconsistent estimators. Therefore, I only include the ordered response models, that is ordered probit or ordered logit, as follows:

An ordered probit model is based on a latent regression, as following:

$$Y^*_{i,t} = \beta X_{i,t} + \varepsilon_{i,t}$$

where

X is the matrix of independent variables

β is the vector of coefficients

$\varepsilon_{i,t}$ is the vector of residuals

Y* is an unobserved, latent variable related to the observed dependent variable in following way:

$y=1 \quad \text{if } y^* \leq \mu_1$

y=2 if $\mu_1 < y^* \leq \mu_2$

………

y= J-1 if $\mu_{J-2} < y^* \leq \mu_{J-1}$

y= J if $\mu_{J-1} < y^*$

Where J is number of thresholds; and μ_i is unknown thresholds estimated by following equations:

Equation 3.1: probabilities of categories expressed by the normal distribution function

$$\Pr(y=1) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(\mu_1 - X\beta)^2} = \Phi(\mu_1, \beta)$$

$$\Pr(y=2) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(\mu_2 - X\beta)^2} - \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(\mu_1 - X\beta)^2} = \Phi(\mu_2, \beta) - \Phi(\mu_1, \beta)$$

……..

$$\Pr(y=J) = 1 - \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(\mu_{J-2} - X\beta)^2} = 1 - \Phi(\mu_{J-1}, \beta)$$

Where Φ denotes the Normal distribution function.

The log-likelihood function and its derivatives then can be obtained easily by natural logarithm of the product of all the probability functions.

$$\mathrm{Ln}[L(\mu, \beta)] = \ln[\Phi(\mu_1, \beta) \mathrm{x}\ [\Phi(\mu_2, \beta) - \Phi(\mu_1, \beta)]\mathrm{x} \ldots\ [1 - \Phi(\mu_{J-1}, \beta)]]$$

Optimisation of the log-likelihood function can be solved in order to estimate all the unknown parameters of the model (β, μ), say $\hat{\beta}_1, \hat{\beta}_2, \ldots, \hat{\beta}_k$ and $\hat{\mu}_1, \hat{\mu}_2, \ldots, \hat{\mu}_{J-1}$ (see Greene, 2012 for more details).

Different to a linear regression, a 1-unit increase in an independent variable, say x_2, does not cause $\hat{\beta}_2$% (assumed to be positive) increase in probabilities that the dependent variable, y, falls into category 1, 2 … J. The increases, called the marginal effects, are products of the estimated coefficient ($\hat{\beta}_2$) and estimations of the probabilities $\Pr\left(y = 1, 2 .. J \mid \hat{\mu}, \hat{\beta}\right)$ at specific points, usually means of the independent variables. For example, the marginal effect of x_2 on the probability that the dependent variable falls into category 2 is estimated as follows:

$$\frac{\Delta \Pr(y=2)}{\Delta x_2} = \hat{\beta}_2 [\Phi(\hat{\mu}_2, \hat{\beta}, \bar{X}) - \Phi\left(\hat{\mu}_1, \hat{\beta}, \bar{X}\right)] \ \%$$

Similarly, an ordered logit model is based on a latent regression, as following:

$$Y^*_{i,t} = \beta X_{i,t} + \varepsilon_{i,t}$$

The unobserved, latent variable, y*, are related to the observed independent variable in following way:

$y=1$ if $y^* \leq \mu_1$

$y=2$ if $\mu_1 < y^* \leq \mu_2$

………

$y= J-1$ if $\mu_{J-2} < y^* \leq \mu_{J-1}$

$y= J$ if $\mu_{J-1} < y^*$

Where J is number of thresholds; and μ_i is unknown thresholds estimated by following equations:

Equation 3.2: probabilities of rating categories expressed by the logistic function

$$\Pr(y=1) = \frac{1}{1+e^{-(\mu_1 - X\beta)}}$$

$$\Pr(y=2) = \frac{1}{1+e^{-(\mu_2 - X\beta)}} - \frac{1}{1+e^{-(\mu_1 - X\beta)}}$$

……..

$$\Pr(y=J) = 1 - \frac{1}{1+e^{-\left(\mu_{J-1} - X\beta\right)}}$$

The log-likelihood function and its derivatives then can be obtained readily, and the optimisation condition of the log-likelihood function can be applied to estimate all the unknown parameters of the model.

Both ordered probit and ordered logit models take into account the discrete, ordinary nature of independent variable and non-linear relationship between the independent and explanatory variables. The only difference between them is that they are based on different distributional assumptions. The probabilities of the events that the independent variable falls into category 1, 2 … J in an ordered probit model are the Normal distribution functions of the explanatory variables. In contrast, they are described by the logistic function in an ordered logit model.

- Application in prior literature

In modelling determinants of credit ratings, some papers apply the Least Square technique (Cantor and Packer, 1996; Mulder and Perrelli, 2001; Butler and Fauver, 2006; Becker and Milbourn 2011), some employ ordered probit or logit estimations (Bissoondoyal-Bheenick, 2005; Bennell et al., 2006; Afonso et al., 2007, 2011; Hill and Faff, 2010). In my views, the ordered response technique, that is orderd probit or logit, is more relevant in investigating determinants of credit ratings rather than Least Square regressions given the fact that some assumptions of the Least Square technique cannot hold causing a high likelihood of bias, inconsistency, and inefficiency of estimated coefficients. Besides, the dependent variable in an Least Square model cannot fully convey the nature of credit ratings which have been criticised section 4.1.1.

Bennell et al. (2006) apply a pooled ordered probit model explaining sovereign credit ratings by macroeconomic indicators. The study shows that all economic variables are highly significant in explaining rating variation. Likelihood ratio test shows that all the economic variables are collectively meaningful in explaining rating variation. However, the paper had pooled all credit ratings from 11 agencies into a dependent variable and compensated by including agency indicator dummy variable into their model. From my perspective, this is not a really advisable approach because the coefficients of their model would be the same for all 11 agencies. This is not true given the split ratings and obvious independence in each agency's methodology and its weighted economic factors. Besides, role of qualitative, political factors which have been disclosed to be crucial in CRAs' sovereign credit rating assignments (Moody's, 2008; Fitch, 2011b; S&P, 2011) has been ignored. Moreover, the study has ignored individual effects, country by country characteristics, which could be nonzero distributed. Therefore, there could be bias and inconsistency in the estimated coefficients.

Afonso et al. (2007, 2011) employ random effects ordered probit models explaining sovereign credit ratings by economic variables, including per capita GDP, GDP real growth rate, government effectiveness, government debt, external debt and external reserves, history of default dummies. Their models do provide high predictive power. On average, 70 percent of all observations on sovereign credit ratings are correctly predicted. The percentage increases to more than 95% when within one notch errors are allowed. In terms of methodology, Afonso et al. (2007, 2011) improve the issue which was criticised in Bennell et al. (2006) with respect to pooling credit ratings from different agencies into one dependent variable by modelling each agency's ratings via separated equations. The results show the coefficients of sovereign credit ratings from the CRAs are different to each other, hence, reassert the methodological differences between the CRAs. Random effects have been achieved by assuming that an individual effect equals to a linear combination of time-averages of economic independent variables plus an error term which is uncorrelated with the regressors. Therefore, they seek to eliminate correlation between error terms of individual effects and regressors and to differentiate between so-called 'short-run' and 'long-run' impacts of economic variables.

However, there is a potential problem with this approach. The time-scale dimension of the datasets in Afonso et al. (2007 2011) is 10 years, from 1995-2005. It could be reasonable for using this approach during that time length and these particular periods. What happens when the dataset covers longer periods or overlaps extreme turbulence such as current crises? Sovereign credit ratings could change frequently causing adequate variation in the dependent variable. As a result, fixed effects could be more relevant as we can both achieve unbiased, consistent estimated coefficients and avoid the degree of freedom problem and losing the explanatory power of an ordered probit model. Moreover, longer-time-averages of economic variables and deviations from these averages could be inappropriate in interpreting to the so-called short-run and long-run effects of these economic variables. For example, the coefficient of the 20-year average of GDP per capita is significant in the model explaining sovereign credit ratings, yet this does not mean that GDP per capita poses a significant effect in determining the ratings at the time of 20-year later on. Besides, Afonso et al. (2007, 2011) do not materialise the effects of social, political factors in modelling sovereign credit ratings, which has been criticised above. Although they can argue that the individual effects can mop up social, political factors, this implicitly assumes that the social, political elements of a country stay constant over the 10-year periods which could be hardly true in reality.

In summary, the ordered response technique is more relevant in investigating determinants of credit ratings rather than OLS estimations given the discrete, ordinal, non-linear relationship between credit rating probabilities and explanatory variables. These could result in a high likelihood of biasness, inconsistency, and inefficiency of OLS estimated coefficients. Among ordered response models, ordered probit has been widely employed in recent literature (Bissoondoyal-Bheenick, 2005; Bennell et al., 2006; Afonso et al., 2007, 2011; Hill and Faff, 2010). The ordered logit essentially is the same logic as the ordered probit except for the function describing probabilities of rating categories.

However, complications arise when applying an ordered probit/ logit model on a panel data set. Pooled technique could be inappropriate if (and usually) individual effects, country by country characteristics, are not zero. In other words, country characteristics vary to a great extent. In this case, a fixed effects ordered probit/ logit could be in flavoured in order to achieve unbiased, effective, and consistent estimated coefficients. The log-likelihood function of an ordered probit model now becomes a function of μ, β, α, where α is (1xN) vector of individidual effects, as follows:

$$\text{Ln}[\text{L}(\mu, \beta,\alpha)] = \ln[\Phi(\mu_1, \beta, \alpha) \text{x } [\Phi(\mu_2, \beta, \alpha) - \Phi(\mu_1, \beta, \alpha)] \text{x} \ldots [1 - \Phi(\mu_{J-1}, \beta, \alpha)]]$$

Maximizing the log-likelihood function, we can find all the unknown parameters, including μ, β, α. However, the fixed effects model can run into the degree of freedom problem when the time-scale dimension of the data (T_i) is short. Moreover, the estimator of an individual effect (α_i) relies on the time-scale dimension of the data (T_i). If T_i is small, the estimator is inconsistent and the estimators of β are downward biased. This is called incidental parameters problem (Neyman and Scott, 1948; Lancaster, 2000). Nervertheless, the bias does drop-off rapidly as the time-scale dimension increases to 3 or more (all $T_i \geq 3$) (Greene, 2004). Another issue with fixed effects is that sovereign credit ratings of an individual might be relatively stable over time, hence, there is a lack of variation in the dependent variable. As a result, fixed effects models, which eliminate cross-sectional variation, are weak in explaining sovereign credit ratings. A random effects ordered probit/ logit could be the best alternative in these cases since variation in both horizontal as well as vertical dimensions is counted. Nervertheless, this technique could be inappropriate if country by country characteristics is proved to be correlated with regressors, own countries' economic and politic variables and this usually happens. In bottom lines, pooled ordered responses models are inappropriate for modelling determinants of credit ratings with respect to a panel data while there is a trade-off between fixed effects and random effects techniques. Ideally, a long time-scale dimension panel data would utilise unbias and consistency of estimators using fixed effects models.

3.8.3. Event study method

- Structure and issues associated with an event study

Event study methodology is widely used in accounting, finance and economics when a researcher seeks to measure effect of a type of (economic) events on a subject, usually stock price, return, value of a firm. There are several versions of this method, yet they follow the same procedure. Firstly, an event of interest and an event window(s) where the event is involved need to be defined. Secondly, selection criteria need to be set up in collecting data for the study. Thirdly, abnormal changes need to be modelled in order to appraise the event's impact. The abnormal change equals to the actual change over the event window minus the normal change that would be expected if the event did not happen. There are several options in modelling the normal change. Constant change, market model, CAPM, APT, or Fama and French 3 factors models could be chosen. Estimation of parameters in the model of the normal change, then, takes place using a subset of the data, known as the estimation window. The normal change, abnormal change and cumulative abnormal change around the event window shall be calculated based on these estimated parameters. The next phase is to design the testing procedure and testing technique where the null hypothesis is that the cumulative abnormal change equals to zero. At this stage, t-test, or non-parametric tests, such as, sign test, rank test, would be employed depending on the distributional assumption of the abnormal change. Finally, empirical results and implications are drawn. (See Campbell et al. (1997) for more details).

Event study is a simple but effective methodology in studying impact of events including rating news on markets. However, there are several issues arising due to misspecification of the normal change, information contamination, event clustering, uncertainty event date, heteroscedasticity, thin trading problem ect. In supplement, a regression explaining the cumulative abnormal change by event dummy variables could be run in order to mitigate some of above issues and to check robustness of the study. This technique poses statistical advantages against event clustering, misspecification of the normal change. However, it often has little economic theoretical power.

- Applications in prior literature

The event study is popular in examining market impact of ratings announcements. Prior papers, including Kaminsky and Schmukler (2002), Brooks et al. (2004), Norden and Weber (2004), Hull et al. (2004), Ismailescu and Kazemi (2010), Afonso et al. (2012), employ event study in investigating the impact of credit rating announcements in different markets.

Using a daily data of sovereign bond yields and stock indices and 244 rating announcements made by Moody's, S&P, Fitch during the period from January 1990 to June 2000, Kaminsky and Schmukler (2002) analyse how the sovereign bond and stock markets response to sovereign credit rating changes. In terms of methodology, they run OLS regressions, explaining daily changes in rated sovereign bond yield spreads (stock indices) by its own lagged values and dummies representing rating news, then complement by an event study examining how the yield spreads (stock indices) behaviour around rating events. The event study is to capture the dynamic effects of credit ratings and also to examine the evolution of sovereign yield spreads and stock indices around rating events, ±10 days, since the regressions only present immediate effects, daily changes, of the events. In order to mitigate event clustering, Kaminsky and Schmukler (2002) only include 103 clean rating events out of the 244 rating announcements in the event study. A clean rating event is the event that does not overlap during the 10-day window. The event study confirms results from the regressions that sovereign credit rating news affects not only rated countries' bond and equity markets but also spills-over to others, especially in the same geographic areas. In addition, outlook changes pose more influential impact than announcements over actual ratings. The contribution of this study cannot be denied, however, it also encounters some weakness in my views. The criticism regarding the Least Square regressions has been mentioned in section 4.1.1. In short, fixed effects, one-notch versus multiple-notch rating news, transparency criteria, small sample size and splitting the sample are main issues that could be criticised. Regarding the event study, some other issues could be considered for potential improvements. [-10,+10] might suffer information contamination and shorter time windows could mitigate the problem. Prior- and post- rating event time windows could help explaining further the markets' behaviour.

Hull et al. (2004) analyses the dynamic relationship between 5-year CDS and Moody's rating on corporations during the period from October 1998 to May 2002, and find that significant increase in adjusted CDS spread leads negative rating events, which include rating downgrades, reviews of downgrade, negative outlooks. This result can be explained by the implication that the CDS market anticipates negative rating events. In contrast, the results for positive rating events were much less significant than those for negative rating events. This finding highlights different evidence of CDS market to bond and equity markets which are found to be more likely to lag negative credit rating changes (Ederington and Goh, 1998; Gande and Parsley, 2005; Ferreira and Gama, 2007). In other words, bond and equity markets anticipate positive rating announcements so that positive information already is contained in the prices of bonds and/or stocks prior the rating announcements whereas CDS market anticipates negative rating changes. This might reflect the lead role of CDS premium in price discovery procedure which has been evidenced in Blanco et al. (2005), Acharya and Johnson (2007), Forte and Pena (2009), and Afonso et al. (2012).

Norden and Weber (2004) examine whether and how strongly CDS market responds to credit rating events, including rating migrations, reviews of rating migrations. The study's data set consists of 5-year maturity CDS spreads and rating announcements, made by Moody's, S&P, Fitch, on 90 companies during the period between 2000 and 2002. In terms of methodology, they use event study to investigate the response. Adjusted CDS change is calculated by daily change in CDS spreads less corresponding changes in CDS index. The index is created by an equally weighted portfolio of all the companies in the sample. Using t-tests (and Wilcoxon rank tests) over null hypotheses that mean values (median values) of adjusted CDS changes within announcements' windows equal to zero, Norden and Weber (2004) find that means (medians) of adjusted CDS changes are significantly greater than zero prior downgrades and reviews of downgrades by all three agencies, and are insignificantly different to zero after rating events. Although the CDS market reaction to rating upgrades and reviews for rating upgrades is insignificant, the study do not consider this result as robust evidence of asymmetric response to rating changes due to the small number of upgrade observations. In general, Norden and Weber (2004) agree with Hull et al. (2004) that CDS market anticipates rating downgrades and reviews for downgrade. The contribution of Norden and Weber (2004) is significant, however they also encounter some methodological issues. Firstly, they use long time-windows up to 90 days before- and after- events which are likely to suffer informational contamination and event clustering, hence, might offer bias implications. Informational contamination and event clustering are regarded critically in recent papers (Gande and Parsley, 2005; Afonso, Furceri, and Gomes, 2012; Alsakka and ap Gwilym, 2012a, 2013) which employ much shorter time-windows, up to 30 days. Gande and Parsley (2005) recognised that rating clustering is serious and about one-third of total rating events in their sample come within 10 days, equivalent to a 5-day before- and after-event window. Of course, this might be different to the sample in Norden and Weber (2004). Nevertheless, they should account for the fact. Secondly, specification problem might arise since the adjusted CDS spreads, which equal to the CDS spreads minus averages of the CDS spreads of all companies in the sample, might not capture the abnormal elements in the CDS movements. Regressions explaining variation in CDS spreads by rating dummies or changes in rating levels could be good candidates for robustness checking.

Ismailescu and Kazemi (2010) investigates the relationship of sovereign credit rating announcements and CDS market basing on a sample S&P's rating changes and daily 5-year maturity CDS premiums on 22 sovereigns over the period from 2001 to 2009. In terms of methodology, they use event study method to test adjusted CDS spread changes in different windows and find that positive events have greater impact on CDS market in 2 day window and are more likely to spill-over to other emerging countries. While the informational content of negative rating announcements is anticipated and already reflected in CDS premiums by the time of credit rating change is announced. In addition, logit regression explaining changes in CDS premiums in previous month by this month credit rating announcements is run and confirms the robustness of the conclusion. In my point of views, there are some problems with the paper. Firstly, the sample size is small making the adjusted CDS spread changes which base on average value of the 22 sovereign CDS spreads not capturing the abnormal segment of each sovereign CDS spread change. Therefore, t-tests, wilcoxon rank tests, and chi-square tests in the paper might infer misleading conclusion. Secondly, there is a confliction between constructing data and using, regressing the data. When transferring comprehensive credit ratings to numerical scale, Ismailescu and Kazemi (2010), consistent with prior literature, create a system reflecting rating level, outlook, and watch status. However, they only used rating level and outlook in their regressions explaining adjusted CDS spread changes by next month rating events. The result of unanticipated positive rating events is likely due to no positive sovereign watch in the sample. Thirdly, time windows up to 90 days before rating events are employed and CDS changes in one month after rating announcements are used in the logit regression. The long time window and CDS spread changes after rating events are likely to suffer from informational contamination, results hence might be questionable. Finally, the study only bases on S&P's rating announcements, thus, cannot highlight obvious split across CRAs.

Afonso et al. (2012) use event study methodology to analyse how sovereign yield and CDS spreads respond to sovereign credit rating level and outlook news. The data set includes rating announcements made by Moody's, S&P, and Fitch on 24 EU from 1995 to 2010. Event time window is defined [-1,+1] in order to mitigate information contamination. Afonso et al. (2012) calculate sovereign yield (CDS) spreads by sovereign yields (CDS premium) minus German sovereign yields (CDS premiums). Adjusted measures of sovereign yield (CDS) spreads are estimated by the sovereign yield (CDS) spreads minus the average spreads of all the countries in the sample in order to control for high correlation between the countries' yield (CDS) spreads. Afonso et al. (2012) find that there is a significant reaction of sovereign yield (CDS) spreads to negative rating events while the reaction to positive events is much more muted. They claim that this result is consistent with previous studies by Norden and Weber (2004), Hull et al. (2004). However, I find that it is not true to a large extent. Norden and Weber (2004), Hull et al. (2004) state that the sovereign CDS market anticipates negative rating events and CDS spreads are insignificantly different to zero after rating events. Meanwhile, Afonso et al. (2012) claim that the CDS market reacts to negative rating signals. The study also runs fixed effects regressions explaining adjusted sovereign yield (CDS) spreads by lagged one values of the spreads and a dummy taking 1 when a rating (and/or outlook) announcement is released. The regressions, aimed at coping with the specification problem, generally agree the event study results that negative rating events pose more significant impact to sovereign yield (CDS) spreads. In addition, [-60,-1] and [-30, -1] time windows are employed in order to clarify whether sovereign bond and/or CDS markets anticipate rating events. The study claims that rating outlooks is not anticipated by the two markets, and that the sovereign bond market does not anticipate any type of rating announcements while there is weak evidence that rating downgrades seem to be anticipated by the CDS market. In my views, this weak evidence of anticipation might arise due to the misspecification of CDS spreads. A CDS spread, different to a bond yield, already captures the default risk of the reference entity and does not need to be deducted a risk free benchmark, such as German CDS spread. In testing the impact or anticipation of the CDS market, CDS spreads, hence, should be employed instead of the CDS spreads over the German CDS spreads (see Norden and Weber (2004), Hull et al. (2004), Blanco et al. (2005)). As Afonso et al. (2012) use the CDS spreads over the German CDS spreads, the abnormal changes in the CDS spreads in prior rating events windows might reduce considerably. Moreover, [-60,-1] and [-30,-1] time windows encounter information contamination. Shorter time windows, such as [-7,-2], [-2,-1] and [0,+1], [+1,+7], could improve results of testing whether sovereign bond and/or CDS markets response and/or anticipate rating announcements.

In summary, event study is a powerful technique in investigating market impacts of sovereign rating announcements. However, number of issues should be considered carefully when using this powerful tool. Time window(s) need to be defined appropriately. Wide time windows are likely to encounter information contamination and rating event clustering while short time windows do not allow illustration of the evolution of markets, such as bond yield, CDS spreads, stock indices, implied volatilities, around rating events. Misspecification of the abnormal changes stimulating by rating announcements is another tough problem. Standard event study approach requires estimation of abnormal differences between model generated and actual movements in markets. Since the model generated changes should be computed for the periods when no rating event happens, and not every case in researching sovereign credit rating announcements are available for this purpose. Thus, the abnormal element in a market's movements, say sovereign yield spreads, usually bases on an equally weighted portfolio of all individuals, say all countries' yield spreads, in the sample of a study. Supplement regressions explaining the abnormal movements by rating dummies could help to mitigate event clustering, autocorrelation between the movements, misspecification problem. However, one using these need to consider the assumptions of a Least Square estimation. Among the assumptions, heteroscedasticity, exogeneity could be troublematic in some prior papers. In addition, country fixed effects should be taken into consideration when modelling the market impacts of sovereign credit ratings in the context of a panel data. Besides, no illustration of the evolution of the market behaviour around rating events could be inferred by the regressions.

3.9. Conclusions

To the best of my knowledge, research on the relationship between sovereign credit ratings and financial market volatility is very sparse.[5] Moreover, prior researchers frequently tackle the question how financial markets response to credit rating changes, but no one has asked whether the relationship is in another way around. In other words, it is worth to consider whether credit ratings (including actual rating, outlook and watch announcements) response to market movements. This likelihood is plausible in the case of derivative markets which is a play field for institutions rather than small investors (Deutsche Borse Group, 2008; McKinsey Global Institute, 2011) and is characterised by a leading role in the price discovery process (Blanco et al., 2005; Acharya and Johnson, 2007; Forte and Pena, 2009; Avino et al., 2013). Also, CRAs often publish market-implied ratings and probably consult with markets given their cost-effective considerations. The next chapter will investigate the bi-directional

[5] Bisoondoyal-Bheenick et al. (2011) examine the impact of rating actions on FX realised volatility, but the study is based on a very small number of rating actions during the Asian crisis of 1997. They do not consider information on outlook nor watch procedures, and there are major methodological flaws. Further, Afonso et al. (2014) investigate the impact of rating actions on bond and stock markets' volatilities based on a limited set of countries in the EU.

relationship between sovereign credit rating dynamics and movements in the stock index option market.

Chapter 4: The bi-directional relationship between sovereign ratings and stock index option implied volatility

4.1. Introduction

CRAs provide valuable functions in assessing credit risk and in financial market development (e.g. Coffee, 2006; Bank of England, 2011). However, "hard-wiring" and "cliff effects" of credit rating signals have been under scrutiny during the global financial crisis (IMF, 2010a; Bank of England, 2011). In response, rating-based rules and guidelines have been under consideration to be dismissed (e.g. SEC 2011a, b), and a new CRA regulation regime has been established in the EU.

This chapter investigates the interaction between sovereign rating news and the equity index option market. This market is typically inhabited by institutional informed traders (see Chakravarty et al., 2004; Chen et al., 2005; Jin et al., 2012). Much literature identifies that the derivative markets play a leading role in the price discovery process (e.g. Blanco et al., 2005; Acharya and Johnson, 2007; Avino et al., 2013). Therefore, the dynamics of derivative markets can provide important information regarding the credit quality of underlying entities. In 2011, the turnover of equity index options traded on organised exchanges over the world was US$ 166 trillion (BIS, 2012). The equity index option market is the second largest segment of exchange-traded financial derivative markets, after interest rate derivatives. Given the prominence of both derivative markets and CRAs, interesting questions about the interaction between the index option market and credit rating actions can be raised. Such investigations must also consider CRAs' 'through the cycle' rating philosophy, which implies that credit ratings are stable and possibly lag behind option market indicators.[6]

[6] Outlook and watch procedures are expected to alleviate the lag to some extent because they help CRAs to avoid rating reversals and to mitigate the tension between rating accuracy and rating stability.

Volatility is of crucial interest to institutional investors who hold large international diversified portfolios. In terms of economic mechanisms, this paper's analysis is motivated by prior literature on the links between sovereign credit risk and the corporate and financial sectors' overall risk, equity market performance and uncertainty (e.g. Arellano, 2008; Acharya et al., 2014; Bedendo and Colla, 2013; Borensztein et al., 2013; Gennaioli et al., 2014). This is discussed further in Section 4.2.2.

To the best of my knowledge, there is no prior investigation of the relationship between credit ratings and option markets. I address a gap in knowledge about the relative information content from the two sources. Moreover, I demonstrate the importance of sovereign rating information in the context of first-mover as well as additional rating signals. Several robustness checks are performed using non-parametric approaches and Monte Carlo experiments. The paper highlights differences in rating policy and varying influence of rating signals from the largest three CRAs, namely Moody's, S&P, and Fitch.

The main findings are summarised as follows. Firstly, sovereign rating news has a significant impact on the option market in various respects depending on the type of news and across CRAs. Secondly, there is strong evidence of causality between movements in the option market and all types of rating signals from S&P and Fitch, but only actual rating changes from Moody's, thus highlighting differences in rating policies. Moreover, the market reactions to S&P and Moody's signals infer that additional ratings are still informative and help reduce market uncertainty. Such results shed light on the price (credit information) discovery process. Finally, the findings contribute to the debate surrounding the regulation of CRAs and their ratings.

The remainder of the chapter is organised as follows. The next section reviews related literature, Section 4.3 describes the data, Section 4.4 discusses the research hypotheses and methodologies, Section 4.5 presents the empirical results and Section 4.6 concludes the chapter.

4.2. Literature review

4.2.1. Credit ratings and regulation

The rating industry performs a gate-keeping role for international capital markets (e.g. Coffee, 2006). Issuers seek ratings to improve the marketability of their financial obligations, and/or to increase their trustworthiness to business counterparties. Investors use ratings as a cost-effective indicator of securities' credit risk. Credit ratings provide three essential economic functions: information production, monitoring, and certification. Firstly, CRAs mitigate the fundamental adverse selection problem between borrowers and investors. Through the gathering and analysis of data relating to creditworthiness, CRAs mitigate informational asymmetry and adverse selection problems, decrease the risk premium of a debt issue, and hence increase the liquidity of assets (Bank of England, 2011).

Secondly, rating-based guidelines and rules perform a monitoring role and mitigate principal-agent problems. Moreover, by signalling a potential downgrade via negative outlooks or watch lists, CRAs also encourage an issuer to improve its creditworthiness (IMF, 2010a). To the extent that investors respond to rating changes by adjusting their portfolios, such negative rating announcements impose the implicit threat on issuers that failure to act will degrade their ability to refinance in the future.

Thirdly, CRAs provide a certification function for fund managers, regulators, central banks, and other market participants in distinguishing between securities with different risk characteristics, and specifying terms and conditions in financial contracts (IMF, 2010a). Examples of credit ratings' certification function can be found in many aspects of investments (e.g. Cantor et al., 2007). The certification function is found in regulatory capital requirements for insurance firms (Campbell and Taksler, 2003; Coffee, 2006), commercial banks and other financial institutions (Basel Committee, 2011), and in SEC's regulatory references (see SEC 2011a, b).

The fact that credit ratings have been "hard-wired" into regulations has widened their influence. Regulators use credit ratings to restrict public managed funds to invest in debts below certain levels of credit ratings, usually the investment-speculative threshold. The motivations for using credit ratings as an instrument for market regulation are: (i) aiming at financial soundness via establishing prudential minimum credit quality for portfolio holdings (e.g. IMF, 2010a; White, 2010); (ii) encouraging a minimum credit quality of securities issuance to protect investors (e.g. Coffee, 2006).

CRAs have faced extensive scrutiny for being too lax in rating structured securities, and this is widely regarded as a contributing factor to the US subprime crisis (e.g. White, 2010; Bank of England, 2011). In response, several regulatory proposals to monitor CRAs have been approved or are under consideration, while rating-based rules and guidelines have been under consideration to be dismissed. Many G-20 countries have introduced or are in the process of implementing new regulatory changes on CRAs (Bank of England, 2011). In the US, the Dodd-Frank Act requires thorough revisions of the role of credit ratings in the US regulatory framework. For instance, in March and April 2011, SEC proposed amendments removing references to credit ratings in the Investment Company Act of 1940 and the Securities Exchange Act of 1934, which are the legal backbone of the US financial system (SEC, 2011a, b). In November 2012, one rule, which regulates Business and Industrial Development companies who operate under state statutes, among six proposals in SEC (2011a) was adopted. As at March 2014, the remaining proposals are still under consideration and have not been legally approved.

CRAs are also accused of precipitating the EU sovereign debt crisis by issuing multiple downgrades on Greece, Ireland, Portugal, Spain, and Italy. Politicians in the EU have called for further regulation to improve quality and transparency in sovereign ratings. Since 2012, all CRAs operating in Europe are required to register with ESMA and to observe demanding rules which incorporate IOSCO Code of Conduct Fundamentals for Credit Rating Agencies.

4.2.2. Economic and market impact of sovereign ratings

Prior literature shows that sovereign credit risk can spill-over to corporate and financial sectors, cross-border investments, and the national economy in numerous ways. Arellano (2008) shows that a sovereign default triggers significant surges in the volatilities of interest rates, consumption and output. Borensztein el al. (2013) and Bedendo and Colla (2013) show that corporate credit risk and borrowing costs are strongly correlated with the evolution of sovereign credit risk. Bedendo and Colla (2013) suggest that a government in financial distress is more likely to "transfer risk" to corporates by increasing taxation, imposing foreign exchange controls, or expropriating private investments.

Acharya et al. (2014) illustrate a strong relation between sovereign and banks' risks. Deterioration in sovereign creditworthiness significantly triggers increases in banks' risks not only because of their large holdings of government bonds but also due to the reduction in the value of government guarantees to banks. For example, in 2011-2012, numerous European banks were downgraded by CRAs who explained these downgrades by deteriorations in their governments' financial capacities and willingness to bailout these entities. Moreover, BIS (2011) highlights how the European sovereign debt crisis affected banks' ability to raise funding. Collateral damage, risk aversion, and crowding-out effects are crucial channels via which deteriorations in sovereign creditworthiness strain banks' funding conditions. The funding difficulties, in turn, force the banks to squeeze the credit supply for the economy and consequently threaten the prospects of the national economy (Gennaioli et al., 2014).

Another strand of literature presents evidence that sovereign credit rating actions are influential in many financial markets. Sovereign credit ratings are a major factor influencing sovereign yield spreads (e.g. Afonso et al., 2012). Generally, the impact of rating news in the debt market is asymmetric. Negative rating news imposes significant impact while the influence of positive actions is much more muted. Moreover, sovereign rating news spills over to other sovereign bond yields (e.g. Gande and Parsley, 2005; Arezki et al., 2011).

Equity markets are also affected by sovereign rating news in a similar asymmetric manner. Kaminsky and Schmukler (2002) find that rating changes (on emerging sovereigns) affect the rated countries' stock indices. Ferreira and Gama (2007) find that (S&P's) sovereign rating changes of one country impose an asymmetric impact on the stock markets of other countries. Sovereign rating downgrades cause negative reactions whereas upgrades have no significant impact. Arezki et al. (2011) reveal that sovereign downgrades have significant spill-over effects not only across (European) countries but also across financial markets, i.e. sovereign credit default swaps (CDS), banking, insurance, and stock markets, during the period overlapping the European sovereign debt crisis. Alsakka and ap Gwilym (2013) find that both positive and negative credit news affects not only the rated country exchange rate but also spills over to other countries' exchange rates. The market reactions vary across CRAs' signals.

For derivatives markets, prior literature on the impact of rating actions is restricted to examining the CDS market. Norden and Weber (2004) find significant increases in (corporate) CDS spreads in advance of negative (corporate) rating events implying that the CDS market anticipates negative rating events. Results for positive rating events are much less significant. Afonso et al. (2012) find that the CDS market reacts to negative sovereign rating events while the reaction to positive events is much more muted. Additionally, rating downgrades seem to be anticipated by the CDS market.

The above issues suggest that strong economic linkages exist between sovereign rating actions and equity market performance and thus market-wide volatility. However, the relationship between sovereign ratings and equity options (or implied volatility) has been ignored by prior literature. I address a gap in knowledge about the relative information content from the two sources.

Given the prior evidence on the economic links between sovereign risk and uncertainty of the national economy, sovereign rating announcements are expected to impact market participants' risk expectations. However, the option market (or implied volatility) will not necessarily react to negative (positive) rating news in a negative (positive) direction like other financial markets, as evidenced in e.g. Kaminsky and Schmukler (2002), Gande and Parsley (2005), Ferreira and Gama (2007), Arezki et al. (2011). Beber and Brandt (2006, 2009) reveal that scheduled macroeconomic news always reduces financial market uncertainty regardless of whether the news is more negative or more positive compared to prior expectations. The higher ex-ante uncertainty over the content of the macroeconomic news, the larger the drop in the market uncertainty when the news is released.

Of course, credit rating news is not scheduled. However, market participants often consult with multiple CRAs (e.g. Cantor et al., 2007; Bongaerts et al., 2012). Therefore, it is rational for investors to expect actions from the other CRAs after a rating announcement from a 'first mover' CRA. We, thus, expect variation in the market reaction across CRAs. Prior literature also shows that there are variations in other market reactions to rating news released by different CRAs (e.g. Alsakka and ap Gwilym, 2013).

The option market is typically inhabited by institutional, informed traders (e.g. Chakravarty et al., 2004; Chen et al., 2005; Jin et al., 2012). Derivative markets also play a leading role in the price discovery process (e.g. Blanco et al., 2005; Acharya and Johnson, 2007; Avino et al., 2013). Sovereign credit issues are less opaque to observe compared to those of corporate, banks and other issuers. Therefore, the market reactions of implied volatility to sovereign rating signals could be in either positive or negative directions.

4.3. Data

This study is based on an unbalanced panel dataset which covers 24 countries during the period from January 2000 to April 2012. The availability of traded stock index options determines the sample size and sample periods, i.e. I include all countries with data available for stock index options, except for five countries without any rating actions during the options sample period (Canada, Malaysia, Norway, Sweden, Switzerland).[7] Table 4.1 lists the countries and the sample periods.

4.3.1. Credit ratings

Rating information is collected from Moody's, S&P, and Fitch publications. This dataset consists of daily observations of long-term foreign-currency credit ratings, outlook and watch status of sovereigns rated by these three leading CRAs. Figure 4.1 presents the distribution of daily ratings of sovereigns for each CRA. None of the 24 sovereigns were rated lower than BBB- (Baa3) by S&P, Fitch, and Moody's during the sample period. About 60% of the daily observations are in the triple-A rating category, and 2%-5%, 4%-7% and around 3.5% are at AA+/Aa1, AA/Aa2 or AA-/Aa3 rating categories. These proportions reflect the developed nature of the sample countries, which obviously coincides with the development of liquid stock index option markets.

[7] Greece is excluded due to very low trading volume for stock index options. Options on Portugal PSI 20 and Ireland ISEQ were not traded during the sample period.

I convert sovereign ratings to numerical scores within a 31-point comprehensive credit rating (CCR) scale in order to capture information on both actual ratings and outlook/watch procedures. On the CCR scale, rating symbols are converted as follows: AAA/Aaa ≡ 31, AA+/Aa1 ≡ 28, AA/Aa2 ≡ 25 ... BBB-/Baa3 ≡ 4, lower than BBB-/Baa3 ≡ 1. Adjustments for (positive/negative) outlook and watch announcements are made by adding ±1 and ±2, respectively, on the CCR scale.

There is non-linearity in the rating scale, which means that the differences between rating levels are not equal. For example, a downgrade from AAA to AA+ or a downgrade from the investment grade to the junk grade have different implications to a downgrade from A to A-. Historical observations on default rates across rating categories also suggest such non-linearity (see e.g. IMF, 2010a, Moody's, 2011b, S&P, 2013 and many others). In order to control for this, I employ a logit-transformation of the rating scale, constructed as follows:

$$LCCR = \ln\left[\frac{CCR}{32 - CCR}\right]$$

Prior literature has used a logarithm transformation of the rating scale (e.g. Sy, 2004; Alsakka and ap Gwilym, 2013), but their transformation is different to ours. Their transformation gives the highest weight for rating changes on AAA and near bankruptcy issuers and the lowest weight for rating changes near the investment-speculative boundary. In contrast, my transformation gives greatest weights for rating changes on AAA and those near the investment-speculative threshold.

There are several reasons why I adopt this particular log-transformation of the rating scale. Firstly, the speculative threshold is considered as very critical among rating users. For example, the U.S. Investment Company Act of 1940 restricts pension funds and municipalities to the investment-grade range. Insurance firms also rely heavily on assets with investment-grade ratings because regulatory capital reserves increase significantly for speculative assets (Campbell and Taksler, 2003). The speculative threshold is one of the most critical concerns to investors (e.g. Cantor et al., 2007; Bongaerts el al., 2012). Therefore, it is reasonable to assign more weight to rating changes around this threshold. Secondly, there is no rating observation lower than BBB- during the sample period. Thirdly, it is reasonable that rating changes at the top of the scale are also given more weight (e.g. as evidenced by the reactions to sovereign downgrades of France, UK, and USA in 2011-2013). Please see Appendix 4.1 for an illustration of how ΔLCCR changes when CCR increases/decreases.

Outlook and watch signals are defined as follows. Negative watch signals include placing a sovereign on watch for possible downgrade and withdrawing watch status for possible upgrade (without an actual upgrade). Positive watch signals include placing a sovereign on watch for possible upgrade and withdrawing watch status for possible downgrade (without an actual downgrade). Negative outlook signals include changes to negative outlook from stable/positive outlook, and changes to stable outlook from positive outlook (without any rating change). Positive outlook signals include changes to positive outlook from stable/negative outlook, and changes to stable outlook from negative outlook (without any rating change). During the period, there are 13 (29), 10 (16), 9 (19) positive (negative) outlook announcements for the sample countries made by S&P's, Moody's, and Fitch, respectively. The corresponding figures of watch actions are 11 (11), 9 (11), and 3 (3) (see Table 4.2).

Table 4.2 presents the sovereign credit rating events for each CRA. In total, there are 78 (126) positive (negative) rating events released by the CRAs during the sample periods for the selected sovereigns. S&P released the most rating news with 33 positive and 56 negative signals. There are 26 (39) positive (negative) rating announcements by Moody's while the figures are 19 (31) by Fitch. Almost all of the rating events are "clean" i.e. are not followed by same direction rating signals from other CRA(s) within at least 1 week. There are only 12 rating events which involve more than one CRA taking action on the same sovereign within one week. This is in support of the view that each CRA has its own policy on rating timeliness and rating stability (e.g. Alsakka and ap Gwilym, 2010a).

The majority of rating events are single, whereby they do not involve both a rating downgrade/upgrade and outlook or watch signals, simultaneously. There are only 2/65 rating events made by Moody's, and 1/50 by Fitch which are such multiple-rating events. S&P have released no such multiple-rating events during the sample periods. The majority of rating events are also within 3-point signals in the CCR scale which mean an outlook or watch announcement or a 1-notch downgrade/upgrade in isolation. There are only 3/89 rating events made by S&P, 6/65 by Moody's, 3/50 by Fitch which are multiple-notch downgrades/upgrades.

4.3.2. Implied volatility

Data on 30-day call option-implied volatility (IV) upon the countries' stock indices is collected from DataStream. The primary sources of data on premium, strike price, and maturity of the call options are the exchanges where these options are traded. The IV is estimated via the Black-Scholes model (for European style contracts) and the Cox-Ross-Rubinstein binomial model (for American style contracts). An interpolation is calculated based on four series of call option contracts: two nearest to at-the-money and two nearest to 30-day maturity. I use at-the-money contracts to mitigate the effects of skewness and smile.[8] Also, the 30-day maturity means that the IV estimates short-term expected volatility which coincides with the short-term horizon of the rating watch procedure.

There are 35,683 daily observations of 30-day implied volatility. Fig. 4.2 presents the distribution of the IV. During the sample periods, there are 315 observations where IV is

[8] Prior studies show that IVs are usually much higher for deep in the money and deep out of the money option contracts compared to at-the-money contracts, and this is known as the "smile" pattern (see Rubinstein, 1985, 1994 and many others).

greater than 100% in Hungary (14/01/2003-16/6/2003), Poland (7/2001, 10-11/2001, 2-8/2002, 11/2002), and Russia (10/2008-4/2009). All (most) of these observations are associated within 1 month to at least one observation of absolute value of the underlying index return larger than 1% (3%). 54% of the observations are associated with at least one observation of absolute value of the index return larger than 10%. There were nine rating signals on the three sovereigns during these periods. Therefore, I do not exclude these observations in order to avoid possible information loss. Moreover, equivalent empirical investigations based on excluding the 315 observations produce qualitatively similar results (discussed further in Section 4.5).

The main interest is in the dynamics of the IV, and Fig. 4.4 presents the distribution of daily changes in the IV. The changes are very much centred around zero with a mean of 0.0000451, median of 0, and standard deviation of 0.031.[9]

4.4. Hypotheses and methodological framework

4.4.1. Hypothesis I: Influence of rating news in the option market

H_0: Credit rating news does not impose a discernable influence on the option market. Therefore, changes in the IV around any type of rating event are not statistically different from zero.

In this stage, I use a standard event study. The event window is one week before and after rating events in order to mitigate any information contamination. Three intervals are defined as [-5, -1], [-1, 1], [1, 5]. t=0 denotes the day when a rating announcement is released. The [-1, 1] window is chosen rather than [0, 1] in order to control for any time zone issue.[10] In addition, I only include clean events which are not followed or overlapped by rating

[9] I exclude 23 observations of the daily ΔIV whose absolute values are greater than 50%, accounting for 0.067% of total observations.
[10] Please note that the [-1, 1] window is equivalent to [0, 1] in other studies which examine financial assets returns because an asset return for day 0 incorporates information on the asset's prices in day -1 and day 0.

announcement(s) on the same sovereign by another CRA(s) within at least 1 week in order to further avoid information contamination.[11] With such a short distance in time (i.e. one week), it is highly plausible that two (or more) CRAs are reacting to the same underlying credit issue. Rating signals from different CRAs are pooled together in order to increase the numbers of events and hence the power of the testing procedure.[12]

Prior literature shows that the option market is efficient and there is no significant evidence of forecastability of implied volatility. Konstantinidi et al. (2008) use numerous economic indicators in several econometric models in an attempt to forecast the evolution of US and European option implied volatilities, but none of these variables is significant and the adjusted R^2 values of all the models are very near to zero. Moreover, out-of-sample forecasting evidence mostly favours the random walk model for evolution of the IVs. Jiang and Tian (2012) also support the random walk hypothesis for modelling the implied volatility extracted from S&P 500 index options. Therefore, I examine changes in the IV instead of modelling an abnormal element in the changes.[13]

In order to avoid any possible bias due to the distribution of the sample mean of the ΔIV due to the limited numbers of rating events, non-parametric tests are employed as robustness checks. The non-parametric tests are sign- and Wilcoxon tests, testing whether the medians of the ΔIV during the time windows are significantly different to zero.

[11] Only for this event study, I exclude 12 'unclean' rating events (mentioned in Section 4.3.1). Later investigations are based on all rating events.
[12] I am aware that the market reaction might vary across CRAs. The potential for varying reactions is examined by later methodologies.
[13] I also conducted Durbin-Watson and Breusch-Godfrey tests for the random walk of IV_t in the sample. For most countries, the null hypothesis that IV_t follows a random walk is accepted. The exceptions are Austria, France, Japan, Russia, Taiwan and USA. Results are available on request.

4.4.2. Hypothesis II: Varying impact across CRAs' actions

H_0: The impact of rating signals on the option market is similar across CRAs.

Varying market reactions to rating news from different CRAs are reported in the literature (e.g. Bongaerts et al., 2012; Alsakka and ap Gwilym, 2013). The following regression is estimated:

$$\Delta IV_{i,\,s} = \alpha + \beta^* \,\Delta LCCR_{i,\,t} + \gamma^* CCR_{\,i,\,t} + \theta^* Co + \psi^* Y + \varepsilon_{i,t} \qquad (4.1)$$

$\Delta IV_{i,s}$ represents changes in the implied volatility for sovereign *i* during time windows *s* around credit signals from each CRA. Time windows are restricted to 3 months before- and after- credit signals. Specifically, [-66, -22], [-22, -5], [-5, -1] capture the market movements preceding rating news by 3 months, 1 month and 1 week, respectively; [-1, 1] conveys the market movements when rating news is released; [1, 5], [5, 22], [22, 66] capture market movements after rating news during 1 week, 1 month, 3 months later.

ΔLCCR measures the sovereign credit signals, representing the 1-day change in the log-transformation of the CCR for sovereign *i* at event date *t*. CCR is the comprehensive credit rating from each CRA, which is included as an explanatory variable to control for macroeconomic news and other fundamentals of the rated sovereigns (e.g. Prati et al., 2012; Alsakka and ap Gwilym, 2013). As macroeconomic and other fundamentals are determinants of sovereign ratings, the inclusion of ratings, in addition to country and year dummies, helps control for the likelihood that IV might be more volatile in countries with weak macroeconomic conditions. Thus, including CCR reduces any potential omitted variable bias.

Co and Y are full vectors of country and year dummies. For each country and year in the data sample, I define one dummy variable. In total, there are 24 country dummies and 13 year dummies (2000-2012).

Estimations of Eq. (4.1) are based on event days plus a country-matched random sample, drawn from the full sample after excluding non-event observations within the time windows around rating events, in order to mitigate rating clustering and market noise issues (see Ferreira and Gama, 2007).[14] It is noteworthy that the sample consists of observations on non-consecutive days that may be very distant from each other. There are two main reasons for choosing regressions of IV instead of using a model from the GARCH family. First, there are limited credit rating events on each country. In this Chapter, the sample is dominated by developed countries which have liquid stock index options markets and developed countries have scare rating events. Second, prior papers using the multivariate GARCH family of models usually employ very few time series of dependant variables (e.g. Engle et al., 1990; Andersen et al., 2003b). In this Chapter, there are 24 time series of IV. This would cause substantial difficulties in generating feasible estimation and sensible economic interpretations.

In order to consider varying impacts across CRAs' actions (if any), I estimate Eq. (4.1) for each CRA separately. For each CRA, there are three separate estimations for different types of signals (i.e. actual rating, outlook, watch announcements) in order to investigate the asymmetric market behaviour (if any). For ease of interpretation, the absolute value of ΔLCCR is used.

Furthermore, I perform Monte Carlo experiments as robustness checks by repeating the country-matched random sampling 10,000 times. Each time, the sample consists of a number of event observations plus the same number of random non-event observations. Based on this sample, regressions for the CRAs are run and the averages of estimated coefficients across the 10,000 times are reported (see Gande and Parsley, 2005).

4.4.3. Hypothesis III: Causality between sovereign rating and IV

H_0: Neither sovereign rating actions nor IV changes cause changes in the other variable.

[14] Equivalent estimations based on the full sample produce qualitatively similar results.

Given the leading role of derivatives markets (Blanco et al., 2005; Acharya and Johnson, 2007; Jin, et al., 2012; Avino et al., 2013), I expect some evidence that the option market leads rating actions. Nonetheless, the lead-lag relationship between the market and ratings assigned by different CRAs could be different since the timeliness and policies of each CRA are not necessarily the same.

Granger causality tests in a panel framework are conducted by estimating separate regressions of changes in the IV and sovereign ratings, as follows:

$$\Delta IV_{i,t} = \alpha_1 + \sum_{j=1}^{k} \beta_1^j * \Delta CCR_{i,t-j} + \sum_{j=1}^{k} \beta_2^j * \Delta IV_{i,t-j} + \sum_{j=1}^{k} \varphi^j * \Delta Z_{i,t-j} + u_{i,t} \qquad (4.2)$$

$$\Delta CCR_{i,t} = \alpha_2 + \sum_{j=1}^{k} \gamma_1^j * \Delta CCR_{i,t-j} + \sum_{j=1}^{k} \gamma_2^j * \Delta IV_{i,t-j} + \sum_{j=1}^{k} \theta^j * \Delta Z_{i,t-j} + v_{i,t} \qquad (4.3)$$

(k=5, 22, 66)

ΔIVi,t denotes daily changes in IV. Consistent with prior literature (e.g. Konstantinidi et al., 2008), I find that ΔIV is stationary. Augmented Dickey-Fuller, KSS (Kapetanios et al., 2003) and KPSS (Kwiatkowski, et al., 1992) tests are employed in order to test the stationarity in the context of individual time series. In addition, existence of a unit-root in the context of panel data is tested using procedures proposed in Choi (2001) and Im et al. (2003). The results from all the tests are in line with each other and strongly support the view that ΔIV is globally stationary (see Appendix 4.2 for details). Please note that my panel sample is unbalanced. As a consequence, LM tests such as those proposed in Hadri (2000) become inapplicable as the test-statistics assume T is the same for each series.

ΔCCR denotes daily changes in the comprehensive credit rating from a given CRA (note that there are limited numbers of rating events during the 12-year sample period). I use ΔCCR instead of ΔLCCR to avoid any possible bias in the lead-lag relationship in the middle of the CCR scale (see Afonso et al., 2012), but I provide further evidence on this in Section

4.5.3. I am interested in the question of whether there are significant market movements prior to rating news or not.

Z is a vector of fundamentals that affect ratings and implied volatility. However, given the fact that daily observations are not available for all the fundamentals, I restrict ΔZ to contain stock market returns[15] (daily log returns of the underlying indices) and changes in CCR from the other two CRAs. Firstly, it is reasonable to include equity markets in models examining the lead-lag behaviour between the option market and credit rating signals due to the fact that the equity market and the option market both play roles in the price discovery process (e.g. Chen et al., 2005). Given the well-known leverage effect (see e.g. Schwert, 1989; Figlewski and Wang, 2000), the stock index return helps control for the fact that credit ratings and the option market do not adjust at the same frequency. Secondly, including lagged values of ratings from other CRAs controls for the fact that both the market participants and CRAs are aware of previous ratings from other CRAs. Market participants usually consult with multiple ratings (e.g. Cantor et al., 2007; Bongaerts et al., 2012). There is also evidence of interdependence between CRAs' sovereign ratings (Alsakka and ap Gwilym, 2010a). Therefore, it would be naïve to assume that either the market participants or CRAs are unaware of previous rating actions from other CRAs.

Equations (4.2) and (4.3) are estimated by the fixed effects technique rather than the Arellano and Bond (1991) GMM technique due to several reasons. Firstly, there are very large numbers of observations for each country. The bias in estimated coefficients of lagged values of dependent variables should be close to zero. Secondly, GMM relies on asymptotic theory and requires a large number of individuals (N), but N=24 in the sample. Moreover, GMM would imply taking the differences of the differences of ratings, IV, and equity returns which would amplify the noise in the regressions. It should be borne in mind that the

[15] The stock market returns are stationary during the sample period.

frequency of rating changes is much less than those of the market indicators. Taking second differences would lead to two consequences which in turn amplify market noise. Firstly, the gap between the frequencies and variability of rating changes and those of market indicators (i.e. IV and stock returns) would be amplified. Secondly, the leverage effect would be neutralized.

I employ the fixed effects estimation rather than the random effects technique due to two main reasons. First, the fixed effects technique is more conservative compared to random effects because it is "assumption free" (e.g. Greene, 2012). Meanwhile, the random effects technique requires several assumptions, especially that the individual effects must be uncorrelated with the disturbance terms and independent variables. Second, prior papers in the closely related literature have typically used the fixed effects technique (e.g. Gande and Parsley, 2005; Ferreira and Gama, 2007).

In testing the possible causality, I employ log-likelihood tests of the joint significance of all coefficients of lagged values of the changes in CCR in Eq. (4.2) and the changes in IV in Eq. (4.3).

4.5. Empirical results

4.5.1. Influence of sovereign rating news in the option market

Table 4.3 presents the results of the event study. Panel A of Table 4.3 demonstrates an asymmetric pattern in the market reaction to rating signals. Specifically, there are significant responses to rating downgrades while the market impact of upgrades is muted. These reactions are confirmed by each testing procedure. Within a week following downgrades, the IV on average reduces by 2.4 percentage points. This is similar to findings in prior literature on the impact of rating signals in other markets in the sense that upgrades generally do not trigger significant reactions from financial markets (Kaminsky and Schmukler, 2002; Gande and Parsley, 2005; Ferreira and Gama, 2007). However, the reduction in IV in response to downgrades is unexpected. Why does the option market consider an equity market in a recently downgraded country (i.e. a lower creditworthiness), to be less uncertain? One possible justification is that the market anticipates credit problems in advance and rating downgrades might serve as means of confirming the market anticipation (see Beber and Brandt, 2006). However, there is no evidence that upgrades and downgrades are anticipated by the market within the prior week. Rating upgrades (downgrades) might be anticipated further in advance. Increasing the length of time windows could answer the question. However, this approach encounters a rating clustering problem and reduces the number of (clean event) observations, hence, the power of the tests. The later methodology relaxes this constraint.

Results from rating outlook signals are presented in Panel B of Table 4.3. There is no evidence that positive outlook signals induce market reactions. For the negative outlook signals, the non-parametric tests present significant evidence that the IV on average decreases by 1.3 percentage points within the subsequent week. Again, the IV reduces in response to negative rating news. The reaction is not immediate but within a short period. The evidence supports the previous conjecture about the confirmation effects of rating news.

Panel C of Table 4.3 presents results from rating watch signals. The IV significantly increases by 1.6 percentage points at the time of both positive and negative watchlist signals. The response to negative watch news is short-lived while the market seems to overreact to positive watch announcements, i.e. the IV reduces by 2.5 percentage points during the following week. Although outlook and watch are monitoring procedures, watchlist is a much stronger statement and CRAs aim at a short-term horizon in resolving the watch status. This contributes to explaining the greater relevance of watch announcements to 30-day IV.

One interesting remark on Table 4.3 is that only watch announcements trigger immediate market responses. The responses are of the same sign, i.e. IV increases, regardless of the sign of watch announcements. In contrast, downgrades induce positive (but not immediate) market reactions, i.e. IV decreases, implying a confirmation effect of actual rating changes. The results suggest that the information content of rating signals for the option market depends on signal types rather than whether they are positive or negative.

4.5.2. Varying responses to CRAs' signals

Tables 4.4 to 4.6 report the estimated coefficients of Equation (4.1) examining changes in IV during the time windows around rating signals from each CRA. The variable of interest is 'ΔLCCR', representing the 1-day change in the log-transformation of the CCR scale of sovereign *i* at event date *t*. It should be noted that 1-unit changes in the CCR cause varying effects on the LCCR depending on the starting level of a sovereign rating. For example, 1-notch downgrades on AAA sovereigns cause 1.488-unit decreases while 1-notch downgrades on A or A- sovereigns cause 0.379-unit decreases in the LCCR.[16] Negative outlook (watch) signals on AAA sovereigns cause 0.726-unit (1.165-unit) decreases while equivalent signals on A or A- sovereigns cause much weaker responses in the LCCR.

Table 4.4 shows that S&P rating news is influential in the market. The only time window where the coefficient of ΔLCCR is significant is [-1, 1]. This holds except for cases of positive watch announcements.[17] The absence of significant coefficients during the other time windows implies immediate and short-lived effects of S&P's rating announcements in the market. Downgrades and upgrades impact the market in opposite manners. In cases of downgrades, the coefficient of ΔLCCR is significantly greater than zero implying that S&P's downgrades trigger an increase in the IV. The magnitude of the increase depends not only on the magnitude of rating downgrades but also the current level of sovereign ratings. The IV,

[16] These are downgrades/upgrades without prior outlook or watch signals.
[17] S&P never put a sovereign issuer on watch for possible upgrade during the sample period. All the positive watch actions in the S&P sample are confirming actual ratings after being on watch for possible downgrades.

on average, increases by 3.8 percentage points in response to 1-notch downgrades on AAA sovereigns (1.488*0.0258). The IV decreases by 3.4 percentage points in response to a 1-notch upgrade of a sovereign to AAA (1.488*0.0227).

Negative outlook/watch announcements increase the IV while positive outlooks reduce the market uncertainty relating to rated sovereigns' equity markets. The magnitude of the market reactions to positive outlook news is less than for negative outlook. In response to negative outlook news on an AAA sovereign, the IV increases 1.7 percentage points (0.726*0.0228). The reactions to negative watch signals are stronger, whereby the IV increases 2.5 percentage points (1.165*0.0216). Coefficients of CCR are generally insignificant, which infers that the current level of creditworthiness does not help to explain the dynamics of IV. In other words, the option market already subsumes current financial, macro-economic fundamentals of the rated sovereigns, which is consistent with the view that the evolution of implied volatility cannot be forecasted (e.g. Konstantinidi et al., 2008; Jiang and Tian, 2012).

Table 4.5 reports the results of Equation (4.1) for Moody's news. There are some statistically significant coefficients of ΔLCCR during the pre-event windows. However, it is problematic to interpret these as evidence of rating anticipation since the coefficients' signs are not consistent with each other. For example, the IV decreases in advance of downgrades but increases prior to negative outlook/watch announcements. All the coefficients of ΔLCCR during the [-1, 1] time window are insignificant while those during the [1, 5] time window are all significant. The results imply that the market does not react immediately to Moody's rating news. The reactions come after Moody's rating news is released, and in an opposite manner to the reactions to S&P signals. Moody's downgrades trigger a decrease in IV while its upgrades trigger an increase. The IV decreases by 3.7 percentage points in response to 1-notch downgrades on AAA sovereigns (1.488*0.0248). However, the IV increases by 9.2

percentage points in response to 1-notch upgrades of sovereigns to AAA (1.488*0.0615). Other results are similar to Table 4.4. Specifically, coefficients of CCR are generally insignificant in explaining changes in IV and strong market reactions are found only during one time window.

Table 4.6 reports the results of Equation (4.1) for Fitch. The results show that Fitch's rating news has limited influence in the option markets. There is no significant evidence that Fitch rating signals trigger movements in the IV except for cases of downgrades. Here, the coefficient of ΔLCCR during the [-1, 1] window is significant and negative implying that Fitch's downgrades induce a decrease in the IV. On average, the IV reduces by 3.3 percentage points in response to 1-notch downgrades on AAA sovereigns (1.488*0.0222). In other words, Fitch's downgrades reduce the market uncertainty. Results for CCR coefficients are very similar to those from Moody's and S&P.

Table 4.7 presents results of the Monte Carlo experiments. The results are strongly consistent with those from Tables 4.4-4.6. Overall, the market reaction varies across CRAs' signals. There is no significant reaction to Fitch announcements while the reactions to rating signals from S&P are opposite to those from Moody's. The only coefficient which is statistically significant in Panel A of Table 4.7 (reporting the market reactions to S&P signals) is of ΔLCCR during the [-1, 1] window. This indicates that S&P's rating actions trigger immediate and short-lived responses from the market. The coefficient is negative meaning that S&P's upgrades (downgrades), where ΔLCCR is positive (negative), significantly reduce (increase) IV during the [-1, 1] window. In contrast, the only coefficient which is statistically significant in Panel B of Table 4.7 (for Moody's signals) is of ΔLCCR during the [1, 5] window. The positive sign of the coefficient indicates significant increases (decreases) in IV following Moody's upgrades (downgrades).

In summary, there is significant evidence that sovereign credit rating signals induce reactions in the option market. There is also an asymmetric pattern in the market reactions. However, the asymmetry is not only between negative and positive rating news but also across CRAs. The influence of Fitch rating changes is less significant. This is consistent with Bongaerts et al. (2012) who reveal that Fitch plays a 'tiebreaker' role when there is a split between Moody's and S&P around the investment-speculative threshold.[18] All sovereigns in the sample are rated at investment-grade (by Moody's and S&P), which could explain the limited impact of Fitch upgrades. The results for Fitch downgrades imply that even downgrades from the 'tiebreaker' do matter and reduce the market uncertainty. This leads to a possible argument that additional ratings are likely to reduce market uncertainty. To some extent, this is in line with Beber and Brandt (2006, 2009) who reveal that scheduled macroeconomic news always reduces market uncertainty (even when news is more negative than prior expectations). Of course, sovereign rating news is not scheduled. However, because market participants usually consult with multiple CRAs (e.g. Cantor et al., 2007; Bongaerts et al., 2012), it is rational for investors to expect actions from the other CRAs after a downgrade from a 'first mover' CRA.

The results from Moody's downgrades and S&P upgrades lend support to this argument. In my sample, all Moody's downgrades followed S&P downgrade(s) on the same sovereign(s) except for downgrades of Hungary in November 2008.[19] Meanwhile, all Moody's upgrades during the period led S&P upgrades on the same sovereigns.[20] This supports the view that S&P tends to lead in sovereign downgrades while Moody's tends to be

[18] Bongaerts el al. (2012) is based on corporate ratings. Their decision to treat Fitch as the additional rater was based on the market shares. The market shares are similar between corporate and sovereign ratings.

[19] Moody's downgraded Hungary on 07/11/2008 while S&P downgraded Hungary on 17/11/2008. However, the former action narrowed while the latter action widened the split between the two CRAs. Some S&P downgrades (on Austria, France, USA) were not followed by Moody's within the sample periods.

[20] Some sovereigns experienced upgrades from only one of these two CRAs (Czech Republic, Finland, Israel, Korea).

‘first mover’ in upgrades (e.g. Alsakka and ap Gwilym, 2010a). This section has reported that Moody’s downgrades and S&P upgrades significantly reduce the market uncertainty. It is worth commenting that the reaction to Moody’s downgrades is found to be significant only during the [1, 5] window not the [-1, 1] time window. Moreover, the positive reaction is found after Moody’s negative news i.e. downgrades. This reaffirms the implication about the confirmation effects of actual rating actions, which was mentioned in Section 4.5.1. Actual rating changes (even downgrades) from CRAs who often lag in a specific type of rating action are likely to reduce the market uncertainty.

In order to further clarify the argument, I re-specify the investigations by including dummies indicating whether a rating event widens or narrows the rating split between each pair of the CRAs. However, there is a lack of variation in the dummies indicating the split changes between Moody’s and S&P in each type of rating news, i.e. downgrades, upgrades (as analysed above). Therefore, it is only meaningful to re-specify the investigations on Fitch rating news. As previous results support Bongaerts et al.’s (2012) view that Fitch plays a ‘tie-breaker’ role, the variable is constructed to consider the split between Fitch actual ratings and average ratings from Moody’s and S&P. The variable takes the value of 1 if Fitch signals reduce the split, -1 if Fitch signals widen the split, and 0 otherwise. The results are qualitatively the same as those in Table 4.6. The only difference is that the significance level of ΔLCCR in explaining ΔIV during the [-1, 1] window becomes 5% (instead of 10%). The coefficient of the variable is significantly negative at 5%. This result indicates that the market consults with Fitch downgrades in the wider context of Moody’s and S&P ratings. Implied volatility is reduced when Fitch downgrades reduce the disagreement between the CRAs about a sovereign’s creditworthiness. This reaffirms the implication about the confirmation effects of actual rating news in Section 4.5.1.

Overall, these findings support the 'information producing' role of credit ratings both in the context of 'first mover' as well as additional ratings. Taken together, the results stress the importance of credit ratings, especially multiple ratings, because additional ratings are likely to reduce the market uncertainty.

4.5.3. Lead-lag relationship between implied volatility and credit ratings

Table 4.8 presents the results of Equations (4.2) and (4.3). The causality between movements of the option-implied volatility and sovereign rating signals varies across CRAs. There is highly significant evidence of relationships between S&P and Fitch signals and the option market. In contrast, Moody's signals exhibit no causality in either direction.

For S&P, the evidence that changes in IV Granger-cause sovereign rating news is stronger than that of the reverse relationship. ΔIV Granger-causes sovereign rating news for each lag length (i.e. within 1 week, 1 month, and 3 months). Meanwhile, S&P rating news only Granger-causes ΔIV for lags within 3 months. The findings are in line with prior papers researching rating anticipation by the CDS market (Norden and Weber, 2004; Afonso et al., 2012) in the sense that rating changes could be anticipated by the derivative market.[21] The results from Fitch demonstrate stronger implications (than from S&P) that movements of the IV Granger-cause rating news instead of vice versa. Specifically, there is no significant evidence that Fitch signals Granger-cause ΔIV even for lags within 3 months while there is significant evidence that ΔIV Granger-causes Fitch rating actions for lags within 1 month and within 3 months. However, I fail to reject the null hypothesis that either ΔIV or Fitch signals leads each other in the very short-term, i.e. lags within 1 week. In general, the evidence for S&P and Fitch supports the view that changes in option-implied volatility help explain

[21] I also estimate probit models testing whether movements in the IV prior to rating events are significant in explaining the probabilities of rating events. The results generally agree that (even) downgrades (from all the CRAs) could be anticipated by the option market.

changes in creditworthiness of underlying entities which is, to some extent, consistent with prior papers (e.g. Collin-Dufresne et al., 2001; Cao et al., 2010).[22]

There is no significant evidence of the causality or lead-lag relationship between ΔIV and Moody's actions, even for lags up to 3 months. Among the CRAs, Moody's explicitly provide details on the methodologies of their market implied ratings, e.g. Moody's KMV™ which incorporates information from financial markets. Therefore, it is hard to argue that Moody's is unaware of the market movements. However, Moody's actions are not following market movements. In other words, Moody's ratings are tardy compared to those from S&P and Fitch. One logical explanation could be Moody's following a policy of rating stability.

In order to further clarify the above argument, I re-estimate Equations (4.2) and (4.3) based on information of actual rating changes and outlook/watch signals, separately. There is significant evidence that ΔIV Granger-causes Moody's actual rating changes for lags up to 3 months, but not vice versa. There is no significant evidence that either ΔIV or Moody's outlook/watch signals Granger-cause each other for all lags. There is strongly significant evidence that both ΔIV and S&P outlook/watch signals Granger-cause each other for all lags. There is also strongly significant evidence that ΔIV Granger-causes Fitch outlook/watch signals, but not vice versa. The results imply that S&P and Fitch are likely to focus on rating accuracy while Moody's results are consistent with a greater emphasis on rating stability.

Furthermore, I conduct equivalent causality investigations using ΔLCCR (instead ΔCCR) in Equations (4.2) and (4.3). The results are qualitatively different. Specifically, the null hypothesis that ΔIV does not Granger-cause ΔLCCR cannot be rejected (even at the 10% significance level). This is true except only for Fitch at lags $k = 66$. Movements in the option market Granger-cause rating changes in the linear scale. However, this causality relationship is insignificant when the non-linearity of the rating scale is taken into account (i.e. there is no

[22] Collin-Dufresne et al. (2001) use bond spreads while Cao et al. (2010) use CDS spreads.

evidence that stronger movements happen prior to rating news on AAA-rated issuers or those rated near the speculative threshold). This implies that the market is aware of credit issues in advance of rating events, yet the magnitude of the credit issues remains uncertain, especially for issuers at the top and bottom of the investment-grade spectrum.

4.5.4. Discussion of results

All sovereigns in the sample are rated at the investment-grade (by each CRA) and many of them are categorised as developed economies. Such economies are usually characterised by informational transparency, which contributes to the possibility that the creditworthiness of these sovereigns is likely to be observable by financial market participants. As a result, rating changes are more likely to be led by market indicators, such as IV. The results shed light on the price (credit quality information) discovery process. The causal relationships suggest that the process is not simply one way, but also cannot dismiss the importance of rating news. Credit rating signals (especially from S&P and Moody's) significantly influence IV.

An interesting question over the informational content of rating news can be raised. If the IV leads rating news, the informational content of the news would be subsumed in the IV. Therefore, there should be no reaction found on and/or after the announcements of the news. Nonetheless, reactions to S&P and Moody's rating news are found to be significant (Tables 4.4, 4.5, and 4.7). The result implies that a significant part of the informational content of rating signals remains until their announcements, even for those led by the option market. Along with the finding that additional ratings are likely to reduce the market uncertainty, the results stress the importance and relevance of sovereign ratings to market sentiment.

In order to check the robustness of the findings against extreme observations, I have also conducted equivalent empirical investigations based on excluding the 315 extreme observations (mentioned in Section 4.3.2). The results are qualitatively similar. Specifically, the findings of the event study and investigations of varying market responses to individual CRAs' signals do not change. There are only two changes in the lead-lag investigations which do not alter the main findings and conclusions.

4.6. Conclusions

This chapter investigates the interaction between the stock index option market and sovereign credit ratings assigned by Moody's, S&P, and Fitch based on a dataset of 24 countries, which covers all countries with liquid stock index options markets (except for countries without rating actions) during 2000 - 2012. The effects of rating signals are evidenced by an event study, and country-matched random sampling regressions. Robustness of the results is confirmed by non-parametric tests and Monte Carlo experiments. Granger-causality tests are employed in order to detect any lead-lag relationships between rating actions and market movements.

A unique contribution to the literature is made by (i) identifying differing influences of CRAs on market uncertainty; (ii) demonstrating the important role of additional sovereign ratings in reducing market uncertainty; (iii) providing evidence of a two-way relationship between sovereign ratings and the equity index option market.

I find an asymmetric pattern in market responses not only between positive and negative events but also varying across CRAs. The market is more likely to react to news from S&P and Moody's rather than from Fitch, consistent with Bongaerts et al. (2012) who argue that Fitch plays a 'tiebreaker' role, at least in corporate ratings. Moreover, Fitch downgrades trigger a decrease in IV, implying that even downgrades from the 'tiebreaker' do matter and reduce the market uncertainty. Furthermore, the market reactions to Moody's and S&P signals reinforce the analysis that additional signals (both negative and positive) are still informative and reduce the market uncertainty. These stress the importance of multiple ratings and support the information production role of credit ratings in the context of both first-mover as well as subsequent rating news. The results are robust across methodological frameworks and specifications. In addition, I find significant causal relationships between market movements and all types of rating actions assigned by S&P and Fitch, but only actual rating changes from Moody's. The finding indicates differences in the CRAs' timeliness and policies. S&P and Fitch credit signals reveal a relatively stronger focus on rating accuracy while Moody's emphasises rating stability. The finding also implies that market participants observe credit issues and react more quickly than CRAs.

From these findings, it is not persuasive to argue that credit rating actions precipitated the European sovereign debt crisis, as was repeatedly suggested by some commentators. By the time of announcements, (even negative) rating actions can serve as a means of confirming the market anticipation and reducing market uncertainty. Some potential policy implications can be raised. The findings support the view of not "shooting the messengers" as expressed by the Association of British Insurers (House of Lords, 2011). In response to the recent crises, credit ratings have been under consideration for removal from regulations as well as investment guidelines. There are clearly benefits of reducing reliance on credit ratings, but proposals such as SEC (2011 a, b) deserve a caveat, particularly in the context of traditional debt ratings. A strong degree of heterogeneity exists in market responses to rating news, differing by signal, direction and CRA.

Table 4.1. List of sample countries

Country	Period		Country	Period
Australia	2010-2012		Israel	2010-2012
Austria	2000-2012		Italy	2007-2012
Belgium	2010-2012		Japan	2007-2012
Brazil	2011-2012		Korea	2009-2012
China	2007-2012		Netherlands	2000-2012
Czech Republic	2002-2009		Poland	2000-2002
Finland	2001-2012		Russia	2008-2012
France	2001-2012		South Africa	2011-2012
Germany	2000-2012		Spain	2007-2012
Hong Kong	2007-2012		Taiwan	2010-2012
Hungary	2002-2009		UK	2001-2012
India	2010-2012		US	2002-2012

The data set covers 24 countries. The availability of traded stock index options determines the sample size and sample periods, i.e. I include all countries during the periods that their stock index options are traded (except for Canada, Malaysia, Norway, Sweden, Switzerland who have not experienced any rating actions during the sample periods and Greece whose stock index option market is very small).

Table 4.2. Rating events

No. of events	S&P			Moody's			Fitch			Total		
	Positive	Negative	∑	Positive	Negative	∑	Positive	Negative	∑	Positive	Negative	∑
Column number	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Actual rating	9	16	25	7	12	19	7	9	16	23	37	60
Outlook	13	29	42	10	16	26	9	19	28	32	64	96
Watch	11	11	22	9	11	20	3	3	6	23	25	48
Total	33	56	89	26	39	65	19	31	50	78	126	204

This table reports numbers of rating events released by the CRAs during the sample periods. Columns (1), (2), (3) report numbers of positive, negative, and total rating signals from S&P, respectively. Similarly, columns (4) to (9) report corresponding numbers from Moody's and Fitch. (10) = (1) + (4) + (7); (11)= (2) + (5) + (8); (12)= (3) + (6) + (9).

Table 4.3. Results of the event study

Time window	[-5,-1]	[-1,1]	[1,5]	[-5,-1]	[-1,1]	[1,5]
Panel A: Actual rating changes						
	Downgrade			**Upgrade**		
$\Delta\overline{IV}$ (%)	-1.044	1.023	**-2.434***	-2.659	0.880	0.854
p-val. of t-test	0.215	0.220	0.066	0.238	0.425	0.685
p-val. of sign test	0.247	0.557	0.009	0.607	0.607	1.000
p-val. of Wilcoxon test	0.163	0.174	0.029	0.543	0.570	0.903
No. of Events	27			19		
Panel B: Outlook signals						
	Negative outlook			**Positive outlook**		
$\Delta\overline{IV}$ (%)	-0.719	1.383	$-1.274^{\dagger}$	-0.955	0.618	-0.312
p-val. of t-test	0.140	0.159	0.118	0.153	0.368	0.566
p-val. of sign test	0.220	0.583	0.027	0.327	0.845	1.000
p-val. of Wilcoxon test	0.199	0.227	0.011	0.214	0.380	0.544
No. of Events	57			29		
Panel C: Watch signals						
	Negative watch			**Positive watch**		
$\Delta\overline{IV}$ (%)	-0.243	**1.551***	-0.382	-0.028	**1.567***	**-2.469****
p-val. of t-test	0.760	0.067	0.706	0.963	0.051	0.017
p-val. of sign test	0.541	0.064	0.838	0.523	0.286	0.000
p-val. of Wilcoxon test	0.931	0.029	0.909	0.592	0.040	0.003
No. of Events	24			22		

Only 'clean' events from all CRAs are used. $\Delta\overline{IV}$ reports mean value of changes in the IV during the time windows in percentage points. Cases in bold denote significance at least at 10% level in both 2-sided t-test and either of 2-sided non-parametric tests. *, ** denotes significant in t-test at 10%, 5% level of significance. † denotes significant in the non-parametric tests and not in the t-test. See Tables 4.1 and 4.2 for details on the data sample. The reason for mis-matches in no. of events compared to columns 10 and 11 of Table 4.2 is the absence of unclean events.

Table 4.4. Estimation results of Eq. (4.1) for the S&P events

Time window	[-66, -22]	[-22,-5]	[-5,-1]	[-1,1]	[1,5]	[5,22]	[22,66]	[-66,-22]	[-22,-5]	[-5,-1]	[-1,1]	[1,5]	[5,22]	[22,66]
Panel A	**Downgrade**							**Upgrade**						
ΔLCCR	0.0083	-0.0111	-0.0094	**0.0258****	-0.0006	-0.0070	0.0074	0.0766	-0.0215	0.0108	**-0.0227****	-0.0176	0.0050	0.0184
	(0.815)	(0.620)	(0.374)	(0.035)	(0.968)	(0.758)	(0.745)	(0.405)	(0.594)	(0.383)	(0.043)	(0.104)	(0.844)	(0.912)
CCR	-0.0073	-0.0016	0.0014	0.0014	0.0018	0.0068	0.0007	-0.0062	0.0009	0.0013	0.00123	0.0013	**0.0077***	-0.0030
	(0.109)	(0.634)	(0.591)	(0.252)	(0.258)	(0.110)	(0.883)	(0.287)	(0.806)	(0.717)	(0.378)	(0.418)	(0.096)	(0.580)
Year/ Co	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	23.80%	45.43%	7.65%	7.99%	10.93%	35.44%	0.78%	20.86%	44.81%	7.04%	8.96%	11.97%	35.47%	1.03%
Panel B	**Negative outlook**							**Positive outlook**						
ΔLCCR	-0.05849	0.0216	-0.0103	**0.0228***	0.0063	0.0055	-0.0483	-0.0096	0.0003	0.0081	**-0.0161***	-0.0046	0.0002	0.0068
	(0.434)	(0.558)	(0.310)	(0.056)	(0.672)	(0.828)	(0.701)	(0.790)	(0.990)	(0.444)	(0.096)	(0.785)	(0.995)	(0.796)
CCR	**-0.0081***	-0.0003	0.0010	0.0019	0.0017	0.0066	-0.0024	**-0.0088***	-0.0020	0.0019	0.00113	0.0019	0.0066	0.0001
	(0.087)	(0.931)	(0.745)	(0.120)	(0.292)	(0.155)	(0.664)	(0.096)	(0.591)	(0.550)	(0.312)	(0.274)	(0.167)	(0.979)
Year/ Co	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	21.04%	44.69%	7.71%	8.67%	9.39%	18.55%	0.95%	24.05%	45.47%	7.96%	13.09%	12.58%	40.33%	0.71%
Panel C	**Negative watch**							**Positive watch**						
ΔLCCR	-0.07302	0.0276	-0.0194	**0.0216***	0.0119	0.0042	-0.0381	0.0519	-0.0450	0.0022	-0.0171	0.0041	-0.0287	0.0594
	(0.518)	(0.562)	(0.139)	(0.082)	(0.501)	(0.894)	(0.848)	(0.643)	(0.337)	(0.870)	(0.298)	(0.854)	(0.355)	(0.766)
CCR	-0.007	-0.0012	0.0017	0.0013	0.0016	0.0068	-0.0013	-0.0075	0.0007	0.0012	0.00159	0.0013	0.0071	-0.0036
	(0.153)	(0.746)	(0.589)	(0.268)	(0.336)	(0.147)	(0.829)	(0.146)	(0.866)	(0.674)	(0.213)	(0.406)	(0.123)	(0.584)
Year/ Co	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	21.05%	44.75%	7.50%	8.70%	9.82%	34.30%	1.02%	21.07%	44.95%	7.21%	7.54%	10.08%	33.68%	1.05%

This table reports the results of estimations of Equation (4.1) with Huber-White robust standard errors. The dependent variable is ΔIV during the time windows. The main independent variable is ΔLCCR, daily changes in the log-transformation of ratings. For the ease of interpretation, absolute value of ΔLCCR is used. p-values are reported in parentheses. *, ** denote significant at 10%, 5% level of significance. Country-matched random sampling from the full sample is used.

Table 4.5. Estimation results of Eq. (4.1) for the Moody's events

Time window	[-66, -22]	[-22,-5]	[-5,-1]	[-1,1]	[1,5]	[5,22]	[22,66]	[-66,-22]	[-22,-5]	[-5,-1]	[-1,1]	[1,5]	[5,22]	[22,66]
Panel A				**Downgrade**							**Upgrade**			
ΔLCCR	0.0448	**-0.0327****	0.0195	0.0019	**-0.0248****	0.0101	0.0014	-0.9433	0.4813	**-0.0707****	0.0106	**0.0615****	-0.0118	0.0112
	(0.105)	(0.026)	(0.131)	(0.859)	(0.037)	(0.620)	(0.945)	(0.178)	(0.119)	(0.035)	(0.333)	(0.016)	(0.761)	(0.762)
CCR	-0.0015	-0.0021	0.0005	0.0006	0.0016	0.0029	0.0011	-0.0316	0.0122	-0.0005	0.0006	**0.0024***	0.0028	-0.0003
	(0.607)	(0.298)	(0.702)	(0.426)	(0.102)	(0.299)	(0.767)	(0.140)	(0.205)	(0.756)	(0.478)	(0.053)	(0.374)	(0.930)
Year/ Co	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	34.72%	25.84%	6.86%	7.16%	7.61%	33.21%	1.02%	28.58%	49.56%	8.29%	7.02%	12.97%	32.98%	1.02%
Panel B				**Negative outlook**							**Positive outlook**			
ΔLCCR	0.4498	-0.2165	**0.0372***	0.0029	**-0.0371****	0.0118	-0.0078	-0.5782	0.2853	-0.0393	-0.0144	**0.0412****	-0.0110	-0.0182
	(0.194)	(0.156)	(0.078)	(0.771)	(0.023)	(0.548)	(0.742)	(0.235)	(0.190)	(0.168)	(0.116)	(0.047)	(0.669)	(0.459)
CCR	-0.0186	0.0061	-2.2E-05	0.0007	**0.0018***	0.0027	0.0009	-0.0207	0.0082	-0.0005	0.0007	**0.0019***	0.0033	-0.0007
	(0.210)	(0.351)	(0.986)	(0.373)	(0.086)	(0.318)	(0.794)	(0.216)	(0.279)	(0.715)	(0.418)	(0.085)	(0.262)	(0.856)
Year/ Co	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	24.85%	46.93%	7.79%	7.06%	12.52%	33.33%	1.03%	25.46%	47.73%	7.84%	7.46%	12.93%	33.51%	1.05%
Panel C				**Negative watch**							**Positive watch**			
ΔLCCR	0.5181	-0.2685	**0.0439***	0.0041	**-0.0328***	0.0041	0.0137	-0.5241	0.2622	-0.0304	-0.0045	**0.0285***	0.0053	0.0027
	(0.216)	(0.160)	(0.098)	(0.711)	(0.052)	(0.860	(0.570)	(0.242)	(0.194)	(0.209)	(0.694)	(0.093)	(0.726)	(0.932)
CCR	-0.0214	0.0084	-0.0003	0.0006	**0.0018***	0.0030	-0.0004	-0.0159	0.0051	-0.0003	0.0007	**0.0020***	0.7260	0.0004
	(0.202)	(0.264)	(0.846)	(0.490)	(0.098)	(0.295)	(0.918)	(0.217)	(0.382)	(0.811)	(0.367)	(0.051)	(0.346)	(0.923)
Year/ Co	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	25.28%	47.56%	7.84%	6.74%	11.82%	33.01%	1.02%	24.98%	47.13%	7.80%	6.98%	11.82%	33.36%	1.00%

This table reports the results of estimations of Equation (4.1) with Huber-White robust standard errors. The dependent variable is ΔIV during the time windows. The main independent variable is ΔLCCR, daily changes in the log-transformation of ratings. For the ease of interpretation, absolute value of ΔLCCR is used. p-values are reported in parentheses. *, ** denote significant at 10%, 5% level of significance. Country-matched random sampling from the full sample is used.

Table 4.6. Estimation results of Eq. (4.1) for the Fitch events

Time window	[-66, -22]	[-22,-5]	[-5,-1]	[-1,1]	[1,5]	[5,22]	[22,66]	[-66,-22]	[-22,-5]	[-5,-1]	[-1,1]	[1,5]	[5,22]	[22,66]
	Downgrade							**Upgrade**						
ΔLCCR	0.0462	0.0425	-0.0124	**-0.0222***	-0.0108	-0.0107	-0.0254	0.0056	0.0275	-0.0282	0.0050	0.0056	-0.0604	0.0101
	(0.206)	(0.341)	(0.636)	(0.062)	(0.636)	(0.607)	(0.389)	(0.886)	(0.498)	(0.267)	(0.780)	(0.705)	(0.346)	(0.877)
CCR	0.0008	-0.0011	-0.0006	0.0014	0.0007	**0.0061***	-0.0007	0.0014	-0.0023	-0.0003	0.0019	0.0003	**0.0071***	0.0003
	(0.825)	(0.701)	(0.796)	(0.313)	(0.655)	(0.068)	(0.895)	(0.721)	(0.450)	(0.903)	(0.206)	(0.883)	(0.066)	(0.962)
Year/ Co	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	20.92%	44.68%	7.34%	7.18%	9.66%	40.84%	0.78%	20.91%	44.70%	7.27%	7.49%	9.33%	33.89%	1.01%
	Negative outlook							**Positive outlook**						
ΔLCCR	**0.0475***	0.0190	-0.0105	-0.0109	-0.0056	0.0243	-0.0480	**-0.0694****	-0.0425	0.0027	0.0119	0.0002	-0.0174	0.0176
	(0.099)	(0.664)	(0.657)	(0.422)	(0.764)	(0.515)	(0.164)	(0.032)	(0.373)	(0.934)	(0.413)	(0.994)	(0.546)	(0.575)
CCR	-0.0005	-0.0015	-0.0003	0.0009	0.0005	**0.0071****	-0.0033	0.0018	0.0001	-0.0007	0.0020	0.0004	**0.0071***	0.0001
	(0.884)	(0.621)	(0.885)	(0.482)	(0.770)	(0.052)	(0.526)	(0.644)	(0.963)	(0.787)	(0.194)	(0.815)	(0.068)	(0.986)
Year/ Co	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	20.97%	44.67%	7.81%	7.27%	9.46%	33.69%	1.03%	20.88%	44.99%	7.49%	7.74%	9.10%	42.31%	0.82%
	Negative watch							**Positive watch**						
ΔLCCR	0.0478	0.0298	0.0007	-0.0188	-0.0036	0.0244	-0.0353	**-0.0469***	-0.0238	0.0030	0.0115	0.0054	-0.0259	0.0389
	(0.120)	(0.480)	(0.978)	(0.119)	(0.840)	(0.507)	(0.276)	(0.098)	(0.570)	(0.901)	(0.367)	(0.760)	(0.472)	(0.242)
CCR	0.0008	-0.0017	-0.0008	0.0019	0.0007	**0.0068***	-0.0001	0.0002	-0.0014	-0.0002	0.0008	0.0005	**0.0072****	-0.0032
	(0.829)	(0.592)	(0.732)	(0.182)	(0.665)	(0.072)	(0.993)	(0.959)	(0.648)	(0.906)	(0.535)	(0.745)	(0.048)	(0.547)
Year/ Co	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	20.92%	44.65%	7.05%	7.60%	9.34%	33.49%	1.02%	20.93%	44.66%	7.04%	7.28%	9.53%	33.57%	1.02%

This table reports the results of estimations of Equation (4.1) with Huber-White robust standard errors. The dependent variable is ΔIV during the time windows. The main independent variable is ΔLCCR, daily changes in the log-transformation of ratings. For the ease of interpretation, absolute value of ΔLCCR is used. p-values are reported in parentheses. *, ** denote significant at 10%, 5% level of significance. Country-matched random sampling from the full sample is used.

Table 4.7. Results of the Monte Carlo experiment

Time window	[-66, -22]	[-22,-5]	[-5,-1]	[-1,1]	[1,5]	[5,22]	[22,66]
Panel A: S&P rating news							
ΔLCCR	0.0346	-0.0282	0.0111	**-0.0202****	-0.0058	0.0121	0.0207
	(0.322)	(-0.443)	(1.092)	(-2.038)	(-0.425)	(0.581)	(0.576)
Year/Co dummies & CCR	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	39.78%	42.11%	19.02%	12.62%	16.57%	30.53%	36.39%
N	253	256	262	262	259	256	248
No. of estimations	10,000	10,000	10,000	10,000	10,000	10,000	10,000
Panel B: Moody's rating news							
ΔLCCR	-0.3203	0.1994	-0.0291	-0.0042	**0.0339****	-0.0088	0.0038
	(-1.329)	(1.381)	(-1.592)	(-0.438)	(1.984)	(-0.418)	(0.167)
Year/Co dummies & CCR	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	41.72%	43.37%	19.67%	11.80%	18.02%	29.86%	36.65%
N	253	256	263	262	259	256	249
No. of estimations	10,000	10,000	10,000	10,000	10,000	10,000	10,000
Panel C: Fitch rating news							
ΔLCCR	-0.0428	-0.0207	0.0128	0.0111	-0.0024	-0.0196	0.0301
	(-1.219)	(-0.457)	(0.575)	(0.968)	(-0.154)	(-0.568)	(0.880)
Year/Co dummies & CCR	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	39.92%	41.82%	18.73%	12.03%	16.29%	29.94%	36.61%
N	254	256	263	262	259	256	249
No. of estimations	10,000	10,000	10,000	10,000	10,000	10,000	10,000

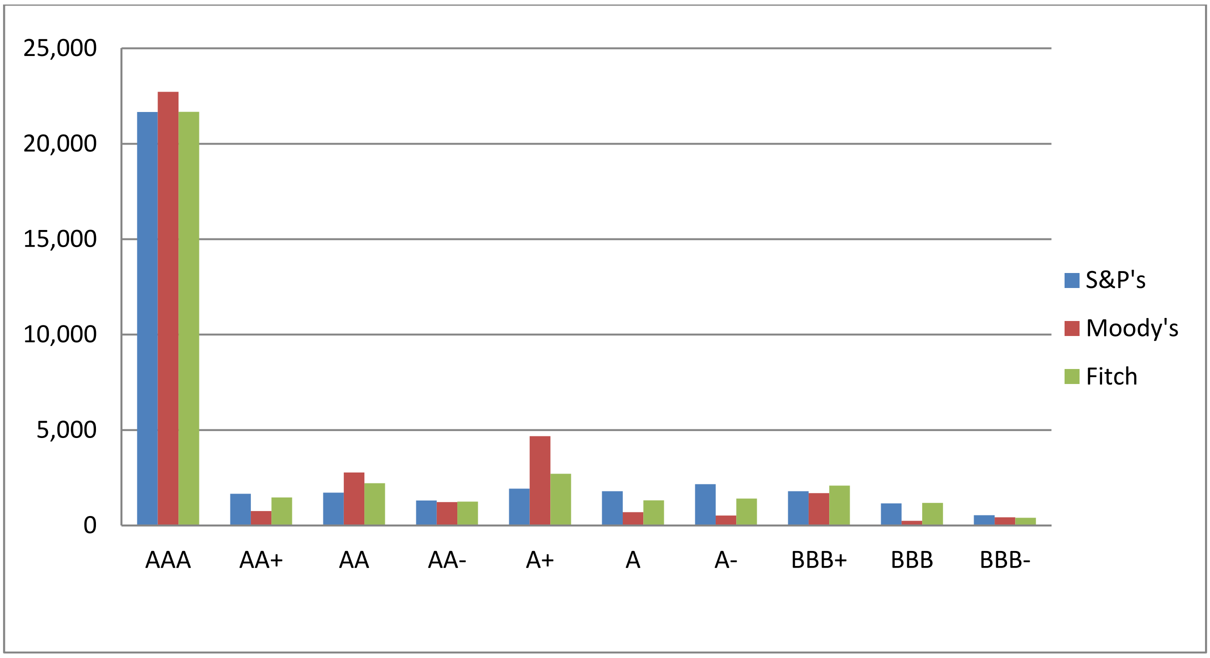
This table reports the averages across all 10,000 estimations of Equation (4.1) with Huber-White robust standard errors. The dependent variable is ΔIV during the time windows. The main independent variable is ΔLCCR, daily changes in the log-transformation of ratings. Each estimation of the equation is based on one independent random country-matched sampling. t-statistics are reported in parentheses. ** denotes significant at 5%. N reports maximum number of observations for one estimation as this number varies slightly between estimations. The estimated coefficients of CCR are not reported for ease of presentation. Different to Tables 4.4-4.6, I do not use absolute value of ΔLCCR here.

Table 4.8. Results of log-likelihood tests of causality between rating actions and implied volatility

	Null hypothesis			Null hypothesis			Null hypothesis		
k = 5 i.e. lags within 1 week	ΔIV does not cause S&P actions	LR-val.	**11.09****	ΔIV does not cause Moody's actions	LR-val.	3.75	ΔIV does not cause Fitch actions	LR-val.	6.88
		p-val.	0.0495		p-val.	0.5853		p-val.	0.2299
	S&P actions do not cause ΔIV	LR-val.	7.71	Moody's actions do not cause ΔIV	LR-val.	7.87	Fitch actions do not cause ΔIV	LR-val.	4.02
		p-val.	0.1730		p-val.	0.1637		p-val.	0.5470
k = 22 i.e. lags within 1 month	ΔIV does not cause S&P actions	LR-val.	**50.60*****	ΔIV does not cause Moody's actions	LR-val.	20.02	ΔIV does not cause Fitch actions	LR-val.	**44.73*****
		p-val.	0.0005		p-val.	0.5818		p-val.	0.0029
	S&P actions do not cause ΔIV	LR-val.	30.13	Moody's actions do not cause ΔIV	LR-val.	10.85	Fitch actions do not cause ΔIV	LR-val.	11.02
		p-val.	0.1153		p-val.	0.9769		p-val.	0.9744
k = 66 i.e. lags within 3 months	ΔIV does not cause S&P actions	LR-val.	**107.90*****	ΔIV does not cause Moody's actions	LR-val.	80.46	ΔIV does not cause Fitch actions	LR-val.	**108.38*****
		p-val.	0.0009		p-val.	0.1087		p-val.	0.0008
	S&P actions do not cause ΔIV	LR-val.	**116.17*****	Moody's actions do not cause ΔIV	LR-val.	45.7	Fitch actions do not cause ΔIV	LR-val.	51.56
		p-val.	0.0001		p-val.	0.9732		p-val.	0.9037

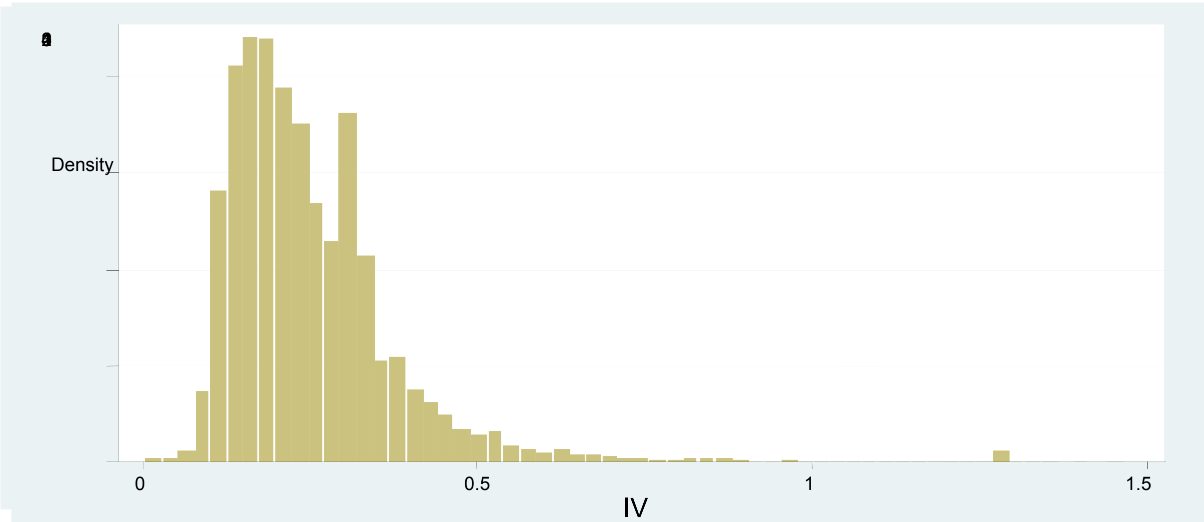
This table reports the results from log-likelihood ratio tests after estimations of Equations (4.2) and (4.3). LR reports the log-likelihood ratio from the tests of null hypothesis that ΔIV (Rating actions) do not cause Rating actions (ΔIV). p-val. reports the p-values from the tests. **, *** denote significance at 5%, 1% levels.

Figure 4.1: Distribution of daily rating observations



Moody's symbols (i.e. Aaa, Aa1, Aa2 ... Baa3) are categorised in equivalent S&P and Fitch ratings categories (i.e. AAA, AA+, AA, ... BBB-). The dataset covers 24 countries during the period from January 2000 to April 2012. I include all countries with traded stock index options, except for 5 countries without any rating actions during the sample periods (Canada, Malaysia, Norway, Sweden and Switzerland) and Greece whose stock index option market is very small.

Figure 4.2: Daily observations of 30-day maturity implied volatility



The dataset covers 24 countries during the period from January 2000 to April 2012. There are 35,683 daily observations of 30-day implied volatility. Among them, there are 315 observations where IV is greater than 100% in Hungary (14/01/2003-16/6/2003), Poland (7/2001, 10-11/2001, 2-8/2002, 11/2002), and Russia (10/2008-4/2009). All (most) of these observations are associated within 1 month to at least one observation of absolute value of underlying index return larger than 1% (3%). 54% of the observations are associated with at least one observation of absolute value of the index return larger than 10%. These were periods of turbulence in the three countries. There were nine rating signals on these three sovereigns during the periods.

Figure 4.3: IV time series of some sampled countries

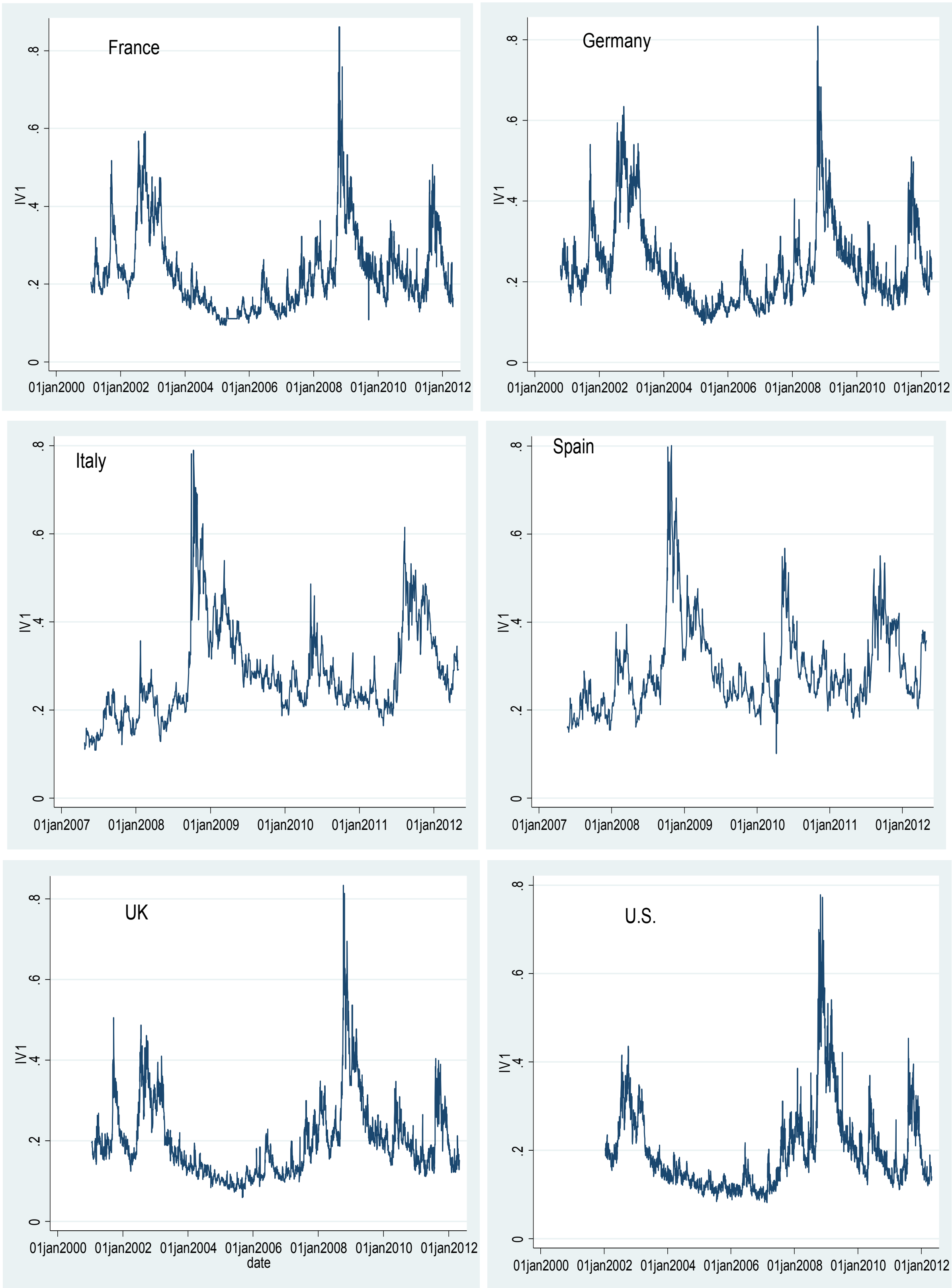
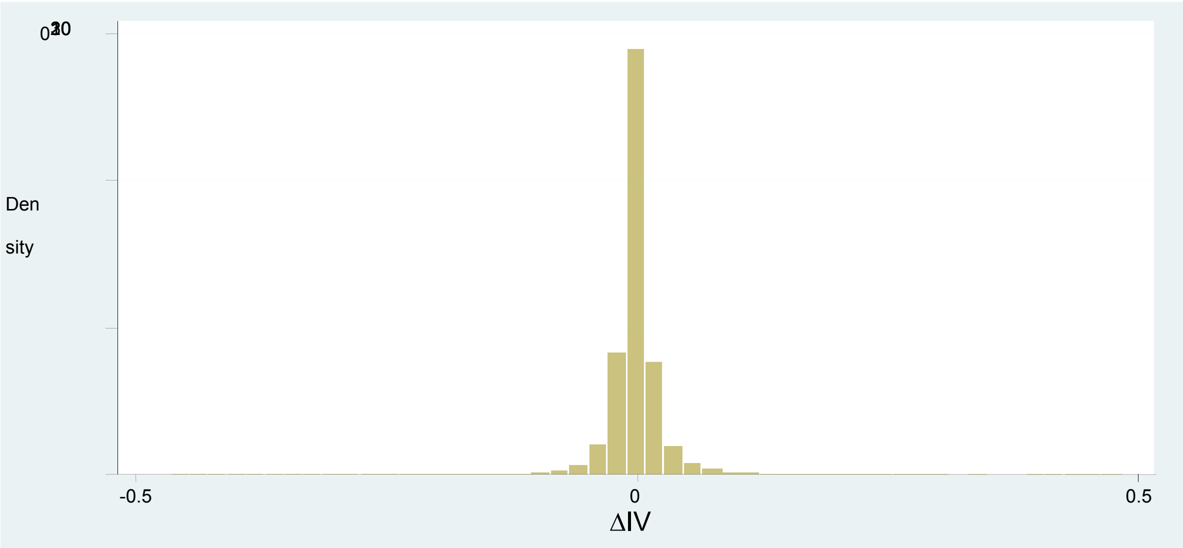


Figure 4.4: Distribution of daily changes in 30-day implied volatility



The dataset covers 24 countries during the period from January 2000 to April 2012. There are 115 observations where ΔIV is more than 20%. All (most) of them are associated within 1 month to at least one observation of absolute value of underlying index return larger than 1% (5%).

Appendix 4.1: Log-transformation of rating scale

$$LCCR = \ln\left[\frac{CCR}{32 - CCR}\right] \qquad \forall CCR \in [1,31]$$

Let's consider CCR as a variable x real and ∈ [1, 31]

we have:

$$\frac{df}{dx} = \frac{32-x}{x} * \frac{32-x+x}{(32-x)^2} = \frac{32}{x*(32-x)}$$

$$\rightarrow \frac{d^2 f}{dx^2} = \frac{-32}{x^2(32-x)^2} * (32-2x)$$

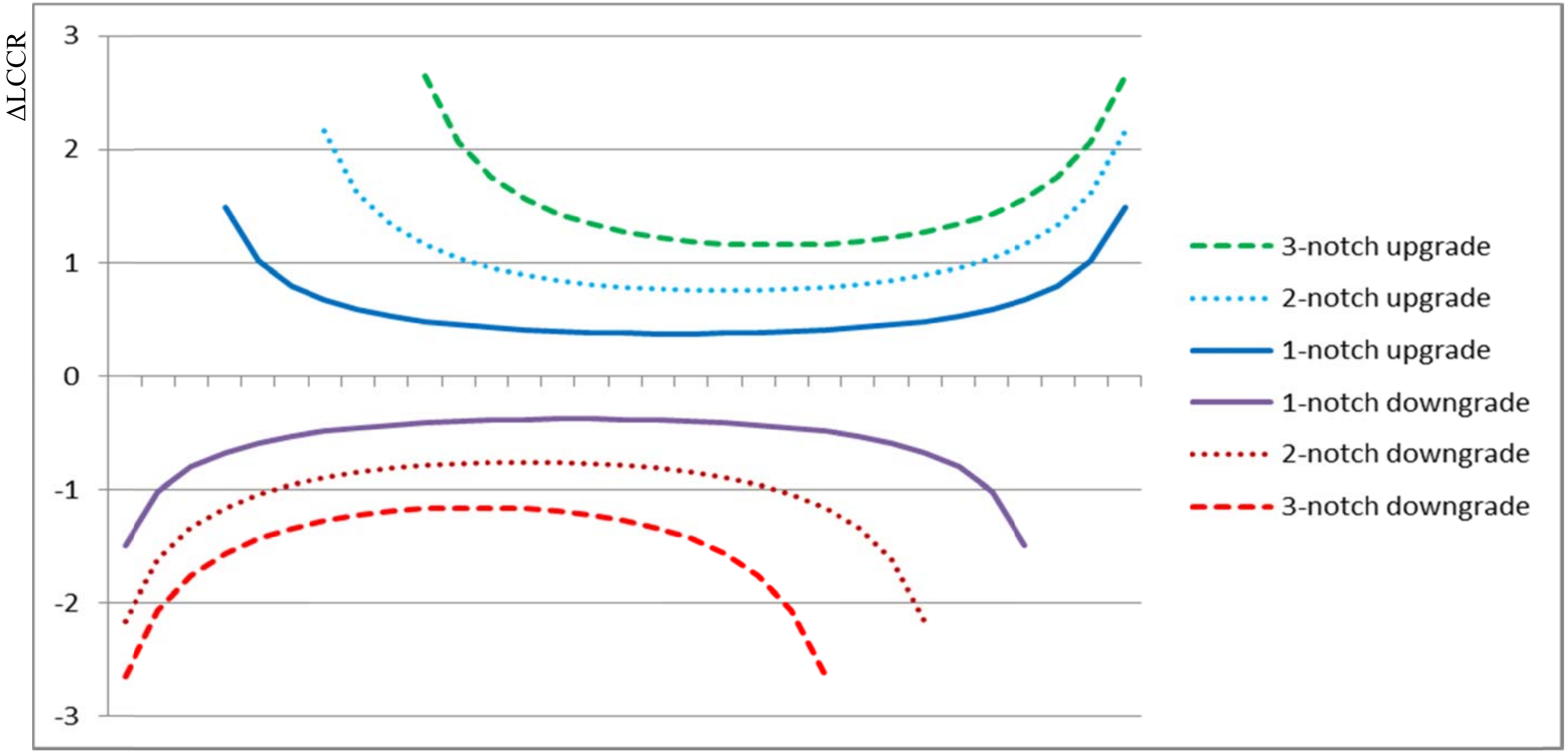
$$\rightarrow \frac{d^2 f}{dx^2} = 0 \Leftrightarrow x = 16$$

And $\rightarrow \frac{d^2 f}{dx^2}$ changes sign from negative to positive at x=16

$\rightarrow \frac{df}{dx}$ gets a minimum at 16. ΔLCCR which is $\frac{df}{dx}$ reduces when x ranges from 1 to 16, then increases when x ranges from 16 to 31.

The following figure presents a visual demonstration of how ΔLCCR changes across the rating scale. The largest changes are designed to be at the top and the bottom. In other words, rating actions on AAA and near the speculative threshold issuers are most influential on the LCCR. In contrast, actions on issuers who are in the middle of investment grades are least influential.

Figure A4.1. Effects of downgrades and upgrades on ΔLCCR



Appendix 4.2: Unit root testing

Test for unit root(s) in individual series

	Country	H_0: ΔIV contains unit root(s)				H_0: ΔIV does not contains unit root(s)
		ADF statistic	p-value	KSS t-statistic	p-value	KPSS LM-statistic
1	Australia	-20.624	0.0000	-4.26	0.000	0.080
2	Austria	-59.349	0.0000	-17.96	0.000	0.011
3	Belgium	-17.809	0.0000	-3.83	0.000	0.087
4	Brazil	-18.081	0.0000	-7.01	0.000	0.137
5	China	-27.427	0.0000	-4.18	0.000	0.040
6	Czech Republic	-33.015	0.0000	-5.20	0.000	0.094
7	Finland	-47.790	0.0000	-5.30	0.000	0.023
8	France	-44.408	0.0000	-8.39	0.000	0.022
9	Germany	-45.404	0.0000	-8.11	0.000	0.019
10	Hong Kong	-29.266	0.0000	-4.50	0.000	0.079
11	Hungary	-32.604	0.0000	-4.34	0.000	0.043
12	India	-22.919	0.0000	-5.11	0.000	0.042
13	Israel	-24.824	0.0000	-8.38	0.000	0.055
14	Italy	-31.024	0.0000	-8.15	0.000	0.040
15	Japan	-31.755	0.0000	-3.91	0.000	0.057
16	Korea	-21.030	0.0000	-5.85	0.000	0.054
17	Netherlands	-49.756	0.0000	-9.61	0.000	0.016
18	Poland	-19.092	0.0000	-2.91	0.004	0.033
19	Russia	-29.020	0.0000	-4.03	0.000	0.159
20	South Africa	-14.907	0.0000	-3.87	0.000	0.108
21	Spain	-28.194	0.0000	-5.46	0.000	0.028
22	Taiwan	-20.514	0.0000	-4.97	0.000	0.063
23	UK	-44.122	0.0000	-7.89	0.000	0.019
24	US	-50.522	0.0000	-9.59	0.000	0.025

Test for unit root(s) in whole panel

H_0: all ΔIV series contains unit root(s)	p-val. from Fisher test based on Dickey-Fuller tests	0.000
	p-val. from Im-Pesaran-Shin test	0.000
	p-val. from Choi test	0.000
H_0: Each ΔIV series does not contains unit root(s)	p-val. from Fisher test based on KPSS tests	1.000

Chapter 5: Multiple ratings and heterogeneous effects on foreign exchange market volatility

5.1. Introduction

The rating industry offers a gate-keeping role for international capital markets. Issuers seek ratings to improve the marketability of their debts while investors use ratings as a cost-effective indicator of securities' credit risk (e.g. IMF, 2010a; Bank of England, 2011). During crisis periods, financial markets are usually characterized by high volatility and sensitivity to new information. In recent years, downgrades of European sovereign ratings led to criticism of CRAs for exacerbating and/or precipitating investors' pessimistic sentiments, hence, contributing to global financial instability. In response, there have been calls for mitigating the role of credit ratings (e.g. Vernazza et al., 2014).

This paper seeks to contribute to this debate by investigating the impact of rating actions upon ex-ante uncertainty (option-implied volatility) and ex-post realised volatility in the foreign exchange (FX) market. This market is the largest and most liquid in the world with an average daily trading volume of US$5.35 trillion in April 2013 (BIS, 2013). It is also characterised by 24-hour over-the-counter (OTC) transactions and typically incorporates new information very quickly. Market volatility is directly relevant to the debate on global financial stability, while FX volatility is of crucial interest to multinational corporates, large banks, and institutional investors who are engaged in direct or indirect foreign investments.

There is a close linkage between a country's fiscal condition and its exchange rates. There is also an inconclusive debate about whether a currency depreciation or appreciation would follow fiscal expansionary shocks (e.g. Obstfeld and Rogoff, 1995; Kim and Roubini, 2008; Enders et al., 2011; Ravn et al., 2012). Meanwhile, a country's fiscal condition is widely considered as a key factor determining the sovereign credit rating level (e.g. Moody's, 2013; S&P, 2012). Recent research shows that sovereign rating news triggers significant reactions in foreign exchange rates (e.g. Alsakka and ap Gwilym, 2012a) and that there is close causality relationship between a sovereign creditworthiness and its exchange rate (e.g. Liu and Morley, 2012). Also, sovereign creditworthiness is an important determinant of FX volatility (e.g. Hui and Chung, 2011). Given the inconclusive debate on whether currency appreciation or depreciation follows fiscal shocks, I expect a strong impact of sovereign rating news on FX market uncertainty and volatility.

If rating actions are found to impact FX volatility, and hence the risk of holding a foreign currency, it would be a significant insight on the information content of rating news, given the enormous size of the FX market. Prior literature investigates the impact of credit rating news on the prices of financial assets, e.g. bonds, stocks, credit default swaps, FX rates, but has largely ignored the impact on financial markets' volatility. This chapter offers new insights by considering the influence of multiple sovereign ratings, the potential for differential effects from different CRAs, and the role of rating outlook and watch. The impact of rating news must be considered on the basis of all three CRAs, and this issue is ignored in much prior literature. The chapter demonstrates the importance of sovereign rating information in the context of first-mover as well as additional rating signals. It also highlights varying influences of rating signals from the largest three CRAs, i.e. S&P, Moody's, and Fitch, and hence illustrates the need to avoid pooling rating events from different CRAs and pooling different types of rating events (as is commonly done in prior research e.g. Kaminsky and Schmukler, 2002; Sy, 2004). A methodological contribution arises from introducing a new log-transformation of the credit rating scale which captures higher sensitivities to rating actions on issuers around the investment-speculative threshold. Several robustness checks are performed using non-parametric approaches and Monte Carlo experiments.

The main findings are summarised as follows. Firstly, sovereign rating news has a significant impact on market uncertainty in various respects depending on the type of news and across CRAs. Secondly, the impact on both ex-ante and ex-post market volatilities is statistically and economically significant. Thirdly, the FX market reactions imply that additional ratings are informative and help reduce both ex-ante market uncertainty and ex-post volatility. The magnitude of the impact on ex-post volatility is larger than upon ex-ante volatility. Finally, the insights contribute to the debate surrounding the information content of ratings and the merits of increased regulation of CRAs.

The rest of this paper is organised as follows: the next section reviews related literature, Section 5.3 describes the data, and Section 5.4 discusses the research hypotheses and methodologies. Sections 5.5 and 5.6 present the empirical results and conclusions.

5.2. The economic rationale and the market impact of sovereign ratings

Prior literature identifies a strong economic linkage between a country's exchange rates and its fiscal conditions. The classic Mundell-Fleming model and its variants predict domestic currency appreciation following exogenous fiscal expansionary shocks if a country adopts a floating exchange rate regime. In contrast, Obstfeld and Rogoff (1995) theoretically predict an immediate depreciation of a country's currency following its (even temporary) fiscal expansionary shocks. Kim and Roubini (2008) empirically demonstrate that fiscal deficit shocks lead to depreciation of the domestic currency. Based on simulations of a general equilibrium model, Enders et al. (2011) suggest that fiscal expansionary shocks depreciate the domestic currency. Their VAR model based on a dataset of industrialized countries during 1975-2005 supports the above prediction. Given the inconclusive debate on whether currency appreciation or depreciation follows fiscal shocks, I expect a strong impact of sovereign rating news on the FX market uncertainty (or volatility).

CRAs explicitly assert the relevance of a country's fiscal condition in determining its sovereign credit rating level (e.g. Moody's, 2013; S&P, 2012). For example, S&P (2012) consider, in total, five criteria in determining a country's indicative sovereign credit rating, as follows: political, monetary, external, economic, fiscal factors. Effectively, changes in a country's fiscal health are directly relevant to its credit rating. Empirical studies also confirm the relevance of fiscal balance in determining a country's credit rating level (e.g. Bennell et al., 2006; Afonso et al., 2011).

Prior empirical studies demonstrate that sovereign ratings are a key element influencing the movement of sovereign bond yield spreads (e.g. Kaminsky and Schmukler, 2002). Sovereign ratings also impose a "ceiling effect" over the creditworthiness of other entities of the same domicile (e.g. Borensztein et al., 2013; Williams et al., 2013). In addition, sovereign bond yields typically act as benchmarks to country-systematic risk, and movements in corporate bond yields are correlated to innovations in sovereign yields (Dittmar and Yuan, 2008). Sovereign rating news also affects exchange rates (Alsakka and ap Gwilym, 2012a; Do et al., 2014). Alsakka and ap Gwilym (2012a) suggest that the FX market is the channel via which sovereign rating news and equity markets are linked. To the best of my knowledge, research on the impact of sovereign rating news on FX market volatility is very sparse.[23]

Given the economic linkages between sovereign ratings, a country's fiscal conditions and its exchange rates, sovereign rating announcements are expected to impact market participants' ex-ante uncertainty as well as the ex-post volatility of the domestic currency value (i.e. the exchange rates against the U.S dollar (USD)). However, the market uncertainty

[23] Bisoondoyal-Bheenick et al. (2011) examine the impact of rating actions on FX realised volatility, but the study is based on a very small number of rating actions during the Asian crisis of 1997. They do not consider information on outlook nor watch procedures, and the overall insights are limited. Further, Afonso et al. (2014) investigate impacts of rating actions on market volatility, their contexts are bond and stock markets. Afonso et al. (2014) use daily data of bond yields, stock indices in a GARCH model. In contrast, this chapter utilises realised volatility based intraday data which is much richer. Afonso et al. (2014) is also based on only EU markets.

and the ex-post volatility do not necessarily react to negative (positive) rating news in a negative (positive) direction like financial assets' prices, as evidenced in e.g. Kaminsky and Schmukler (2002), Gande and Parsley (2005), Ferreira and Gama (2007). Another strand of literature reveals that scheduled macroeconomic news always reduces financial market uncertainty regardless of whether the news is negative or positive (e.g. Beber and Brandt, 2006, 2009). Credit rating news is not scheduled, but market participants often consult with multiple CRAs (e.g. Cantor et al., 2007; Bongaerts et al., 2012). Therefore, investors are likely to expect actions from the other CRAs after rating announcements from a 'first mover' CRA. Thus, I expect a certain degree of variation in the market reactions and FX volatility reactions to rating announcements could be in either positive or negative directions.

Prior literature focuses on examining the impact of rating actions on financial assets' prices (i.e. bond yields spreads, stock abnormal returns, exchange rates). By investigating the reactions of market volatilities, I can demonstrate that many types of rating news influence market behaviour. In that sense, rating actions do not necessarily have to incorporate private information in order to impact the market. Additional rating news could play an important role in aiding the market consensus because a strong degree of heterogeneity in market perceptions of risk inevitably exists.

5.3. Data

This study is based on an unbalanced data panel which covers 41 countries during the period from January 2007 to April 2013 as listed in Table 5.1. I include all countries whose currencies are named in BIS (2013) except for nine countries as follows: China, Hong Kong, Saudi Arabia, Denmark whose FX regimes are categorised as (crawling) pegged/fixed in at least one version of IMF de facto classifications, and Canada, Norway, Singapore, Sweden, Switzerland who did not experience any rating actions by the three largest CRAs (i.e. S&P, Moody's, and Fitch) during the sample period.[24]

5.3.1. Sovereign credit ratings

This dataset consists of daily observations of long-term foreign-currency credit ratings, outlook and watch status of sovereigns rated by Moody's, S&P and Fitch, sourced from the CRAs' publications. I convert sovereign ratings to numerical scores within a 58-point comprehensive credit rating (CCR) scale in order to capture information on both actual ratings and outlook/watch procedures. In the CCR scale, rating symbols are converted as follows: AAA/Aaa ≡ 58, AA+/Aa1 ≡ 55, AA/Aa2 ≡ 52 ... CCC-/Caa3 ≡ 4, CC-D ≡ 1. Adjustments for (positive/negative) outlook and watch signals are made by adding ±1 and ±2, respectively. Non-linearity in the rating scale is plausible, which means that the differences between rating levels are not equal. Historical observations on actual rates of default across rating categories suggest non-linearity in the rating scale (see e.g. IMF, 2010a; Moody's, 2011b; S&P, 2013). In order to control for this, I employ a logit-transformation of the rating scale, as follows:

$$LCCR = \begin{cases} \ln\left[\dfrac{CCR}{28 - CCR}\right] & \forall CCR \in [1..28] \\ \ln\left[\dfrac{(CCR - 28) * (CCR + 28)^{\sqrt{\pi}}}{59 - CCR}\right] & \forall CCR \in [29..58] \end{cases}$$

Prior literature has used a logarithm transformation of the rating scale (e.g. Sy, 2004; Alsakka and ap Gwilym, 2012a), but their transformation is different to the above. Their transformation assigns the highest weights for rating changes on AAA and near default issuers but the lowest weight for rating changes near the investment-speculative boundary. It

[24] USD is used as the reference currency given its dominance in international trades (i.e. 87% of global trades (BIS, 2013)). Therefore, USA is not included in the list of sample countries. The USA credit rating remains AAA during most of the sample period. In August 2011, S&P downgraded USA to AA+ while Moody's and Fitch kept its ratings at AAA until the end of the sample period (with negative outlook from August and November 2011, respectively).

is reasonable for creditworthiness changes to be more significant when relating to near default or triple-A rated issuers (e.g. as evidenced by the reactions to sovereign downgrades of France, UK, and USA in 2011-2013). However, the speculative threshold is of critical concern to rating users, regulators, and investment guidelines (e.g. Cantor et al., 2007; Bongaerts el al., 2012). For example, the U.S. Investment Company Act of 1940 restricts pension funds and municipalities to investment-grade securities. My log-transformation of the rating scale addresses this issue by assigning greater weight for creditworthiness changes to issuers at or near (i) triple-A; (ii) default; (iii) the speculative-investment threshold (and assigning the lowest weight when rating news is on issuers in the middle of the investment-grade or the middle of the speculative-grade). The log-transformation is derived by matching the optimisations of the derivative function of the log-transformation to specific points in the rating scale. This is a unique contribution to the ratings literature. Please see Appendix 5.1 for an illustration of how ΔLCCR changes when CCR increases/decreases.

Table 5.2 presents the numbers of sovereign rating events for each CRA. The CRAs released 521 rating events during the sample periods for the selected sovereigns. S&P released the most rating news with 202 signals. There are 166 rating announcements by Moody's while the figure is 153 by Fitch. During the sample period, there are 38 (47), 19 (36), 28 (38) positive (negative) outlook signals[25] for the sample countries by S&P, Moody's, and Fitch, respectively. The corresponding figures of watch actions are 7 (27), 12 (23), and 3 (14). There are 17 combined rating actions by S&P whereby both a rating downgrade/upgrade and outlook or watch signals are announced simultaneously. The equivalent figures from Moody's and Fitch are 28 and 14, respectively. About two thirds of rating events are within 3-point changes in the CCR scale which mean an outlook/watch

[25] Outlook signals are defined as follows. Negative (positive) outlook signals include placing a sovereign on negative (positive) outlook and changing positive (negative) to stable outlook. Watch signals are defined similarly.

announcement or a 1-notch downgrade/upgrade in isolation.[26] There are only 21 (202) rating actions by S&P, 24 (166) by Moody's, and 22 (153) by Fitch which are multiple-notch downgrades (upgrades). Most downgrades are preceded by negative outlook or watch procedure. All S&P downgrades follow negative outlook or watch while the corresponding proportions for Moody's and Fitch are 89.6% and 86.7%, respectively. The equivalent figures for upgrades are 70.4%, 89.3%, and 52.0%. These figures imply heavy utilisation of outlook/watch procedures prior to actual rating changes by the CRAs during the sample period. Along with the fact that most rating actions are 1-notch downgrades/upgrades or outlook/watch announcements in isolation, this leads to an expectation that downgrades/upgrades from some CRAs might play a "confirmation role".

5.3.2. Foreign exchange market volatility data

The dataset of OTC bilateral exchange rates against the USD covers all currencies named in BIS (2013) during the period from January 2007 to April 2013. There are 17 EU countries using the Euro, which are included in the sample depending on when they started using the Euro.[27] All the sample countries are categorised as having free floating or floating FX regimes in every IMF de facto classification since the classification began in 2006. There are two exceptions (Malaysia and Russia) categorised in "Other managed arrangement" in the IMF de facto classifications in 2010 and 2012. This category is a residual and is used when the exchange rate arrangement does not meet the criteria for any of the other categories. The final data covers 41 countries and major currencies that account for 90% of global FX market trades during the sample period (author's calculations based on BIS, 2013).

[26] Note that a 1-notch downgrade/upgrade is equivalent a 3-point change while an outlook (watch) announcement is equivalent to a 1-point (2-point) change in the CCR scale.

[27] All EU countries are included from beginning of the sample period except for Cyprus, Malta, Slovakia, and Estonia. These countries are included as follows: Cyprus and Malta from January 2008, Slovakia from January 2009, Estonia from January 2011.

I use data on 1-month maturity[28] at-the-money (ATM) option-implied volatility (IV) and intraday realised volatility (RV) to capture FX market volatility. IV measures the FX option market participants' expected volatility of the underlying exchange rates over the next month. In other words, IV represents ex-ante market uncertainty about the value of a currency against the USD. Meanwhile, RV measures the ex-post volatility of spot exchange rates and represents the degree of disagreement between FX market participants about the value of a currency against the USD on a given day.

Daily data of mid-quoted OTC FX 1-month maturity ATM IV is retrieved from DataStream (the primary source is Thomson Reuters). In OTC FX markets, dealers typically quote implied volatilities (rather than option premiums) which in turn can be converted to call or put options premiums using the Garman and Kohlhagen (1983) version of the Black-Scholes model (see e.g. Carr and Wu, 2007; Burnside et al., 2011; Chalamandaris and Tsekrekos, 2011 for more details).[29] Figure 5.1a presents the distribution of the 1-month maturity IV. During the sample period, there are 64,715 daily observations of 1-month IV. There are 83 observations where IV is greater than 50% in Brazil, Indonesia, Korea, South Africa (during October – November 2008), Mexico (during October 2008), and Poland (during December 2008). Figure 5.1b presents the distribution of daily changes in the 1-month maturity IV. The changes are very much centred around zero with a mean of -0.0013, median of 0, and standard deviation of 0.7962.[30] This is consistent with the view that IV cannot be forecasted (e.g. Konstantinidi et al., 2008).

[28] Investigations on IVs for other maturities (i.e. 3-, 6-month, 1-year) produce qualitatively similar results (reported in Appendix Table A5.2.2).

[29] The key difference between the Garman-Kohlhagen and Black-Scholes models is the role of risk-free interest rates. Garman and Kohlhagen (1983) consider domestic and foreign risk-free interest rates and compare the advantages of holding an FX option and its underlying currency based on the no-arbitrage principle. ATM IVs are for delta-neutral straddles which consist of call and put options with same maturities and strike prices. In the Garman-Kohlhagen model, selecting strike prices close to spot FX rates makes the straddles delta-neutral.

[30] 0.1% winsorisation is used in order to mitigate the effects of outliers while avoiding information loss.

RV derived from intraday spot exchange rates contains relevant information regarding the future evolution of assets' volatility, and is an unbiased and efficient estimator of future theoretical latent volatility (e.g. Andersen et al., 2001a, b, 2003a). Daily RV data is collected from Bloomberg.[31] RV is estimated based on 30-minute frequency spot FX rates using the following formula:[32]

$$RV_t = \sqrt{\sum_{k=1}^{48} r_{k,t}^2}$$

RV_t is FX realised volatility at day t, and $r_{k,t}$ is the k^{th} 30-minute FX log-return at day t.

Given the construction of RV, different behaviour of RV compared to IV in response to news would be expected. Let us assume that pertinent information is released today which triggers a significant movement in intraday FX rates, and hence RV would increase today. Tomorrow, RV would tend to reduce if no other pertinent information is released (as intraday FX returns stabilise or even approach zero). In contrast, IV would remain at a similar level if no other pertinent information was released. Therefore, RV is very sensitive to new information and offers a powerful tool to examine the existence of an influence of rating news (if any). Moreover, RV represents the ex-post variance of intraday log-returns on a given day under the assumption that prices follow a semi-martingale process (Andersen et al., 2003a), and therefore measures the degree of disagreements between market participants within a given trading day.

There are 58,994 daily observations of RV. Figure 5.2a presents the distribution of RV. During the sample period, there are 218 observations where RV is greater than 50% in Australia, Brazil, Chile, Colombia, Indonesia, Japan, Korea, Mexico, New Zealand, South Africa, Turkey during October and November 2008 and Russia in January 2009. Figure 5.2b

[31] Bloomberg started recording RV based on intraday data from March 2007. Therefore, the dataset of RV covers the period from March 2007 to April 2013 compared to January 2007 to April 2013 for IV.
[32] Andersen et al. (2003a) use the 30-minute frequency as a satisfactory balance between the accuracy of RV measurement and avoiding market microstructure frictions.

presents the distribution of daily changes in RV. The mean, median, and standard deviation are -0.0021, -0.0468, and 5.2871, respectively.[33] Compared to daily changes in 1-month maturity IV, the standard deviation of daily changes in RV is almost 7-times larger. This indicates a much more volatile distribution and implies higher sensitivity of RV to news than IV during the sample period (consistent with some prior studies e.g. Christensen and Prabhala, 1998). This is also reasonable since RV measures ex-post volatility or market participants' disagreements on a day when news is released, whereas IV measures the expected volatility or market participants' ex-ante uncertainty over a longer period, i.e. with a horizon of the following month after a news event.

5.4. Hypotheses and methodological framework

5.4.1. Immediacy of the impact of sovereign rating news

H_1: Credit rating news triggers significant movements in FX market volatility. Therefore, changes in the volatility measurements during or after rating events are statistically different from zero.

A standard event study is used to examine changes in the market volatility during time windows around rating announcements. The time windows are [-1, 0], [0, 1], [1, 5] in order to mitigate the information contamination problem. t=0 denotes the day when a rating announcement is released.[34] The reverse direction of causality is not realistic, i.e. it is implausible that very short-run changes in FX market volatility will trigger rating actions, and I found no CRA press release which mentioned this as a factor in rating actions. Therefore, I do not report results for pre-event windows, such as [-5, -1].

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[33] As for IV, 0.1% winsorisation is used.

[34] It is noteworthy that [-1, 0] and [0, 1] windows are equivalent to one-day windows ([0, 0] and [1, 1]) in other studies which examine financial asset returns. For example, an asset return during the [0, 0] window incorporates information about the asset's prices in day -1 and day 0.

The OTC FX market is 24 hours and can incorporate new information very quickly. Therefore, I use both [-1, 0] and [0, 1] windows to capture the market reactions following releases of rating news. The primary data source is Thomson Reuters which quotes the closing FX prices at 16:30 GMT. As a result, the [-1, 0] ([0, 1]) window captures the responses of RV and IV to rating news which is released before (after) 16:30 GMT. In my sample, most countries belong to time zones earlier than GMT+00; only six countries (i.e. Brazil, Canada, Chile, Colombia, Mexico, Peru) are after the GMT+00 time zone. CRAs' releasing offices are usually located in geographic proximity to the rated countries. Therefore, rating news is likely to be released before 16:30 GMT. Moreover, London is by far the largest centre for FX trades (around 40% of global trading, BIS (2013)). Thus, the FX market responses (if any) are most likely to materialise in the [-1, 0] window.

Prior literature shows that there is no significant evidence of option-implied volatility forecastability (e.g. Konstantinidi et al., 2008). FX rates are often assumed to follow a martingale process (e.g. Andersen et al., 2003a). Therefore, I examine changes in IV and RV rather than modelling expected and abnormal elements in the changes.

In order to avoid any possible bias due to the distribution of the sample mean of changes in volatilities, non-parametric tests are employed as robustness checks. The non-parametric tests are sign- and Wilcoxon tests, testing whether the medians of the changes in volatilities during the time windows are significantly different to zero. Rating news from each CRA is used separately in order to examine if there are varying impacts between the CRAs.

The tests in this section cannot control for macroeconomic fundamentals and treat ratings linearly. In other words, the tests are based on assumptions that rating actions on different levels of creditworthiness would trigger similar market reactions (if any). This limitation will be dealt with by the later methodology. Moreover, it is important to investigate whether rating actions impose any significant impact in longer time windows. Increasing the length of time windows encounters rating clustering and information contamination problems. Therefore, regression methods will be used in the next section.

It is highly unlikely for important monetary policy announcements and rating news to be released coincidentally on the same day. I have also investigated base interest rate changes during the sample period.[35] There were 3 (2) base interest cuts (increases) announcements on the same day as a sovereign rating event from any CRA during the sample period. The number of equivalent announcements within one week around a rating event is 33 (13). In the regressions, I also include reference interest rate changes as part of the robustness checks.

5.4.2. Duration of the impact of rating news

H_2: The impact of rating news (if any) is not short-lived and changes in the volatility measurements during days after rating events are statistically different from zero.

To examine H_2, I estimate the following equations:

$$\Delta IV_{i,s} = \alpha + \beta * \Delta LCCR_{i,t} + \gamma * CCR_{i,t} + \varsigma * C + \xi * Y + u_{i,t} \tag{5.1}$$

$$\Delta RV_{i,s} = \alpha + \beta * \Delta LCCR_{i,t} + \gamma * CCR_{i,t} + \varsigma * C + \xi * Y + u_{i,t} \tag{5.2}$$

$\Delta IV_{i,s}$ is the log-change in IV on the USD exchange rate of sovereign *i* during the time window *s*, where *s* is [-1, 0], [0, 1], [1, 5], [5, 22]. Day 0 denotes event days.

$\Delta RV_{i,s}$ is the log-change in RV on the USD exchange rate of sovereign *i* during the time window *s*.

$\Delta LCCR_{i,t}$ represents changes in the log-transformed rating of sovereign *i* at day *t*. For ease of interpretation, absolute values of $\Delta LCCR_{i,t}$ are used for negative credit signals.

CCR is the Comprehensive Credit Rating. CCR is included as an explanatory variable to control for macroeconomic news and other fundamentals of the rated sovereigns. As

[35] The reference interest rate changes are collected from Bloomberg and the central bank websites (for countries where this is not available via Bloomberg).

macroeconomic and other fundamentals are determinants of sovereign ratings, the inclusion of ratings, in addition to country and year dummies, helps control for the likelihood that IV or RV might be more volatile in countries with weak macroeconomic conditions. Therefore, including CCR reduces the omitted variable bias.

C and Y are full vectors of country and year dummies.

Estimations of Eq. (5.1) and Eq. (5.2) are based on event days plus a country-matched random sample, drawn from the full sample after excluding non-event observations within one month around rating announcements.[36] This is done in order to mitigate rating clustering and market noise issues (see Ferreira and Gama, 2007).[37] There are several reasons for choosing regressions of IV and RV instead of a model from the GARCH family. First, there are limited credit rating events on each country. In this Chapter, the sample is dominated by countries whose currencies are major in international trades (i.e. named in BIS (2013)). Even for emerging countries, credit rating events happen once every several months at the highest frequency. Second, prior papers using the multivariate GARCH family of models usually employ very few time series of dependant variables (e.g. Engle et al., 1990; Andersen et al., 2003b). In this Chapter, there are 41 time series of IV and 41 time series of RV. This would cause substantial difficulties in generating feasible estimation and sensible economic interpretations.

In order to consider possible varying impact across CRAs' actions, I estimate Eq. (5.1) and Eq. (5.2) for each CRA separately. For each CRA, there are six separate estimations for different types of signals (i.e. downgrades, upgrades, negative and positive outlook and watch signals) in order to investigate the varying market reations (if any).

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[36] Please note that the data sample for estimation consists of observations on non-consecutive days that may be very distant from each other. Therefore, the estimations are not time series investigations.

[37] Estimations based on the full sample produce qualitatively similar results. In these estimations, lagged values of dependent variables (ΔIV and ΔRV) are included (see Appendix Table A5.2.3).

As robustness checks, I perform Monte Carlo experiments based on 10,000 estimations of Eq. (5.1) and Eq. (5.2). Each estimation is based on one independent country-matched random sample. The estimations are for each CRA separately in order to consider varying impact across CRAs' actions (if any). For each CRA, there are two separate estimations based on grouping negative (positive) rating actions together.

5.5. Empirical results

5.5.1. Immediate impact

Table 5.3 presents the results of the event study for IV. In general, rating actions are influential and reactions (if any) of the IV are short-lived, i.e. significant during either the [-1, 0] or [0, 1] time windows. There is evidence of varying behaviour across CRAs' actions. Panel A reports reactions of the IV to S&P rating actions. The IV reacts significantly to S&P negative actions while the impact of S&P positive news is muted. S&P downgrades, negative outlook, and negative watch announcements trigger immediate increases of approximately 1.3% in the IV. The reactions to S&P actions are in line with prior research which finds limited effects of S&P positive news while S&P negative news affects financial markets in a negative direction (e.g. Gande and Parsley, 2005; Ferreira and Gama, 2007).

In contrast, negative and positive news from both Moody's and Fitch are influential on IV. Outlook signals from both CRAs trigger increases in IV regardless of the content of the announcements. The IV increases by 3.28% (0.97%) in response to Moody's positive (negative) outlook announcements while the equivalent figures for Fitch are 1.1% (1.91%). Moody's and Fitch downgrades impact the IV in opposite directions. While Moody's downgrades induce a minimal increase of 0.70% in IV, Fitch downgrades trigger a significant decrease of 2.09%. The reduction in IV in response to Fitch downgrades is unexpected. Why do market participants consider domestic currencies of countries currently downgraded, i.e. lower credit quality, less uncertain? Lower quality is usually associated with higher expected volatility. One possible justification is that the market participants consult with multiple CRAs (e.g. Cantor et al., 2007) and Fitch actions are considered as additional information (e.g. Bongaerts et al., 2012) which confirm the market consensus on the creditworthiness of rated sovereigns. To some extent, this resonates with Beber and Brandt (2006, 2009) who reveal that scheduled (even negative) macroeconomic news always reduces market uncertainty. While sovereign rating news is not scheduled, it is rational for investors to expect actions from the other CRAs after a 'first-mover' downgrade from one CRA.

Table 5.4 reports reactions of RV to rating actions. Similar to Table 5.3, there is evidence of varying market reactions across CRAs but with larger magnitude (compared to IV reactions). This is reasonable because RV captures ex-post volatility or market participants' disagreements on the day when rating news is released. The formula for constructing RV indicates high sensitivity to new information (see Section 5.3.2).

Generally, RV reacts more significantly to S&P and Moody's actions than Fitch actions, where only reactions to downgrades are statistically significant. S&P downgrades, upgrades, and negative watch announcements trigger immediate increases in RV of 11.69%, 45.99%, and 6.78%, respectively. Moody's negative news also triggers immediate increases in RV. The magnitude of the increases is larger than those in response to S&P negative news. This is potentially due to the larger number of Moody's multiple-notch downgrades compared to those from S&P (see Table 5.2). The RV increases during [-1, 0] then reduces on the following day. Increases followed by decreases on consecutive days serve to confirm a genuine event day given the formula for RV (see Section 5.3.2). The magnitude of the reduction is approximately half of the previous increase. Moody's positive news triggers by far the largest reactions in RV.

Fitch downgrades induce an immediate average decrease of 9.16% in RV. The reduction in RV in response to Fitch negative news (i.e. downgrades) is unexpected yet similar to the reduction of IV in response to Fitch downgrades in Table 5.3. This strengthens the above argument that the market participants consult with multiple CRAs and Fitch actions are considered as additional information which could play a "confirmation role".

An important remark on Tables 5.3 and 5.4 is that market responses (if any) to rating actions from all the CRAs are immediate. The responses are of the same sign, i.e. IV, RV increase, except for the reductions in response to Fitch downgrades. The results suggest that the information content of rating signals for the FX market depends on CRAs rather than only on whether they are positive or negative.

5.5.2. How long does the impact on IV last?

Table 5.5 reports the estimated coefficients of Eq. (5.1). It should be noted that 1-unit changes in the CCR are associated with varying effects on the LCCR depending on the starting level of a sovereign rating. For example, 1-notch downgrades on AAA or BBB-[38] sovereigns, respectively, imply 1.56-unit or 1.66-unit decreases in the LCCR while 1-notch downgrades on A+ or A[39] sovereigns imply 0.46-unit decreases. Negative outlook (watch) signals on AAA sovereigns translate to 0.75-unit (1.21-unit) LCCR decreases while equivalent signals on A+ or A sovereigns translate to much weaker reductions in the LCCR of approximately 0.15-unit (0.30-unit).

Panel A of Table 5.5 shows that S&P negative news is influential in the market whereas S&P positive news is not, except for positive outlook announcements. The only time window where the coefficient of ΔLCCR is significant is [-1, 0] for negative news (and [5, 22] in the case of positive outlook), implying immediate and short-lived effects of S&P's negative events. S&P's negative actions trigger increases in IV of 3.57% or 3.80% in response to 1-notch downgrades of AAA or BBB- sovereigns (1.56*0.0229 or 1.66*0.0229). Negative outlook announcements on AAA sovereigns increase IV by 1.64% (0.75*0.0219), while negative watch signals increase IV by 2.77% (1.21*0.0229). On the other hand, S&P positive outlook announcements on AA+ sovereigns induce a reduction of 9.45% in IV (0.75*0.126), but the reduction is not immediate. S&P often lags in positive sovereign rating

[38] This is the lowest rating category in the investment grade. In other words, 1-notch downgrades will put BBB- issuers into the speculative grade.
[39] A+ and A are rating categories in the middle of the investment grade. Effects of rating news on issuers around the middle of the speculative grade are very similar (within the log-transformation).

actions compared to Moody's (e.g. Alsakka and ap Gwilym, 2010a, 2012a), hence this may indicate "confirmation". Coefficients of CCR are insignificant, inferring that the current level of creditworthiness does not explain the dynamics of IV.

Panel B of Table 5.5 reports the market reactions to Moody's actions. Responses to Moody's downgrades are not immediate but from one week to one month later. Unexpectedly, the IV does not increase but significantly reduces in response to Moody's downgrades. The magnitude of the reduction is similar to the reactions to S&P downgrades, i.e. IV reduces 3.48% or 3.70% in response to 1-notch downgrades of AAA or BBB- sovereigns (1.56*0.0223 or 1.66*0.0223). The hypothesis of the "confirmation role" of rating actions is again supported, since Moody's often lags behind S&P in sovereign downgrades (Alsakka and ap Gwilym, 2010a). Meanwhile, Moody's upgrades trigger immediate reductions in IV. The magnitude of the reduction is almost double the magnitude of the reaction to Moody's downgrades. For example, IV reduces 7.16% or 7.62% in response to 1-notch upgrades of AA+ or BB+ sovereigns (1.56*0.0459 or 1.66*0.0459). Most of Moody's upgrades (89%) are preceded by a positive outlook/watch status for that issuer, and all upgrades are 1-notch. Therefore, it could be argued that the main informational content of the news was brought to the public domain by the prior outlook/watch announcements. As a result, Moody's upgrades by the time of announcements bring no surprise content to the market. Instead, they play a "confirmation role" and reduce the market uncertainty.

Moody's outlook and negative watch announcements trigger immediate increases in the market uncertainty. However, there is evidence that the market overreacts to Moody's negative outlook/watch signals while this is not the case for the positive counterparts. After immediate increases, the market stabilises and IV reduces significantly within one month. One important remark is that the magnitude of the subsequent reduction is larger than the immediate increases in IV. For example, the IV increases 1.31% when Moody's releases a negative watch on an Aaa sovereign (1.21*0.0108). Subsequently, the IV readjusts and reduces almost 6.64% within one week (1.21*0.0549). On the other hand, Moody's positive outlook actions trigger large immediate increases in the market uncertainty, consistent with my argument over the information content of Moody's upgrades. IV jumps 7% (0.75*0.0937) in response to positive outlook signals on AA+ sovereigns.

Panel C of Table 5.5 shows that Fitch downgrades trigger an immediate reduction in IV. On average, IV reduces over 1% in response to Fitch 1-notch downgrades of AAA or BBB- sovereigns (1.56*0.0073 or 1.66*0.0073). In contrast, Fitch outlook/watch signals trigger increases in IV. The increases are immediate in response to negative outlook/watch news but later within 1 week in response to the positive counterparts. The market over-reacts to Fitch negative outlook signals, i.e. significant reductions within one month follow immediate increases in IV. The magnitude of the subsequent reductions is much larger than that of the immediate increases. It is noteworthy that the reduction of IV in response to Fitch downgrades is consistent with the analyses in Section 5.5.1. The reduction in IV could also be interpreted as the passing of an anticipated event. This, again, strengthens the argument that market participants consult with multiple CRAs and Fitch actions are considered as additional information which could play a "confirmation role".

5.5.3. How long does the impact on RV last?

Table 5.6 reports the estimated coefficients of Eq. (5.2) which explains changes in RV during the time windows around rating actions from each CRA. Overall, the results in Table 5.6 are qualitatively similar to those in Table 5.5.

Panel A of Table 5.6 shows that S&P negative news ignites significant, immediate reactions in RV while positive signals trigger no immediate response or no response at all. The magnitude of the impact of S&P negative news on RV is much larger than the impact on IV. This is conceivable, for reasons discussed above. S&P 1-notch downgrades of AAA or

BBB- sovereigns trigger an immediate increase of over 10% (1.56*0.0651 or 1.66*0.0651) in RV (compared to 3.57% in IV, see Table 5.4, Panel A). Negative watch signals on AAA sovereigns trigger an immediate increase of over 18% (1.21*0.15), by far the largest magnitude of the market volatility increases. RV increases by over 11% (0.75*0.149) then declines by 10% (0.75*0.135) in response to an S&P negative outlook action on an AAA sovereign, indicating a genuine event day given the construction formula of RV. A 1-notch upgrade from BB+ to the investment-grade reduces RV by over 35% (1.66*0.213) during the following week.[40]

Panel B of Table 5.6 shows that Moody's rating news is also influential on RV, but in a different fashion to S&P. The magnitude of the impact is much larger than for S&P. In other words, Moody's news induces huge movements in the spot FX market volatility. The significant movements also strengthen the view about the informational content of Moody's both negative and positive rating news. Again, increases followed by decreases in RV on consecutive days are found. 1-notch downgrades on Aaa sovereigns ignite an immediate increase of over 14% (1.56*0.0956) and a subsequent adjustment of 9% (1.56*0.0582) in RV. Similar behaviour is found in response to Moody's upgrades, and both negative and positive outlook. One important difference is that there is a large reduction in RV within the month following Moody's upgrades. Moody's negative watch actions do not trigger any significant movement in RV.

Panel C of Table 5.6 shows that both positive and negative news from Fitch affect the RV significantly. This confirms that the FX market reacts to Fitch actions differently to those from S&P and Moody's. RV increases almost 24.5% in response to 1-notch upgrades of AA+ sovereigns (1.56*0.157). Fitch downgrades induce immediate reductions in RV. The magnitude of the reduction is almost 13.9% in response to 1-notch downgrades on AAA

[40] During the sample period, S&P did not upgrade any sovereign to AAA. A 1-notch upgrade to the investment-grade implies a 1.66-unit increase in LCCR, rather than 1.56-units in cases of 1-notch upgrades to AAA.

sovereigns (1.56*0.089). Outlook announcements by Fitch do not induce any significant response from the market volatility while negative watch news triggers large increases in RV.

The results suggest a strong degree of heterogeneity among investors' beliefs. Credit events (including positive ones) trigger immediate increases in the measurement of the market ex-post volatility or market participants' disagreements in a given day, implying heterogeneous reactions or perceptions of an underlying credit issue.

5.5.4. Robustness test

Table 5.7 presents results of the Monte Carlo experiment examining the impact of positive and negative rating actions across the CRAs. Overall, the market reaction varies across CRAs' signals. RV is more responsive to rating news than IV, not only in terms of the numbers of significant coefficients but also the magnitude of the market reactions. This continues to support the view of market heterogeneity (see Section 5.5.3).

In the FX option market (Panel A of Table 5.7), S&P's influence is asymmetric. Only negative (not positive) news from S&P matters. There is no significant reaction to Moody's news, which is likely caused by grouping downgrades (upgrades) and negative (positive) outlook/watch events in the specifications. Moody's downgrades/upgrades play an important confirmation role and reduce the market uncertainty (see Panel B of Table 5.5), while their outlook/watch actions increase the market uncertainty. Therefore, grouping them together induces insignificant results.[41] Fitch negative news reduces market uncertainty while the positive counterpart does the opposite, increasing the market uncertainty.

In the spot market (Panel B of Table 5.7), all CRAs' actions influence the market volatility in different manners. S&P negative news and Moody's both negative and positive news trigger immediate increases in the market volatility while Fitch negative news reduces

[41] Monte Carlo experiments based on separating different types of Moody's rating actions confirm that Moody's outlook announcements trigger increases in IV while Moody's upgrades (not downgrades) reduce IV (reported in Appendix Table A5.2.4).

the market volatility. This reaffirms the view that Fitch is likely to play a role as an additional rater. On the other hand, S&P and Moody's positive news reduces market volatility within one month after the news is released.

5.5.5. Discussion of results

S&P negative news trigger immediate increases in the FX market ex-ante uncertainty and ex-post volatility, implying that they are likely to bring surprise elements to the public domain. In contrast, IV and RV reduce in response to Fitch downgrades (and Moody's downgrades in the case of IV). This infers that Fitch and Moody's downgrades could play a "confirmation role". Such role is obvious in the case of responses to Moody's downgrades where the market reactions are not immediate but within one month after the releases of the downgrades. Fitch might play the role of the third rater as the reduction in IV occurs immediately when they release their downgrades (consistent with Bongaerts et al. (2012)). However, Fitch upgrades trigger immediate increases in RV, inferring surprise elements contained in Fitch upgrades. Fitch upgrades are the least likely to follow positive outlook/watch events compared to the other CRAs (see Table 5.2). This is consistent with Alsakka and ap Gwilym (2012a) who find that both Fitch upgrades and downgrades and Moody's downgrades impact exchange rates. As additional rating signals are likely to reduce FX uncertainty and impact exchange rates, the "confirmation role" could also be economically meaningful in facilitating international trade and capital flows.

An important contribution to the debate over the information content of rating news could be proposed. Prior literature finds significant reactions of financial assets' prices to (mostly negative) rating news. In a different approach, I demonstrate that even rating news which is not new to the public can influence market behaviour. As a strong degree of heterogeneity in the market perception of volatility risk exists prior to changes in sovereign budget conditions and creditworthiness, additional rating news could play an important role in aiding the market consensus.

5.6. Conclusions

This paper investigates the impact of sovereign credit rating actions assigned by Moody's, S&P, and Fitch on FX market volatility. I use a dataset of 41 countries during the period from January 2007 to April 2013. This covers all main currencies used in global trades except currencies under non-floating FX regimes and countries without rating actions. The effects of rating signals are evidenced by an event study and regression analyses. Robustness of the results is confirmed by non-parametric tests and Monte Carlo experiments.

The unique contributions to the literature are as follows: (i) Identifying differing influences of CRAs on FX market uncertainty; (ii) The influence of each CRA is sometimes in an opposite direction to others. Therefore, the study illustrates the need to avoid pooling data across CRAs and across different types of rating events in CRA research; (iii) Demonstrating the important role of additional sovereign ratings in reducing market uncertainty (volatility); (iv) The study contributes to the debates on the informational content of ratings and the regulation of CRAs; (v) Introducing a new log-transformation of the rating scale which allows higher sensitivities to rating actions on issuers at the top and the bottom of the rating scale, and also around the investment-speculative threshold.

I find an asymmetric pattern in market responses not only between positive and negative events but also varying across CRAs. The market is more likely to react to negative news from S&P and both negative and positive news from Moody's compared to Fitch. This is consistent with Bongaerts et al. (2012) who argue that Fitch plays a 'tiebreaker' role and markets' participants are likely to consult Fitch ratings in the wider context of S&P and Moody's ratings. Moreover, Fitch downgrades trigger a decrease in IV and RV. This finding implies that even downgrades from the ‘tiebreaker' do matter and reduce the market uncertainty (volatility). Furthermore, the market reactions to Moody’s signals reinforce that additional signals are still informative and reduce the market uncertainty. These stress the importance of multiple ratings and support the ‘information producing’ role of credit ratings in the context of both first-mover as well as subsequent rating news.

The findings raise a prudential proposal against calls for removing credit ratings from investment guidelines and regulations, such as SEC (2011a, b), at least on sovereign debts. There are clearly benefits of reducing overreliance on credit ratings. However, a strong degree of heterogeneity exists in the market perception of FX volatility risk prior to changes in sovereign creditworthiness. Sovereign rating signals, especially additional ones, could play an important “confirmation role” and reduce market uncertainty, and therefore could facilitate international trade and fund flows. There is also a clear implication for regulators’ efforts to encourage new entrants to the rating industry.

Table 5.1: List of sample countries

	Country	No. of events			Country	No. of events
1	Australia	1		22	Luxembourg	4
2	Austria	4		23	Malaysia †	4
3	Belgium	11		24	Malta	6
4	Brazil	14		25	Mexico	9
5	Chile	9		26	Netherlands	4
6	Colombia	12		27	New Zealand	5
7	Cyprus	32		28	Peru	16
8	Czech Republic	7		29	Philippines	12
9	Estonia	6		30	Poland	5
10	Finland	3		31	Portugal	24
11	France	5		32	Romania	6
12	Germany	3		33	Russia †	13
13	Greece	38		34	Slovakia	5
14	Hungary	22		35	Slovenia	16
15	India	4		36	South Africa	14
16	Indonesia	17		37	Spain	24
17	Ireland	25		38	Taiwan	3
18	Israel	7		39	Thailand	6
19	Italy	12		40	Turkey	16
20	Japan	10		41	UK	8
21	Korea	10				

The data set covers 41 countries during sample period from 2007-2013. Among them, 17 EU countries using the Euro are included in the sample according to when they started using the Euro. All the countries are categorised as free floating or floating FX regimes in every IMF de facto classifications since it began in 2006 except for 2 countries marked by † categorised in "Other managed arrangement" in the IMF de facto classifications in 2010 and 2012. This category is a residual and is used when the exchange rate arrangement does not meet the criteria for any of the other categories.

Table 5.2: Rating events

No. of events	S&P			Moody's			Fitch			Total		
	Positive	**Negative**	**Σ**	**Positive**	**Negative**	**Σ**	**Positive**	**Negative**	**Σ**	**Positive**	**Negative**	**Σ**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Upgrade/ downgrade	27	56	83	28	48	76	25	45	70	80	149	229
Of which:												
- Multiple-notch	*4*	*17*	*21*	*0*	*24*	*24*	*2*	*20*	*22*	*6*	*61*	*67*
(percentage)	*(14.8%)*	*(30.4%)*	*(25.3%)*	*(0.0%)*	*(50.0%)*	*(31.6%)*	*(8.0%)*	*(44.4%)*	*(31.4%)*	*(7.5%)*	*(40.9%)*	*(29.3%)*
- Preceded by outlook/watch	*19*	*56*	*75*	*25*	*43*	*68*	*13*	*39*	*52*	*57*	*138*	*195*
(percentage)	*(70.4%)*	*(100%)*	*(90.4%)*	*(89.3%)*	*(89.6%)*	*(89.5%)*	*(52.0%)*	*(86.7%)*	*(74.3%)*	*(71.3%)*	*(92.6%)*	*(85.2%)*
Outlook	38	47	85	19	36	55	28	38	66	85	121	206
Watch	7	27	34	12	23	35	3	14	17	22	64	86
Total	**72**	**130**	**202**	**59**	**107**	**166**	**56**	**97**	**153**	**187**	**334**	**521**
Of which:												
- Combined events	*1*	*16*	*17*	*3*	*25*	*28*	*0*	*14*	*14*	*4*	*55*	*59*

This table reports the numbers of rating events released by the CRAs on sampled countries during the sample period (Jan 2007 - April 2013). Columns (1), (2), (3) report numbers of positive, negative, and total rating signals from S&P, respectively. Similarly, columns (4) to (9) report corresponding numbers from Moody's and Fitch. Column (10) = (1) + (4) + (7); (11) = (2) + (5) + (8); (12) = (3) + (6) + (9). Row "Upgrade/ downgrade" reports numbers of upgrades/ downgrades; row "Multiple-notch" reports numbers of more-than-one-notch rating events; row "(percentage)" reports percentages of multiple-notch upgrades/ downgrades over total numbers of upgrades/ downgrades; row "Preceded by outlook/watch" reports numbers of downgrades/ upgrades which were preceded by outlook or watch procedure; row "(percentage)" reports percentages of upgrades/ downgrades preceded by outlook/ watch procedure over total numbers of upgrades/ downgrades; row "Outlook" reports numbers of outlook announcements; row "Watch" reports numbers of rating watch or reviews; row "Total" reports total numbers of rating events; row "Combined events" reports numbers of rating events which involve both actual rating change and outlook or watch announcement.

Table 5.3: Results of event study for implied volatility

Panel A: S&P

Time windows	[-1,0]	[0,1]	[1,5]	[-1,0]	[0,1]	[1,5]
	Downgrades			**Upgrades**		
$\Delta\overline{IV}$	**1.32*** **	0.09	-1.75	1.15	-0.74	1.16
p-val. t-test	0.0096	0.4298	0.1431	0.1353	0.1227	0.2702
p-val. sign test	0.0011	0.2094	0.1336	0.1917	0.0262	0.7878
p-val. Wilcoxon test	0.0121	0.5112	0.0599	0.2113	0.0812	0.8390
n	56	56	56	26	26	26
	Negative outlook			**Positive outlook**		
$\Delta\overline{IV}$	1.23	**1.39*** **	-1.34	0.83	-0.41	0.05
p-val. t-test	0.1484	0.0058	0.1474	0.1494	0.3221	0.4860
p-val. sign test	0.0769	0.0192	0.0330	0.2923	0.3038	0.6321
p-val. Wilcoxon test	0.1460	0.0080	0.0254	0.5451	0.6685	0.8789
n	47	47	47	38	38	38
	Negative watch					
$\Delta\overline{IV}$	**1.35***	-0.91	1.60			
p-val. t-test	0.0743	0.1424	0.1465			
p-val. sign test	0.0003	0.0047	0.0610			
p-val. Wilcoxon test	0.0238	0.0254	0.4940			
n	27	27	27			

Panel B: Moody's

Time windows	[-1,0]	[0,1]	[1,5]	[-1,0]	[0,1]	[1,5]
	Downgrades			**Upgrades**		
$\Delta\overline{IV}$	-0.34	**0.70***	-0.52	2.08	-0.88	0.53
p-val. t-test	0.2651	0.0984	0.3204	0.1811	0.2475	0.4002
p-val. sign test	0.0920	0.0481	0.0967	0.5841	0.3388	0.9157
p-val. Wilcoxon test	0.2015	0.0709	0.3832	0.8997	0.4171	0.4784
n	48	48	48	28	28	28
	Negative outlook			**Positive outlook**		
$\Delta\overline{IV}$	0.62	**0.97****	-0.62	3.55	**3.28***	-0.57
p-val. t-test	0.2256	0.0451	0.3014	0.1647	0.0724	0.4443
p-val. sign test	0.8853	0.0068	0.0662	0.6855	0.0898	0.2272
p-val. Wilcoxon test	0.8197	0.0169	0.3458	0.9518	0.0584	0.2260
n	36	36	36	19	19	19
	Negative watch					
$\Delta\overline{IV}$	0.66	1.31	-2.62†			
p-val. t-test	0.2022	0.1068	0.0405			
p-val. sign test	0.5000	0.5841	0.5000			
p-val. Wilcoxon test	0.5620	0.2802	0.2604			
n	23	23	23			

Table 5.3. Continued.

Panel C: Fitch

Time windows	[-1,0]	[0,1]	[1,5]	[-1,0]	[0,1]	[1,5]
	Downgrades			**Upgrades**		
$\Delta\overline{IV}$	**-2.09****	0.77	-1.92†	0.90	1.05	1.65
p-val. t-test	0.0395	0.0621	0.0294	0.1860	0.1473	0.1915
p-val. sign test	0.0326	0.4402	0.1110	0.3318	0.2617	0.4194
p-val. Wilcoxon test	0.0167	0.1755	0.0405	0.5867	0.2635	0.5011
n	45	45	45	24	25	25
	Negative outlook			**Positive outlook**		
$\Delta\overline{IV}$	0.84	**1.91****	0.03	**1.10****	0.57	2.61†
p-val. t-test	0.2669	0.0212	0.4941	0.0487	0.2081	0.0835
p-val. sign test	0.5000	0.0877	0.9506	0.0378	0.6550	0.3506
p-val. Wilcoxon test	0.8328	0.0909	0.1510	0.0661	0.8008	0.3871
n	38	38	38	27	27	27

Note: $\Delta\overline{IV}$ report mean value of percentage changes in the during the time windows. n reports numbers of observations. Cases in bold denote significant at least at 10% level in all tests. *, **, *** denotes significant at 10%, 5%, 1% in the t-test. † denotes significant at the t-test but not in the non-parametric tests. There were few credit events in certain types (i.e. all the CRAs' positive watch and Fitch negative watch announcements) during the sample period (see Table 5.2 for details). Therefore, results for these types are not reported. The winsorisation does not alter the results at all. The result based on logarithm changes in IV is very similar (reported in Appendix A5.2.1).

Table 5.4: Results of event study for realised volatility

Panel A: S&P

	Downgrades [-1,0]	Downgrades [0,1]	Downgrades [1,5]	Upgrade [-1,0]	Upgrade [0,1]	Upgrade [1,5]
$\Delta\overline{RV}$	**11.69*****	-4.84	3.34	**45.99****	31.73	-13.37†
p-val. t-test	0.0005	0.1564	0.2319	0.0191	0.0709	0.0437
p-val. sign test	0.0120	0.0120	0.3899	0.0758	0.5806	0.1537
p-val. Wilcoxon test	0.0011	0.0332	0.6593	0.0258	0.6682	0.0919
n	51	51	51	24	24	24

	Negative outlook [-1,0]	Negative outlook [0,1]	Negative outlook [1,5]	Positive outlook [-1,0]	Positive outlook [0,1]	Positive outlook [1,5]
$\Delta\overline{RV}$	11.09†	0.47	10.01†	9.24	0.2420	16.99†
p-val. t-test	0.0137	0.4819	0.0946	0.1022	0.4866	0.0608
p-val. sign test	0.1400	0.9960	0.2204	0.5000	0.9522	0.6321
p-val. Wilcoxon test	0.0724	0.0318	0.4267	0.5888	0.4222	0.4915
n	42	42	42	35	35	35

	Negative watch [-1,0]	Negative watch [0,1]	Negative watch [1,5]
$\Delta\overline{RV}$	**6.78****	1.61	-7.63†
p-val. t-test	0.0110	0.4010	0.0222
p-val. sign test	0.0216	0.9999	0.9784
p-val. Wilcoxon test	0.0202	0.0188	0.7941
n	25	25	25

Panel B: Moody's

Time windows	Downgrades [-1,0]	Downgrades [0,1]	Downgrades [1,5]	Upgrade [-1,0]	Upgrade [0,1]	Upgrade [1,5]
$\Delta\overline{RV}$	**21.21****	-1.24	4.84	22.85†	**-13.31****	34.49†
p-val. t-test	0.0007	0.3793	0.1981	0.0113	0.0371	0.0205
p-val. sign test	0.0001	0.1456	0.9887	0.1635	0.0145	0.2786
p-val. Wilcoxon test	0.0005	0.5361	0.7973	0.0585	0.0462	0.0962
n	44	44	44	26	26	26

	Negative outlook [-1,0]	Negative outlook [0,1]	Negative outlook [1,5]	Positive outlook [-1,0]	Positive outlook [0,1]	Positive outlook [1,5]
$\Delta\overline{RV}$	**9.14****	-0.99	3.39	**64.55****	**-25.89*****	64.46
p-val. t-test	0.0243	0.4099	0.2820	0.0153	0.0077	0.0341
p-val. sign test	0.0122	0.4321	0.8042	0.0384	0.0106	0.1051
p-val. Wilcoxon test	0.0544	0.9115	0.9932	0.0151	0.0262	0.0787
n	34	34	34	16	16	16

	Negative watch [-1,0]	Negative watch [0,1]	Negative watch [1,5]
$\Delta\overline{RV}$	15.12†	-4.09	0.23
p-val. t-test	0.0492	0.1785	0.4851
p-val. sign test	0.1431	0.2617	0.9738
p-val. Wilcoxon test	0.1011	0.3220	0.7089
n	22	22	22

Table 5.4. Continued.

Panel C: Fitch

Time windows	[-1,0]	[0,1]	[1,5]	[-1,0]	[0,1]	[1,5]
	Downgrade			**Upgrade**		
$\Delta\overline{RV}$	3.56	**-9.16****	11.72†	13.19	31.46†	-0.38
p-val. t-test	0.2308	0.0137	0.0606	0.1469	0.0884	0.4872
p-val. sign test	0.8256	0.0298	0.2664	0.5881	0.8684	0.5881
p-val. Wilcoxon test	0.9535	0.0207	0.1927	0.3317	0.5503	0.7938
n	41	41	41	20	20	20
	Negative outlook			**Positive outlook**		
$\Delta\overline{RV}$	2.73	19.60†	10.43	21.89	31.05†	10.49
p-val. t-test	0.3320	0.0922	0.1575	0.1408	0.0847	0.2377
p-val. sign test	0.7502	0.7502	0.6321	0.5000	0.6682	0.5000
p-val. Wilcoxon test	0.8828	0.9608	0.7431	0.5663	0.7151	0.4979
n	35	35	35	21	21	21

Note: $\Delta\overline{RV}$ report mean value of percentage changes in RV during the time windows. n reports numbers of observations. Cases in bold denote significant at least at 10% level in all tests. *, **, *** denotes significant at 10%, 5%, 1% in the t-test. † denotes significant at the t-test but not in the non-parametric tests. There were few credit events in certain types (i.e. all the CRAs' positive watch and Fitch negative watch announcements) during the sample period (see Table 5.2 for details). Therefore, results for these types are not reported. The winsorisation does not alter the results at all. The result based on logarithm changes in RV is very similar (reported in Appendix A5.2.1).

Table 5.5: How long does the impact on IV last?

Panel A: Responses to S&P actions

Time window	[-1,0]	[0, 1]	[1, 5]	[5, 22]	[-1,0]	[0, 1]	[1, 5]	[5, 22]
	Downgrade				**Upgrade**			
ΔLCCR	**0.0229*****	0.0023	-0.0248	0.0081	0.0127	-0.0064	0.0236	0.0026
(t-val.)	(4.40)	(0.49)	(-1.55)	(0.40)	(1.33)	(-0.73)	(1.14)	(0.09)
CCR	0.00007	0.0001	-0.0008	-0.0015	-0.00005	0.0004	-0.0007	-0.0019
(t-val.)	(0.17)	(0.25)	(-1.18)	(-1.31)	(-0.12)	(0.88)	(-0.98)	(-1.45)
Year/ Co	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	19.03%	11.36%	12.20%	11.49%	16.40%	10.71%	10.10%	11.73%
	Negative outlook				**Positive outlook**			
ΔLCCR	**0.0219*****	0.0175	-0.0289	-0.0115	0.0336	-0.0249	0.0511	**-0.1260****
(t-val.)	(2.59)	(1.62)	(-1.25)	(-0.55)	(1.61)	(-1.12)	(1.31)	(-2.04)
CCR	-0.0001	0.0002	-0.0008	-0.0008	0.0001	0.0005	-0.0006	-0.0019
(t-val.)	(-0.26)	(0.48)	(-1.17)	(-0.71)	(0.27)	(1.00)	(-0.78)	(-1.59)
Year/ Co	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	12.13%	11.69%	8.08%	9.78%	16.36%	9.60%	19.53%	12.88%
	Negative watch							
ΔLCCR	**0.0229****	-0.0102	0.0144	-0.0827				
(t-val.)	(2.10)	(-1.27)	(0.63)	(-0.73)				
CCR	-0.00006	0.0005	-0.0008	-0.0019				
(t-val.)	(-0.12)	(0.90)	(-0.97)	(-1.57)				
Year/ Co	Yes	Yes	Yes	Yes				
R^2	18.32%	12.17%	19.17%	13.34%				

Panel B: Responses to Moody's actions

Time window	[-1,0]	[0, 1]	[1, 5]	[5, 22]	[-1,0]	[0, 1]	[1, 5]	[5, 22]
	Downgrade				**Upgrade**			
ΔLCCR	0.0016	0.0056	-0.0060	**-0.0223****	0.0549	**-0.0459****	0.0472	-0.0368
(t-val.)	(0.45)	(1.45)	(-0.46)	(-2.11)	(1.15	(-2.01)	(1.47)	(-0.70)
CCR	0.00006	0.0002	-0.0007	-0.0015	0.0002	0.0003	-0.0010	-0.0016
(t-val.)	(0.18)	(0.41)	(-1.17)	(-1.53)	(0.44)	(0.75)	(-1.59)	(-1.49)
Year/ Co	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	18.04%	11.48%	18.50%	12.33%	17.93%	9.28%	20.77%	11.83%

Table 5.5. Continued.

	Negative outlook			
ΔLCCR	**0.0106***	**0.0131*****	0.0089	**-0.0265***
(t-val.)	(1.78)	(3.02)	(0.61)	(-1.73)
CCR	0.00003	0.0002	-0.0007	-0.0012
(t-val.)	(0.09)	(0.52)	(-1.18)	(-1.30)
Year/ Co	Yes	Yes	Yes	Yes
R^2	16.88%	11.61%	20.50%	12.31%

	Positive outlook			
ΔLCCR	0.0381	**0.0937***	0.0798	-0.1450
(t-val.)	(0.52)	(1.68)	(0.84)	(-1.15)
CCR	-0.0002	0.0005	-0.0007	-0.0016
(t-val.)	(-0.44)	(0.98)	(-1.09)	(-1.59)
Year/ Co	Yes	Yes	Yes	Yes
R^2	11.81%	12.29%	21.05%	13.27%

	Negative watch			
ΔLCCR	0.0022	**0.0108****	**-0.0549*****	-0.0314
(t-val.)	(0.32)	(1.97)	(-3.43)	(-1.05)
CCR	0.00005	0.0004	-0.0007	-0.0012
(t-val.)	(0.13)	(0.89)	(-1.25)	(-1.18)
Year/ Co	Yes	Yes	Yes	Yes
R^2	18.16%	11.96%	21.13%	12.48%

Panel C: Responses to Fitch actions

	Downgrade			
ΔLCCR	-0.0077	**-0.0073***	-0.0153	-0.0188
(t-val.)	(-1.43)	(-1.65)	(-1.45)	(-0.89)
CCR	0.0001	0.0003	**-0.0013***	-0.0015
(t-val.)	(0.28)	(0.57)	(-1.83)	-1.22)
Year/ Co	Yes	Yes	Yes	Yes
R^2	24.94%	11.35%	18.06%	12.19%

	Upgrade			
ΔLCCR	0.0095	0.0117	0.0045	-0.0521
(t-val.)	(1.05)	(1.43)	(0.26)	(-1.44)
CCR	0.0003	0.0004	-0.0011	-0.0019
(t-val.)	(0.74)	(0.76)	(-1.47)	(-1.32)
Year/ Co	Yes	Yes	Yes	Yes
R^2	16.34%	10.84%	15.88%	11.38%

	Negative outlook			
ΔLCCR	0.0134	**0.0250***	**-0.0405***	**-0.1190*****
(t-val.)	(0.80)	(1.94)	(-1.94)	(-3.50)
CCR	0.00003	0.0002	-0.0008	-0.0015
(t-val.)	(0.06)	(0.52)	(-1.02)	(-1.12)
Year/ Co	Yes	Yes	Yes	Yes
R^2	11.66%	12.11%	18.35%	11.57%

	Positive outlook			
ΔLCCR	0.0051	0.0140	**0.0728****	-0.1160
(t-val.)	(0.21)	(0.48)	(1.99)	(-1.32)
CCR	0.00009	0.0003	**-0.0013***	-0.0015
(t-val.)	(0.20)	(0.62)	(-1.69)	(-1.08)
Year/ Co	Yes	Yes	Yes	Yes
R^2	18.40%	11.04%	19.78%	11.35%

	Negative watch			
ΔLCCR	-0.0055	**0.0224****	-0.0084	-0.0125
(t-val.)	(-0.40)	(1.98)	(-0.49)	(-0.48)
CCR	0.0001	0.0003	-0.0010	-0.0015
(t-val.)	(0.35)	(0.54)	(-1.35)	(-1.16)
Year/ Co	Yes	Yes	Yes	Yes
R^2	18.85%	12.01%	19.89%	12.40%

This table reports the results of estimations of Eq. (5.1) with Huber-White robust standard errors. The dependent variable is ΔIV over the time windows. The main independent variable is ΔLCCR, daily changes in the log-transformation of ratings. For the ease of interpretation, absolute value of ΔLCCR is used. t-values are reported in parentheses. *, **, *** denote significant at 10%, 5%, 1% level of significance. Country-matched random sampling from the full sample is used.

Table 5.6: How long does the impact on RV last?

Panel A: Responses to S&P actions

Time window	[-1,0]	[0, 1]	[1, 5]	[5, 22]	[-1,0]	[0, 1]	[1, 5]	[5, 22]
	Downgrade				**Upgrade**			
ΔLCCR	**0.0651****	-0.0345	-0.0598	0.0787	0.1410	0.0585	**-0.2130*****	0.0909
(t-val.)	(2.38)	(-0.66)	(-1.01)	(1.15)	(1.42)	(0.75)	(-2.69)	(0.85)
CCR	-0.0004	-0.0046	-0.0024	-0.0001	0.0014	-0.0031	-0.0015	-0.0038
(t-val.)	(-0.11)	(-1.31)	(-0.54)	(-0.02)	(0.33)	(-0.77)	(-0.29)	(-0.75)
Year/ Co	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	10.95%	9.14%	9.44%	10.13%	7.62%	9.00%	10.43%	10.03%
	Negative outlook				**Positive outlook**			
ΔLCCR	**0.1490****	**-0.1350*****	0.0658	0.0936	0.2540	-0.1330	0.0978	-0.0762
(t-val.)	(2.24)	(-3.51)	(1.19)	(1.47)	(1.44)	(-0.64)	(0.33)	(-0.29)
CCR	-0.0007	-0.0040	-0.0021	0.0018	-0.0008	-0.0030	-0.0038	0.0003
(t-val.)	(-0.19)	(-1.12)	(-0.45)	(0.37)	(-0.21)	(-0.76)	(-0.75)	(0.06)
Year/ Co	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	10.11%	11.00%	10.42%	10.41%	9.15%	10.23%	10.14%	10.38%
	Negative watch							
ΔLCCR	**0.1500*****	-0.0130	-0.0380	-0.1770				
(t-val.)	(2.76)	(-0.12)	(-0.27)	(-1.38)				
CCR	-0.0017	-0.0045	-0.0018	0.0008				
(t-val.)	(-0.45)	(-1.14)	(-0.34)	(0.16)				
Year/ Co	Yes	Yes	Yes	Yes				
R^2	10.99%	9.75%	10.28%	10.03%				

Panel B: Responses to Moody's actions

Time window	[-1,0]	[0, 1]	[1, 5]	[5, 22]	[-1,0]	[0, 1]	[1, 5]	[5, 22]
	Downgrade				**Upgrade**			
ΔLCCR	**0.0925*****	**-0.0582****	-0.0073	-0.0050	**0.2720*****	**-0.2610***	0.1880	**-0.3050***
(t-val.)	(2.72)	(-2.16)	(-0.13)	(-0.10)	(2.80)	(-1.66)	(1.04)	(-1.70)
CCR	-0.0011	-0.0034	-0.0013	0.0002	-0.0017	-0.0038	-0.0030	0.0024
(t-val.)	(-0.37)	(-1.15)	(-0.34)	(0.05)	(-0.59)	(-1.18)	(-0.72)	(0.56)
Year/ Co	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	11.10%	10.23%	10.83%	10.60%	11.88%	10.90%	11.29%	13.30%

Table 5.6. Continued.

	Negative outlook			
ΔLCCR	**0.1160*** **	**-0.0597***	0.0442	0.0267
(t-val.)	(2.63)	(-1.79)	(0.48)	(0.30)
CCR	-0.0013	-0.0034	-0.0014	0.0013
(t-val.)	(-0.45)	(-1.16)	(-0.36)	(0.34)
Year/ Co	Yes	Yes	Yes	Yes
R^2	10.77%	9.93%	10.81%	10.01%

	Positive outlook			
ΔLCCR	**0.1080****	**-0.1220***	0.6200	-0.1200
(t-val.)	(2.24)	(-1.91)	(0.86)	(-0.17)
CCR	-0.0009	-0.0028	-0.0021	-0.0002
(t-val.)	(-0.28)	(-0.86)	(-0.49)	(-0.04)
Year/ Co	Yes	Yes	Yes	Yes
R^2	12.96%	14.54%	10.06%	10.36%

	Negative watch			
ΔLCCR	0.0240	-0.0326	-0.0056	-0.0124
(t-val.)	(0.51)	(-0.79)	(-0.14)	(-0.23)
CCR	-0.0008	-0.0029	-0.0023	0.0009
(t-val.)	(-0.29)	(-0.96)	(-0.57)	(0.21)
Year/ Co	Yes	Yes	Yes	Yes
R^2	11.08%	9.80%	10.60%	10.76%

Panel C: Responses to Fitch actions

	Downgrade			
ΔLCCR	0.0414	**-0.0890***	-0.0226	0.0095
(t-val.)	(0.90)	(-1.87)	(-0.36)	(0.14)
CCR	0.0024	-0.0048	-0.0034	0.0003
(t-val.)	(0.66)	(-1.37)	(-0.73)	(0.06)
Year/ Co	Yes	Yes	Yes	Yes
R^2	10.24%	10.60%	10.32%	10.34%

	Upgrade			
ΔLCCR	**0.1570***	-0.0380	-0.1160	0.0279
(t-val.)	(1.89)	(-0.40)	(-1.49)	(0.34)
CCR	0.0014	-0.0048	-0.0039	0.0007
(t-val.)	(0.37)	(-1.23)	(-0.79)	(0.13)
Year/ Co	Yes	Yes	Yes	Yes
R^2	10.47%	11.26%	11.07%	10.87%

	Negative outlook			
ΔLCCR	0.0725	-0.1180	0.0777	-0.1790
(t-val.)	(0.64)	(-1.20)	(0.68)	(-1.23)
CCR	0.0003	-0.0054	-0.0022	0.0017
(t-val.)	(0.07)	(-1.47)	(-0.45)	(0.34)
Year/ Co	Yes	Yes	Yes	Yes
R^2	10.18%	10.36%	10.94%	10.26%

	Positive outlook			
ΔLCCR	0.1790	0.2920	-0.2280	-0.9750
(t-val.)	(0.41)	(0.49)	(-0.35)	(-1.22)
CCR	-0.0004	-0.0043	-0.0032	0.0018
(t-val.)	(-0.09)	(-1.12)	(-0.63)	(0.33)
Year/ Co	Yes	Yes	Yes	Yes
R^2	10.70%	9.95%	9.56%	10.50%

	Negative watch			
ΔLCCR	**0.0521***	-0.0695	0.0021	-0.0330
(t-val.)	(1.73)	(-0.83)	(0.04)	(-0.22)
CCR	0.0007	-0.0034	-0.0037	-0.00005
(t-val.)	(0.19)	(-0.93)	(-0.77)	(-0.01)
Year/ Co	Yes	Yes	Yes	Yes
R^2	11.91%	10.00%	11.45%	10.67%

This table reports the results of estimations of Eq. (5.2) with Huber-White robust standard errors. The dependent variable is ΔIV over the time windows. The main independent variable is ΔLCCR, daily changes in the log-transformation of ratings. For the ease of interpretation, absolute value of ΔLCCR is used. t-values are reported in parentheses. *, **, *** denote significant at 10%, 5%, 1% level of significance. Country-matched random sampling from the full sample is used. See Table 5.1 and 5.2 for details on the data sample.

Table 5.7: Monte Carlo experiment

Time window	[-1,0]	[0, 1]	[1, 5]	[5, 22]	[-1,0]	[0, 1]	[1, 5]	[5, 22]

Panel A: Responses of implied volatility

S&P	Negative news				Positive news			
ΔLCCR	**0.0157*****	-0.0005	-0.0111	0.0050	0.0120	-0.0047	0.0119	0.0072
(t-val.)	(2.82)	(-0.10)	(-1.35)	(0.29)	(1.54)	(-0.68)	(0.86)	(0.30)
CCR	0.0001	-0.0001	-0.0001	0.0008	0.00006	0.00008	4.89e-06	-0.0003
(t-val.)	(0.23)	(-0.26)	(-0.19)	(0.77)	(0.14)	(0.19)	(0.009)	(-0.24)
Year/ Co	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	568	568	568	566	525	525	525	522
R^2	10.76%	9.45%	10.13%	11.78%	9.96%	9.62%	10.18%	13.43%
No. of est.	10,000	10,000	10,000	10,000	10,000	10,000	10,000	10,000

Moody’s	Negative news				Positive news			
ΔLCCR	-0.0025	0.0059	-0.0054	-0.0154	0.0446	-0.0232	0.0206	-0.0277
(t-val.)	(-0.70)	(1.56)	(-0.46)	(-1.49)	(1.15)	(-1.16)	(0.67)	(-0.66)
CCR	0.0001	0.0001	-0.0001	0.0002	-2.86e-06	7.06e-06	3.20e-06	-0.0002
(t-val.)	(0.43)	(0.34)	(-0.29)	(0.25)	(-0.007)	(0.01)	(-0.0005)	(-0.22)
Year/ Co	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	537	537	537	535	510	511	510	508
R^2	10.53%	10.29%	10.29%	14.23%	11.01%	9.16%	10.18%	13.66%
No. of est.	10,000	10,000	10,000	10,000	10,000	10,000	10,000	10,000

Fitch	Negative news				Positive news			
ΔLCCR	**-0.0139****	0.0044	-0.0077	-0.0155	0.0051	**0.0140***	0.0010	-0.0539
(t-val.)	(-2.30)	(0.94)	(-0.86)	(-0.72)	(0.57)	(1.70)	(0.05)	(-1.49)
CCR	0.0002	-0.0001	-0.00007	0.0004	0.0002	-0.0001	-0.0003	-0.00008
(t-val.)	(0.42)	(-0.26)	(-0.10)	(0.36)	(0.41)	(0.32)	(-0.47)	(-0.05)
Year/ Co	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	538	538	537	534	509	510	510	509
R^2	9.01%	9.94%	10.19%	12.03%	9.96%	10.17%	10.37%	13.95%
No. of est.	10,000	10,000	10,000	10,000	10,000	10,000	10,000	10,000

Table 5.7. Continued.

Time window	[-1,0]	[0, 1]	[1, 5]	[5, 22]	[-1,0]	[0, 1]	[1, 5]	[5, 22]
Panel B: Responses of realised volatility								
S&P	**Negative news**				**Positive news**			
ΔLCCR	**0.0524***	-0.0358	-0.0429	**0.0934****	0.0861	0.0025	**-0.1566****	0.0955
(t-val.)	(1.81)	(-0.76)	(-0.96)	(2.10)	(1.08)	(0.04)	(-2.02)	(1.12)
CCR	0.0011	-0.0008	-0.0007	0.0024	0.0022	0.0009	0.0003	-0.0018
(t-val.)	(0.39)	(-0.27)	(-0.23)	(0.66)	(0.57)	(0.26)	(0.08)	(-0.41)
Year/ Co	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	520	522	522	521	482	484	484	483
R^2	10.19%	10.06%	10.22%	9.98%	9.13%	9.47%	10.82%	10.01%
No. of est.	10,000	10,000	10,000	10,000	10,000	10,000	10,000	10,000
Moody's	**Negative news**				**Positive news**			
ΔLCCR	**0.0635****	-0.0385	-0.0105	0.0137	**0.2841****	**-0.3252****	0.1272	-0.1381
(t-val.)	(2.04)	(-1.47)	(-0.19)	(0.26)	(2.42)	(-2.32)	(0.83)	(-0.85)
CCR	-0.00009	-0.0007	0.0004	0.00002	-0.0012	-0.0002	0.0006	-0.0004
(t-val.)	(-0.04)	(-0.27)	(0.13)	(0.005)	(-0.42)	(-0.09)	(0.17)	(-0.10)
Year/ Co	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	493	495	495	494	464	466	465	464
R^2	10.78%	10.44%	10.20%	10.63%	11.60%	11.69%	9.77%	9.72%
No. of est.	10,000	10,000	10,000	10,000	10,000	10,000	10,000	10,000
Fitch	**Negative news**				**Positive news**			
ΔLCCR	0.0151	**-0.0840***	-0.0164	0.0127	0.0914	-0.0646	-0.0592	-0.0404
(t-val.)	(0.34)	(-1.84)	(-0.29)	(0.21)	(1.16)	(-0.70)	(-0.72)	(-0.41)
CCR	0.0035	-0.0025	0.0016	-0.0004	0.0002	-0.0013	0.0004	0.0005
(t-val.)	(1.03)	(-0.78)	(0.44)	(-0.10)	(0.06)	(-0.36)	(0.11)	(0.13)
Year/ Co	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	493	495	495	494	461	463	463	462
R^2	10.50%	11.17%	10.57%	10.53%	10.10%	10.40%	10.16%	10.10%
No. of est.	10,000	10,000	10,000	10,000	10,000	10,000	10,000	10,000

Note: ΔLCCR, CCR report averages coefficients of ΔLCCR and CCR across 10,000 estimations of Eq. (5.1) and Eq. (5.2). Average t-statistics are reported in parentheses and heteroskedasticity robust using the Huber-White correction. N reports maximum number of observations for one estimation as this number varies slightly across estimations. R^2 reports averages R-square from the estimations. "No. of est." reports numbers of estimations. Each estimation of the equations is based on one independently random sampling. For the ease of interpretation, absolute value of ΔLCCR is used. *, **, *** denote significant at 10%, 5%, 1% level of significance.

Figure 5.1: Implied volatility

Figure 5.1a: Distribution of daily implied volatility

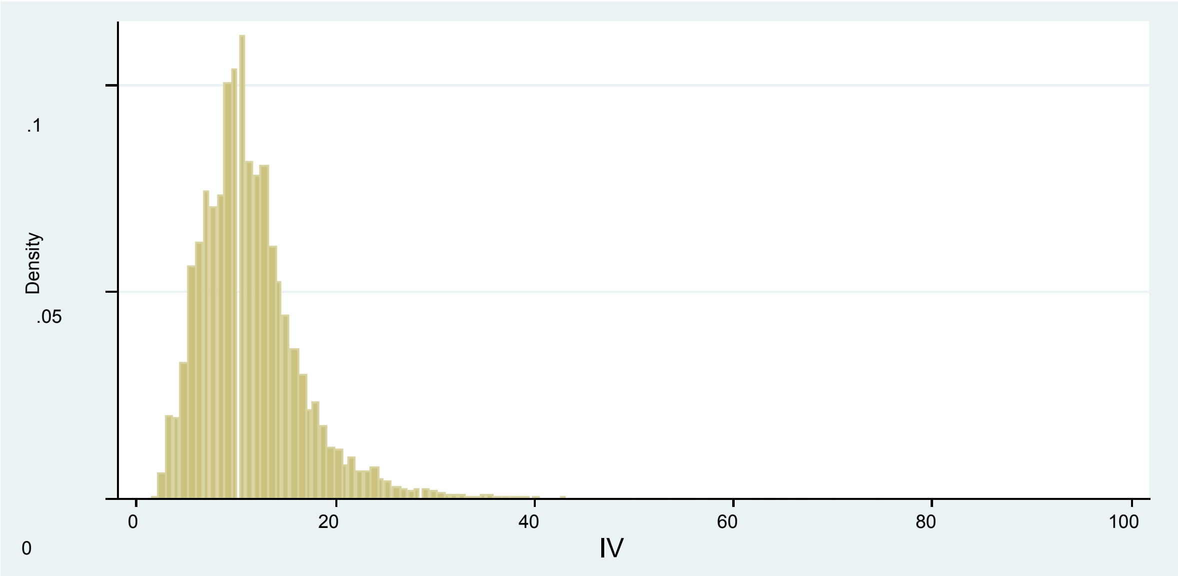
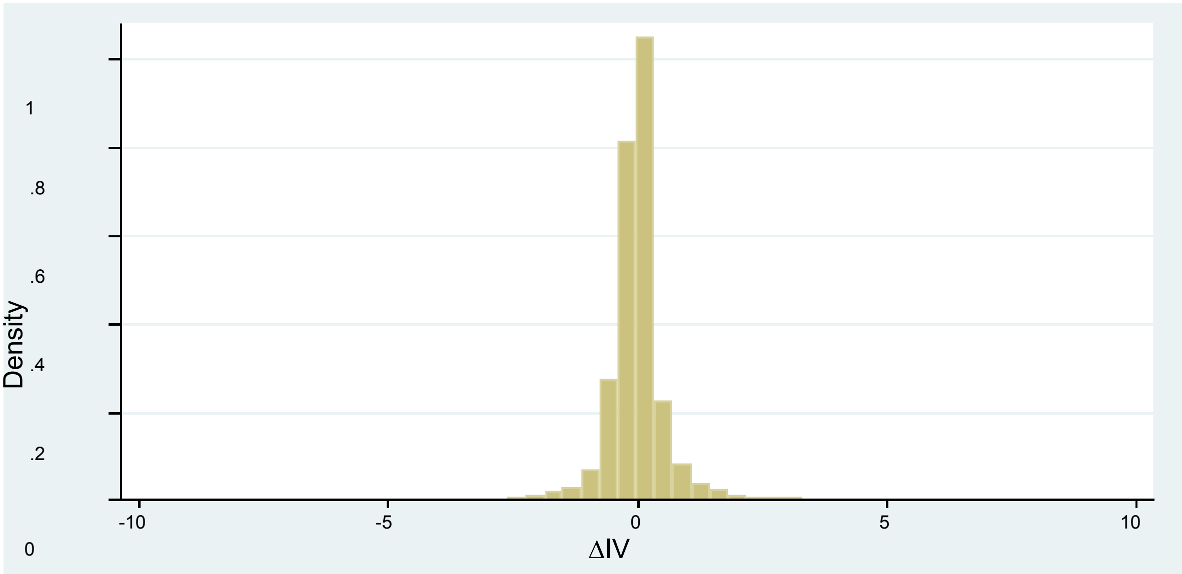


Figure 5.1b: Distribution of daily changes in implied volatility



Note: The dataset covers 41 countries during the period from January 2007 to April 2013. There are 64,715 daily observations of 1-month implied volatility. There are 57 observations where |ΔIV| is greater than 10% in Brazil (2 obs. in Oct-Nov 2008), Chile (4 obs. in Oct 2008 and Sep2011), Colombia (1 obs. in Oct 2008), Indonesia (20 obs. in Oct–Nov 2008, Feb 2009), Japan (1 obs. in Oct 2008), Korea (11 obs. in Oct 2009 – Feb 2009), Mexico (7 obs. in Oct-Nov 2008), Poland (3 obs. in Oct and Dec 2008), Russia (2 obs. in Oct 2008), South Africa (2 obs. in Oct 2008), and Turkey (4 obs. in Oct-Nov 2008).

Figure 5.2: Realised volatility

Figure 5.2a: Distribution of daily realised volatility

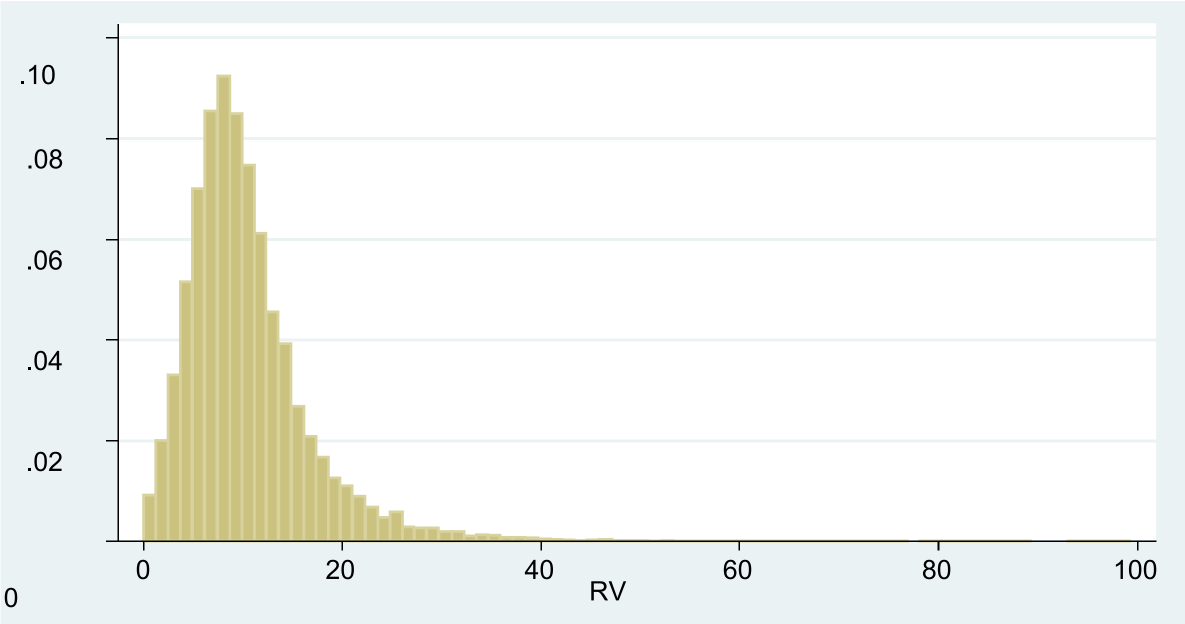
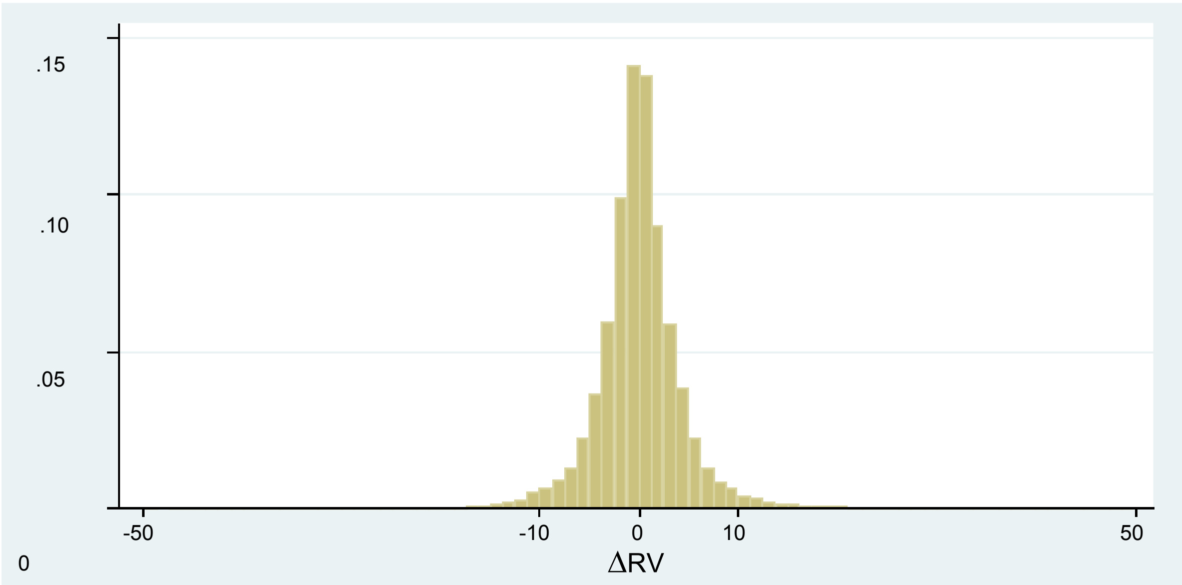
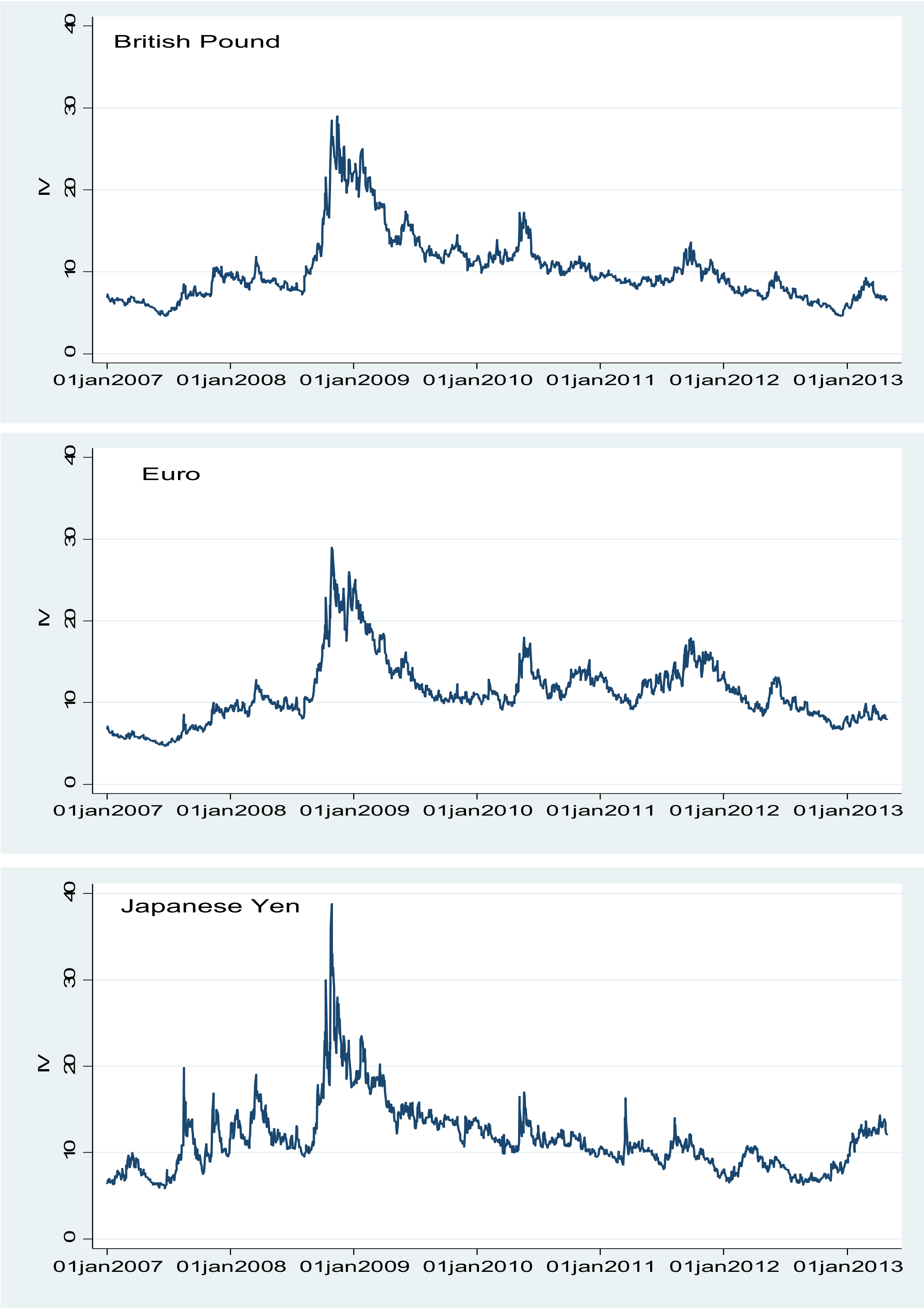


Figure 5.2b: Distribution of daily changes in realised volatility



Note: The dataset covers 41 countries during the period from March 2007 to April 2013. There are 58,994 daily observations of realised volatility. There are 3,051 observations where |ΔRV| is greater than 10% in all the sample countries, implying a more volatile distribution of ΔRV compared to the distribution of ΔIV in Figure 5.1b.

Figure 5.3: IV time series of some sampled currencies



Appendix 5.1: Log-transformation of rating scale

$$\mathrm{LCCR} = \begin{cases} \ln[\frac{CCR}{29 - CCR}] & \forall CCR \in [1..28] \\ \ln[\frac{(CCR-28)(CCR+28)^{\sqrt{\pi}}}{59 - CCR}] & \forall \mathrm{CCR} \in [29..58] \end{cases}$$

Let's consider CCR as a variable x real and ϵ [1, 58]

$$\mathrm{LCCR} = \mathrm{f(x)} = \begin{cases} \ln[\frac{x}{29 - x}] & \forall x \in [1..28] \\ \ln[\frac{(x-28)(x+28)^{\sqrt{\pi}}}{59 - x}] & \forall \mathrm{x} \in [29..58] \end{cases}$$

1. $\forall \boldsymbol{x} \in [\mathbf{1..28}]$**, we have:**

$$\frac{df}{dx} = \frac{29 - x}{x} * \frac{29 - x - x*(-1)}{(29 - x)^2} = \frac{29}{x*(29 - x)}$$

$$\rightarrow \quad \frac{d^2f}{dx^2} = \frac{-29}{x^2(29 - x)^2} * (29 - x - x) = \frac{-29}{x^2(29 - x)^2} * (29 - 2x)$$

→ $\frac{d^2f}{dx^2} = 0 \, when \; x = \frac{29}{2} = 14.5$ and $\frac{d^2f}{dx^2}$ changes sign from negative to positive at x=14.5 ➔ $\frac{df}{dx}$ gets a local minimum at 14.5. ΔLCCR which is $\frac{df}{dx}$ reduces when x ranges from 1 to 14.5, then increases when x ranges from 14.5 to 28.

2. $\forall \boldsymbol{x} \in [\mathbf{29..58}]$**, we have:**

$$\frac{df}{dx} = \frac{1}{59 - x} + \frac{1}{x - 28} + \frac{\sqrt{\pi}}{x + 28}$$

$$\rightarrow \frac{d^2f}{dx^2} = \frac{1}{(59 - x)^2} - \frac{1}{(x - 28)^2} - \frac{\sqrt{\pi}}{(x + 28)^2}$$

$$\rightarrow \quad \frac{d^2f}{dx^2} = 0 \, when \; x = 43.8196$$

and $\frac{d^2f}{dx^2}$ changes sign from negative to positive at x=43.8196 ➔ $\frac{df}{dx}$ gets a local minimum at 43. 8196. ΔLCCR which is $\frac{df}{dx}$ reduces when x ranges from 29 to 43.8196, then increases when x ranges from 43.8196 to 58.

The following figures present visual demonstration how ΔLCCR changes across the rating scale. The largest changes are on the top, the bottom and around the point of 31 (i.e. investment-speculative threshold). In other words, rating actions on AAA, near default, and near investment-speculative threshold issuers are most powerful to the LCCR. In contrast, actions on issuers who are in the middle of speculative or investment grades are least influential.

Figure A5.1.1. Effects of downgrades and upgrades on ΔLCCR

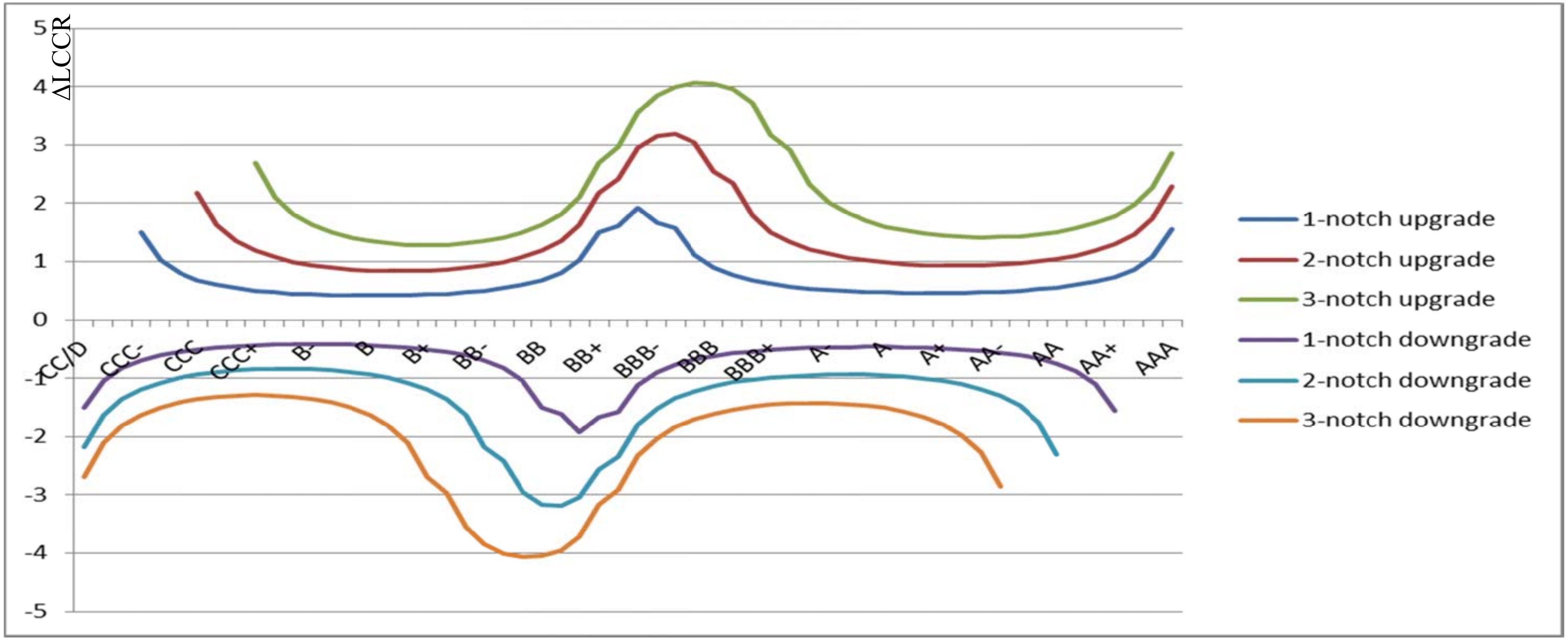
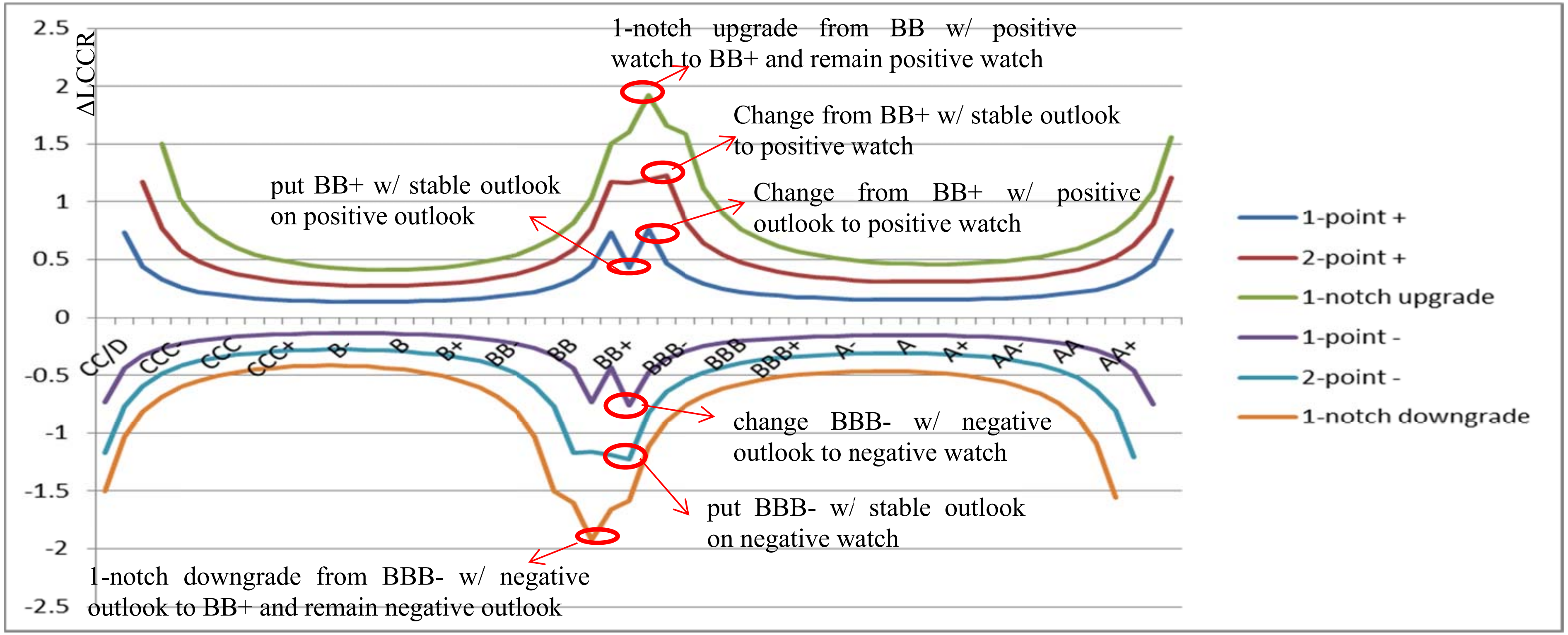


Figure A5.1.2. Effects of rating actions within 1-notch upgrade/ downgrade on ΔLCCR



Appendix 5.2: Extra empirical results

Table A5.2.1: Results of the event study – responses of log-changes

Panel A: Response of 1-month implied volatility

S&P

	[-1,0]	[0,1]	[1,5]	[-1,0]	[0,1]	[1,5]
	Downgrades			**Upgrades**		
$\Delta\overline{IV}$	**0.0123****	0.0002	**-0.0205****	0.0102	-0.0080	0.0074
p-val. t-test	0.0133	0.4873	0.0232	0.1516	0.1114	0.3424
p-val. sign test	0.0011	0.2094	0.0668	0.1917	0.0262	0.7878
p-val. Wilcoxon test	0.0128	0.5541	0.0506	0.2207	0.0812	0.8589
n	56	56	56	26	26	26
	Negative outlook			**Positive outlook**		
$\Delta\overline{IV}$	0.0094	**0.0131*****	**-0.0168***	0.0072	-0.0056	-0.0036
p-val. t-test	0.1978	0.0075	0.0786	0.1711	0.2712	0.4047
p-val. sign test	0.0769	0.0192	0.0330	0.2923	0.3038	0.5000
p-val. Wilcoxon test	0.1520	0.0090	0.0227	0.5647	0.6475	0.8561
n	47	47	47	38	38	38
	Negative watch					
$\Delta\overline{IV}$	**0.0124***	-0.0010	0.0130			
p-val. t-test	0.0879	0.1110	0.1944			
p-val. sign test	0.0003	0.0047	0.0610			
p-val. Wilcoxon test	0.0238	0.0254	0.4940			
n	27	27	27			

Moody's

	[-1,0]	[0,1]	[1,5]	[-1,0]	[0,1]	[1,5]
	Downgrades			**Upgrades**		
$\Delta\overline{IV}$	-0.0040	0.0063	-0.0081	0.0156	-0.0111	0.0002
p-val. t-test	0.2241	0.1246	0.2333	0.1969	0.1984	0.4968
p-val. sign test	0.0920	0.0481	0.0967	0.5841	0.3388	0.9157
p-val. Wilcoxon test	0.1908	0.725	0.3298	0.9361	0.3666	0.4784
n	48	48	48	28	28	27
	Negative outlook			**Positive outlook**		
$\Delta\overline{IV}$	0.0051	**0.0091***	-0.0087	0.0259	**0.0286***	-0.0187
p-val. t-test	0.2628	0.0585	0.2342	0.2036	0.0853	0.3124
p-val. sign test	0.8853	0.0068	0.0662	0.6855	0.0898	0.2272
p-val. Wilcoxon test	0.8197	0.0169	0.3071	0.9198	0.0584	0.1966
n	36	36	36	19	19	19
	Negative watch					
$\Delta\overline{IV}$	0.0059	0.0120	-0.0290†			
p-val. t-test	0.2220	0.1144	0.0344			
p-val. sign test	0.5000	0.5841	0.5000			
p-val. Wilcoxon test	0.5620	0.3228	0.2604			
n	23	23	23			

Table A5.2.1 Continued.

	Fitch					
	[-1,0]	[0,1]	[1,5]	[-1,0]	[0,1]	[1,5]
	Downgrades			**Upgrades**		
$\Delta\overline{IV}$	**-0.0265***	0.0072†	-0.0216†	0.0080	0.0093	0.1205
p-val. t-test	0.0556	0.0751	0.0191	0.2021	0.1779	0.2460
p-val. sign test	0.0326	0.4402	0.1110	0.3318	0.2617	0.4194
p-val. Wilcoxon test	0.0167	0.1828	0.0341	0.6065	0.2635	0.5449
n	45	45	44	24	25	25
	Negative outlook			**Positive outlook**		
$\Delta\overline{IV}$	0.0056	**0.0175***	-0.0051	**0.0105**	0.0051	0.0218
p-val. t-test	0.3232	0.0264	0.3791	0.0562	0.2286	0.1088
p-val. sign test	0.5000	0.0877	0.0939	0.0378	0.6550	0.3506
p-val. Wilcoxon test	0.8215	0.0937	0.1390	0.0815	0.8194	0.4004
n	38	38	38	28	28	28
	Negative watch					
	-0.0399***	0.0102†	**-0.0167****			
	0.0003	0.0741	0.0291			
	0.0065	0.0898	0.0112			
	0.0048	0.2961	0.0365			
	14	14	14			

Panel B: Response of realised volatility

	S&P					
	[-1,0]	[0,1]	[1,5]	[-1,0]	[0,1]	[1,5]
	Downgrades			**Upgrade**		
$\Delta\overline{RV}$	**0.0879*****	**-0.1004*****	-0.0149	**0.3016****	0.0958	-0.3014†
p-val. t-test	0.0028	0.0122	0.3702	0.0421	0.2033	0.0261
p-val. sign test	0.0120	0.0120	0.7121	0.0758	0.5806	0.1537
p-val. Wilcoxon test	0.0025	0.0110	0.8512	0.0520	0.7971	0.0425
n	51	51	51	24	24	24
	Negative outlook			**Positive outlook**		
$\Delta\overline{RV}$	0.0687†	**-0.1054***	0.0275	0.0197	-0.07634	0.0112
p-val. t-test	0.0540	0.0562	0.3095	0.3789	0.1347	0.4542
p-val. sign test	0.1400	0.0098	0.2204	0.5000	0.0877	0.6321
p-val. Wilcoxon test	0.1283	0.0121	0. 6477	0.8186	0.2132	0.8186
n	42	42	42	35	35	35
	Negative watch					
$\Delta\overline{RV}$	**0.0565****	-0.0147	-0.1066†			
p-val. t-test	0.0287	0.3750	0.0286			
p-val. sign test	0.0216	0.0005	0.9784			
p-val. Wilcoxon test	0.0218	0.0162	0.7941			

Table A5.2.1 Continued.

Moody's	[-1,0]	[0,1]	[1,5]	[-1,0]	[0,1]	[1,5]
	Downgrades			**Upgrade**		
$\Delta\overline{RV}$	**0.1463*** **	-0.0469	-0.0144	0.1332†	**-0.2345*** **	0.1853†
p-val. t-test	0.0011	0.1245	0.3965	0.0481	0.0073	0.0562
p-val. sign test	0.0001	0.1456	0.0244	0.1635	0.0145	0.2122
p-val. Wilcoxon test	0.0013	0.2828	0.6239	0.1068	0.0201	0.1094
n	44	44	44	26	26	25
	Negative outlook			**Positive outlook**		
$\Delta\overline{RV}$	0.0595†	-0.0423	-0.0154	**0.3724** **	**-0.4882*** **	0.3010
p-val. t-test	0.0806	0.1761	0.3895	0.0116	0.0084	0.0648
p-val. sign test	0.0122	0.4321	0.3038	0.0384	0.0106	0.1051
p-val. Wilcoxon test	0.1177	0.4674	0.9251	0.0200	0.0151	0.1089
n	34	34	34	16	16	16
	Negative watch					
$\Delta\overline{RV}$	0.098†	-0.0643†	-0.0407			
p-val. t-test	0.0553	0.0931	0.2718			
p-val. sign test	0.1431	0.2617	0.0669			
p-val. Wilcoxon test	0.1230	0.2360	0.5481			
n	22	22	22			

Fitch	[-1,0]	[0,1]	[1,5]	[-1,0]	[0,1]	[1,5]
	Downgrade			**Upgrade**		
$\Delta\overline{RV}$	-0.0017	**-0.1386*** **	0.0391	-0.0103	0.0228	-0.1480
p-val. t-test	0.4839	0.0029	0.2548	0.4684	0.4441	0.1327
p-val. sign test	0.2664	0.0298	0.2664	0.5881	0.8684	0.5881
p-val. Wilcoxon test	0.7410	0.0131	05054	0.7938	0.9702	0.4553
n	41	41	41	20	20	20
	Negative outlook			**Positive outlook**		
$\Delta\overline{RV}$	-0.0491	0.0278	-0.0427	0.0106	0.0707	-0.1078
p-val. t-test	02565	0.3746	0.3275	0.4688	0.3003	0.2470
p-val. sign test	03679	0.7502	0.5000	0.5000	0.6682	0.6682
p-val. Wilcoxon test	0.6464	0.7932	0.8059	0.8484	0.9308	0.4342
n	35	35	35	21	21	21

Note: $\Delta\overline{IV}$ and $\Delta\overline{RV}$ report mean value of logarithm changes in the IV and RV, respectively, during the time windows. Cases in bold denote significant at least at 10% level in all tests. *, **, *** denotes significant at 10%, 5%, 1% in the t-test. † denotes significant at the t-test but not in the non-parametric tests. The winsorisation does not alter the results at all. There were few rating actions in certain types (i.e. all the CRAs' positive watch, and Fitch negative watch announcements) during the sample period (please refer Table 5.2 for details).

Table A5.2.2. Results of regressions on 3-, 6-, 12-month implied volatilities
Panel A: Responses to S&P actions

Time window	[-1,0]	[0, 1]	[1, 5]	[5, 22]	[-1,0]	[0, 1]	[1, 5]	[5, 22]
3-month implied volatility								
	Downgrades				**Upgrades**			
ΔLCCR	**0.0172*** **	0.00181	-0.00827	0.00147	0.00553	-0.00569	**-0.0143***	0.00875
t-val.	3.99	0.61	-1.00	0.09	1.02	-0.83	-1.73	0.51
CCR	0.0004	-0.00005	-0.0006	-0.001	0.0004	0.00005	-0.0005	-0.002
t-val.	1.03	-0.17	-1.14	-1.31	1.28	0.16	-0.91	-1.63
N	441	441	440	435	414	414	413	408
R-sq	12.79%	8.10%	20.24%	14.26%	11.89%	8.49%	20.89%	14.41%
	Negative outlook				**Positive outlook**			
ΔLCCR	**0.0153****	0.00735	-0.00594	-0.0131	0.0178	0.00513	0.0614	**-0.103****
t-val.	1.96	1.59	-0.51	-0.88	1.17	0.32	1.57	-2.02
CCR	0.0002	0.00002	-0.0006	-0.0007	0.0004	0.0002	-0.0004	-0.002
t-val.	0.58	0.07	-1.14	-0.79	1.19	0.68	-0.67	-1.51
N	431	431	430	425	421	421	420	415
R-sq	6.11%	8.38%	19.75%	12.00%	10.89%	9.35%	19.67%	16.35%
	Negative watch							
ΔLCCR	0.00597	-0.00243	0.00775	-0.0595				
t-val.	1.59	-0.46	0.41	-1.50				
CCR	0.0004	0.0001	-0.0006	-0.002				
t-val.	0.97	0.39	-0.91	-1.51				
N	416	416	415	410				
R-sq	12.21%	8.26%	19.83%	15.27%				

Table A5.2.2 Continued.

6-month implied volatility									
Time window	[-1,0]	[0, 1]	[1, 5]	[5, 22]		[-1,0]	[0, 1]	[1, 5]	[5, 22]
	Downgrades					**Upgrades**			
ΔLCCR	**0.0109*****	0.00401	-0.00653	0.00164		0.00213	-0.00347	0.0127	0.0110
t-val.	2.75	1.60	-1.04	0.12		0.49	-0.74	1.52	0.76
CCR	0.0004	-0.0002	-0.0008	-0.0006		0.0005	-0.0001	-0.0008	-0.0009
t-val.	1.31	-0.82	-1.38	-0.71		1.51	-0.55	-1.16	-0.91
N	437	437	436	431		410	410	409	404
R-sq	9.30%	9.55%	21.05%	12.96%		8.58%	9.22%	20.69%	12.37%
	Negative outlook					**Positive outlook**			
ΔLCCR	0.0116	**0.0112****	-0.00463	-0.0182		0.00438	0.0100	**0.0660****	**-0.135*****
t-val.	1.46	2.55	-0.55	-1.42		0.30	0.56	2.45	-2.65
CCR	0.0002	-0.0002	-0.0008	-0.0003		0.0005	-0.00002	-0.0007	-0.0006
t-val.	0.60	-0.72	-1.17	-0.28		1.49	-0.06	-1.00	-0.64
N	425	425	424	419		416	416	415	410
R-sq	3.27%	9.63%	19.72%	11.06%		7.75%	10.94%	19.67%	14.57%
	Negative watch								
ΔLCCR	**0.00656***	0.000703	0.00800	-0.0470					
t-val.	1.80	0.14	0.50	-1.38					
CCR	0.0005	-0.0001	-0.0008	-0.0008					
t-val.	1.37	-0.36	-1.13	-0.80					
N	412	412	411	406					
R-sq	9.30%	10.24%	20.30%	13.37%					

Table A5.2.2 Continued.

1-year implied volatility								
Time window	[-1,0]	[0, 1]	[1, 5]	[5, 22]	[-1,0]	[0, 1]	[1, 5]	[5, 22]
	Downgrades				**Upgrades**			
ΔLCCR	**0.00784*** **	0.00288	-0.00204	0.00382	-0.00481	-0.00176	0.0116	0.0142
t-val.	2.61	1.47	-0.35	0.36	-1.03	-0.42	1.45	1.19
CCR	0.0002	0.00002	-0.0005	-0.0006	0.0001	0.00007	-0.0003	-0.0008
t-val.	0.61	0.12	-1.16	-0.87	0.48	0.29	-0.68	-0.98
N	441	441	440	435	414	414	413	408
R-sq	17.65%	9.59%	22.02%	14.79%	17.59%	9.22%	21.41%	14.65%

	Negative outlook				**Positive outlook**			
ΔLCCR	**0.0088***	**0.00869****	-0.00424	-0.00724	0.00811	0.0142	**0.0521****	**-0.104****
t-val.	1.97	2.50	-0.61	-0.56	0.65	0.78	2.41	-2.32
CCR	-0.00001	0.00002	-0.0005	-0.0002	0.0002	0.00005	-0.0004	-0.0005
t-val.	-0.03	0.10	-1.12	-0.21	0.70	0.19	-0.72	-0.63
N	431	431	430	425	421	421	420	415
R-sq	4.21%	9.10%	21.57%	11.23%	16.21%	16.45%	21.35%	15.16%

	Negative watch			
ΔLCCR	**0.0121***	**-0.00882****	0.0128	-0.0349
t-val.	1.66	-2.39	1.03	-0.99
CCR	0.0002	0.00007	-0.0005	-0.0007
t-val.	0.61	0.29	-0.97	-0.91
N	416	416	415	410
R-sq	18.39%	10.17%	22.29%	15.04%

Table A5.2.2 Continued.
Panel B: responses to Moody's actions

3-month implied volatility

Time window	[-1,0]	[0, 1]	[1, 5]	[5, 22]	[-1,0]	[0, 1]	[1, 5]	[5, 22]
	Downgrades				**Upgrades**			
ΔLCCR	0.00159	0.00273	0.000541	**-0.0137***	0.0572	-0.0593	0.0844	-0.00723
t-val.	0.48	0.83	0.06	-1.66	0.95	-1.12	1.31	-0.21
CCR	0.0004	-0.00003	-0.0005	-0.001	0.0006**	-0.00009	-0.0005	-0.001
t-val.	1.49	-0.11	-1.09	-1.61	2.06	-0.36	-1.01	-1.63
N	435	435	434	429	414	414	413	408
R-sq	11.55%	7.23%	18.97%	15.01%	14.29%	13.63%	21.14%	14.46%
	Negative outlook				**Positive outlook**			
ΔLCCR	**0.0116****	**0.0108*****	0.00380	-0.0197	0.0353	-0.0294	-0.0317	-0.0572
t-val.	2.26	2.87	0.33	-1.63	0.50	-0.26	-0.62	-0.78
CCR	0.0004	0.00006	-0.0005	-0.0009	0.0001	0.0003	-0.0005	-0.001
t-val.	1.40	0.29	-1.23	-1.18	0.41	0.89	-1.07	-1.36
N	423	423	422	417	408	408	407	402
R-sq	11.24%	7.91%	22.49%	14.62%	4.59%	5.43%	26.10%	15.65%
	Negative watch				**Positive watch**			
ΔLCCR	0.000728	**0.00736****	**-0.0359*****	-0.0216	0.0233	0.0119	0.00669	-0.0466
t-val.	0.15	2.23	-2.66	-1.32	1.51	0.62	0.28	-1.29
CCR	0.0005*	0.00008	-0.0005	-0.001	0.0004	-0.00002	-0.0005	-0.001
t-val.	1.74	0.36	-1.00	-1.37	1.37	-0.08	-1.01	-1.39
N	413	413	412	407	399	399	398	393
R-sq	12.33%	9.27%	21.55%	14.77%	12.76%	8.78%	20.91%	14.91%

Table A5.2.2 Continued.

	6-month implied volatility							
Time window	[-1,0]	[0, 1]	[1, 5]	[5, 22]	[-1,0]	[0, 1]	[1, 5]	[5, 22]
	Downgrades				**Upgrades**			
ΔLCCR	0.000289	0.00291	0.000784	-0.00927	0.0590	-0.0585	0.0779	-0.0194
t-val.	0.11	1.15	0.11	-1.22	1.09	-1.15	1.24	-0.83
CCR	0.0005*	-0.0002	-0.0007	-0.0006	0.0007**	-0.0003	-0.0006	-0.0007
t-val.	1.91	-0.84	-1.28	-0.88	2.33	-1.08	-1.01	-0.87
N	431	431	430	425	410	410	409	404
R-sq	9.30%	9.26%	20.25%	13.05%	12.52%	15.47%	18.73%	13.71%
	Negative outlook				**Positive outlook**			
ΔLCCR	0.00699	**0.00971*** **	0.00203	-0.0147	0.0287	0.0510	-0.0203	-0.0964
t-val.	1.64	2.76	0.22	-1.48	0.39	1.20	-0.37	-1.14
CCR	0.0005*	-0.00009	-0.0007	-0.0003	0.0003	0.00007	-0.0007	-0.0005
t-val.	1.75	-0.43	-1.33	-0.40	0.87	0.28	-1.14	-0.65
N	419	419	418	413	404	404	403	398
R-sq	8.98%	9.73%	24.29%	13.03%	3.84%	8.48%	27.21%	14.09%
	Negative watch				**Positive watch**			
ΔLCCR	-0.00187	**0.00705** **	**-0.0264** **	-0.0129	0.0128	0.00895	0.0151	-0.0254
t-val.	-0.44	2.42	-2.47	-0.90	0.79	0.86	0.71	-0.83
CCR	0.0005**	-0.00009	-0.0007	-0.0005	0.0005*	-0.0001	-0.0007	-0.0005
t-val.	2.03	-0.43	-1.21	-0.61	1.72	-0.66	-1.25	-0.61
N	409	409	408	403	395	395	394	389
R-sq	9.74%	10.48%	21.42%	12.96%	9.73%	10.50%	21.03%	12.91%

Table A5.2.2 Continued.

	1-year implied volatility							
Time window	[-1,0]	[0, 1]	[1, 5]	[5, 22]	[-1,0]	[0, 1]	[1, 5]	[5, 22]
	Downgrades				**Upgrades**			
ΔLCCR	0.00128	0.00136	0.000561	-0.00436	0.0587	-0.0540	0.0729	-0.00714
t-val.	0.48	0.78	0.11	-0.58	1.22	-1.12	1.26	-0.41
CCR	0.0002	0.00001	-0.0004	-0.0007	0.0003	-0.00008	-0.0003	-0.0006
t-val.	0.94	0.07	-1.09	-1.17	1.27	-0.42	-0.64	-0.97
N	435	435	434	429	414	414	413	408
R-sq	17.50%	9.30%	21.87%	14.48%	19.62%	14.36%	17.98%	15.97%
	Negative outlook				**Positive outlook**			
ΔLCCR	**0.00964****	0.00470	-0.00264	-0.00957	-0.0138	0.0498	0.0372	-0.123
t-val.	2.42	1.61	-0.33	-1.07	-0.13	1.32	0.35	-1.55
CCR	0.0002	0.00008	-0.0004	-0.0003	0.00005	0.0002	-0.0003	-0.0005
t-val.	0.85	0.49	-0.94	-0.56	0.19	0.80	-0.80	-0.81
N	423	423	422	417	408	408	407	402
R-sq	16.80%	9.09%	26.38%	14.49%	4.20%	9.68%	22.34%	15.97%
	Negative watch				**Positive watch**			
ΔLCCR	-0.000655	**0.00548****	**-0.0190****	-0.00171	0.00599	-0.0118	0.0333	0.0159
t-val.	-0.15	2.10	-2.15	-0.11	0.38	-0.57	1.84	0.64
CCR	0.0002	0.00006	-0.0004	-0.0006	0.000187	0.00002	-0.0004	-0.0006
t-val.	0.99	0.36	-0.99	-0.99	0.76	0.11	-1.02	-0.86
N	413	413	412	407	399	399	398	393
R-sq	18.37%	9.92%	22.71%	14.72%	18.45%	10.19%	22.39%	15.04%

Table A5.2.2 Continued.
Panel C: Responses to Fitch actions

3-month implied volatility								
Time window	[-1,0]	[0, 1]	[1, 5]	[5, 22]	[-1,0]	[0, 1]	[1, 5]	[5, 22]
	Downgrades				**Upgrades**			
ΔLCCR	0.00101	0.00103	-0.00699	-0.00568	0.00904	0.00460	0.00581	-0.0436
t-val.	0.21	0.22	-0.76	-0.34	1.41	1.05	0.35	-1.28
CCR	0.0004	-0.00001	-0.0009*	-0.001	0.0006**	0.00003	-0.0009	-0.001
t-val.	1.52	-0.04	-1.68	-1.27	2.13	0.11	-1.53	-1.04
N	431	431	430	424	412	412	411	406
R-sq	16.58%	6.93%	18.60%	15.14%	10.76%	8.29%	16.14%	12.83%
	Negative outlook				**Positive outlook**			
ΔLCCR	0.0166	**0.0209****	**-0.0356****	**-0.0969*****	0.0161	0.0176	**0.104***	-0.102
t-val.	1.01	2.17	-2.55	-3.44	0.48	0.53	1.90	-1.04
CCR	0.0004	0.00002	-0.0006	-0.001	0.0005	0.000004	-0.0009	-0.001
t-val.	1.10	0.05	-0.93	-1.10	1.52	0.01	-1.49	-1.08
N	423	423	422	417	410	410	409	404
R-sq	4.05%	9.68%	19.58%	14.33%	12.39%	8.14%	20.96%	13.86%
	Negative watch							
ΔLCCR	0.000353	0.00648	0.00289	**-0.0377***				
t-val.	0.04	0.60	0.23	-1.91				
CCR	0.0004	0.00003	-0.0007	-0.001				
t-val.	1.37	0.11	-1.15	-1.12				
N	405	405	404	399				
R-sq	12.88%	8.63%	20.68%	14.35%				

Table A5.2.2 Continued.

6-month implied volatility								
Time window	[-1,0]	[0, 1]	[1, 5]	[5, 22]	[-1,0]	[0, 1]	[1, 5]	[5, 22]
	Downgrades				Upgrades			
ΔLCCR	-0.00427	0.000876	-0.00475	-0.00291	0.00831	0.00422	0.00518	-0.0388
t-val.	-0.82	0.23	-0.65	-0.21	1.42	1.16	0.39	-1.29
CCR	0.0005*	-0.0002	-0.001	-0.0005	0.0006**	-0.0001	-0.001	-0.0007
t-val.	1.82	-0.82	-1.63	-0.59	2.52	-0.47	-1.63	-0.71
N	427	427	426	420	408	408	407	402
R-sq	16.42%	9.17%	18.55%	13.50%	8.03%	9.88%	17.84%	11.84%
	Negative outlook				Positive outlook			
ΔLCCR	0.0112	**0.0130****	**-0.0179**	**-0.0818*****	-0.00571	0.0303	**0.0824***	**-0.126***
t-val.	0.70	2.13	-1.35	-3.23	-0.26	1.09	1.72	-1.72
CCR	0.0004	-0.0002	-0.0009	-0.0004	0.0005*	-0.0002	-0.001	-0.0004
t-val.	1.45	-0.84	-1.22	-0.39	1.93	-0.96	-1.48	-0.38
N	418	418	417	412	406	406	405	400
R-sq	3.15%	10.43%	19.88%	12.23%	9.12%	9.98%	20.29%	12.45%
	Negative watch							
ΔLCCR	-0.00155	**0.00600***	0.00553	**-0.0351***				
t-val.	-0.17	1.78	0.62	-1.95				
CCR	0.0005*	-0.0002	-0.0009	-0.0004				
t-val.	1.80	-0.84	-1.28	-0.42				
N	401	401	400	395				
R-sq	9.89%	10.18%	21.06%	12.69%				

Table A5.2.2 Continued.

1-year implied volatility								
Time window	[-1,0]	[0, 1]	[1, 5]	[5, 22]	[-1,0]	[0, 1]	[1, 5]	[5, 22]
	Downgrades				**Upgrades**			
ΔLCCR	-0.00271	**-0.00210***	-0.00203	-0.000850	0.00401	0.00329	0.00174	-0.0235
t-val.	-0.46	-1.73	-0.34	-0.07	0.59	0.66	0.19	-0.86
CCR	0.0003	-0.00004	-0.0007	-0.0006	0.0003	0.0002	-0.0008	-0.0008
t-val.	1.01	-0.19	-1.51	-0.78	1.08	0.66	-1.56	-0.90
N	431	431	430	424	412	412	411	406
R-sq	27.91%	8.67%	20.91%	15.10%	23.13%	15.21%	20.63%	13.52%
	Negative outlook				**Positive outlook**			
ΔLCCR	0.0188	**0.0100***	**-0.0198***	**-0.0634*****	-0.00471	0.0143	0.0584	-0.0761
t-val.	1.04	1.84	-1.94	-2.71	-0.20	0.48	1.36	-1.33
CCR	0.0002	-0.00006	-0.0005	-0.0004	0.0003	-0.00008	-0.0006	-0.0004
t-val.	0.55	-0.25	-0.93	-0.54	1.23	-0.35	-1.26	-0.51
N	423	423	422	417	410	410	409	404
R-sq	4.16%	9.26%	21.68%	12.84%	18.09%	9.04%	21.36%	14.94%
	Negative watch							
ΔLCCR	0.00750	-0.00286	0.00628	**-0.0354****				
t-val.	0.94	-0.47	0.82	-2.25				
CCR	0.0003	-0.00005	-0.0006	-0.0004				
t-val.	0.95	-0.22	-1.14	-0.51				
N	405	405	404	399				
R-sq	18.89%	9.79%	22.60%	14.61%				

This table reports the results of estimations of equation (5.1) with Huber-White robust standard errors. The dependent variable is ΔIV during the time windows. The main independent variable is ΔLCCR, daily changes in the log-transformation of ratings. For the ease of interpretation, absolute value of ΔLCCR is used. *, **, *** denote significant at 10%, 5%, 1% level of significance. Country-matched random sampling from the full sample is used. Year and country dummies are included but not reported for ease brevity.

Table A5.2.3: Results of regression based on full sample

Responses of Realised volatility to S&P actions

	[-1, 0]	[0, 1]	[1, 5]	[5, 22]	[-1, 0]	[0, 1]	[1, 5]	[5, 22]
	Downgrade				**Upgrade**			
ΔLCCR	**0.0554*****	-0.0634	-0.0310	**0.0842****	0.0771	-0.0433	**-0.113****	**0.105***
t-val.	3.04	-1.61	-0.83	2.25	1.62	-0.84	-2.13	1.82
CCR	0.0001	0.00004	0.00009	0.0003	0.0001	0.00006	0.00009	0.0003
t-val.	0.41	0.10	0.21	0.69	0.41	0.15	0.21	0.59
N	63,666	63,446	63,240	62,534	63,638	63,418	63,212	62,506
R^2	30.91%	0.47%	0.19%	0.43%	30.97%	0.47%	0.20%	0.43%
	Negative outlook				**Positive outlook**			
ΔLCCR	**0.0549*****	**-0.0875****	-0.00719	**0.0998*****	0.0378	-0.0190	-0.0714	0.112
t-val.	3.43	-2.07	-0.18	2.72	0.61	-0.28	-1.08	1.30
CCR	0.0001	0.00007	0.00008	0.0003	0.0001	0.00006	0.00009	0.0003
t-val.	0.35	0.17	0.19	0.66	0.34	0.16	0.21	0.59
N	63,609	63,389	63,183	62,477	63,569	63,349	63,143	62,437
R^2	30.92%	0.47%	0.19%	0.43%	30.91%	0.46%	0.19%	0.43%
	Negative watch							
ΔLCCR	**0.0284***	0.000813	-0.0656	0.0564				
t-val.	1.91	0.02	-1.57	1.10				
CCR	0.0001	0.00004	0.00008	0.0003				
t-val.	0.40	0.10	0.20	0.69				
N	63,608	63,388	63,182	62,476				
R^2	30.92%	0.46%	0.19%	0.43%				

Table A5.2.3. Continued.

Responses of 1-month implied volatility to S&P actions	[-1, 0]	[0, 1]	[1, 5]	[5, 22]	[-1, 0]	[0, 1]	[1, 5]	[5, 22]
	Downgrade				**Upgrade**			
ΔLCCR	**0.0131****	-0.000204	-0.00997	0.00259	**0.00977***	-0.00505	0.0131	-0.0178
t-val.	2.44	-0.06	-1.46	0.17	1.89	-1.27	1.28	-0.83
CCR	0.00003	0.00001	0.00007	0.0004***	0.00002	0.00002	0.00006	0.0004***
t-val.	0.54	0.25	0.80	3.17	0.45	0.34	0.78	3.20
N	70,522	70,424	70,219	69,412	70,492	70,394	70,189	69,382
R^2	9.63%	0.33%	1.28%	3.69%	9.63%	0.33%	1.28%	3.69%
	Negative outlook				**Positive outlook**			
ΔLCCR	**0.0118****	0.000320	-0.0107	0.00815	**0.0161****	-0.00565	**0.0236***	0.00723
t-val.	2.35	0.08	-1.36	0.47	1.97	-0.89	1.79	0.29
CCR	0.00002	0.00001	0.00006	0.0004***	0.00002	0.00002	0.00006	0.0004***
t-val.	0.49	0.22	0.79	3.22	0.48	0.31	0.80	3.13
N	70,459	70,361	70,156	69,350	70,415	70,317	70,112	69,305
R^2	9.63%	0.33%	1.28%	3.69%	9.63%	0.33%	1.28%	3.70%
	Negative watch							
ΔLCCR	**0.0118***	-0.00377	-0.00104	0.00467				
t-val.	1.69	-0.87	-0.14	0.23				
CCR	0.00003	0.00002	0.00007	0.0004***				
t-val.	0.50	0.30	0.82	3.25				
N	70,459	70,361	70,156	69,350				
R^2	9.63%	0.33%	1.28%	3.69%				

Table A5.2.3. Continued.

Responses of Realised volatility to Moody's actions

	[-1, 0]	[0, 1]	[1, 5]	[5, 22]	[-1, 0]	[0, 1]	[1, 5]	[5, 22]
	Downgrade				**Upgrade**			
ΔLCCR	**0.0685*****	**-0.0686*****	-0.00576	0.0204	**0.247*****	**-0.272*****	0.0988	-0.0596
t-val.	2.68	-2.76	-0.13	0.48	4.63	-2.99	1.06	-0.67
CCR	0.00004	0.00002	0.00003	0.0002	0.00003	0.00003	0.00001	0.0001
t-val.	0.17	0.06	0.08	0.45	0.14	0.10	0.04	0.46
N	63,666	63,446	63,241	62,535	63,645	63,425	63,219	62,513
R^2	30.97%	0.47%	0.19%	0.43%	30.98%	0.49%	0.19%	0.43%
	Negative outlook				**Positive outlook**			
ΔLCCR	**0.0628*****	**-0.0501****	-0.0255	0.0311	**0.429*****	**-0.371*****	0.0561	-0.0230
t-val.	2.63	-1.98	-0.41	0.56	5.19	-2.59	0.39	-0.15
CCR	0.00004	0.00002	0.00003	0.0002	0.00003	0.00004	0.000006	0.0002
t-val.	0.14	0.05	0.08	0.44	0.14	0.13	0.02	0.45
N	63,632	63,412	63,207	62,501	63,600	63,380	63,175	62,469
R^2	30.99%	0.47%	0.20%	0.42%	30.99%	0.48%	0.19%	0.42%
	Negative watch							
ΔLCCR	0.0414	-0.00642	-0.0714	0.0242				
t-val.	1.14	-0.18	-1.56	0.48				
CCR	0.00005	0.00002	0.000005	0.0002				
t-val.	0.19	0.08	0.01	0.48				
N	63,624	63,404	63,199	62,493				
R^2	30.99%	0.47%	0.20%	0.43%				

Table A5.2.3. Continued.

Responses of 1-month implied volatility to Moody's actions

	[-1, 0]	[0, 1]	[1, 5]	[5, 22]	[-1, 0]	[0, 1]	[1, 5]	[5, 22]
	Downgrade				**Upgrade**			
ΔLCCR	-0.000526	**0.00616***	-0.00349	**-0.0158****	0.0344	-0.00579	0.00624	**-0.0464***
t-val.	-0.15	1.77	-0.38	-2.05	1.39	-1.42	0.31	-1.93
CCR	0.00001	0.00001	0.00005	0.0003**	0.00001	0.000009	0.00004	0.0003***
t-val.	0.33	0.25	0.72	2.57	0.30	0.24	0.71	2.58
N	70,522	70,424	70,220	69,413	70,500	70,402	70,197	69,390
R^2	9.63%	0.33%	1.28%	3.68%	9.64%	0.33%	1.28%	3.69%
	Negative outlook				**Positive outlook**			
ΔLCCR	-0.00114	**0.00659***	-0.000860	-0.0120	0.0583	**0.0381***	0.0336	**-0.0651***
t-val.	-0.28	1.75	-0.09	-1.34	1.20	1.70	1.05	-1.67
CCR	0.00001	0.000006	0.00005	0.0003**	0.00001	0.000008	0.00005	0.0003**
t-val.	0.34	0.16	0.74	2.55	0.30	0.21	0.74	2.56
N	70,481	70,383	70,179	69,372	70,449	70,351	70,146	69,339
R^2	9.63%	0.33%	1.28%	3.68%	9.65%	0.34%	1.28%	3.69%
	Negative watch							
ΔLCCR	0.000858	0.00543	-0.0122	-0.0134				
t-val.	0.17	1.06	-1.05	-1.09				
CCR	0.00001	0.00001	0.00004	0.0003***				
t-val.	0.37	0.24	0.71	2.58				
N	70,474	70,376	70,172	69,365				
R^2	9.63%	0.33%	1.28%	3.68%				

Table A5.2.3. Continued.

Responses of Realised volatility to Fitch actions	[-1, 0]	[0, 1]	[1, 5]	[5, 22]	[-1, 0]	[0, 1]	[1, 5]	[5, 22]
	Downgrade				**Upgrade**			
ΔLCCR	-0.00295	**-0.0798****	-0.0149	0.0333	**0.107***	-0.0795	-0.0592	0.0240
t-val.	-0.09	-2.18	-0.34	0.65	1.80	-0.91	-0.84	0.33
CCR	0.00008	0.00002	-0.000009	0.0001	0.00007	0.00002	0.000006	0.0001
t-val.	0.25	0.04	-0.02	0.25	0.23	0.06	0.01	0.23
N	63,670	63,450	63,244	62,538	63,648	63,428	63,222	62,517
R^2	30.96%	0.48%	0.19%	0.42%	30.97%	0.47%	0.19%	0.42%
	Negative outlook				**Positive outlook**			
ΔLCCR	0.00343	0.0760	-0.0176	0.0555	**0.178****	**-0.162***	-0.00388	-0.0578
t-val.	0.10	1.04	-0.34	1.10	2.57	-1.68	-0.06	-0.69
CCR	0.00006	0.00001	-0.00001	0.0001	0.00006	0.000008	-0.000008	0.0001
t-val.	0.20	0.04	-0.03	0.31	0.20	0.02	-0.02	0.30
N	63,630	63,410	63,204	62,498	63,603	63,383	63,177	62,472
R^2	30.97%	0.47%	0.19%	0.43%	30.98%	0.48%	0.19%	0.43%
	Negative watch							
ΔLCCR	-0.0114	-0.0709	-0.0147	0.0668				
t-val.	-0.32	-1.08	-0.32	1.25				
CCR	0.00009	0.000005	0.0000003	0.0001				
t-val.	0.28	0.01	0.00	0.24				
N	63,636	63,416	63,210	62,505				
R^2	30.97%	0.47%	0.19%	0.43%				

Table A5.2.3. Continued. Responses of 1-month Implied volatility to Fitch actions

	[-1, 0]	[0, 1]	[1, 5]	[5, 22]	[-1, 0]	[0, 1]	[1, 5]	[5, 22]
	Downgrade				**Upgrade**			
ΔLCCR	**-0.0165*****	**0.00703****	-0.00504	-0.0151	-0.000114	**0.0123****	0.00173	**-0.0689****
t-val.	-3.48	2.05	-0.74	-0.83	-0.02	2.16	0.14	-2.25
CCR	0.00002	0.00001	0.00005	0.0004***	0.00002	0.00001	0.00005	0.0004***
t-val.	0.37	0.24	0.66	2.77	0.38	0.28	0.68	2.77
N	70,524	70,426	70,221	69,414	70,503	70,405	70,201	69,395
R^2	9.63%	0.33%	1.28%	3.69%	9.62%	0.33%	1.28%	3.70%
	Negative outlook				**Positive outlook**			
ΔLCCR	**-0.0122*****	**0.00588***	-0.00912	-0.0134	-0.00179	**0.0145****	-0.00277	-0.0248
t-val.	-3.45	1.80	-1.14	-0.63	-0.53	2.12	-0.23	-1.18
CCR	0.00001	0.00001	0.00005	0.0004***	0.00001	0.00002	0.00005	0.0004***
t-val.	0.27	0.29	0.66	2.78	0.28	0.31	0.63	2.80
N	70,477	70,379	70,174	69,367	70,452	70,354	70,150	69,344
R^2	9.63%	0.33%	1.28%	3.69%	9.63%	0.33%	1.28%	3.70%
	Negative watch							
ΔLCCR	**0.0180*****	0.00386	-0.00131	-0.0123				
t-val.	3.23	1.07	-0.19	-0.58				
CCR	0.00002	0.00001	0.00005	0.0004***				
t-val.	0.33	0.29	0.67	2.80				
N	70,484	70,386	70,181	69,375				
R^2	9.63%	0.33%	1.28%	3.69%				

This table reports the results of estimations of equations (5.1), (5.2) with Huber-White robust standard errors based on full sample after excluding non-event observations around rating events within one month. The dependent variables are ΔIV and ΔRV during the time windows. Main independent variable is ΔLCCR, daily changes in log-transformation of credit ratings. For the ease of interpretation, absolute value of ΔLCCR is used. *, **, *** denote significant at 10%, 5%, 1% level of significance. Lagged (1 to 5 days) values of dependent variables, year and country dummies are included but not reported for ease of brevity.

Table A5.2.4: Monte Carlo experiment - Responses of IV to different types of Moody's actions

Time window	[-1,0]	[0, 1]	[1, 5]	[5, 22]	[-1,0]	[0, 1]	[1, 5]	[5, 22]
	Downgrades				**Upgrades**			
ΔLCCR	-0.0041	0.0032	-0.0021	-0.0169	0.0497	**-0.0358***	0.0245	-0.0251
t-val.	-1.14	0.81	-0.17	-1.54	1.05	-1.78	0.67	-0.50
CCR	0.00009	-0.00004	-0.000001	0.0002	0.0001	-0.00007	-0.0002	-0.00004
t-val.	0.23	-0.12	-0.02	0.19	0.36	-0.18	-0.30	-0.04
Year/ Co	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	503	503	503	501	483	483	482	480
R^2	11.14%	11.01%	10.92%	14.32%	12.31%	11.38%	11.03%	14.39%
No. of est.	10,000	10,000	10,000	10,000	10,000	10,000	10,000	10,000
	Negative outlook				**Positive outlook**			
ΔLCCR	0.0034	**0.0101****	0.0085	-0.0194	0.0202	**0.1070***	0.0175	-0.0936
t-val.	0.67	2.24	0.61	-1.23	0.29	1.78	0.18	-0.72
CCR	0.00009	-0.00001	8.42e-06	0.0003	-0.0002	0.0002	0.0001	0.0001
t-val.	0.25	-0.05	0.01	0.31	-0.47	0.50	0.23	0.11
Year/ Co	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	491	491	491	489	474	474	474	472
R^2	10.88%	10.98%	11.01%	14.66%	10.96%	11.34%	10.86%	14.56%
No. of est.	10,000	10,000	10,000	10,000	10,000	10,000	10,000	10,000
	Negative watch							
ΔLCCR	-0.0054	0.0078	**-0.0476*****	-0.0286				
t-val.	-0.90	1.35	-3.17	-1.56				
CCR	0.00008	0.0001	-0.00009	0.0005				
t-val.	0.20	0.38	-0.16	0.50				
Year/ Co	Yes	Yes	Yes	Yes				
N	478	478	478	476				
R^2	11.32%	11.30%	12.39%	14.86%				
No. of est.	10,000	10,000	10,000	10,000				

Note: ΔLCCR, CCR report averages coefficients of ΔLCCR and CCR across the estimations of equation (5.1). Average t-statistics are heteroskedasticity robust using the Huber-White correction. N reports maximum number of observations for one estimation as this number varies slightly across estimations. R^2 reports averages R-square from the estimations. "No. of est." reports numbers of estimations. Each estimation of the equations is based on one independently random sampling. For the ease of interpretation, absolute value of ΔLCCR is used. *, **, *** denote significant at 10%, 5%, 1% level of significance.

Chapter 6: Volatility spill-overs arising from sovereign rating actions

6.1. Introduction

During periods of crises, financial markets are usually characterized by high volatility and sensitivity to new information. Cross-border linkages in the global economy play an important role in causing financial contagion. Good and bad news which triggers movements in one country's financial market volatility could also spill-over to elsewhere via several channels (Engle et al., 1990; King and Wadhwani, 1990; Dornbusch et al., 2000; Kaminsky et al., 2003).

The rating industry performs valuable functions for international capital markets, by measuring, monitoring, and disclosing credit risk information (e.g. Boot et al., 2006; IMF, 2010a; Bank of England, 2011). Numerous prior papers have shown that sovereign rating actions not only influence a country's own financial markets but also could spill-over to others. Financial asset returns, including bond yields, equity abnormal returns, credit default swaps (CDS) spreads, foreign exchange rates, change significantly following rating announcements on foreign sovereigns (Gande and Parsley, 2005; Ferreira and Gama, 2007; Afonso et al. 2012; Alsakka and ap Gwilym, 2012a, 2013). There has been widespread criticism and debate about whether CRAs precipitate and/or exacerbate currency crises, financial crises, and/or destabilize financial markets (e.g. House of Lords, 2011). Chapters 4 and 5 show that rating news has an impact on volatilities of equity and foreign exchange (FX) markets with both statistical and economic significance. The impacts vary across CRAs and rating action types. Importantly, rating news does not always increase market volatility/ uncertainty. In particular, additional rating news is likely to reduce both market ex-ante uncertainty and ex-post volatility. This chapter seeks to answer the question whether sovereign rating actions on one country spill-over to the volatilities of other countries' exchange rates.

To the best of my knowledge, there is no prior paper looking at the volatility spill-over effects of credit rating news. I seek to contribute to the above mentioned debate about whether rating news destabilizes the international financial markets.

The remainder of this chapter is organised as follows: the next section reviews related literature, Section 6.3 describes the data, Section 6.4 discusses the research hypotheses and methodologies, Section 6.5 and 6.6 present the empirical results and conclusion.

6.2. Literature review

The volatility spillover phenomena between financial markets has been extensively documented in prior literature (e.g. Engle et al., 1990; King and Wadhwani, 1990; Dornbusch et al., 2000; Kaminsky et al., 2003; Andersen et al., 2003b and many others). Using GARCH like models, Engle et al. (1990) show that spillover effects play an important role in determining the FX market volatility. Both country-specific news and "world-wide" news cause changes in the conditional volatility of exchange rates across markets. Engle et al. (1990), Hogan and Melvin (1994), and Li and Muzere (2010) attribute the spillover effects of news to heterogeneous beliefs and expectations upon the economic fundamentals among the market participants which take time to be resolved. In addition, Li and Muzere (2010) demonstrate that the assumption of homogeneous beliefs would yield predictions from their theoretical model to that are not consistent with volatility spillover phenomena.

Prior literature attributes spillover or contagion phenomena to financial and economic linkages between economies (e.g. Dornbusch et al., 2000; Hernandez and Valdes, 2001; Kaminsky et al., 2003; Rigobon, 2003). Hernandez and Valdes (2001) find that financial and banking competition between countries plays the most dominant channel for contagions during Asian, Brazilian, and Russian crises. Dornbusch et al. (2000) and Kaminsky et al. (2003) attribute the spillover impacts or contagion in FX markets to financial and trade linkages between economies, and to a competitive devaluation mechanism. Devaluation in a country hit by a crisis reduces the export competitiveness of the countries with which it competes in a third market, therefore putting pressures on the currencies of other countries. The subject in this chapter is not currency crises but credit rating events. However, there is a strong economic link between a country's exchange rates and its fiscal health which in turn directly relates to sovereign credit ratings (discussed in detail below). Therefore, the competiveness between countries in international trades is expected to play an important channel via which credit rating spillover impacts transmit through the FX markets.

Another strand of literature identifies the clear relevant of a country fiscal health to its exchange rates (e.g. Dornbusch, 1976; Obstfeld and Rogofff, 1995; Tornell and Velasco, 2000; Kim and Roubini, 2008; Enders et al. 2011). There is also an inconclusive debate on whether fiscal shocks would lead to a currency depreciation or appreciation (see Chapter 5, Section 5.2 for detail discussions). Meanwhile, all CRAs explicitly identify the key relevance of a country's fiscal condition in determining the country's sovereign credit rating level (Moody's, 2008, 2013; Fitch, 2011b; S&P, 2011; see Chapter 5, Section 5.2 for details). Empirical research also confirms the relevance of fiscal deficit/surplus in determining a country's credit rating level (e.g. Cantor and Packer, 1996; Bennell et al., 2006; Afonso et al., 2011).

Moreover, sovereign bonds and debts act as the benchmark for the borrowing costs of other agents in the local economy, thus have wider implications on the general credit conditions and the performance of the national economy (e.g. Arellano, 2008; Dittmar and Yuan, 2008; Acharya et al., 2014; Gennaioli et al., 2014). Therefore, sovereign bond yields could play another significant channel via which credit rating spillovers are transmitted.

Numerous prior papers report evidence of spillover impacts from sovereign rating actions. Gande and Parsley (2005) and Arezki et al. (2011) show that sovereign rating news on one country spills over to other sovereign bond yields. The spill-over impacts of rating news are also found significant in equity markets (e.g. Ferreira and Gama, 2007). Arezki et al. (2011) reveal that sovereign downgrades have significant spill-over effects across European countries and across financial markets during the European sovereign debt crisis period. Alsakka and ap Gwilym (2012a, 2013) find evidence of regional spillover impacts of sovereign rating news, especially during the period of recent financial and European sovereign debt crises.

The above issues imply a significant influence of sovereign credit rating news on the FX market. Given the inconclusive debate on whether currency appreciation or depreciation follows fiscal shocks, the impact of sovereign rating news on the FX market uncertainty/volatility is expected to be even stronger than on FX rates. Therefore, a certain degree of spillover arising from sovereign credit rating news is expected. To the best of my knowledge, there is no prior paper which investigates the volatility spill-over effects of credit rating news. This chapter seeks to contribute to the debate about whether rating news destabilize the international financial market. The topic has been a matter of concern for both researchers and policy makers.

Given the prior evidence on the economic linkages between sovereign ratings, a country's fiscal conditions and its exchange rates, sovereign rating announcements are expected to cause spillover effects on both ex-ante uncertainty and ex-post volatility of the domestic currency value (i.e. the exchange rates against the U.S dollar (USD)). However, the market uncertainty and the ex-post volatility do not necessarily react to negative (positive) rating news in a negative (positive) direction like financial assets' prices, as evidenced in e.g. Gande and Parsley (2005), Ferreira and Gama (2007), Arezki et al. (2011). Rating actions might play a "confirmation role" (see Chapters 4 and 5 for more details). Therefore, the spillover impacts of rating news could lead to reactions of volatilities in either positive or negative directions.

6.3. Data

This study is based on an unbalanced data panel which covers 46 countries during the period from January 2007 to September 2013. Table 6.1 reports the list of the countries and the number of rating events on each country. The data sample includes all countries whose currencies are listed in BIS (2013). There are only four exceptions which are China, Hong Kong, Saudi Arabia, Denmark, whose FX regimes are categorised as (crawling) pegged/fixed in IMF de facto classifications (IMF 2006, 2007, 2010c, 2012).

It is noteworthy that the sampled countries are located in different geographic regions. Some prior papers on contagion and spillover effects employs datasets within regional groupings of countries (e.g. Hernandez and Valdes, 2001; Rigobon, 2003; Alsakka and ap Gwilym, 2012a, 2013). On the other hands, there are also papers based on datasets which are not restricted to geographic regions (e.g. Engle et al., 1990; Andersen et al., 2003b; Gande and Parsley, 2005). While the former approach allows more significant expectations of spillover evidence given the closeness between sampled economies, the latter is more conservative, hence, offers robust findings on spillover effects (if any).

Sovereign credit ratings, watch and outlook announcements are drawn from my supervisors' dataset and verified by Standard and Poor's (S&P), Moody's, and Fitch publications. FX volatilities data is retrieved from Data Stream and Bloomberg.

6.3.1. Sovereign credit ratings

The data on sovereign ratings consists of daily observations of long-term foreign-currency credit ratings, outlook and watch status of sovereigns rated by the three leading CRAs. Figure 6.1 presents the distribution of daily ratings of sovereigns for each CRA.

Sovereign ratings are converted to numerical scores within a 58-point comprehensive credit rating (CCR) scale in order to capture information on both actual ratings and outlook/watch procedures. In the CCR scale, rating symbols are converted as follows: AAA/Aaa ≡ 58, AA+/Aa1 ≡ 55, AA/Aa2 ≡ 52 ... CCC-/Caa3 ≡ 4, C-D ≡ 1. Adjustments for (positive/negative) outlook and watch announcements are made by adding ±1 and ±2, respectively, on the CCR scale (see Sy, 2004).

In order to control for the possible existence of non-linearity in the CCR scale, a logit-transformation of the rating scale is employed (Please see Chapter 5 – Section 5.3.1 for more details). The logit-transformation is constructed, as follows:

$$\mathrm{LCCR} = \begin{cases} \ln[\dfrac{CCR}{29 - CCR}] & \forall \mathrm{CCR} \in [1..28] \\ \ln[\dfrac{(CCR-28)(CCR+28)^{\sqrt{\pi}}}{59 - CCR}] & \forall \mathrm{CCR} \in [29..58] \end{cases}$$

Table 6.2 presents numbers of sovereign credit rating events for each CRA. The CRAs released 583 rating events on the selected sovereigns during the sample period. S&P released the most rating news with 226 signals. There are 182 (175) rating announcements by Moody’s (Fitch). During the period, there were 59 (34), 49 (31), 51 (31) downgrades (upgrades) by S&P, Moody’s, and Fitch, respectively. The equivalent numbers of negative (positive) outlook announcements are 53 (43), 38 (24), 43 (31). The corresponding figures of watch actions are 29 (8), 24 (16), and 14 (5). There are 17 combined rating events made by S&P whereby both a rating downgrade/upgrade and outlook or watch signals are announced simultaneously. The equivalent figures from Moody’s and Fitch are 29 and 15, respectively. Most rating events (≈88%) are within 3-point changes in the CCR scale which mean an outlook/ watch announcement or a 1-notch downgrade/upgrade in isolation. There are only 23/226 of rating events made by S&P, 25/182 by Moody's, 24/175 by Fitch which are multiple-notch downgrades/upgrades. Almost all (58/59=98.3%) downgrades by S&P are preceded by either negative outlook or watch procedures whereas the corresponding proportion of S&P upgrades is only 70.6%. The equivalent numbers from Moody's are 89.8%, 87.1%, and those from Fitch are 86.8%, 54.8%.

6.3.2. Foreign exchange market volatilities

The FX market is the largest and most liquid market in the world with an average daily trading volume of US$5.35 trillion in April 2013 (BIS, 2013). The FX market is dominated by over-the-counter (OTC) transactions which were almost 32 times larger than those via organized exchanges in terms of daily turnover amounts (BIS, 2013). This study examines responses of OTC option-implied volatility with an underlying asset of bilateral exchange rates against the USD during the period from Jan 2007 - September 2013. The sample covers all currencies named in BIS (2013), account for 97.7% global FX market trades.[42] There are 46 sampled countries during sample periods from 2007-2013. Among them, 17 EU countries using the Euro are included in the sample when they started using the Euro. All the sampled countries' exchange rates are categorised as free floating or floating regimes in every IMF de facto classifications since IMF started the de facto classification in 2006. There are three exceptions i.e. Malaysia, Singapore, Russia which were categorised in "Other managed arrangement" in IMF de facto classifications 2010 and 2012. This category is a residual and is used when the exchange rate arrangement does not meet the criteria for any of the other categories.

[42] In order to control for FX regimes, only currencies categorised as (free) floating in all versions of in IMF de facto classifications are included. For that reason, Four currencies (i.e. Chinese Remibi, Hong Kong dollar, Saudi Riyal, Danish krone which are categorised as (crawling) pegged/fixed against the USD/ Euro/a composite of currencies) are excluded.

At-the-money option-implied volatility (IV) and intraday realised volatility (RV) are used to proxy the volatility of exchange rates against the USD. IV captures market ex-ante uncertainty over the value of a given currency against USD while RV measures the ex-post volatility of the value in a given day.

Daily data of mid-quoted OTC FX 1-month maturity ATM IV is retrieved from Data Stream.[43] The primary source is Thomson Reuters. In OTC FX markets, dealers typically do not quote option premiums but implied volatilities which in turn can be converted to call or put options premiums using Garma and Kohlhagen (1983) version of the Black-Scholes model (Please see Chapter 5 – Section 5.3.2 for more details). Figure 6.2 presents the distribution of the 1-month maturity IV. During the sample periods, there are 77,989 daily observations of 1-month implied volatility. Among them, there are 83 observations where IV is greater than 50 percentage points in Brazil, Indonesia, Korea, South Africa (during Oct-Nov2008), Mexico (during Oct2008), and Poland (during Dec2008). The main interest is in the dynamics of the IV, and Figure 6.3 presents the distribution of daily changes in the 1-month maturity IV. The changes are very much centred around zero with a mean of -2.5*10^{-4} percentage points, median of 0, and standard deviation of 0.75 percentage points.[44]

Realised volatility based on intraday spot FX rates contains relevant information regarding the future evolution of underlying assets' volatility (Andersen et al., 2003a). Data of daily realised volatility (RV) is collected from Bloomberg. The realised volatility is estimated based on per 30 minutes spot FX rates in following formula:

$$RV_t = \sqrt{\sum_{k=1}^{48} r_{k,t}^2}$$

Where

RV_t is FX realised volatility at day t

[43] Empirical investigations on other maturities (i.e. 3-, 6-month, 1-year) IVs produce qualitatively similar results (available upon request).

[44] 0.1% winsorisation is used in order to mitigate the effects of outliers and avoid possible information loss.

$r_{k,t}$ is k^{th} 30-minute FX return at day t

Using very high-frequency data suffers from market microstructure frictions (e.g. Zumbach el al., 2002). Andersen et al. (2003a) use the 30-minute frequency as a satisfactory balance between the accuracy of the realised volatility measure and avoiding market microstructure frictions. There are 71,880 daily observations of realised volatility.[45] Figure 6.4 presents the distribution of the RV. During the sample periods, there are 261 observations where the RV is greater than 50 percentage points in Australia, Brazil, Chile, Colombia, Indonesia, Japan, Korea, Mexico, New Zealand, Norway, South Africa, Sweden, Switzerland, Turkey in October - November 2008 and Russia in January 2009. The focus here is the dynamics of the RV, and Figure 6.5 presents the distribution of daily changes in the RV. The mean, median, and standard deviation are $-3.5*10^{-4}$, -0.045, and 5.22 percentage points, respectively.[46] Consistent with analyses in Chapter 5, the standard deviation of daily changes in RV is almost 7 times larger than the equivalent figure of IV. This indicates a much more volatile distribution and implies higher sensitivity of RV to news than IV. This is reasonable since RV measures ex-post volatility or market participants' disagreements on a day when news is released. In contrast, IV measures the expected volatility or market participants' ex-ante uncertainty over a longer period, i.e. with a horizon of the following month after news is released.

6.4. Hypotheses and methodological framework

6.4.1. Event study - preliminary analysis

H_0: Credit rating news does not spill-over to other countries' FX market volatilities. Therefore, movements in these markets' volatilities after releases of rating events are not statistically different from zero.

[45] Bloomberg provides intraday data of foreign exchange rates from March 2007 at the earliest. Therefore, the number of observations on RV is smaller than the corresponding number on IV.
[46] 0.1% winsorisation is used in order to mitigate the effects of outliers and avoid possible information loss.

H_a: Credit rating news on one country triggers significant movements in other countries' FX market volatility. Therefore, changes in the volatility measurements after rating events are statistically different to zero.

In terms of methodology, a standard event study is used to examine logarithm changes in the FX volatilities of non-rating-event countries (hereafter called home countries or non-event countries, interchangeably) during time windows after rating announcements on other countries (hereafter called foreign countries or rating event countries, interchangeably). The time windows are [-1, 0], [0, 1], [1, 5] in order to mitigate the information contamination problem. t=0 denotes the day when a rating announcement is released.[47] Six types of rating news from all the CRAs are examined separately, i.e. downgrades, upgrades, negative/positive outlook and watch announcements.

The reverse direction of causality is highly unlikely to happen. In other words, it is highly implausible for movements in the volatility of one country's exchange rates to cause rating changes on another country. Therefore, pre-event windows, i.e. [-5, -1] are not included. This is different to Chapter 4 where equity option markets are under investigation because CRAs closely observe movements in equity markets and periodically publicise market-implied ratings (e.g. Moody's KMV™).

The OTC FX market operates on a 24 hours basis and can incorporate new information very quickly. Therefore, both [-1, 0] and [0, 1] windows are used to capture the market reactions following releases of rating news. The primary data source is Thomson Reuters which quotes the closing FX prices at 4:30 pm GMT. As a result, the [-1, 0] ([0, 1]) window captures the responses of RV and IV to rating news which is released before (after) 4:30pm GMT. Within this sample, most countries belong to time zones earlier than GMT+00; only six countries (i.e. Brazil, Canada, Chile, Colombia, Mexico, Peru) are after the GMT+00

[47] It is noteworthy that the time windows [-1, 0] and [0, 1] are equivalent to one-day windows (i.e. [0, 0] and [1, 1]) in other studies which examine financial assets returns. For example, an asset return during the [0, 0] window incorporates information about the asset's prices in day -1 and day 0.

time zone. CRAs' releasing offices are usually located in geographic proximity to the rated countries. For example, Moody's releasing offices in Europe and East Asia are in London and Singapore, respectively. Therefore, rating news is likely to be released before 4.30 pm GMT. Moreover, London is by far the largest centre for FX trades (around 40% of global trading according to BIS, 2010, 2013). Thus, the FX market responses (if any) are likely to materialise in the [-1, 0] window.

Observations on FX volatility of home countries which encounter any rating event(s) from any CRA within one week beforehand are excluded. This is done to eliminate possible contamination from the impacts of rating news on own country FX. All rating events on EU countries are included, but the Euro/US$ volatility is only counted once for each rating event on a non-euro-zone country.

The univariate analyses in this section cannot both control for macroeconomic fundamentals and treat ratings linearly. In other words, the analyses are based on an assumption that rating actions on different event countries at different levels of creditworthiness would trigger the same reactions from the FX volatilities of home countries which in turn are also at different levels of creditworthiness as well as having different macroeconomic conditions. This limitation is acceptable in this section which aims at preliminarily investigations on whether a volatility spill-over impact of rating news exists in FX markets rather than seeking the exact sign and magnitude of the spill-over impact (if any).

The limitation will be dealt with by the later methodology. Besides, it is compelling to investigate whether spill-over effects last in longer time windows, especially if a confirmation role of rating news exists. Increasing the length of the time windows could help, but this approach is also associated with increased informational contamination. Therefore, auxiliary multivariate regressions will be used in the next section. Importantly, further multivariate analyses allow investigations on dominant channels via which a spill-over impact (if any) is transmitted.

6.4.2. Multivariate analysis

H_0: The spill-over impact of rating news (if any) is short-lived and market movements beyond the day of news releases are not statistically different from zero.

H_a: Changes in the volatility measurements during days after rating events are statistically different to zero.

In terms of methodology, regressions explaining changes in the FX volatilities of home countries by changes in rating levels of foreign countries and control variables are run, as follows:

$$\Delta IV_{i,s} = \alpha + \beta * \Delta LCCR_{j,t} + \gamma_1 * CCR_{i,t} + \gamma_2 * CCR_{j,t} + \zeta * C + \varsigma * Y + u_{i,t} \; \forall j \neq i \quad (6.1)$$

$$\Delta RV_{i,s} = \alpha + \beta * \Delta LCCR_{j,t} + \gamma_1 * CCR_{i,t} + \gamma_2 * CCR_{j,t} + \zeta * C + \varsigma * Y + u_{i,t} \; \forall j \neq i \quad (6.2)$$

$\Delta IV_{i,s}$, $\Delta RV_{i,s}$ are log-changes in IV and RV of home country i at day t.

$\Delta LCCR_{j,t}$ is change in the log-transformation rating scale of foreign country j at day t. All sovereign credit rating events on foreign countries are included in this variable ($\Delta LCCR_{j,t}$). Please note that $\Delta LCCR_{j,t}$ is a variable which captures credit changes in all foreign countries. Technically, the variable is constructed as follows: (i) in an event day (t=τ), the value of the change in the log-transformation of the rating scale in the event country ($\Delta LCCR_{i,\tau}$) is assigned to all foreign non-event countries ($\Delta LCCR_{j,\tau} = \Delta LCCR_{i,\tau} \; \forall j \neq i$); (ii), $\Delta LCCR_{i,\tau}$ in the event country, then, is set to nil. There were very few multiple rating event days during the sample period. Results based on excluding multiple rating event days are similar (Appendix 6.1).

$CCR_{i,t}$ is Comprehensive Credit Rating (i.e. rating level including information of actual rating level and outlook/watch procedure) of home country i at day t.

$CCR_{j,\,t}$ is Comprehensive Credit Rating of foreign country j at day t.

C and Y are full vectors of home country, foreign country and year dummies. They are included to control for business cycle and home country, foreign country characteristics. In total, there are 46 home country dummies, 41 foreign country dummies (because there are five countries without any rating event, please refer to Table 6.1 for details), and seven year dummies (sampled period from 2007 - 2013).

All rating events on EU countries are included, but the Euro/US$ volatility is only counted once for each rating event on a non-euro-zone country. In order to eliminate possible contamination from impacts of rating news on own country FX volatility, observations on FX volatility of home countries which encounter any rating event(s) from any CRA within one month beforehand are excluded.

Estimations of Equations (6.1) and (6.2) are based on a sample of event days plus random country-matched non-event days, drawn from the full sample excluding non-event observations within one month before and after rating announcements (see Fereirra and Gama, 2007). For example, in 01/01/2008 S&P downgraded a given country. The sample will include observations on non-event countries' FX volatilities in two days: i) 01/01/2008 and ii) a random non-event day either before 31/12/2007 or after 31/01/2008. This is done for two purposes: i) disentangle genuine spill-over impact from market noise; ii) mitigate rating clustering and information contamination. Prior papers in spillover effects of rating news (on financial assets' prices) usually employ sample of event days only (e.g. Alsakka and ap Gwilym, 2012a, 2013). This approach only accounts for varability (of dependent variables) among non-event home countries when rating changes happen on foreign countries (i.e. only when the main independent variable, changes in rating levels of the foreign countries, is different from zero). In other words, the approach ignores the varability (of dependent variables) in non-event home countries between event days and non-event days. A key advantage of this appoach is to compare volatility changes in non-event countries in event days to themselves in non-event days (after controlling for the business cycle) in order to answer the question whether spillover impact exists or not in the first place.

In order to consider varying impacts across CRAs' actions (if any), equations for each CRA are estimated separately. For each CRA, there are five separate estimations for different types of signals (i.e. downgrades, upgrades, negative/positive outlook, negative watch announcements) in order to investigate the asymmetric market behaviour (if any). Please note that there are limited numbers of watch announcements for the CRAs (see Table 6.2 for details).

As robustness checks, Monte Carlo experiments are performed based on 10,000 estimations of Equations (6.1) and (6.2). Each estimation is based on one independent country-matched random sample. The estimations are for each CRA separately in order to consider varying impact across CRAs' actions (if any). For each CRA, there are two separate estimations based on grouping negative (positive) rating actions together.

6.5. Empirical results

6.5.1. Event study - preliminary analysis

Table 6.3 presents the results of the event study. Panel A of the table reports reactions of a home country's IV to rating news on a foreign country. In general, there is significant evidence of IV spill-over impacts and the impacts are varying across CRAs and types of rating actions.

S&P downgrades on foreign countries do not trigger spill-over impact on the home country's FX option-implied volatility while there is evidence of the spill-over impact from S&P upgrades. Specifically, IV increases when S&P announces an upgrade on a foreign country, i.e. during the window [-1, 0]. Within one week after the announcement, IV reduces significantly. It is noteworthy that the magnitude of the subsequent reduction is larger than the initial increase. S&P negative outlook and watch signals also impose significant spillover impacts, i.e. IV reduces either immediately or within one week after the releases of the negative outlook and watch announcements. The magnitude of the spill-over is modest, from 0.68% to 1.22%. The largest reaction is the reduction of 1.49% when S&P announces negative watch signals. There is no significant evidence that S&P positive outlook announcements could spill-over across FX option-implied volatility.

In contrast, both negative and positive news from Moody's instigates a spillover to other countries' FX option-implied volatilities. IV reduces about 1% within one week after Moody's downgrades. Moody's upgrades trigger immediate reduction of 0.87% (0.56%+0.31%) in IV. Negative outlook announcements trigger immediate increase of 0.47% and subsequent reduction of 0.51% within one week. The largest reaction to Moody's rating news is the reduction of 2.16% within one week after negative watch announcements. Positive outlook announcements trigger immediate modest reduction of 0.70% in IV. Overall, Moody's rating news reduces IV either immediate or within one week after Moody's announcements. It is noteworthy that Moody's positive news trigger immediate reduction in IV meanwhile the reduction of IV in response to Moody's negative news is found later, within one week after the announcements.

Fitch downgrades, upgrades, and negative outlook announcements spill-over to non-event countries' FX option-implied volatilities. Again, the spill-over impact is not usual in the sense that negative news triggers negative reactions (i.e. the FX IVs of non-event countries increase). Instead, the IV reduces in response to even Fitch downgrades, negative outlook announcements.[48]

[48] This is consistent with Chapters 4 and 5 which found that equity index and FX option-implied volatilities of event countries reduce when Fitch announces sovereign rating downgrades.

Panel B of Table 6.3 reports reactions of RV of a home country to rating news on a foreign country. Similarly, there is significant evidence of spill-over impacts, varying across CRAs' actions but with larger magnitude (compared to reactions of IV). This is reasonable because RV captures ex-post volatility or market participants' disagreements on the day when rating news is released. Meanwhile, IV measures the expected volatility or market participants' ex-ante uncertainty over a longer period, i.e. in the following month after rating news is released. Moreover, the formula for constructing RV indicates high sensitivity to new information (please see Section 6.3.2 for details).

S&P downgrades and upgrades trigger immediate increases in RV of over 4%. The increase in response to S&P downgrades is short-lived while there are subsequent large reductions of over 11% within one week after S&P upgrades. S&P negative outlook announcements trigger an immediate increase and a subsequent reduction in RV of over 3%. S&P positive outlook and negative watch announcements reduce RV by 3.37% and 8.89%, respectively.

Moody's downgrades trigger an immediate reduction in RV of 2.65%. Negative outlook induce an increase and a subsequent reduction of similar magnitude, over 5%. There is no significant reaction of RV to other Moody's rating news.

Fitch rating news induces reductions in RV except for Fitch upgrades which do not spill-over to non-event countries' RV. The significant reduction in RV in response to Fitch downgrades is consistent with the reduction of IV in response to Fitch downgrade in Panel A. Again, this continues to support the analyses in Chapters 4 and 5 that market participants consult with multiple CRAs and Fitch actions are considered as additional information which could play a "confirmation role" and contributes to reassure market participants.

The argument about the "confirmation role" is, to some extent, in line with Beber and Brandt (2006, 2009) who reveal that scheduled (even negative) macroeconomic news always reduce market uncertainty. Of course, sovereign rating news is not scheduled. However, since market participants usually consult with multiple CRAs, it is rational for investors to expect actions from the other CRAs after a 'first-mover' downgrade from one CRA. It is noteworthy that Chapters 4 and 5 investigated impacts of rating news on uncertainty/volatility over event country's financial markets whereas this chapter examines the spill-over impacts. The magnitude of spillover impacts is in general much smaller than the magnitude of impact on event country financial market uncertainty/ volatility. This, however, does not mitigate the relevance of rating information, especially additional ratings, to investor sentiment.

6.5.2. Spill-over effects in option-implied volatility - Multivariate analysis

Table 6.4 reports the estimated coefficients of Eq. (6.1) which explains changes in IV of home countries during the time windows after rating actions on a foreign country. The (independent) variable of interest is 'ΔLCCR', representing the 1-day change in the log-transformation of the CCR scale of a foreign sovereign j at event date t. It is noteworthy that 1-unit changes in the CCR cause varying effects on the LCCR depending on the starting level of the sovereign rating. For example, 1-notch downgrades on AAA or BBB-[49] sovereigns, respectively, cause 1.56-unit or 1.66-unit decreases while 1-notch downgrades on A+ or A[50] sovereigns cause 0.46-unit decreases in the LCCR. Negative outlook (watch) signals on AAA sovereigns cause 0.75-unit (1.21-unit) decreases while equivalent signals on A+ or A sovereigns cause much weaker responses in the LCCR of approximately 0.15-unit (0.30-unit) decreases.

Panel A of Table 6.4 shows that S&P actions spillover and affect FX option-implied volatility. The impacts do vary across types of rating actions, but in general increase the FX

[49] This is the lowest rating category in the investment grade. In other words, 1-notch downgrades will put BBB- issuers into the speculative grade.
[50] A+ and A are rating categories in the middle of the investment grade. Effects of rating news on the log-transformation of sovereigns around the middle of the speculative grade are very similar.

market ex-ante uncertainty. The coefficient of ΔLCCR is significant during different time windows depending on types of S&P actions. This is opposite to corresponding empirical results in Chapters 4 and 5 where the coefficient of ΔLCCR is significant in only one time window, i.e. [-1, 0]. It is noteworthy that Chapters 4 and 5 examine impacts of rating news on own countries' financial market uncertainty while this chapter investigate the spill-over effects of rating news. It is reasonable that spill-over effects happen later rather than immediately when rating news is released. A certain degree of heterogeneity inevitably exists in market participants' beliefs and expectations over the linkages to the event countries as well as economic interpretations which in turns take time to be fully conveyed (e.g. Engle et al., 1990; Hogan and Melvin, 1994). To some extent, this is also consistent with Andersen et al. (2003b) who find that the spillover impact of macroeconomic news on the conditional volatility of exchange rates is gradual in contrast to the immediate spillover impact on the exchange rates.

The magnitude of the increases in IV depends not only on the magnitude of rating actions but also the current level of sovereign ratings. Within one month after S&P releases 1-notch downgrades on AAA sovereigns,[51] IV increases 2.07% (1.56*0.0133). S&P corresponding upgrades induce an immediate increase of 1.03% (1.56*0.0066) and a subsequent increase by 1.34% (1.56*0.0086) within one month later. Similarly, S&P outlook announcements trigger both immediate and subsequent reactions from the IV. The immediate reductions of 0.37% (0.75*0.0049) and 0.44% (0.75*0.0058) are followed by increases of 0.49% (0.75*0.0065) and 2.65% (0.75*(0.0122+0.0231)) in responses to S&P negative news on AAA issuers and positive outlook news on AA+ issuers, respectively. In contrast, S&P negative watch announcements trigger only immediate reactions from IV. The market

[51] From now on, interpretation is based on the magnitude of market reactions to negative (positive) rating news on AAA (AA+) rated issuers, for sake of brevity. The magnitude of corresponding reactions to rating news on BBB- (BB+) rated issuers and issuers in the middle of the investment-grade/ the speculative-grade can be easily computed using the weights of 1.06 (=1.66/1.56) and 0.3 (=0.46/1.56), respectively.

uncertainty increases 4.37% (1.21*0.0361) and reduces 5.2% (1.21*0.043) during [-1, 0] and [0, 1] windows. CCR of home and event countries' creditworthiness are not significant in explaining the changes in the FX market uncertainty.

Panel B of Table 6.4 presents the results for Moody's rating actions. Similar to S&P, the impacts of Moody's actions vary across types of rating actions. However, Moody's rating news tends to reduce the FX market uncertainty, opposite to S&P. IV reduces immediately when Moody's releases rating downgrades. The evidence is consistent with analyses in Chapters 4 and 5 that Moody's downgrades are likely to play a confirmation role and reduce financial market uncertainty. However, the magnitude of the reaction is much smaller compared to those from S&P. Specifically, Moody's downgrades on Aaa issuers induce a slight reduction of 0.20% (1.56*0.0013) while S&P equivalent downgrades trigger an increase of 2.07%, over ten-times larger. This is different to the evidence in Chapters 4 and 5 where the magnitude of market reactions to S&P and Moody's downgrades are more or less the same. Please bear in mind that this chapter analyses spill-over effects while the impacts of rating actions on own countries are the subject in Chapters 4 and 5. The results indicate that the increases of uncertainty in response to S&P downgrades transmit (i.e. spill-over) much stronger than the reductions of uncertainty due to the 'confirmation role' of Moody's downgrades do.

Moody's upgrades also reduce the FX market uncertainty. The market reactions are found significant not only immediate but also in subsequent days. In response to Moody's 1-notch upgrades issuers to the Aaa status, IV immediately decreases by 0.92% (1.56*0.0059) and the reduction continues within one month by 4.03% (1.56*0.0258). During the sample period, Moody's have released no multiple-notch upgrade. Besides, almost all (≈86%) of the upgrades were preceded by positive outlook/watch procedures. Therefore, the new information content of Moody's upgrades is likely to be conveyed in the prior positive outlook/watch procedures, at least in the context of this particular dataset. By the time of announcements, Moody's upgrades, hence, bring no surprise to the public domain but play the confirmation role and reduce market uncertainty. It is noteworthy that the magnitude of the immediate reduction is much smaller than the subsequent reduction in the market uncertainty. This is consistent with the above analysis that spill-over effects happen later rather than immediately when rating news is released since heterogeneous beliefs and expectations exist among market participants (e.g. Engle et al. 1990; Hogan and Melvin, 1994). Moreover, market reactions to positive outlook announcements strengthen the above argument. IV initially reduces by less than 0.4% (0.75*0.0053) and later surges by almost 3.8% (0.75*0.0506). The later reaction is strongly statistically and economically significant. The underlying positive content must be brought to the public by Moody's outlook signals. Therefore, IV increases after outlook announcements and reduces after Moody's confirms these by actual 1-notch upgrades.

Moody's negative outlook/watch releases tends to reduce the FX market uncertainty. This is consistent with evidence in Chapter 4 where negative actions from Moody's tend to reduce equity market uncertainty. A remark on Panel B of Table 6.4 is that the magnitude of reactions to Moody's positive news is much larger than those of negative counterparts, except for Moody's negative watch news where there is no result for Moody's positive counterparts. There are limited numbers of Moody's positive watch announcements during the sample period (please see Table 6.2 for details). This is consistent with the analyses that Moody's is quicker than S&P in conveying positive information in their ratings (e.g. Alsakka and ap Gwilym, 2010a; Chapters 4 and 5 of this thesis).

Panel C of Table 6.4 presents the results for Fitch rating actions. The FX market uncertainty reduces in response to Fitch rating news regardless of the positive or negative nature of the news. The magnitudes of the reductions in IV in response to Fitch downgrades (upgrades), negative (positive) outlook announcements on AAA (AA+) issuers respectively are 3.46% (3.82%), 2.62% (0.55%).[52] The result is consistent with analyses in Chapters 4 and 5 and is in support of the view that Fitch is likely to play a third rater and a confirmation role (e.g. Bongaerts et al., 2012), hence, its actions are likely to reduce the market uncertainty. Different to Moody's, the magnitude of the spillover of Fitch downgrades (and upgrades) is not smaller than that of S&P corresponding actions, implying that Fitch "confirmation role" transmits more strongly than Moody's. The result reinforces the argument that Fitch is likely to play a third rater role, reduces market ex-ante uncertainty and helps form a consensus among FX market participants.

6.5.3. Spill-over effects in realised volatility – Multivariate analysis

Table 6.5 reports the estimated coefficients of Eq. (6.2) which explains changes in RV of home countries during the time windows after rating actions on a foreign country. Overall, the results in Table 6.5 are qualitatively similar to those in Table 6.4 except for the larger magnitude of market reactions. This is conceivable given the different nature of RV compared to IV. RV measures the disagreements between market participants in a given day whereas IV measures the expected volatility over a longer period (i.e. 30 days) after rating news. Therefore, RV is much more volatile and sensitive to news compared to IV (please see Section 6.3.2 for more details).

Panel A of Table 6.5 shows that S&P actions spillover and affect the ex-post volatility measurement for the FX market. The impacts vary across types of rating actions, but in general increase the FX market ex-post volatility. The coefficient of ΔLCCR is significant during different time windows depending on types of S&P actions. S&P downgrades trigger increases in RV both immediately and within one month. This differs from the corresponding

[52] The calculation method of these figures is similar those in Panel A and B (of Table 6.4) above, thus, omitted for sake of brevity.

empirical results in Table 6.4 where significant reactions of IV are found only from one week to one month after S&P downgrades. This again could be explained by the news sensitive nature of RV compared to IV (please see Section 6.3.2 for more details). The magnitude of the increases in RV depends not only on the magnitude of rating actions but also the current level of sovereign ratings. In response to S&P 1-notch downgrades on AAA sovereigns, RV increases 3.79% (1.56*0.0243) immediately when the news is released, i.e. during the [-1, 0] window. Within one week, RV reduces by 3.28% (1.56*0.021) then increases again by 4.82% (1.56*0.0309) within one month. In aggregate, within one month S&P 1-notch downgrades on AAA issuers induce 5.33% increases in RV. S&P negative watch announcements trigger immediate increases of huge magnitude. For example, S&P negative watch announcements on AAA issuers spark immediate increases of over 24% (1.21*0.205), by far the largest magnitude of market volatility reactions. Within one week later, RV reduces by 17.5% (1.21*0.145) which is also very large in magnitude. Combined with above analysis on S&P downgrades, this huge reactions of RV is in supports of the view that S&P negative rating news is informative (Gande and Parsley, 2005; Ferreira and Gama, 2007; Azeki et al., 2011; Afonso et al., 2012 and many others). A logical implication could be drawn. Rating actions which incorporate new (negative) information come to the public domain at cost of increasing not only the own country's financial market volatility but also spill-over to others.

S&P positive news induces later responses from RV. S&P upgrades cause both immediate and subsequent reactions from RV. The immediate reduction of 5.19% (1.56*0.0333) is followed by increases of 6.75% (1.56*0.0433) in responses to S&P upgrades of AA+ rated issuers to AAA. Positive outlook news on AA+ issuers also induces increases of 2.87% (0.75*0.0382) and subsequent reductions of 4.08% (0.75*0.0544) during [1, 5] and [5, 22] windows. The levels of home and event countries' creditworthiness are not significant in explaining the changes in uncertainty over home countries' domestic currencies.

Panel B of Table 6.5 shows that Moody's rating news is also influential, but in a different fashion to S&P. Consistent with results in Panel B of Table 6.4, both Moody's downgrades and upgrades induce reductions in RV. The reactions to Moody's downgrades are not immediate but within one month after the downgrades. During one week after Moody's 1-notch downgrades of Aaa issuers, RV increases by 2.14% (1.56*0.0137) followed by a subsequent reduction of 2.67% (1.56*0.0171). In aggregate, RV reduces by 0.53% (2.67% - 2.14%) within one month after Moody's 1-notch downgrades on Aaa issuers. The figure is very small compared to the magnitude of market reactions to corresponding downgrades from S&P (i.e. 5.33%), consistent with the reactions of IV (see Table 6.4). This affirms the analysis in Section 6.5.2 above that the increases of market volatility in response to S&P downgrades transmit (i.e. spill-over) much more strongly than the reductions of volatility due to the 'confirmation role' of Moody's downgrades.

Similar to the corresponding result in Panel B of Table 6.4, Moody's upgrades reduce ex-post volatility. Significant reactions of RV are found only during the [-1, 0] window implying that Moody's upgrades induce immediate and short-lived reductions the market ex-post volatility. This is different to the pattern of reactions of IV to Moody's upgrades where the reductions in IV last up to one month after Moody's releases its upgrades. The result might be explained by different characteristics between RV and IV. Please note that Moody's upgrades likely play a "confirmation role" given the fact that most of the underlying new positive information is conveyed in preceding positive outlook/watch procedures (please see Section 6.5.2). RV decreases by 3.32% (1.56*0.0213) in response to Moody's upgrades of issuers from Aa1 to the Aaa status. RV reactions to Moody's positive outlook announcements are consistent with the corresponding result in Table 6.4 and strengthen the above argument that most of underlying new positive information is conveyed in positive outlook/watch procedures, and Moody's upgrades, thus, are likely to play a confirmation role. The RV increases by almost 3.2% (0.75*0.0426) within one month after Moody's announces positive outlook on an Aa1 issuer.

Moody's negative outlook/watch releases induce immediate reductions in RV. However, the reactions are not short-lived. Significant market movements are found in the subsequent time windows. In aggregate, Moody's negative outlook news on Aaa issuers induce an increase of 0.87% (0.75*(-0.0231+0.0593-0.0246)) while corresponding negative watch news trigger a much higher increase of 11.13% (1.21*(-0.058+0.150)) within one month after the rating announcements.

Panel C of Table 6.5 presents the results for Fitch rating actions. The FX market ex-post volatility reduces in response to Fitch rating news regardless negative or positive nature of the news. The magnitudes of the reductions in RV in response to Fitch downgrade (upgrade), negative (positive) outlook announcements on AAA (AA+) issuers respectively are 5.73% (4.26%), 5% (3.41%).[53] The result is consistent with analyses in Chapters 4 and 5 and is in support of the view that Fitch is likely to play a third rater and a confirmation role (e.g. Bongaerts et al., 2012), hence, its actions are likely to reduce the market volatility. In other words, Fitch rating announcements are likely to reduce the disagreements between the FX market participants over the value of a currency.

The magnitude of the spillover from Fitch downgrades (and upgrades) is not smaller than S&P corresponding signals. Again, this is opposite to Moody's downgrades, implying that Fitch confirmation role transmits stronger than Moody's does in the context of both ex-ante uncertainty and ex-post volatility. The results are consistent with those in Table 6.4 and continue to support the argument that Fitch is likely to play a third rater role and helps form common consensus among the FX market participants.

[53] The calculation method of these figures is similar those in Panel A and B (of Table 6.5) above, thus, is omitted here for sake of brevity.

6.5.4. Monte Carlo experiment

Table 6.6 presents the results of the Monte Carlo experiment by repeating country-matched random sampling 10,000 times. Each sample consists of a number of event days plus the same number of country-matched non-event days. The averages across 10,000 estimations of Eq. (6.1) and Eq. (6.2) are reported.

Overall, the results are strongly consistent with results in Table 6.4 and 6.5. There is significant evidence that rating actions impose volatility spill-over impacts across the global FX market. The pattern of market reactions varies across CRAs as well as across type of rating signals (i.e. negative or positive). RV which measures the market ex-post volatility is more responsive to rating news than IV which measures the market ex-ante uncertainty, in terms of magnitude of the market reactions.

Panel A of Table 6.6 shows that S&P (both negative and positive) news and Moody's positive news tend to increase IV whereas Moody's negative news and Fitch (both negative and positive) news does the opposite, reducing the market ex-ante uncertainty. The significance level of spill-over impacts by Moody's negative news is only 10%. In addition, the magnitude of the spill-over impacts by Moody's both negative and positive news is small compared to S&P. This is likely caused by the fact that downgrades (upgrades) and negative (positive) outlook/watch procedures are grouped in the specifications. Moody's downgrades/upgrades, different to S&P actions, play an important confirmation role and reduce the market volatility. Meanwhile, their outlook/watch actions do not. Therefore, grouping them together causes insignificant results.[54] Fitch rating news reduces market uncertainty regardless of the directional content of the news (i.e. negative or positive). Magnitude of the spillover impacts by Fitch negative news is larger than Moody's negative news, and more or less the same as S&P negative news.

[54] Monte Carlo experiment based on separating different types of Moody's rating actions confirm that Moody's (both negative and positive) outlook announcements trigger increases in IV while Moody's upgrades (not downgrades) reduce IV (see Appendix 6.2 for details).

Panel B of Table 6.6 shows that all the CRAs influence the market volatility in different manners. S&P negative news and Moody's both negative and positive news spill-over and increases the market volatility while Fitch (both negative and positive) news again reduces the market volatility. This reaffirms the view that Fitch is likely to play a role as an additional rater.

6.6. Conclusions

This Chapter investigates the volatility spillover impact of sovereign credit rating actions assigned by Moody's, S&P, and Fitch on FX market. A dataset of 46 countries during the period from January 2007 to September 2013 is employed. This covers all main currencies used in global trades, i.e. named in BIS (2013), except currencies under non-floating FX regimes. The effects of rating signals are evidenced by an event study and country-matched regression analyses. A Monte Carlo experiment and several alternative specifications are employed as robustness checks. The results and findings are robust throughout several specifications as well as methodological frameworks.

The unique contributions to the literature are as follows: (i) Identifying spillover effects of rating news on FX market uncertainty/volatility; ii) Demonstrating the important role of additional sovereign ratings in reducing market uncertainty/volatility; iii) contributing to the debate about whether rating news destabilize the international markets, hence, the regulation of CRAs.

The main findings are summarised as follows. There is evidence of volatility spillovers arising from rating news. The spillover is asymmetric not only between positive and negative events but also varying across CRAs. Negative rating news from S&P on one country is likely to increase FX volatility/ uncertainty elsewhere whereas negative news from Moody's and Fitch is doing the opposite, reducing the FX volatility/ uncertainty. These effects are attributed to the "confirmation role" of additional ratings consistent with analyses in Chapters 4 and Chapter 5. The spillover impacts of rating news takes place much later than the impacts on own country's FX volatility/ uncertainty, i.e. within one month after rating announcements.

Combined with analyses in Chapter 4 where significant evidence of rating news anticipation is presented and Chapter 5 where additional rating news has shown to play a confirmation role and reduce FX uncertainty/ volatility, the findings raise a prudential proposal against calls for removing credit ratings from investment guidelines and regulations at least on sovereign debts. There are clearly benefits of reducing mechanic overreliance on credit ratings. However, sovereign rating signals, especially additional ones, help to reassure the FX market over anticipated credit issues. The "confirmation role" of rating news is beneficial not only rating event countries but also others.

Table 6.1: List of sample countries

	Country	Sample period	No. of events		Country	Sample period	No. of events
1	Australia	2007-2013	1	24	Malaysia[†]	2007-2013	5
2	Austria	2007-2013	4	25	Malta	2008-2013	10
3	Belgium	2007-2013	12	26	Mexico	2007-2013	10
4	Brazil	2007-2013	15	27	Netherlands	2007-2013	4
5	Canada[††]	2007-2013	0	28	New Zealand	2007-2013	6
6	Chile	2007-2013	9	29	Norway[††]	2007-2013	0
7	Colombia	2007-2013	14	30	Peru	2007-2013	17
8	Cyprus	2008-2013	40	31	Philippines	2007-2013	14
9	Czech Republic	2007-2013	7	32	Poland	2007-2013	6
10	Estonia	2011-2013	23	33	Portugal	2007-2013	27
11	Finland	2007-2013	3	34	Romania	2007-2013	9
12	France	2007-2013	6	35	Russia[†]	2007-2013	13
13	Germany	2007-2013	3	36	Singapore[†, ††]	2007-2013	0
14	Greece	2007-2013	40	37	Slovakia	2009-2013	11
15	Hungary	2007-2013	25	38	Slovenia	2007-2013	18
16	India	2007-2013	6	39	South Africa	2007-2013	14
17	Indonesia	2007-2013	18	40	Spain	2007-2013	24
18	Ireland	2007-2013	28	41	Sweden[††]	2007-2013	0
19	Israel	2007-2013	7	42	Switzerland[††]	2007-2013	0
20	Italy	2007-2013	13	43	Taiwan	2007-2013	3
21	Japan	2007-2013	10	44	Thailand	2007-2013	7
22	Korea	2007-2013	10	45	Turkey	2007-2013	17
23	Luxembourg	2007-2013	4	46	UK	2007-2013	8

Note: The data set covers 46 countries during the period from 01/01/2007 - 30/09/2013. Among them, four EU countries (i.e. Cyprus, Estonia, Malta, and Slovakia) are included in the sample after 01/01/2007 depending on when they started using the Euro currency. All the countries categorised as free floating or floating FX regimes in every IMF de facto classifications since IMF started the de facto classification in 2006 except for three countries marked by [†].

[†] denotes countries whose currencies were categorised in "Other managed arrangement" in IMF de facto classifications 2010 and 2012. This category is a residual and is used when the exchange rate arrangement does not meet the criteria for any of the other categories.

[††] denotes countries which did not experience any rating changes during the sample period but are included for the spill-over investigations because their currencies are among main currencies for global FX trades (BIS, 2013).

Table 6.2: Rating events

No. of events	S&P			Moody's			Fitch			Total		
	Positive	Negative	Σ	Positive	Negative	Σ	Positive	Negative	Σ	Positive	Negative	Σ
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Upgrade/ downgrade	34	59	93	31	49	80	31	51	82	96	159	255
Of which:												
- Multiple-notch	*5*	*18*	*23*	*0*	*25*	*25*	*4*	*20*	*24*	*9*	*63*	*72*
(percentage)	*14.7%*	*30.5%*	*24.7%*	*0%*	*51.0%*	*31.3%*	*12.9%*	*39.2%*	*29.3%*	*9.4%*	*39.6%*	*28.2%*
- Preceded by outlook/watch	*24*	*58*	*82*	*27*	*44*	*71*	*17*	*44*	*61*	*68*	*146*	*214*
(percentage)	*70.6%*	*98.3%*	*88.2%*	*87.1%*	*89.8%*	*88.8%*	*54.8%*	*86.8%*	*74.4%*	*70.8%*	*91.8%*	*83.9%*
Outlook	43	53	96	24	38	62	31	43	74	98	134	232
Watch	8	29	37	16	24	40	5	14	19	29	67	96
Total	85	141	226	71	111	182	67	108	175	223	360	583
Of which:												
- *Combined events*	*1*	*16*	*17*	*4*	*25*	*29*	*0*	*15*	*15*	*5*	*56*	*61*
(percentage)	*1.2%*	*11.4%*	*7.5%*	*5.6%*	*22.5%*	*15.9%*	*0%*	*13.9%*	*8.6%*	*2.2%*	*15.6%*	*10.5%*

Note: This table reports numbers of rating events released by the CRAs on sampled countries during the sample periods (Jan 2007 - September 2013). Columns (1), (2), (3) report numbers of positive, negative, and total rating signals from S&P, respectively. Similarly, columns (4) to (9) report corresponding numbers from Moody's and Fitch. (10) = (1) + (4) + (7); (11) = (2) + (5) + (8); (12) = (3) + (6) + (9). Row "Upgrade/ downgrade" reports numbers of upgrades/ downgrades; row "Multiple-notch" reports numbers of more-than-one-notch rating events; row "(percentage)" reports percentages of multiple-notch upgrades/ downgrades over total numbers of upgrades/ downgrades; row "Preceded by outlook/watch" reports numbers of downgrades/ upgrades which were preceded by outlook or watch procedure; row "(percentage)" reports percentages of upgrades/ downgrades preceded by outlook/ watch procedure over total numbers of upgrades/ downgrades; row "Outlook" reports numbers of outlook announcements; row "Watch" reports numbers of rating watch or reviews; row "Total" reports total numbers of rating events; row "Combined events" reports numbers of rating events which involve both actual rating change and outlook or watch announcement.

Table 6.3: Result of the event study

Panel A: Response of implied volatility

	[-1,0]	[0,1]	[1,5]	[-1,0]	[0,1]	[1,5]
S&P						
	Downgrades			**Upgrades**		
$\Delta\overline{IV}$	-0.0025	-0.0024	0.0018	**0.0068*** **	-0.0021	**-0.0122*** **
t-val.	-1.15	-1.12	0.60	2.83	-0.85	-3.27
n	1,322	1,320	1,316	899	897	897
	Negative outlook			**Positive outlook**		
$\Delta\overline{IV}$	0.0024	0.0017	**-0.0084** **	-0.0005	0.0007	-0.0044
t-val.	0.89	0.72	-2.57	-0.26	0.36	-1.61
n	1,175	1,174	1,173	1,124	1,126	1,126
	Negative watch					
$\Delta\overline{IV}$	**-0.0149*** **	0.0069	-0.0046			
t-val.	-2.63	1.03	-0.72			
n	440	440	439			
Moody's						
	Downgrades			**Upgrades**		
$\Delta\overline{IV}$	0.0016	-0.0028	**-0.0101*** **	**-0.0056** **	**-0.0031* **	-0.0005
t-val.	0.85	-1.24	-3.06	-2.41	-1.84	-0.18
n	1,172	1,171	1,172	780	775	773
	Negative outlook			**Positive outlook**		
$\Delta\overline{IV}$	**0.0047* **	0.0014	**-0.0051* **	**-0.0070*** **	0.0024	-0.0057
t-val.	1.86	0.63	-1.68	-2.77	0.91	-1.63
n	863	863	864	644	643	642
	Negative watch					
$\Delta\overline{IV}$	0.0035	0.0047	**-0.0216*** **			
t-val.	1.21	1.43	-5.14			
n	633	631	633			
Fitch						
	Downgrades			**Upgrades**		
$\Delta\overline{IV}$	**-0.0058*** **	**0.0041** **	**-0.0066* **	**-0.006*** **	**-0.006** **	0.0027
t-val.	-2.66	2.03	-1.89	-2.75	-2.13	0.74
n	1,185	1,185	1,183	791	791	792
	Negative outlook			**Positive outlook**		
$\Delta\overline{IV}$	**-0.0077*** **	0.0029	**-0.0123*** **	0.0051	-0.0025	-0.0015
t-val.	-2.81	1.07	-2.84	1.62	-0.79	-0.39
n	877	878	881	816	816	816

Table 6.3. Continued - ***Panel B: Response of realised volatility***

	[-1,0]	[0,1]	[1,5]	[-1,0]	[0,1]	[1,5]
S&P						
	Downgrades			**Upgrades**		
$\Delta\overline{RV}$	**0.0412*** **	-0.0112	-0.0011	**0.0428** **	0.0157	**-0.1127*** **
t-val.	3.63	-0.90	-0.07	2.22	0.89	-4.52
N	1,222	1,222	1,221	772	782	773
	Negative outlook			**Positive outlook**		
$\Delta\overline{RV}$	**0.0315** **	-0.0210	**-0.0312* **	-0.0029	**-0.0337** **	-0.0025
t-val.	1.99	-1.39	-1.93	-0.19	-2.31	-0.15
N	1,075	1,074	1,076	1005	998	994
	Negative watch					
$\Delta\overline{RV}$	0.0022	0.0270	**-0.0889*** **			
t-val.	0.09	0.99	-3.43			
N	409	408	406			
Moody's						
	Downgrades			**Upgrades**		
$\Delta\overline{RV}$	0.0144	**-0.0265** **	0.0167	0.0079	0.0239	0.0119
t-val.	1.07	-2.01	-1.04	0.45	1.35	0.55
N	1,093	1,091	1,082	702	706	708
	Negative outlook			**Positive outlook**		
$\Delta\overline{RV}$	**0.0586*** **	**-0.055*** **	0.0311	-0.0308	-0.0206	0.0006
t-val.	3.67	-3.54	1.60	-1.39	-1.04	0.02
N	803	800	796	531	529	532
	Negative watch					
$\Delta\overline{RV}$	0.0059	-0.0298	-0.0079			
t-val.	0.27	-1.64	-0.39			
N	591	593	590			
Fitch						
	Downgrades			**Upgrades**		
$\Delta\overline{RV}$	**-0.0517*** **	**-0.0565*** **	0.0126	-0.0242	0.0183	-0.0061
t-val.	-3.75	-4.13	0.82	-1.37	0.97	-0.32
N	1,099	1,101	1,099	692	692	696
	Negative outlook			**Positive outlook**		
$\Delta\overline{RV}$	0.0026	**-0.0707*** **	0.0027	0.0220	**-0.0751*** **	0.0423
t-val.	0.16	-3.97	0.15	1.17	-3.42	1.63
N	819	821	819	675	679	681

Note: $\Delta\overline{IV}$ and $\Delta\overline{RV}$ report mean value of log-changes in the IV and RV, respectively, during the time windows. The time windows [-1, 0] and [0, 1] are equivalent to one-day windows (i.e. [0, 0] and [1, 1]) in studies which examine financial assets returns. n reports numbers of observations. n varies across the time windows because of missing IV or RV data at the beginning or the end of the sample period. *, **, *** denotes significant at 10%, 5%, 1%. Equivalent event study excluding multiple-event days produces qualitatively similar results (reported in Appendix 6.1).

Table 6.4: Multivariate analysis – Implied volatility spill-over

Panel A: S&P actions

	Downgrade [-1,0]	Downgrade [0, 1]	Downgrade [1, 5]	Downgrade [5, 22]	Upgrade [-1,0]	Upgrade [0, 1]	Upgrade [1, 5]	Upgrade [5, 22]
ΔLCCR	0.0022	0.0002	0.0004	**0.0133*** **	0.0002	**0.0066*** **	-0.0045	**0.0086***
	(0.95)	(0.13)	(0.25)	(2.77)	(0.14)	(2.60)	(-1.51)	(1.67)
CCR_{home}	0.0001	0.0005	-0.0005	-0.0001	0.0003	0.0004	-0.0008	0.0009
	(0.19)	(0.89)	(-0.72)	(-0.08)	(0.52)	(0.74)	(-1.02)	(0.62)
CCR_{event}	3E-05	7E-05	-0.0003	1E-05	-9E-06	3E-05	-0.0003	3E-05
	(0.39)	(0.88)	(-0.07)	(0.07)	(-0.12)	(0.35)	(-1.43)	(0.16)
Y/Co	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	8,833	8,829	8,785	8,758	8,472	8,468	8,429	8,400
R^2	1.58%	1.20%	1.82%	6.77%	1.41%	1.32%	2.29%	7.58%

	Negative outlook [-1,0]	Negative outlook [0, 1]	Negative outlook [1, 5]	Negative outlook [5, 22]	Positive outlook [-1,0]	Positive outlook [0, 1]	Positive outlook [1, 5]	Positive outlook [5, 22]
ΔLCCR	-0.0036	**-0.0049** **	**0.0065*** **	-0.0054	0.0011	**-0.0058** **	**0.0122*** **	**0.0231*** **
	(-0.87)	(-2.52)	(3.11)	(-1.01)	(0.58)	(-2.51)	(3.70)	(5.52)
CCR_{home}	0.0002	0.0005	-0.0006	0.0005	-1E-05	0.0005	-0.0006	0.0001
	(0.36)	(0.78)	(-0.81)	(0.32)	(-0.03)	(0.83)	(-0.79)	(0.09)
CCR_{event}	-3E-05	5E-05	-0.0003	0.0001	4E-06	3E-05	-0.0003	-0.0001
	(-0.34)	(0.64)	(-0.90)	(0.72)	(0.04)	(0.43)	(-0.92)	(-0.55)
Y/Co	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	8,696	8,693	8,653	8,626	8,659	8,658	8,618	8,587
R^2	1.33%	1.55%	2.10%	7.47%	1.17%	1.43%	1.90%	6.98%

	Negative watch [-1,0]	Negative watch [0, 1]	Negative watch [1, 5]	Negative watch [5, 22]
ΔLCCR	**0.0361***	**-0.0430** **	-0.0090	-0.0083
	(1.81)	(-2.07)	(-0.38)	(-0.35)
CCR_{home}	0.0002	0.0005	-0.0005	0.0001
	(0.33)	(0.76)	(-0.59)	(0.09)
CCR_{event}	2E-06	6E-05	-0.0004	-9E-05
	(0.02)	(0.74)	(-0.08)	(-0.48)
Y/Co	Yes	Yes	Yes	Yes
N	8,068	8,066	8,025	7,969
R^2	1.21%	0.82%	1.23%	6.24%

Panel B: Moody's actions

	Downgrade [-1,0]	Downgrade [0, 1]	Downgrade [1, 5]	Downgrade [5, 22]	Upgrade [-1,0]	Upgrade [0, 1]	Upgrade [1, 5]	Upgrade [5, 22]
ΔLCCR	**-0.0013***	-0.0009	-0.0005	0.0027	**-0.0059** **	-0.0003	-0.0020	**-0.0258*** **
	(-1.81)	(-0.83)	(-0.36)	(1.13)	(-2.49)	(-0.14)	(-0.94)	(-7.57)
CCR_{home}	0.0006	0.00009	-0.0009	-0.0002	0.0006	0.0001	-0.0006	-0.0002
	(1.38)	(0.20)	(-1.46)	(-0.19)	(1.53)	(0.26)	(-1.10)	(-0.18)
CCR_{event}	-5E-06	-3E-05	-0.0003	9E-06	-5E-07	-1E-06	-0.0003	-3E-05
	(-0.08)	(-0.40)	(-0.96)	(0.05)	(-0.01)	(-0.02)	(-0.95)	(-0.19)
Y/Co	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	8,710	8,707	8,668	8,638	8,369	8,365	8,323	8,296
R^2	1.19%	0.98%	2.29%	7.37%	1.25%	0.99%	1.30%	6.17%

	Negative outlook [-1,0]	[0, 1]	[1, 5]	[5, 22]	Positive outlook [-1,0]	[0, 1]	[1, 5]	[5, 22]
ΔLCCR	**-0.0052*** **	-0.0002	**0.0036***	-0.0033	**-0.0053*** **	-0.0008	0.0020	**0.0506*** **
	(-5.15)	(-0.17)	(1.84)	(-1.21)	(-3.75)	(-0.52)	(0.83)	(8.45)
CCR_{home}	0.0005	-2E-05	-0.0007	7E-06	0.0005	0.0002	-0.0007	0.0001
	(1.19)	(-0.04)	(-1.10)	(0.01)	(1.18)	(0.44)	(-1.12)	(0.08)
CCR_{event}	-1E-05	-7E-06	-0.0003	0.0001	-2E-05	-2E-05	-0.0003	-2E-05
	(-0.18)	(-0.10)	(-1.57)	(0.60)	(-0.27)	(-0.29)	(-1.59)	(-0.12)
Y/Co	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	8,440	8,438	8,399	8,368	8,241	8,238	8,197	8,141
R^2	1.86%	1.15%	2.40%	6.74%	1.32%	0.95%	1.43%	6.51%

	Negative watch [-1,0]	[0, 1]	[1, 5]	[5, 22]
ΔLCCR	**-0.0105*** **	**0.0054***	**-0.0357*** **	0.0049
	(-4.05)	(1.90)	(-6.79)	(0.79)
CCR_{home}	0.0007	0.0001	-0.0006	-0.0003
	(1.54)	(0.29)	(-0.98)	(-0.29)
CCR_{event}	-4E-06	2E-05	-0.0003	0.0002
	(-0.07)	(0.35)	(-1.12)	(0.86)
Y/Co	Yes	Yes	Yes	Yes
N	8,238	8,234	8,195	8,166
R^2	1.70%	1.46%	2.03%	6.16%

Panel C: Fitch actions

	Downgrade [-1,0]	[0, 1]	[1, 5]	[5, 22]	Upgrade [-1,0]	[0, 1]	[1, 5]	[5, 22]
ΔLCCR	**-0.0039*** **	0.0013	**-0.0065*** **	**-0.0118*** **	**-0.0021***	0.0009	**-0.0074** **	**-0.0150*** **
	(-2.62)	(0.79)	(-4.42)	(-5.04)	(-1.76)	(0.35)	(-2.46)	(-3.67)
CCR_{home}	0.0006	-0.0002	0.00007	0.0001	0.0002	0.0002	-0.0005	0.0010
	(1.04)	(-0.29)	(0.08)	(0.10)	(0.38)	(0.33)	(-0.57)	(0.68)
CCR_{event}	1E-05	-1E-05	-0.0004	-6E-05	-8E-06	-3E-05	-0.0003	3E-05
	(0.16)	(-0.17)	(-1.46)	(-0.03)	(-0.11)	(-0.38)	(-1.52)	(0.13)
Y/Co	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	8,723	8,721	8,679	8,622	8,361	8,359	8,320	8,292
R^2	1.48%	1.30%	2.64%	6.80%	1.19%	1.40%	1.37%	6.07%

	Negative outlook [-1,0]	[0, 1]	[1, 5]	[5, 22]	Positive outlook [-1,0]	[0, 1]	[1, 5]	[5, 22]
ΔLCCR	0.0008	-0.0020	**-0.0175*** **	**-0.0174*** **	0.0030	-0.0006	**-0.0073** **	0.0048
	(0.39)	(-0.94)	(-4.45)	(-3.81)	(1.50)	(-0.24)	(-2.02)	(0.94)
CCR_{home}	0.0005	-0.0001	-0.0002	0.0012	0.0004	0.0003	-0.0003	0.0010
	(0.79)	(-0.15)	(-0.24)	(0.78)	(0.66)	(0.41)	(-0.40)	(0.68)
CCR_{event}	-2E-05	-2E-05	-0.0004	4E-05	-2E-05	-2E-05	-0.0003	-9E-06
	(-0.28)	(-0.24)	(-1.13)	(0.19)	(-0.20)	(-0.21)	(-1.17)	(-0.04)
Y/Co	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	8,437	8,436	8,398	8,369	8,393	8,391	8,350	8,320
R^2	1.77%	1.40%	2.54%	6.86%	2.02%	1.37%	2.56%	5.93%

This table reports the results of estimations of Eq. (6.1) with Huber-White standard errors. For the ease of interpretation, absolute value of ΔLCCR is used. t-values are reported in parentheses. *, **, *** denote significant at 10%, 5%, 1% level of significance. Row "ΔLCCR", "CCR_{home}, "CCR_{event}" reports the estimated coefficient of ΔLCCR, CCR of home country, rating event country, respectively. Year, home-, and event-countries dummies are included, but not presented.

Table 6.5: Multivariate analysis – Realised volatility spill-over

Panel A: S&P actions

	Downgrade [-1,0]	Downgrade [0, 1]	Downgrade [1, 5]	Downgrade [5, 22]	Upgrade [-1,0]	Upgrade [0, 1]	Upgrade [1, 5]	Upgrade [5, 22]
ΔLCCR	**0.0243*****	0.0060	**-0.0210****	**0.0309*****	0.0139	**-0.0333****	-0.0016	**0.0433****
	(2.61)	(0.84)	(-1.99)	(2.78)	(0.89)	(-2.29)	(-0.09)	(2.37)
CCR_{home}	-0.0042	0.0086	0.0014	-0.0057	-0.0017	0.0089	-0.0002	-0.0035
	(-0.91)	(0.82)	(0.26)	(-0.95)	(-0.35)	(0.84)	(-0.03)	(-0.58)
CCR_{event}	0.0001	-2E-05	-3E-05	-0.0007	-7E-05	-0.0001	0.0005	-0.0010
	(0.25)	(-0.04)	(-0.05)	(-1.06)	(-0.13)	(-0.26)	(0.86)	(-1.41)
Y/Co	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	7,840	7,836	7,814	7,806	7,453	7,459	7,430	7,426
R^2	1.18%	1.15%	1.21%	1.53%	1.47%	1.64%	1.56%	3.42%

	Negative outlook [-1,0]	Negative outlook [0, 1]	Negative outlook [1, 5]	Negative outlook [5, 22]	Positive outlook [-1,0]	Positive outlook [0, 1]	Positive outlook [1, 5]	Positive outlook [5, 22]
ΔLCCR	0.0021	-0.0102	0.0156	-0.0171	0.0153	-0.0033	**0.0382****	**-0.0544*****
	(0.15)	(-0.88)	(0.81)	(-0.98)	(1.00)	(-0.20)	(2.20)	(-3.35)
CCR_{home}	-0.0052	0.0097	-0.0001	-0.0007	-0.0028	0.0092	-0.0008	-0.0019
	(-1.11)	(1.04)	(-0.03)	(-0.12)	(-0.59)	(0.92)	(-0.16)	(-0.33)
CCR_{event}	0.00003	-0.0003	0.0005	-0.0007	-0.0002	-0.0003	0.0005	-0.0009
	(0.05)	(-0.64)	(0.82)	(-1.01)	(-0.34)	(-0.56)	(0.75)	(-1.32)
Y/Co	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	7,704	7,699	7,681	7,681	7,656	7,645	7,621	7,625
R^2	1.20%	1.85%	1.41%	2.21%	1.71%	1.66%	1.73%	2.57%

	Negative watch [-1,0]	Negative watch [0, 1]	Negative watch [1, 5]	Negative watch [5, 22]
ΔLCCR	**0.205****	0.0520	**-0.145****	-0.0911
	(2.46)	(0.56)	(-2.39)	(-0.94)
CCR_{home}	-0.0051	0.0109	-0.0016	-0.00005
	(-1.03)	(1.15)	(-0.28)	(-0.01)
CCR_{event}	-0.0002	-0.0004	0.0006	-0.0008
	(-0.29)	(-0.82)	(1.02)	(-1.05)
Y/Co	Yes	Yes	Yes	Yes
N	7,133	7,128	7,105	7,075
R^2	1.16%	0.98%	1.20%	1.55%

Panel B: Moody's actions

	Downgrade [-1,0]	Downgrade [0, 1]	Downgrade [1, 5]	Downgrade [5, 22]	Upgrade [-1,0]	Upgrade [0, 1]	Upgrade [1, 5]	Upgrade [5, 22]
ΔLCCR	0.0021	-0.0017	**0.0137****	**-0.0171****	**-0.0213***	0.0087	-0.0154	-0.0034
	(0.38)	(-0.33)	(2.15)	(-2.17)	(-1.90)	(0.70)	(-1.02)	(-0.26)
CCR_{home}	-0.0011	0.0080	-0.0053	0.0015	-0.0014	0.0094	-0.0078	0.0048
	(-0.24)	(0.72)	(-1.04)	(0.27)	(-0.31)	(1.04)	(-1.54)	(0.82)
CCR_{event}	-0.00001	-0.0007	0.0004	-0.0005	-0.0002	-0.0004	0.0002	-0.0008
	(-0.02)	(-1.44)	(0.65)	(-0.86)	(-0.46)	(-0.79)	(0.36)	(-1.31)
Y/Co	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	7,734	7,728	7,701	7,694	7,405	7,405	7,384	7,374
R^2	1.18%	1.14%	2.15%	2.56%	1.13%	0.98%	1.29%	1.64%

	[-1,0]	[0, 1]	[1, 5]	[5, 22]	[-1,0]	[0, 1]	[1, 5]	[5, 22]
	Negative outlook				Positive outlook			
ΔLCCR	**-0.0231****	0.0096	**0.0593*****	**-0.0246****	0.0205	-0.0262	-0.0131	**0.0426***
	(-2.28)	(1.16)	(5.50)	(-2.02)	(0.92)	(-1.44)	(-0.53)	(1.66)
CCR_{home}	-0.0007	0.0089	-0.0069	0.0023	-0.0025	0.0093	-0.0063	0.0031
	(-0.16)	(0.92)	(-1.39)	(0.40)	(-0.53)	(1.01)	(-1.25)	(0.53)
CCR_{event}	-0.0001	-0.0005	0.0003	-0.0004	0.00002	-0.0004	-0.0001	-0.0006
	(-0.29)	(-1.06)	(0.53)	(-0.68)	(0.05)	(-0.92)	(-0.20)	(-0.97)
Y/Co	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	7,483	7,476	7,452	7,445	7,241	7,236	7,217	7,186
R^2	1.73%	1.50%	1.87%	1.63%	1.66%	1.16%	0.97%	2.24%

	Negative watch			
ΔLCCR	**-0.0580****	-0.0111	-0.0153	**0.150*****
	(-2.48)	(-0.49)	(-0.57)	(4.88)
CCR_{home}	-0.0037	0.0112	-0.0072	0.0027
	(-0.78)	(1.33)	(-1.37)	(0.46)
CCR_{event}	0.00007	-0.0004	-0.0001	-0.0003
	(0.15)	(-0.90)	(-0.19)	(-0.53)
Y/Co	Yes	Yes	Yes	Yes
N	7,299	7,297	7,273	7,268
R^2	1.52%	1.15%	0.85%	1.45%

Panel C: Fitch actions

	Downgrade				Upgrade			
ΔLCCR	**-0.0171****	0.0023	**0.0420*****	**-0.0616*****	0.0123	-0.0146	-0.0185	**-0.0273***
	(-2.05)	(0.28)	(4.09)	(-5.54)	(1.06)	(-1.08)	(-1.37)	(-1.92)
CCR_{home}	-0.0058	0.0113	-0.0030	0.0016	-0.0059	0.0093	-0.0028	0.0043
	(-1.29)	(1.48)	(-0.59)	(0.27)	(-1.28)	(0.97)	(-0.52)	(0.71)
CCR_{event}	-0.00009	-0.0008	0.0004	-0.0003	-0.0002	-0.0008	0.0003	-0.0006
	(-0.17)	(-1.51)	(0.62)	(-0.46)	(-0.39)	(-1.40)	(0.48)	(-0.80)
Y/Co	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	7,744	7,743	7,720	7,687	7,374	7,370	7,353	7,351
R^2	2.02%	1.73%	1.42%	1.72%	1.44%	1.16%	1.15%	1.88%

	Negative outlook				Positive outlook			
ΔLCCR	0.0104	**-0.0365*****	**0.0318****	**-0.0619*****	-0.0177	**-0.0454*****	-0.0029	0.0200
	(0.91)	(-2.91)	(2.23)	(-3.08)	(-1.24)	(-3.01)	(-0.17)	(0.68)
CCR_{home}	-0.0079	0.0121	-0.0044	0.0058	-0.0053	0.0098	-0.0024	0.0040
	(-1.12)	(1.59)	(-0.83)	(0.97)	(-1.14)	(1.11)	(-0.45)	(0.66)
CCR_{event}	-0.00008	-0.0008	0.0002	-0.0003	-0.0002	-0.0008	0.0003	-0.0005
	(-0.15)	(-1.40)	(0.24)	(-0.44)	(-0.43)	(-1.38)	(0.45)	(-0.75)
Y/Co	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	7,483	7,481	7,458	7,453	7,373	7,372	7,353	7,348
R^2	1.63%	2.08%	1.64%	2.54%	2.70%	2.04%	1.77%	2.03%

This table reports the results of estimations of Eq. (6.2) with Huber-White standard errors. For the ease of interpretation, absolute value of ΔLCCR is used. t-values are reported in parentheses. *, **, *** denote significant at 10%, 5%, 1% level of significance. Row "ΔLCCR", "CCR_{home}", "CCR_{event}" reports the estimated coefficient of ΔLCCR, CCR of home country, rating event country, respectively. Year, home-, and event-countries dummies are included, but not presented.

Table 6.6: Monte Carlo experiment

Panel A: Responses of implied volatility

S&P	Negative news				Positive news			
Window	[-1,0]	[0, 1]	[1, 5]	[5, 22]	[-1,0]	[0, 1]	[1, 5]	[5, 22]
ΔLCCR	0.0021	-0.0013	0.0008	**0.0173*** **	-0.0006	-0.0002	**0.0038***	**0.0129*** **
	(1.23)	(-1.11)	(0.57)	(4.39)	(-0.59)	(-0.14)	(1.96)	(4.43)
CCR_{home}	1.1E-04	2.2E-04	6.5E-04	1.6E-03	1.3E-04	1.6E-04	3.3E-04	1.6E-03
	(0.21)	(0.40)	(0.92)	(1.24)	(0.29)	(0.35)	(0.48)	(1.33)
CCR_{event}	-1.7E-05	8.4E-05	-1.8E-05	2.3E-04	1.4E-05	1.5E-05	-6.7E-06	4.9E-05
	(-0.24)	(1.21)	(-0.17)	(1.44)	(0.22)	(0.22)	(-0.05)	(0.32)
Y/ Co	Included	Included	Included	Included	Included	Included	Included	Included
R^2	0.96%	1.39%	2.41%	7.39%	0.93%	1.08%	2.53%	6.42%
N	12,066	12,067	12,000	11,883	11,553	11,556	11,496	11,402
No. of est.	10,000	10,000	10,000	10,000	10,000	10,000	10,000	10,000

Moody's	Negative news				Positive news			
Window	[-1,0]	[0, 1]	[1, 5]	[5, 22]	[-1,0]	[0, 1]	[1, 5]	[5, 22]
ΔLCCR	**-0.0013***	-0.0010	-0.0011	0.0049	-0.0014	-0.0006	**0.0018***	**0.0058*** **
	(-1.70)	(-0.88)	(-0.83)	(1.30)	(-1.51)	(-0.51)	(1.72)	(2.51)
CCR_{home}	9.9E-05	1.1E-04	1.6E-04	1.1E-03	7.1E-05	1.8E-04	3.2E-04	9.1E-04
	(0.25)	(0.27)	(0.29)	(1.09)	(0.18)	(0.48)	(0.59)	(0.91)
CCR_{event}	1.2E-05	-4.2E-06	2.1E-06	-6.1E-05	8.7E-06	1.1E-06	7.1E-07	-1.4E-04
	(0.21)	(-0.06)	(0.04)	(-0.38)	(0.15)	(0.02)	(0.03)	(-0.91)
Y/ Co	Included	Included	Included	Included	Included	Included	Included	Included
R^2	1.31%	1.11%	2.68%	6.36%	0.89%	0.74%	1.96%	5.34%
N	11,554	11,555	11,497	11,402	11,277	11,273	11,209	11,093
No. of est.	10,000	10,000	10,000	10,000	10,000	10,000	10,000	10,000

Fitch	Negative news				Positive news			
Window	[-1,0]	[0, 1]	[1, 5]	[5, 22]	[-1,0]	[0, 1]	[1, 5]	[5, 22]
ΔLCCR	**-0.0029***	-0.0013	**-0.0086*** **	**-0.0056*** **	-0.0001	**-0.0032***	-0.0021	0.0008
	(-1.94)	(-0.74)	(-5.77)	(-2.82)	(-0.16)	(-1.73)	(-1.10)	(0.30)
CCR_{home}	4.3E-04	-3.3E-04	9.4E-04	6.9E-04	1.6E-05	3.7E-04	1.6E-04	1.1E-03
	(0.80)	(-0.60)	(1.21)	(0.53)	(0.02)	(0.66)	(0.22)	(0.89)
CCR_{event}	5.2E-06	1.5E-05	-5.1E-05	-1.1E-04	1.5E-05	-4.1E-05	1.2E-05	1.4E-05
	(0.08)	(0.23)	(-0.49)	(-0.64)	(0.22	(-0.55)	(0.13)	(0.11)
Y/ Co	Included	Included	Included	Included	Included	Included	Included	Included
R^2	1.27%	1.34%	3.41%	6.69%	1.01%	1.23%	2.58%	5.55%
N	11,503	1,510	11,449	11,308	11,325	11,334	11,271	11,161
No. of est.	10,000	10,000	10,000	10,000	10,000	10,000	10,000	10,000

Window	[-1,0]	[0, 1]	[1, 5]	[5, 22]	[-1,0]	[0, 1]	[1, 5]	[5, 22]

Panel B: Responses of realised volatility

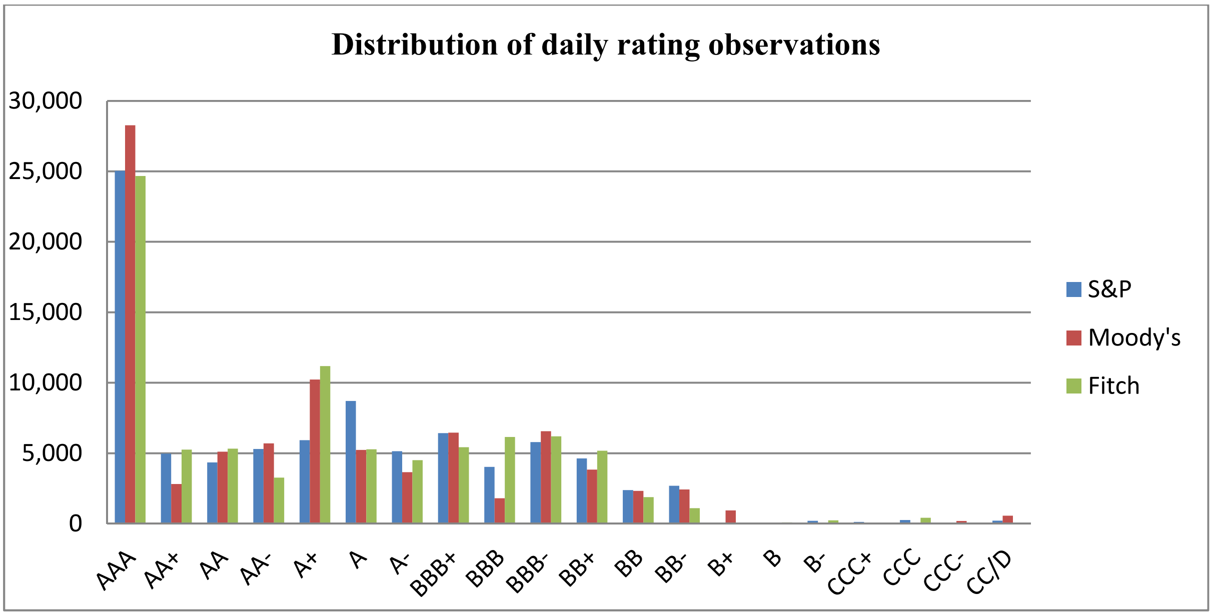
S&P	**Negative news**				**Positive news**			
ΔLCCR	0.0092	0.0046	-0.0002	**0.0302*****	0.0109	-0.0107	0.0069	0.0125
	(1.13)	(0.75)	(-0.03)	(2.92)	(1.21)	(-1.20)	(0.61)	(1.09)
CCR_{home}	-3.9E-04	-3.2E-04	-1.1E-04	9.2E-04	2.9E-03	-2.1E-03	5.2E-05	1.7E-03
	(-0.10)	(-0.08)	(-0.03)	(0.18)	(0.73)	(-0.53)	(0.01)	(0.34)
CCR_{event}	4.7E-05	1.6E-04	-1.6E-04	2.7E-04	-1.4E-04	3.4E-04	-8.3E-05	-2.1E-04
	(0.10)	(0.36)	(-0.32)	(0.47)	(-0.30)	(0.74)	(-0.15)	(-0.34)
Y/ Co	Included	Included	Included	Included	Included	Included	Included	Included
R^2	1.24%	1.61%	1.79%	1.92%	1.43%	2.09%	1.84%	3.30%
N	10,832	10,853	10,792	10,702	10,294	10,319	10,247	10,193
No. of est.	10,000	10,000	10,000	10,000	10,000	10,000	10,000	10,000

Moody's	**Negative news**				**Positive news**			
ΔLCCR	0.0029	0.0039	**0.0115***	-0.0038	-0.0030	**0.0104***	-0.0108	0.0100
	(0.56)	(0.82)	(1.84)	(-0.48)	(-0.47)	(1.77)	(-1.47)	(1.25)
CCR_{home}	1.8E-04	-1.6E-03	-1.7E-03	2.2E-03	-3.8E-04	-6.1E-04	-1.5E-03	3.4E-03
	(0.04)	(-0.42)	(-0.40)	(0.45)	(-0.10)	(-0.16)	(-0.35)	(0.68)
CCR_{event}	-7.3E-05	-2.2E-04	3.1E-04	-2.4E-04	-1.3E-05	1.9E-04	-2.7E-04	3.5E-05
	(-0.17)	(-0.51)	(0.65)	(-0.44)	(-0.03)	(0.45)	(-0.55)	(0.07)
Y/ Co	Included	Included	Included	Included	Included	Included	Included	Included
R^2	1.68%	1.30%	2.09%	2.60%	1.04%	0.91%	1.35%	1.55%
N	10,388	10,406	10,336	10,273	10,028	10,050	9,990	9,895
No. of est.	10,000	10,000	10,000	10,000	10,000	10,000	10,000	10,000

Fitch	**Negative news**				**Positive news**			
ΔLCCR	-0.0040	**-0.0171*****	**0.0306*****	**-0.0411*****	**-0.0137***	**-0.0221*****	0.0013	0.0086
	(-0.58)	(-2.57)	(3.99)	(-4.48)	(-1.97)	(-2.97)	(0.16)	(0.88)
CCR_{home}	-7.5E-04	2.4E-03	-3.5E-03	2.2E-03	-4.1E-04	-3.7E-04	5.6E-05	-4.9E-04
	(-0.20)	(0.62)	(-0.81)	(0.43)	(-0.11)	(-0.09)	(0.01)	(-0.10)
CCR_{event}	-2.1E-04	-1.7E-05	2.5E-04	-2.6E-04	2.6E-04	1.6E-05	-1.3E-04	-6.1E-06
	(-0.43)	(-0.04)	(0.49)	(-0.44)	(0.53)	(0.03)	(-0.25)	(-0.01)
Y/ Co	Included	Included	Included	Included	Included	Included	Included	Included
R^2	1.89%	1.59%	1.73%	2.28%	1.71%	1.55%	1.68%	2.01%
N	10,342	10,364	10,296	10,206	10,054	10,080	10,026	9,966
No. of est.	10,000	10,000	10,000	10,000	10,000	10,000	10,000	10,000

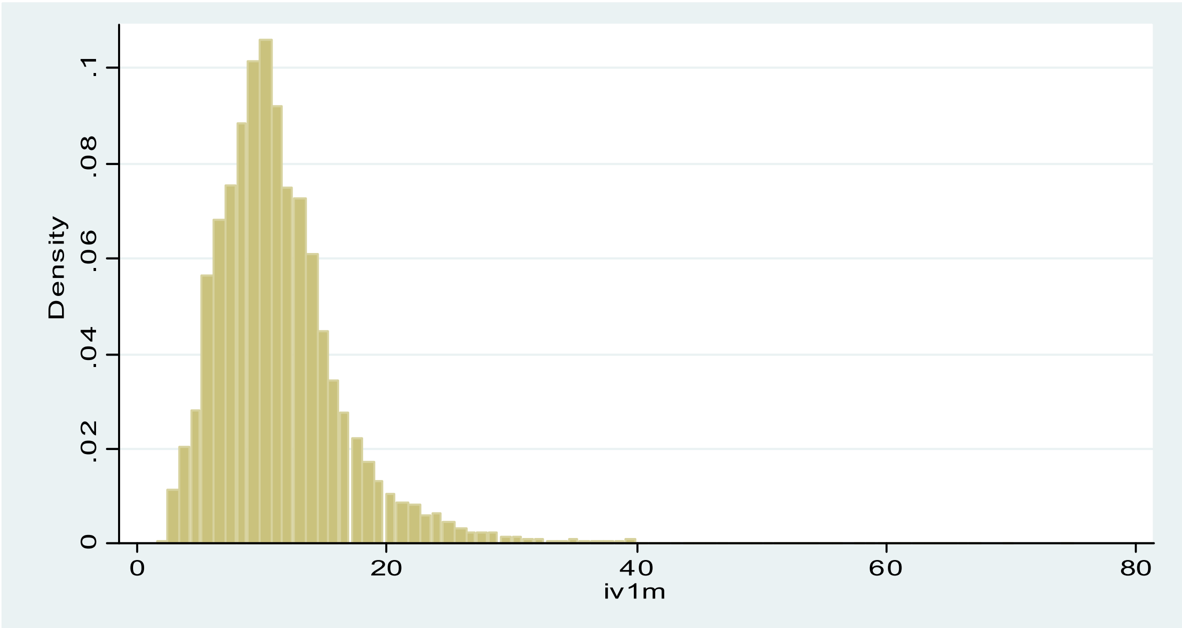
ΔLCCR, CCR report averages coefficients of ΔLCCR and CCR across the estimations of equation (6.1) and (6.2) but based on pooling all types of negative (positive) rating news together. Average t-statistics are reported in parentheses and heteroskedasticity robust using the Huber-White correction. N reports maximum number of observations for one estimation as this number varies slightly across estimations. R^2 reports averages R-square from the estimations. "No. of est." reports numbers of estimations. Year, home country, and event country dummies are included but not reported for ease of brevity. For the ease of interpretation, absolute value of ΔLCCR is used. *, **, *** denote significant at 10%, 5%, 1% level of significance.

Figure 6.1. Distribution of daily observations



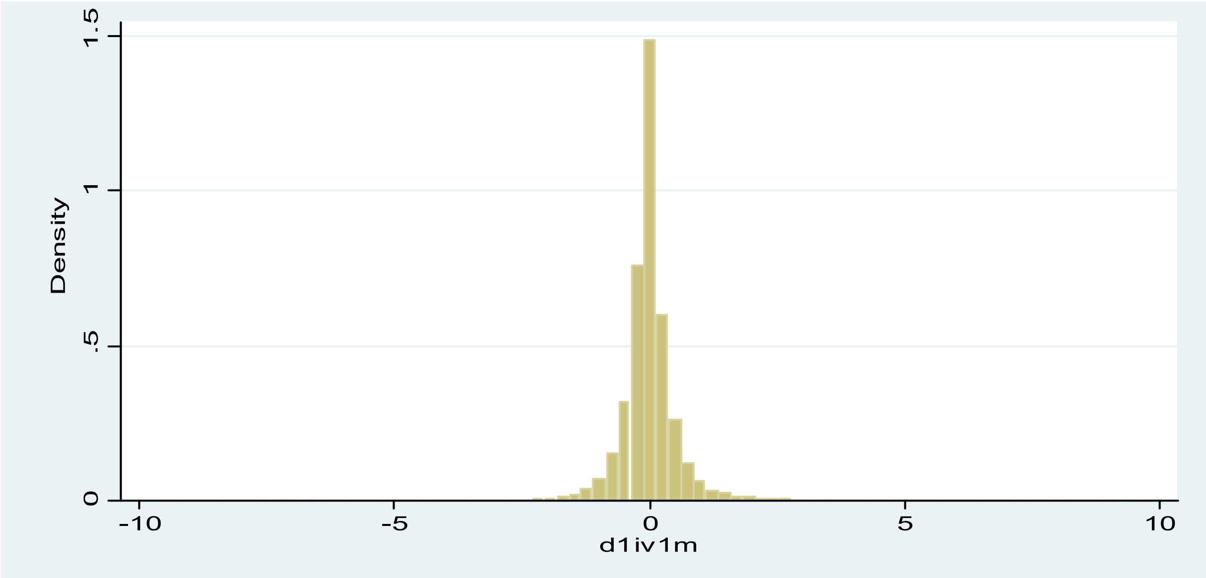
Note: Moody's symbols (i.e. Aaa, Aa1, Aa2 ... Caa3) are categorised in equivalent S&P and Fitch ratings categories (i.e. AAA, AA+, AA ... CCC-).

Figure 6.2: Distribution of the implied volatility



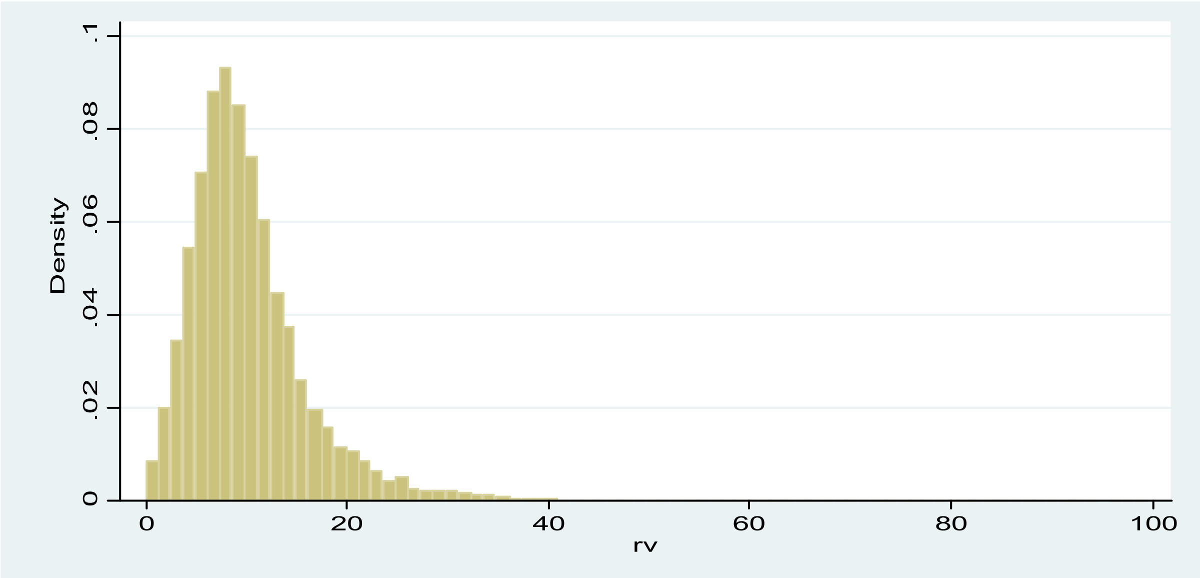
Note: The dataset covers 46 countries during the period from January 2007 to September 2013. There are 77,989 daily observations of 1-month implied volatility. Among them, there are 83 observations where IV is greater than 50 percentage points in Brazil, Indonesia, Korea, South Africa (during Oct-Nov 2008), Mexico (during Oct 2008), and Poland (during Dec 2008).

Figure 6.3: Distribution of daily changes in the implied volatility



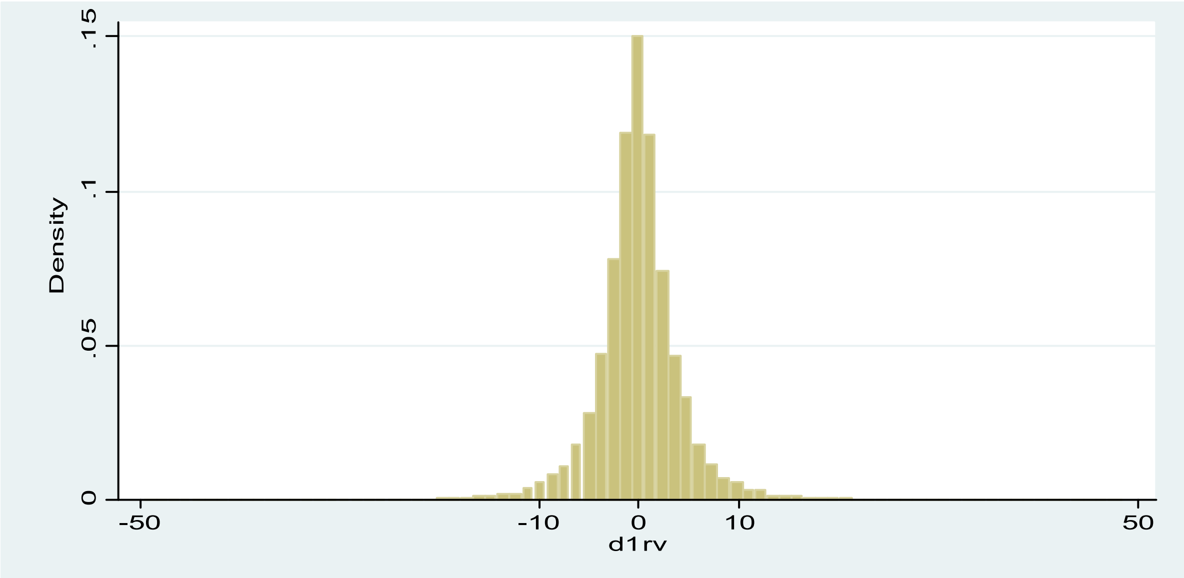
Note: The dataset covers 46 countries during the period from January 2007 to September 2013. There are 57 observations where |ΔIV| is larger than 10 percentage points in Brazil (2 obs. in Oct-Nov 2008), Chile (4 obs. in Oct 2008 and Sep2011), Colombia (1 obs. in Oct 2008), Indonesia (20 obs. in Oct–Nov 2008, Feb 2009), Japan (1 obs. in Oct 2008), Korea (11 obs. in Oct 2009 – Feb 2009), Mexico (7 obs. in Oct-Nov 2008), Poland (3 obs. in Oct and Dec 2008), Russia (2 obs. in Oct 2008), South Africa (2 obs. in Oct 2008), and Turkey (4 obs. in Oct-Nov 2008).

Figure 6.4: Distribution of daily realised volatility



Note: The dataset covers 46 countries during the period from March 2007 to September 2013. There are 71,880 daily observations of realised volatility. During the sample periods, there are 261 observations where the RV is greater than 50 percentage points in Australia, Brazil, Chile, Colombia, Indonesia, Japan, Korea, Mexico, New Zealand, Norway, South Africa, Sweden, Switzerland, Turkey in October - November 2008 and Russia in January 2009.

Figure 6.5: Distribution of daily changes in realised volatility



Note: The dataset covers 46 countries during the period from March 2007 to September 2013. There are 3,388 observations where |ΔRV| is larger than 10 percentage points in all the sample countries implying more volatile distribution of ΔRV compared to the distribution of ΔIV in Figure 6.3

Appendix 6.1: Result of event study after excluding multi-event days

Panel A: Response of implied volatility

S&P

	[-1,0]	[0,1]	[1,5]	[-1,0]	[0,1]	[1,5]
	Downgrades			**Upgrades**		
$\Delta\overline{IV}$	**-0.0053****	**-0.0047***	0.0030	**0.0072*****	0.0011	-0.0062
t-val.	-2.07	-1.84	0.89	2.94	0.38	-1.48
n	1,011	1,009	1,006	757	755	756
	Negative outlook			**Positive outlook**		
$\Delta\overline{IV}$	0.0029	0.0008	**-0.0090****	-0.0006	0.0012	-0.0015
t-val.	0.84	0.27	-2.45	-0.23	0.49	-0.47
n	838	837	836	822	824	825
	Negative watch					
$\Delta\overline{IV}$	**-0.0205****	0.0039	-0.0033			
t-val.	-2.36	0.39	-0.38			
n	275	275	274			

Moody's

	[-1,0]	[0,1]	[1,5]	[-1,0]	[0,1]	[1,5]
	Downgrades			**Upgrades**		
$\Delta\overline{IV}$	**0.0043***	-0.0035	**-0.0084****	**-0.0070****	**-0.0055*****	0.0032
t-val.	1.89	-1.43	-2.14	-2.52	-2.92	1.07
n	863	861	862	630	625	623
	Negative outlook			**Positive outlook**		
$\Delta\overline{IV}$	**0.0067****	-0.0009	**-0.0114****	**-0.0124*****	-0.0001	-0.0062
t-val.	2.06	-0.33	-2.46	-4.26	-0.04	-1.61
n	576	575	576	515	515	514
	Negative watch			**Positive watch**		
$\Delta\overline{IV}$	**0.0081****	**0.0089***	**-0.0261*****	**0.0067****	**-0.0082*****	0.0046
t-val.	1.98	1.97	-5.37	2.20	-2.64	0.91
n	442	441	443	373	372	372

Fitch

	[-1,0]	[0,1]	[1,5]	[-1,0]	[0,1]	[1,5]
	Downgrades			**Upgrades**		
$\Delta\overline{IV}$	-0.0026	**0.0046***	-0.0035	**-0.0053****	**-0.0073****	0.0021
t-val.	-0.89	1.73	-0.78	-2.09	-2.26	0.52
n	815	815	816	662	662	663
	Negative outlook			**Positive outlook**		
$\Delta\overline{IV}$	-0.0052	**0.0070***	**-0.0090***	0.0006	-0.0025	**-0.0123*****
t-val.	-1.47	1.92	-1.68	0.17	-0.72	-2.81
n	633	634	637	570	570	570

Panel B: Response of realised volatility

S&P

	[-1,0]	[0,1]	[1,5]	[-1,0]	[0,1]	[1,5]
	Downgrades			Upgrades		
$\Delta\overline{RV}$	0.0398***	-0.0250*	0.0125	0.0234	0.0305	-0.1254***
t-val.	2.81	-1.78	0.72	1.11	1.58	-4.63
n	933	934	932	655	659	649
	Negative outlook			Positive outlook		
$\Delta\overline{RV}$	0.0493***	-0.0293*	-0.0326*	0.0010	-0.0408**	0.0212
t-val.	2.61	-1.68	-1.70	0.06	-2.40	1.13
n	763	761	763	732	725	723
	Negative watch					
$\Delta\overline{RV}$	0.0316	0.0642*	-0.159****			
t-val.	1.02	1.89	-4.87			
N	258	258	256			

Moody's

	[-1,0]	[0,1]	[1,5]	[-1,0]	[0,1]	[1,5]
	Downgrades			Upgrades		
$\Delta\overline{RV}$	0.0303*	-0.0368**	-0.0432**	-0.0238	0.0025	0.0862***
t-val.	1.87	-2.30	-2.30	-1.29	0.13	4.02
n	802	800	794	567	571	572
	Negative outlook			Positive outlook		
$\Delta\overline{RV}$	0.0849***	-0.0804***	0.0252	-0.0496**	-0.0091	0.0261
t-val.	4.43	-4.20	1.11	-2.25	-0.42	1.08
n	535	533	530	437	435	438
	Negative watch			Positive watch		
$\Delta\overline{RV}$	0.0091	-0.0535**	-0.0308	-0.0365	-0.0394	0.0779**
t-val.	0.34	-2.42	-1.20	-1.35	-1.58	2.30
n	413	414	412	333	332	332

Fitch

	[-1,0]	[0,1]	[1,5]	[-1,0]	[0,1]	[1,5]
	Downgrades			Upgrades		
$\Delta\overline{RV}$	-0.0481***	-0.0409***	0.0058	-0.0364*	0.0400*	-0.0329
t-val.	-3.11	-2.59	0.31	-1.86	1.91	-1.59
n	755	757	756	574	574	577
	Negative outlook			Positive outlook		
$\Delta\overline{RV}$	-0.0269	-0.0335	0.0217	-0.0053	-0.1119***	0.0197
t-val.	-1.46	-1.62	1.10	-0.25	-4.16	0.66
n	591	591	589	486	486	488

Note: $\Delta\overline{IV}$ and $\Delta\overline{RV}$ report mean value of log-changes in the IV and RV, respectively, during the time windows. n reports numbers of observations. Occasionally, n varies across the time windows because of missing IV or RV data at the beginning or the end of the sample period. *, **, *** denotes significant at 10%, 5%, 1%.

Appendix 6.2: Monte Carlo experiment for Moody's different types of rating actions

Window	[-1,0]	[0, 1]	[1, 5]	[5, 22]	[-1,0]	[0, 1]	[1, 5]	[5, 22]
	Downgrades				**Upgrades**			
ΔLCCR	-0.0011	-0.0011	-2.8E-6	0.0037	**-0.0054****	-0.0014	-0.0010	**-0.0242*****
t-val.	-1.56	-0.93	-0.002	1.50	-2.39	-0.70	-0.51	-7.36
CCR_{home}	0.0002	0.0001	6E-5	0.0009	0.0002	0.0001	0.0003	0.0008
t-val.	0.45	0.32	0.11	0.89	0.54	0.31	0.54	0.71
CCR_{event}	1E-5	-3E-5	-7E-6	-5E-5	2E-5	1.6E-6	-1E-5	-4E-5
t-val.	0.22	-0.43	-0.05	-0.31	0.29	0.03	-0.11	-0.24
Y/ Co	Included	Included	Included	Included	Included	Included	Included	Included
R^2	0.71%	0.78%	2.54%	6.68%	0.79%	0.67%	1.68%	6.00%
N	10,912	10,880	10,848	10,698	10,520	10,490	10,454	10,310
No. of est.	10,000	10,000	10,000	10,000	10,000	10,000	10,000	10,000
	Negative outlook				**Positive outlook**			
ΔLCCR	**0.0047*****	0.0002	**0.0035***	-0.0011	**-0.0057*****	0.0005	0.0032	**0.0490*****
t-val.	4.66	0.19	1.88	-0.42	-4.20	0.33	1.35	8.74
CCR_{home}	0.0001	0.00001	0.0003	0.0010	0.0001	0.0002	0.0003	0.0010
t-val.	0.36	0.0266	0.44	0.95	0.29	0.42	0.48	0.95
CCR_{event}	-3.9E-7	-9.8E-6	0.00002	0.00003	1.7E-6	-1E-05	1.9E-6	-0.00003
t-val.	0.004	-0.15	0.25	0.20	0.04	-0.19	0.04	-0.15
Y/ Co	Included	Included	Included	Included	Included	Included	Included	Included
R^2	1.34%	0.89%	2.65%	6.09%	0.83%	0.70%	1.77%	6.06%
N	10,606	10,576	10,544	10,392	10,400	10,366	10,332	10,158
No. of est.	10,000	10,000	10,000	10,000	10,000	10,000	10,000	10,000
	Negative watch							
ΔLCCR	**0.0119*****	0.0030	**-0.0302*****	-0.0003				
t-val.	5.05	1.16	-6.55	-0.06				
CCR_{home}	0.0002	0.0001	0.0004	0.0007				
t-val.	0.51	0.36	0.68	0.61				
CCR_{event}	6.5E-6	0.00002	-0.00002	0.00009				
t-val.	0.11	0.37	-0.18	0.58				
Y/ Co	Included	Included	Included	Included				
R^2	1.10%	1.18%	2.49%	5.85%				
N	10,390	10,358	10,322	10,178				
No. of est.	10,000	10,000	10,000	10,000				

This table reports average coefficients across 10,000 estimations of equation (6.1) based on different types of Moody's actions. Average t-statistics are heteroskedasticity robust using the Huber-White correction. N reports maximum number of observations for one estimation as this number varies slightly across estimations. R^2 reports averages R-square from the estimations. "No. of est." reports numbers of estimations. Year, home country, and event country dummies are included but not reported for ease of brevity. For the ease of interpretation, absolute value of ΔLCCR is used. *, **, *** denote significant at 10%, 5%, 1% level of significance.

Chapter 7: Thesis summary and conclusions

Recent financial crises have placed CRAs under close scrutiny. Credit ratings have been accused of lagging public information (e.g. Vernazza et al., 2014). Thus, rating changes such as recent downgrades of certain European government debt arguably bring no additional information, but exacerbate the European debt crisis and provoke global financial instability. This accusation is repeatedly discussed in the media, but somewhat lacking concrete scientific evidence. Prior literature focuses on the impact of credit rating actions on financial assets' returns. Market volatility, which is directly related to the heart of the above accusations on CRAs, has attracted little attention. Moreover, an investigation on this matter needs to consider the lead-lag relationship between credit rating dynamics and market movements. This thesis addresses the void in literature by investigating the inter-relation between sovereign credit rating and market volatility dynamics.

Chapter 2 discussed the main concepts and recent developments related to the credit rating business and CRA regulation. The "through-the-cycle" rating philosophy and differences CRAs' methodologies are among the most important considerations for analyses in the later chapters. In general, all CRAs aim at achieving an appropriate balance between rating accuracy and rating stability because different rating users appreciate both aspects. Very active high frequency traders, such as short-sellers, hedge funds, speculators, are highly unlikely to rely only on credit ratings which typically change once in several months. Intraday information hunting is a critical part of their business. Meanwhile, other market participants, such as passive funds, pension funds, regulators, particularly dislike rating reversals and desire for a relatively accurate but very stable rating system. An accurate but wildly volatile rating system induces unbearably high operating costs for such market participants.

Each CRA, then, implement its own strategy aiming at the balance between rating accuracy and rating stability given cost-effectiveness considerations. Moreover, each CRA follows different rating methodology. In this thesis, sovereign ratings from S&P, Moody's, and Fitch are examined. The three CRAs account for more than 95% of the sovereign rating market (SEC, 2011c, 2012, 2013). Rating methodology varies across the three CRAs. For example, S&P considers probability of default while Moody's assesses loss given default in their ratings and Fitch considers recovery given default. Therefore, hypotheses of the heterogeneous impact and of the lead-lag relationship between sovereign rating actions and market movements are expected which is also underpinned by the literature review in the next chapter.

Chapter 3 reviews the published literature on sovereign credit ratings. To the best of my knowledge, prior literature focuses on examining the impact of sovereign rating actions on asset returns (e.g. bond yields, equity abnormal returns, CDS premiums, exchange rates), but it is largely silent on market volatility.[55] Moreover, the bi-directional relationship between rating actions and market movements has been unexplored. Given the balance between rating accuracy and rating stability, credit ratings are likely lag information which is already incorporated in market data (this is also evidenced in prior empirical investigations, e.g. Sy, 2004), rating downgrades, hence, probably confirm what is already known to the public. Nonetheless, there is a difference between being known and being confirmed. Prior literature evidences significant reactions of financial assets returns to mostly negative rating actions. Negative reactions of assets returns combined with evidence of tardy rating changes lead to angry accusations toward CRAs for being uninformative and exacerbating investors'

[55] There are only a few exceptions as follows: Bisoondoyal-Bheenick et al. (2011) examine the impact of rating actions on FX realised volatility, but the study is based on a very small number of rating actions during the Asian crisis of 1997. They do not consider information on outlook nor watch procedures, and there are also methodological issues. Afonso et al. (2014) focus only on EU markets.

pessimistic sentiments. The gaps in the literature motivate empirical investigations on market volatility in later chapters.

Chapter 4 examines the bi-directional relationship between sovereign credit rating actions and equity index option-implied volatility dynamics. As discussed above, credit ratings are likely to lag market movements given (i) the "through-the-cycle" rating philosophy; (ii) the trade-off between rating accuracy and rating stability; and (iii) cost-effectiveness considerations. In addition, CRAs periodically publish market-implied ratings (e.g. Moody's KMV™). This is obvious evidence of CRAs' awareness and potential consultation with market movements. Moreover, derivative markets are mostly inhabited by institutional investors and informed traders (ISDA, 2012). The markets also play a leading role in the price (credit information) discovery process (e.g. Acharya and Johnson, 2007). Therefore, the existence of a lead-lag relationship between rating actions and option-implied volatility is expected. Besides, heterogeneous effects of sovereign rating news are also expected, for the reasons discussed in the paragraphs above.

The data sample for Chapter 4 covers all (24) countries with liquid stock index option markets (except for countries without rating actions) during the period from 2000 to 2012. Performance of equity markets is linked to sovereign creditworthiness in numerous ways. For example, a sovereign default triggers significant surges in the volatilities of interest rates, consumption and output (Arellano, 2008). Corporate credit risk and borrowing costs are strongly correlated with the evolution of sovereign credit risk (Dittmar and Yuan, 2008; Borensztein el al., 2013; Bedendo and Colla, 2013). There is also a strong linkage between a sovereign and banks' risks given their large holdings of government debt and government capacity to bailout too big to fail entities in cases of catastrophe (e.g. Acharya et al., 2014; Gennaioli et al., 2014). Therefore, strong economic linkages exist between sovereign rating actions and equity market performance and thus market-wide volatility are expected.

The effects of rating signals are evidenced by an event study, and country-matched random sampling regressions. Robustness of the results is confirmed by non-parametric tests and Monte Carlo experiments. Granger-causality tests are employed in order to detect any lead-lag relationships between rating actions and market movements. Probit models are also employed for robustness checks.

I find heterogeneous impact of sovereign rating actions on stock index option-implied volatility. The market response varies not only between positive and negative events but also across CRAs. The market is more likely to react to news from S&P and Moody's rather than from Fitch, consistent with Bongaerts et al. (2012) who argue that Fitch plays a 'tiebreaker' role and matters when S&P and Moody's disagree around the investment-speculative threshold. Moreover, Fitch downgrades trigger a decrease in IV, implying that even downgrades from the 'tiebreaker' do matter and reduce the market uncertainty. Furthermore, the market reactions to Moody's and S&P signals reinforce the analysis that additional signals (both negative and positive) are still informative and reduce the market uncertainty. These stress the importance of multiple ratings and support the information production role of credit ratings in the context of both first-mover as well as subsequent rating news. The results are robust across methodological frameworks and specifications. Another interesting but much expected finding (for the reason discussed above) is the evidence of significant causal relationships between market movements and rating actions. The lead-lag relationship also varies across CRAs, implying differences in the CRAs' timeliness and policies which, in turn, offer explanation to heterogeneous effects of rating actions. S&P and Fitch tend to focus more on rating accuracy while Moody's emphasises rating stability. The finding also implies that market participants observe credit issues more quickly than CRAs. Rating anticipation is also affirmed by probit model investigations.

An interesting question arises. Why do market participants react to a credit issue which is already known to them? The key answer lies in the above sentence: Being known is different to being confirmed. The lead-lag relationship combined with evidence of reduced option-implied volatility in response to certain (even negative) rating announcements reveals an important “confirmation role” of credit rating news which is largely unnoticed in prior literature. From these findings, it is also not persuasive to argue that credit rating actions exacerbated and/or precipitated the European sovereign debt crisis, as was repeatedly suggested by some commentators. Informative rating news likely comes at the cost of raising market volatility, while additional (even negative) rating actions can serve as a means of confirming the market anticipation and reduce market uncertainty. Some potential policy implications can be raised. The findings support the view of “no point shooting the messengers” as expressed by the Association of British Insurers (House of Lords, 2011).

Chapter 5 investigates the impact of sovereign rating actions on foreign exchange (FX) market ex-ante uncertainty and ex-post volatility. FX market ex-ante uncertainty is measured by FX option-implied volatility, while the market ex-post volatility is captured by realised volatility based on intraday data (e.g. Andersen et al., 2003a). This chapter aims at contributing to the debate on the information content of rating news given the enormous size of the FX market. The matter has been a concern for market participants, policy makers, and academic circles. The topic is also closely relevant to the debate on the global financial stability.

Prior literature identifies a strong economic linkage between a country’s exchange rates and its fiscal conditions. There is also an inconclusive debate on whether currency appreciation or depreciation follows fiscal shocks (e.g. Dornbusch, 1976; Obstfeld and Rogoff, 1995; Kim and Roubini, 2008; Enders et al., 2011). Besides, CRAs explicitly assert the relevance of a country’s fiscal condition in determining its sovereign credit rating level (e.g. Moody's, 2013; S&P, 2012). Empirical studies also confirm the relevance of fiscal deficit/surplus in determining a country's credit rating level (e.g. Afonso et al., 2011). Sovereign creditworthiness also imposes a "ceiling effect" over the creditworthiness of other entities of the same domicile (e.g. Borensztein et al., 2013) and influence national economy and volatility of national equity market (as analysed in Chapter 4). There is also a strong link between equity and FX markets (e.g Phylaktis and Ravazzolo, 2005). These issues suggest a significant impact of sovereign rating news on the FX market uncertainty and ex-post volatility.

The main approach in Chapter 5 is similar to Chapter 4, but the context is FX market which is enormous (e.g. BIS, 2013). Moreover, the chapter utilises realised volatility based on intraday data which is much richer (in addition to option-implied volatility). Monetary policy and persistence in the volatility measurements are controlled for. The data for this chapter covers all (41) countries whose currencies are named in BIS (2013) except for some countries which did not encounter any credit rating event or are categorised as (crawling) fixed/pegged FX regimes in any version of the IMF defacto classifications. The currencies included in this sample account for 90% of the global FX market trades (author's calculations based on BIS, 2013). The sample period is from 2007 to 2013 which overlapped recent financial and debt crises.

Consistent with the previous chapter, this chapter presents concrete evidence of the heterogeneous effects and the "confirmation role" of sovereign credit rating news. The "confirmation role" is attributed to the mechanism where CRAs co-ordinate heterogeneous beliefs and expectations among market participants. The chapter illustrates that certain degree of heterogeneity inevitably exists among market participants. In response to informative rating news, market uncertainty and ex-post volatility increase which can be interpreted as evidence of market heterogeneity. Ex-post (realised) volatility based on intraday data captures the variance of intraday returns if exchange rates follow a semi-martingale process (Andersen et al., 2003a). The variance, in turn, could be interpreted as a measurement of the degree of disagreements between market participants on a given trading day. Therefore, increased realised volatility evidences the increased degree of disagreements between market participants in response to a credit issue. Additional rating news which is not new to the public comes with reduced market uncertainty and ex-post volatility. These findings illustrate the usefulness of multiple ratings and again present evidence against the accusation of CRAs for exacerbating and/or precipitating recent financial crises. From the findings, CRAs are much likely to play a role of messengers rather than fortune tellers who can predict future events. From my perspective, there are clearly incentives to reduce overreliance on credit ratings. Nonetheless, there are also clearly incentives not to eliminate the role of credit ratings, especially multiple ratings, in safeguarding financial markets, especially looking from the cost-effectiveness aspect.

Chapter 6 investigates the volatility spillovers of sovereign credit rating news in the global FX market. Specifically, the chapter investigates whether and to what extent sovereign rating actions on one country increase or reduce volatility of other countries' exchange rates against the U.S. dollar. The topic is compelling and has been ignored by prior literature. This is also directly related to the above debate on whether sovereign rating news provokes global financial instability.

The main motivation for the investigations in this chapter is the literature on mechanisms underlying the well-known spillover phenomenon in international finance (e.g. Engle et al., 1990; King and Wadhwani, 1990; Dornbusch et al., 2000; Andersen et al., 2003b; Kaminsky et al., 2003; Li and Muzere, 2010). Engle et al. (1990), Hogan and Melvin (1994), and Li and Muzere (2010) attribute the spillover effects of news to heterogeneous beliefs and expectations among the market participants. In contrast, Dornbusch et al. (2000)

and Kaminsky et al. (2003) attribute the spillover impacts or contagion in FX markets to (financial and trade) linkages between economies and to a competitive devaluation mechanism. Specifically, negative news on one economy (and its currency) is not necessarily negative for others with whom it competes. Therefore, I suspect that an (even negative) credit event on one country could be interpreted as a good signal for others and for the global financial market as a whole.

The sample data for this chapter covers all (46) countries whose currencies are named in BIS (2013) during the period from 2007 to 2013. There are only four exceptions which are countries categorised as exercising (crawling) fixed/pegged FX regimes in any version of the IMF defacto classifications. Similar to Chapter 5, this chapter utilises both FX option-implied volatility and realised volatility which is based on intraday data. Methodologies using in this chapter include an event study, non-parametric tests, multivariate regressions, and Monte Carlo experiments. In the multivariate regressions, daily changes in the FX volatilities of a home country are explained by rating events on foreign countries and control variables. Observation on FX volatility of home countries which encounter any rating event(s) from any CRA within one month beforehand are excluded in order to eliminate possible contamination from the impact of rating news on own country FX volatility.

I find evidence of volatility spillover arising from sovereign rating news. The spillover effect varies across CRAs. Negative rating news from S&P on one country increases ex-post volatility and ex-ante uncertainty over other countries' currencies whereas negative news from Moody's and Fitch is doing the opposite, reducing the FX volatility/ uncertainty. These effects are attributed to the "confirmation role" of additional ratings consistent with analyses in Chapters 4 and Chapter 5. The spillover impact of rating news takes place much later than the impact on own country's FX volatility/ uncertainty, i.e. within one month after rating announcements.

Combined with analyses in Chapter 4 where significant evidence of rating news anticipation is presented and Chapter 5 where additional rating news has shown to play a confirmation role and reduce FX uncertainty/ volatility, the findings strengthen the view that CRAs are playing a role of messengers. Voices from additional messengers reassure financial markets over observable credit issues. The "confirmation role" of rating news, thus, benefits not only a rating event country but others, hence, facilitate international trades and flows.

This thesis contributes to literature in a number of respects. The thesis addresses the void in prior literature by investigating the impact of rating news on financial market volatility. In addition, the volatility spill-over effect of rating news is another significant contribution. The information content of rating news is a significant contribution which is of interest for researchers and multiple market participants. The findings could be also of particular interest for policy makers and regulators since they are directly related to the debates on CRAs which motivate recent regulatory developments. The findings also have important practical implications for option traders, multinational banks and financial institutions, CRAs, international portfolio managers, and other investors whose interests lie in asset volatility.

Finally, the limitations of this thesis and suggestions for future research are outlined as follows. Chapter 4 is restricted by the number of sampled countries due to liquid stock index option markets being present only in mature economies. In fact, this chapter included all countries with liquid stock index option markets. Nonetheless, given the importance of the topic, future revisions of this chapter could be compelling when more stock indices are traded on option markets. Chapters 5 and 6 are also not without limitations. Time series econometric models (e.g. GARCH family, Markov switching models) could be applied as robustness tests. Given the limited numbers of credit rating events (i.e. ratings on sovereigns associated with the major currencies tend to be stable over time), grouping countries together could be an optimal technique. However, this needs to be carefully designed in order to achieve sensible economic merits and interpretations. In addition, direct investigations on channels or mechanisms via which the impact and the spill-over of sovereign credit rating news are transmitted are potential avenues for future studies. Expanding this theme of research toward corporate and banking sectors is also promising given the close linkages between sovereign and corporate/ banking risks. A theoretical model which accommodates the empirical findings in this thesis could be considered by future research.

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