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The evolution and determinants of the non-performing loan burden in Italian banking

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ABSTRACT

We investigate the factors influencing Non-Performing Loans (NPLs) in the Italian banking sector from 2011 to 2017, a period marked by significant challenges. Using dynamic panel data methods and considering both bank-specific and macroeconomic variables, our empirical analysis reveals the complexity of NPL volumes in Italy. Our findings highlight that better capitalised banks tend to exhibit lower levels of NPLs, indicating reduced incentives for engaging in riskier practices. We document an inverse relationship between credit growth and NPLs, suggesting a potential outcome of demand-driven credit expansion. Additionally, the countercyclical nature of NPL stocks is evident, with banks' NPL volumes influenced by the economic conditions of the country.

1. Introduction

The Italian banking sector, hampered by a persistently large volume of Non-Performing Loans (NPLs), has been at the core of the asset quality problem in Europe. Under the spotlight for high uncertainty, debated rescues and several capital raising exercises, Italian banks have experienced severe turmoil in the past decade.[1] The adverse situation has significantly impacted banks' market performance, their profitability, and their capability to lend to the real economy. The Italian government has taken several initiatives to address the NPL problem, including the introduction of a state-backed guarantee on senior tranches of securitised bad loans ("Garanzia Cartolarizzazione Sofferenze", GACS) in early 2016. In addition, from March 2017, as a part of a comprehensive EU-wide strategy, the

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[1] In June 2017, two regional banks, known as the Veneto banks, underwent liquidation. Their viable operations were acquired by Intesa Sanpaolo for a nominal fee of €1. The Italian government allocated €17 billion to mitigate potential losses stemming from the distress of these two banks. Since 2008, Banca Monte dei Paschi di Siena (MPS) has been at the centre of several accounting scandals and has faced significant challenges in resolving its NPLs. In July 2017, the EC approved a precautionary and last resort recapitalisation plan for €5.4bn to support MPS. In more recent years, other institutions like Banca Carige and Banca Popolare di Bari were hampered by high volumes of NPLs and needed public capital injections.

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European Central Bank (ECB), the European Commission (EC) and the European Banking Authority (EBA) adopted several measures which aim to effectively tackle NPLs and prevent the problem from reigniting.[2]

Stricter regulations imposed by European authorities, such as higher collateral requirements and levels of provisions, represent a necessary step to address one of the most challenging issues in the euro area financial system. Originally designed to encompass the outstanding stock of NPLs, the proposed rules introducing a common minimum coverage requirement were diluted to avoid severe repercussions on the banking sectors of more fragile European economies. In Italy, concerns were raised regarding the potential for adverse impacts on bank profitability and new lending. Despite the adjustments, the implementation of calendar provisioning and introduction of more stringent guidelines on loan origination exerted pressure on Italian banks impacting NPL management strategies and business practices.[3] The imperative to alleviate the NPL burden within the Italian banking sector emerged as a top-tier priority for policymakers aiming to break the stubborn vicious circle between banks and sluggish economic growth. Thus, bank supervisors persisted in thoroughly scrutinizing and challenging bank strategies and plans to improve their asset quality (IMF, 2020).

We first offer a comprehensive overview of the key developments and dynamics in the NPL sphere in the Italian banking sector during the most acute phase of the issue. Subsequently, we shift the focus towards identifying both the idiosyncratic and systemic factors that influenced the build-up of high volumes of NPLs across Italian banks. We complement our empirical analysis by discussing the main initiatives of the Italian government to alleviate the NPL problem.

In a robust empirical framework, in line with the extant literature on the determinants of NPLs and their impact on bank activities, we employ Generalized Method of Moments (GMM) estimators for dynamic panels. We conduct the analysis on a representative sample comprising 73 Italian listed and unlisted banks, characterised by different business models, and covering the period from 2011 to 2017. Our approach uses bank-specific variables to capture within-sample heterogeneity and macroeconomic variables to account for prevailing economic conditions in the country. Understanding the factors driving ex-post credit risk, as manifested in NPLs, is crucial for regulatory authorities seeking financial stability and the management of banks. Furthermore, the potentially significant impediments to real economic growth arising from the high level of NPLs in the banking sector, pose a substantial challenge for policymakers and bank supervisors. Hence, addressing the NPL problem has been a primary objective for ECB banking supervision since the ECB assumed this responsibility in 2014. A resolution of the NPL issue in Italy and at the European level has been deemed essential to enhance the resilience of banks and equip them to face future challenges (Enria, 2019).

Our contribution to the existing literature on NPLs is twofold. First, we provide in-depth insights into the problems and challenges faced by the European country with the largest stock of NPLs during the past decade (Fig. 1).

The distinctive characteristics of the Italian case provide a unique framework for examining the diverse factors contributing to the substantial accumulation of NPLs during times of crisis. Additionally, the focus on a single country mitigates potential challenges stemming from heterogeneous definitions and measurement methods for NPLs across countries, addressing the complexities that make international comparisons “an arduous task” (Chortareas et al., 2020, p.3). We complement the core empirical analysis by providing insights into the policy developments and initiatives undertaken by the Italian government to address the NPL challenge. Thus, we fill the gap created by the scarcity of academic research on the key NPL-events in Italy over the past decade. Since our sample period encompasses the European sovereign debt crisis and subsequent double-dip economic recession, we can examine banks that faced significant problems, potentially affecting European financial stability, and were subject to close scrutiny by the Single Supervisory Mechanism (SSM).

Second, the dynamic framework allows our empirical analysis to focus on the influence of both bank-level and macroeconomic factors on the evolution of NPLs over time. Examining idiosyncratic factors separately allows for a more complete understanding of their contribution to the problem. In contrast to previous studies on NPLs in Italian banking (Bofondi and Ropele, 2011; Anastasiou, 2017), we do not limit our investigation to exogenous (systemic) factors, potentially affecting all banks, since we are motivated to capture the role of microeconomic differences across institutions. The relevance of our research is framed in a context where the banking sector plays a significant role in providing funds to the private sector. According to World Bank data, in 2017 the level of domestic bank credit to the private sector in Italy accounted for 80.8% of GDP (with an average of 88.6% for the period 2011–2017).

To preview our primary findings, bank capitalisation emerges as a significant factor in easing the NPL burden in Italy. We observe an inverse relationship between credit growth and NPLs possibly stemming from demand-driven credit expansion. Additionally, our empirical results confirm the counter-cyclical nature of NPLs and highlight a substantial impact of past unemployment rates. Lastly, the dimension of public debt does not appear to exert a notable influence on the asset quality of Italian banks.

We organise the remainder of this paper as follows. Section 2 discusses the evolution of the NPL problem in the Italian banking sector. Section 3 reviews the literature on the determinants of NPLs and formulates the hypotheses. Section 4 describes the sample construction and the data. Section 5 outlines the econometric methodology. Section 6 discusses the empirical results and Section 7 offers policy implications and future research directions.

[2] In March 2017 the ECB issued non-binding guidance to banks concerning NPLs. This guidance was supplemented in October 2017 with an addendum aimed at promoting timely provisions and strengthening write-off practices. Subsequently, in March 2018, the EC introduce a package of measures to tackle high NPL ratios across banks in Europe. In October 2018, the EBA issued a set of guidelines focused on the management of NPLs and forborne exposures.

[3] Within this framework, banks were mandated to allocate additional funds to mitigate the inherent risk associated with potential NPLs. Specifically, a minimum coverage requirement, referred to as “a statutory prudential backstop”, was introduced to cover losses caused by loans originated after 26th April 2019 that subsequently become non-performing with corresponding capital deductions. The pertinent Regulation (EU) 2019/630 amending Regulation (EU) 2013/575 was adopted in April 2019.

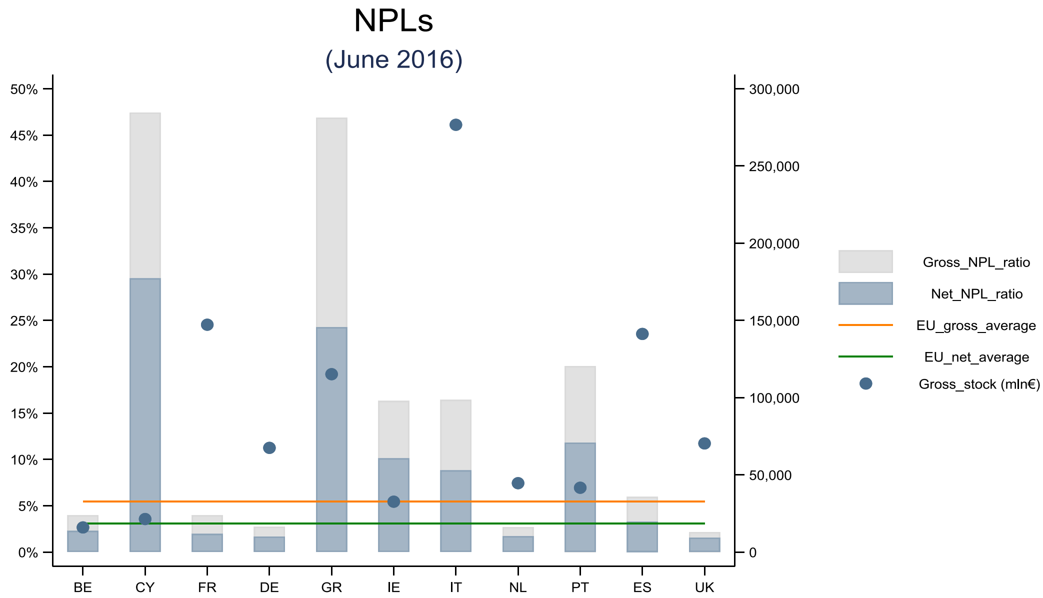


Fig. 1. NPLs in selected EU countries.
Description: For selected EU countries, this figure displays the NPL ratios (gross and net figures) and the gross stock values (millions of euros). The EU average values are also reported.
Source: EBA EU-wide transparency exercise, June 2016. Own elaboration.

2. The evolution of the NPL problem in the Italian banking system

Following the global financial and sovereign debt crises, a protracted period of recession tested the resilience of Italian firms and borrowers. This created conditions for a deterioration in bank balance sheets and a significant increase in the volume of NPLs. Between 2009 and 2015, the total amount of gross NPLs on Italian banks' books grew substantially from €133bn to a peak of €341bn at the end of 2015. Gross bad loans ("*sofferenze*" in Italian) were mainly concentrated in the corporate sector (Ernst and Young (EY), 2019). A deep review of bank operating models as well as an extensive deleveraging process supported by policy initiatives at both national and European levels contributed to the remarkable positive developments, which became especially evident in 2018.

Since 2017, a more favourable European economic environment, coupled with a moderate Italian recovery, created conducive conditions for bank asset quality to improve. European real GDP growth reached 2.4% in 2017 with parallel increases in Italy from 1.1% in 2016 to 1.6% in 2017. From the 2014 peak of 12.7%, and thanks to improved conditions in the labour market, the unemployment rate in Italy declined over time reaching 11.2% in 2017 (Fig. 2).

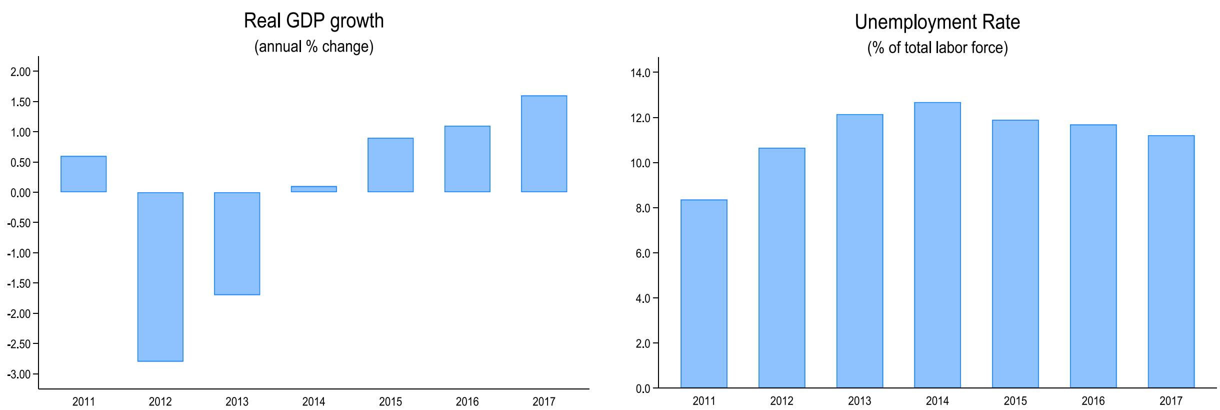


Fig. 2. The evolution of the GDP growth and the unemployment rate in Italy.
Description: This figure displays the evolution of the real GDP growth (annual percentage change) and the unemployment rate (as a percentage of the total labour force) during 2011–2017.
Source: IMF and World Bank databases. Own elaboration.

Table 1
Government gross debt ratio: cross-country evolution.

	2011	2012	2013	2014	2015	2016	2017
France	87.80	90.60	93.40	94.90	95.60	96.60	98.50
Germany	78.60	79.90	77.40	74.50	70.80	67.90	63.90
Greece	180.60	159.60	177.90	180.20	177.80	181.10	179.30
Italy	**116.50**	**123.40**	**129.00**	**131.80**	**131.60**	**131.30**	**131.30**
Spain	69.50	85.70	95.50	100.40	99.30	99.00	98.10
UK	80.80	84.10	85.20	87.00	87.90	87.90	87.10
Euro area	86.60	89.70	91.60	91.80	89.90	89.10	86.80
EU	81.80	85.30	87.20	87.80	86.20	85.30	83.30

Source: IMF database. Own elaboration.
Description: For selected EU countries, this table reports the evolution over the years 2011–2017 of the government gross debt ratio (as a percentage of the GDP).

Following an increase of about 13% since 2011, and peaking at 131.8% in 2014, the Italian government's gross debt ratio remained relatively stable from 2015 to 2017. The elevated level of public debt exposed the Italian economy to risks associated with financial market tensions and constrained the potential for fiscal policies to support productive activity during the period of low growth (Bank of Italy, 2019 - Table 1).

In 2016, Italian banks marked a significant milestone by recording the first decline in gross NPLs in eight years. At the end of 2016, the net stock of NPLs stood at 9.4% of outstanding loans, showcasing a notable improvement from the corresponding figure of 10.9% at the end of 2015. The stock of gross NPLs represented 17.4% of outstanding loans in 2016 reflecting a decrease from the 18.2% reported in 2015. This positive trend persisted in 2017 with ratios continuing to decrease (Fig. 3). Based on statistics from the Bank of Italy, the NPL coverage ratio for the banking sector increased by approximately 16% from 45.4% in 2015 to 52.7% in 2017. At the end of 2017, bad loans represented the largest share of the gross stock of NPLs (9.1%, equivalent to €178bn) while UTP (unlikely-to-pay) exposures were the largest portion in terms of net values (3.7%, equivalent to €67bn).

In 2016, Italy was the most dynamic loan sale market in Europe, disposing of €36bn in 43 completed deals. This momentum continued in 2017 as transaction volume exceeded €65bn (PricewaterhouseCoopers (PwC), 2018). The notable achievement of repairing bank asset quality is attributable, among other factors, to a series of initiatives undertaken by the Italian government to improve the efficiency and speed of both judicial and extra-judicial insolvency procedures functioning to boost the reduction of problem loans while increasing the valuation of NPL portfolios.[4] Thus, overall improvements to the transaction environment, coupled with a strong political commitment to resolve the NPL problem, have played a pivotal role in developing a functional market for distressed debt. In addition, the introduction of the GACS framework in early 2016, alongside amendments to bankruptcy foreclosure proceedings and the advantageous tax treatments on bank loan provisions, exemplifies the proactive stance taken by the Italian government.[5]

3. Related literature and hypotheses development

3.1. Determinants of NPLs

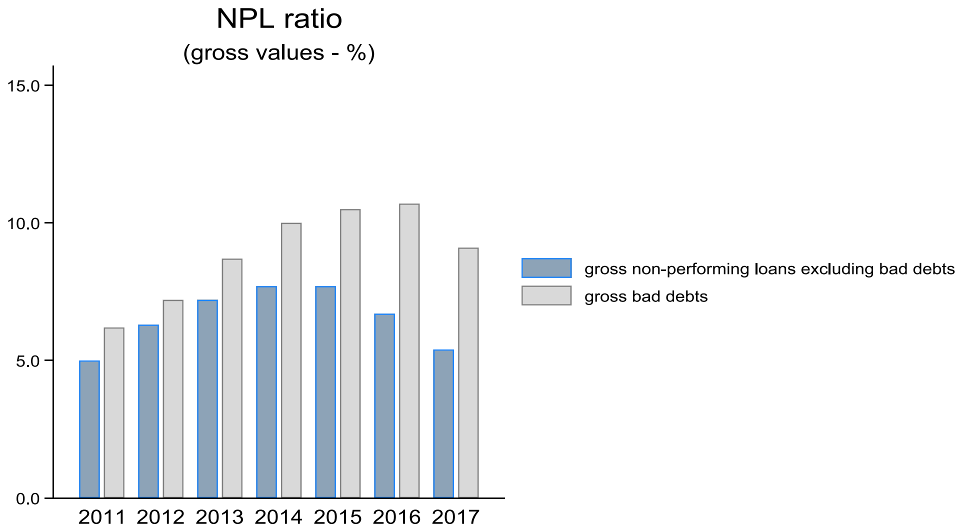
The extant academic literature identifies two primary categories of factors that explain the dynamics of NPL volumes over time. The first category includes variables reflecting the broader macroeconomic environment that influence borrowers' capacities to meet their financial obligations. The second set of determinants focuses on bank-specific characteristics. Prior empirical research, including the seminal contribution by Berger and DeYoung (1997), as well as studies by Klein (2013), Louzis et al. (2012), Ghosh, 2015 and Anastasiou et al. (2019), among others, consistently presents evidence supporting the significance of both of these types of factors.

3.1.1. Macroeconomic factors

Theoretical frameworks that develop business cycle models and account for the role of financial intermediation identify a relationship between bank asset quality and economic activity. The financial accelerator theory, as discussed in seminal works such as Bernanke et al. (1999) and Kiyotaki and Moore (1997), represents the most influential theoretical framework to explain the relationship between NPLs and the broader macroeconomic environment. Pesaran et al. (2006) propose a model that links the value of a credit portfolio to the global macroeconomic landscape. They emphasize the crucial role played by the interconnectedness of firms and business cycles in influencing default probabilities. Insights into the macroeconomic determinants of NPLs are found in the theoretical literature on life-cycle consumption models. Lawrence (1995) explicitly introduces the probability of default and suggests that

[4] Relevant legal reforms adopted in Italy include Law 132/2015 ("Giustizia per la crescita") that amended the private and civil bankruptcy laws to improve the efficiency of insolvency procedures and property foreclosures. Law 49/2016 introduced measures on the cooperative credit system, the GACS guarantee scheme and the cadastral tax. Law 59/2016 ("Decreto banche") introduced provisions on foreclosure, insolvency proceedings and guarantees, which aim to shorten the length of judicial procedures and simplify the auction process.

[5] See Appendix B for further details on the GACS scheme.



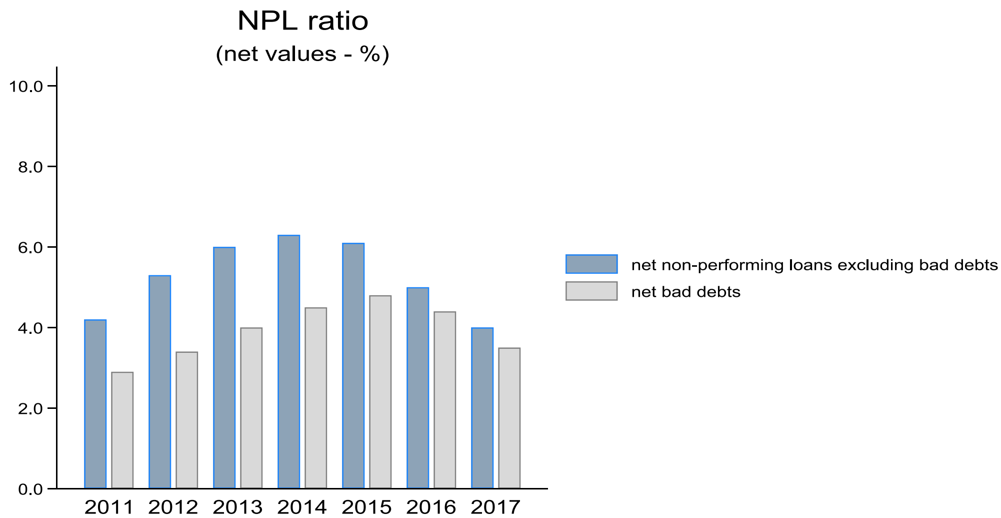


Fig. 3. The evolution of NPL ratios in Italy.
Description: This figure displays the evolution of the NPL ratios (gross and net values).
Note: Other than bad loans, NPLs include UTP and past due exposures during 2011–2017.
Source: Financial Stability Report, Bank of Italy, various years. Own elaboration.

low-income household borrowers face an elevated likelihood of default due to a higher risk of unemployment. Building on this model, Rinaldi and Sanchis-Arellano (2006) argue that the probability of default for household borrowers depends, among other factors, on current income and the unemployment rate, which in turn relate to uncertainty surrounding future income and lending rates.

From an empirical perspective, Salas and Saurina (2002) examine a sample of Spanish commercial and saving banks from 1985 to 1987 and find a negative correlation between GDP growth and NPLs.[6] Similarly, within the Spanish context from 1984 to 2002, Jiménez and Saurina (2006) present findings which show that both credit growth and the economic cycle exert a substantial impact on loan quality. Espinoza and Prasad (2010) employ data for the Gulf Cooperation Council (GCC) region for the period 1995 to 2008 and demonstrate that lower economic growth and higher interest rates coincide with an increase in NPLs. Additionally, their analysis unveils the existence of a short-lived feedback effect from weakened bank balance sheets to the broader economy.

Nkusu (2011) analyses a sample of 26 advanced countries spanning 1998 to 2009 and finds that adverse economic conditions are linked to a rise in NPLs. Additionally, Nkusu suggests that a substantial increase in NPLs contributes to the weakening of macroeconomic performance. De Bock and Demyanets (2012) examine data for 25 emerging market economies from 1996 to 2010. They find

[6] Salas and Saurina (2002) also report that credit risk is significantly influenced by bank-level variables related to growth policies and managerial incentives.

an inverse relationship between the ratio of aggregate NPLs and countries' economic growth and emphasize the existence of significant feedback effects originating from the banking sector that impact the real economy (i.e., economic growth slows as a result of increasing NPLs or credit contraction). Beck et al. (2015) analyse the role of key macroeconomic factors across 75 advanced and emerging countries from 2000 to 2010 and confirm the pivotal role played by real GDP growth in driving NPL volumes. In addition, they highlight the significant explanatory power stemming from nominal effective exchange rates, share prices, and real lending rates. Chavan and Gambacorta (2019) examine the relationship between NPLs and the credit cycle in India from 2000 to 2014. They reveal that bank NPL ratios exhibit sensitivity to both the prevailing interest rate environment and the economic growth of the country.

Using a panel of Italian banks from 1985 to 2002, Quagliariello (2007) finds that the dynamics of the macroeconomic environment exert a substantial influence on bank risk profiles. Bofondi and Ropele (2011) study the period from 1990 to 2010 and offer further insights. They establish an inverse relationship between the quality of bank loans to both corporates and households and the prevailing conditions of the business cycle. The adverse impact of the 2008–2015 recessionary period on the evolution of bad debt for Italian banks is highlighted by Notarpietro and Rodano (2016). Anastasiou (2017) analyses a sample of 47 banks from 1995 to 2014 and reaffirms the negative influence of weak macroeconomic conditions on NPL levels. Accornero et al. (2017) investigate the impact of NPLs on bank credit supply to the non-financial sector between 2008 and 2015. The authors document an inverse relationship between NPL ratios and credit growth that is primarily attributed to changes in firm conditions and other demand factors. Mohaddes et al. (2017), in a panel threshold analysis, estimate the growth rate needed for a significant decline in bank NPL ratios to be persistently above 1.2%.

The extant empirical evidence is supportive of the view that NPLs are anti-cyclical. The rationale is that a growing economy is usually associated with increased available income that subsequently enhances borrowers' capacity to repay debts. Conversely, during an economic downturn, the level of NPLs is likely to increase due to elevated unemployment and borrowers experiencing greater difficulties in servicing obligations (Salas and Saurina, 2002; Louzis et al., 2012; Kanas and Molyneux, 2018).

3.1.2. Bank-specific factors

A second strand of literature emphasizes the impact of bank-specific (idiosyncratic) factors on NPL levels. Berger and DeYoung (1997) explore the interconnectedness among loan quality, cost efficiency, and the level of capitalization for a sample of US commercial banks spanning 1985 to 1994. Their findings lend support to the "bad management" hypothesis, indicating a positive association between low-cost efficiency and future increases in NPLs. Additionally, their research validates the "moral hazard" hypothesis, revealing an inverse relationship between the level of capitalization and NPLs. Williams (2004) applies these tests to a sample of European savings banks from 1990 to 1998. While bad management is a pressing problem for both US and European banks, there is only weak statistical evidence to support the moral hazard hypothesis at European banks.

For the period spanning 2003 to 2009, Louzis et al. (2012) analyse the determinants of NPLs across various loan categories for nine large Greek banks. Their findings confirm the need to incorporate both macroeconomic factors and bank-specific variables when modelling the evolution of NPLs. Whilst the level of impaired loans is positively linked to unemployment and real lending rates, it is inversely related to GDP growth. Across all loan types, poor management quality, reflected in both cost inefficiency and past profitability issues, emerges as a contributing factor to the escalation of NPL levels.

Klein (2013) investigates the determinants of NPLs in Central, Eastern and South-Eastern European (CESEE) countries between 1998 and 2011. NPLs are explained by a combination of macroeconomic and bank-level factors although the latter exhibit relatively lower explanatory power. Furthermore, Klein (2013) examines the feedback effects from the banking system to the real economy and provides evidence supporting the existence of significant macro-financial interconnections. In a related context, Ghosh (2015) investigates state banking-industry-specific and regional determinants of NPLs using a comprehensive sample of U.S. commercial and savings banks from 1984 to 2013. The results show that higher levels of capital, liquidity risks, low credit quality, inefficient cost management, and large bank size contribute to explaining higher NPL volumes. Additional variables positively associated with the level of NPLs include state unemployment rates, inflation, as well as U.S. public debt. Conversely, bank profitability, real GDP, and the house price index are inversely related to NPL volumes.

Miyajima (2016) assesses the determinants of NPLs for nine banks in Saudi Arabia from 1994 to 2004. Utilizing a comprehensive set of macroeconomic and bank-level variables, the author identifies an inverse relationship between NPLs and both oil prices and economic growth. Furthermore, the author documents the existence of a feedback loop between bank balance sheet variables and economic activity. Weaker macroeconomic conditions increase the vulnerability of bank balance sheets, which, in turn, further weaken overall macroeconomic conditions. Anastasiou et al. (2019) examine the determinants of NPLs for a sample of euro area commercial banks from 2003 to 2016. Employing a combination of country and bank-specific variables, the authors find a significant inverse association between real GDP growth and NPLs, coupled with a positive link between the rate of unemployment and problem loans. Additionally, their study sheds light on the significant role played by both management quality and moral hazard behaviour in influencing the levels of NPLs. Cucinelli et al. (2021) investigate the determinants of UTP loans from 2010 to 2016. They find a positive association between bank capital and the emergence of new UTPs. Additionally, the study shows that lower bank efficiency is linked to increased new flows of UTPs.

Despite the high profile of the NPL problem in recent years, empirical studies on the Italian banking sector are limited. This paper enhances the existing literature by testing the relevance of both macroeconomic and bank-specific factors in shaping banks' asset quality during the most critical phase of the NPL challenge. To achieve this, we employ a comprehensive dynamic panel framework, including both Difference and System GMM approaches, with their variants. Our sample comprises 73 listed and unlisted banks, representing different institutional forms, including entities that faced significant NPLs-related challenges during the period of observation.

3.2. Hypotheses development

An extensive theoretical literature examines the effects of bank capital regulation on bank behaviour (see VanHoose, 2007). In the context of this paper, our principal focus is the relationships between bank capital and NPLs, and loan growth and NPLs. We survey extant literature to develop the hypotheses that we test later for a sample of Italian banks.

Inter alia the bank capital literature considers the relationship between levels of capital or leverage and incentives for excessive risk-taking by banks that influences the probability of bank default. In our framework, we contend that selecting a riskier mix of assets is likely to cause an increase in NPLs.

Several papers perceive banks to be managers of portfolios of assets operating under non-risk-based capital constraints. A tightening of the leverage ratio (assets-to-equity) constrains the bank's efficient asset investment frontier causing the bank to alter the mix of assets in its portfolio per unit of capital. The possible outcomes are conditional upon the distribution of risk aversion across banks. For relatively non-risk-averse (riskier) banks, an increase in capital requirements causes bank managers to choose a riskier mix of assets than before, which raises the probability of default. In contrast, risk averse banks select a safer mix of assets (see Kahane, 1977; Koehn and Santomero, 1980).

Banks face moral hazard incentives arising from government safety net arrangements that can cause greater risk-taking and higher volumes of NPLs in the future. Keeley and Furlong (1990), Furlong and Keeley (1989), and Flannery (1989) incorporate the option value of deposit insurance to banks into their models and show that increasing capital requirements reduces bank asset risk. Whereas safety net arrangements should enhance financial stability, they can insulate banks from market discipline while exposing others to possible losses emanating from excessive risk-taking. Nonetheless, market discipline influences banks' capital choices. If purchasers of bank liabilities punish riskier banks by demanding higher returns, banks increase capital to lower their default probabilities although not all banks behave in this way if deposits are insured. Furthermore, the market can discipline banks into holding more capital if the market perceives bank capital as too low (Berger, 1995). Relatedly, the signalling hypothesis contends that bank managers hold private information about future cash flows and signal this information through their capital choices (Acharya, 1988). Hence, good banks signal their higher quality by holding more capital. However, holding more capital can, under conditions of asymmetric information, imply that bank insiders consider their assets to be riskier (Berger et al., 1995). Notwithstanding a signalling equilibrium exists in which banks that expect to have better future performance have higher capital (Berger, 1995).

The relationship between capital and risk might not be linear. If bank capital is very low, banks face moral hazard incentives to hold riskier loan portfolios to maximise the option value of deposit insurance (see Fegatelli, 2010, for further discussion). With potential upside risk outweighing downside risk, thinly capitalised banks are more prone to excessive risks taking and larger volumes of NPLs (Berger and DeYoung, 1997). However, managers face incentives to increase capital because excessive risk-taking threatens the charter value of banks. Since the probability of default for very highly capitalised banks is very low, further tightening of capital requirements might induce banks to assume more risk to benefit from the upside, which could lead to higher NPLs in the future (Calem and Rob, 1999).

An unhealthy sector creates more moral hazard incentives. In this scenario, entrenched managers assume more risks and not less. Should the level of competition be expected to increase, and due to information asymmetries bank managers possess superior information on the quality of the loan portfolio, stakeholders can pressurise managers into pursuing an expansionary strategy that is more risky *ex post* (Gorton and Rosen, 1995).

Our discussion implies that capital requirements increase the magnitude of banks' capital cushions. For riskier or more thinly capitalised banks, tighter capital requirements create moral hazard incentives that increase risk-taking and default probabilities with higher NPLs as one result. Even though capital regulations make better capitalised banks safer, it is possible that highly capitalised banks with extremely low default probabilities face incentives to benefit from upside risk. It is possible for a sizeable capital cushion to rapidly dissipate if banks react to capital regulation by making riskier choices or failing to devote sufficient resources to evaluate adverse selection or moral hazard problems (VanHoose, 2007). Despite theoretical priors, the effect of capital on banking sector stability depends on the distribution of risk aversion across banks implying that more than one outcome is possible.

Based on this discussion, we propose our first hypothesis:

H1. Banks with lower Tier 1 capital ratios assume more risk that produces larger amounts of NPLs.

The financial sector is procyclical tending to move in tandem with the business cycle. Thus, lending increases significantly during upswings and reduces considerably during downturns. In several crisis situations, the contraction of lending has caused a credit crunch in which increases in loan rates exacerbate adverse selection and moral hazard problems in credit markets. In such cases, the changes in lending are more than proportional to the decline in economic activity. It implies that changes in bank loan supply accentuate the business cycle. Furthermore, bank loan performance problems follow a pattern over the business cycle. Problem loans and provisioning are very low during most of the expansion phase. Problems emerge when the expansion is ending and increase rapidly during the downturn. It implies that banks assume higher levels of risk during upswings. The risks manifest later because it takes time for problem loans to appear. Berger and Udell (2004) propose and find support for the institutional memory hypothesis in explaining the procyclicality of bank lending. Their evidence shows that credit standards ease the longer the elapse of time since the bank's last loan problem issue.

Salas and Saurina (2002) also note the positive association between rapid growth in lending and heightened problems in bank loan portfolios. In explanation, an increasing supply of bank loans under competitive conditions weakens the quality of the loan portfolio if poorer quality borrowers obtain loans. The problem is compounded if banks use finer loan pricing or compromise credit standards to attract new and retain existing customers. Due to the time needed to determine the creditworthiness of new borrowers, banks face significant adverse selection problems. Furthermore, rapid credit growth might negate the effectiveness of banks' monitoring capabilities, which increases moral hazards. By implication, the probability of borrower default increases and banks must contend with larger amounts of NPLs in the future (Jiménez and Saurina, 2006). Moreover, due to the time necessary to establish the risk profile of a new customer, banks are negatively affected by adverse selection, which might imply a higher probability of borrower defaults.

Based on this discussion, we propose our second hypothesis:

H2. Banks with faster loan growth are burdened by larger amounts of NPLs in the future.

4. Sample construction and data

Our initial sample of banks, excluding publicly owned or specialized institutions, comprises 77 entities, each with total assets exceeding €2bn as of December 2017.[7] To refine our focus on banks primarily engaged in traditional lending activities, we apply a further criterion, namely, excluding four institutions with gross loans-to-total assets ratios consistently below 50% over a three-year period. The final sample comprises 73 banks of various institutional forms, i.e. commercial, savings and cooperative banks, including both listed and unlisted entities. Overall, the sample accounts for about 86% of Italian banking sector assets at the end of 2017. The period from 2011 to 2017 covers the most acute phase of the NPL issue in Italy and corresponds to the European sovereign debt crisis and subsequent recession. We include in the sample banks that experienced significant challenges in this period, such as Banca Carige, Banca Popolare di Bari, Banca Popolare di Vicenza, MPS and Veneto Banca to capture heterogeneity across banks.[8] Fig. 4 shows that the NPL ratios for Italy's five largest banks exhibited a substantial decline from 2017, dipping below 10% for most, with MPS standing out as a unique case to some extent. Our decision to end the observation period in 2018 is taken to mitigate any potentially confounding impact associated with the introduction of IFRS 9, which effectively replaced IAS 39 in January 2018.[9] We source bank-level factors from S&P Global Market Intelligence and retrieve macroeconomic variables from International Monetary Fund and World Bank databases. Due to the lack of comprehensive higher frequency bank balance sheet data (e.g., quarterly data), we sample on an annual basis.

Our dependent variable is the ratio of NPLs to customers-to-total gross loans.[10] In 2014, the EBA introduced a standard definition of NPEs for supervisory reporting purposes. This definition includes any exposure that is more than 90 days past due or unlikely to be repaid without realization of the collateral, including the "forborne" exposures. However, it is important to note that harmonization across European jurisdictions and banks is still not fully achieved.[11] Thus, using data for banks within a single jurisdiction ensures a higher level of consistency and homogeneity. Following common practice (see Salas and Saurina, 2002; Jiménez and Saurina, 2006; Ghosh, 2015), we use a logit transformation and express the dependent variable as $log(NPLs/(1-NPLs))$. Since the NPL ratio is inherently constrained between 0 and 1, this transformation creates an unrestricted variable spanning the interval $[-\infty;+\infty]$ which is distributed symmetrically. Furthermore, Wezel et al. (2014) state that this transformation helps to avoid non-normality in the error component and accommodates potential nonlinearities. For instance, larger shocks to the regressors may result in a substantial, nonlinear reaction in the transformed dependent variable. Table 2 presents the set of explanatory variables employed in the empirical analysis, the dependent variable, data sources, and the expected signs of the coefficients.

Consistent with existing literature on NPL determinants (Klein, 2013; Louzis et al., 2012; Ghosh, 2015), our bank-specific variables include (i) the ratio of Tier 1 capital-to-total risk-weighted assets (*Tier1*) to proxy capitalisation; (ii) the natural logarithm of total assets (*Total_Asset*) to measure bank size; (iii) return to equity (*ROE*) to proxy bank profitability; (iv) the yearly percentage change in gross loans (*Loan_g*) to proxy credit expansion; and (v) the ratio of non-interest income-to-total income (*NII*) to proxy bank diversification.

Bank capitalisation

Managers at thinly capitalised institutions face a potential incentive (based on the moral hazard hypothesis) to increase riskier lending practices, associated with poor evaluation of borrowers' creditworthiness and weak monitoring processes (Zhang et al., 2016). Moreover, poorly capitalised banks are more prone to lend to weaker borrowers in a "gamble for resurrection", especially under conditions of information opacity. Thus, we expect an inverse link between capitalisation and NPLs if greater capital strength lowers the incentive to assume extra risk (Salas and Saurina, 2002).

Bank profitability

The charter value hypothesis posits that higher (lower) levels of bank profitability reduce (increase) incentives for managers to take excessive risks (Keeley and Furlong, 1990). A priori increases in competition erode bank market power thereby lowering the value of a banking charter and encouraging moral hazard behaviour by banks. In this case, we expect an inverse relationship between profitability and NPLs. The "bad management" hypothesis also posits that profitability will be inversely associated with NPLs (Berger and

[7] We choose this threshold to focus on sufficiently large banks for which it is possible to retrieve reliable data, especially NPL ratios, thereby reducing the problem of missing observations and enhancing the robustness of the analysis.

[8] Banca Popolare di Milano and Banco Popolare were considered as separate entities, despite their merger, effective from the 1st January 2017, which led to the establishment of Banco BPM.

[9] IFRS 9 has significantly changed how banks manage loans on their balance sheets by introducing a new impairment approach based on expected rather than incurred losses, among other amendments.

[10] Limitations related to the availability of data from commercial databases dictate the selection of the main variable of interest. Using more disaggregated data, such as NPL information relative to specific counterparties or loan types, was not feasible.

[11] In addition to the supervisory definition of NPEs, there is the accounting definition of "impaired" based on IFRS 9, as well as the prudential definition of "default" outlined in the Regulation (EU) No 575/2013, commonly referred to as "The Capital Requirement Regulation" (CRR).

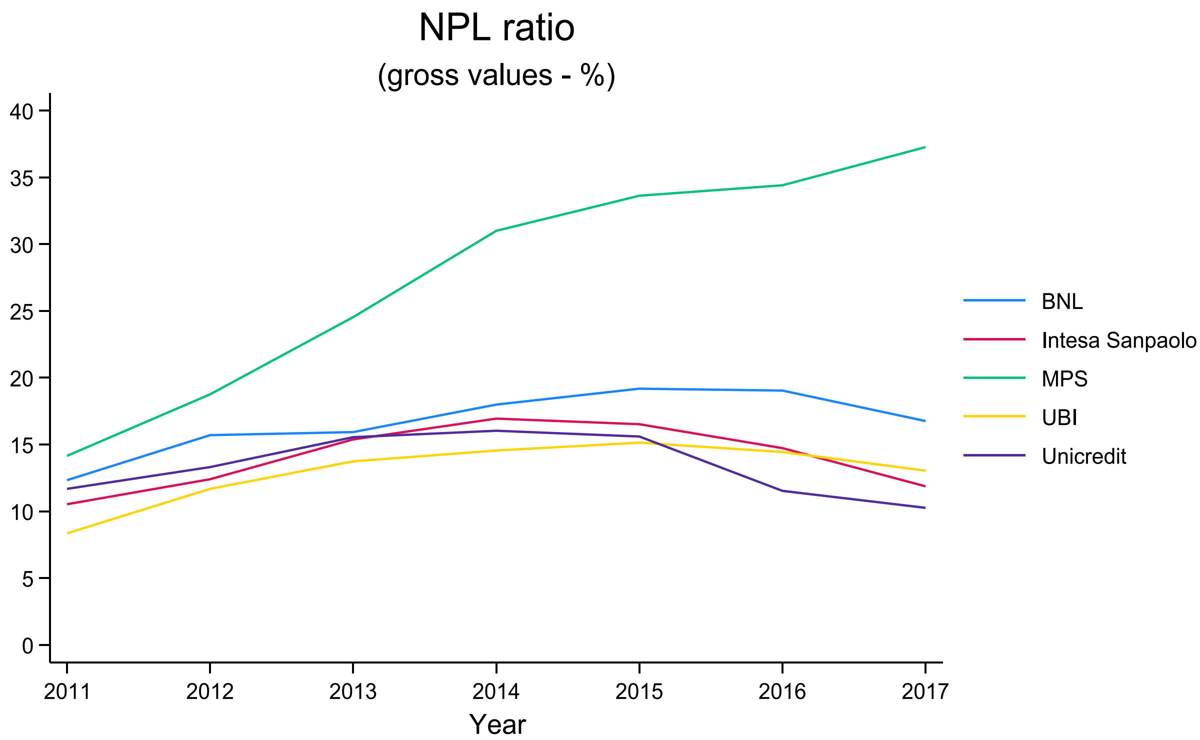


Fig. 4. The evolution of NPL ratios for the five largest Italian banks.
Description: This figure displays the evolution of the NPL ratios (gross values) for the five largest Italian banks during 2011–2017 (based on total assets as of 2017).
Source: S&P Global Market Intelligence. Own elaboration.

Table 2
Definition of variables, data sources and expected signs.

Label	Description	Indicator	Source	Exp. sign
NPL	Non-performing loans to gross loans (%)	Asset Quality	S&P Global Market Intelligence	
Bank variables				
Tier1	Tier 1 capital-to-risk-weighted assets (%)	Capitalisation	S&P Global Market Intelligence	(−)
ROE	Net income-to-total equity (%)	Profitability	S&P Global Market Intelligence	(−)/(+)
Total_Asset	Total assets (Ln)	Size	S&P Global Market Intelligence	(+)
Loan_g	Annual growth of gross loans (%)	Lending Activity	S&P Global Market Intelligence	(+)
NII	Non-interest income-to-total income (%)	Diversification	S&P Global Market Intelligence	(−)
Commercial	Dummy variable equals to 1 if the bank is a commercial bank (0 otherwise)			
North	Dummy variable equals to 1 if the bank's headquarters is in a NUT2-region in Northern Italy (0 otherwise)			
Listed	Dummy variable equals to 1 if the bank is listed (0 otherwise)			
Macroeconomic variables				
GDP_g	Real GDP growth (%)		IMF	(−)
Debt	General government gross debt-to-GDP (%)		IMF	(+)
Unemp	Unemployment rate (% of labour force)		World Bank	(+)
Lending	Lending interest rate (%)		World Bank	(+)

Description: This table presents the variables employed in the empirical analysis, their definitions, the data sources, and the expected coefficient sign in the estimated models.

DeYoung, 1997).[12] Although more market power in loan markets can lead to increases in loan portfolio risk if higher loan rates encourage borrowers to shift into riskier activities, the level of overall risk can decrease if the bank protects the higher franchise value arising from its market power in loan markets by choosing to increase capital (Berger et al., 2009). Better performance could cause

[12] Moreover, increases in loan loss provisions because of rising levels of NPLs depress bank profitability, which can consequently turn to be negative (Accornero et al., 2017).

increases in NPLs. Rajan (1994) proposes a model that links bank credit policy not only to the earnings maximisation objective, but also to the short-term reputational interests of (rational) bank managers. Hence, current earnings might be subjected to manipulative actions appealing to liberal credit policies. Accordingly, bank management influences financial market perceptions by altering current earnings at the expense of future bank asset quality. Consequently, we expect a positive relationship between the selected performance ratio ROE (measured as the ratio of net income-to-equity) and NPL levels. In sum, the expected relationship between profitability and NPLs could be positive or negative.

Bank size

According to the "too-big-to-fail" (TBTF) hypothesis, large banks engage in excessively risky activities (i.e., granting credit to low-quality borrowers) based on implicit expectations of government protection in subsequent cases of distress. This perception arises from the potential threat to overall financial stability associated with the failure of a large-sized bank of systemic importance (Laeven et al., 2016). Furthermore, an institution of large dimensions might experience greater difficulties in accessing (soft) information about borrowers' financial conditions (Berger et al., 2005). Therefore, we expect a positive association between bank size and NPLs.

Loan growth

A rapid increase in the volume of lending is a major cause of problem loans (Salas and Saurina, 2002) and is positively linked with future increases in NPLs (Jiménez and Saurina, 2006). Rapidly increasing the supply of loans in a competitive environment often reduces the quality of bank loan portfolios. To obtain new business, banks reduce loan rates and lower credit standards, for instance, by relaxing collateral requirements. As noted in Section 4, this situation heightens adverse selection problems. Therefore, we expect that the loan growth indicator is positively related to NPLs.

Bank diversification

The level of diversification in banking activities can influence the quality of the loan portfolio. We expect an inverse relationship between the degree of diversification and NPLs based on the inherent aim of the diversification strategy to lower credit risk. Under this perspective, the ratio of non-interest income-to-total income reflects banks' reliance on other sources of income (arising from fee-based and off-balance-sheet activities) beyond that generated by traditional lending activity.[13]

Table 3 shows descriptive statistics for our bank-level variables, including the dependent variable. To account for potential outliers, we winsorize all variables at 1% in each tail of the distribution.[14] The NPL ratio ranges from 1.88% to 37.10%, with an average value of 15.92%. More specifically, the average NPL ratio rose from 9.55% in 2011 to 20.26% in 2016 before declining to 16.86% in 2017.

Our vector of macroeconomic variables includes (i) real GDP growth (GDP_g); (ii) the ratio of general government gross debt-to-GDP (Debt); (iii) the ratio of unemployment-to-the total labour force (Unemp); and (iv) the loan interest rate (Lending). Table 4 reports descriptive statistics for the macroeconomic variables from 2011 to 2017.

Aggregated economy activity

Substantial empirical evidence supports the anti-cyclical nature of NPLs (Klein, 2013). The underlying justification arises from the fact that a growing economy is usually associated with higher available income, which in turn improves borrowers' capabilities to repay debt. When there is a downturn in the economy, the level of NPLs likely increases because of higher unemployment and borrowers experiencing difficulties in servicing their obligations (Salas and Saurina, 2002; Louzis et al., 2012; Kanas and Molyneux, 2018). Accordingly, we expect that real GDP growth, a proxy for the general state of the economy, is negatively associated with bank NPLs.

Government debt

A vicious feedback effect between banking and sovereign risk has been identified as being at the core of the European sovereign debt crisis (Acharya et al., 2014). In some countries (e.g., Greece and Ireland), substantial sovereign debt tensions led to subsequent credit rating downgrades. This severely affected the domestic banking sector in terms of liquidity constraints and/or impaired market access. Banks, in turn, transfer these pressures onto clients, typically by impeding credit supply. Difficulties for borrowers in refinancing debts are likely to arise. Additionally, an increase in the sovereign debt burden may lead to fiscal adjustments, especially in the form of expenditure cuts. Cuts commonly target the social welfare area and the wage component of government consumption (Alesina and Perotti, 1997). The consequent negative impact on household incomes may imply failures in the repayment of outstanding loans; second-order negative effects may involve corporate loans due to a reduction in the level of demand. Following Louzis et al. (2012) and Ghosh (2015), we employ the ratio of public debt-to-GDP and expect that an increasing sovereign debt burden is associated with increasing NPLs.

Unemployment

An upsurge in the unemployment rate adversely impacts debtors' capability to meet contractual obligations. For households, an increase in the unemployment rate constrains their cash flows, boosting their debt burden. When considering businesses, rises in the unemployment rate may reflect a reduction in the level of production due to a decline in the demand side. This might imply a decrease in revenues and a deteriorated debt condition (Bofondi and Ropele, 2011; Louzis et al., 2012; Anastasiou et al., 2019). Therefore, we expect that the unemployment rate is positively associated with NPLs.

Lending rates

Increases in the prices of loans worsen borrowers' financial conditions and their debt-servicing capacity, especially for variable rate

[13] As in Salas and Saurina (2002), the bank size indicator can be considered as an alternative proxy for the degree of diversification, based on the assumption that a larger balance sheet allows for greater diversification (i.e., beyond the traditional intermediation activity).

[14] To check for stationarity in the variables of interest, we employ Fisher-type unit root tests for panel data (i.e., Augmented Dickey-Fuller and Phillips-Perron tests), with and without time trend. The results (unreported) do not indicate evidence of the presence of a unit root.

Table 3
Descriptive statistics of the bank-specific variables.

Variables	Obs.	Min	Max	Mean	Std. Dev.
NPL	504	1.88	37.10	15.92	7.80
Tier1	506	6.07	24.30	13.04	3.89
ROE	503	−87.64	22.59	−2.23	15.66
Total_Asset	506	12.65	20.55	15.85	1.51
Loan_g	496	−35.78	91.03	3.03	14.71
NII	503	19.78	72.95	47.68	9.74
Commercial	511	0.00	1.00	0.34	0.47
North	511	0.00	1.00	0.78	0.41
Listed	511	0.00	1.00	0.40	0.49

Description: This table presents the descriptive statistics for the dependent variable (NPL) and the bank explanatory variables employed in the empirical analysis. It reports the number of observations ("Obs.") based on bank-years in the sample, the minimum ("Min") and maximum ("Max") values, the mean ("Mean") and the standard deviation ("Std. Dev."). The sample period is from 2011 to 2017. A definition of the variables is provided in Table 2.

Table 4
Descriptive statistics of the macroeconomic variables.

Variables	Obs.	Min	Max	Mean	Std. Dev.
GDP_g	511	−2.80	1.60	−0.03	1.50
Debt	511	116.50	131.80	127.84	5.40
Unemp	511	8.36	12.68	11.23	1.32
Lending	511	3.00	5.22	4.35	0.79

Description: This table presents the descriptive statistics for the macroeconomic variables. It reports the number of observations ("Obs.") based on bank-years in the sample, the minimum ("Min") and maximum ("Max") values, the mean ("Mean") and the standard deviation ("Std. Dev."). The sample period is from 2011 to 2017. A definition of the variables is provided in Table 2.

agreements. Thus, we expect the level of NPLs to be positively associated with the level of real lending interest rate (Nkusu, 2011; Louzis et al., 2012; Beck et al., 2015).

5. Econometric methodology and model estimation

5.1. Dynamic panel data estimators

In line with existing studies on credit risk and NPL determinants (Salas and Saurina, 2002; Louzis et al., 2012; Ghosh, 2015; Cheng and Qu, 2020, among others), we adopt a dynamic approach to account for potential time persistence in the dependent variable. NPL ratios typically exhibit persistence, indicating high serial correlation in their dynamics. Moreover, the response of credit losses to the economic environment may take time to manifest, leading to the accumulation of significant levels of NPLs over time (Klein, 2013). Therefore, incorporating at least one lagged value of the dependent variable in the set of regressors allows for a suitable representation of the dynamic adjustment process.

The estimation of a dynamic model using an Ordinary Least Squares (OLS) approach or a within-groups (fixed-effects) method may yield biased and inconsistent parameter estimates due to the correlation between the lagged dependent variable and the (unobservable) individual fixed-effects.[15] To address this problem, we employ both Difference GMM (Arellano and Bond, 1991) and its augmented version (Arellano and Bover, 1995; Blundell and Bond, 1998). The latter estimator (namely, System GMM) is particularly efficient in cases of highly persistent series where untransformed lags may represent weak instruments for transformed variables. We employ both the one-step and two-step GMM estimators with the latter incorporating the correction by Windmeijer (2005) to alleviate severely downward biased standard errors.

A key practical aspect of using GMM estimators is determining the appropriate number of moment conditions to avoid potential overfitting bias (Roodman, 2009b). It is crucial to limit the number of instruments, which grows quadratically with the sample time dimension, and report the associated instrument count. Subsequently, we test the overall validity of the instruments using the Hansen (1982) test of over-identifying restrictions. The GMM framework handles unbalanced panels and potential endogenous regressors, offering an effective way to avoid the biases associated with OLS and fixed-effects methods. These characteristics make this approach highly suitable for the empirical analysis conducted in this paper. We draw further validation of its suitability from related literature, notably Salas and Saurina (2002); Jiménez and Saurina (2006); Louzis et al. (2012); Klein (2013); Ghosh (2015) and Vithessonthi (2016), which underscores the dynamic nature of the NPL variable.

[15] In relation to pooled OLS and within-groups estimators for dynamic panel models, Nickell (1981) demonstrates the inconsistency, especially for samples with a short time dimension, and the negative) bias of the estimators. This bias leads to the underestimation of the coefficient on the lagged dependent variable and is often referred to as the "Nickell bias".

5.2. Econometric specification

Our analysis employs a multi-step approach, utilizing two main model specifications. The first specification includes only bank-specific variables while the second incorporates both bank and macroeconomic regressors. We consider various econometric estimation techniques, including OLS regression, fixed-effects model, and Difference/System GMM estimations (one- and two-step variants). We use the (unreported) OLS model and the fixed-effects frameworks to establish a valid range for the coefficient on the lagged dependent variable to ensure dynamic stability.[16] In the GMM framework, we apply the forward orthogonalization procedure (Arellano and Bover, 1995) to alleviate the negative impact of missing data, which would otherwise be exacerbated in the case of first-difference transformation. Lastly, we use the collapse procedure to limit the number of instruments.

Eq. (1) expresses the model specification with only bank-level variables:

$$NPL_{it} = \alpha NPL_{it-1} + \beta Tier1_{it-j} + \beta ROE_{it-j} + \beta Total\_Asset_{it-j} + \beta Loan\_g_{it-j} + \beta NII_{it-j} + \eta_i + \varepsilon_{it} \tag{1}$$

where the dependent variable is the logarithmic transformation of the NPL ratio. *i* indicates bank, *t* time and *j* the lag-order. *Tier*1 is the ratio of tier1 capital-to-risk-weighted assets, *ROE* is the ratio of net income-to-equity, *Total_Asset* is the natural logarithm of total assets, *Loan_g* is the loan growth rate to proxy credit expansion and *NII* is the ratio of non-interest income-to-total income. η_i are unobserved bank-specific effects; ε_{it} is the error term.

Eq. (2) shows the model specification that accounts for both bank-level and macroeconomic variables:

$$NPL_{it} = \alpha NPL_{it-1} + \beta Tier1_{it-j} + \beta ROE_{it-j} + \beta Total\_Asset_{it-j} + \beta Loan\_g_{it-j} + BNII_{it-j} + \gamma GDP\_g_{it-j} + \gamma Unemp_{it-j} + \gamma Lending_{it-j} + \eta_i + \varepsilon_{it} \tag{2}$$

where *GDP_g* is real GDP growth, *Unemp* is the ratio of unemployment-to-the total labour force and *Lending* is the lending interest rate. In addition, we include the variable *Debt*, representing the ratio of general government gross debt-to-GDP as an alternative to the Unemployment variable (due to the high correlation between the two variables) to capture the potential negative impact of sovereign debt tensions on the level of NPLs in Italy.

In both model specifications (Eqs. (1) and (2)), we treat the NPL variable as endogenous. We assume a weak form of exogeneity for the bank-specific variables while we consider macroeconomic factors as strictly exogenous and instrumented in the standard IV style. In this way, every regressor is included, in some form, in the instrument matrix (Roodman, 2009b). Furthermore, beyond the contemporaneous values, and to account for the limited time dimension of the considered sample, we impose a maximum lag-length of 1 for the variables specified in both models.

We conduct the dynamic GMM-based analysis by simultaneously adhering to several fundamental conditions. Firstly, we aim that the estimate for the coefficient on the lagged dependent variable is credible and therefore lies between the values obtained via OLS and fixed-effects methods, which are characterised by opposing biases (upward and downward, respectively). Secondly, while we expect the presence first-order serial correlation in the differenced residuals by construction, we ensure the absence of first-order serial correlation in the residuals in levels by testing for no-second-order serial correlation in the first-differenced residuals. Thirdly, we maintain the number of instruments below the number of groups to prevent instrument proliferation. Lastly, we verify the overall validity of the employed instruments by examining the *p*-value on the Hansen J statistic.

By adopting a recursive approach that allows the variable lag-order to vary, in the next section, we report and discuss results for both the model specifications that satisfy all these conditions.

6. Empirical results

This section presents the results obtained from Eqs. (1) and (2), applying both Difference and System GMM in one- and two-step variants.[17] Roodman (2009b) emphasizes the significance of transparently documenting the numerous choices inherent to the use of these methodologies in empirical studies. Thus, we carefully detail the steps undertaken to select the reported specifications and results, along with the associated criteria.

In further refining the selection of the results, we adhere to additional and more stringent criteria following Roodman (2009a). Firstly, the *p*-value associated with the Hansen J statistic is required to be lower than 0.25. A p-value of 0.25 should raise concerns, prompting scepticism towards the typical approach of deeming *p*-values above the “conventional significance levels” (i.e., 0.05, 0.10) as satisfactory. Secondly, the coefficient on the lagged dependent variable is expected to be below 1.00, ensuring a credible estimate within a stable dynamic process. Lastly, for both estimators, we focus on the model specification for which we obtained results meeting the specified conditions for both the one- and two-step variants.

[16] The concept of dynamic stability entails ensuring that the estimate for the coefficient on the lagged dependent variable falls within the range established by the lower estimate through OLS and the upper value derived from the fixed-effects method.

[17] We employ cluster-robust standard errors for the one-step estimator and correct the two-step estimations of the robust standard errors following Windmeijer (2005).

6.1. NPLs and bank-specific variables

Table 5 shows GMM coefficient estimates for Eq. (1) (with only bank-specific variables). Panel A presents the short-term coefficients while Panel B displays the estimated coefficients in the long run. For each estimation (Difference and System GMM, one- and two-steps variants), we report the number of observations, groups and instruments along with the results from the two Arellano and Bond tests for autocorrelation and the Hansen J test. For the System GMM (columns 3 and 4), we include three dummies to account for the choice of bank business model, the geographical location of bank headquarters, and whether the bank is listed or not. In particular, *Commercial* is a dummy variable equal to 1 if the bank is a commercial bank, 0 otherwise. In our sample, 34% of the banks are commercial banks. Based on NUTS 2-level information, *North* is a dummy variable equal to 1 if a bank's headquarters is in a northern region of Italy, 0 otherwise. *Listed* is a dummy variable equal to 1 if a bank is listed, 0 otherwise.[18]

As discussed in previous sections, for each estimation method, the number of instruments is below the number of groups. The Arellano and Bond tests for first and second autocorrelation of the residuals (AR(1) and AR(2), respectively), and the associated p-values, satisfy the necessary conditions. The Hansen test of over-identifying restrictions further confirms that the instruments used in all specifications are suitable (i.e., not correlated with the error component) and that the models are adequately specified. Lastly, the p-value associated with the Hansen test assumes reasonable values, staying below 0.25.

As expected, the positive and highly significant coefficients on the lagged dependent variable (ranging from 0.491 to 0.646), reveal a strong persistence in the level of NPLs. This suggests that a shock to asset quality in the past has a prolonged impact wherein elevated levels of past NPLs are reflected in higher current NPLs. From this perspective, our choice of econometric methodology is further justified. The estimations show that higher levels of capitalisation are associated with lower volumes of NPLs. The coefficient on the *Tier1* variable is consistently negative and statistically significant in three out of four estimations (columns 1, 3 and 4). It suggests that better capitalised banks have fewer incentives to engage in riskier lending and at the same time are better equipped to handle deteriorating asset quality. Based on this result, the evidence accepts our first hypothesis that banks with lower Tier 1 capital ratios assume more risk which leads to larger volumes of NPLs in the future.

We find a positive association between bank performance, measured by *ROE*, and levels of NPLs, which is overall statistically significant. This evidence indicates a potential inclination towards engaging in riskier activities to enhance weak bank profitability, resulting in a deterioration of the loan portfolio quality. With a lack of statistical significance in all regressions, the bank size indicator (*Total_asset*) does not appear to be relevant in explaining the levels of NPLs.

The empirical results diverge from a priori expectations of a positive coefficient on the proxy for credit expansion, represented by the *Loan_g* variable. Interestingly, an increase in lending volumes does not lead to a deterioration in the bank loan portfolio. The corresponding coefficients are consistently negative and statistically significant at different levels. This inverse relationship with the level of NPLs suggests that more expansionary lending policies do not necessarily lead to a less accurate selection of borrowers (Quagliariello, 2007). Moreover, it implies that bank credit growth may be more influenced by demand factors rather than supply-side elements. In this context, Accornero et al. (2017) find that the negative relation between Italian NPLs and bank credit growth is primarily driven by firm-related factors, such as a contraction in the demand for loans. Vithessonthi (2016) documents a similar inverse association between NPLs and credit growth in the Japanese banking sector, especially in the post-global financial crisis years. Based on our results, we cannot accept our second hypothesis that banks with faster loan growth are burdened by larger amounts of NPLs in the future.

Contrary to a priori expectations, our evidence suggests that a higher degree of diversification in banking activities in the past corresponds to a higher level of NPLs. This result is inconsistent with the diversification hypothesis. This finding aligns with Louzis et al. (2012), who, in analysing the determinants of NPLs in the Greek banking system, reached a similar conclusion, attributing mixed effects to greater diversification. Findings in Ghosh (2015) also cast doubt on the benefits of higher reliance on non-interest income in terms of mitigating bank credit risk. The negative and statistically significant coefficient on the *Commercial* dummy implies that, ceteris paribus, commercial banks in Italy have lower levels of NPLs compared to cooperative and savings banks (columns 3 and 4 of Table 5). Additionally, the negative and statistically significant coefficient on the *North* dummy variable indicates that, all else being equal, banks headquartered in the North of Italy have lower volumes of NPLs compared to banks located in the rest of the country. Being listed or unlisted does not appear to be relevant in explaining differences in NPL levels across Italian banks.[19]

Finally, the analysis of the long-run coefficients complements the main investigation. Findings seem to confirm the relevance in the long term of the level of bank capitalisation, loan growth and degree of diversification in explaining the variation of banks' NPLs across banks. The coefficients on the proxy for the bank capitalisation are statistically significant in the System GMM estimations. In the long term, a 1% increase in the Tier 1 capital ratio is associated with a reduction between 0.09% and 0.17% in NPL levels. In the case of loan growth, the inverse relationship is significant also in the long run, with a 1% increase in *Loan_g* corresponding to a roughly 0.02% decline in NPL volumes. The degree of bank diversification, as proxied by the NII variable, maintains its relevance as a driver for NPLs also in the long term. In particular, a 1% increase in *NII* corresponds to an increase in the dependent variable spanning between 0.02% and 0.03%.

[18] Table 3 reports the summary statistics for the 3 dummy variables.

[19] In a further regression, we add a dummy variable to account for the introduction of the GACS framework in early 2016. Specifically, the dummy equals 1 for years 2016 and 2017, 0 otherwise. Appendix B reports the results.

Table 5
NPLs and bank-specific variables.

	(1)		(2)		(3)		(4)	
	Diff-one		Diff-two		Sys-one		Sys-two	
Panel A: Short-term coefficients								
L.NPL	0.491	**	0.525	***	0.646	***	0.607	***
	(0.194)		(0.182)		(0.159)		(0.061)	
Tier1	−0.073	*	−0.028		−0.059	**	−0.035	**
	(0.039)		(0.034)		(0.028)		(0.034)	
ROE	0.010		0.008	**	0.025	**	0.007	*
	(0.007)		(0.004)		(0.011)		(0.004)	
Total_Asset	0.059		0.060		0.024		−0.013	
	(0.329)		(0.336)		(0.050)		(0.026)	
Loan_g	−0.010	**	−0.010	*	−0.013	**	−0.009	***
	(0.005)		(0.005)		(0.006)		(0.003)	
L.NII	0.017	**	0.012		0.012	*	0.008	*
	(0.008)		(0.008)		(0.012)		(0.004)	
Commercial					−0.282	**	−0.258	***
					(0.127)		(0.098)	
North					−0.488	**	−0.231	
					(0.235)		(0.144)	
Listed					−0.151		0.037	
					(0.199)		(0.138)	
Panel B: Long-run coefficients								
Tier1	−0.143				−0.167	*	−0.089	**
	(0.109)				(0.086)		(0.043)	
ROE			0.017		0.071		0.0186	*
			(0.012)		(0.053)		(0.011)	
Total_Asset								
Loan_g	−0.019	*	−0.021		−0.037		−0.022	***
	(0.011)		(0.014)		(0.030)		(0.008)	
L.NII	0.034	***			0.033		0.020	**
	(0.010)				(0.026)		(0.008)	
Observations	355		355		428		428	
Groups	73		73		73		73	
Instruments	23		24		15		35	
AR(1) p-value	0.020		0.035		0.023		0.039	
AR(2) p-value	0.205		0.283		0.297		0.346	
Hansen J p-value	0.125		0.116		0.203		0.174	

Description: This table presents the results for the Difference and System GMM estimations (one- and two-step variants) based on the model presented in Eq. (1), Section 6.2. Panel A reports the short-term coefficients, while Panel B displays the coefficients in the long-run. See Table 2 for variable definitions. The number of observations, groups and instruments are also reported. The sample period is from 2011 to 2017. The *p*-values associated with the two Arellano and Bond tests for autocorrelation of the residuals, as well as the p-value for the Hansen J test are included. Cluster-robust standard errors, reported in parentheses, are corrected according to Windmeijer (2005) in the two-step estimations.
Note: *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

6.2. NPLs, bank-specific and macroeconomic variables

Table 6 reports the results from GMM estimations, one- and two-step variants, of Eq. (2). The bank-specific variables remain consistent with results obtained from Eq. (1), while for the macroeconomic variables, we allow the lag-order to vary between zero and one. As for the bank-focused estimation, all GMM estimations adhere to the discussed constraints to ensure their validity. The number of instruments is consistently lower than the number of groups across all model estimations. Diagnostic tests, including the two Arellano and Bond tests and the Hansen test, confirm proper model specification and the appropriateness of the instruments.

Consistent with the model with only bank-level variables, the estimations reveal a strong persistence of lagged NPL volumes with the corresponding positive coefficients ranging between 0.673 and 0.893. In accordance with Hypothesis 1, capital strength is influential in shaping banks' risk-taking behaviour and, consequently, their asset quality. Less capitalised banks are more vulnerable to higher levels of NPLs compared to better capitalised banks. Only for the System GMM estimations (columns 3 and 4 of Table 6), are the estimated coefficients on the bank size indicator (*Total_asset*) negative and statistically significant at the 1 and 5% levels. This evidence could be interpreted as larger banks having a greater capability to diversify their loan portfolios, leading to a reduction in credit risk (Salas and Saurina, 2002). Additionally, larger banks may be better equipped to leverage their greater resources to select higher-quality borrowers. With reference to the two-step Difference GMM estimation (column 2), the inverse relationship with the loan growth variable is confirmed. As for the estimations including only bank variables, the degree of diversification, proxied by the lagged ratio of non-interest income-to-total income, exerts a positive influence on the level of bank NPLs.

The results for the macroeconomic variables align with expectations. The estimated coefficient on the contemporaneous real GDP growth consistently shows an inverse relationship with the level of NPLs across all estimations, in line with previous literature (Salas and Saurina, 2002; Louzis et al., 2012; Ghosh, 2015, among others). The observed impact of contemporary macroeconomic conditions is substantial with coefficients ranging between −0.095 and − 0.279. The statistical significance of these estimates at various levels suggests a relatively rapid transmission of macroeconomic fluctuations to the asset quality of banks. The lagged unemployment rate exhibits a positive influence on levels of NPLs in Italy, with statistically significant coefficients ranging between 0.099 and 0.197. The findings confirm the hypothesis that elevated unemployment levels negatively impact borrowers, limiting their capability to fulfil obligations and consequently exerting adverse effects on bank balance sheets. Lastly, lending rates do not play a significant role in explaining NPL volumes.

Table 7 reports the results for the GMM estimations incorporating the variable Debt as an alternative to the Unemployment variable. The results confirm the persistency of the lagged NPLs, and relationships between NPLs and both the level of bank capitalisation and loan growth are corroborated. Nonetheless, the overall statistical significance of the selected variables is reduced across the different estimations, compared to the results including the Unemployment variable. Unexpectedly, the Debt variable does not exhibit a significant influence on bank NPLs, suggesting that sovereign debt tensions may not directly affect the asset quality of banks. The one-year lagged GDP growth rate does not show a significant impact on NPL levels, confirming a relatively swift mechanism linking the country’s economic conditions to banks’ asset quality. In contrast to previous findings, the coefficients on lending rates turn positive and statistically significant, indicating their relevance in explaining the variable of interest. This evidence aligns with prior literature (Louzis et al., 2012; Beck et al., 2015; Ghosh, 2015).

7. Conclusions and policy implications

Understanding the evolution and determinants of excessive volumes of NPLs is a crucial task within the process of developing effective and lasting policy responses to prevent any recurrence of such a problem. This paper investigates the factors driving high NPL levels in the Italian banking sector during an especially challenging phase following the global financial and European sovereign debt crises.

Our findings indicate that during the period from 2011 to 2017, the levels of NPLs in Italian banks were influenced by both idiosyncratic and systemic factors. In particular, the analysis supports the moral hazard hypothesis, suggesting that better capitalised banks tended to maintain a higher quality loan portfolio. Notably, the observed propensity of the Italian government to substantially support the banking sector during times of distress contributes to the evidence that weaker banks may be more susceptible to moral hazard incentives, engaging in higher risk lending practices and thus creating a detrimental cycle.

Table 6
NPLs, bank-specific and macroeconomic variables.

	(1)		(2)		(3)		(4)	
	Diff-one		Diff-two		Sys-one		Sys-two	
L.NPL	0.673	***	0.709	***	0.893	***	0.752	***
	(0.268)		(0.227)		(0.129)		(0.142)	
Tier1	−0.021		−0.056	**	−0.049	**	−0.064	*
	(0.035)		(0.021)		(0.024)		(0.033)	
ROE	0.000		−0.001		0.013	*	−0.002	
	(0.005)		(0.002)		(0.007)		(0.008)	
Total_Asset	0.204		0.064		−0.066	***	−0.093	**
	(0.326)		(0.321)		(0.025)		(0.035)	
Loan_g	0.006		−0.006	***	0.001		0.003	
	(0.010)		(0.002)		(0.005)		(0.004)	
L.NII	0.015	**	0.001		0.012	*	0.019	*
	(0.006)		(0.004)		(0.006)		(0.010)	
GDP_g	−0.279	**	−0.095	*	−0.186	**	−0.192	*
	(0.135)		(0.052)		(0.092)		(0.103)	
L.Unemp	0.197	**	0.099	**	0.119	*	0.120	*
	(0.084)		(0.040)		(0.060)		(0.060)	
Lending	−0.137		−0.014		−0.061		−0.061	
	(0.123)		(0.060)		(0.101)		(0.105)	
Observations	355		347		428		428	
Groups	73		73		73		73	
Instruments	24		20		21		22	
AR(1) p-value	0.018		0.048		0.028		0.029	
AR(2) p-value	0.446		0.664		0.244		0.982	
Hansen J p-value	0.120		0.156		0.201		0.134	

Description: This table presents the results for the Difference and System GMM estimations (one- and two-step variants) based on the model presented in Eq. (2), Section 6.2. See Table 2 for variable definitions. The number of observations, groups and instruments are also reported. The p-values associated with the two Arellano and Bond tests for autocorrelation of the residuals, as well as the p-value for the Hansen J test are included. Cluster-robust standard errors, reported in parentheses, are corrected according to Windmeijer (2005) in the two-step estimations. The sample period is from 2011 to 2017.

Note: *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

Table 7
NPLs, bank-specific and macroeconomic variables (inclusion of debt variable).

	(1)		(2)		(3)		(4)	
	Diff-one		Diff-two		Sys-one		Sys-two	
L.NPL	0.778	**	0.915	**	0.758	***	0.866	***
	(0.360)		(0.418)		(0.132)		(0.117)	
Tier1	−0.103	*	−0.060	**	−0.013		−0.039	*
	(0.061)		(0.027)		(0.030)		(0.020)	
ROE	0.003		0.004		0.012	*	0.012	*
	(0.006)		(0.009)		(0.007)		(0.007)	
Total_Asset	−0.081		0.014		0.060		−0.089	
	(0.428)		(0.538)		(0.062)		(0.077)	
Loan_g	−0.012	*	−0.013	**	−0.004		−0.009	*
	(0.007)		(0.006)		(0.006)		(0.004)	
L.NII	0.017		0.000		0.021	**	0.002	
	(0.016)		(0.007)		(0.009)		(0.005)	
L.GDP_g	0.025		0.032		−0.018		0.026	
	(0.041)		(0.031)		(0.019)		(0.026)	
Debt	0.008		0.012		−0.020	*	0.009	
	(0.046)		(0.027)		(0.011)		(0.011)	
Lending	0.145	*	0.123	**	0.108	*	0.128	***
	(0.083)		(0.061)		(0.056)		(0.129)	
Observations	355		347		428		428	
Groups	73		73		73		73	
Instruments	18		19		20		31	
AR(1) p-value	0.030		0.042		0.014		0.034	
AR(2) p-value	0.798		0.591		0.256		0.303	
Hansen J p-value	0.214		0.171		0.204		0.207	

Description: This table presents the results for the Difference and System GMM estimations (one- and two-step variants) based on the model presented in Eq. (2). See Table 2 for variable definitions. The number of observations, groups and instruments are also reported. The p-values associated with the two Arellano and Bond tests for autocorrelation of the residuals, as well as the p-value for the Hansen J test are included. Cluster-robust standard errors are corrected according to Windmeijer (2005) in the two-step estimations. The sample period is from 2011 to 2017.
Note: *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

Interestingly, we document an inverse relationship between NPL levels and credit growth. This evidence suggests that credit growth in Italy during the period under investigation was primarily driven by demand factors rather than by an aggressive supply policy. This aligns with findings in both Accornero et al. (2017) and Resti (2017), which indicate that the negative association between NPLs and credit growth in Italian banking in the post-crisis years has been mostly attributable to firm-related factors and reduced demand for loans. At the macroeconomic level, we confirm the countercyclical nature of NPL levels. Specifically, we find evidence of an inverse relationship between NPL levels and GDP growth, indicating a relatively rapid transmission of macroeconomic fluctuations to banks' asset quality. Based on our results, the past level of unemployment is detrimental to borrowers' capability to fulfil their obligations, with negative repercussions on banks' balance sheets. While increasing lending rates were linked to a deterioration in the quality of banks' loan portfolios, the level of public debt did not appear to be a significant factor in influencing NPL volumes across banks in Italy.

Since 2016, as part of a broader effort at the European level to address the NPL challenge, the Italian government has implemented a series of structural reforms and strategic initiatives aimed at enhancing the stability of the banking sector. A noteworthy intervention in this regard was the introduction, in early 2016, of the GACS framework to facilitate the securitisation of bad loans and expedite the reduction of NPL volumes across banks. The development of an effective NPL market significantly contributed to the cleanup of banks' balance sheets in subsequent years. However, more recent government proposals in support of borrowers in financial difficulty, following the Covid-19 pandemic and the challenging post-pandemic economic environment, create uncertainty among investors that could potentially undermine banks' efforts to dispose of NPLs.[20]

Establishing robust procedures and strategies for the continuous assessment and management of credit risk and NPLs is a key priority in ensuring financial stability. This objective becomes even more relevant within the Italian context, notably characterised by a persistent and significant interconnectedness between bank fragility and sovereign risk. Achieving and sustaining effective risk reduction is a fundamental prerequisite for advancing the objectives of the European Banking Union project initiated in November 2014 with the establishment of the Single Supervisory Mechanism. Improving bank asset quality is essential, not only for individual institutions, but also to advance the overarching goal of strengthening and deepening the euro area banking sector, enabling it to better withstand future shocks.

Future research in this area can benefit from an extended time frame, also encompassing events, such as the Covid-19 pandemic and the post-pandemic phase characterised by persistent inflation, high interest rates and stagnant economies. These factors present

[20] See https://www.spglobal.com/marketintelligence/en/news-insights/latest-news-headlines/italy-s-new-bad-loan-plan-poses-risks-to-banks-npl-market-77468940.

considerable potential to significantly influence borrowers' ability to meet their debt obligations. For instance, the impact on Italian banks' balance sheets could be noteworthy, especially in relation to the heightened risk associated with the substantial financing facilitated by public guarantees initiated since 2020 in response to the Covid-19 crisis (exceeding 340 billion euros according to PricewaterhouseCoopers (PwC), 2018). The opportunity to broaden the analysis to include other European countries could also be a promising avenue for future research. This extension, however, should ideally follow a period of greater harmonization of NPL definitions, enabling meaningful comparisons across different jurisdictions. Analysing the impact on bank asset quality resulting from changes in accounting rules and loan classification criteria, under the IFRS9, would also be relevant.

CRediT authorship contribution statement

Livia Pancotto: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Owain ap Gwilym:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Conceptualization. **Jonathan Williams:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Conceptualization.

Appendix A. The government-backed scheme (GACS) for NPL securitisation

In January 2016, the Italian government reached an agreement with the European Commission on a scheme providing state guarantees for the securitisation of bad loans (formally introduced with the Decree of Law n.18). The primary objective of this government-sponsored initiative was to enhance liquidity in the NPL market by streamlining portfolio disposal processes.

Under this mechanism, applicable exclusively to "*sofferenze*" or bad loans, banks have the option to transfer their NPLs to a Special Purpose Vehicle (SPV). The financing for this transfer can be achieved through the issuance of a junior tranche (without guarantee) and a senior tranche eligible for a state guarantee. The acquisition of the state guarantee is contingent on the senior notes obtaining an investment-grade rating from an independent External Credit Assessment Institution (ECAI). Consequently, government intervention is limited to covering interest and capital payment obligations solely on the senior tranches of notes. To avoid classifying the guarantee as State Aid, its annual cost is determined at market conditions based on a set of Credit Default Swaps (CDS) on Italian companies with comparable risk profiles. Furthermore, the guaranteed fee increases over time if the senior tranches are not fully repaid within a fixed period after the state guarantee is granted. This feature is intended to serve as an incentive to expedite the recovery of securitised debt. Complementing this initiative, a GACS-related fund was established with an initial budget of €100 million.

In October 2016, BP Bari completed the first securitisation facilitated by the GACS scheme. The securitised portfolio, which included both retail and corporate bad loans, carried a total Gross Book Value (GBV) of €480 million and was transferred to the SPV at a price equivalent to approximately 31% of the portfolio value, amounting to €150.5 million. In 2018, MPS sealed the largest GACS deal in terms of GBV, amounting to €24 billion. During the years after its launch in 2016, the GACS framework was renewed several times and supported Italian banks to successfully offload €117 billion in bad debt across over 40 guaranteed transactions.[21] The Scheme expired in June 2022.

Appendix B

To assess the effectiveness of the GACS scheme, introduced by the Italian government in early 2016 to address the NPL challenge, we include a dummy variable in our baseline model specification with bank-specific variables. Specifically, the dummy is equal to 1 for the years 2016 and 2017, and zero otherwise. The findings exhibit overall consistency with the main results regarding the direction and magnitude of the coefficients. However, there is a reduction in the statistical significance across the estimations. The consistently negative and highly statistically significant coefficient on the GACS dummy seems to indicate a meaningful role played by the government-backed scheme in strengthening the downward trend in NPL volumes (Table B1).

Table B1
NPLs, bank-specific variables and GACS.

	(1)		(2)		(3)		(4)	
	Diff-one		Diff-two		Sys-one		Sys-two	
L.NPL	0.607	***	0.625	***	0.671	***	0.725	***
	(0.144)		(0.129)		(0.121)		(0.067)	
Tier1	−0.062	*	−0.027		−0.049	*	−0.030	*
	(0.035)		(0.023)		(0.026)		(0.015)	
ROE	0.003		−0.001		0.001		0.003	
	(0.007)		(0.005)		(0.012)		(0.005)	
Total_Asset	0.142		0.175		−0.034		−0.016	
	(0.283)		(0.293)		(0.028)		(0.014)	

(*continued on next page*)

[21] See https://www.reuters.com/markets/europe/italy-puts-renewal-gacs-bad-loan-scheme-hold-sources-say-2023-04-14/.

Table B1 (*continued*)

	(1)		(2)		(3)		(4)	
	Diff-one		Diff-two		Sys-one		Sys-two	
Loan_g	−0.005		−0.006		0.002		−0.005	
	(0.005)		(0.007)		(0.006)		(0.007)	
L.NII	0.015	**	0.011	**	0.016	**	0.006	*
	(0.006)		(0.005)		(0.007)		(0.004)	
GACS	−0.135	**	−0.135	***	−0.201	***	−0.116	**
	(0.055)		(0.048)		(0.044)		(0.048)	
Observations	355		355		428		428	
Groups	73		73		73		73	
Instruments	24		25		13		33	
AR(1) p-value	0.029		0.028		0.014		0.048	
AR(2) p-value	0.340		0.585		0.514		0.490	
Hansen J *p*-value	0.249		0.109		0.273		0.180	

Description: This table presents the results for the Difference and System GMM estimations (one- and two-step variants) based on the model presented in Eq. (1), Section 6.2. The specification includes a dummy variable for GACS equal to 1 for the years 2016 and 2017, and 0 otherwise. See Table 2 for variable definitions. The number of observations, groups and instruments are also reported. The sample period is from 2011 to 2017.
The *p*-values associated with the two Arellano and Bond tests for autocorrelation of the residuals, as well as the p-value for the Hansen J test are included. Cluster-robust standard errors, reported in parentheses, are corrected according to Windmeijer (2005) in the two-step estimations.
Note: *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

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