Essays on European Banking

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Inevitably, to Richard

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List of Abbreviations

BCBS: Basel Committee on Banking Supervision, 156
BHCs: Bank Holding Companies, 167
BLs: Bad Loans, 29
BMA: Bayesian Model Averaging, 123
C: Centre, 81
CCoB: Capital Conservation Buffer, 161
CCyB: Countercyclical Capital Buffer, 161
CE: Cost Efficiency, 76
CET1: Common Equity Tier 1, 161
DFE-QR: Dynamic Fixed Effect Quantile Regression, 125
DFR: Deposit Facility Rate, 178
EA: Euro Area, 19
EBA: European Banking Authority, 119
ECB: European Central Bank, 19
ESRB: European Systemic Risk Board, 19
EU: European Union, 39
Euribor: Euro Interbank Offered, 179
FE: Fixed Effects, 47
FED: Federal Reserve, 122
FFF: Fourier-flexible functional form, 60
FMA: Frequentist Model Averaging, 157
FSAPs: Financial Sector Assessment Programs, 123
GDP: Gross Domestic Product, 27
GFC: Global Financial Crisis, 19
GMM: Generalised Methods of Moments, 21
G-SIIs: Global Systemically Important Institutions, 161
HFC: Heteroskedastic Four-Component, 60
IMF: International Monetary Fund, 28
LGD: Loss Given Default, 120
LLPs: Loan Loss Provisions, 31
LLRs: Loan Loss Reserves, 37
MAD: Median Absolute Deviation, 102
MM: Modigliani-Miller, 163
MUF: Model Uncertainty Framework, 157
NE: North-East, 81
NFCs: Non-Financial Corporations, 156
NPLs: Non-performing Loans, 19
NW: North-West, 81
OECD: Organisation for Economic Co-operation and Development, 23
OLS: Ordinary Least Squared, 127
O-SIIs: Other Systemically Important Institutions, 161
P&L: Profit and Loss, 121
PDs: Probabilities of Defaults, 120
PRA: Prudential Regulatory Authority, 122
PVAR: Panel-Vector Autoregressive, 38
QR: Quantile Regression, 135
ROE: Return on Equity, 40
RWA: Risk-Weighted Assets, 115
S: South, 81
SDC: Sovereign Debt Crisis, 26
SE: Standard Error, 188
SFA: Stochastic Frontier Analysis, 21
SGMM: System Generalised Method of Moments, 47
SMEs: Small and Medium Enterprises, 116
SNA: System of National Accounts, 23
SREP: Supervisory and Review Evaluation Process, 122
SSM: Single Supervisory Mechanism, 19
SyRB: Systemic Risk Buffer, 161
TBTF: Too-Big-to-Fail, 52
TC: Total Costs, 71
TLTROs: Targeted-Long Term Refinancing Operations, 162
UK: United Kingdom, 122
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Introduction

This Thesis studies key issues faced by the European banking industry following a decade characterised by two crises that have completely reshaped the environment in which banks operate and that have left deep wounds on their balance sheet. The Thesis focuses on three different, yet interlinked, topics related to European banks: the relationship between bank cost efficiency and non-performing loans; forecasting non-performing loans in the presence of non-linear effects; and the dynamics between regulatory capital and bank lending. We contribute to the existing literature and provide interesting avenues for future research. Additionally, the findings coming from investigating these topics aim to give timely and highly relevant implications for both banks and regulatory authorities.

Undoubtedly, since the outbreak of the global financial crisis in 2008, the European banking industry's major concern has been non-performing loans. Therefore, studies aimed at shedding light on the drivers of loan quality in European countries have great value for both banks and policymakers that are called to resolve the non-performing loan problem. Thus, in the first chapter, we investigate the relationship between bank cost efficiency and non-performing loans building on the seminal work of Berger and De Young (1997) (Berger, A.N. and DeYoung, R., 1997. Problem loans and cost efficiency in commercial banks. *Journal of Banking & Finance*, 21(6), pp.849-870). We expand their research by taking advantage of the latest advancements in the Stochastic Frontier Analysis literature to disentangle cost efficiency into its transient (short-term) and persistent (long-term) components. In doing so, we propose two additional hypotheses on the relationship between cost efficiency and non-performing loans that capture aspects previously ignored by the literature. Using a sample of Italian banks, our first novel finding is that the primary source of bank inefficiencies stems from long-term, permanent, structural features of the Italian banking industry, while temporal managerial inefficiencies of the individual financial institutions play a smaller role. In the second step, we examine the relationship between transient and persistent cost efficiency and non-performing loans, finding that are both powerful predictors of the quality of banks' loan books. Deteriorations in short-term cost efficiency precede the worsening of banks' asset quality, suggesting that non-performing loans are the outcome of temporal behavioural shortcomings and “non-systematic management mistakes”. Nonetheless, the lower quality of bank loans can also be explained by higher levels of long-term efficiency, which is a result hinting at problems of misallocation of resources due to inefficient regulation and/or structural problems. Our approach to disentangling cost efficiency into its short- and long-term components and investigating their effects on non-performing loans has been accepted in the literature by publication (see Badunenko O., Dadoukis A., Fusi G., and Simper R., 2021, The impact of efficiency on asset quality in banking, *The European Journal of Finance*, 28(6), pp.596-620).

The second chapter continues to focus on the issue of non-performing loans. Considering the long-term consequences of non-performing loans on banks' performance, we present a model aimed at informing in a forward-looking manner about the evolution of bank credit quality following a shock, such as a crisis. This chapter fits in the literature developed in the context of stress-test exercises, which, after the financial crisis, have become an integral part of prudential and supervisory authorities' toolkits to ensure financial stability. We contribute to the literature by estimating the non-linear effects existing between a sample of euro area banks' non-performing loans and their main macro-financial risk factors using state-of-the-art quantile regression models. First, we document that our selected macroeconomic variables have different explanatory powers at different quantiles of the distribution of non-performing loans. These findings represent novel evidence of the presence of heterogenous drivers of loan quality in euro area banks depending on the quantile of non-performing loan distribution. In the second step of the analysis, we produce bank-specific conditional forecasts of non-performing loans under a baseline, adverse and disaster scenario by combining the estimated coefficients of the quantile regression models with the forecasted values of the macroeconomic variables found to affect loan quality. By using quantile regressions, we are able to produce conditional forecasts using various sets of coefficients estimated at different percentiles, thus mimicking the stress conditions that banks would face during a turmoil. Our model can serve both micro- and macro-prudential authorities, as it can be employed to identify individual financial institutions that would suffer from above-than-average non-performing loans increases following a shock, while also providing an assessment of the resilience of the banking sector as a whole - given the assumed evolution of the macroeconomic conditions.

The last chapter focuses on one of the most investigated research questions in the banking literature. The global financial crisis revealed that banks had engaged in excessive risk-taking in the decade before, while being undercapitalised and thus unable to absorb the losses coming from the default of the risky loans in which they had invested. As a consequence, the capital requirements regulation underwent a drastic tightening. To comply with the more stringent requirements, banks are expected to modify the size and/or the composition of their asset side. Intuitively, this raises concerns about the implications from the point of view of bank credit supply. Following the above discussion, in the third chapter, we investigate the relationship between bank regulatory capital and credit supply of a sample of euro area banks using a novel empirical approach. Our research design relies on a model uncertainty framework, whereby we do not restrict our analysis to a few model specifications, but rather we explore the relationship between capital and lending across all the theoretically informed specifications. This methodology is in stark contrast with traditional approaches found in the literature, where only a small set of curated models - almost always reporting statistically significant results - are presented. The first set of results obtained running a baseline specification suggests that, on average, there is a negative - albeit insignificant - relationship between the amount of regulatory capital held by banks and their lending behaviour. However, we show that our results might lead to an overconfident representation of reality because they do not take into account the array of other possible models that could have been tested. We demonstrate how changing some of the control variables or the use of multiple operational definitions of the same explanatory variable in the regression can lead to dramatically different findings. By running more than 20 thousand regressions, we conclude that there is no evidence of a robust relationship between capital and lending, as only one-quarter of the models display statistically significant results. In light of this, we advocate that researchers should consider adopting a computational robustness framework to support the credibility of their analyses by providing evidence of the stability of the sign and significant rate of the variable of interest across all the possible model combinations and operational definitions. Additionally, we argue that regulators should base the implementation of policies and regulations on studies that provide exhaustive evidence of robust results across all the unique combinations of possible (theoretically informed) “model ingredients”, thus avoiding studies that present only a few carefully selected models.

Chapter 1

The Impact of Efficiency on Asset Quality in Banking: Empirical Evidence from Italy

1. Introduction

The global financial crisis (GFC) that occurred in 2007/2009 stimulated renewed interest and research into the factors that trigger banking crises. In particular, the issue of non-performing loans (NPLs) attracted attention as the financial crisis was marked by the significant deterioration of the loan quality of financial institutions in the majority of developed western countries.[1] Notably severe was the deterioration of bank loan quality in European banking, where the level of NPLs reached around €1.0 trillion (5.1% of total outstanding gross loans) at the end of 2016 (European Systemic Risk Board, ESRB, 2017)

NPLs represent a major concern for the economy (hampering real economic growth), regulators and policymakers as well as internally in the bank. This is because high levels of NPLs affect bank earnings, bank capital and lending (Jassaud and Kang, 2015). That is, NPLs depress bank profitability, in turn hindering the capacity of banks to strengthen their capital positions to support new lending. High levels of NPLs also represent a threat to financial stability by weakening banking systems' resilience to shocks and/or further economic downturns (Cerulli et al., 2020). Further, NPLs can also involve higher legal and administrative costs related to the managing, restructuring and disposal of bad loans, as well as higher staff costs and operational expenses (Berger and DeYoung, 1997). Finally, holding low quality loans can cast doubts on banks' long-term viability, increase uncertainty and undermine a bank's market valuation, ultimately increasing the cost of external financing (see Jassaud and Kang 2015).

Since the launch of the Comprehensive Assessment by the European Central Bank (ECB) in 2014, addressing asset-quality problems has become a supervisory priority (Fiordelisi, et al., 2017).[2] In 2019, the Single Supervisory Mechanism (SSM) – the supervision arm of the ECB - identified credit risk in the euro area (EA) banking industry as a high-level regulatory and supervisory priority (see 'ECB Banking Supervision: SSM Supervisory Priorities 2019'). The importance of this

[1] For example, over the period 2007-2009, NPLs in the United State grew from 1.4% to 5%, in the United Kingdom from 0.9% to 3.5%, in Spain from 0.9% to 4.1%, in Ireland from 0.6% to 9.8%.

[2] In 2014, the ECB launched the Comprehensive Assessment (CA) to ensure: i) adequate levels of bank capitalisation and ii) banks' resilience to financial shocks. The assessment comprised an asset quality review (AQR), which revealed a significantly larger stock of impaired bank loans in the euro area than previously disclosed, thus triggering the ECB's focus on resolving NPLs.

topic for European policymakers is also evident from the recent speeches of Andrea Enria and Sabine Lautenschläger Chair and (former) Vice-Chair of the Supervisory Board of the ECB, where NPLs have been referred to as one biggest issues facing banks in the euro area.[3]

As a result, a comprehensive understanding of the drivers of NPLs has become indispensable to ensure the design of effective policy responses. To this end, a number of recent empirical studies examining the determinants of bank asset quality have been produced, which mainly distinguish between macroeconomic factors and bank-specific drivers of NPLs (see, for example, Louzis et al. 2012; Beck et al. 2015; Assaf et al., 2019; Baldini and Causi 2020). With respect to the former, unfavourable macroeconomic conditions such as high unemployment rates, negative economic growth and high interest rates have been often observed to play a key role in driving the accumulation of impaired loans (see Espinoza and Prasad, 2010; Klein, 2013, Castro, 2013). Concerning the latter, mixed results have emerged when assessing the relationship between NPLs and bank profitability, level of capitalization, lending rates and operating efficiencies (see Louzis et al., 2012; Chaibi and Ftiti, 2015; Ghosh, 2015, 2017).

An additional strand of literature has examined the drivers of credit risk by linking the risk-taking behaviour to bank managerial efficiency (see, for example, Kwan and Eisenbeis, 1997; Williams, 2004; Podpiera and Weill, 2008; Fiordelisi et al., 2011; Assaf et al., 2019). This group of studies builds on the seminal paper by Berger and DeYoung (1997), which hypothesise that three aspects of managerial behaviour (*bad management*, *skimping* and *bad luck*) could explain the temporal relationships occurring between bank risk (proxied by NPLs) and bank cost efficiency. These studies argue that cost efficiency could exert an effect on NPLs since inefficient managers (*bad management*) fail, due to the costs of monitoring, to oversee their loan portfolios, resulting in a worsening of the bank's asset quality. Also, an increase in the risk borne by banks could influence cost efficiency by causing a rise in expenditures to deal with problem loans (see, for example, Williams, 2004).

[3] See the speeches of Andrea Enria, Chair of the Supervisory Board of the ECB at the Conference "EDIS, NPLs, Sovereign Debt and Safe Assets" (Frankfurt, 14 June 2019) and Sabine Lautenschläger, former Vice-Chair of the Supervisory Board of the ECB, at the 14th Asia-Pacific High-Level meeting on Banking Supervision (Sidney, 13 February 2019).

This chapter analyses an overlooked factor in the existing literature on the drivers of credit risk: the lack of consideration for latent, persistent, long-term bank inefficiencies due to regulatory constraints, sectorial rigidities and/or recurring factor misallocations as a source of problem loans. This is because the long-standing literature on bank efficiency is narrowed to the estimation of an overall, time-varying measure of profit/cost efficiency (for example, Radić et al. 2012; Fiordelisi and Mare 2014; Casu et al., 2017).

The approach adopted in this chapter addresses this limitation by exploiting the features of a new stochastic frontier analysis (SFA) model, developed by Badunenko and Kumbhakar (2017), which allows the disentanglement of efficiency into its *transient* (short-term, time-varying) and *persistent* (long-term, time-invariant) components. Throughout the rest of the chapter, we use the terms transient, managerial, short-term, and time-varying efficiency interchangeably. Likewise, we refer interchangeably to persistent, structural, long-term and time-invariant efficiency. Decomposing efficiency provides new insights into the channels through which bank cost efficiency – which measures the proximity of a bank's cost to that of a best practice bank that produces the same output bundle under the same environmental conditions - exerts an effect on credit risk. This approach is particularly relevant for policymakers as it can help ensure targeted policy responses, but also to bankers trying to manage credit risk.

This chapter concentrates on the Italian banking sector, exploiting a large sample of Italian banks over the period 2006 to 2015 to investigate the relationship between short- and long-term cost efficiency and NPLs. We argue that Italy represents an interesting scenario to explore these links as, at the end of 2015, Italian banks were buried under approximately €360 billion of non-performing loans, corresponding to 18.2% of total outstanding loans in Italy and one-third of the Euro Area total (Garrido et al., 2016). Employing a Granger causality panel data generalised methods of moments (GMM) estimator, the study is the first – to the best of our knowledge - to find that Italian banks' NPLs are driven by both short- and long-term bank inefficiencies.

Specifically, the first finding of this chapter is that the primary source of inefficiencies in Italian banks originates from long-term, permanent, structural inefficiencies of the banking industry, rather than from temporal managerial inefficiencies of the individual financial institutions. In particular, bank specialization and the geographical location of banks' headquarters are identified as factors affecting persistent efficiency.

The second finding of this chapter is that deteriorations in short-term cost efficiency precede the worsening of banks' asset quality, suggesting that NPLs are the outcome of temporal behavioural shortcomings and 'non-systematic management mistakes'. From the point of view of managers and owners, this implies that banks may be in the position to prevent bad loans arising from lax practices by means of improved day-to-day practices related, for example, to loan underwriting, monitoring and control. From a policymaker's point of view, transient efficiency could be regarded as a valuable early warning quantitative parameter to predict future NPLs. Thus, the findings place emphasis on the necessity to monitor managerial performance- by carefully assessing changes in banks' level of transient efficiency - to detect those banks that could suffer from problem loans.

The third finding of this chapter is somewhat unexpected as it shows that a lower quality of bank loans (i.e., higher credit risk) can be explained by higher levels of long-term efficiency. We argue that this result potentially denotes that banks achieve greater efficiency in the long-run by diverting resources from managing the loan portfolio towards coping with the external environment. Thus, this finding hints at problems of misallocation of resources due to inefficient regulation and/or structural problems as well as embedded business practised. It follows that any policy response aimed at addressing NPLs needs to carefully consider that part of banks' NPLs materialising because of structural, latent weaknesses of the banking industry that affect banks' ability to devote sufficient resources to the loan portfolio.

The chapter also contributes to the existing literature by proposing the use of a 'Granger-Sims causality' formulation to allay concerns of "reverse causality" between NPLs and cost efficiency. This allows us to overcome the limitations of a 'two-step' procedure in which cost efficiency is used as a dependent variable (see Wang and Schmidt 2002). Finally, the chapter provides an up-to-date and comprehensive assessment of credit risk in Italian banks by covering the period that included the European sovereign debt crisis and by investigating the role of institutional features in driving increases in NPLs

The rest of the chapter is organised as follows. In Section 1.1, the chapter defines non-performing loans, explains the consequences of high levels of NPLs and provides an overview of the current state of the Italian banking industry. Section 1.2 reviews the literature on the determinants of NPLs, focusing on the use of cost efficiency indicators as a proxy for managerial ability. Section 1.3 introduces the methodology, model specifications and variables included to test the intertemporal relationships between NPLs and cost efficiency. Section 1.4 discusses the methodology of the cost efficiency measurements. In Section 1.5, the main findings are discussed along with the results of the sensitivity analyses. Finally, Section 1.6 presents the conclusions and policy recommendations.

1.1 The issue of non-performing loans and the case of the Italian banking system

1.1.1 What are non-performing loans?

Before proceeding to understand the implications arising from the presence of NPLs in banks' balance sheets, it is essential to define non-performing loans and to understand their accounting treatment according to the Italian legal framework.

A non-performing loan can be broadly defined as:

> "a loan where a borrower is not making repayments in accordance with contractual obligations" (Bholat et al., 2016, pp. 2).

Countries that adhere to the International Monetary Fund or that are under the supervision of the European Central Bank follow the guidelines for the recognition of NPLs as provided by the United Nations System of National Accounts (SNA).[4]

> "a loan is non-performing when payments of interest or principal are past due by 90 days or more, or interest payments equal to 90 days or more have been capitalized, refinanced, or delayed by agreement, or payments are less than 90 days overdue, but there are other good reasons (such as a debtor filing for bankruptcy) to doubt that payments will be made in full" (2008, p. 628).

[4] The SNA is a joint publication promoted by five organizations, namely the United Nations, the European Commission, the Organisation for Economic Co-operation and Development (OECD), the International Monetary Fund and the World Bank Group.

However, significant discretion in the treatment of non-performing loans is left to national supervisory bodies. In the case of Italy, before 2015, banks classified non-performing loans in four sub-categories, namely; past due exposures ("*Crediti Scaduti*"); restructured loans ("*Crediti Ristrutturati*"); substandard loans ("*Incagli*"), and bad/doubtful loans ("*Sofferenze*") (see Table 1).[5] These categories differ in terms of the likelihood of recovery, with the last group, bad loans, identifying all those loans where the borrower has been recognised as insolvent.

This study focuses on the latter category of impaired loans, in line with Quagliariello (2007) and Bofondi and Ropele (2011), for two reasons. First, bad loans represent the bulk of NPLs. At the end of 2015, Italian banks reported €360 billion of gross NPLs (i.e., NPLs before provisions) of which €160 billion were classified as "probable to default" (past due date, restructured loans, and substandard loans) and approximately €200 billion fell into the category of "bad loans" (Italian Ministry of Economy and Finance, 2015). Second, the additional categories of NPLs suffered from data limitations. For example, Banskcope – which is the database in use for this Chapter - does not report data on "Restructured Loans" while the category of "Past Due Loans" has approximately 52% of missing data.[6]

[5] From 2015, these classes are reallocated to 3 new classes, namely Bad exposures ("*Sofferenze*"), Unlikely to Pay ("*Inadempienze probabili*") and Non-Performing Past due Exposures ("*Esposizioni scadute e/o sconfinamenti deteriorate*"). According to the new rule introduced in 2015, the new class "Unlikely to Pay" includes the Substandard/Non-performing loans ("*Incagli*") and Restructured Loans ("*Esposizioni ristrutturate*").

[6] Bankscope Database, now Orbis BankFocus, offer wide range of banking data for 30,000 banks worldwide. The information provided by the database, includes among others, detailed financial statements, ratings from FitchRatings, Moody's, Standard & Poor's and Capital Intelligence, country risk and country finance reports, detailed bank structures, stock data for listed banks.

Table 1. Classification of Non-performing Loans in Italy

Category	Definition according to the Italian Regulation
***Crediti scaduti* (Past Due)**	Exposures other than those classified as bad loans, substandard or restructured exposure that are past due for more than 90 days on a continuous basis.
***Crediti Ristrutturati* (Restructured Loans)**	Exposures in which a pool of banks or an individual bank, as a result of the deterioration of the borrower's financial situation, agree to change the original conditions (rescheduling deadlines; reduction of the interest rate), giving rise to a loss.
***Incagli* (Substandard Loans)**	Exposures to counterparty facing temporary difficulties – defined on the basis of objective factors - that is expected to be overcome within a reasonable period of time
***Sofferenze* (Bad Loans/ Doubtful Loans)**	Exposures to an insolvent counterparty (even if insolvency is not legally ascertained) or in equivalent situations, regardless of any loss estimate made by the bank and irrespective of any possible collateral or guarantee.

Source: Bank of Italy (2013)

1.1.2 What are the implications of high levels of NPLs?

To comprehend the specific case of the Italian banking system, it is fundamental to understand the implications of high levels of non-performing loans for the activities of banks. First, NPLs depress bank profitability by generating a "negative carry," that is, they do not produce cash interest revenues, yet they require funding at market rates. As a consequence, banks may increase the interest charges on new and existing loans – to compensate for the lost revenues- (Jassaud and Kang, 2015), ultimately hampering the effective transmission of monetary policy (Aiyar et al., 2015) and potentially giving rise to a vicious circle whereby the increase in interest rates hinders borrowers' capacity to repay the loans, resulting in a further wave of corporate and households defaults.

A large NPLs burden has also been shown to affect the supply of credit (Tölö and Virén, 2021; Huljak et al., 2022), which given the vital role of bank lending for Italian corporates and households, represents a key policymaker concern. In this regard, Jobst and Weber (2016) note that impaired assets and the associated cost for continued provisioning have dragged down banks' earnings capacity, hindering banks' capacity to build-up capital buffers which ultimately affects the credit supply. Likewise, even if bad loans are adequately provisioned, they absorb a significant amount of bank capital that otherwise would be available for new lending (i.e., holding NPLs has a significant cost of capital for banks as these loans have higher risk-weights).[7] As such, NPLs give rise to a "vicious circle" between earnings, capital and lending, that is, NPLs depress bank profitability, which in turn hampers the capacity of banks to strengthen their capital position in order to support new lending.

Finally, NPLs have immediate repercussions on the costs borne by banks. On the one hand, banks could face higher legal and administrative costs related to managing, restructuring and disposal of bad loans, as well as higher human and operational expenses (Berger and DeYoung, 1997; European Commission, 2017). On the other hand, the weak asset quality of banks undermines banks' market valuations as it casts doubt on i) banks' ability to generate revenue streams in the future and ii) banks' future viability, leading to heightened risk perceptions on the part of investors and higher cost of wholesale funding.

1.1.3 The case of the Italian banking sector

In light of the implications arising from the presence of a high level of NPLs, this Chapter focuses on Italy because it represents an interesting setting for testing the presence of a relationship between short- and long-term efficiency and credit risk for at least two reasons. First, among European countries suffering from high levels of NPLs, Italy represents a noteworthy case as its volumes of impaired loans account for one-third (€360 billion at the end of 2015) of all NPLs. The Italian financial system has come under considerable strain during the last 15 years. Banks were first affected by the global financial crisis (GFC, 2007-2009) that originated in the United States (US) and, at a later time, by the European Sovereign Debt Crisis (SDC, 2010-2012) triggered in early 2010 by the rise of the sovereign risk of Southern European countries (i.e., Greece and Portugal) and Ireland.[8,9] The events of the last 15 years have likely caused changes in the level of short-term cost efficiency of Italian banks.

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[7] For example, UniCredit Group (2014), the second largest Italian commercial bank, estimated that their NPLs were absorbing around 6% of Common Equity Tier 1 (CET1) which otherwise would have been available for new lending (Jassaud and Kang, 2015).

[8] See Lane (2012) for an in-depth analysis concerning the European Crisis.

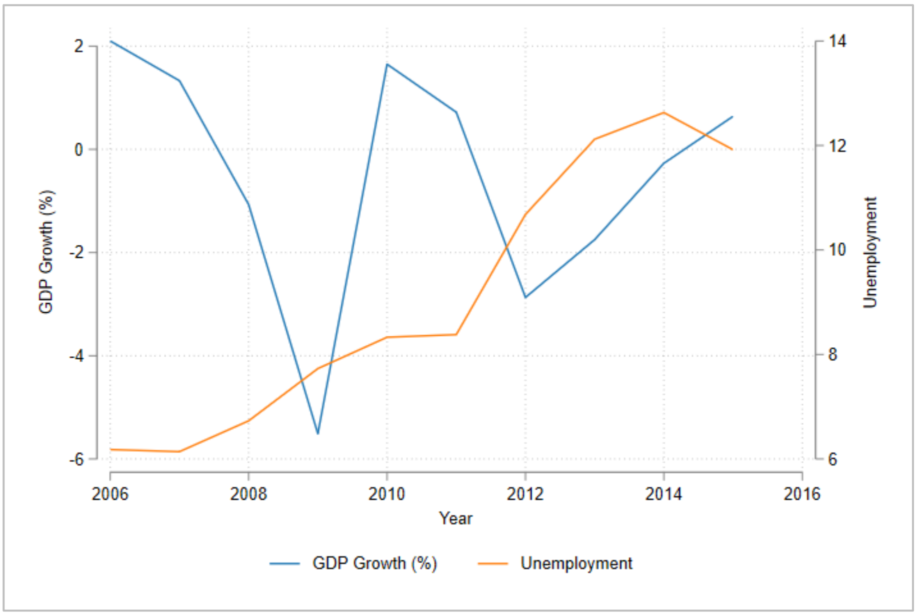
[9] As noted by the International Monetary Fund (2013), these crises had a 'dual-stage' impact on Italian intermediaries:"[Italian] banks weathered the initial impact of the global financial crisis in 2008 relatively well thanks to their "traditional" business model, but were hit hard by the subsequent sovereign- debt crisis and double-dip recession (p. 9)".

Thus, Italy represents the perfect setting to investigate whether and how deviations in short-term cost efficiency affect NPLs.

The second reason to focus on Italy relates to the presence of long-standing, persistent characteristics of the regulatory and institutional environment in which they operate and that might have (latently) affected the efficiency of banks. In particular, the role of 1) bank specialization (that is, cooperative and commercial banks) and ii) geographical location of banks (that is, North-West, North-East, Centre and South) (see Section 1.4.3 for further details).

Before proceeding further, it is pivotal to analyse the fundamentals concerning the macroeconomic developments and the banking sector to gain a better understanding of the repercussions of the two crises on the economic environment and the activities of Italian banks. The understanding of the macroeconomic environment is fundamental when assessing the drivers of banks' non-performing loans as several studies have shown that credit quality in banking is strongly associated with the economic conditions of a country (see Bofondi and Ropele, 2011; Louzis et al., 2012; Castro, 2013). Figure 1 depicts the evolution of Gross Domestic Product (GDP) growth and the unemployment rate over the period 2006-2015, where the two drops in GDP growth correspond to the two crises associated with a rapid increase in the unemployment rate. The rate of GDP growth began contracting in 2007, reaching frightening lows in 2009 and 2012 (-5.5% and -2.8%, respectively). This economic contraction was paired with a dramatic increase in the level of the unemployment rate, which jumped from 6.6% in 2006 to 11.6% in 2015.

Figure 1. The effect of the crises on the Italian economy



Source: World Bank. **Note**: GDP Growth refers to the left-hand y-axis while the Unemployment Rate refers to the right-hand y-axis.

The worsening of the Italian macroeconomic conditions was associated with an increase in the level of banks' non-performing loans. The recessions exposed the vulnerabilities inherent in the close interlinkage between Italian banks and firms (the so-called 'bank-firm nexus'). This is the result of Italy being fundamentally a bank-centred economy, which means financial institutions are the primary, and often the exclusive, source of credit for both firms and households (European Commission, 2015).[10] The strong bank-corporate nexus means that Italian banks are particularly sensitive to the deterioration in macroeconomic conditions, which will lead to, ceteris paribus, a rise in non-performing loans. In this regard, the International Monetary Fund (IMF) (2013) notes:

> "Italian banks have a strong focus on traditional lending activities, with the bulk of bank credit going to the corporate sector. As a result, the transmission of the shock in the real economy to Italy's banks has been particularly strong. For a large number of firms, profits have sharply fallen and debt burden has

[10] For instance, in 2013, bank loans represented 64.7 % of Italian firms' total financial debt, more than 20 percentage points higher than the euro area average which stood at 42.9%. The only other country where firms were more depended on bank credit was Greece, where bank loans accounted for almost 70% of total firm financing. Considering Italy's peer countries, the share of bank loans over total financial firm debt is 32.2% in France, 51.8% in Spain and 52.1% in Germany (European Commission, 2015).

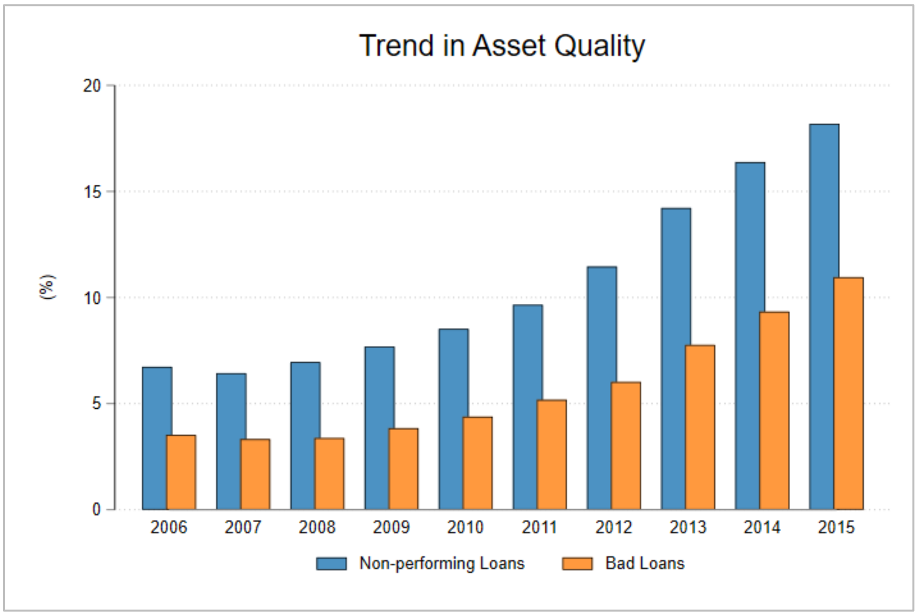
> increased since 2008. As a result, nonperforming loans in the banking system have reached systemic levels (p. 17)"

This is shown in Figure 2, Panel A. Between 2006 and 2015, NPLs dramatically increased from 6.8% to 18.2 % (blue bar). The bulk of these impaired loans refers to "bad loans" (henceforth BLs), which are the most severe category of NPLs where the borrower has been declared insolvent (see Table 1 for additional details). Bad loans (red bar) progressively increased in Italy from 3.5% in 2006 to 11% in 2015, which translated into the volume of bad loans in the entire Italian banking industry increasing from €6 billion to approximately €207 billion in 2015.

Examining Panel B of Figure 2, it can be seen that there is a pronounced geographical dimension, which does not significantly change over time. The South and Centre areas of Italy suffered from worse asset quality than the North-West and North-East areas of Italy. However, the striking feature of Figure 2 is the volume of BLs already on Italian banks' balance sheets in the lead-up to the financial crisis (2006-2008), especially in the South, suggesting the presence of persistent, structural problems in the Italian banking industry and in the country overall. To a lesser extent, divergences in bank asset quality are also noticeable across bank types. This evidence supports our choice of modelling structural inefficiencies as a function of banks' specialization and geographical location (see Section 1.4.3 for a discussion on the model specifications).

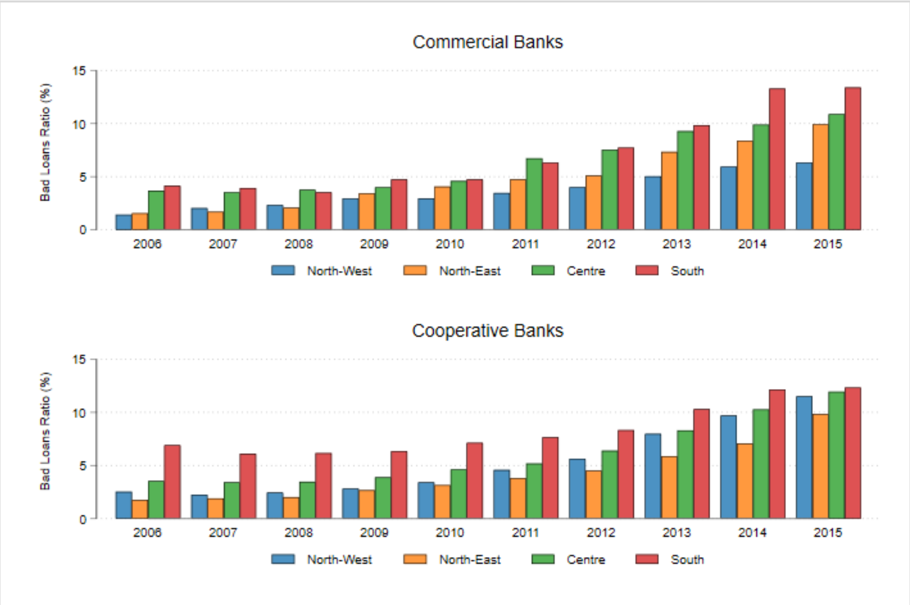
Figure 2. Evolution of loan quality of Italian banks

Panel A. Evolution of NPLs and bad loans



Source: Bankscope Data. **Note**: bad loans ratio refers to the most severe category of non-performing loans.

Panel B. Evolution of bad loans by bank specialisation and geographical area



Note: The figure shows the evolution of bad loans over the sample period and across bank specialisation (commercial, cooperative) and geographical location in Italy (North-West, North-East, Centre, South).

1.1.4 Reasons behind the slow pace of non-performing loans resolution

As Figure 2 depicts, the level of NPLs has increased throughout the period 2006-2015, even after 2012 when the most severe phase of the SDC had ended. This is the result of banks' inability to timely remove bad loans from their balance sheet paired with the prolonged recession that caused a constant inflow of new NPLs.

What are the reasons behind the slow pace of NPLs resolution? For banks, the easiest and quickest way to offload bad loans from their balance sheet is to i) write them off or ii) sell the bad loans to a third party. As concerns banks' write-offs, Jassaud and Kang (2015) note that there are limited incentives for Italian banks to pursue this strategy. In the first place, banks have low levels of Loan Loss Provisions (LLPs), meaning that write-offs generate losses that need to be absorbed by the capital. In detail, banks offset credit risk by estimating the expected future loss on their loan portfolio and by booking a corresponding provision. In the event of a loan default, the losses are first absorbed by the provisions set aside. However, if the provisions are insufficient, banks will have to resort to their capital cushions to cover the losses. After the two crises, the capital levels of Italian banks was too thin (i.e., too close to the minimum capital requirements) to absorb these losses, and thus banks prefer keeping bad loans on their balance sheets.[11] Furthermore, due to market pressure, banks may delay the disposal of NPLs as they have low levels of provisioning coverage ratios (defined as the ratio between loan loss provisions and gross loans).[12] Moreover, Italian banks rely heavily on collaterals. That is, two-thirds of loans are covered by collateral in the form of personal guarantees or real estate. This encourages banks to delay the NPLs' disposal in favour of their collection at the end of the foreclosure process.

Likewise, Italian banks could prefer delaying the disposal of NPLs while waiting for better economic conditions and structural reforms to improve the recovery prospects of such loans. In other words, Italian banks tend to devote their

[11] For instance, at the end of December 2013, 13 out of the 15 largest Italian banks had a Common Equity Tier 1 (CET1) ratio below their Euro Area peer average (11.4%).

[12] Jassaud and Kang (2015) note that "writing off bad loans that are highly or fully provisioned reduces the provisioning coverage ratio by lowering gross loans more than the level of provisioning. In normal times when NPLs are low, banks may be indifferent to the impact of NPL disposal on their coverage ratios. However, when NPLs are high and coverage is low, banks may face strong market pressure to maintain their provisioning coverage ratio and hold on to highly provisioned loans, rather than disposing (p. 11)"

efforts to pursuing internal collection and loan restructuring rather than actively cleaning up their balance sheet (Jassaud and Kang, 2015). Also, the European Commission (2017) reports that:

> "some banks might be reluctant to terminate client relationships […]. Furthermore, the sale of large impaired loan portfolios may have an adverse effect on some parameters of banks' internal rating models (e.g., the loss-given-default parameter) which determine banks' capital requirements […]. Finally, small banks' NPL portfolios may tend to lack critical mass and be insufficiently diversified to attract investors (European Commission, 2017, p. 37)".

Moreover, the low NPLs disposal could be attributable to the significant divergences in the expectations on the price of NPLs between banks and private investors. Indeed,

> "the pricing gap – defined as the difference between NPLs' net book value on banks' balance sheets and specialised investors' bid prices – is currently estimated at around 20 percentage points. This means that banks would have to book considerable losses when selling NPLs under current market conditions (European Commission, 2017, p. 36)".

The pricing gap could be ascribable to the inefficiencies of the Italian judicial system, with particular emphasis on the insolvency system and debt collection. For example, in 2014, the average length of bankruptcy procedures was 2709 days (i.e., 7 years and 4 months) whilst, on average, it can take up to 3 years to foreclose on real estate collateral (see, European Commission, 2016).[13] The uncertainty about the length and the outcome of the insolvency and foreclosure procedures has negatively

[13] With respect to the inefficiencies of the juridical system, Garrido et al. (2016) note that, "the Italian insolvency regime is characterized by its high complexity, providing multiple procedures and debt restructuring tools that appear to lack coordination and a unified vision […]. The system is divided between a generally applicable insolvency regime, and special regimes that apply to large enterprises, small enterprises and individuals, and enterprises subject to special supervisory regimes. Even within the general regime, there are a number of procedural avenues and options whose interplay and coordination is not always clear. Procedural complexity could be an explaining factor of the high litigiousness, and it is also likely that it assists debtors in implementing delaying strategies (pp. 17-18)". In this respect, "the bulk of distressed enterprises in Italy can use different debt restructuring procedures, formal reorganization, and liquidation. […]. Large enterprises (with more than 200 employees) can use special procedures ("*amministrazione straordinaria*" […]). Small enterprises are not subject to general insolvency law, and fall within the scope of the personal insolvency regime. Enterprises subject to special supervisory or regulatory regimes have their own liquidation procedure ("*liquidazione coatta amministrativa")* (Garrido et al., 2016, p. 18)".

affected the investor's valuation of banks' impaired loans since the delays depreciate the value of NPLs (Garrido, 2016).[14]

An additional reason for the build-up of NPLs has been identified in the lack of tax incentives for banks to write off loans (see, European Commission, 2016). Until the 2013 tax reform, write-offs were not tax deductible without a court declaration of insolvency, which, as above mentioned, could take several years. Furthermore, banks were allowed to deduct LLPs from taxable income only up to 0.3% of outstanding loans, with the remaining part treated as deferred tax assets, which were deductible over a period of 18 years. Hence, this cap created a considerable disincentive for banks to aggressively provision and hampered their ability to increase the coverage ratios and to systemically clean up their balance sheets (for details, see Jassaud and Kang, 2015). The 2013 reform allowed banks to deduct provisions and write-offs in equal instalments over five years and with a higher tax rate. A second tax reform was passed in 2015, finally allowing banks to deduct loan losses from their taxable income within the year.

Finally, the slow pace of NPLs' write-offs has been driven by the presence of small banks, which lack risk management capacity, NPL management experience, and access to distressed debt markets (Garrido et al., 2016, p. 17).

This initial Section aimed to provide a contextual background of what are non-performing loans and why their presence on the balance sheet of banks has consequences for banks' profitability and credit supply. Additionally, this Section has provided an overview of the current state of the Italian banking system. In the next section, we provide a review of the literature concerning bank credit risk and the use of efficiency as a proxy for management quality, which serves as a basis for our subsequent empirical estimation of cost efficiency and NPLs modelling.

[14] Other reasons may have hampered the ability of Italian financial intermediaries to sell NPLs through the securitization process. For instance, the European Commission notes that "the pricing gap is driven by several factors: (i) the difficulties which some bank experience in adequately raising NPL coverage ratios given their low profitability […] (ii) banks' and specialised investors' use of different valuation criteria (e.g., the factor used to discount expected cashflows, the accounting method for indirect costs of problem loan management); (iii) information asymmetries between sellers and buyers of impaired loans, often linked to a lack of granular data on loan portfolios due to inadequate loan management and record-keeping (European Commission, 2017, p. 36)".

1.2 Empirical literature review and hypotheses development

1.2.1 Cost efficiency as a proxy for managerial abilities

Levels of inefficiency in a company have been linked to poor management as far back as Farrell (1957) with more recent work by Demerjian et al., (2012) and Assaf et al., (2019), interpreting systematic deviations from some optimal frontier as inefficiencies attributable to the lack of managerial skills/abilities in minimizing banks' costs while maintaining output levels. Following this, this study assumes that the observed managerial inefficiencies have a direct impact on banks' credit risk.

The study contributes to the growing body of literature exploring the importance of management characteristics (e.g., talent, quality, ability) for firms' decision-making processes and outcomes. For example, Bertrand and Schoar (2003) report that heterogeneity in managerial corporate practices is systematically related to differences in corporate performance. Likewise, Chemmanur and Paeglis (2005) and Chemmanur et al. (2009), show that management quality positively influences firms' IPOs performance. Employing frontier estimation techniques, Demerjian et al. (2012) and Demerjian et al. (2013) demonstrate that managerial skills are positively associated with price reactions to management departures from the firm and earnings quality. In addition, Andreou et al. (2017) document that higher managerial ability led to greater investment during the financial crisis via the capacity of these firms to secure greater financing and resiliency. Andreou et al. (2016) also provide evidence that managerial ability can explain increased bank performance, risk-taking (measured by risk-weighted assets over total assets) and liquidity creation.[15]

In this study, the recent developments in the literature regarding stochastic frontier analysis are utilised and cost efficiency is separated into transient (short-term, time-varying) and persistent (long-term, time-invariant) efficiency. The motivation for this approach is based upon the work of Badunenko and Kumbhakar (2017) and Lien et al. (2018), who argue that it is restrictive, and potentially unrealistic, to consider inefficiency as either time-varying or time-invariant. This is because decomposing

[15] Demerjian et al. (2012), Demerjian et al. (2013) and Andreou et al. (2017) proxy managerial abilities using efficiency scores estimated via Data Envelope Analysis (DEA). In contrast, Andreou et al. (2016) adopt a different approach where in the first step, they estimate efficiency score using Stochastic Frontier Analysis (SFA) and in the second step they run a Tobit regression to purge this measure of all firm- specific effects. It is worth pointing out the two-step methodology employed by Andreou et al. (2016) has been amply criticised (see Wang and Schmidt, 2002) (see also Section 1.5.3)

efficiency allows for uncovering different aspects of the managerial practices of a firm. For example, consider the case where inefficiency is associated with (unobserved) management. Assuming that management is time-invariant, inefficiency will also be time-invariant. More realistically, we can assume that management changes over time, although a part of it will remain constant. If management has a time-invariant and a time-varying component, it follows that the efficiency estimation needs to accommodate the dual nature of management (see e.g., Tsionas and Kumbhakar, 2014). In other words, it is plausible that banks are characterised by both short-term and long-term inefficiencies, which this chapter argues have potential distinct effects on the quality of banks' loan books.

The following sections contextualise the academic literature regarding NPLs and efficiency in the following way. First, I focus on the seminal paper of Berger and DeYoung (1997) and I review the numerous studies that have adopted their theoretical framework to investigate the link between efficiency and bank risk-taking. Later, I provide an overview of the studies focusing on macro-determinants of impaired loans. Finally, I outline the hypotheses that have been developed and that will be tested in this chapter.

1.2.2 The theoretical framework: cost efficiency and bank credit risk

Berger and DeYoung (1997) developed the theoretical and empirical framework upon which the vast majority of later studies on cost efficiency and loan quality are based. In particular, they put forward three hypotheses, namely *bad management*, *skimping* and *bad luck*, explaining the link between bank cost efficiency and risk-taking (in their case, proxied by NPLs).

Under the *bad management* hypothesis, (and controlling for systemic events and the performance of other banks) observed low cost efficiency is considered to be signalling poor management practices with respect to day-to-day activities, including the managing of the loan portfolio. The inefficiency of the management is reflected in a low measured cost efficiency because of poor senior management that shows inadequate control over operating expenses. Additionally, as 'bad managers', they will show poor practices in:

- the screening process of the borrowers, therefore choosing a high proportion of the investments with low or negative net present values;

- the monitoring and controlling of the borrowers;
- evaluate the actual value of the collaterals pledged against the loans

It follows that these actions will lead to an increase in the level of NPLs because, as time passes, delinquencies begin to rise, ceteris paribus. Therefore, according to the *bad management* hypothesis, a decrease in cost efficiency is expected to Granger-cause an increase in the volume of NPLs. [16]

In contrast, under the *skimping* hypothesis, bank managers may be tempted to trade short-run increases in cost efficiencies for long-run reductions in the quality of their loan portfolios. Management that engages in *skimping* behaviour could allocate fewer resources to loan underwriting, collateral appraisal, monitoring, and control processes, which will immediately result in greater cost efficiency since fewer operating expenses are supporting the same quantity of loans (and other outputs). However, intuitively, this reduction in resources allocated to the management of the loan portfolio could eventually lead to a worsening in the credit quality of banks. As time passes, borrowers start defaulting on their loans, revealing the previous oversights made during the screening and monitoring process of the loan portfolio. Thus, according to the *skimping* hypothesis, higher cost efficiency is expected to Granger-cause rises in the volume of NPLs.

However, shocks to a bank's loan quality could also exert a negative effect on bank cost efficiency, as suggested by the *bad luck* hypothesis. External exogenous events (e.g., economic downturn or local plant closing) could affect the creditworthiness of bank borrowers, resulting in higher credit risk in banks' balance sheets. It follows that banks will have to increase managerial efforts, incurring higher operating expenses as a result of more resources allocated to:

- monitor the delinquent debtors and value their collaterals
- analyse and negotiate possible workout arrangements
- maintain the soundness and safety of the bank in order to limit the concerns of regulators and market participants and,
- size and dispose of the collaterals in case of the default of the borrowers.

[16] A variable x is said to Granger-cause y if, given past values of y, past values of x are able to predict current values of y. This relationship is typically estimated by regressing lagged values of y and x on y and by testing the null hypothesis that the estimated coefficient of the lagged values of x are jointly zero. Failing to reject the null implies no causation running from x to y. For a more extended discussion of the Granger causality framework see Section 4.

A rise in NPLs may also divert managers' attention away from solving other operational problems, exacerbating the drop in bank cost efficiency.[17] Therefore, for this hypothesis to be confirmed, an increase in NPLs should be found to Granger-cause a decrease in cost efficiency.

Closely related to Berger and DeYoung (1997), the work of Kwan and Eisenbeis (1997) examines the relationship between operating efficiency, capitalization and risk (interest and credit risk) using a simultaneous equation framework. Focusing on US banks between 1995Q4 and 1997Q2, they observe that operating inefficiency is positively related to credit, supporting the hypothesis that poor performers are more vulnerable to risk-taking. In addition, they find evidence of a positive relationship between inefficiency and the level of capital of the banks, concluding that regulatory pressures seem to play a significant role in forcing underperforming firms to hold more capital.

The subsequent literature has expanded the original model specifications of Berger and DeYoung (1997) by adopting different definitions of bank credit risk. For instance, Williams (2004) replicates the study of Berger and DeYoung using the level of loan loss provisions as a measure of credit risk for a sample of European savings banks (1990-1998) and finds strong evidence in favour of *bad management* and a strong rejection of the *skimping* hypothesis. Likewise, Rossi et al. (2005) examine the intertemporal relationship between cost/profit efficiency, capital and LLPs covering a sample of Central and Eastern European nations over the period 1995-2002. They estimate a Granger causality model using a dynamic panel data estimator and find support for the *bad luck* hypothesis, (i.e., negative external shocks temporally precede a drop in the level of cost efficiency). In contrast, by employing a static simultaneous equation model, Altunbas et al. (2007) examine the relationship between capital, risk (measured as Loan Loss Reserves, LLRs) and cost efficiency in European banking over the period 1992-2000. They provide evidence that inefficient European banks tend to hold more capital and are more risk-averse than their efficient counterparts. Further, they do not find a positive relationship between

[17] Importantly, Berger and DeYoung (1997) note that "under the bad luck hypothesis, the extra expenses associated with problem loans create the appearance, but not necessarily the reality, of lower cost efficiency. Faced with an exogenous increase in nonperforming loans, even the most cost efficient banks have to purchase the additional inputs necessary to administer these problem credits (p. 852)".

inefficiency and bank-risk taking while they observe that the financial strength of the corporate sector helps to reduce risk-taking behaviours. Podpiera and Weill (2008) focus on a sample of Czech banks between 1994 and 2005, finding support for the *bad management* hypothesis whereas they reject the *bad luck* hypothesis as they fail to observe a significant and negative impact of non-performing loans on cost efficiency. With respect to the work of Fiordelisi et al. (2011), they test for the presence of *bad management, bad luck and skimping* in a sample of 26 European countries over the period 1997-2007. By adopting several definitions of risk (NPLs, 1-Year Expected Default Frequency and 5-Year Expected Default Frequency), efficiency (cost, profit and revenue efficiency) and capital, they find support for the *bad management* hypothesis.

Finally, it is worth mentioning the papers of Koutsomanoli-Filippaki and Mamatzakis (2009) and Saeed and Izzeldin (2016) among the studies that test for the *bad management* and the *skimping* hypotheses adopting a measure of efficiency estimated via SFA. They differ from the majority of studies as they adopt an indicator of the probability of default (calculated as Merton-type bank default risk, Merton, 1974) as a bank risk proxy. Overall, using a sample of 27 European countries between 1998 and 2006 and adopting a Panel-Vector Autoregressive technique (PVAR) approach, Koutsomanoli-Filippaki and Mamatzakis (2009) observe that in the case of foreign and domestic banks, cost inefficiency may cause risk, consistent with the *bad management* hypothesis. Saeed and Izzeldin (2016) explore the relationship between efficiency and default risk in Islamic banks and Conventional banks over the period 2002-2010. Employing a PVAR approach, they provide evidence to support the *skimping* hypothesis.

1.2.3 Macroeconomic and bank-specific determinants of non-performing loans

While the studies reviewed above have focused mainly on assessing the presence of an intertemporal relationship between cost efficiency and credit risk, other studies have more broadly investigated the macroeconomic and bank-specific drivers of the quality of loan books.

When investigating banks' asset quality, it is fundamental to control the macroeconomic environment in which banks are operating as periods of economic depression affect the ability of households and firms to service their debt. Given the environment in Italian banking discussed in the previous section and the rise in NPLs, it is important to review those studies that have focused on macroeconomic determinants of impaired loans.

For example, Rinaldi and Sanchis-Arellano (2006) focus on macroeconomic determinants of households problem loans in seven European Union (EU) countries over a period spanning from 1989Q3 to 2004Q2 and find that an increase in unemployment, inflation, and the real lending rate worsen the financial conditions of debtors. Interestingly, they also observe that house prices are negatively related to NPLs, suggesting that i) private wealth can act as a buffer against unexpected losses or ii) housing wealth can be used as collateral to facilitate access to credit.[18] Likewise, Berge and Boye (2007) observe that the asset quality of Nordic banks (1993-2005) is negatively related to developments in real interest rates and unemployment. Nkusu (2011) explores the consequences of shocks in the level of NPLs on macro-financial conditions in 26 advanced economies for the period 1998-2009, finding that slower growth, higher unemployment rate and fall in asset prices significantly affect are associated with debt service problems. Similar results were obtained by Castro (2013), who investigates the link between the macroeconomic environment and credit risk in a group of five European countries (Greece, Ireland, Portugal, Spain and Italy) and concludes that 'the banking credit risk is significantly affected by the macroeconomic environment'.

Other studies have taken a global perspective in analysing drivers of NPLs. For instance, Beck et al. (2015) study the macroeconomic determinants of NPLs in 75 countries over the period 2000-2010. Using GMM, they find that real GDP growth was the main driver of impaired loans. Furthermore, exchange rate depreciation could also determine higher NPLs in countries with a high degree of lending in foreign currencies to unhedged borrowers while a drop in stock prices is found to negatively affect bank asset quality, in particular in countries with large stock markets relative to the economy.

[18] Specifically, they conclude that "in the short-run the role of financial wealth and housing wealth (proxied by the house price index) tends to confirm the idea that wealth is used as a buffer in case of unexpected shocks. Even though, on the one hand, housing wealth, being less liquid, plays a minor role in relieving financial stress as compared to financial assets, on the other hand, it still helps, in accordance with the view that collateral can be used to overcome asymmetric information problems (Rinaldi and Sanchis-Arellano 2006, p. 29)".

Other papers have expanded the previous group of studies by also considering bank-specific drivers of NPLs (often, these additional studies have also tested for the Berger and DeYoung (1997) hypotheses). Among the papers focusing on European banking systems, Salas and Saurina (2002) assess the macroeconomic and bank-specific determinants of problem loans in Spanish commercial and savings banks between 1985 and 1997. Their findings suggest that the two types of banks have different drivers of NPLs, that is, commercial banks are more sensitive to the business cycle while saving banks are more exposed to institution-specific characteristics. Interestingly, the measure of inefficiency (proxied by cost-to-income ratio) is statistically significant only for cooperative banks. This finding provides support for the choice to control for bank specialization when investigating cost efficiency (see Section 1.4.3). In addition, Louzis et al. (2012) examine the determinants of NPLs in Greece by employing a unique dataset provided by the Bank of Greece that allows the disaggregation of NPLs into consumer, business and mortgage loans. In their case, the *bad management* and the *skimping* hypotheses are tested for employing both a measure of profitability (i.e., return on equity, ROE) and the cost-to-income ratio. Employing a GMM framework, they observe that Greek NPLs appear to be mainly explained by macro-factors (i.e., GDP, unemployment, interest rate and public debt). Also, bank-specific variables such as performance and efficiency have additional explanatory power when incorporated into their baseline model, providing support for the *bad management* hypothesis. More recently, the study of Klein (2013) has investigated the global, macroeconomic and bank-level drivers of NPLs using data from 16 Central, Eastern and South-Eastern European nations between 1998 and 2011. Both bank-specific and macroeconomic factors are found to be significant in explaining the asset quality of CESEE banks while he also reports evidence in favour of the *bad management* hypothesis (tested using ROE).

In a further analysis of NPLs in European countries, Chaibi and Ftiti (2015) compare the macro and micro drivers of impaired loans in commercial banks in a market-based economy (i.e., France) and a bank-based economy (i.e., Germany) during the period 2005-2011. Their findings indicate that the set of macroeconomics determinants (GDP growth, unemployment rate and exchange rate) is shared between the two countries. Furthermore, evidence in favour of the *bad management* hypotheses is found for both France and Germany when using ROE as a proxy for managerial abilities whilst the cost-to-income indicator is found to be significant only for France. Finally, the most recent investigation of NPLs in Europe is the study of Dimitrios et al. (2016), who employ country-specific and bank-specific variables for a sample of 15 European countries over the period 1990Q1 and 2015Q2. In line with the previous findings on the relationship between the macro environment and bank asset quality, they report that an increase in the unemployment rate worsens the credit quality of banks while GDP growth helps to reduce NPLs. Further, ROA and ROE are found to be negative and statistically significant, suggesting that more profitable banks will display better asset quality, in line with the notion of *bad management.*

Other papers have examined problem loans in the US context, such as those of Ghosh (2015, 2017). In detail, Ghosh (2015) studies state-level bank-specific and region economic determinants of NPLs in a sample of commercial and savings banks between 1984 and 2013. Ghosh finds evidence that greater capitalization, liquidity risk and greater operating inefficiency (measured as non-interest expenses divided by total assets) significantly increase NPLs while higher profitability appears to lead to more prudent lending. A significant role in explaining US NPLs is also found to be played by macro-drivers (i.e., real GDP and personal income growth, unemployment rates, housing price indices and homeownership rates). In a subsequent study, Ghosh (2017) analyses sector-specific NPLs for the 100 largest US commercial banks over the period 1994Q4- 2016Q1. Specifically, he examines bank-specific and macroeconomic drivers of NPLs in four categories of loans, that is, real estate, commercial and industrial, individual and farm loans, finding a positive relationship between the level of capitalization and loan growth and NPLs while more diversified and more profitable banks tend to display lower levels of NPLs, as suggested by the *bad management* hypothesis.[19]

Before concluding this Section, we review a few studies focusing exclusively on Italy. Marcucci and Quagliariello (2008) assess the effects of business cycle conditions on the rate of default of banks' customers for the period 1990-2004. By

[19] Furthermore, Ghosh (2017) observes a rather heterogeneous response to macroeconomic shocks. Specifically, he concludes that "while real GDP growth reduces both total and real estate NPLs, it increases agricultural production NPLs suggesting sound economic health spurs banks to engage in farm loans without their proper evaluation, and is something banks should be wary of. Likewise an increase in mortgage rates increases both total and real estate NPLs, but a rise in bank prime loan rate reduces non-performing C&I loans. The opposite holds for housing prices (p. 44)"

employing a reduced-form PVAR, they observe that default rates follow a cyclical pattern, decreasing during business cycle expansion and increasing during downturns. In the same spirit, Quagliariello (2007) shows that NPLs follow a cyclical pattern for a panel of Italian banks observed between 1985 and 2002. Consistent results are found by Bofondi and Ropele (2011) when investigating the macroeconomic drivers of Italian banks' bad loans over the period 1990-2010. Employing a single-equation time series regression, they find that the new bad loans ratio in relation to lending for households is negatively related to real GDP growth and house prices, while it is positively related to the level of the unemployment rate and short-term interest rate. Concerning the bad loans ratio for firms, it increases with the unemployment rate and the level of firms' debt, while it diminishes as the consumption of durables increases. More recently, Cotugno et al. (2013) investigate the role of the structural and organizational profiles of banks (proxy by size, functional distance and labour intensity) in explaining the level of default rate (DR) of loans for a sample of Italian banks between 2005 and 2010.[20] They find that larger banks are those that produce more NPLs, while they observe a negative relationship between NPLs and the level of GDP growth and the capital ratio. Finally, Garrido et al. (2016) find that both bank-level and macroeconomic factors have affected Italian banks' asset quality between 2005 and 2014. Their main findings are as follows: lower profitability in the past is associated with higher NPL levels; higher lending in the past—measured by (lagged) loan growth—is related to higher NPLs; Lower growth, exchange rate appreciations, and falling house prices are significantly associated with higher NPLs.

[20] The Default Rate measure used by Cotugno et al., (2013) is argued to better "capture the new risk generated by the bank during a specific year, thus providing a more clean and appropriate risk measure". This variable is estimated as follows: "In the numerator, the new NPLs generated during the year *t* are used, so we can correctly assess the bank's screening ability. We insert in the denominator the performing [gross loans] of the year *t* -1 (p.578)".

1.2.4 Hypotheses development

In the previous sections, the chapter has introduced the seminal paper by Berger and DeYoung (1997), which constitutes the theoretical framework for this study, while also providing an overview of the vast body of research on the drivers of credit risk. In this Section, we formalise the hypotheses that this Chapter aims to test. In particular, we start from the hypotheses put forward by Berger and DeYoung (1997), but we revisit them in light of the recent advancements in the literature on Stochastic Frontier Analysis. That is, we exploit the Badunenko and Khumbakar (2017) model that splits efficiency into transient (short-term) and persistent (long-term) efficiency and we re-formulate the *bad management, skimping* and *bad luck* hypotheses while putting forward two additional hypotheses to be tested (*bad habits* and *resource misallocation*).

To test the link between *transient* efficiency and credit risk, we exploit the aforementioned theoretical framework constituted by the *bad management, skimping* and *bad luck* hypotheses. Short-term inefficiency captures 'non-systematic behavioural failures' of management and 'singular management mistakes' (Filippini et al. 2018, p. 75) and, relates to temporal behavioural aspects of management that can be solved in the short-term. For example, short-term inefficiency may denote the presence of failures in the day-to-day practices carried out by bank employees (e.g., lax practices in the loan underwriting, monitoring and control by loan officers), which ultimately affect the risk profile of banks. In light of this, we seek to test the following hypotheses that link transient cost efficiency to NPLs (and vice versa):

> **H_1: Bad Management Hypothesis**. A decrease in the banks' transient efficiency temporally precedes an increase in the level of bad loans.
>
> **H_2: Skimping Hypothesis**. An increase in the banks' transient efficiency temporally precedes an increase in the level of bad loans.
>
> **H_3: Bad Luck Hypothesis**. An increase in banks' NPLs temporally precedes a decrease in transient efficiency.

However, we expand this literature by introducing the notion of *persistent* efficiency as a key driver of banks' credit risk. Specifically, long-term efficiency captures deviations from the best-practice cost frontier that could be attributed to structural problems of the industry, regulatory constraints, and 'systematic behavioural shortcomings' (Blasch et al. 2017, p. 92) of the management. Low levels of long-term efficiency could capture embedded, latent negligence of Italian banks, lasting/recurring wasteful habits of the management or systematic inefficiencies (e.g., recurring mistakes in the managing of the loan portfolio due to 'systematic shortfalls in the managerial capabilities' – Filippini and Greene 2016). It follows that banks characterised by low levels of structural efficiency are potentially more likely to be associated with higher bad loans, which is the *bad habits* hypothesis.

Alternatively, we formulate the *resources misallocation* hypothesis, which posits that banks could face a trade-off between long-term efficiency and asset quality. High measured structural efficiency could reflect the tendency of banks to systematically shift resources away from the managing and monitoring of the loan portfolio to cope with regulatory constraints, structural rigidities of the industry or recurring managerial behaviours that tend to waste inputs and that can be difficult to change over time. In other words, high levels of structural efficiency might denote that banks are able to manage negative externalities and systematically minimise their costs by misallocating resources away from the management of the loan portfolio. It follows that high levels of structural efficiency are achieved at the expense of lower asset quality. Accordingly, we test the following hypotheses:

H_4: Bad Habits Hypothesis. Persistent efficiency and bad loans are negatively related, that is, banks reporting a low level of persistent efficiency suffer from higher BLs.

H_5: Resources Misallocation Hypothesis. Persistent efficiency and bad loans are positively related, that is, banks reporting a high level of persistent efficiency suffer from higher BLs.

In this Section, we introduced the theoretical framework governing this Chapter, while also contextualising this framework in the broader stand of literature on bank credit risk. In the next Section, we introduce the empirical methodology and the data used in this Chapter to assess the links between transient and persistent cost efficiency and NPLs.

1.3 Empirical methodology

To empirically test the intertemporal relationship between NPLs and cost efficiency, we rely on Granger-causality techniques, in line with a broad body of literature that includes, but is not limited to, Berger and DeYoung (1997), Williams (2004), Podpiera and Weill (2008), Casu and Girardone (2009); Fiordelisi et al. (2011) and Luo et al., (2016). The outcome of the Granger causality test allows us to assess whether two variables share a causal relationship, that is, a variable x is said to Granger-causes y if, given past values of y, past values of x are able to explain current valuesof y (Granger, 1969).[21] However, it is worth noting that the term causality shou not be taken 'literally', that is

> "[….] Granger causality tests […] only indicate that changes in one variable precede changes in another variable of interest (with a positive or negative sign) rather than establishing causation in the traditional sense of the word (Casu and Girardone, 2009, p. 136)".

As such, as noted by Berger and DeYoung (1997), the outcome of a Granger-causality test does not produce evidence of economic causation but it will only indicate whether the data are consistent or inconsistent with the three hypotheses of management behaviour (i.e., *bad luck, bad management, skimping*). In other words, if lagged values of x have explanatory power for current values of y, that *may* suggest a causal relationship between the two aforementioned variables. Nonetheless, there is no guarantee that x actually causes y and for this reason, throughout the rest of the paper, we will refer to 'Granger-causality' and not simply 'causality'.

[21] Interestingly, Professor Granger has spent his student life and a significant part of his academic life at the University of Nottingham, from where, in 1955, he graduated with a BA in mathematics. In 1956, he started a PhD in Statistics and the same year he received his first academic appointment as an assistant professor in statistics. He stayed at the University of Nottingham until 1974, when he was offered a professorship at the University of San Diego, California. Professor Granger' international reputation grew during his permanence in Nottingham, thanks to series of influential research publications on the spectral shape of economic time series (in Econometrica, 1966) and on testing for a form of causality between time series variables (Econometrica, 1969), which was later termed "Granger causality" (The Guardian, 2009). In 2003, together with Roberg Engle, he was awarded the Nobel Prize in Economic Science for their work on the concept of co-integration in time-series. Professor Granger received a knighthood in 2005 and in the same year, Nottingham University's economics and geography department premises were renamed the Sir Clive Granger Building. Professor Granger passed away the 27th of May 2009.

For explanatory purposes, we begin by considering the following 2-year lag Granger-causality model, Eq. (1.1)

$$y_{it} = \alpha_0 + \alpha_1 y_{it-1} + \alpha_2 y_{it-2} + \beta_1 x_{it-1} + \beta_2 x_{it-2} + \varepsilon_{it}. \tag{1.1}$$

Where y_{it} denotes the dependent variables, x_{it} are explanatory variables and ε_{it} is the error term. The causal relationship is estimated by regressing lagged values of y_{it} and x_{it} on current values of y_{it} and by testing the null hypothesis that the two lags of x_{it} are jointly equal to zero, that is, $\beta_1 = \beta_2 = 0$. Rejecting the null hypothesis of no causality indicates that the variable x_{it} Granger-causes y_{it}, with the direction of the causality being determined by the sum of the lagged coefficient, that is $\beta_1 + \beta_2$. To elaborate, a positive (negative) sign implies that the causal relationship is positive (negative), that is, an increase (decrease) in x_{it} in the past increases (decreases) y_{it} in the present. Furthermore, we check for the stability over time (or 'long-run effect') of the dependent variable y_{it} by testing the following restriction, $\alpha_1 + \alpha_2 = 0$ and $\beta_1 + \beta_2 = 0$. A rejection of the null hypotheses points towards the presence of a long-run effect of the examined explanatory variable on the dependent variable y_{it}.[22]

1.3.1 Granger-causality specifications

For the purpose of this study, we estimate the following dynamic panel data regression using Eqs. (1.2) and (1.3).

$$BL_{it} = a + \sum_{j=1}^{J} \beta_j BL_{it-j} + \sum_{j=1}^{J} \gamma_{1j} Transient_{it-j} + \gamma Persistent_i + bank\_controls + \eta_i + \varepsilon_{it} \tag{1.2}$$

[22] Recent developments in the estimation of Granger-causality include the specification of Dumitrescu and Hurlin (2012), who note that "one of the main issues specific to panel data models refers to the specification of the heterogeneity between cross-section units. In this Granger causality context, the heterogeneity has two main dimensions. We hence distinguish between the heterogeneity of the regression model and that of the causal relationship from x to y. Indeed, the model considered may be different from an individual to another, whereas there is a causal relationship from x to y for all individuals (Dumitrescu and Hurlin, 2012, pp. 1450-1451)". In other words, they specify a model that is able to detect causality within subgroups of cross units. Nonetheless, their model requires $T > 5 + 2K$ where T is the time and K is the number of explanatory variables. Consequently, as shown later in the study, we cannot rely on this model specification for our analysis since our period consists of 10 years and we employ 12 explanatory variables.

$$BL_{it} = a + \sum_{j=1}^{J} \beta_j BL_{it-j} + \sum_{j=1}^{J} \gamma_{1j} Transient_{it-j} + \gamma Persistent_i + bank\_controls + macro\_controls + \eta_i + \varepsilon_{it} \quad 1.3$$

Where, following the credit risk literature, the dependent variable in both equations is the logit transformation of bad loans (BL), that is, $ln\ (\frac{BL}{1-BL})$, where BL is the ratio of bad loans over gross loans (see Espinoza and Prasad, 2010; Klein, 2013; Ghosh, 2015). The logit transformation ensures that the dependent variable spans over the interval $[-\infty; +\infty]$ as opposed to the [0;1] interval and is distributed symmetrically.[23] On the right-hand side of the equations, we include two lags of the dependent variable to capture the effect of omitted explanatory variables and the persistence of BL (see Nkusu, 2011; Castro, 2013; Chaibi and Ftiti, 2015). In all the models, $bank\_controls$ denotes a vector of bank-specific control variables in lags and levels (see Section 1.3.2), $macro\_controls$ represents lagged macroeconomic controls (see Section 1.3.3), η_i are bank fixed effects (FE) and ε_{it} is the random error.

The introduction of the lagged dependent variable as a predictor renders the standard ordinary least squares and the within estimator inconsistent (see Nickell 1981). Thus, we estimate Eqs. (1.2) and (1.3) using the system generalised method of moments (SGMM) procedure proposed by Arellano and Bond (1991), Arellano and Bover (1995) and Blundell and Bond (1998) (a detailed overview of the GMM estimator is provided in Appendix A.2.1). Under the assumption of independent and homoscedastic residuals, consistent parameter estimates can be obtained, while controlling for time-invariant unobserved heterogeneity and simultaneity bias.

This autoregressive distributed lag panel data model also allows us to examine the impact of efficiency on BLs in two interrelated ways. First, by estimating the long-run multiplier ($\sum_{j=1}^{J} \gamma_{1j}$, for $J = 2$, Casu and Girardone, 2009) we can examine how a permanent decrease/increase in efficiency would affect BLs (for example, the impact of a decrease in efficiency in period t, which is also maintained in subsequent

[23] Furthermore, the logit transformation prevents non-normality in the error term and accounts for non-linearities, that is, larger shocks to the explanatory variables may cause a large, nonlinear response in the transformed dependent variable (Wezel, et al. 2014, Ghosh, 2015). In Appendix A, we show the distribution of NPLs ratio before and after the logit transformation (see Figure A1 and Figure A2).

periods). In the absence of a long-run effect (if $\sum_{j=1}^{J} \gamma_{1j} = 0$), then efficiency has only a temporary effect and BLs depend on the change in the efficiency rather than its levels, an effect also known as "momentum". This can be seen by simplifying Eqs. (1.2) and (1.3) and keeping only $Transient$, in which case our specification is equivalent to Eq. (A), $BL_{it} = a + \delta_1 Transient_{it-1} + \delta_2 (Transient_{it-1} - Transient_{it-2})$, where δ_2 is defined as the "momentum" coefficient, and $\delta_1 = \gamma_1 + \gamma_2$; $\delta_2 = -\gamma_2$. Substituting δ_1 and δ_2 into Eq. (A) we obtain our specification, $BL_{it} = a + \gamma_1 Transient_{it-1} + \gamma_2 Transient_{it-2}$, which suggest that the coefficient $-\gamma_2$ in Eq. (1.2) can be directly interpreted as the "momentum effect". The above would suggest that negative changes in the efficiency (even for high-efficiency banks) would cause adverse changes in BLs.

1.3.2 Bank-specific determinants on bad loans

1.3.2.1 Transient and persistent cost efficiency

On the right-hand side of Equations (1.2) and (1.3), we include a measure of time-varying cost efficiency (i.e., $Transient$) to test the above-outlined *bad management* (H_1) and *skimping* hypotheses (H_2) (see above, Section 1.2.4). We incorporate the level of *persistent efficiency* ($Persistent$) to assess how bad loans may be influenced by long-run, latent inefficiencies embedded in Italian banks and we test the aforementioned H_4 and H_5.[24]

We estimate transient and persistent efficiency using the Stochastic Frontier Analysis method introduced by Aigner et al. (1977) and Meeusen and van den Broeck (1977). In detail, we employ the heteroskedastic four-component error model specification introduced by Badunenko and Kumbhakar (2017), where inefficiency (and production risk) is allowed to be systematically related to bank characteristics, as well as geographical and macroeconomic factors. Given that the transient and persistent components represent key variables of interest for the purpose of this Chapter, Section 1.4 is entirely dedicated to a detailed discussion on the estimation of these components, focusing on the SFA methodology, the selection

[24] It is worth noting that given the time-invariant nature of persistent efficiency, it is not possible to directly test for the intertemporal relationship between persistent cost efficiency and NPLs.

of input/outputs and frontier used in this study and the determinants of each inefficiency component.

1.3.2.2 Bank-specific determinants of bad loans

As in the original specification of Berger and DeYoung (1997), we include the lagged values of the level of equity over total assets (CAP_{it}) to test the *moral hazard* hypothesis. Poorly capitalized banks may be tempted to increase the riskiness of their loan portfolio as they have less "skin in the game" and the risk is borne by another party (e.g., shareholders), resulting in higher impaired loans. Moreover, Jeitschko and Jeung (2005) argue that the presence of information frictions and agency problems may lead to bank managers taking on greater risks when a bank has lower levels of capital. Albeit the moral hazard hypothesis does not explain the relationship between cost efficiency and NPLs, Berger and DeYoung (1997) argue that

> "moral hazard gives an alternative explanation for nonperforming loans, so the effects of measured cost efficiency on nonperforming loans could be biased if the potential effects of capital were neglected. Second, moral hazard effects can magnify the effects of the other three hypotheses, and any of those hypotheses could be the primary cause of reduced capital and moral hazard incentives (Berger and DeYoung, 1997, p. 854)".

In other words, omitting from our modelling strategy the level of capital could lead to spurious inference on the relationship between NPLs and cost efficiency.[25] Furthermore, under-capitalization may give rise to the phenomenon of "zombie lending". Rather than writing-off loans and absorbing the losses, banks that are close to the minimum regulatory capital are more likely to keep "gambling for resurrection" of their borrowers that are close to or in default (the so-called *zombie firms*), keeping them "artificially" alive in the hope they will recover and service

[25] In this respect, Berger and DeYoung (1997) point out that the four hypotheses ('bad management', 'skimping', 'bad luck', and 'moral hazard') are mutually non-exclusive: "in an extreme case, all four hypotheses could affect the same bank at the same time. For example, bad luck could befall a poorly managed bank that also happens to be skimping on loan monitoring expenses. Any loss of capital as a result of the bad luck, bad management, and skimping might cause the bank to respond to moral hazard incentives and take increased risks. Similarly, banks responding to moral hazard incentives may take increased risks by skimping (p. 854)".

outstanding debt (Jiménez et al., 2017; Schivardi et al., 2017).[26] Finally, it is worth mentioning that, conversely to Berger and DeYoung (1997), we do not test for this hypothesis only on a sub-sample of weakly capitalized banks but, in line with Fiordelisi et al. (2011); Louzis et al. (2012), we rely on the entire sample. The rationale is that a strong capital position may potentially act as an incentive for the intermediaries to increase their portfolio risk as higher levels of capital allow to increase the riskiness of the granted loans, increasing the likelihood of future loans' defaults (Tan and Floros, 2013).[27] To test this hypothesis, we use the two-years lags of the capital ratio.

The natural logarithm value of total assets ($Size$) is incorporated to control for potential size effects as in Chaibi and Ftiti (2015), Vithessonthi (2016) and Zhang et al. (2016). The relationship between banks' size and NPLs can be ambiguous. On the one hand, large banks may have better diversification opportunities, that is, they can spread their investments in different geographical areas or business sectors, reducing the risk of loan defaults (see Salas and Saurina, 2002; Chaibi and Ftiti, 2015). Nonetheless, Stern and Feldman (2008) have pointed out how large banks, being perceived as Too-Big-to-Fail (TBTF), tend to engage in riskier activities because they are subjected to moral hazard problems and lower market discipline is imposed by their creditors.[28] The TBTF status comes with implicit subsidy and protection from governments in the event of a bank's failure. It follows that large banks may be taking on greater risks, increasing their likelihood of suffering from NPLs.

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[26] Schivardi et al. (2017) find that low-capitalized Italian banks engaged in significantly more zombie lending, compared to other banks in the aftermath of the financial crisis.

[27] Also, as argued by Ghosh (2015), "managers in banks that are highly capitalized may resort to a liberal credit policy under the notion of 'too big to fail' (Rajan, 1994) implying a positive relationship between capital and NPLs (p. 95)".

[28] The use of the term "too big to fail" is first associated with a quote from Congressman Stewart McKinney, who during hearings into the bailout of Continental Illinois said, "We have a new kind of bank. It is called too big to fail ..." (Inquiry into Continental Illinois Corp. and Continental Illinois Bank, 1984, pg. 300, as quoted in Nurisso and Prescott (2017)). The TBTF problem in banking can be broadly defined as "the unwillingness of regulators to close a large troubled bank because of a belief that the short-term costs of a bank failure are too high (Nurisso and Prescott, 2017, p. 1)". This attitude of the regulators can justified "on the basis of the adverse consequences of the failure of one institution for the whole financial system (and perhaps the economy at large) (Moosa, 2010, P. 319)." The main concerns with respect to these institutions relate to the significant moral hazards incentives to which TBTF banks are exposed. Indeed, the TBTF status encourages banks to increase investments in higher-risk projects because, in case of financial troubles, they can rely on the government bailouts (see, for an extensive discusion of the TBTF problem Stern and Feldman (2008, 2009).

Furthermore, in line with Castro (2013), Klein (2013) and Ghosh (2015), we specify the ratio of net loans over total assets ($CreditGR$) as a measure of the credit growth. Keeton (1999) finds evidence that banks that experience faster loan growth tend to suffer from more delinquencies. An explanation is that when banks increase their credit supply, they tend to do so by lowering their interest rate charges on loans and thereby lowering the standards for loan approvals.[29] Therefore, higher lending rates, especially during periods of economic slowdown, may be achieved by Italian banks through the adoption of lax credit standards, resulting in credit quality deterioration in the future. Also, as for the case of capital, investigating the relationship between credit growth and NPLs could capture the *"zombie lending"* phenomenon. An increase in the overall supply of credit could lead to higher NPLs if this credit is allocated to zombie firms following a "gamble for resurrection" type of logic (Angelini, 2018).[30] To capture the relationship between credit growth and NPLs we include the variable $CreditGR$ with two-years lags.

The dummy variable $Supervised$ takes the value of one if the bank is classified by the European Central Bank as *'significant supervised entity'* and as such is directly supervised by the ECB rather than by the Italian Central Bank (Banca d'Italia).[31,32] Similarly to $Size$, the relationship between $Supervised$ banks and NPLs is ambiguous. That is, being under the direct supervision of ECB could reduce moral hazard incentives as these banks are subject to a closer supervision and

[29] Likewise, Salas and Saurina (2002) note that "a target of rapid increase in market share can force the bank to reduce the quality of its borrowers (p. 212)".

[30] Furthermore, Cubillas et al. (2012) report evidence that, following a banking crisis, market discipline tends to be weakened by intervention policies during the crisis period. It is likely to assume that following the interventions of the Italian and European regulators, Italian banks were monitored less intensively in the aftermath of the crises, thus increasing the likelihood of banks lowering the lending standards and engaging in riskier investments, which ultimately could lead to higher the chances of borrowers' defaults (Vithessonthi, 2016).

[31] The ECB determines whether banks are considered significant according to four significance criteria: *size* (the total value of its assets exceeds €30 billion), e*conomic importance* (for the specific country or the EU economy as a whole), c*ross border activities* (the total value of its assets exceeds €5 billion and the ratio of its cross-border assets/liabilities in more than one other participating Member State to its total assets/liabilities is above 20%), d*irect public financial assistance* (it has requested or received funding from the European Stability Mechanism or the European Financial Stability Facility). Furthermore, a supervised bank can also be considered significant if it is one of the three most significant banks established in a particular country (see also Table 24, Section 2.3.3).

[32] As of 2015, the Italian Systemically Important Banks (SIB) included: UniCredit Spa, Banca Carige SpA, Veneto Banca, Unione di Banche Italiane (UBI), Intesa Sanpaolo, Mediobanca, Credito Emiliano, Banca Popolare di Vicenza, Banca Popolare di Sondrio, Banca Popolare di Milano, Banca Popolare dell'Emilia Romagna, Banco Popolare, Monte dei Paschi di Siena Spa (European Central Bank, 2016).

monitoring process from the regulatory authorities. However, the TBTF status entails that supervisors and governments will intervene in the event of bank failure, potentially leading to banks not assessing correctly the risk characteristics of current and past loan portfolios.

We control for the impact of the financial crisis by including a dummy variable $Crisis$ that takes the value of one for the post-crisis period (i.e., 2009-2015) and zero for the pre-crisis period (i.e., 2006-2008) as in Beaton et al. (2016). We expect to find a positive coefficient, meaning that, on average, banks experience higher NPLs in the post-crisis period.

Finally, a dummy variable $Industry$ capturing bank specialization is included and takes a value of one if the bank operates as a cooperative bank and zero if the bank operates as a commercial intermediary.[33] We expect cooperative banks to suffer from lower rates of NPLs due to their business model characterised by the so-called *relationship lending* and their ability to collect *soft* information on their existing and new customers. This helps cooperative banks reduce the asymmetric information between the lender and the borrower and hence reduces potential future defaults (see, for example, Stefani, 2016). Nonetheless, we recognise that the strong connections between cooperative banks and their customers (exemplified by the belonging to the same local community or through the presence of personal connections) could lead to these financial institutions being reluctant to terminate long-standing client relationships, thus resulting in cooperative banks continuing to extend credit to firms even when the conditions are not sustainable (see Calligaris et al., 2016). In this regard, De Mitri et al., (2010) note that ‘relationship lending may lead to a sub-optimal portfolio diversification and lock in the investment in case of firm distress (p. 6)’. Furthermore, cooperative banks may have fewer opportunities to dispose of their bad loans as they lack the size and expertise to attract specialized investors to the secondary market.

[33] According to the Italian Banking Law, two types of banks are allowed to operate under the legal framework of “Cooperative banks”, namely Popular banks and Cooperative banks. Throughout this paper we do not make this distinction so that when we refer to cooperative banks we refer to both popular and cooperative banks.

1.3.3 Macroeconomic determinants on bad loans

Concerning the vector of macroeconomic variables ($macro\_controls$), GDP growth ($GDPGR$) is included to capture the effect of the economic business cycle on the credit quality of banks. Prior studies tend to observe a counter-cyclical behaviour of NPLs, that is, higher $GDPGR$ is negatively correlated with NPLs. In fact, during upswings across the business cycle, the financial conditions of households and firms improve, reducing the likelihood of insolvencies. Conversely, during economic slowdowns, debtors will face financial difficulties as the unemployment rate increases, impairing borrowers' debt servicing capacity (see, Quagliariello, 2007; Castro, 2013; Klein, 2013). However, empirical studies have also found that during periods of economic growth banks may tend to increase their lending as they are overconfident about the economic cycle and the capacity of households and firms to repay their loans. That is, this general overoptimism makes banks taking on greater risks by lowering their credit standards. It follows that periods of economic growth could be followed by higher volumes of NPLs. To capture this relationship, we include in the model specification lagged values of $GDPGR$ as we assume that the impact of $GDPGR$ on NPL happens with two lags as in Beaton et al. (2016) and Dimitrios et al. (2016).

The level of sovereign debt ($SDEBT$) is included to measure the impact of rising sovereign tensions during the Sovereign Debt Crisis on banks' asset quality (see Louzis et al. 2012; Castro, 2013; and Ghosh, 2015) (Figure A3 in Appendix A depicts the evolution of the debt-to-GDP ratio in Italy for the period 2006-2015). We can identify two main channels through which sovereign tensions affect the banking system. On the one hand, a reduction in the value of government bonds held in portfolios of intermediaries affects their income and possibly their capital positions, thus undermining their funding ability. As depicted in Figure A4 in Appendix A, Italian intermediaries were the main buyers of Italian government bonds and played an essential role in the financing of the public sector thus making them particularly exposed to the worsening of sovereign indebtedness (Albertazzi et al. 2014; European Commission, 2015). Likewise, the deterioration of public finances places a 'ceiling' on the market evaluation, credibility and rating of national banks, hampering their funding capacity.[34] When the funding ability of banks is under strain, banks tend to cut their lending and thus debtors may potentially become unable to refinance their debts, leading to subsequent loan defaults (Louzis et al., 2012; Ghosh, 2015). In contrast, an increase in public debt is often followed by a cut in social expenditures and the wage component of government consumption (Perotti, 1996). This may render unserviceable a number of outstanding loans as households' finances are likely to experience a negative shock, while the second-order effect in corporate loans may take place due to decreasing demand (see Louzis et al., 2012; Ghosh, 2015). Furthermore, empirical studies have confirmed the link between banking and sovereign debt crises and found that the former most often either precedes or coincides with the latter (see Reinhart and Rogoff, 2011). In light of this discussion, we expect to find a positive relationship between the level of NPL and the Italian sovereign debt. Specifically, we specify two-years lags of $SDEBT$, that is, we assume that higher Sovereign debt in period $t-2$ and $t-1$ will result in higher NPL in period t.

Finally, the House Price Index (HPI) is included to capture the 'housing wealth' of Italian borrowers (see also Rinaldi and Sanchis-Arellano, 2006; Bofondi and Ropele, 2011; and Ghosh, 2015). In particular, an increase in the value of residential properties could negatively affect NPLs in several ways. For example, a higher value of the property improves the financial wealth of the borrower, thus helping him to face unexpected financial shocks and facilitating debt renegotiation, ultimately limiting the risk of becoming an insolvent debtor. Similarly, rising home prices could ease access to credit by boosting the underlying value of the houses used as collateral, which in turn reduces the likelihood of default. (see Nkusu, 2011; Beck et al., 2015; Ghosh, 2015). Furthermore, Bofondi and Ropele (2011) posit that:

> "house prices are positively related with the housing market cycle; thus, when the housing market is buoyant, a household that has difficulty meeting its debt obligations may find it easier to sell its house and extinguish the loan, without defaulting (p. 13)".

Therefore, our hypothesis is that HPI and NPL share a negative relationship.
We assume that the effect of higher HPI on NPLs happens with a one-year lag.

[34] Furthermore, Alberazzi et al. (2014) note that when the bank is downgraded, ""threshold effects'' – such as the exclusion of a bank's liabilities from the basket of securities that certain categories of investor are allowed to purchase – can further worsen its funding conditions (p. 338)".

1.3.4 Data

The dataset employed in this study consists of an unbalanced panel of 3641 observations on Italian banks spanning the period 2006-2015. Our analysis starts in 2006 due to the implementation of the International Accounting Standards (IAS) that occurred in 2005, making the individual balance sheets before and after 2005 non-comparable. The dataset includes observations on two types of financial institutions (i.e., commercial and cooperative banks), distributed across Italy (i.e., North West, North-East, Central and South). As shown in Table 2, the dataset consists of 460 observations of commercial banks and 3181 observations of cooperative banks.[35] The majority of commercial banks are located in the North-West of Italy, while for cooperative banks, almost half of the observations are located in the North-East and are less widespread in North-West Italy.[36] The data have been collected from the Bureau van Dijk Bankscope Database.[37]

Table 2. Distribution of bank-specific observations

SPECIALIZATION			
AREA	**Commercial**	**Cooperative**	**Total**
North-West	174	432	606 (16.64%)
North-East	97	1244	1341 (36.83%)
Centre	105	678	783 (21.51%)
South	84	827	911 (25.02%
Total	460 (12.63%)	3181 (87.37%)	3641

Note: the figures refer to the number of observations. In parentheses, we report the proportion of observations belonging to that Area/Specialization. **Source**: Bankscope Database

[35] The sample of cooperative banks includes 249 observations referring to popular banks.

[36] Within the Cooperative banks, one can identify three additional types of banks operating according to this legal framework. That is, Cooperative Banks (“Banche di Credito Cooperativo”), Rural banks (“Casse rurali”) and Raiffeisen banks (“Casse Raiffeisen”). The strong presence of Cooperative banks in North-East Italy is attributable to the great presence of these two last latter types of cooperative banks in Trentino-Aldo Adige (one of the twenty Italian regions). Indeed, out of the 1244 observations, 596 refer to banks operating in this region which correspond to 76 banks over a total of 337 cooperative banks in Italy (i.e., approximately 23% of Cooperative banks are located in this single region).

[37] Now Orbis Bank Focus.

The final dataset has been obtained after a series of preliminary data treatments. First, we exclude banks that present missing values as well as values equal to or less than zero. In addition, to accommodate the panel, only those banks for which at least three years of data were available have been included in the analysis. The average duration of the banks in the sample is approximately 9 years.

Table 3 reports the total observations per year. The sample includes fewer observations in the years at the endpoints mainly because of the lack of availability of data on NPLs. Table 4 and Table 5 describe the variables used in the Granger-causality models and their summary statistics, respectively. Table 6 presents the correlation matrix for the variables used in our estimation. None of the bank-specific variables exhibits a very high correlation, mitigating any multicollinearity concerns.[38] Concerning the macroeconomic variables, we observe that the highest correlation is between $SDEBT$ and HPI (-0.735). We also estimated the baseline models without HPI and the results remain unaltered.

Table 3. Total observations per Year

Year	Frequency	Percent (%)	Cumulative (%)
2006	284	7.80	7.80
2007	324	8.90	16.70
2008	366	10.05	26.75
2009	345	9.48	36.23
2010	360	9.89	46.11
2011	399	10.96	57.07
2012	403	11.07	68.14
2013	410	11.26	79.40
2014	410	11.26	90.66
2015	340	9.34	100.00
Total	**3,641**	**100.00**	

[38] The issue of multicollinearity arises when a strong linear relationship exists between two or more explanatory variables in a model. When two variables suffer from multicollinearity, the regression may present the following symptoms: Small changes in the data produce wide swings in the parameter estimates. Coefficients may have very high standard errors and low significance levels even though they are jointly significant and the R^2 for the regression is quite high. Coefficients may have the "wrong" sign or implausible magnitudes (see Greene, 2012).

Table 4. Variables Definition used for the Granger-causality models

Symbol	Variable	Description	Source	Expected Sign
		Dependent Variable		
$\boldsymbol{BL}$	Bad Loans	Logit Transformation of the ratio of BLs over Gross Loans	Bankscope	
		Bank-Specific Variables-Baseline Model		
$\boldsymbol{Transient}$	Transient Efficiency	Estimated level of Transient Efficiency	Author’s calculations	+/-
$\boldsymbol{Persistent}$	Persistent Efficiency	Estimated level of Persistent Cost Efficiency	Author’s calculations	+/-
$\boldsymbol{CAP}$	Capital	The ratio of Equity over Total Assets	Bankscope	+/-
$\boldsymbol{Size}$	Total Assets	The logarithm of total assets	Bankscope	+/-
$\boldsymbol{CreditGR}$	Net Loans to Assets	The ratio of Net Loans over Total Assets	Bankscope	+
$\boldsymbol{Supervised}$	Supervised Dummy	Dummy=1 if the bank is directly supervised by the ECB	European Central Bank	+/-
$\boldsymbol{Crisis}$	Crisis Dummy	Dummy=1 fo the post-crisis period 2009-2015	-	+
$\boldsymbol{Industry}$	Specialization Dummy	Dummy=1 if the bank is a Popular or Cooperative banks	Bankscope	+/-
		Macroeconomic Variables-Extended Model		
$\boldsymbol{GDPGR}$	GDP Growth	Annual Change in the Gross Domestic Product	World Bank	-/+
$\boldsymbol{SDEBT}$	Sovereign Debt	Government Debt to GDP Ratio	Bloomberg	+
$\boldsymbol{HPI}$	House Price Index	Annual Change in Residential House Prices	ECB Statistical Data Warehouse	-

Table 5. Descriptive Statistics of all variables

Variable	Obs	Mean	Std. Dev.	Min	Max
$\boldsymbol{BL}$	3,641	-3.118	0.961	-7.785	-0.420
$\boldsymbol{Transient}$	3,641	0.972	0.027	0.691	0.999
$\boldsymbol{Persistent}$	3,641	0.926	0.046	0.669	0.980
$\boldsymbol{CAP}$	3,641	10.58	3.628	1.11	37.1
$\boldsymbol{Size}$	3,641	6.288	1.535	3.095	13.86
$\boldsymbol{CreditGR}$	3,641	0.636	0.148	0.030	0.961
$\boldsymbol{GDPGR}$	3,641	-0.590	2.185	-5.51	2.1
$\boldsymbol{SDEBT}$	3,641	117.31	11.45	99.8	131.8
$\boldsymbol{HPI}$	3,641	101.62	5.745	90.81	107.6

Note: NPL refers to logit transformation of the ratio of NPLs over gross loans, $Transient$ refers to the measure of transient/time-varying efficiency (%), CAP is the ratio of equity over total assets (%), Size is the logarithm of total assets, $Persistent$ is the measure of persistent/time-invariant efficiency(%), $CreditGR$ refers to the ratio of net loans to total assets (%), $GDPGR$ is the Gross Domestic Product Growth (%), $SDEBT$ measures the ratio of debt over GDP (%), HPI is the annual change in residential house prices.

Table 6. Matrix of Correlation

	NPL	***Transient***	***CAP***	***Size***	***Persistent***	***CreditGR***	***GDPGR***	***SDEBT***	***HPI***
BL	1.0000								
Transient	**-0.0300****	1.0000							
CAP	**-0.1708*****	**0.0873*****	1.0000						
Size	**0.0523*****	**-0.0502*****	**-0.3777*****	1.0000					
Persistent	**-0.1174*****	0.0249	**0.1957*****	**-0.4487*****	1.0000				
CreditGR	**-0.3216*****	-0.0097	**-0.0334****	**0.1211*****	**0.2937*****	1.0000			
GDPGR	**-0.0318***	**0.2047*****	0.0004	-0.0121	-0.0033	0.0249	1.0000		
SDEBT	**0.5013*****	**-0.0780*****	**-0.1917*****	**0.1305*****	**-0.0408****	**-0.3242*****	**-0.1826*****	1.0000	
HPI	**-0.4296*****	**-0.1725*****	**0.1301*****	**-0.0960*****	**0.0351****	**0.3627*****	**-0.2021*****	**-0.7352*****	1.0000

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ refer to the level of significance of each correlation coefficient. The coefficients in bold are statistically significant. NPL refers to logit transformation of the ratio of NPL over gross loans, $Transient$ refers to the measure of transient/time-varying efficiency (%), CAP is the ratio of equity over total assets (%), Size is the logarithm of total assets, $Persistent$ is the measure of persistent/time-invariant efficiency(%), $CreditGR$ refers to the ratio of net loans to total assets (%), $GDPGR$ is the Gross Domestic Product Growth (%), $SDEBT$ measures the ratio of debt over GDP (%), HPI is the annual change in residential house prices.

1.4 Efficiency estimation[39]

To measure the cost efficiency of Italian financial intermediaries, we rely on the Stochastic Frontier Analysis method, which allows benchmarking the relative performance of a bank against a hypothetical best practice frontier. SFA is a valuable tool for both policy and managerial purposes and it is superior to the use of accounting-based financial ratios because is it a more inclusive and complete approach. In the following section, we introduce the econometric features of the SFA models.

1.4.1 Stochastic Frontier Analysis

Stochastic Frontier Analysis finds its origin in the two papers of Aigner et al. (1977) and Meeusen and van den Broeck (1977).[40] A detailed overview of the evolution of SFA from its origin to date is provided in Appendix A.2.2. For this study, we employ the heteroskedastic four-component (HFC) error model of Badunenko and Kumbhakar (2017), which takes the form of Eq. (1.4)

$$lnTC_{it} = f(y_{it}, w_{it}, \theta) + v_{0i} + v_{it} + u_{0i} + u_{it} \tag{1.4}$$

where $lnTC_{it}$ is the logarithm of the total costs of bank i for year t, y_{it} is a vector of outputs of the bank, w_{it} is a vector of input prices, θ refers to a vector of technology parameters to be estimated, v_{0i} denotes bank latent heterogeneity (i.e., bank fixed effects), v_{it} is the standard noise that captures random shocks, u_{0i} represents structural/time-invariant inefficiency while the u_{it} term captures managerial/time-varying inefficiency.

Rewriting Eq. (1.4) in full form, short-term and long-term efficiency are estimated using the following Fourier-flexible functional form (FFF):[41]

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[39] The empirical estimation of the efficiency scores has been done by Dr Badunenko in the context of the following publication: Badunenko O., Dadoukis A., Fusi G., and Simper R., 2021, The impact of efficiency on asset quality in banking, *The European Journal of Finance*.

[40] The literature that directly influenced the development of SFA was the theoretical literature on productive efficiency, which started in the 1950s with the work of Koopmans (1951), Debreu (1951) and Shepard (1953). (Kumbhakar and Lovell, 2003).

[41] The Fourier-flexible functional form (FFF) is a semi-non parametric approach that limits the issues arising when estimating the relationship between certain variables and the true functional form of this

$$lnTC_{it} = \alpha_0 + \sum_{i=1}^{3}\alpha_i lnY_i + \sum_{j=1}^{2}\beta_j lnW_j + \tau_1 t + \lambda_1 lnE$$
$$+ \frac{1}{2}\left[\sum_{i=1}^{3}\sum_{m=1}^{3}\gamma_{im} lnY_i lnY_m\right.$$
$$\left. + \sum_{j=1}^{2}\sum_{n=1}^{2}\delta_{jn} lnW_j lnW_n + \tau_{11} tt + \lambda_{11} lnE lnE\right] + \sum_{i=1}^{3}\sum_{j=1}^{2}\rho_{ij} lnY_i lnW_j \qquad 1.5$$
$$+ \sum_{i=1}^{3}[a_i \cos(z_i) + b_i \sin(z_i)]$$
$$+ \sum_{i=1}^{3}\sum_{j=1}^{3}\left[a_{ij}\cos(z_i + z_j) + b_{ij}\sin(z_i + z_j)\right] + v_{0i} + u_{oi} + v_{it}$$
$$+ u_{it}$$

We normalise the total cost ($lnTC$) as Eq. (1.5) is required to satisfy the following price homogeneity restrictions:

$$\sum_{i=1}^{3}\beta_m = 1; \quad \sum_{i=1}^{3}\delta_{jn} = 0; \quad \sum_{i=1}^{3}\rho_{ij} = 0$$

That is, multiplying all inputs prices by an amount $k > 0$ will cause a k −fold increase in the costs of the firm, holding output constant (e.g., doubling all input prices will double costs) (Coelli et al., 2005). The price homogeneity condition can be imposed by normalizing cost and input prices by one of the input prices. In our case, we normalize $lnTC$, lnW_1 and lnW_2 by the price lnW_3.

Furthermore, in the Fourier specification, z_i is the "adjusted" values of lnY_i. This is because the use of the FFF requires the data to be scaled to avoid the difference between the minimum and the maximum value of each input/output variable exceeding 2π (Mitchell and Onvural, 1996; Feng and Serletis, 2008).[42]

relationship is unknown. The FFF has been associated with Gallant (1981) and it combines the parametric Translog functional form with a series of trigonometric terms and has the advantage of being more flexible than the Translog and the Cobb-Douglas, thus allowing the data to reveal the true cost function of the industry rather than requiring the *a priori* assumption of it. The FFF is able to potentially represent any well-behaved multivariate function *f(x)* since the sine and cosine terms are mutually orthogonal and function-space-spanning (Mitchell and Onvural, 1996; Yu et al, 2011).

[42] That is, given that the trigonometric terms (i.e., the sine and cosine functions) are mutually orthogonal over the $[0, 2\pi]$ interval, it is required the rescaling of z_i such as the trigonometric terms span over the interval $[0.1 \times 2 \times \pi, \; 0.9 \times 2 \times \pi]$ in order to reduce the approximation problems near

In addition, following Altunbas et al. (2000), Girardone et al. (2004) and Beccalli and Frantz (2009), the trigonometric terms in the FFF are included only for the output quantities while input prices are solely defined by the Translog terms. The standard symmetry conditions have been imposed on the Translog portion of the FFF function:

$$\gamma_{im} = \gamma_{mi}, \forall \text{ i, m} \quad \text{and} \quad \delta_{jn} = \delta_{nj} \ \forall \text{ n, j}$$

That is, an effect of increases in the price of factor i on the demand for factor m is the same as the effect of a rise in the price of factor m on the demand for factor i.

1.4.2 Advantages of the use of the four-error components

In this section, we stress that the use of the HFC model is a major improvement over prior literature for the following reasons. First, estimating a model with only one type of inefficiency is likely to give incorrect estimates of inefficiency (Tsionas and Kumbhakar, 2014), implying that prior studies may have conveyed misleading results on both the levels and sources of the inefficiency of Italian banks.

Secondly, by explicitly estimating and modelling the short and long-term parts of efficiency, we contribute to the understanding of where bank inefficiencies are stemming from. This allows the firm's management and policymakers to respond with different improvement strategies, something that was not possible if the standard measure of overall efficiency were to be employed. For instance, if some of the determinants are policy related, we can infer the effect of changing regulation on efficiency (see Kumbhakar et al., 2014). The importance for policy purpose of the parametrization of the error terms is best stressed by Lien et al. (2018), who note that:

> "establishing determinants of persistent inefficiency could help decision-makers to develop strategies to remove long-term impediments, such as too rigid regulations or other structural rigidities. On the other hand, transient inefficiency can be due to bad luck, management mistakes, etc., that can get corrected. Knowledge about these drivers of transient inefficiency may help

the endpoints $z_i = u_i(\ln \mathrm{Y_n} + w_i)$, where u_i *and* w_i are scaling factors that limit the periodic sine and cosine trigonometric functions wititnh one period length 2π.

in improving the efficiency of individual firms in the short-run (p.54)".

This is because the *persistent inefficiency* term (u_{0i}) captures time-invariant and therefore can determine long-run sources of inefficiency, which may arise from "systematic behavioural shortcomings" (Blasch et al., 2017, p. 92) such as recurring identical management failures, investment in inefficient infrastructures or machines, structural problems within the industry (e.g., inefficient regulation), sector rigidities or resources misallocations which can be difficult to change over time (see Filippini et al., 2018). Conversely, *transient inefficiency* (u_{it}) refers to short-run, time-varying sources related to inefficiencies. These may relate to "non-systematic management problems that can be solved in the short term" (Filippini and Greene, 2016, p. 187) such as the sub-optimal use of certain machines. It follows that the parametrization of the *transient* and *persistent efficiency* terms helps to tackle different concerns with respect to bank inefficiencies. That is, the choice of the determinants of *persistent inefficiency* could be driven by considerations about those factors that could represent long-run sources of inefficiency (e.g., the regulatory framework and geographical location of the firms) while determinants of *transient inefficiency* could be identified by considering those factors that cause a temporary change in the inefficiency level of firms.

1.4.3 Specifications of the error components

Transient Efficiency

As aforementioned, in the HFC model, the heteroskedasticities of the inefficiency terms, both time-invariant (u_{0i}) and time-varying (u_{it}), can be interpreted as determinants of the inefficiencies components. The determinants of *transient inefficiencies* are incorporated in the pre-truncated variance of u_{it}:

$$u_{it} \sim N^{+}\left(0, \sigma_{uit}^2\right) \text{ where } \sigma_{uit}^2 = \sigma_u^2 \exp(z_{uit}\gamma_u), \quad \mathrm{i} = 1, \dots, \mathrm{n}, \quad \mathrm{t} = 1, \dots, \mathrm{T_i} \qquad 1.6$$

where z_{uit} is a vector of variables that explains time-varying inefficiency. The determinants of transient inefficiencies can be firm-specific and time-varying. Thus, u_{it} is modelled as a function of the size of the bank ($lnTA$), of a dummy to control for the financial crisis and as a function of time in both linear and quadratic form (t, t^2) (see Eq. (1.7)):

$$\sigma_{uit}^2 = \sigma_u^2 \exp(z_{uit}\gamma_u), \quad \mathrm{i} = 1, \dots, \mathrm{n}, \qquad \mathrm{t} = 1, \dots, \mathrm{T_i}$$
$$where \;\; z_{uit} = t, t^2, Post - Crisis, ln(TA) \tag{1.7}$$

As aforementioned, the transient part of inefficiency could stem from non-systematic management mistakes or non-systematic minimization issues that can be corrected in the short-run. As such, we include the dummy variable, $Post - Crisis$, taking the value of 1 for the post-crisis years 2009-2015 and zero for the pre-crisis period 2006-2008, to investigate the impact of the global financial crisis. This is because the financial shock could have given rise to temporary minimization problems (e.g., higher borrowing costs), resulting in higher short-term inefficiencies. Furthermore, we control for the size of banks by including the logarithmic value of total assets ($lnTA$). Large banks tend to have a more diversified portfolio than smaller intermediaries and this enables them to borrow at lower costs because the market perceived them as "safer" (Bertay et al., 2013). Analogously, the superior portfolio's diversification could help to reduce the marginal cost of risk management (see Feldman, 2010 and Huges and Mester, 2013). Also, lower borrowing costs are achieved if these large banks are perceived as being too-big-to-fail. Indeed, as noted by Davies and Tracey (2014):

> "There are potential funding cost advantages for banks considered by investors to be TBTF. Bank debt investors may not demand a risk premium that corresponds to the true risk level of a bank, owing to expectations of government support to avert its failure (p. 220)".

The technological innovations that are reshaping the banking industry may also bring additional advantages to large banks in the form of reduced costs for acquiring information, eroding the traditional advantages that small intermediaries had in collecting *soft* information. Additionally, the costs of investments in information technology systems are better absorbed by large banks because IT costs are *fixed costs* that can be spread over a wider customer base (Wheelock and Wilson, 2018). Overall, the rationale for controlling for the size of banks relates to the potential presence of scale economies among large banks, which could imply lower costs and thus higher short-term efficiency for these intermediaries. It is also worth mentioning that, if size relates positively to market power, large banks could be expected to pay less for their inputs (Hauner, 2005). Finally, a reasonable assumption is that large banks have an advantage in the job market by being able to "attract the best people", that is, they are able to hire more talented workers than smaller banks. Recalling Section 1.2.1, our view is that inefficiency can be thought of as an index of managerial abilities. As such, it is important to control for the possibility that large financial institutions employ higher-quality personnel that could make a difference in the cost-minimization behaviour of banks.

Finally, as in Casu et al. (2013) and Casu et al. (2017), the linear and quadratic time trend terms (t, t^2) are used to capture temporal variations in transient inefficiency that could results from the adoption of new technologies, *ceteris paribus* (Wang, 2002; Lai and Kumbhakar, 2016).

Persistent Efficiency

Concerning *persistent efficiency*, these determinants are introduced in the pre-truncated variance of u_{0i}, (see Eq. (1.8):

$$u_{0i} \sim N^{+}\left(0, \sigma_{u0i}^{2}\right) \text{ where } \sigma_{u0i}^{2} = \sigma_{u0}^{2} \exp(z_{u0i}\gamma_{u0}), \quad \mathrm{i} = 1, \dots, \mathrm{n}, \qquad 1.8$$

where z_{u0i} is a vector of covariates that define the heterosckedasticity function of persistent inefficiency and, by definition, is time-invariant. That is, z_{u0i} is a vector of variables that can be viewed as drivers of *persistent inefficiencies*. Factors appearing in z_{u0i} are firm-specific but time-invariant. It follows that the variance σ_{u0i}^{2} is explained only by *natural* time-invariant variables (e.g., regional location, a period with persistent policy regime, education, etc.) that are outside banks' control (Lien et al., 2018).

In this study, we assume that banks' business model and the geographical location of banks' headquarter affect the level of persistent inefficiency exhibited by Italian banks. Thus, u_{0i} depends on a dummy capturing the specialization of the bank, taking the values of 1 if the bank is a cooperative bank and zero if the bank is a commercial bank, and on a dummy representing the four macro geographical areas of Italy (i.e., North-West, North-East, Centre and South).[43] Recalling Eq. (1.8):

$$\sigma_{u0i}^2 = \sigma_{u0}^2\, exp(z_{u0i}\gamma_{u0})\,, \;\; i = 1, \dots, n, \qquad 1.9$$

$$where\; z_{u0i} = \; Specialization\,, Area$$

With the dummy for $Specialization$, we aim to capture the institutional and regulatory framework in which Italian banks operate, as cooperative banks and commercial banks are subject to remarkably different legal requirements. In particular, Italian Banking Law requires cooperative banks to be *local* and *mutual.*[44,45] These requirements entail that, for instance, cooperative banks have limited opportunity to expand their branch network as they are required to operate within a strictly defined territory. Additionally, the *mutuality* requirement is likely to result in different managerial objectives compared to commercial banks.[46] For instance, it could be the case that cooperative banks have different objectives other than cost minimization behaviour, such as serving the local community and maximizing profits for members (Girardone, et al., 2004). It is important to clarify that bank specialization is considered a source of persistent inefficiency as the business practices of these banks are the outcome of regulations which have been in

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[43] North-West includes the following regions: Piedmont, Valle d'Aosta, Lombardy and Liguria. North-East includes: Trentino, Veneto, Friuli Venezia Giulia and Emilia Romagna. Centre includes Tuscany, Umbria, Marche, and Lazio. South includes Abruzzo Molise, Campania, Puglia, Basilicata, Calabria, Sicily, and Sardinia.

[44] The Banking Law that regulates the Italian banking System is the "Testo Unico Bancario" (D.Lgs. n. 385/93), updated in 2016 (D.Lgs. n. 223/16). Cooperative banks are regulated accordingly to the Article 28

[45] As it will be outlined in Section 5.3.2, our sample of cooperative banks includes both the types of banks that are allowed to operates under this legal framework, that is, Cooperative banks *("Banche di Credito Cooperativo")* and Popular banks ("*Banche Popolari*"). Popular banks are, on average, significantly larger than cooperative banks and they are not subject to the requirement of "mutuality" and "locality". Nonetheless, in line with cooperative banks, they give equal voting rights to all members (one member-one vote) and place limits to ownership rights.

[46] Being *mutual* and *local* consists of the following legal features: 1) having at least 50% of risky assets towards their members or invested in government bonds; 2) members must have their domicile and/or continuative business within the territory where the bank operates (the area of competency is identified as i) the municipalities where the cooperative bank has the registered office ii) the municipalities where there are branches of the cooperative banks and iii) adjacent municipalities to the municipalities where there are registered offices or branches; 3) every member of the cooperative banks has one vote, independently of how many shares he/she owns; 4) cooperative banks must have five hundred shareholders; 5) the maximum individual participation cannot exceed one hundred thousand euros. (Article 34), 6) at least 70% of the annual earnings allocated to legal reserves (with at least 3% of the annual earnings allocated to mutual funds for the development of the cooperative).

place for decades, and thus are now embedded in the practices of these banks. Studies that have identified bank specialization as a potentials source of cost inefficiency include, but are not limited to Altunbas et al. (2001), Maudos et al. (2002), Girardone et al. (2004), and Berger et al. (2009).

In a similar manner, the geographical location of the banks could represent a source of persistent inefficiency. Italy is well-known for its deep-rooted differences in terms of culture, wealth and economic development within its territory that result in significant structural imbalances (Montagnoli et al., 2016). Several studies have demonstrated how regional disparities can indeed exist and potentially had affected the development, structure and features of the banking system. These disparities have been documented by Faini et al. (1992) who found that commercial banks in Southern Italy have typically higher operating costs and tend to charge higher interest rates compared to their counterparts in North Italy. Their findings also suggested poor screening and monitoring practices in South Italy (this seems to be confirmed by Figure 2, Panel B). Similarly, Usai and Vannini (2005) reported how the interest rate applied by Southern banks has been regularly a few percentage points above those from the Northern part of Italy throughout the period 1970-1992. Both Faini et al. (1992) and Usai and Vannini (2005) explained the interest rate gap in terms of differences in the risk conditions and lack of competition among banks in the South. Furthermore, Resti (1997), evaluating the efficiency of Italian intermediaries between 1988 and 1992, concludes that the Italian banking system is split in two: “the banks in North Italy are closer to the middle-European efficiency levels, while the South and the Centre of the country lag behind (p. 246)”. Similar conclusions were reached by Montagnoli et al. (2016), who report stark differences in the pass-through and speed of adjustment of the Italian regional interest rate to changes in the money market rate. In light of this, we expect to find that the geographical location determines the overall level of persistent inefficiency encountered by banks. Among the studies that recognise regional disparities across Italy as a factor determining the level of bank efficiency, there are Resti (1997), Girardone et al., (2004), Battaglia et al., (2010), Aiello and Bonanno (2013).

To conclude, we assume that both the characteristics of the Italian institutional framework (e.g., legal requirements, type of ownership) and the geographical location of intermediaries could represent potential sources of long-term inefficiencies because these features of the Italian banking system have a time-invariant nature and the management of the banks cannot change/remove these inefficiencies in the short-term (e.g., closing down the entire branch network in one area to move it in another is a process that, if not impossible/improbable, may take several years to happen and to be implemented). In light of this discussion, it is worth recalling the aforementioned differences in NPLs that can be observed across regions and types of banks (see Section 1.1.3 and Figure 2), which suggest that these characteristics may have an important role in explaining bank performance in Italy.

Random noise component

The HFC model of Badunenko and Kumbhakar (2017) also accommodates heteroskedasticity in the firm-specific effects term (v_{0i}) and in the random noise (v_{it}). In this case, the heteroskedasticities are viewed as persistent and long-run 'production risk', respectively. The interpretation of the heteroskedasticities of v_{0i} and v_{it} relies on the argument advanced by production economists, mainly in agriculture, in considering the variance of production shocks as risk, which in turn, can be explained by some observed phenomena (see, for instance, Jaenicke et al., 2003; Guttormsen and Roll, 2014).[47] The random noise component has been specified as in Eq. (1.10):

$$v_{it} \sim N\left(0, \sigma_{vit}^2\right) \text{ where } \sigma_{vit}^2 = \sigma_v^2 \exp(z_{vit}\gamma_v), \quad \mathrm{i} = 1, \dots, \mathrm{n}, \quad \mathrm{t} = 1, \dots, \mathrm{T_i} \tag{1.10}$$

where z_{vit} denotes a vector of covariates that define time-varying production risk. In our study, v_{it} has been parametrised in terms of macro-variables, namely GDP Growth ($GDPGR$), inflation and unemployment rate:

$$\sigma_{vit}^2 = \sigma_v^2 \exp(z_{vit}\gamma_v), \quad \mathrm{i} = 1, \dots, \mathrm{n}, \quad \mathrm{t} = 1, \dots, \mathrm{T_i} \tag{1.11}$$

$$where\ z_{vit} = GDPGR, Inflation, Unemployment$$

The assumption is that the conditions of the economic environment in which banks operate can be interpreted as production risk.

[47] The concept of 'production risk' has been introduced by Just and Pope (1978), who first suggested to consider the heterosckedasticy of the noise terms as risk.

Concerning firm effects, we specify Eq. (1.12):

$$v_{0i} \sim N(0, \sigma_{v0i}^2) \text{ where } \sigma_{v0i}^2 = \sigma_{v0}^2 \exp(z_{v0i}\gamma_{v0}), \quad \mathrm{i} = 1, \dots, \mathrm{n} \tag{1.12}$$

Where z_{v0i} represents a vector of time-invariant covariates that determines persistent production risk. Given the absence of naturally time-invariant determinants of production risk, the bank specific effect component v_{0i} has not been parametrised but it is assumed to be independently and identically distributed (i.i.d).

Table 7 summarizes the variables used to explain the levels of efficiency and production risk of Italian banks.

Table 7. Determinants of Inefficiency and Production Risk

Error Component	Determinants
Persistent Inefficiency ($\boldsymbol{u_{0i}}$)	$Specialization, Area$
Transient Inefficiency ($\boldsymbol{u_{it}}$)	$t, t^2, \ln(TA), Post - Crisis$
Random Noise ($\boldsymbol{v_{it}}$)	$GDP\ Growth, Inflation, Unemployment$
Banks Specific Effects ($\boldsymbol{v_{0i}}$)	i.i.d.

1.4.4 The choice of a cost function

As an additional consideration, we briefly discuss the choice to use a *cost function* to measure bank efficiency (see Eq. (1.4)). Using Stochastic Frontier Analysis, we are able to measure inefficiency in terms of a deviation from a best practice frontier that represents the industry's underlying production technology (Goddard et al., 2014). Empirical studies on banking efficiency have mainly focused on three concepts of inefficiency, namely cost, standard profit and alternative profit inefficiency.[48,49]

The study adopts a cost frontier approach for the following reasons. First, cost efficiency captures the ability of banks to provide services without wasting resources (Fethi and Pasiouras, 2010), which in the long term will result also in higher levels of profit efficiency. Therefore, despite it is reasonable to assume that

[48] Other, less common frontiers include: revenue frontier, input-oriented distance function, output-oriented distance function.
[49] In the profit efficiency frameworks, efficiency measures by how close a bank comes to earning maximum profits given its output level rather than its output prices.

profit efficiency is "the natural ultimate goal" of banks, cost efficiency can be viewed as an important means of reaching long-run profit efficiency (Delis et al., 2009). Secondly, we favour a cost minimization behaviour given the contracting economic environment and the current severe issues faced by the Italian banking system (e.g., NPLs). That is, in the aftermath of the financial crisis and the sovereign debt crisis, it is legitimate to presume such cost minimization behaviour among Italian banks, which, for example, may have involved branch closure and reduction in the workforce.[50]

Thirdly, as noted by Kumbhakar and Lovell (2000),

> "[the cost minimization objective] is particularly appropriate in competitive environments in which input prices (rather than input quantities) are exogenous, and in which output is demand-driven and so also can be considered as exogenous (p. 132)".

In other words, in competitive settings such as the banking industry, the cost minimization criterion is particularly applicable. Finally, in a recent study, (Assaf et al., 2019) find that cost efficiency is superior to profit efficiency in predicting bank failures, concluding that cost efficiency is a better proxy for managerial ability.

1.4.5 The choice of inputs, outputs and risk variables

After presenting the features of the four-error component model and the rationale to use a cost function, this section discusses the parameters of Eq. (1.5) that remain to be defined.

One of the main challenges faced by researchers investigating bank efficiencies relates to the identification and definition of inputs (w_{it}) and outputs (y_{it}) for multi-product financial firms (see Eq. (1.5) above). In particular, the most debated issue concerns the role played by bank deposits, which can have both input and output characteristics. Three main approaches to model the role of deposits appear in the literature: the *production approach* (Benston and Smith, 1976), the

[50] Table A1 in Appendix A reports the number of bank branches and the number of employees of domestic credit institutions in Italy over the period 2006-2015. It emerges that the number of branches decreased from 32,334 in 2006 to 30,475 in 2015. Similarly, the number of employees declined from 339 thousand in 2006 to 299 thousand in 2015.

value-added approach (Dietsch and Lozano-Vivas, 2000; S. Rossi et al., 2005; Yildirim and Philippatos, 2007) and the *intermediation approach.*

The approach adopted in this chapter is the *intermediation approach,* which considers banks as intermediaries between those individuals who possess a surplus of funds and those who seek financing (Sealey and Lindley, 1977). That is, banks are thought of as firms whose main role is the collection and transformation of deposits, using physical capital and labour, into loanable funds, rendering deposits as the primary input of the production process of banks. The *intermediation approach* is the most common approach used when modelling banking efficiency (see, for example, the extensive review by Fethi and Pasiouras, 2010).[51] It has also been extensively used in the context of Italy (see Casu and Girardone, 2002; Girardone, et al., 2004; Aiello and Bonanno, 2013; Giordano and Lopes, 2015) as this approach best describes the production process of Italian financial intermediaries. Indeed, as noted by Favero and Papi (1995):

> "[the intermediation] approach is particularly appropriate for banks where most activities consist of turning large deposits and funds purchased from other financial institutions into loans and financial investments (p.338)".

Italian intermediaries are characterised by a traditional business model, heavily based on lending activities and with a stable retail funding base (Cosma and Gualandri, 2012), thus making this approach particularly applicable in the Italian setting. Therefore, following the intermediation approach, we define three inputs (X) and three outputs (Y). The input variables are Personnel Expenses (X_1)), Total Interest Expenses (X_2) and Other Operating Expenses (X_3). Concerning the choice of outputs, we select three variables: Net Loans (Y_1), Total Non-Interest Operating Income (Y_2) and Other Earning Assets (Y_3). The price of Labour (W_1) has been computed as personal expenses over the number of employees, the price of Borrowed Funds (W_2) as total interest expenses over total deposits, Money Market and Short-

[51] For instance, with respect to the role of deposits, they find "around 95 applications in bank efficiency where the monetary value of deposits is part of the input vector and 20 applications where deposits are part of the output vector.10 Around 30 studies use interest expenses as an input without using the stock of deposits […]. In another 7 applications, the stock of deposits is used as an output and the interest expense paid on deposits constitutes an input […]. Furthermore, 7 studies use time deposits and saving deposits as input and demand deposits as output […]. Finally, in a few applications the deposits are included as both an input and an output […] (Fethi and Pasiouras, 2010, p.191)"

term Funding and the price of Physical Capital (W_3) as other operating expenses over total assets.[52] The Total Cost (TC) of banks is computed by summing the three input variables (i.e. X_1, X_2 and X_3). The summary statistics for the variables used to model the efficiency of Italian financial institutions are displayed in Table 8 while the definitions of the variables are presented in Table 9 together with examples of papers that have employed similar input/input prices/output definitions.

Additionally, when modelling cost efficiency, it is also pivotal to account for potential risk factors in the production process of banks and, in this regard, we include the logarithm value of total common equity in its linear and quadratic form ($lnE;lnE^2$).[53] The regulatory regime in which banks operate may force the institutions to hold a minimum capital-to-assets ratio that is above the optimal cost-minimising level that banks otherwise would maintain (Huges and Mester, 1993). Analogously, risk-averse managers may hold more capital than the optimal cost-minimising level. Including equity in the model specifications allows to control for managerial risk preferences and prevents from labelling as inefficient an "optimally behaving bank" (Yildirim and Philippatos, 2007, p. 131). Furthermore, Berger and Mester (1997) note that failing to account for financial capital may lead to scale bias arising from the different funding preferences between large and small intermediaries. Capital, in fact, can be considered an alternative to deposits as a source of funds for loans. Given that raising equity is more costly than collecting deposits, whether banks fund themselves with debt financing (as large banks may be prone to do) or through the collection of deposits may play an essential role in cost analyses. Finally, the level of equity determines the probability of insolvency of the institutions, directly affecting the cost of banks through i) the risk premium that they have to pay for raising funds ii) the "intensity of risk management activities that banks undertake" (Berger and Mester, 1997, p. 909). A similar approach to account for bank risk preferences has been used by Altunbas et al., (2000), Maudos et al. (2002), Akhigbe and McNulty (2003) and Fiordelisi et al. (2011), and Dimitras et al. (2018).

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[52] With respect to the price of Physical Capital, it is usually measured by the ratio of operating expenses over fixed assets (e.g., Altunbaş et al., 2001; Goddard et al., 2014). Nonetheless, due to data availability, we used the value of total assets as a proxy for fixed assets.

[53] As Mester (1996) states, "there is good reason to believe that cost-minimization does not fully explain a bank's capital level (p. 1026)".

Finally, we include in Eq. (1.5) a time trend variable t and t^2 to capture technological changes. Advancements in banking technology may include improvements in information technology (e.g., technology through which banks and other creditors collect and share data about the creditworthiness of a particular borrower), electronic payment technologies (e.g., new methods of transferring funds electronically), internet and mobile banking (Berger, 2003). Technological progress could also capture

> “learning by doing and organisational changes allowing for the more efficient use of existing inputs“ (Altunbas et al., 2001, p.1939).

More generally, technological change refers to all those factors that are not explicitly taken into account in the modelling strategy such as regulatory changes and financial innovation (Hunter and Timme, 1991).

Table 8. Summary Statistic of Input, Outputs and Input Prices

	Variable	Observations	Mean	Std. Dev.	Min	Max
			Dependent Variable			
Total Cost	TC	3,641	229.5718	2011.63	1	53984
	Inputs					
Personnel Expenses	X_1	3,641	68.38	547.20	0.4	10025.4
Interest Expenses	X_2	3,641	105.241	1057.34	0.153	36068.6
Other Operating Expenses	X_3	3,641	55.95	467.18	0.3	9999.4
	Outputs					
Net Loans	Y_1	3,641	4067.43	32329.41	8.2	602763.3
Non-Interest Operating Income	Y_2	3,641	69.70	548.48	0.1	11308
Other Earning Assets	Y_3	3,641	2171.29	19894.8	2.1	354432.9
	Input Prices					
Price of Labour	W_1	3,641	0.069	0.008	0.010	0.186
Price of Borrowed Funds	W_2	3,641	0.024	0.015	0.000	0.111
Price of Physical Capital	W_3	3,641	0.009	0.004	0.000	0.1101
	Risk Variable					
Total Common Equity	EQ	3,641	484.764	3820.816	2.1	67703.2

Source: Bankscope Database. **Note**: all the variables are adjusted for inflation using the GDP deflator and are expressed in millions of euros.

Table 9. Variables Definition

Symbol	Variable	Definition	Papers
		Dependent Variable	
TC	Total Cost	Sum of X_1, X_2 and X_3	
		Inputs	
X_1	Personnel Expenses	Includes wages, salaries, social security costs, pension costs and other staff costs, including expensing of staff stock options	Maudos et al., (2002); Yildirim and Philippatos, (2007)
X_2	Total Interest Expenses	Includes Interest Expenses on Customer Deposits + Other Interest Expenses + Preferred Dividends Paid and Declared	Beccalli and Frantz, (2009); Battaglia et al., (2010)
X_3	Other Operating Expenses	Includes Depreciation, Amortisation, Administration Expenses such as IT, Marketing, Rent, Audit and Professional Fees, Operating Lease rentals	Altunbaş et al., 2001; Beccalli et al., (2006)
		Outputs	
Y_1	Net Loans	Includes Residential Mortgage Loans, Other Mortgage Loans, Other Consumer/Retail Loans Corporate And Commercial Loans) – (Loan Loss Reserves)	Koutsomanoli-Filippaki et al., (2009); Duygun et al., (2013)
Y_2	Non-Interest Operating Income	Includes Net Gains (losses) on Trading & Derivatives + Net Gains (losses) on other Securities + Net Insurance Income + Net Fees and Commissions + Other Operating Income	Yildirim and Philippatos, (2007); Xiang, et al., (2013); Dong et al., (2017);
Y_3	Other Earning Assets	Loans and Advances to Banks and Securities Investments	Beccalli et al. (2015); Staikouras et al., 2008; Dimitras et al. (2018)
		Input Prices	
W_1	Price of Labour	X_1 / Number of Employees	Girardone et al., (2004); Xiang et al., (2013); Assaf et al., (2019)
W_2	Price of Borrowed Funds	X_2 / Total Deposits, Money Market and Short-term Funding	Girardone et al., (2004); Carvallo and Kasman, (2005);
W_3	Price of Physical Capital	X_3 / Total Assets	
		Risk Variable	
EQ	Total Common Equity	Includes Common Shares and Premium, retained earnings, reserves for general banking risks and statutory reserves	Dong et al., (2017); Dimitras et al. (2018) ; Assaf et al., (2019)

Source: Bankscope Database

1.5 Empirical results

1.5.1 Cost efficiency results

In this section, we present the cost efficiency results obtained from the estimation of the recently developed model of Badunenko and Kumbhakar (2017) (see Section 1.4 above). These results will be later employed in our Granger-causality model (see Section 1.3.1 above) to examine the intertemporal relationship between NPLs and cost efficiency.

Overall, the Fourier cost function estimation results show a good fit and are in line with the theory and other studies - implying that higher prices of the inputs used in the bank production process will be reflected in higher costs (see Table A2 in Appendix A) (see Badunenko and Kumhakar, 2017).[54,55]

1.5.1.1 Overall cost efficiency

We begin our analysis by focusing on the overall measure of efficiency. Following Badunenko and Kumbhakar (2017), we obtain a measure of overall cost efficiency (CE) as the product of transient (u_{it}) and persistent efficiency (u_i):

$$Overall\ Cost\ Efficiency = u_i \times \ u_{it} \tag{1.13}$$

We first focus on this aggregated measure because it allows us to better appreciate the importance of decomposing efficiency into its transient and persistent components. From a general perspective, overall efficiency is found to range between 46.9% and 97.9% with an average value of 90.1% (see Table 10), and we note that this is the result of average transient efficiencies of approximately 97.3% and average persistent efficiencies of 92.6%. This suggests that the primary source of inefficiencies originates from long-term, permanent, structural inefficiencies of the Italian banking industry, while temporal managerial inefficiencies of the individual

[54] As a first step, to select the functional form that best approximates the technology of our sample, we perform a Likelihood Ratio (LR) test of the validity of the hypothesis that all the coefficients of the trigonometric terms of the FFF are jointly equal to zero. The LR statistic for testing the Translog against the Fourier is 103.72, which exceeds the critical value of a mixed χ^2_{18} distribution of 34.16, confirming our model specification.

[55] The parameters of the Fourier cost function have been estimated simultaneously using the single-step full maximum likelihood procedure first proposed in Colombi et al. (2014) and extended by Badunenko and Kumbhakar (2017). For an extended discussion concerning this procedure see Badunenko and Kumbhakar (2017).

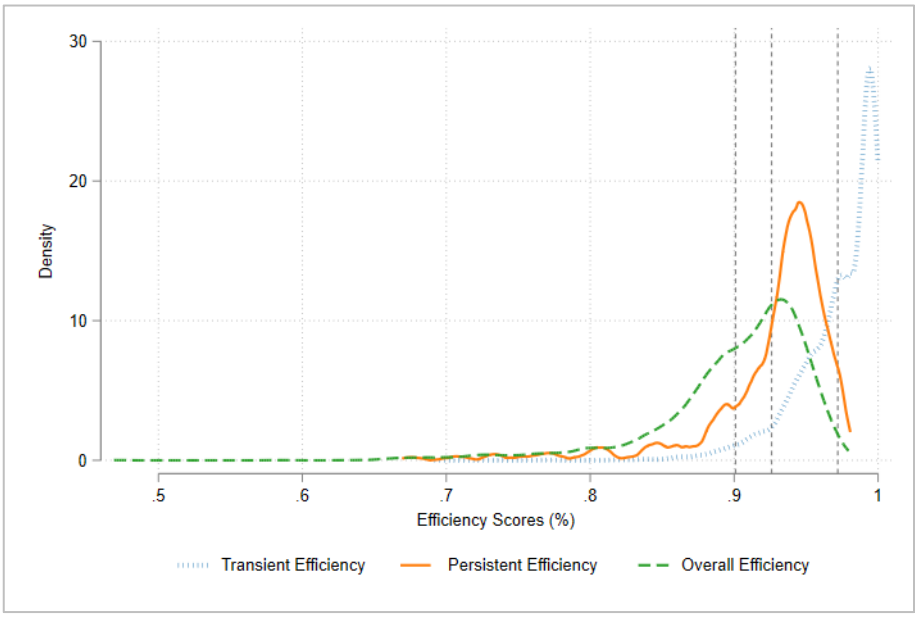
financial institutions play a minor role. A graphical representation of these differences is shown in Figure 3, which displays the kernel densities functions of the predicted transient, persistent and overall efficiency scores. We note that the distribution of transient efficiency scores is remarkably skewed towards one whilst the distributions of persistent efficiency, and thus of overall efficiency, are characterised by a greater dispersion.

Table 10. Summary Statistics of Cost Efficiency

Variable	Obs.	Mean	Median	Std. Dev.	Min	Max
Transient Efficiency	3,641	0.973	0.9804	0.027	0.691	0.999
Persistent Efficiency	3,641	0.926	0.9399	0.046	0.669	0.980
Overall Efficiency	3,641	0.901	0.9138	0.052	0.469	0.979

Note: the measure of overall efficiency is given by the product of transient and persistent efficiency.

Figure 3. Densities Functions of Transient, Persistent and Overall Efficiency



Note: the blue solid vertical line refers to the average value of transient efficiency (0.972), the red vertical line refers to the average value of persistent efficiency (0.926) while the green dotted vertical line refers to the average value of overall efficiency (0.901). The distributions refer to the estimated kernel densities.

1.5.1.2 Transient cost efficiency: determinants and overall trend

In the four-error decomposition model, the transient component captures temporary minimization problems of the bank as well as non-systematic sources of inefficiencies that could be resolved in the short term. Over the period 2006-2015, Italian banks have had an average level of transient efficiency of approximately 97.2% with estimates ranging from 69.1% to 99.9% (see Table 10), suggesting an overall negligible level of short-term inefficiencies. Table 11 reports the coefficient estimates of the determinants of the transient inefficiency component as defined in Section 1.4.3.

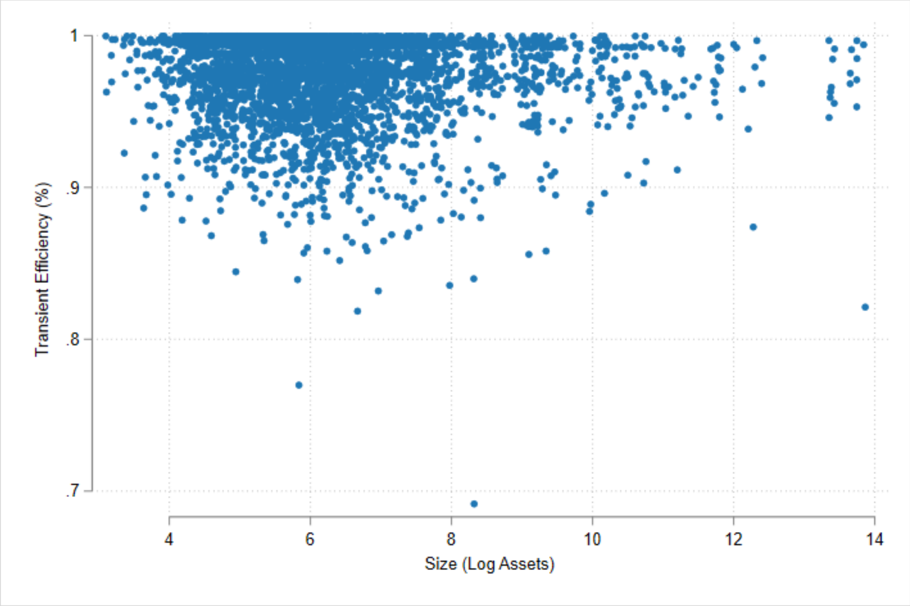
Overall, the size of banks ($lnTA$) does not contribute to explaining the level of time-varying inefficiencies of Italian banks given the statistically insignificant coefficient (0.055). A simple scatter diagram (Figure 4) shows that the transient efficiencies scores are clustered towards one, without any particular relationship with the size of the bank. These results contrast with the findings of Aiello and Bonanno (2013), who report a significant and negative relationship between bank size and the cost efficiency performance of Italian banks for the period 2006-2011 (albeit using a different approach to estimate cost efficiency). However, in line with our results, Girardone, et al. (2004) do not find statistical evidence that larger banks are more or less efficient than their smaller counterparts when assessing the efficiency of Italian banks over the period 1993-1996. The insignificant relationship between the size of the financial institutions and the level of short-term managerial inefficiencies is an interesting result as it could suggest that large Italian banks do not display economies of scale or that they are not able to exert enough market power to enjoy lower input prices.

Table 11. Determinants of the variance of the transient efficiency component

	Coefficient	**Z-value**
$\boldsymbol{Intercept}$	-24.917***	(-11.09)
$\boldsymbol{lnTA}$	0.055	(1.30)
$\boldsymbol{t}$	8.277***	(8.93)
$\boldsymbol{t^2}$	-0.568***	(-8.71)
$\boldsymbol{Post-Crisis}$	-10.883***	(-9.59)

Note: ***, **, and * indicate the statistical significance at the 1, 5, and 10 %, respectively. t and t^2 refer to the linear and quadratic time trend term, $lnTA$ refers to the logarithm of total bank assets and $Post\ Crisis\ Dummy$ captures the post-financial crisis period (2009-2015).

Figure 4. Scatter Diagram between Bank Size and Efficiency Scores



Next, the results show a significant concave relationship between time ((t) and (t^2)) and short-term inefficiencies, which suggests that technological advances increase inefficiencies at a decreasing rate over time. As expected, the crisis dummy $(Post - Crisis)$ indicates that short-term inefficiencies were higher in the period including the global financial crisis (see Table 11).

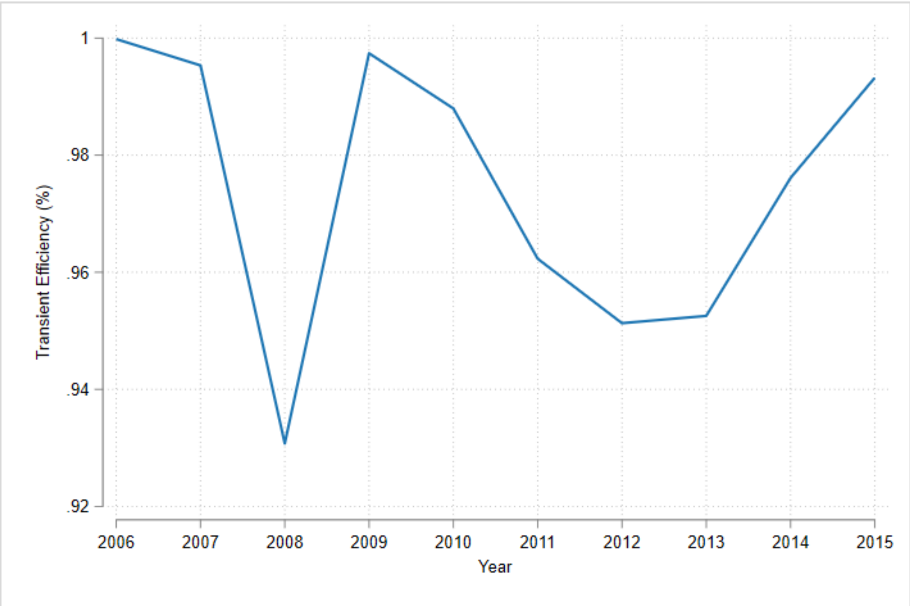
In light of the two crises that hit Italian banks over the past decade, it is of particular interest to depict the trend of short-term efficiency over time. At the aggregate level, we observe that banks moved from an average transient efficiency of 99.9% in 2006 to 99.3% in 2015, therefore showing only a marginal worsening of the short-term inefficiencies (see Table 12 and Figure 5). Nonetheless, two significant falls mark the evolution over time of transient efficiency, coinciding with the outbreaks of the Global Financial Crisis (2008) and of the European Sovereign Debt Crisis (2011-2012) (see Figure 5). Short-term efficiencies reached their trough in 2008 with a value of 93% compared to 99.5% in the previous year. After a two-year period of recovery, the outbreak of the European crisis led Italian banks to suffer from another decrease in the efficiencies level, with a trough in 2012 when transient efficiency reached approximately 95.1%.

Table 12. Evolution of Transient Efficiency between 2006 and 2015

Year	Obs.	Mean	Std. Dev.	Min	Max
2006	284	0.9998	0.0006	0.9998	0.9998
2007	324	0.9953	0.0002	0.9938	0.9962
2008	366	0.9308	0.0319	0.7700	0.9865
2009	345	0.9974	0.0001	0.9968	0.9972
2010	360	0.988	0.0016	0.9790	0.9920
2011	399	0.9623	0.0137	0.9199	0.9874
2012	403	0.9513	0.0280	0.6918	0.9903
2013	410	0.9526	0.0217	0.8187	0.9896
2014	410	0.9761	0.0070	0.9304	0.9888
2015	340	0.9932	0.0006	0.9903	0.9946
Overall	**3641**	**0.9729**	**0.0279**	**0.6918**	**0.9998**

Source: Author's own calculations

Figure 5. Time series plot of Transient Efficiency



Source: Author's own calculations

1.5.1.3 Persistent cost efficiency

Moving to the long-run component of inefficiency, this is found to have an average value of 92.6%, with banks ranging from 66.9% to 98% (see Table 10 above). Concerning the determinants of persistent inefficiencies, the coefficient of $Specialization$ is negative and statistically significant (-1.434) (Table 13), meaning that, on average, cooperative banks suffer from lower levels of persistent inefficiencies than commercial banks. With respect to the effect of the geographical location, we find that banks located in North-West (NW) and the South (S) have higher levels of persistent inefficiencies than the Central (i.e., the area "Central" is our area of reference and the coefficients of NW and S are positive and statistically significant, 0.774 and 0.484, respectively). By contrast, banks in the Northern East (NE) show greater persistent efficiencies than Central (C) given the negative and statistically significant coefficient (-0.508).

Table 13. Determinants of the variance of the persistent efficiency component

	Coefficient	**Z-value**
$\boldsymbol{Intercept}$	-3.571^{***}	(-28.30)
$\boldsymbol{Specialization}$	-1.434^{***}	(-10.15)
$\boldsymbol{Area: North - West}$	0.774^{***}	(5.60)
$\boldsymbol{Area: North - East}$	-0.508^{***}	(-4.17)
$\boldsymbol{Area: South}$	0.484^{***}	(3.50)

Note: *** indicates statistical significance at the 1% level. The Specialization dummy takes the value of 1 is the bank is categorised as a cooperative bank and zero if it is a commercial bank.

Persistent Efficiencies per Specialization

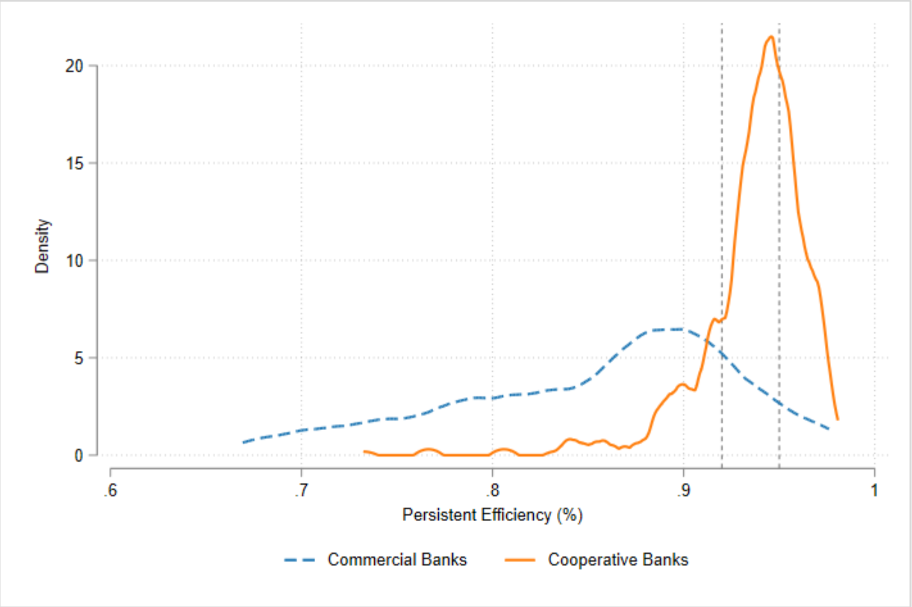
It is of interest to further explore how long-run inefficiencies vary across the two bank specializations. Table 14 reports that commercial banks have had persistent inefficiencies of approximately 14.7% compared to 6.4% of the other financial intermediaries. Similarly, the kernel distributions of persistent efficiency (Figure 6) show that the efficiency scores of commercial banks are characterised by a great dispersion whereas the estimated scores for cooperative banks are clustered above 90%. Similar results – albeit using a different approach to estimate cost efficiency – are found by Girardone, et al., (2004) in the context of Italy, by Altunbas, et al, (2001) for Germany, and by Maudos, et al., (2002) for the Spanish banking sector. A reason for our finding is that cooperative banks may constantly enjoy lower costs of funds and higher revenues due to their quasi-monopolistic power in certain local markets (Girardone, et al., 2004).

Table 14. Summary Statistics of Persistent Efficiency per Bank Specialization

Specialization	Obs.	Mean	Median	Std. Dev.	Min	Max
Commercial	460	0.8535	0.8743	0.0743	0.6693	0.9760
Cooperative	3181	0.9368	0.9420	0.0290	0.7323	0.9807
Mean	3,641	0.9263	0.9399	0.0469	0.6693	0.9807

Note: the most and least efficient commercial banks are Mediobanca (97.6%) and CheBanca SpA. (66.9%), respectively. With respect to cooperative banks, the most efficient is Cassa Rurale di Caldonazzo - Banca di Credito Cooperativo (98%) and the least efficient is Banca di Credito Cooperativo di Cherasco (73.2%).

Figure 6. Distributions of Persistent Efficiency per Bank Specialization



Note: the blue dashed vertical line refers to the average value of persistent efficiency of Commercial banks (0.853) while the red vertical line refers to the average value of persistent efficiency of Cooperative banks (0.936). The distributions refer to the estimated kernel densities.

Persistent Efficiencies per Geographical Areas

We now discuss the level of persistent efficiency observed in Italian banks according to their geographical location. We observe that North-West Italy is the area that suffers the most from structural, long-term inefficiencies, with an average inefficiency of 10%. By contrast, the North-Eastern part of Italy displays the lowest persistent inefficiencies with an average value of 5.2%. The average persistent inefficiencies of Central and South are 7.5% and 8.9%, respectively (see Table 15). Through the graphical representation of the kernel distributions (see Figure 7), we notice that the efficiency scores of banks in the North-West are the most dispersed, ranging from 66.9% to 97.8%. By contrast, banks located in North-East are clustered around 95% and the least efficient bank is 80.6% compared to 66.9%, 70.5% and 73% of North-West, Central and South Italy.

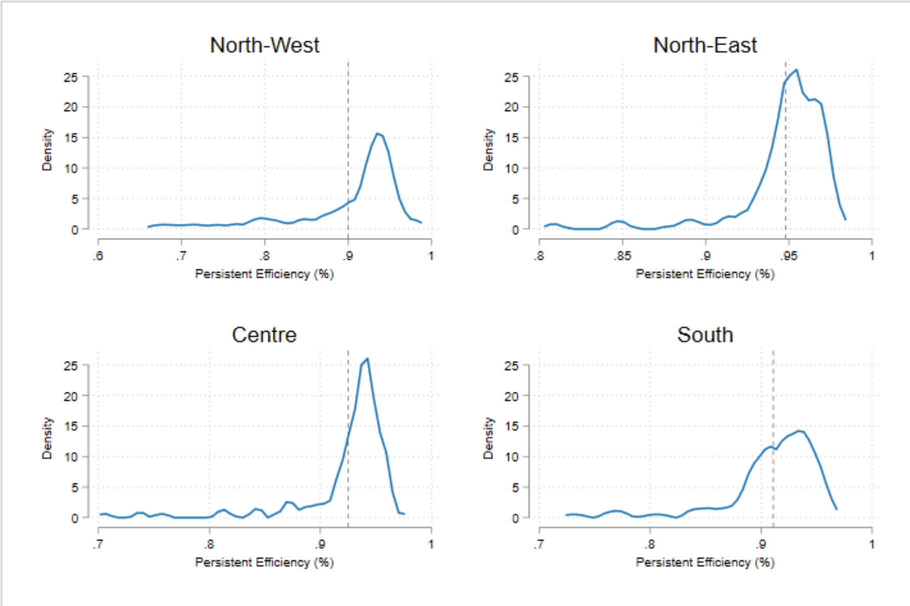
These findings are in contrast with prior literature on Italian banks' efficiency, where the South has been systematically observed to be the least efficient macro area (see, for instance, Resti, 1997; Girardone et al., 2004; Battaglia et al., 2010; Aiello and Bonanno, 2016). This could be the result of past studies limiting their analysis of geographical differences to a descriptive level, whereas we allow the inefficiency function to directly depend on these geographical differences. Indeed, the only other empirical study that uses banks' geographical location as a determinant of inefficiency is by Aiello and Bonanno (2013). Interestingly, in line with these results, they find that the South and the Centre outperform the North-West area, thus suggesting that i) regional disparities play a key role in explaining differences in the efficiency levels of Italian banks and ii) failing to account for the location of the banks in the inefficiency function could lead to incorrect inference concerning the best/worst macro area.

Table 15. Summary Statistics of Persistent Efficiency per Geographical Area

	Obs.	**Mean**	**Median**	**Std. Dev.**	**Min**	**Max**
North-West	606	0.9003	0.9303	0.0685	0.6693	0.9785
North-East	1341	0.9489	0.9533	0.0260	0.8065	0.9807
Centre	783	0.9253	0.9377	0.0422	0.7052	0.9722
South	911	0.9111	0.9195	0.0414	0.7308	0.9615
Mean	3,641	0.9263	0.9399	0.0469	0.6693	0.9807

Note: a bank is assigned to a given region if it has its headquarter in that area.

Figure 7. Distributions of Persistent Efficiency per Geographical Area



Note: the red vertical lines refer to the average value of persistent efficiency accordingly to the area in which banks are located (i.e., 0.900 for North-West, 0.948 for North-East, 0.925 for the Centre and 0.911 for the South). The distributions refer to the estimated kernel densities. Source: Author's own calculations

1.5.1.4 Production risk

Finally, as discussed in Section 1.4.3, the heteroskedastic four-error component model allows us to parametrize the variance of the random noise term (σ_{vit}^2) to incorporate determinants of production risk. This error component is assumed to capture random shocks that could affect the cost-minimization behaviour of banks. In this regard, the approach taken is to specify the σ_{vit}^2 function in terms of GDP growth, inflation and unemployment rate (see Eq. (1.11)). The interpretation taken of the coefficients of these variables is the elasticity of time-varying production risk with respect to these macro variables (see Badunenko and Kumbhakar, 2017).

From Table 16, the GDP growth elasticity of time-varying risk is found to be positive and significant (0.133) while the elasticities of inflation and unemployment are negative and significant (-0.355 and -0.142, respectively). This implies that changes in GDP have a negative effect on the production risk of Italian banks (i.e., it increases the time-varying production risk). Conversely, the positive relationship between inflation and unemployment and production risk indicates that changes in these variables diminish the time-varying production risk.

Table 16. Determinants of the variance of the noise term

Determinants of Random noise component ($log\ \sigma^2_{vit}$)		
	Coefficient	**Z-value**
$Intercept$	-4.398***	(-17.03)
$GDP\ Growth$	0.133***	(7.99)
$Inflation$	-0.355***	(-6.51)
$Unemployment$	-0.142***	(-6.09)

Note: ***, **, and * indicate the statistical significance at the 1, 5, and 10 %, respectively.

To conclude this section, the identification of two sources of inefficiency represents a major novelty in the literature for two reasons. First, models that fail to disentangle efficiency are likely to give incorrect estimates of inefficiency (Tsionas and Kumbhakar, 2014), implying that prior studies may have reported misleading and incorrect results on the levels and sources of the inefficiency of Italian banks. Second, by explicitly estimating and modelling the short and long-term parts of efficiency, we contribute to the understanding of where bank inefficiencies are emanating. This permits the firm’s management and policymakers to respond with different improvement strategies. For Italian banks, the long-term component of inefficiency, which is indicative of structural problems and systematic behavioural shortcomings in the cost-minimization process, is considerably larger than the short-term component. This entails that policy interventions aimed at addressing long-term inefficiency should be prioritized. (Khumbakar et al., 2014). In particular, these results are the first to show that the well-documented strong regional disparities (in terms of social, economic and demographic conditions) that characterised Italy and the bank type have a direct impact on the ability of banks to operate efficiently and to survive in the long-run.

1.5.2 Granger-causality results

In the previous section, we presented the results of the estimation of the transient and persistent efficiency. These components enter Equations 1.2. and 1.3 (see Section 1.3.1), which are employed to investigate the relationship between cost efficiency and loan quality of Italian banks via SGMM. Thus, this Section is divided into four main parts. First, in Subsection 1.5.2.1, the post-estimation diagnostics of the SGMM estimator, which ensure the validity of our results, are presented. Second, in Subsection 1.5.2.2, we focus on the findings from the estimation of the Granger-causality models as outlined in Eqs. (1.2) and (1.3). In Subsection 1.5.3, the methodology used to test the "bad luck hypothesis" is introduced and the results are presented. Finally, Subsection 1.5.4 presents the robustness checks.

1.5.2.1 Post-estimation diagnostic of the GMM estimator

The validity of our system GMM estimation depends on two crucial tests: the test for second-order (or above) serial correlation and the Hansen test of over-identification (also known in the literature as Hansen J-statistic).

Testing for second-order serial correlation

Arellano and Bond developed a test to check for the presence of autocorrelation (AR) in the idiosyncratic disturbance error term v_{it}. The presence of autocorrelation in the v_{it} would render some lags invalid as instruments. In our case, we assess the assumption of non-serially correlated error terms by testing for the presence of second, third and fourth order serial correlation in the differenced error terms. In this regard, given that Δv_{it} is mathematically related to $\Delta v_{i,t-1}$ via the shared $v_{i,t-1}$ term,

> "negative first-order serial correlation is expected in differences and evidence of it is uninformative. Thus to check for first-order serial correlation in levels, we look for second-order correlation in difference […] (Roodman, 2009, p. 119)".

In other words, we test for autocorrelation of order l in levels by looking for correlation order $l + 1$ in differences. In line with the expectations, serial correlation of order one *(AR (1))* is found while the results fail to reject the null hypothesis of no serial correlation in the remaining cases (see Table 19).

Choice and Validity of the Instrumental Variables: The Hansen J-statistic

Concerning the choice of instrumental variables, we specify two sets of instruments in each model. The first set of instruments refers to the predetermined variables, that is, the lagged dependent variable (i.e., BL_{t-1}, BL_{t-2}).[56] In Model 1, the lagged dependent variables are instrumentalised using GMM-style instruments lag 1 and above while in Model 2 employing lag 2 and above. The second set of instruments relates to the group of endogenous variables (i.e., $Transient,\ Persistent,\ CAP, Size, CreditGR$). In both Eqs. (1.2) and (1.3), the endogenous variables are instrumentalised with GMM-style instruments lag 3 and above whilst, with respect to Model 2, using lag 2 and 3. In our modelling strategy, $Supervised,\ Industry$ and $Crisis$ and the macroeconomic factors have been treated as strictly exogenous variables.[57]

We conduct the Hansen test of over-identification to evaluate the crucial assumption that the instruments are exogenous to the error term. Thus, the joint null hypothesis of the Hansen test is that the instruments are valid (i.e., jointly uncorrelated with the error term) and that the excluded instruments are correctly excluded from the estimated equation. In both Eqs. (1.2) and (1.3), we fail to reject the null hypothesis that our instruments are valid thus confirming their validity. In detail, our estimated Hansen statistics are equal to 0.353 and 0.526 for Model 1 and Model 2, respectively, hence falling within the credible range higher than 0.25 and not close to 1.000, as proposed by Roodman (2009a) (see Table 19).[58]

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[56] A predetermined variables is a variable that it is not strictly exogenous; that is, it is independent of current disturbances but it can be influenced by past ones. The lagged dependent variable is the most common example (Roodman, 2009a).

[57] In this respect, we acknowledge that the inclusion of the sovereign debt ratio could raise problems of endogeneity because if it is true that rising sovereign tensions affect the funding and credit supply ability of financial intermediaries, it may be also true the opposite that the deterioration of asset quality of banks determines an increase in government expenditure by forcing state interventions aimed at the bail out or at the recapitalization of stressed banks. However, as noted by Del Giovane et al. (2013), “in Italy – unlike other countries –the causal link clearly runs from the sovereign debt tensions to the difficulties of the banking system, and not the other way round”. Accordingly, it is reasonable to treat $SDEBT$ as an exogenous regressors (see also Bofondi et al. 2013).

[58] In this respect, Roodman (2009a) points out that researchers should not “do not take comfort in a Hansen test p-value below 0.1. View higher values, such as 0.25, as potential signs of trouble (p.129)”. Specifically, “a p-value as high as, say, 0.25 should be viewed with concern. Taken at face value, it means that if the specification is valid, the odds are only one in four that one would observe a J statistic so large (Roodman, 2009b, p. 142)”.

Dynamic Stability of the GMM Estimator and Persistence of NPLs

In both Eqs. (1.2) and (1.3), the sum of the lagged coefficients of the dependent variable (see Table 19), $BL(Total)$, is found to be statistically significant at 1% level and with a value between 0 and 1 (0.93 and 0.96, respectively), indicating dynamic stability and BL persistence (Ghosh, 2017). The implication of finding a persistent process is that, all else being equal, a positive (negative) movement in the BLs ratio is statistically more likely to be followed by another positive (negative) movement (see Bofondi and Ropele, 2011). This means that BLs are likely to increase when they have increased in the previous year. Also, this implies that banks with a high share of bad loans will need substantial time to remove them from their balance sheets (Ghosh, 2017). More specifically, our findings indicate high persistence of BLs, with the previous year's BLs affecting the present year's by 79-92% (columns 1 and 2 of Table 19).

This persistence of bad loans can be in part explained by the stagnation of the Italian economy over the last decade. However, part of this persistence is likely attributable to obstacles to BLs resolutions: the heavy reliance on collaterals, lack of tax incentives to provision loans, low capital and coverage ratios, inefficiencies in the judicial system, divergences in the BLs' price expectations between banks and private investors, and lack of a secondary market for distressed debt – which delay banks' write offs (see Jassaud and Kang 2015). Finally, the time persistence of bad loans is depicted also in Table 17, which reports evidence of a strong correlation between current values of BL and its own lags (see, for instance, Haile et al., 2017).

Table 17. Time persistence in bad loans

	$\boldsymbol{BL}$
$\boldsymbol{BL_{t-1}}$	0.929***
$\boldsymbol{BL_{t-2}}$	0.854***

Note: *** indicates statistical significance at 1% level. The table reports the correlation coefficients estimates between the current values of bad loans and its own lags.

1.5.2.2 Discussion of the results

The results of estimating Eqs. (1.2) and (1.3) are presented in Table 19.[59] Focusing on columns (1) and (2), the lagged coefficients of the measure of transient efficiency are found to be jointly significant at 1% and 5% (Wald test p-values=0.000 and 0.041), suggesting Granger-causality between short-term efficiency and bad loans. The sign of the sum of the coefficients is negative (-0.201 and -0.705), as expected by the *bad management* hypothesis; that is, a decrease in the short-term cost efficiency temporally precedes a worsening in banks' asset quality. We do not find evidence of a "long-run effect" of transient efficiency on BL, the sum of the lagged coefficients being insignificant different from zero. With respect to the long-term multiplier (recall, $\sum_{j=1}^{J} \gamma_{1j}$, for $J = 2$) we find that the positive marginal effect of the second lag is offset by the negative marginal effect of the shorter lag. That is, the long-term effect is not statistically different from zero, indicating that permanent changes in efficiency have temporary effects on BL and suggesting that BLs react to annual negative changes in efficiency over the last two years ($momentum$). Taken together, this would suggest that maintaining cost efficiency stability and reducing annual negative variation over the two-year horizon, would help minimize the negative impact of short-term efficiency on BLs. Concerning persistent efficiency, the finding is somewhat unexpected but in line with our *resource misallocation* hypothesis. The coefficient is found to be positive and significant at the 5% level (1.560 and 1.835), that is, banks that display higher levels of persistent efficiency tend to show, on average, a higher volume of defaulted loans.

These findings represent the first tentative evidence that the asset quality of Italian banks can be explained in terms of both institutional (transient) and structural (persistent) inefficiencies of the banking sector. More precisely, the negative relationship between transient efficiency and BL suggests that bad loans are the outcome of temporal behavioural shortcomings and 'non-systematic management

[59] It is worth reminding how we formally test for the presence of Granger-causality between the explanatory variables and the dependent variable. In line with Casu and Girardone (2009) and Fiordelisi et al. (2011), the causal relationship is assessed by testing the null hypothesis that the two lags of the explanatory variable (e.g., x_{it}) are jointly equal to zero. Rejecting the null hypothesis of no causality indicates that the variable x_{it} Granger-causes y_{it}, with the direction of the causality being determined by the sum of the lagged coefficient. Therefore, a positive (negative) sign implies that the causal relationship is positive (negative), that is, an increase (decrease) in x_{it} in the past increases (decreases) y_{it} in the present.

mistakes'. This finding bears substantial implications for both firms and regulators. From the institution's side, low observed transient efficiency could denote the presence of slack management who is unable to adequately oversee and monitor their operating expenses. "Bad managers" may follow poor or inadequate risk management practices, thus investing in projects with a negative net present value or lower quality loans. Unavoidably, those banks where bad managers are in charge will experience an increase in the risk of their loan portfolio and consequently, a rise in future delinquencies. In light of this discussion, we argue that it is within the control of the senior management to prevent bad loans arising from lax practices by means of improved day-to-day practices. In particular, emphasis should be placed on the management of credit risk, entailing devoting enough resources to enhance loan underwriting practices (e.g., improved evaluations of collateral) and strengthening the monitoring and control of outstanding loans. That is, while persistent inefficiencies relate to latent inefficiencies that are impossible to remove in the short-term, transient inefficiencies denote the presence of management mistakes that are characterised by a "non-systematic" nature, that is, they stem from temporal behavioural aspects of the management and, as such, can be solved in the short term (Filippini and Greene, 2016; Filippini, et al., 2018). From the policymakers' perspective, the negative relationship between short-term efficiency and bad loans places emphasis on the necessity for prudential regulators to monitor managerial performance in order to detect those financial institutions that could suffer from problems loans. That is, the levels of short-term efficiency could act as an early warning indicator for future increases in bad loans. In this respect, regulators could consider strengthening the regulatory framework for individual accountability, that is, they could introduce a mandatory certification to ensure the fitness and propriety of people performing key roles in the bank, such as mortgage and retail investment advisers.[60]

[60] For instance, the UK regulators introduced the "Senior Managers and Certification Regime (SM&CR)" with the objective of strengthen the individual accountability of firm's management and employees. One of the key component of the SM&CR is the "Certification Regime (CR)", which "covers specific functions that aren't Senior Management Functions, but can have a significant impact on customers, the firm and/or market integrity (Finance Conduct Authority, FCA, 2018, p. 31)". Specifically, "if a role meets the definition of a Certification Function, a firm needs to make sure that anyone doing that role has been certified. This means the firm must check and confirm that the person is fit and proper to do the job, and issue them with a certificate. This certification must be done at least once a year, and firms should take into account whether the individual: has obtained a qualification;

Concerning the evidence in favour of the *resources misallocation* hypothesis, this indicates that Italian banks could face a trade-off between asset quality and long-term cost efficiency. The challenges arising from the external environment could force banks to shift the available resources away from the management of the loan portfolio towards coping, for example, with the sub-optimal regulation, the excessively strict legal requirements (e.g., restrictions on voting rights, caps on ownership, membership requirements, limit to branch expansion), the shortcomings arising from the ownership type or geographical-specific issues. Put differently, if greater persistent efficiency is achieved at the expense of lower asset quality, the policy interventions of regulators should target those factors that give rise to these "systematic minimization problems" in the first place. By removing these exogenous hindrances, banks could be able to increase the resources devoted to the adequate management of the loan portfolio, potentially improving their asset quality. It is worth pointing out that these findings imply that Italian banks are likely to suffer from poor loan quality also in the future unless there is a major restructuring. In other words, we provide initial evidence that the level of bad loans currently affecting the Italian banking industry has (part of) its roots in the presence of these structural inefficiencies.

At this point, it is particularly interesting to observe the evolution of non-performing loans across some European countries (see Table 18 below). The most striking feature of this table relates to the amount of NPLs that were already present in Italian banks' balance sheets during the pre-crisis period (2005-2008). For example, in 2005, NPLs accounted for 7% of total loans in Italian banks compared to an average of 0.8% and 4.1% in Spain and Germany, respectively. We argue that this could be potentially traceable to the presence of long-term inefficiencies and, as such, it is likely that the asset quality of Italian banks will remain poor unless the removal of these latent inefficiencies takes place.

has undergone, or is undergoing, training; and possesses a level of competence. Certificates issued by firms should: state that the authorised person is satisfied that the person is a fit and proper person to perform the Certification Function; set out the aspects of the firm's business in which the individual will be involved (FCA, 2018, p. 31)". Among the roles that the FCA considers as relevant we find mortgage advisers, retail investment advisers, pension transfer specialists as well as financial advisers, people who are involved in corporate finance business and people who are involved in dealing or arranging deals in investments and investment managers. Despite critics (e.g., the firm itself is required to certify its own employees) the SM&CR has the potential to mitigate some of corporate governance issues emerged throughout the crisis by forcing individuals to undertake specific training and comply with the requirements.

Table 18. Bank Loan Quality in European Countries

	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Italy	**7.00**	**6.57**	**5.78**	**6.28**	**9.45**	**10.03**	**11.74**	**13.75**	**16.54**	**18.03**	**18.06**
Austria		2.74	2.24	1.90	2.25	2.83	2.71	2.81	2.87	3.47	3.39
Belgium		1.28	1.16	1.65	3.08	2.80	3.30	3.74	4.24	4.18	3.79
Cyprus				3.59	4.51	5.82	9.99	18.37	38.56	44.97	47.75
France				2.82	4.02	3.76	4.29	4.29	4.50	4.16	4.05
Germany	4.05	3.41	2.65	2.85	3.31	3.20	3.03	2.86	2.70	2.34	1.97
Greece				4.67	6.95	9.12	14.43	23.27	31.90	33.78	36.65
Ireland	0.48	0.53	0.63	1.92	9.80	13.05	16.12	24.99	25.71	20.65	14.93
Malta	8.21	6.47	5.31	5.01	5.78	7.02	7.09	7.75	8.95	8.83	7.10
Netherlands				1.68	3.20	2.83	2.71	3.10	3.23	2.98	2.71
Portugal			2.85	3.60	5.13	5.31	7.47	9.74	10.62	11.91	17.48
Spain	0.79	0.70	0.90	2.81	4.12	4.67	6.01	7.48	9.38	8.45	6.16

Source: World Bank Financial Soundness Indicators. **Note**: the data refer to the ratio of Non-performing Loans over Gross Loans (%).

Moving to the relationship between capital (CAP) and BL, we find support for the *moral hazard hypothesis*, that is, a weakening in the capital position of banks tends to temporally precede higher BL. Indeed, the Wald test indicates that the lagged coefficients are jointly statistically significant at 5% in both columns (1) and (2), respectively, suggesting that Granger-causality exists, running from CAP to BL (see Table 19). The direction of causality is given by the sum of the lagged coefficients ($CAP\ (Total)$), which is negative, in line with the notion that a deterioration of the capital position may act as an incentive for banks to increase the riskiness of their investments since, in the event of default, these financial institutions have less 'skin in the game' (Williams, 2004). Furthermore, $CAP\ (Total)$ is statistically significant at either 1% or 5% level, suggesting the presence of a long-run effect of capital on the level of bad loans. Similar results were found by Berger and DeYoung, (1997), Salas and Saurina (2002), Espinoza and Prasad (2010) and Klein (2013) whereas Fiordelisi et al. (2011) found a positive and statistically significant relationship.

Furthermore, we find that the growth policy of banks affects the level of loan defaults. The lagged coefficients of credit growth are jointly significant at 1% and 5% level (Wald test p-value=0.000 and 0.021) and their sum, $CreditGr(Total)$, is found to be positive (0.397 and 0.311). That is consistent with the hypothesis that higher levels of bank lending could increase the probability of borrowers' default in the future because higher lending rates may be achieved through reductions in the credit standards for loan approvals (Castro, 2013). Similar conclusions were reached by Garrido et al. (2016) while investigating the drivers of NPLs in Italy between 2005-2014. Other studies that find a positive relationship between asset expansion and deterioration of credit quality are those of Castro (2013), Klein (2013) and Ghosh (2015). Finally, $CreditGr$ is observed to have a long-run effect on BL, given that the sum of the coefficients is statistically significant at 1% level in both the models.

The findings on the relationship between BL and capital and credit growth also hint at the presence of "*zombie lending*" behaviour in Italian banks. In this respect, Schivardi et al. (2017) have observed that low-capitalized Italian banks were engaging in significant zombie lending between 2008 and 2013, concluding that

> "low capital banks may be particularly averse to absorb losses, especially during a recession, and may therefore be relatively more willing to keep lending to weak firms that otherwise would not be able to service their debt (Schivardi et al., 2017, p. 15)".

Thus, our results may capture the tendency of Italian distressed banks to extend the credit towards low-productivity firms to keep them artificially alive and not register the losses in their balance sheet, which would push these banks against the minimum capital levels. Likewise, the positive relationship between $CreditGr$ and bad loans could capture the credit extensions of Italian banks towards unprofitable borrowers to keep them from going bankrupt while 'gambling for their resurrection'.

Moving to the effect of banks' size on BL, $Size$ is found to be significant at the 5% level and negative only in the model excluding macro variables. Notwithstanding the weakness of this finding, this suggests that, on average, large financial intermediaries seem to suffer from a lower ratio of bad loans compared to smaller banks. Large banks are potentially less exposed to asymmetric shocks arising from economic downturns in a specific geographical area or a specific industrial sector, lowering the likelihood of a rise in BL (Salas and Saurina, 2002). Furthermore, these banks may have an advantage over smaller institutions in terms of expertise in managing BL. That is, large financial intermediaries are potentially more active on the secondary market where they are capable to dispose of their BL to third parties through securitization.[61] A negative relationship between bad loans and size was also found by Salas and Saurina (2002) and Fiordelisi et al. (2011) while, conversely, Louzis et al. (2012), Chaibi and Ftiti (2015) and Zhang et al. (2016) reported a positive relationship.

However, interestingly, the dummy $Supervised$ is positive and statistically significant, in line with the Too-Big-To-Fail notion that financial institutions that are recognised as systemically important may be subject to moral hazard incentives and lower market discipline by their creditors. These banks may be tempted to increase the riskiness of their loan portfolio if they are certain about government support in the event of financial troubles. At the same time, if investors recognise this implicit subsidy from the government, they tend to impose lower market discipline on the bank. Anecdotal evidence provided by the noteworthy financial scandals involving the Italian banking industry in recent years seems to provide support for these results. In fact, our group of banks directly supervised by the ECB includes Monte dei Paschi di Siena (MPS), Banca Carige, Banca Popolare di Vicenza and Veneto Banca (these two last banks were two of the largest Italian Popular banks), which have been hit by a series of scandals that revealed the extremely poor lending practices of these intermediaries. At the end of 2015, these banks reported a level of NPLs (BLs) of 34% (20%), 28% (15%), 31% (15%) and 28% (14%), respectively. The unavoidable financial losses that followed the scandals deepened the already precarious conditions of these intermediaries, forcing the Italian government to intervene to limit the spillovers effects that the potential failure of one of these banks could have had over the rest of the banking industry.[62]

The relationship between the bank specialization and NPL, the $Industry$ dummy is found to be negative and significant at 5% and 10%, indicating that, on average, banks that operate as "cooperative" report fewer problems loans than commercial counterparts. As mentioned before, one explanation for this could relate to the reliance of cooperative banks on the so-called *relationship lending*, which

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[61] Indeed, as reported by the European Commission, "the disposal of non-performing loans is likely to be more difficult for [small and medium-sized banks] as they may lack the required size and experience to attract specialized investors (European Commission, 2016, p. 44)".

[62] The Italian government provided MPS with €4.1 billion in while it was able to resolve the situation of the two Popular banks by reaching an agreement with Intesa Sanpaolo bank, which assented to acquire the "good assets" and the branch network of two banks while the NPLs were transferred to an Asset Management Company (see, for an extensive outline of the financial scandals of these banks, the "Parliamentary Enquiry on the banking and financial system", 2018).

allows these smaller intermediaries to collect soft information on the potential borrowers thereby reducing the asymmetric information between the lender and the borrowers and improving the overall credit quality of banks (Becchetti et al., 2016).

In line with the expectations, the dummy capturing the post-global financial crisis period ($Crisis$) is positive and statistically significant at 1% in the model excluding macro variables. That is, on average, all else equal, banks display a higher level of BL in the aftermath of the crisis compared to the period 2006-2008.[63]

We now focus on column (2), which includes macroeconomic drivers of loan quality. We find evidence that following a period of growth in the GDP, Italian banks tend to display higher BL, in line with the hypothesis that during periods of economic growth, banks may be overconfident about the capacity of debtors to service their debt, resulting in a subsequent worsening of the asset quality. This result corroborates our findings concerning the previously observed relationship between asset quality and credit growth. That is, during expansionary phases of the economy Italian banks may engage in excessive lending driven by over-optimism about the business environment. This positive relationship between $GDPGR$ and credit quality contrasts with the findings of Garrido et al. (2016), who concluded that an increase in GDP reduces the level of NPLs for Italian banks.

Interestingly, the effect of Sovereign Debt ($SDEBT$) on bad loans does not reflect our initial hypothesis that sovereign tensions worsen the credit quality of banks. The lagged coefficients of $SDEBT$ are found to be jointly significant at the 5% significance level (Wald test p-value=0.037) whereas their sums are negative, implying that an increase in the Italian government debt Granger-causes a decrease in BL. One interpretation is that lower sovereign indebtedness implies eased funding conditions for banks, resulting in a greater supply of loans and thus increased credit risk, consistent with the findings concerning credit growth. This evidence contrasts with the finding of Ghosh (2015), who reported that an increase in the public deficit of the US States leads to a higher volume of NPL.

[63] For completeness, we replace the dummy $Crisis$ with a dummy capturing the Sovereign Debt Crisis (i.e., the dummy takes the value of 1 for the period 2013-2015 and zero for the period 2006-2012). In both Model 1 and Model 2, the dummy is positive but it is statistically significant at 5% level only in Model 2, suggesting that in the aftermath of the Euro crisis, NPLs are, on average, higher than the preceding period, in line with the notion that the debt crisis further worsened the credit quality of Italian Banks. Nonetheless, it is worth noting that part of the increase in the NPLs ratio may be denominator-driven, that is, determined by the contractions of outstanding credit to firms (European Commission, 2015).

Following the notion that higher house prices lower the probability of borrowers' defaults by acting as a buffer against adverse shocks, the lagged value of the HPI is found negative (-0.013) and but statistically insignificant.

Finally, in line with Ben Naceur et al. (2018), we perform robustness checks by replacing the set of macroeconomic variables with time-fixed effects (column (3) of Table 19). Overall, results on bank-specific features are robust across both ways of controlling for macroeconomic conditions, and we strongly confirm the presence of *bad management* (H_1) and *resources misallocation* (H_5).

1.5.3 Testing for the Bad Luck hypothesis

We assess the presence of bi-directional causality between BLs and cost efficiency by testing for the *bad luck* hypothesis (H_3), that is, whether exogenously driven increases in BLs exert an effect on the levels of efficiency. To the best of our knowledge, the entire body of research that has tested this hypothesis (see, for example, Berger and DeYoung, 1997; Altunbas et al., 2007; Podpiera and Weill, 2008; Fiordelisi et al., 2011; Tan and Floros, 2013)) proceeded by specifying a regression model where cost efficiency is regressed on a set of explanatory variables, the most important of which being NPLs. Put differently, these studies follow the following two-step procedure:

> "in the first step, one estimates the stochastic frontier model and the firms' efficiency levels, ignoring z [the set of exogenous variables that affect efficiency]. In the second step, one tries to see how efficiency levels vary with *z*, perhaps by regressing a measure of efficiency on *z* (Wang and Schmidt, 2002, pp. 129-130)".

As clearly illustrated by Wang and Schmidt (2002), the two-step approach is incorrect, on the basis that it can be subject to i) omitted variable bias and under-dispersed efficiencies in step 1 and ii) downward biased coefficients in step 2. [64,65]

[64] "Such a two-step procedure will give biased results because the model estimated at the first step is misspecified. The solution to this bias problem is a one-step procedure based on the correctly specified model for the distribution of *y* given *x* and *z*. In the one-step procedure, the assumed relationship between *z* and technical efficiency is imposed in estimating the technology and the firms' efficiency levels, not just at the last stage of the exercise (Wang and Schmidt, 2002, p. 130)".

[65] Recall, in our case, we estimate *transient* and *persistent* efficiency using the heteroskedastic model of Badunenko and Kumbhakar (2017), which allows the specification of the determinants of inefficiencies using a one-step approach.

To avoid these severe pitfalls, we augment our specifications (see Section 1.3.1) and we estimate the following regression (Eq. (1.14):

$$\begin{aligned} BL_{it} = {} & a + \sum_{j=1}^{J} \beta_j BL_{it-j} + \sum_{j=1}^{J} \gamma_{1j} Transient_{it-j} + \gamma_2 Transient_{it} \\ & + \sum_{k=1}^{K} \gamma_{3k} Transient_{it+k} + \gamma Persistent_i + bank\_controls \\ & + \eta_i + \varepsilon_{it} \; for \; J = K = 2 \end{aligned} \quad 1.14$$

In this augmented regression, we include the current and future values of transient efficiency and rejection of the restriction $H_0: \gamma_{3k} = \cdots = \gamma_{3K} = 0$, would suggest a causal relationship between BLs and future levels of efficiency, providing evidence in favour of the *bad luck* hypothesis (Eq. (1.14) is akin to a multivariate Granger – Sims (1972) causality specification). The above regression has two appealing properties. First, as stated above, it enables us to test for bad luck while overcoming the limitations of the two-step procedure. Second, given the disaggregated nature of efficiency used in our model, it permits us to include in the regression simultaneously both components of efficiency ($transient$ and $persistent$), something that would not have been possible if we were to proceed with a second-stage regression of time-varying efficiency on BLs. It is important to highlight that, from the above regression, our focus is on the joint significance of the two lagged values of transient efficiency to confirm *bad management/skimping* and the joint significance of the lead values to confirm or reject the notion of 'bad luck'.

The results are reported in column (4) of Table 19. We note that adding the current and lead values of short-term cost efficiency reduces the fraction of the variation in BLs explained by the other explanatory variables and only the two lags of $CreditGR$ remains jointly significant. Long-term efficiency maintains its positive sign; however, the effect becomes statistically insignificant. With respect to the coefficients of interest, we fail to reject the null hypothesis of joint significance for the lead values of efficiency (p-value = 0.310), thus confirming the absence of bi-directional causality and bad luck. This lack of causality between BLs and efficiency could be explained by the slow pace of resolution of impaired loans and therefore the lack of additional costs associated with disposing of bad loans or the need to monitor the existing performing loans more closely (Jassaud and Kang, 2015). Once again, we confirm the *bad management* hypothesis, as the two lags of short-term efficiency remain jointly statistically significant (p-value = 0.030), with a negative (but insignificant) long-run coefficient of -1.188.

Table 19. Granger Causality Results

Dependent variable: BL_{it}	(1) Transient & Persistent Efficiency	(2) Transient & Persistent Efficiency with $macro\_controls$	(3) Transient & Persistent Efficiency and Time FE	(4) Sims Causality Transient & Persistent Efficiency
BL_{it-1}	0.922***	0.790***	0.897***	0.692***
	(0.078)	(0.074)	(0.090)	(0.127)
BL_{it-2}	0.038	0.091	0.034	0.197
	(0.078)	(0.061)	(0.085)	(0.125)
$BL(Total)$	0.960***	0.880***	0.930***	0.889***
	(0.018)	(0.032)	(0.027)	(0.044)
$Transient_{it-1}$	-0.767***	-0.834**	-1.357*	-1.363*
	(0.245)	(0.407)	(0.720)	(0.724)
$Transient_{it-2}$	0.566***	0.130	0.512*	0.174
	(0.215)	(0.693)	(0.308)	(0.430)
$Transient$				-1.786*
				(0.965)
$Transient_{it+1}$				-0.952
				(0.985)
$Transient_{it+2}$				-1.315
				(1.316)
$Transient(Total - lags)$	-0.201	-0.705	-0.846	-1.189
	(0.357)	(0.969)	(0.700)	(1.037)
$Persistent$	1.560**	1.835**	1.848***	0.891
	(0.727)	(0.803)	(0.664)	(1.219)
CAP_{it-1}	0.205	-2.004	-1.837	2.032
	(1.047)	(1.507)	(1.423)	(1.864)
CAP_{it-2}	-2.126*	0.287	0.524	-2.931
	(1.167)	(1.782)	(1.535)	(2.014)
$CAP(Total)$	-1.921***	-1.716**	-1.313**	-0.900
	(0.647)	(0.715)	(0.666)	1.070
$CreditGR_{it-1}$	-0.981***	-0.728	0.017	-1.781***
	(0.226)	(0.463)	(0.443)	(0.453)
$CreditGR_{it-2}$	1.378***	1.039**	0.382	1.878***
	(0.227)	(0.466)	(0.456)	(0.464)
$CreditGR(Total)$	0.397***	0.311*	0.399***	0.096
	(0.109)	(0.153)	(0.121)	(0.243)
$Size$	-0.048**	-0.038	-0.030	-0.036
	(0.023)	(0.025)	(0.022)	(0.040)
$Crisis$	0.077***	-0.036	0.006	0.130
	(0.027)	(0.063)	(0.054)	(0.081)

$Supervised$	0.234**	0.235*	0.166	0.247
	(0.107)	(0.128)	(0.101)	(0.200)
$Industry$	-0.194**	-0.150*	-0.166**	-0.123
	(0.077)	(0.082)	(0.067)	(0.097)
$GDPGR_{it-1}$		9.384**		
		(4.486)		
$GDPGR_{it-2}$		3.008**		
		(1.504)		
$GDPGR(Total)$		12.39**		
		(5.954)		
$SDEBT_{it-1}$		6.599**		
		(3.096)		
$SDEBT_{it-2}$		-6.831**		
		(3.398)		
$SDEBT(Total)$		-0.231		
		(0.400)		
HPI_{it-1}		-0.013		
		(0.008)		
$Constant$	-0.844	0.624	-0.795	4.360
	(0.706)	(1.637)	(0.853)	(3.017)
$Wald\ Test\ (Transient-\ lags)$	0.000	0.041	0.0841	0.030
$Wald\ Test\ (Transient-\ leads)$				0.310
$Wald\ Test\ (CAP)$	0.010	0.011	0.071	0.333
$Wald\ Test\ (CreditGR)$	0.000	0.021	0.004	0.000
$Wald\ Test\ (GDPGR)$		0.112		
$Wald\ Test\ (SDEBT)$		0.037		
$Wald\ Test\ (Time\ Fixed\ Effects)$			0.089	
$AR(1)$	0.000	0.000	0.000	0.000
$AR(2)$	0.400	0.727	0.293	0.777
$Hansen\ Test\ of\ Overidentification$	0.526	0.429	0.534	0.149
$Goodness\ of\ fit$	0.870	0.870	0.873	0.852
$N\_of\ instruments\ (N\_groups)$	182 (426)	268 (426)	188 (426)	89 (426)
$N\_observations$	2,522	2,522	2,522	1,623

This table reports the results on the determinants of BLs estimated using the two-step system GMM estimator as specified in Eqs. (1.2) and (1.3). Windmeijer (2005) robust standard errors are reported in parentheses. The variables $BL(Total)$, $Transient(Total)$, $CAP(Total)$, $CreditGr(Total)$, $GDPGR(Total)$ and $SDEBT(Total)$ are the estimated coefficients for the test that the sum of the respective lagged terms are equal to zero (standard errors are obtained by the Delta method). In all cases, $BL(Total)$ is statistically different from one. The Wald test is the test for the joint significance of the coefficients of the lagged explanatory variables; we report the p-value. $AR(1)$, $AR(2)$ are tests of first- and second-order serial correlation in the first-differenced residuals, under the null of no serial correlation. The Hansen test of overidentification is under the null that all the instruments are valid. $Goodness\ of\ fit$ is the square correlated coefficient between actual and predicted values of the dependent variable (Bloom et al. 2007). Variables are defined as in Sections 1.3.2 and 1.3.3. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

1.5.4 Robustness Analyses

Models including either transient or persistent efficiency

We perform sensitivity analyses on our findings by estimating four additional models where we alternatively include or exclude the measure of short-term and long-term efficiency (Table 20, columns (1)-(4)). Specifically, we first include solely the index of transient efficiency (column 1), and next, we saturate the model with macro determinants (column 2). Likewise, we estimate one regression incorporating only persistent efficiency (column 3), and finally, we augment the specification with macro variables (column 4). In all four columns, the post-estimation diagnostics confirm the validity of our GMM estimator. Furthermore, the sum of the lagged coefficients of BL is found to be between 0 and 1, indicating dynamic stability of the model and persistence of BL.

Overall, the results are consistent with the previous findings. We show evidence of bad management in Italian banks, the lagged coefficients of transient efficiency being jointly statistically significant and negative. Likewise, persistent efficiency is found positive and statistically significant in both columns (3) and (4), suggesting a tendency of banks to allocate resources away from the loan portfolio in order to withstand the external environment (*resources misallocation* hypothesis). Also the remaining set of firm-specific and macroeconomic explanatory variables retain their signs.

Analyses on subsamples of the bank population

To further evaluate the robustness of our results to the data, we provide additional analyses conducted in subsamples of the bank population (Table 21). First, we examine size effects by splitting the sample between small and large banks; second, we analyse regional heterogeneity and divide the sample into North and South, based on the location of banks' headquarters; third, we confirm that our findings are not driven by TBTF considerations by removing SIB form the sample; and finally, we remove commercial banks from the estimation.[66] Concerning transient efficiency, we strongly confirm H_1, *bad management*, with the exception of the sub-sample of banks located in the Southern regions. For these banks, the

[66] We cannot estimate the SGMM for the SIBs of the commercial banks as the reduced samples do not contain enough cross-sections for a SGMM (13 SIBs and 62 commercial banks).

relationship between bad loans and $Transient$ is positive, suggesting the presence of a skimping behaviour, H_2. (column (4)). With respect to long-term efficiency, we broadly confirm H_5, the resource misallocation hypothesis, in all regressions except for small banks and banks in the South of Italy, where we report a negative, but insignificant coefficient for $Persistent$ (columns (1) and (4) respectively). The remaining control variables maintain their signs and significance in all cases but for CAP when estimated for large banks, where we find no evidence of moral hazard.

Controlling for Outliers

Finally, we thoroughly investigate the impact of outliers on our estimates (Table 22). We do so in three ways. First, we remove outliers identified as the largest prediction errors, after excluding the observations corresponding to the largest 1% of squared residuals (columns (1)-(3)). Second, we control for outliers in the dependent variable using the Median Absolute Deviation method (MAD) (columns (4)-(6)). This method is generally more effective than the standard deviation method, which may fail as outliers increase the standard deviation. Third, we winsorize all financial data at the top and bottom 1% (columns (7)-(9)). In all these additional regressions, our main results remain unaffected, strongly confirming the two channels through which transient and structural efficiency have an impact on bad loans. As a final robustness exercise, we use an alternative specification of the dependent variable, that is the logarithmic transformation of bad loans ($lnBL$) and we re-estimate the baseline specifications (see Table 23).[67] All results remain qualitatively similar and confirm the *bad management* and *resources misallocation* hypotheses.

[67] We do not employ Loan Loss Provisions (LLP) or Loan Loss Reserves (LLR) as alternative proxies for risk as managers may exploit information advantages and depart from normal levels of LLP/LLR for objectives other than provisioning for NPLs. Prior research suggests that discretionary LLP behaviour (which feeds back to LLR), could be due to a number of factors, such as, income smoothing, capital management and/or signalling among others (see for example, Beatty and Liao, 2014).

Table 20. Models Incorporating either Transient or Persistent Efficiency

Dependent variable: BL_{it}	(1) Excluding Persistent Efficiency	(2) Excluding Persistent Efficiency with $macro\_controls$	(3) Excluding Transient Efficiency	(4) Excluding Transient Efficiency with $macro\_controls$
BL_{it-1}	0.957***	0.911***	0.881***	0.793***
	(0.080)	(0.091)	(0.086)	(0.094)
BL_{it-2}	0.006	0.002	0.078	0.098
	(0.078)	(0.079)	(0.084)	(0.083)
$BL(Total)$	0.962***	0.913***	0.960***	0.892***
	(0.018)	(0.029)	(0.019)	(0.030)
$Transient_{it-1}$	-0.826***	-0.682		
	(0.272)	(0.476)		
$Transient_{it-2}$	0.575***	0.549		
	(0.218)	(0.952)		
$Transient(Total - lags)$	-0.251	-0.133		
	(0.352)	(1.313)		
$Persistent$			2.529***	3.271***
			(0.836)	(1.114)
CAP_{it-1}	0.069	-2.974**	-0.388	-0.765
	(1.020)	(1.499)	(1.157)	(1.968)
CAP_{it-2}	-2.086**	0.938	-1.445	-0.840
	(1.019)	(1.689)	(1.213)	(2.241)
$CAP(Total)$	-2.017***	-2.036**	-1.833***	-1.605**
	(0.634)	(0.819)	(0.709)	(0.758)
$CreditGR_{it-1}$	-0.864***	-0.362	-0.769***	-1.194***
	(0.223)	(0.518)	(0.199)	(0.403)
$CreditGR_{it-2}$	1.334***	0.848*	1.193***	1.477***
	(0.207)	(0.515)	(0.201)	(0.405)
$CreditGR(Total)$	0.469***	0.486***	0.424***	0.284
	(0.095)	(0.139)	(0.117)	(0.175)
$Size$	-0.045**	-0.044**	-0.042	-0.048
	(0.020)	(0.022)	(0.028)	(0.038)
$Crisis$	0.072***	-0.018	0.093***	0.047
	(0.028)	(0.068)	(0.029)	(0.057)
$Supervised$	0.149	0.165*	0.237*	0.305
	(0.091)	(0.091)	(0.138)	(0.187)
$Industry$	-0.071	-0.024	-0.242***	-0.299**
	(0.046)	(0.050)	(0.086)	(0.130)
$GDPGR_{it-1}$		10.092**		9.377**

		(4.823)		(4.447)
$GDPGR_{it-2}$		3.607**		3.027**
		(1.558)		(1.524)
$GDPGR(Total)$		13.70**		12.40**
		(6.326)		(5.949)
$SDEBT_{it-1}$		7.308**		5.993*
		(3.205)		(3.087)
$SDEBT_{it-2}$		-7.746**		-6.430*
		(3.499)		(3.419)
$SDEBT(Total)$		-0.438		-0.437
		(0.403)		(0.403)
HPI_{it-1}		-0.018**		-0.013
		(0.008)		(0.008)
$Constant$	0.489	2.441	-1.965***	-0.940
	(0.384)	(1.859)	(0.714)	(1.667)
$Wald\ Test\ (Transient-\ lags)$	0.000	0.048		
$Wald\ Test\ (Transient-\ leads)$				
$Wald\ Test\ (CAP)$	0.003	0.007	0.034	0.076
$Wald\ Test\ (CreditGR)$	0.000	0.001	0.000	0.000
$Wald\ Test\ (GDPGR)$		0.063		0.099
$Wald\ Test\ (SDEBT)$		0.058		0.110
$Wald\ Test\ (Time\ Fixed\ Effects)$				
$AR(1)$	0.000	0.000	0.000	0.000
$AR(2)$	0.243	0.205	0.603	0.905
$Hansen\ Test\ of\ Overidentification$	0.564	0.601	0.289	0.220
$Goodness\ of\ fit$	0.877	0.879	0.862	0.851
$N\_of\ instruments\ (N\_groups)$	207 (426)	194 (426)	181 (426)	222 (426)
$N\_observations$	2,522	2,522	2,522	2,522

This table reports the results on the determinants of BLs estimated using the two-step system GMM estimator as specified in Eqs.(1) and (2). Windmeijer (2005) robust standard errors are reported in parentheses. The variables $BL(Total)$, $Transient(Total)$, $CAP(Total)$, $CreditGr(Total)$, $GDPGR(Total)$ and $SDEBT(Total)$ are the estimated coefficients for the test that the sum of the respective lagged terms are equal to zero (standard errors are obtained by the Delta method). In all cases, $BL(Total)$ is statistically different from one. The Wald test is the test for the joint significance of the coefficients of the lagged explanatory variables; we report the p-value. $AR(1)$, $AR(2)$ are tests of first- and second-order serial correlation in the first-differenced residuals, under the null of no serial correlation. The Hansen test of overidentification is under the null that all the instruments are valid. $Goodness\ of\ fit$ is the square correlated coefficient between actual and predicted values of the dependent variable (Bloom et al. 2007). Variables are defined as in Sections 1.3.2 and 1.3.3. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 21. Granger Causality Results – Different samples

Dependent variable: BL_{it}	(1) Small	(2) Large	(3) North	(4) South	(5) Excluding SIBs	(6) Cooperative Banks
BL_{it-1}	0.771***	1.085***	0.867***	1.055***	0.913***	0.798***
	(0.080)	(0.062)	(0.100)	(0.074)	(0.088)	(0.085)
BL_{it-2}	0.095	-0.105	0.048	-0.085	0.052	0.125
	(0.078)	(0.065)	(0.101)	(0.071)	(0.088)	(0.081)
$BL(Total)$	0.866***	0.980***	0.916***	0.970***	0.965***	0.924***
	(0.043)	(0.015)	(0.024)	(0.024)	(0.019)	(0.023)
$Transient_{it-1}$	-0.960*	-0.842***	-0.944**	-0.657	-0.796***	-0.625*
	(0.553)	(0.308)	(0.399)	(0.410)	(0.283)	(0.350)
$Transient_{it-2}$	0.756	0.631**	0.359	0.747*	0.585**	0.610**
	(0.490)	(0.259)	(0.294)	(0.383)	(0.233)	(0.265)
$Transient(Total - lags)$	-0.205	-0.211	-0.585	0.089	-0.210	-0.014
	(0.816)	(0.447)	(0.508)	(0.657)	(0.401)	(0.521)
$Persistent$	-0.484	1.067**	1.959**	-1.176	1.438*	1.927*
	(1.439)	(0.499)	(0.943)	(0.731)	(0.771)	(0.993)
CAP_{it-1}	-0.192	1.081	-2.283	2.219*	0.198	-0.448
	(1.539)	(1.257)	(1.647)	(1.336)	(1.088)	(1.379)
CAP_{it-2}	-2.275	-1.367	-0.351	-2.966**	-2.064*	-2.376
	(1.415)	(1.176)	(1.728)	(1.364)	(1.223)	(1.448)
$CAP(Total)$	-2.467***	-0.286	-2.634**	-0.747	-1.865***	-2.824***
	(0.907)	(0.545)	(1.045)	(0.644)	(0.649)	(0.889)
$CreditGR_{it-1}$	-1.056***	-0.928***	-0.984***	-0.556*	-0.993***	-1.151***
	(0.396)	(0.267)	(0.319)	(0.332)	(0.240)	(0.301)
$CreditGR_{it-2}$	1.192***	1.260***	1.244***	1.052***	1.408***	1.453***
	(0.425)	(0.292)	(0.346)	(0.365)	(0.243)	(0.289)
$CreditGR(Total)$	0.136	0.332***	0.260	0.496***	0.415***	0.302**
	(0.198)	(0.117)	(0.179)	(0.121)	(0.116)	(0.126)
$Size$	-0.049	-0.032	-0.021	-0.041*	-0.046**	-0.030
	(0.062)	(0.026)	(0.031)	(0.023)	(0.023)	(0.029)
$Crisis$	0.132***	0.022	0.094*	0.094***	0.082***	0.108***
	(0.042)	(0.027)	(0.049)	(0.033)	(0.028)	(0.030)
$Supervised$		0.133	0.154	0.250		0.130

		(0.102)	(0.142)	(0.199)		(0.136)
$Industry$	-0.137	-0.120**	-0.141	0.013	-0.180**	
	(0.091)	(0.051)	(0.111)	(0.069)	(0.082)	
$Constant$	0.890	-0.550	-1.073	0.988	-0.753	-1.637*
	(1.406)	(0.632)	(0.902)	(0.860)	(0.747)	(0.984)
$Wald\ Test\ (Transient-\ lags)$	0.031	0.000	0.024	0.006	0.000	0.000
$Wald\ Test\ (CAP)$	0.012	0.462	0.030	0.079	0.014	0.005
$Wald\ Test\ (CreditGR)$	0.018	0.000	0.001	0.000	0.000	0.000
$AR(1)$	0.000	0.000	0.000	0.000	0.000	0.000
$AR(2)$	0.994	0.040	0.423	0.272	0.514	0.886
$Hansen\ Test\ of\ Overidentification$	0.272	0.596	0.355	0.385	0.331	0.270
$Goodness\ of\ fit$	0.839	0.917	0.852	0.889	0.869	0.863
$N\_of\ instruments\ (N\_groups)$	181 (217)	182 (209)	182 (229)	182 (197)	181 (413)	181 (367)
$N\_observations$	1,199	1,323	1,349	1,173	2,464	2,220

This table reports the results on the determinants of BLs estimated using the two-step system GMM estimator as specified in Eqs.(1) and (2) for different samples of banks: Small: Banks with average total assets below or equal to the sample median. Large: Banks with average total assets greater than the sample median. North: Banks located in the North East or North West. South: Banks located in the Central or South. Windmeijer (2005) robust standard errors are reported in parentheses. The variables $BL(Total)$, $Transient(Total)$, $CAP(Total)$, $CreditGr(Total)$, $GDPGR(Total)$ and $SDEBT(Total)$ are the estimated coefficients for the test that the sum of the respective lagged terms are equal to zero (standard errors are obtained by the Delta method). In all cases, $BL(Total)$ is statistically different from one. The Wald test is the test for the joint significance of the coefficients of the lagged explanatory variables; we report the p-value. $AR(1)$, $AR(2)$ are tests of first- and second-order serial correlation in the first-differenced residuals, under the null of no serial correlation. The Hansen test of overidentification is under the null that all the instruments are valid. $Goodness\ of\ fit$ is the square correlated coefficient between actual and predicted values of the dependent variable (Bloom et al. 2007). Variables are defined as in Sections 1.3.2 and 1.3.3. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 22. Granger Sims Causality – Controlling for Outliers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Trimmed Residuals			Median Absolute Deviation			Winsorised Variables		
Dependent variable: BL_{it}	Transient & Persistent Efficiency	Transient & Persistent Efficiency with $macro\_contr$	Sims Causality Transient & Persistent Efficiency	Transient & Persistent Efficiency	Transient & Persistent Efficiency with $macro\_controls$	Sims Causality Transient & Persistent Efficiency	Transient & Persistent Efficiency	Transient & Persistent Efficiency with $macro\_controls$	Sims Causality Transient & Persistent Efficiency
BL_{it-1}	0.986***	0.852***	0.756***	0.913***	0.848***	0.661***	0.907***	0.800***	0.672***
	(0.069)	(0.063)	(0.117)	(0.085)	(0.065)	(0.111)	(0.080)	(0.066)	(0.123)
BL_{it-2}	-0.028	0.036	0.118	0.041	0.035	0.208**	0.043	0.087	0.196*
	(0.066)	(0.057)	(0.105)	(0.086)	(0.059)	(0.098)	(0.080)	(0.057)	(0.117)
$BL(Total)$	0.958***	0.887***	0.874***	0.954***	0.882***	0.870***	0.950***	0.887***	0.868***
	(0.017)	(0.024)	(0.040)	(0.016)	(0.025)	(0.042)	(0.017)	(0.028)	(0.043)
$Transient_{it-1}$	-0.558**	-0.585*	-1.498**	-0.718***	-0.565	-1.357*	-0.747***	-0.748**	-1.572**
	(0.246)	(0.355)	(0.720)	(0.235)	(0.384)	(0.729)	(0.231)	(0.380)	(0.696)
$Transient_{it-2}$	0.494**	0.542	0.152	0.546**	0.391	0.129	0.577***	0.279	0.095
	(0.214)	(0.608)	(0.423)	(0.216)	(0.577)	(0.396)	(0.217)	(0.654)	(0.434)
$Transient$			-2.005**			-2.297***			-2.006**
			(0.914)			(0.880)			(0.964)
$Transient_{it+1}$			-0.997			-0.677			-1.185
			(0.977)			(0.930)			(1.014)
$Transient_{it+2}$			-1.440			-1.574			-1.429
			(1.273)			(1.287)			(1.229)
$Transient(Total - lags)$	-0.063	-0.042	-1.346	-0.172	-0.174	-1.228	-0.170	-0.469	-1.477
	(0.364)	(0.867)	(1.026)	(0.355)	(0.844)	(1.020)	(0.352)	(0.884)	(1.021)
$Persistent$	1.262*	1.636**	0.130	1.701**	1.842**	0.267	1.845**	2.058**	0.751
	(0.681)	(0.725)	(1.156)	(0.787)	(0.752)	(1.172)	(0.791)	(0.833)	(1.112)
CAP_{it-1}	0.066	-1.761	2.352	-0.079	-1.981	1.974	0.776	-1.623	2.129
	(1.028)	(1.251)	(1.761)	(0.975)	(1.300)	(1.753)	(1.106)	(1.513)	(1.799)
CAP_{it-2}	-1.628	-0.068	-3.103	-1.588	0.369	-2.871	-2.519**	-0.294	-2.633
	(1.097)	(1.418)	(1.993)	(1.066)	(1.446)	(2.005)	(1.254)	(1.718)	(1.951)
$CAP(Total)$	-1.562**	-1.829***	-0.751	-1.666***	-1.612***	-0.897	-1.744**	-1.917***	-0.504
	(0.636)	(0.608)	(1.017)	(0.575)	(0.618)	(0.956)	(0.682)	(0.687)	(1.006)
$CreditGR_{it-1}$	-0.970***	-0.790*	-1.739***	-1.001***	-0.704*	-1.813***	-0.976***	-0.649	-1.840***
	(0.222)	(0.412)	(0.447)	(0.228)	(0.385)	(0.427)	(0.223)	(0.443)	(0.452)
$CreditGR_{it-2}$	1.312***	1.044***	1.931***	1.347***	0.940**	1.983***	1.325***	0.926**	1.877***
	(0.220)	(0.403)	(0.456)	(0.227)	(0.376)	(0.446)	(0.221)	(0.441)	(0.468)
$CreditGR(Total)$	0.342***	0.254**	0.192	0.346	0.236	0.170	0.349***	0.277*	0.0363**
	(0.096)	(0.119)	(0.213)	(0.102)	(0.129)	(0.233)	(0.109)	(0.147)	(0.241)
$Size$	-0.027	-0.022	-0.060*	-0.043*	-0.028	-0.060	-0.040	-0.028	-0.016
	(0.021)	(0.021)	(0.036)	(0.022)	(0.021)	(0.039)	(0.025)	(0.025)	(0.041)
$Crisis$	0.072***	-0.015	0.123	0.084***	-0.020	0.165**	0.086***	-0.030	0.127

	(0.025)	(0.054)	(0.078)	(0.026)	(0.052)	(0.075)	(0.027)	(0.054)	(0.078)
$Supervised$	0.134	0.139	0.329*	0.229**	0.182*	0.337*	0.208*	0.182	0.139
	(0.096)	(0.104)	(0.186)	(0.109)	(0.103)	(0.199)	(0.115)	(0.111)	(0.176)
$Industry$	-0.131*	-0.107	-0.134	-0.200**	-0.139*	-0.141	-0.197**	-0.136	-0.077
	(0.070)	(0.072)	(0.093)	(0.082)	(0.078)	(0.099)	(0.088)	(0.086)	(0.100)
$GDPGR_{it-1}$		7.792*			8.721**			8.427**	
		(4.144)			(3.764)			(3.861)	
$GDPGR_{it-2}$		2.604*			2.918**			2.845**	
		(1.354)			(1.221)			(1.271)	
$GDPGR(Total)$		10.40*			11.64**			11.27**	
		(5.462)			(4.946)			(5.090)	
$SDEBT_{it-1}$		5.596**			6.164**			6.073**	
		(2.795)			(2.501)			(2.618)	
$SDEBT_{it-2}$		-5.785*			-6.385**			-6.250**	
		(3.075)			(2.761)			(2.889)	
$SDEBT(Total)$		-0.189			-0.221			-0.176	
		(0.358)			(0.353)			(0.375)	
HPI_{it-1}		-0.011			-0.012*			-0.011	
		(0.007)			(0.007)			(0.007)	
$Constant$	-0.909	-0.139	5.620*	-1.048	0.001	5.482*	-1.210*	-0.049	5.080*
	(0.631)	(1.497)	(2.995)	(0.731)	(1.466)	(3.077)	(0.707)	(1.463)	(2.929)
$Wald\ Test\ (Transient-\ lags)$	0.000	0.017	0.017	0.000	0.081	0.032	0.000	0.055	0.010
$Wald\ Test\ (Transient-\ leads)$			0.274			0.327			0.181
$Wald\ Test\ (CAP)$	0.041	0.003	0.298	0.014	0.010	0.345	0.025	0.008	0.402
$Wald\ Test\ (CreditGR)$	0.000	0.005	0.000	0.000	0.012	0.000	0.000	0.031	0.000
$Wald\ Test\ (GDPGR)$		0.157			0.057			0.080	
$Wald\ Test\ (SDEBT)$		0.042			0.013			0.020	
$AR(1)$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$AR(2)$	0.219	0.517	0.668	0.676	0.510	0.247	0.536	0.746	0.637
$Hansen\ Test\ of\ Overidentificationio$	0.318	0.384	0.144	0.454	0.415	0.199	0.467	0.438	0.190
$Goodness\ of\ fit$	0.872	0.871	0.844	0.869	0.871	0.844	0.870	0.870	0.855
$N\_of\ instruments\ (N\_groups)$	182 (422)	268 (422)	89 (368)	182 (426)	268 (423)	89 (369)	182 (426)	268 (426)	89 (374)
$N\_observations$	2480	2480	1591	2,495	2,495	1,600	2,522	2,522	1,623

This table reports the results on the determinants of BLs estimated using the two-step system GMM estimator as specified in Eqs.(1) and (2) when controlling for outliers. Columns 1-3 report results excluding the observations corresponding to the largest 1% of squared residuals; columns 4-6 report results for using the Median Absolute Deviation method on BL; columns 7-9 report results from winsorizing all financial data at the top and bottom 1%. Windmeijer (2005) robust standard errors are reported in parentheses. The variables $BL(Total)$, $Transient(Total)$, $CAP(Total)$, $CreditGr(Total)$, $GDPGR(Total)$ and $SDEBT(Total)$ are the estimated coefficients for the test that the sum of the respective lagged terms are equal to zero (standard errors are obtained by the Delta method). In all cases, $BL(Total)$ is statistically different from one. The Wald test is the test for the joint significance of the coefficients of the lagged explanatory variables; we report the p-value. $AR(1)$, $AR(2)$ are tests of first- and second-order serial correlation in the first-differenced residuals, under the null of no serial correlation. The Hansen test of overidentification is under the null that all the instruments are valid. $Goodness\ of\ fit$ is the square correlated coefficient between actual and predicted values of the dependent variable (Bloom et al. 2007). Variables are defined as in Sections 1.3.2 and 1.3.3. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 23. Granger-Sims Causality Results – logarithm of BL

Dependent variable: $lnBL_{it}$	(1) Transient & Persistent Efficiency and Time FE	(2) Excluding Persistent Efficiency	(3) Excluding Persistent Efficiency with $macro\_controls$	(4) Excluding Transient Efficiency	(5) Excluding Transient Efficiency with $macro\_controls$	(6) Managerial & Persistent Efficiency	(7) Managerial & Persistent Efficiency with $macro\_controls$	(8) Sims Causality Transient & Persistent Efficiency
BL_{it-1}	0.887***	0.946***	0.897***	0.869***	0.775***	0.912***	0.778***	0.695***
	(0.091)	(0.081)	(0.092)	(0.088)	(0.095)	(0.078)	(0.074)	(0.125)
BL_{it-2}	0.036	0.004	0.003	0.079	0.104	0.039	0.090	0.189
	(0.085)	(0.077)	(0.078)	(0.085)	(0.084)	(0.078)	(0.061)	(0.123)
$BL(Total)$	0.923***	0.951***	0.901***	0.948***	0.880***	0.951***	0.869***	0.884***
	(0.027)	(0.018)	(0.030)	(0.019)	(0.030)	(0.017)	(0.032)	(0.043)
$Transient_{it-1}$	-1.314*	-0.777***	-0.641			-0.731***	-0.750**	-1.284*
	(0.674)	(0.257)	(0.454)			(0.228)	(0.375)	(0.678)
$Transient_{it-2}$	0.460	0.553***	0.468			0.524***	0.121	0.162
	(0.287)	(0.204)	(0.909)			(0.200)	(0.637)	(0.408)
$Transient$								-1.594*
								(0.923)
$Transient_{it+1}$								-0.953
								(0.930)
$Transient_{it+2}$								-1.180
								(1.260)
$Transient(Total - lags)$	-0.854	-0.224	-0.173			-0.207	-0.629	-1.122
	(0.654)	(0.331)	(1.255)			(0.330)	(0.883)	(0.975)
$Persistent$	1.771***			2.447***	3.127***	1.517**	1.755**	0.958
	(0.613)			(0.793)	(1.041)	(0.667)	(0.744)	(1.134)
CAP_{it-1}	-1.575	0.088	-2.674*	-0.346	-0.708	0.190	-1.763	1.883
	(1.358)	(0.976)	(1.406)	(1.101)	(1.826)	(0.995)	(1.435)	(1.706)
CAP_{it-2}	0.371	-1.979**	0.853	-1.357	-0.716	-1.958*	0.219	-2.703
	(1.459)	(0.968)	(1.575)	(1.156)	(2.053)	(1.109)	(1.701)	(1.869)
$CAP(Total)$	-1.204*	-1.892**	-1.820**	-1.703**	-1.424**	-1.768**	-1.544**	-0.820
	(0.626)	(0.598)	(0.756)	(0.675)	(0.704)	(0.610)	(0.677)	(1.008)
$CreditGR_{it-1}$	-0.009	-0.807***	-0.348	-0.706***	-1.138***	-0.890***	-0.699	-1.627***
	(0.420)	(0.208)	(0.482)	(0.191)	(0.387)	(0.208)	(0.428)	(0.426)
$CreditGR_{it-2}$	0.382	1.254***	0.799*	1.109***	1.395***	1.274***	0.982**	1.702***
	(0.434)	(0.193)	(0.479)	(0.189)	(0.390)	(0.209)	(0.435)	(0.437)
$CreditGR(Total)$	0.373***	0.448***	0.452***	0.402***	0.257	0.384*	0.282*	0.075
	(0.115)	(0.091)	(0.133)	(0.112)	(0.164)	(0.101)	(0.145)	(0.230)
$Size$	-0.028	-0.042**	-0.039*	-0.041	-0.043	-0.044**	-0.033	-0.030
	(0.021)	(0.018)	(0.020)	(0.026)	(0.035)	(0.021)	(0.023)	(0.038)
$Crisis$	0.005	0.071***	-0.011	0.092***	0.048	0.074***	-0.025	0.119
	(0.051)	(0.027)	(0.064)	(0.028)	(0.054)	(0.026)	(0.058)	(0.076)
$Supervised$	0.159*	0.140	0.147*	0.231*	0.278	0.221**	0.216*	0.218
	(0.096)	(0.086)	(0.084)	(0.131)	(0.178)	(0.101)	(0.120)	(0.189)

$Industry$	-0.160**	-0.065	-0.017	-0.234***	-0.280**	-0.185**	-0.139*	-0.115
	(0.063)	(0.043)	(0.046)	(0.082)	(0.122)	(0.072)	(0.077)	(0.091)
$GDPGR_{it-1}$			9.304**		8.588**		8.618**	
			(4.458)		(4.230)		(4.130)	
$GDPGR_{it-2}$			3.316**		2.759*		2.776**	
			(1.429)		(1.449)		(1.390)	
$GDPGR(Total)$			12.62**		11.35**		11.39**	
			(5.833)		(5.658)		(5.485)	
$SDEBT_{it-1}$			6.708**		5.480*		6.024**	
			(2.951)		(2.924)		(2.854)	
$SDEBT_{it-2}$			-7.095**		-5.850*		-6.229**	
			(3.219)		(3.241)		(3.131)	
$SDEBT(Total)$			-0.387		-0.370		-0.205	
			(0.380)		(0.389)		(0.375)	
HPI_{it-1}			-0.016**		-0.011		-0.011	
			(0.007)		(0.008)		(0.008)	
$Constant$	-0.753	0.393	2.161	-1.952***	-1.154	-0.873	0.373	3.855
	(0.795)	(0.360)	(1.749)	(0.680)	(1.589)	(0.643)	(1.487)	(2.831)
$Wald\ Test\ (Managerial - lags)$	0.081	0.000	0.060			0.000	0.055	0.029
$Wald\ Test\ (Managerial - leads)$								0.298
$Wald\ Test\ (CAP)$	0.091	0.003	0.010	0.040	0.102	0.013	0.017	0.343
$Wald\ Test\ (CreditGR)$	0.005	0.000	0.001	0.000	0.001	0.000	0.025	0.000
$Wald\ Test\ (GDPGR)$			0.063		0.115		0.113	
$Wald\ Test\ (SDEBT)$			0.059		0.118		0.042	
$Wald\ Test\ (Time\ Fixed\ Effects)$	0.130							
$AR(1)$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$AR(2)$	0.306	0.238	0.209	0.603	0.938	0.394	0.713	0.846
$Goodness\ of\ fit$	0.871	0.874	0.877	0.859	0.849	0.868	0.868	0.852
$Hansen\ Test\ of\ Overidentification$	0.574	0.603	0.622	0.295	0.225	0.597	0.460	0.177
$N\_of\ instruments\ (N\_groups)$	188 (426)	207 (426)	194 (426)	181 (426)	222 (426)	182 (426)	268 (426)	89 (374)
$N\_observations$	2,522	2,522	2,522	2,522	2,522	2,522	2,522	1,623

This table reports the results on the determinants of BLs estimated using the two-step system GMM estimator as specified in Eqs.(1) and (2) when using the logarithm of BL as dependent variable. Windmeijer (2005) robust standard errors are reported in parentheses. The variables $BL(Total)$, $Managerial(Total)$, $CAP(Total)$, $CreditGr(Total)$, $GDPGR(Total)$ and $SDEBT(Total)$ are the estimated coefficients for the test that the sum of the respective lagged terms are equal to zero (standard errors are obtained by the Delta method). In all cases, $BL(Total)$ is statistically different from one. The Wald test is the test for the joint significance of the coefficients of the lagged explanatory variables; we report the p-value. $AR(1)$, $AR(2)$ are tests of first- and second-order serial correlation in the first-differenced residuals, under the null of no serial correlation. The Hansen test of overidentification is under the null that all the instruments are valid. $Goodness\ of\ fit$ is the square correlated coefficient between actual and predicted values of the dependent variable (Bloom et al. 2007). Variables are defined as in Sections 1.3.2 and 1.3.3. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

1.6 Conclusions and Policy Implications

The global financial crisis has brought the issue of bank non-performing loans under the spotlight of regulators and policymakers. NPLs have been identified as a key indicator to assess the stability and the soundness of the financial system and they have also proved to be a valuable early warning indicator for banking crises. The objective of this study was to assess the intertemporal relationship between NPLs and bank cost efficiency in a sample of Italian banks over the period 2006-2015. More precisely, we test for the hypotheses of managerial behaviour (i.e., *bad management/skimping/bad luck)* as suggested by Berger and DeYoung (1997) and, in doing this, we advance the prior literature by employing a new measure of cost efficiency recently introduced by Badunenko and Kumbhakar (2017) that disentangles cost efficiency into two separate components: time-invariant (*persistent*) inefficiency and time-varying (*transient*) inefficiency. Transient inefficiency relates to short-term sources of inefficiency that may originate from non-systematic management problems whereas persistent inefficiency refers to long-term sources of inefficiencies that may arise from systematic behavioural shortcomings or regulatory and structural constraints.

We divide the study into two stages. In the first stage, we estimate persistent and transient cost efficiency via Stochastic Frontier Analysis, finding that, at the aggregate level, Italian banks could reduce their costs by up to 2.8% and 7.4% if they were to eliminate transient and persistent inefficiencies, respectively. Specifically, short-term inefficiencies suffered from a steep decline in correspondence of the outbreaks of the global financial crisis and of the sovereign debt crisis whereas they do not appear to be related to the size of the financial institutions. Furthermore, we are the first to show that the well-documented strong regional disparities (in terms of social, economic and demographic conditions) that characterised Italy and the bank type (commercial, cooperative) have a direct impact on the ability of banks to operate efficiently and to survive in the long-run.

In the second stage of the study, we investigate the drivers of the credit quality of banks by assessing the intertemporal relationship between bad loans and efficiency using a Granger-causality framework. Our findings have several implications in terms of regulation and policy. First, we observe a negative intertemporal relationship between *transient efficiency* and asset quality. This could imply that it is within the control of the senior management to remove short-term inefficiencies, thus preventing the increase of that part of NPLs that stem because of banks' lax practices in loan underwriting, monitoring and control. In this respect, regulators should consider intensifying the regulatory framework for individual accountability by introducing, for instance, a mandatory certification to ensure the fitness and propriety of people performing key roles in the bank such as mortgage and retail investment advisers.

Furthermore, we observe that higher persistent efficiency is associated with higher volumes of NPLs, potentially denoting that banks achieve greater efficiency in the long-run by diverting resources from managing the loan portfolio towards coping with the external environment (*resources misallocation* hypothesis). Therefore, the primary objective of regulators should relate to the removal of these structural inefficiencies, which we report are related to the geographical location and the legal form of banks. By mitigating these latent inefficiencies, banks could be able to free up resources to allocate to the screening of customers, the appraisal of loan collaterals and the monitoring of loans.

Concerning additional drivers of BLs, in both models we find support for the moral hazard hypothesis, suggesting that weak capital positions may incentivize banks to engage in riskier activities. Moreover, we provide evidence that higher bad loans tend to follow periods of higher lending rates and higher GDP growth, indicating that credit risk accumulates during the expansionary phase of the economy. It follows that regulators should strengthen the supervision process to ensure the enforcement of the prudential rules for the granting of loans. For example, supervisory bodies should consider verifying that the risk premium charged by banks in each loan operation corresponds to the actual level of risk borne by the institutions. Furthermore, policymakers should focus on the issue of *zombie lending*, which affects the resource allocation process and hampers real economic growth.[68]

Finally, we find that, on average, large banks have better asset quality than small banks. However, TBTF banks represent an important exception. Banks directly supervised by the ECB display, on average, a higher level of impaired loans

[68] As noted by Balgova et al. (2016), "when banks channel most new credit into the existing troubled sectors and companies ("zombie lending"), they help to prevent second-round business failures, but this also diverts funds away from new, more productive parts of the economy (p. 7)".

than the rest of the industry, indicating that TBTF banks could resort to lax credit policies that eventually will result in lower credit quality. This evidence prompts policymakers to consider reducing TBTF incentives such as the certainty about the provision of public funds from the government in case of financial distress.[69] Our findings are corroborated by a series of robustness tests.

[69] The issue of TBTF banks have found renewed attention following the financial crisis and preliminary actions have been implemented by regulators to mitigate the moral hazard incentives associated with the prospect of bailouts. For example, the ECB has introduced the *bail-in* tool that aims to provide an orderly resolution of (large) failing institutions by shifting the burden of the losses from the taxpayers to the shareholders and the creditors of the bank. By making bank creditors accountable for the losses of their firm, the *bail-in* resolution tool may result in improved corporate governance practices and lower risk-taking

Chapter 2

Forecasting Non-Performing Loans in the Euro Area: A quantile regression approach

2.1 Introduction

Over the last decade, the issue of non-performing loans (hereafter NPLs) has been at the centre of prudential and supervisory authorities' discussions and priorities.[70] This is because high levels of impaired loans in banks' balance sheets have micro- and macroprudential implications for banks and policymakers (European Systemic Risk Board, 2017).

From the point of view of individual financial institutions (micro-prudential perspective), a high volume of NPLs creates a "vicious circle" between profitability, capital, and lending. Non-performing assets depress profitability because they required banks to book provisions for credit losses, directly impacting their income and internal capital generation capacity via lower retained earnings. Furthermore, while NPLs do not generate income, they are still required to be funded at market costs, which will be higher for those banks with high levels of impaired assets as NPLs increase the risk premium demanded by market participants (Jassaud and Kang, 2015). Additionally, NPLs challenge banks' profitability via higher operating costs. Banks have to incur higher expenses related to staff resources that need to be dedicated to managing, restructuring and eventually disposing of these impaired loans (Berger and DeYoung, 1997; Badunenko et al., 2021). The weakened earnings profile ultimately hinders the capacity of these institutions to strengthen their capital positions, limiting their ability and willingness to support new lending to the real economy (Baldini and Causi, 2020; Huljak et al., 2022). Banks' capital is also affected by NPLs via increased risk-weighted assets (RWA) as impaired loans are subject to higher risk weights. As such, these banks have to raise more capital to keep operating above their minimum regulatory capital requirements. However, tapping into equity markets with weak fundamentals might prove to be particularly difficult and costly given the investors' perception of banks' riskiness.

From a macroprudential perspective, a large stock of NPLs represents a threat to systemic risk and financial stability by weakening banks' balance sheets and rendering the banking sector as a whole more vulnerable to future shocks (European Systemic Risk Board, 2017). Further, banks' resources are locked in by the management of NPLs, impairing the core role of banks as financial intermediaries.

[70] For example, the Single Supervisory Mechanism, the supervisory arm of the European Central Bank, has identified credit risk management as a key supervisory priority since 2016 (see Supervisory priorities for 2021 (europa.eu))

An elevated stock of NPLs implies that banks might be unable (and unwilling) to adequately support the recovery of the economy by extending the necessary credit, especially after a crisis where bank loans might be needed the most (Tölö and Virén, 2021). In bank-dependent economies, such as the euro area countries, credit supply constraints represent a major obstacle to economic growth and recovery. This is particularly relevant in the context of the euro area corporate sector, where small and medium enterprises (SMEs) - which represent the backbone of the euro area economy - are mostly bank-dependent for their financing needs. A lack of access to bank credit may result in stagnating job creation and lower productivity growth, as firms cannot afford to invest, expand or maintain capacity (European Systemic Risk Board, 2017).[71] Similar concerns for the economy arise when the high stock of NPLs is a signal of a debt overhang problem, whereby the excessive leverage of corporate and household sectors hinders economic growth via lower investments (European Systemic Risk Board, 2017). An additional dimension to take into consideration relates to the conditions under which households and corporates will be able to access credit in a banking sector characterised by high NPLs. In such a context, borrowers may face tightened credit standards and higher interest rates as high NPLs banks might try to compensate for the higher funding costs and depressed profits, ultimately fuelling another vicious circle, whereby the higher cost of debt for borrowers translates into financial distress and defaults (Accornero et al., 2017).

The elevated levels of NPLs burdening euro area banks are mainly a legacy of the Global Financial Crisis (2007-2009) and the Sovereign Debt Crisis (2010-2012). Looking at the dashed red line in Figure 8, we notice that, on average, the asset quality of euro area banks began to deteriorate from the end of 2008 until mid-2010 as a consequence of the wave of corporate and household defaults that followed the financial crisis. The ratio of NPLs started to rise again from the end of 2010, following the increase in tensions in the sovereign markets, until the end of 2013. After a few years of sluggish reduction in NPLs, banks began to clean up their balance sheet starting in 2017, after the NPLs stock in banks' balance sheets reached an all-time-high record of €1 trillion at the end-2016 (European Systemic Risk Board, 2017). At the end of 2020, our sample of euro area banks reported an average NPLs ratio of 4.6% and a median ratio of 3.2% (see Figure 8).

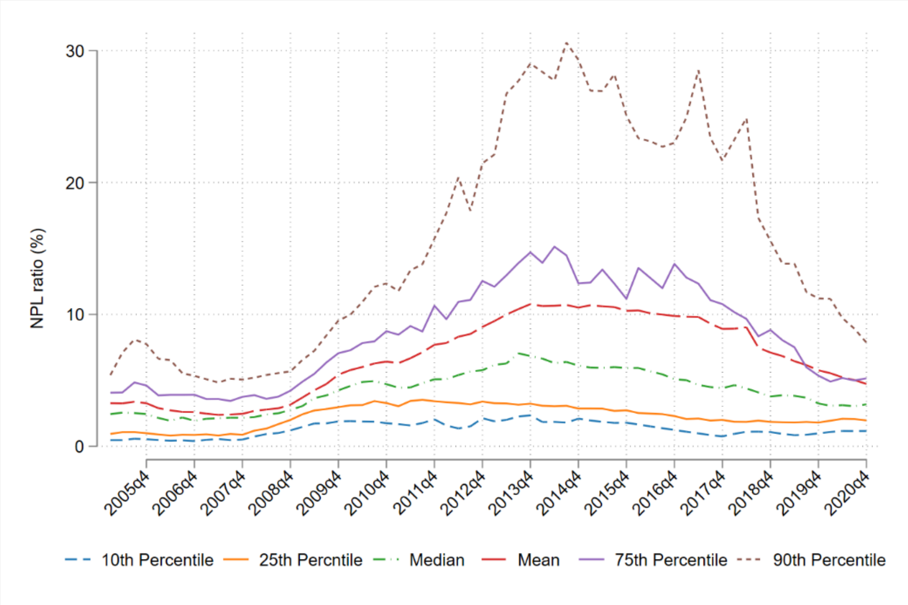
[71] This is for instance the lesson learnt from the "Japanese lost decade" (European Systemic Risk Board, 2017).

While over the recent years the euro area banks have made great efforts to reduce defaulted loans in their balance sheets, it remains interesting to notice the great dispersion in NPLs by looking at the different percentiles of the NPLs of the distribution. In particular, Figure 8 suggests the presence of a fat right tail in the distribution of NPLs.[72] In fact, while the line representing the 10th and 25th percentile are relatively close to each other, those capturing the NPLs ratio at the 75th and 90th signal the presence of banks with remarkably elevated impaired loans. The great dispersion is the result of the heterogeneity across countries and banks in how NPLs have built up after the crises, but also in how NPLs have been managed and disposed of during recent years. For example, Figure 9 shows the median NPLs ratio across countries at selected periods (i.e., 2005, 2015, 2015, 2020). Greece and Cyprus stand out, with the median NPLs ratio surpassing 40% in 2015 and remaining significantly above 10% in 2020. Following the COVID-19 pandemic and the global economic slowdown triggered by the Russia-Ukraine war, non-performing loans are likely to become once again an important problem.

In light of the micro- and macroprudential consequences of non-performing loans, investigating the evolution of credit quality during crisis periods becomes of utmost importance. For this reason, models aimed at informing in a forward-looking manner on the performance of banks, such as stress test exercises, have become an integral part of prudential and supervisory authorities' toolkits in the context of the increased efforts to ensure financial stability. This chapter presents a credit risk model aimed at i) detecting non-linearities between NPLs and macro-financial variables and ii) conditionally forecasting the evolution of banks' non-performing loans under a baseline and an adverse scenario using non-linear panel data models.

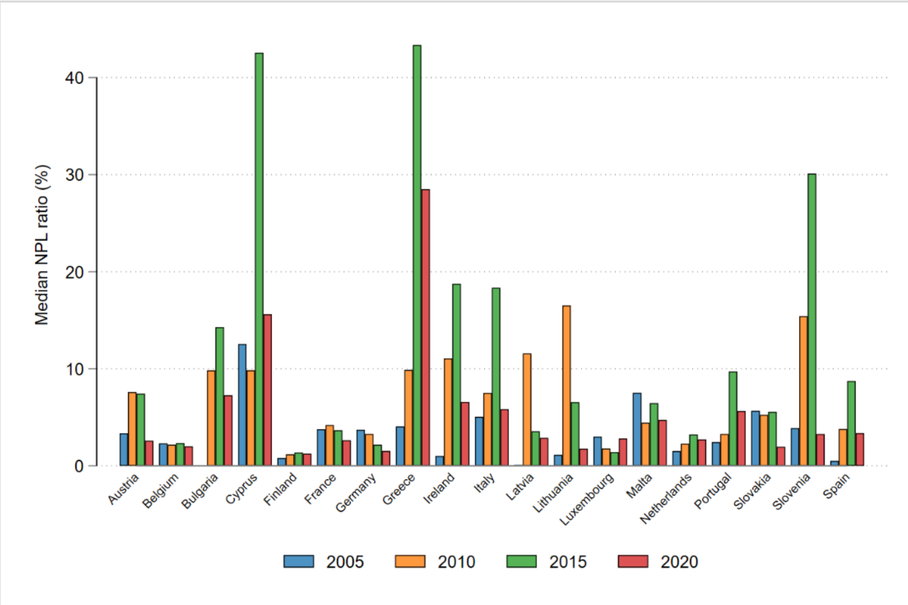
[72] It is interesting to notice that the line representing the mean and the 75th percentile of the NPL ratio cross starting from 2020, suggesting the presence of a significantly left-sked distribution of NPL ratio in the euro area with few banks on the right tail with considerably high levels of impaired loans.

Figure 8. Evolution of NPL Ratios in the euro area



Source: Author's calculation based on data from Fitch Connect and a sample of 106 banks

Figure 9 Median NPL Ratio across euro area countries (2005-2020)



Source: Author's calculation based on data from Fitch Connect and a sample of 106 banks

We start the analysis by studying the non-linear effects existing in the linkages between a sample of euro area banks' NPLs and their main macro-financial risk factors between 2005 and 2020. We contribute to the existing literature on the drivers of NPLs by using state-of-the-art dynamic fixed effects quantile regressions (Machado and Santos Silva, 2019) and investigating whether and how different explanatory variables affect different parts of the distribution of non-performing loans. The main advantage of quantile models is the *informational gains* they provide. Quantile regressions allow inference about the importance of the explanatory variables at different levels of the conditional distribution of the dependent variable. This is particularly relevant because the relationship between macro-financial factors and NPLs might vary across the business cycle. In particular, this technique allows us to focus on the tails of the distributions of NPLs and to make inference on what drives high levels of NPLs, which is of key interest to prudential authorities. By contrast, past approaches (see, among many others, Espinoza and Prasad, 2010; Bofondi and Ropele, 2011; Castro, 2013; Klein, 2013; Makri, Tsagkanos and Bellas, 2014; Ghosh, 2015; Chaibi and Ftiti, 2015; Staehr and Uuskula, 2017; Cerulli et al., 2020) that focus on the conditional mean and use standard ordinary least squares models might overlook the potential heterogeneity across the relationships between macro-financial factors and banks' NPLs.

We document that our selected macroeconomic variables have different explanatory powers at different quantiles of the distribution of NPLs. Specifically, we find that GDP growth, unemployment, and inflation do not explain the left tail of the distribution of NPLs (i.e., banks with low NPLs) while the slope of the yield curve has no predictive power on the highest quantiles of NPLs. The house price index is the only control found negative and statistically significant across the entire quantile distribution. Our findings represent novel evidence of the presence of heterogenous drivers of asset quality in euro area banks depending on the quantile of NPLs distribution. By relying on standard linear models, past studies failed to detect non-linear effects in the relationship between credit risk and macro-financial factors.

In the second step of the analysis, we produce bank-specific conditional forecasts of NPLs by combining the estimated coefficients of the quantile regression models with the forecasted values of the macroeconomic variables found to affect NPLs. Producing paths of the evolution of NPLs helps inform prudential and supervisory authorities on the risks that may arise during specific macroeconomic developments and on the ability of banks to withstand the materialisation of *severe but plausible scenarios*. By relying on quantile regressions, we are able to produce conditional forecasts using various sets of coefficients estimated at different percentiles, according to the severity of the scenario that one wants to investigate and thus somehow mimicking the stress conditions that banks would face during turmoil. First, we show that our models have a good in-sample predictive power by showing that the model is able to track the evolution of NPLs occurred in the euro area over the past 15 years. In the second step, we use the macro scenarios employed during the 2021 European Banking Authority (EBA) Stress Test exercise to produce bank-specific conditional forecasts of NPLs according to the given baseline and adverse scenarios.

We distinguish ourselves from past studies by producing bank-specific paths of the NPLs evolution, while most of the past studies focus on time-series aggregated at the country level (Schechtman and Gaglianone, 2012; Kanas and Molyneux, 2018). We do so by factoring in the role of time-invariant bank-specific effects (i.e., bank-fixed effects) that we estimate by employing the Machado and Santos Silva (2019) estimator. Lastly, our results are easily reproducible as we rely on publicly available data, whereas the majority of credit risk forecasting models are developed using proprietary data internal to central banks (e.g., Boss et al., 2009; Gross, Georgescu and Hilberg, 2017).

The rest of the Chapter is organized as follows. Section 2.2 reviews the empirical literature focused on estimating banks' drivers of NPLs with the objective of producing forecasts of banks' asset quality in the context of stress test exercises. Section 2.3 presents the methodological framework employed to model NPL ratios, the explanatory variables selected and the features of the sample. Section 2.4 presents the estimation results, the in-sample fit and the in-sample forecast performance of the model as well as an example of how to use the proposed methodology to produce out-of-sample forecasts of NPLs. Section 2.5 concludes.

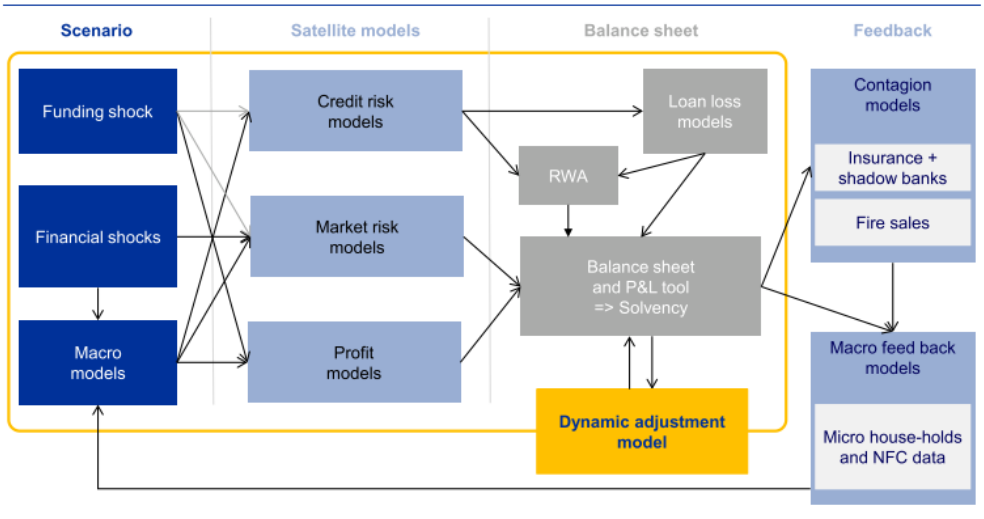
2.2 Forecasting credit risk – a stress test approach

In this section, we introduce the framework for stress tests currently adopted by the European Central Bank (ECB). This serves as an example to introduce the several building blocks that constitute the framework and to show where and how the model proposed in this Chapter fits. Additionally, we review the most relevant literature focusing on credit risk models employed for forecasting purposes. While several of these models have been developed within prudential authorities and central banks, thus benefitting from disaggregated proprietary data and detailed credit risk parameters (e.g., probabilities of defaults (PDs), loss given default (LGD)), other models have focused on producing a forecast of NPL ratios using data available from public providers.

Scenario-based analyses of bank credit risk aim at assessing in a forward-looking manner the resilience of the banking sector to severe but plausible adverse macro-financial and economic shocks. Stress test exercises are an example of scenario analyses. Stress tests have become standard practice following the global financial crisis and are an essential element in the toolkit of the supervisory, resolution, and central bank authorities (see Dees et al., 2017; Budnik et al., 2020).

A stress test exercise comprises several blocks of analysis. Borrowing the structure of the ECB framework for stress tests (Figure 10), the first block concerns the design of a macroeconomic scenario to be applied to the banking sector.[73] In the second block, satellite models are employed to assess the impact of the macroeconomic variables on banks' balance sheets and profit and loss (P&L) components. In the third block, the estimated elasticities (i.e., coefficients) from the satellite models are used to generate conditional forecasts of balance sheets and P&L components of individual banks, ultimately assessing the impact on each bank's solvency position. Finally, the last block usually concerns the estimation of contagion and feedback loop effects.

Figure 10. The four-pillar structure of the ECB solvency analysis framework



Source: Dees et al. (2017)

[73]In the design of the macroeconomic scenario, the *narrative* employed represents the key element of every Stress Test exercise. The narrative refers to the assumptions used to produce the path of the macroeconomic variables under the baseline and adverse scenario. For additional information, see Section 2.4.5.

When considering stress test frameworks, one can distinguish between two types of approaches, namely the bottom-up and the top-down approach. The former type of exercise is carried out by the banks, which produce themselves impact calculations given the scenarios and using their internal data and models. By contrast, the top-down stress tests are run by the regulatory authorities using data and models available at central banks. The two approaches to stress tests can be seen as complementary to each other, each carrying advantages and drawbacks. On the one hand, the bottom-up approach benefits from detailed and broad internal bank data, making the calculations more precise. Nonetheless, the increase in reliability and accuracy comes at the expense of comparability across banks. Indeed, an advantage of using a top-down approach is to provide a level playing field across banks. That is, top-down exercises are important to benchmark the calculations provided by the banks in the context of bottom-up stress tests, and eventually to challenge such results and open a dialogue with the bank and the banking sector in general (Daniëls et al., 2017).

As aforementioned, after the GFC, banks' solvency positions in the event of severe macroeconomic conditions are being regularly assessed via system-wide stress test exercises. For instance, the European Banking Authority runs a bi-annual EU-wide stress test exercise in cooperation with the ECB, the European Systemic Risk Board (ESRB), and the national supervisory authorities covering the largest European banks. The EBA framework is a constrained bottom-up approach, meaning that the banks perform the calculations using their own data and in-house models, but they are subject to certain constraints in the calculations.[74,75] In addition, the ECB carries out annual stress test exercises for those banks under the direct supervision of the Single Supervisory Mechanism, the results of which are a key input for the Supervisory and Review Evaluation Process (SREP).[76] In the United Kingdom (UK), the Bank of England performs an annual stress test exercise covering

[74] For instance, in the last Stress Test exercise, the EBA constrained the projections of fees & commissions (F&C) provided by the individual banks in the following ways: in the baseline scenarios, F&C cannot exceed the starting point level, while in the adverse scenario, a minimum reduction compared to the starting point is prescribed for the cumulative projections.

[75] From 2023, the EBA is moving to a hybrid approach to stress tests, combining bottom-up and top-down.

[76]The results from the annual ECB stress tests are included in the SREP assessment in two ways. Qualitative outcome from the stress test influences the setting of Pillar 2 Requirements (P2R), while quantitative outcome determine the Pillar 2 Guidance requirements (P2G). SSM-wide stress test 2021 - final results (europa.eu)

banks and building societies, which helps inform the Prudential Regulatory Authority (PRA) on the setting of capital buffers. Likewise, in the US, the Federal Reserve (FED) conducts the stress test annually, assessing how large bank holding companies are likely to perform under a hypothetical recession. The outcome of the FED stress test will (partly) determine the capital requirements of banks (Board Of Governors Of The Federal Reserve System, 2022). Stress Tests are also an integral part of the Financial Sector Assessment Programs (FSAPs) conducted by the International Monetary Fund.[77]

In light of this, it is not surprising that a significant part of the literature and methodological advances on stress test models for *credit risk* emanates from central banks' studies. Models developed within central banks benefit from the use of highly disaggregated proprietary data with often long-time series. For instance, Boss et al. (2009) present the model used at the Austrian central bank to model the PDs of various sectors of the Austrian economy using data from 1970. Using proprietary data on Brazilian banks, Schechtman and Gaglianone (2012) assess the credit risk coming from the household sector between 1995Q1 and 2009Q3 focusing on the tails of the distribution of the risk variable. To this end, they employ two methodological frameworks: the Wilson (1997) approach, whereby macroeconomic surprises affect the macro-credit risk relationship, and a quantile regression approach where the relative importance of the macro variables can vary along the credit risk distribution. The Dutch National Bank developed models to translate macroeconomic shocks into changes in PDs and LGD risk parameters for each bank portfolio (e.g., corporate, retail) (Daniëls et al., 2017).[78] Gross, Georgescu and Hilberg (2017) present the methodology of the satellite models used by the European Central Bank to model country and loan portfolio-level PDs and LGD parameters. For PDs, they employ an Autoregressive Distributed Lag specification that is estimated via a Bayesian Model Averaging (BMA) methodology whereas for the LGD model, a structural model that does not require historical data except for the starting points is developed.[79]

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[77] Established in 1999, the FSAP is an in-depth assessment of a country's financial sector, with a focus on assessing the resilience of the financial sector, the quality of the regulatory and supervisory framework, and the capacity to manage and resolve financial crises (see Financial Sector Assessment Program (FSAP) (imf.org))

[78] For instance, the PD of the mortgage portfolio will be affected by interest rates, unemployment and economic growth trends. The LGD of mortgage loan portfolios will largely be driven by house price movements and fire sale assumptions.

[79] For the PD model, the stock of NPLs is conditional on the previous period's NPLs stock, which decreases at the write-off rate w, plus the portion of the stock of gross loans that will default with

Recently, Budnik et al. (2020) introduced the Banking Euro Area Stress Test (BEAST) model developed for macroprudential stress testing of the euro area banking sector. The main contribution of the BEAST model is that banks can adjust the size and composition of their assets, along with interest rates or dividend payouts. This is a stark difference in comparison with other stress test frameworks that rely on the "static balance sheet" assumption (see the discussion in Section 2.3.2).

Closer to the spirit of this Chapter, other studies have focused on assessing the drivers of NPLs and producing forecasts of their paths. Among these studies, it is worth mentioning the IMF approach. Using a Generalized Method of Moments (GMM) approach, Wezel, Canta and Luy (2014) model the logistic transformation of the NPLs ratio as a function of real GDP growth, changes in unemployment, changes in external sector variables and interest rates and project their evolution under three different macroescenarios. Covas, et al. (2014) propose an econometric framework for estimating capital shortfalls of US bank holding companies. For the credit risk block, they model the quarterly net charge-off rates for eight major loan categories using a quantile autoregressive model, which according to their results, delivers a superior out-of-sample forecasting performance relative to the standard linear framework. Staehr and Uuskula (2017) forecast the NPL ratios of 26 European countries between 1997Q4 to 2017Q1. The authors employ fixed effects linear regressions and a sample at the country-level, distinguishing between household and mortgage loans. Kanas and Molyneux (2018) propose an additive semi-parametric quantile approach to model the dynamics of NPLs in the US banking system between 1984 and 2013. By focusing on the tails of the NPLs distributions, the authors claim to uncover drivers of asset quality that a linear model would otherwise fail to show, concluding that their methodology provides a more flexible and accurate methodology for assessing banks' solvency. Bonaccorsi Di Patti and Cascarino (2020) provide conditional forecasts of households and corporate NPLs in the context of the Italian banking sector. To link the flow of new non-performing loans to macroeconomic and financial variables, the authors employ a Bayesian Model Averaging approach. Finally, in the context of the COVID-19 pandemic, the Organisation for Economic Co-operation and Development (OECD, 2021) conducted a simulation analysis on 37 economies aimed at assessing the extent of the

probability PD and minus the amount of loans that move from the NPL to the performing loan category.

potential rise in NPLs depending on the severity of the COVID-19 crisis on the global economic environment. The model is based on country-level annual data on 37 economies and the relationship between NPLs and macro-financial variables is investigated using linear fixed effect models.

As outlined above, the body of research on forecasting credit risk is relatively broad and mainly developed by prudential authorities in the context of stress test exercises. However, with a very limited number of exceptions (e.g., Covas, et al., 2014; Kanas and Molyneux, 2018), non-linearities between macro-financial factors and NPLs (or other credit risk parameters) have not been taken into consideration by the literature. This is a severe limitation given that the distribution of credit risk variables is often skewed and linear models would fail to capture the sensitivity of the explanatory variables at the tails of the distribution. Additionally, many of these models aim at producing forecasts at the country-level, without considering how credit risk can be significantly dependent on bank-specific features.

This chapter contributes to this literature by focusing on the second and third blocks of a stress test framework. We propose a top-down model to i) assess the drivers of NPLs using quantile regressions and ii) produce bank-specific conditional forecasts of banks' credit risk given the path of macroeconomic variables. In the next section, we introduce the methodological framework, the explanatory variables and the data used in this Chapter.

2.3 The econometric approach and data

In this section, we introduce the empirical approach used to assess the drivers of NPLs and we present the rationale behind the choice of the explanatory variables in the models. Finally, we present the data and the sample employed for the analyses of this Chapter.

2.3.1 Quantile dynamic fixed effect panel model

To estimate the drivers of non-performing loans, we implement a dynamic fixed effect quantile regression (DFE-QR hereafter) estimated via the approach proposed by Machado and Santos Silva (2019). Specifically, we estimate the following equations (2.1) and (2.2):

$$npls\_logit_{i,j,t} = \alpha + \beta npls\_logit_{i,j,t-1} + \gamma Z_{j,t-1} + v_i + \varepsilon_{i,j,t} \qquad 2.1$$

$$npls\_logit_{i,j,t} = \alpha + \beta npls\_logit_{i,j,t-1} + \theta X_{i,j,t-1} + \gamma Z_{j,t-1} + v_i + \varepsilon_{i,j,t} \qquad 2.2$$

where $npls\_logit_{i,j,t}$ represents the variable of interest for bank *i*, country *j* at time *t*, $Z_{j,t-1}$ is a vector containing all the macro-financial variables, v_i represents the bank fixed-effects and $\varepsilon_{i,j,t}$ is the error term. In Eq. (2.2), $X_{i,j,t-1}$ represents a vector containing bank-level control variables. In line with the approach used by the literature (see, among others, Espinoza and Prasad, 2010; Ghosh, 2015) and in line with Chapter 1 (see Section 1.3.1), we use as a dependent variable the logistic transformation of the NPLs ratio. The logit is constructed as follows: $npls\_logit_{i,j,t} = ln\left(\frac{NPLs\ ratio_{i,j,t}}{1-NPLs\ ratio_{i,j,t}}\right)$. The logit transformation ensures that the dependent variable spans over the interval [-∞;+∞] as opposed to the [0;1] interval and is distributed symmetrically.

When modelling non-performing loans, it is important to take into consideration the persistence of this variable. Therefore, we augment the model with the autoregressive component, which helps explain how long it takes for the dependent variable to reach its steady state (cyclical component). Specifically, in Eqs. (2.1) and (2.2), the persistency of the NPLs ratio over time is captured by the coefficient β. In this regard, we argue that our time dimension (T>30) minimises the issue related to the inclusion of the lagged dependent variable in our models, and we expect the bias on the estimated coefficient of the autoregressive components to be small (Nickell, 1981; Machado and Santos Silva, 2019) (see also Section 1.3.1 of Chapter 1 and Section A.2.1 of Appendix A).

The estimated coefficients from Eqs. (2.1) and (2.2) will serve as input for our forecasts. Specifically, the coefficients γ and θ represent the elasticities of NPLs to macroeconomic, financial and bank-specific variables. In practical terms, to produce the projections of the NPLs logit, we will multiply the coefficients from the quantile regressions by the forecasted values of the macroeconomic variables under the different scenarios one wants to investigate. The projected NPL logit is then transformed back to obtain the NPLs ratio using the following formula:

$NPLs\, ratio = \frac{1}{1+\exp(-npls\_logit_{it})}$. The logit transformation also ensures that the model only produces predictions of NPLs ratio between 0 and 1. Figure B1 in Appendix B illustrates the density distributions of the NPLs (Panel A) and the logit transformation (Panel B).

The choice to adopt the DFE-QR approach is driven by several considerations. First, the main advantage of quantile regressions is the *informational gains* they provide in comparison to linear models (Machado and Santos Silva, 2019). That is, although the literature on credit risk is dominated by linear models, these models are ill-equipped to approximate relationships that may materialise during severe shocks (Ong et al., 2014). By contrast, using quantile regressions, one can differentiate between the macro-financial factors driving high and low non-performing loans. Thus, this technique allows us to focus on the tails of the distributions of NPLs and to make inference on what drives high levels of NPLs, which is of key interest to prudential authorities. This is in sharp contrast to ordinary least squared (OLS) estimators that focus on the conditional mean and do not allow inference at different points of the distribution of the dependent variable. Specifically, while OLS provides information about the slope at different points of the explanatory variables, quantile regressions allow inference about the slope at different points of the dependent variable (NPLs ratio) given the set of explanatory variables (see Schaeck, 2008). Additionally, interpreting conditional-mean coefficients can lead to misleading results when the response variable is skewed. In these cases, the mean effect might be more a reflection of what is happening in the upper tails of the distributions than a reflection of what is happening in the middle (Hao and Naiman, 2007).

In the context of scenario analyses, and especially of stress test exercises, quantile regressions allow accounting for potential non-linearities arising during adverse or crisis scenarios when high credit risk materialises (Chavleishvili and Manganelli, 2020). This is a major advantage as the relative importance of the macro variables might vary according to the quantile of credit risk distribution. That is, one could observe macro-variables that have a negligible effect at the mean of the distribution, whereas they gain relevance at higher (or lower) quantiles of the distribution of the NPL ratios. Likewise, the effect of the various control variables could be different in the lower and upper tail of the distribution of NPLs, thus capturing various phases of the business cycle (Chuliá et al., 2017). As such, quantile regressions are particularly useful when the objective is to assess the relationship between variables in periods of macroeconomic stress when non-linear relationships might materialize. In light of this discussion, it emerges clearly that by offering a more complete picture of the effects of the covariates, quantiles models are particularly relevant from a policymaker's perspective (Mydland et al., 2018).

Additionally, the approach proposed by Machado and Santos Silva (2019) permits the inclusion of bank fixed-effects (FE), allowing us to introduce a level difference in the intercept among banks and capturing any remaining time-invariant bank-specific heterogeneity that is not captured by bank-specific covariates ($X_{i,j,t-1}$). The inclusion of FE represents a major improvement over past studies applying quantiles regressions (e.g., Schechtman and Piazza Gaglianone, 2012; Kanas and Molyneux, 2018) as these past papers could not benefit from the recent advancements in quantile regression methods, that is, the Machado and Santos Silvia (2019) estimator. The importance of FE is better appreciated with a simple example. Consider two banks, with similar levels of NPLs operating in Germany. Without the presence of FE, the forecasts would provide similar paths of the evolution of NPLs, as they are conditional on macroeconomic variables (that are the same for both German banks) and on the autoregressive components (that will be similar given similar NPLs ratios). FE allow us to introduce an additional factor, which captures unobserved time-invariant bank-specific behaviour, upon which the forecast can depend. This is pivotal for micro-prudential regulators because it allows bank-specific assessment of the resilience to a deterioration of the economic outlook.

Lastly, it is worth mentioning that our empirical approach is close to the recent study by Giglio et al., (2021) where the authors derive the empirical conditional cumulative distribution function of net trading income of euro area banks using the Machado and Santos Silvia (2019) estimator. However, instead of producing conditional forecasts based on macroeconomic scenarios, the authors use the conditional distributions to estimate tail risk and expected losses across euro area banks, and to perform a series of multi-step ahead density forecasts.

2.3.2 Drivers of non-performing loans

After introducing the empirical methodology used to study the drivers of NPLs, in this section, we review some of the literature on the determinants of credit risk that have been found in the literature. Given the significant synergies between this Chapter and Chapter 1, a broader review of the literature on NPLs determinants can be found in Section 1.2.3, Chapter 1).

The analysis of the drivers of non-performing loans has been the subject of a considerable number of studies (see, among many others, Rinaldi and Sanchis-Arellano, 2006; Berge and Boye, 2007; Marcucci and Quagliariello, 2008; Bofondi and Ropele, 2011; Nkusu, 2011; Castro, 2013; Beck, Jakubik and Piloiu, 2015). Following the literature, the non-performing loans ratio is regressed against a set of macroeconomic and bank-specific variables that capture the ability of corporates and households to service their debt.

Before starting the discussion on the explanatory variables included in Eqs. (2.1) and (2.2), it is important to clarify how, in the context of conditional forecasting, the choice of regressors is driven by two considerations.[80] First, the selection of the variables for the regression is constrained by the macroeconomic variables for which we can obtain forecasts under different scenarios. The paths of macroeconomic factors are the outcome of the first block of the stress test exercise (see Figure 3 above) and are usually produced by the central banks jointly with the national prudential authorities using Dynamic Stochastic General Equilibrium (DSGE) models. For the purpose of this Chapter, as input for our forecasts, we rely on the scenario prepared by the European Systemic Risk Board for the 2021 EU-wide banking sector stress test (see Section 2.4.5 for additional details) and thus we are constrained by the macroeconomic variables that were part of the exercise. The second consideration, in the context of conditional forecasts, relates to the balance that the regressions need to strike between bias and model overfitting. As aforementioned, the literature on the drivers of NPLs is extensive and comprehensive, encompassing macroeconomic, financial, institutional, and bank-

[80] With conditional forecast, we mean forecasts that are conditional on a set of other variables.

specific determinants. However, while adding more regressors could reduce bias, it could also lead to an increase in forecast variance (Bonaccorsi di Patti and Cascarino, 2020).

An additional clarification relates to the set of bank-specific variables ($X_{i,j,t-1}$). The inclusion of controls at the bank-level is *not* standard in the literature on top-down stress tests because of the assumption of "*static balance sheet"*. This assumption implies that:

> "[…] banks maintain the same business mix and model (in terms of geographical range, product strategies and operations) throughout the time horizon. With respect to the P&L revenues and costs, assumptions made by banks should be in line with the constraints of zero growth and a stable business mix (EBA 2021 EU-Wide Stress Test Methodological Note, pag. 17)".

In other words, one of the assumptions of the current stress test framework is that banks cannot assume any portfolio management actions in response to the stress scenarios (e.g., portfolio rebalancing or liquidation). Consequently, top-down models tend to exclude bank-specific variables as they are not assumed to play a role in the time horizon after the shock. Nonetheless, the literature on the relationship between bank characteristics and asset quality stresses the importance of these factors. To avoid our elasticities from suffering from omitted variable bias, we present the forecast of NPLs when the model includes also bank-specific variables, which are assumed to remain constant over the forecasted horizon.

Starting with the macroeconomic drivers, the model includes (lagged) GDP growth (gdp_growth) to account for the effects of the business cycle on the credit risk of banks. We do not have an a priori belief on the sign of the coefficient. Intuitively, the logit dictates that we can expect to find a negative relationship between the economic environment and NPLs, as improvements in the economic conditions, ceteris paribus, result in reductions of NPLs via a lower probability of borrowers' defaults. However, during economic upswings, favourable economic conditions may result in over-optimistic behaviour from banks, which materializes in excessive credit granted and future deteriorations of asset quality (Salas and Saurina, 2002; Klein, 2013; Ghosh, 2017). In line with economic theory, we expect a positive relationship between the unemployment rate ($unemployment$) and banks' loan quality as job losses directly affect the capacity of borrowers to service their debt

(Berge and Boye, 2007; Louzis, Vouldis and Metaxas, 2012; Castro, 2013). Moving to inflation ($inflation$), we do not have a priori expectations on the sign of the relationship with NPLs. On the one hand, inflation helps the borrower to reduce the real value of its debt. On the other hand, high inflation passes through to higher nominal interest rates, making debt servicing more onerous (Rinaldi and Sanchis-Arellano, 2006; Nkusu, 2011).

We include in the specification an indicator of changes in house prices (hpi), for which we expect a negative relationship with NPLs. A higher property value implies an increased value of the collateral used to access the loans, leading to a greater ability of the borrower to repay the debt. Furthermore, rising house prices improve the financial wealth of the borrower, thus helping him/her to face unexpected financial shocks, facilitating debt renegotiation and limiting the risk of becoming an insolvent debtor (Ghosh, 2015).

We further saturate the model including the slope ($slope$) of the yield curve - calculated as the difference between the 10-year country government bond and the 3-month Euribor rate to capture the interest rate environment (Espinoza and Prasad, 2010; Bofondi and Ropele, 2011). From a theoretical point of view, a steepening of the slope, due to rising long-term rates, signals an improvement in the macroeconomic conditions, and thus it should display a negative relationship with NPLs. Furthermore, we introduced a linear trend ($trend$) to reduce the importance of the autoregressive component and capture the deterministic part. This variable is akin to the inclusion of time fixed effects, but it is a more parsimonious specification. We do not have a priori expectation on the sign for the linear trend, as NPLs have first increased sharply up until 2013 while in recent years there has been a significant reduction due to large NPLs disposals.

As aforementioned, while it is not standard practice in the literature on stress testing, we present an additional model where we include bank-specific controls in order to limit the problem of omitted variable bias. We include the natural logarithm of total assets ($size$) to account for the size of banks. There are several ways in which bank size can explain NPLs. First, larger banks enjoy economies of scale in terms of information collection and processing (Louzis et al. 2012), which allows larger banks to devote more resources to the selection of borrowers, thus reducing the risk of future defaults. Large banks have also more geographical diversification opportunities, thus being more resilient in the event of NPLs rising because of shocks in local markets. However, larger banks may have an incentive to riskier balance sheets because of their status of too-big-to-fail, which comes with lower market discipline imposed by market participants because of the implicit subsidy and protection from the government in the case of the bank's failure (Stern and Feldman, 2009).

Furthermore, we include the equity-to-asset ratio ($equity/assets$) to control for moral hazard behaviour. Poorly capitalized banks may engage in riskier activities as they have less "skin in the game", resulting in higher levels of distressed debt on their balance sheets. However, a positive relationship can also be justified if banks increase the riskiness of their investments because their stronger capital position allows it, ultimately suffering from more problem loans (Tan and Floros, 2013). Finally, we control for the level of profitability of banks using the return on equity (ROE). More profitable banks can generate retained earnings, which can be use to boost capital and give banks the ability to absorb the losses arising from the selling and disposing of bad loans (Chaibi and Ftiti, 2015; Ghosh, 2015).[81]

2.3.3 Data

The sample employed in this Chapter consists of 106 euro area banks featuring quarterly data spanning from the first quarter of 2005 to the fourth quarter of 2020. The banks included in our datasets are those falling under the remit of the Single Supervisory Mechanism (SSM). The SSM is the supervisory arm of the European Central Bank and it has the mandate to directly supervise the most significant institutions in the euro area, whereby smaller banks are supervised by the national central banks. Specifically, our sample encompasses those banks supervised by the SSM because they fulfil at least one of the following criteria:

[81] We offer a more in-depth discussion on bank-specific drivers of NPLs in Chapter 1, Section 1.2.3.

Table 24. Significance Criteria

Size	The total value of its assets exceeds €30 billion
Economic importance	For the specific country or the EU economy as a whole
Cross-border activities	The total value of its assets exceeds €5 billion and the ratio of its cross-border assets/liabilities in more than one other participating Member State to its total assets/liabilities is above 20%
Direct public financial assistance	It has requested or received funding from the European Stability Mechanism or the European Financial Stability Facility
Source: European Central Bank. **Note**: A supervised bank can also be considered significant if it is one of the three most significant banks established in a particular country.	

We source bank-specific balance sheet and income statement data from Fitch Connect. The macroeconomic variables are collected from the ECB Statistical Data Warehouse while market data are collected from Bloomberg. Table 25 shows the number of banks in each of the 19 euro area countries.[82] Not surprisingly, banks in the four largest economies (i.e., Germany, France, Italy and Spain) constitute almost half of the sample. Table 26 provides the summary statistics at different percentiles of the distribution. Focusing on the statistics of our dependent variables, it is interesting to notice the difference between the mean (7.5%) and the median (4.1%) value of the NPLs ratio, which is the outcome of a left skewed distribution with a very long right tail (see also Figure B1 in Appendix B).

Table 25. Sample Composition

Country	Number of Banks	Country	Number of Banks
Austria	8	**Latvia**	3
Belgium	5	**Lithuania**	3
Bulgaria	1	**Luxembourg**	3
Cyprus	3	**Malta**	3
Germany	17	**Netherland**	7
Finland	3	**Portugal**	4
France	8	**Slovenia**	3
Greece	4	**Slovakia**	3
Ireland	5	**Spain**	11
Italy	12	**TOTAL**	106

[82] Note that the sample includes Bulgaria, which is not officially part of the euro area yet, but for which the SSM has started supervising one institution in view of the fact that Bulgaria will join in 2024. The sample also exclude Estonia, for which we miss data on the yield prices. We do not include Croatia, which is a similar case to Bulgaria, because the three largest institutions in the countries are subsidiaries of banks directly supervised by SSM and therefore are represented under those groups.

Table 26 Summary Statistics

	Obs	Min	p5	p10	p25	Mean	Median	p75	p90	p95	Max
$npls\_ratio$	5003	0.0007	0.0072	0.0111	0.0227	0.0750	0.0410	0.0846	0.1822	0.2824	0.8434
$size$	5003	7.5194	8.4566	8.7936	10.0150	11.1319	11.0307	12.3007	13.5137	14.0566	14.5191
$equity/assets$	5003	0.0119	0.0233	0.0302	0.0460	0.0698	0.0639	0.0865	0.1166	0.1377	0.2075
ROE	5003	-0.9229	-0.2728	-0.0924	0.0184	0.0345	0.0632	0.1108	0.1640	0.2100	0.4569
gdp_growth	5003	-0.2150	-0.0670	-0.0370	0.0000	0.0092	0.0160	0.0280	0.0440	0.0590	0.2920
$unemployment$	5003	0.0290	0.0367	0.0443	0.0577	0.0950	0.0813	0.1163	0.1707	0.2123	0.2803
$inflation$	5003	-0.0387	-0.0063	-0.0027	0.0040	0.0141	0.0131	0.0220	0.0309	0.0369	0.1753
hpi	5003	-0.4225	-0.0804	-0.0540	-0.0081	0.0232	0.0321	0.0624	0.0845	0.1056	0.3967
$slope$	5003	-0.7233	-0.1467	0.1567	0.6300	1.9399	1.2800	2.5067	4.2000	5.7633	24.7067

2.4 Results

In this section, we show the estimated coefficients of the quantile models and we discuss the results, focusing on how the factors affecting NPLs change across quantiles. Additionally, we present the in-sample fit of the models and the in-sample performance for forecasting purposes. We conclude the section by showing a practical application of our forecasting model in the context of stress tests.

2.4.1 Quantile models

We report the estimated coefficients of Model 1 (Eq. 2.1) and Model 2 (Eq. 2.2) in Table 27 and Table 28, respectively. In both tables, column (1) reports the results from running a linear fixed effect model, while columns (2) to (8) refer to Quantile Regression (QR) regression at the 5^{th}, 10^{th}, 25^{th}, 50^{th}, 75^{th}, 90^{th} and 95^{th} percentile.

As mentioned before, linear regression models do not allow inference at the different points of the distribution of the dependent variable. However, prudential and supervisory authorities are usually interested in understanding the dynamics at the tails of the distributions, that is, they are more concerned with the factors driving high levels of non-performing loans. Quantile regressions allow us to perform this analysis as we can investigate the effect of the regressors on the banks with the highest levels of NPLs.

We start by describing the findings of running the model including only macroeconomic variables (Table 27). As expected, the lagged dependent variable shows a high and statistically significant degree of persistency across the distribution of NPLs, being between 0.91 and 0.98 for the QR models. This implies that higher NPL ratios in the previous quarters tend to be followed by high ratios in the following quarter. Also, this implies that banks with a high share of bad loans will need substantial time to remove them from their balance sheets (Ghosh, 2017). Similar results have been observed for the sample of Italian banks employed in Chapter 1 (see Section 1.5.2.1).

Moving to the macroeconomic factors driving a build-up of NPLs, we show evidence of a negative relationship between gdp_growth and asset quality across the entire distribution on NPLs. However, the magnitude and significance of gdp_growth change substantially when moving across quantiles. The magnitude of the coefficient of GDP moves from -0.01 for the lowest quantile (5th) to -0.62 for the model estimated at the 95th quantile, while the coefficient is statistically significant starting from the 25th percentile. The growth in economic activity does not reduce NPLs for the banks located on the left tail of the distribution (i.e., banks with low NPLs), whereby GDP has strong explanatory power for the highest quantiles when NPLs are high. It is worth noticing that the linear OLS model (column 1) shows a negative and significant relationship between GDP growth and NPLs and that this is in line with previous studies (Castro, 2013; Chaibi and Ftiti, 2015; Cerulli et al., 2020), whereas, using quantile regressions, we show that the significance holds only from the 25th percentile and higher.

Similar considerations can be done for the coefficient of $inflation$, which is strongly positive and significant only starting from the 25th percentile of the distribution, while for the lower percentiles the relationship is statistically insignificant. Inflation is a key driver for banks with medium and high levels of NPLs, while it does not sort any effect on banks with low credit risk.

As expected, we find a negative relationship between the house price index and NPLs, in line with Bofondi and Ropele (2011) and Ghosh (2015, 2017). This variable is the only one where the coefficient remains statistically significant along the entire distribution of NPLs. However, the magnitude is larger and the statistical significance is stronger for lower quantiles of the distribution. These findings suggest that higher real estate prices tend to be associated with lower default rates of borrowers, especially for banks on the left tail of the distribution.

Furthermore, we document a positive relationship between the $slope$ of the yield curve and loan quality, which is a somewhat unexpected result but in line with Bofondi and Ropele (2011). The coefficient is positive throughout the distribution of NPLs but loses statistical significance on the right tail (i.e., for banks with elevated NPLs levels). In light of this, we argue that a steepening in the yield curve might be driven by a sharp drop in the short-term interest rates rather than an increase in long-term rates, thus indicating a weakening of the economy. As such, it is not surprising that the significance is only found on the left tail because low NPLs are usually observed during periods of favourable macroeconomic conditions, that is, in periods that precede a deterioration of the outlook. Finally, the $trend$ variable is negative and significant in all models, suggesting a decreasing path over time of the NPLs ratio.

Overall, comparing the results from columns (2) to (8) with those from column (1), it appears clear how the OLS estimator provides a very limited view of the drivers of NPLs. For instance, in the case of gdp_growth, $inflation$ and $slope$, the OLS regression provides a statistically significant coefficient, when, in reality, these variables play a different role depending on the NPLs ratios on the banks.

Moving to Model 2 (Table 28), we notice that including bank-specific controls does not change substantially the coefficients of the macroeconomic variables included, and the findings from Model 1 hold also for Model 2. We report an interesting relationship between bank $size$ and NPLs. While there is a positive and statistically significant association with NPLs at the lowest quantiles (5^{th}, 10^{th} and 25^{th} percentile), the coefficient turns negative starting from the 75^{th} percentile and it becomes significant at the 90^{th} and 95^{th} percentile. The results imply that size contributes to increasing NPLs for low-NPL banks whereas it helps reduce them for high NPLs banks. That is, size is an important factor during crises period - when high-NPLs materialize - as it may help off-loading impaired loans faster thanks to better work-out practices and a greater ability to sell NPLs to the market. The findings related to the evolution of the coefficients across the distribution of NPLs are in stark contrast with the results coming from the fixed-effect regression (column 1), which suggests that size does not have explanatory power for NPL ratios.

Further, we document that profitability levels are important drivers of asset quality for euro area banks. With the exclusion of the lowest quantile, we find a negative and statistically significant relationship between ROE and NPLs, with the coefficient that doubles in magnitude when moving from the 10^{th} percentile to the 95^{th}. Profitability is a key driver in reducing credit risk for banks across the entire distribution of NPLs. This is because profitable banks are able to build up capital via retained earnings, ultimately strengthening their ability to absorb the losses coming from the disposal of bad loans. Finally, we do not find any significant relationship between the capitalisation levels of banks and their holding of NPLs.

We conclude this section by presenting in Figure 11 the quantile regression estimates for the autoregressive component (β) and the explanatory variables (γ) as a solid blue curve across the entire distribution of NPLs (as opposed to the selected percentiles reported in the Tables above). These estimates illustrate a one-unit change of the regressor on NPLs, holding the other covariates constant. The vertical y axis indicates the effect of the explanatory variable while the horizontal x axis represents the quantiles. The light blue area shows a 95% confidence band for the quantile regressions. Additionally, the black horizontal line represents the coefficient of the OLS regression (column 1 of Table 27 and Table 28), while the dashed lines are the confidence interval of the OLS estimator.

As already previously noticed, the OLS regressions fail to shed light on how the covariates affect differently NPLs depending on their levels. This is particularly striking for certain explanatory variables such as the autoregressive components, GDP growth, inflation and size. The magnitude of the coefficients of these controls varies substantially across percentiles, sometimes also changing sign (e.g., size), painting a more informative picture compared to the linear models.

Table 27. OLS and Quantile Regression estimates

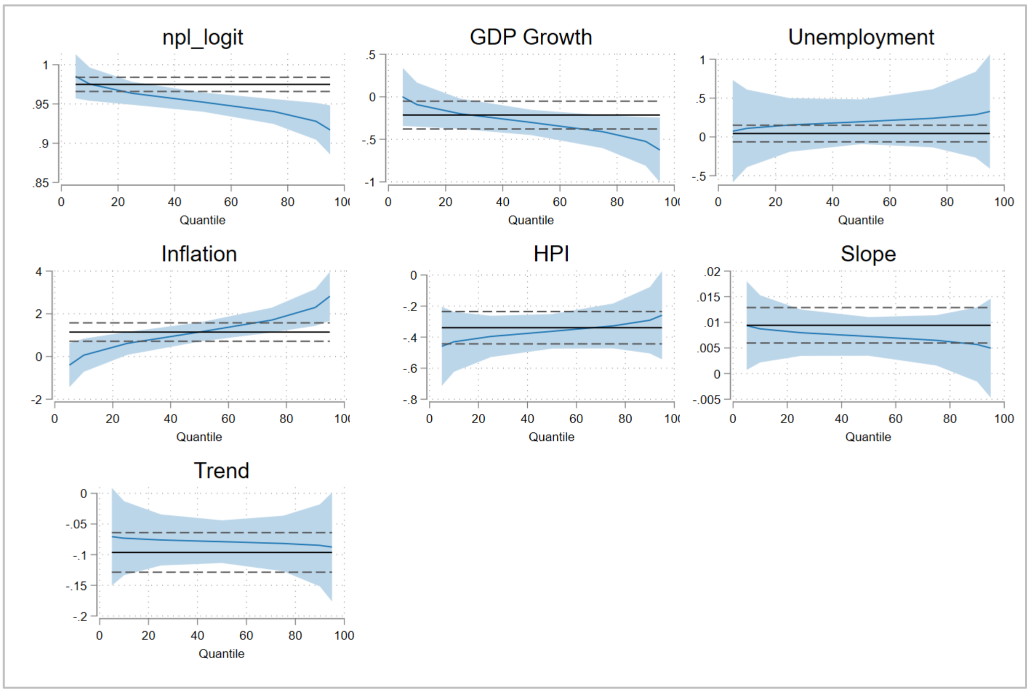
	(1) **OLS**	(2) **0.05**	(3) **0.10**	(4) **0.25**	(5) **0.50**	(6) **0.75**	(7) **0.90**	(8) **0.95**
$npls\_logit_{i,t-1}$	0.9523***	0.9853***	0.9753***	0.9636***	0.9523***	0.9404***	0.9279***	0.9169***
	(0.0064)	(0.0143)	(0.0108)	(0.0075)	(0.0062)	(0.0081)	(0.0120)	(0.0160)
$gdp\_growth_{j,t-1}$	-0.3017***	-0.0012	-0.0919	-0.1985**	-0.3014***	-0.4099***	-0.5240***	-0.6248***
	(0.0866)	(0.1743)	(0.1319)	(0.0911)	(0.0761)	(0.0989)	(0.1462)	(0.1946)
$unemployment_{j,t-1}$	0.1960	0.0732	0.1103	0.1538	0.1958	0.2402	0.2868	0.3280
	(0.2018)	(0.3364)	(0.2547)	(0.1760)	(0.1470)	(0.1911)	(0.2822)	(0.3758)
$inflation_{j,t-1}$	1.1469***	-0.4080	0.0617	0.6132**	1.1455***	1.7072***	2.2974***	2.8191***
	(0.3746)	(0.5254)	(0.3966)	(0.2736)	(0.2286)	(0.2970)	(0.4400)	(0.5857)
$hpi_{j,t-1}$	-0.3625***	-0.4590***	-0.4299***	-0.3956***	-0.3626***	-0.3277***	-0.2911***	-0.2587*
	(0.0687)	(0.1300)	(0.0984)	(0.0680)	(0.0568)	(0.0738)	(0.1091)	(0.1452)
$slope_{j,t}$	0.0072***	0.0094**	0.0087***	0.0080***	0.0072***	0.0065***	0.0057	0.0050
	(0.0018)	(0.0044)	(0.0033)	(0.0023)	(0.0019)	(0.0025)	(0.0037)	(0.0049)
$trend_t$	-0.0789***	-0.0707*	-0.0732**	-0.0761***	-0.0788***	-0.0818***	-0.0849**	-0.0876*
	(0.0261)	(0.0406)	(0.0308)	(0.0213)	(0.0178)	(0.0231)	(0.0341)	(0.0454)
N	5012	5012	5012	5012	5012	5012	5012	5012
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 28. OLS and Quantile Regression estimates including bank-specific controls

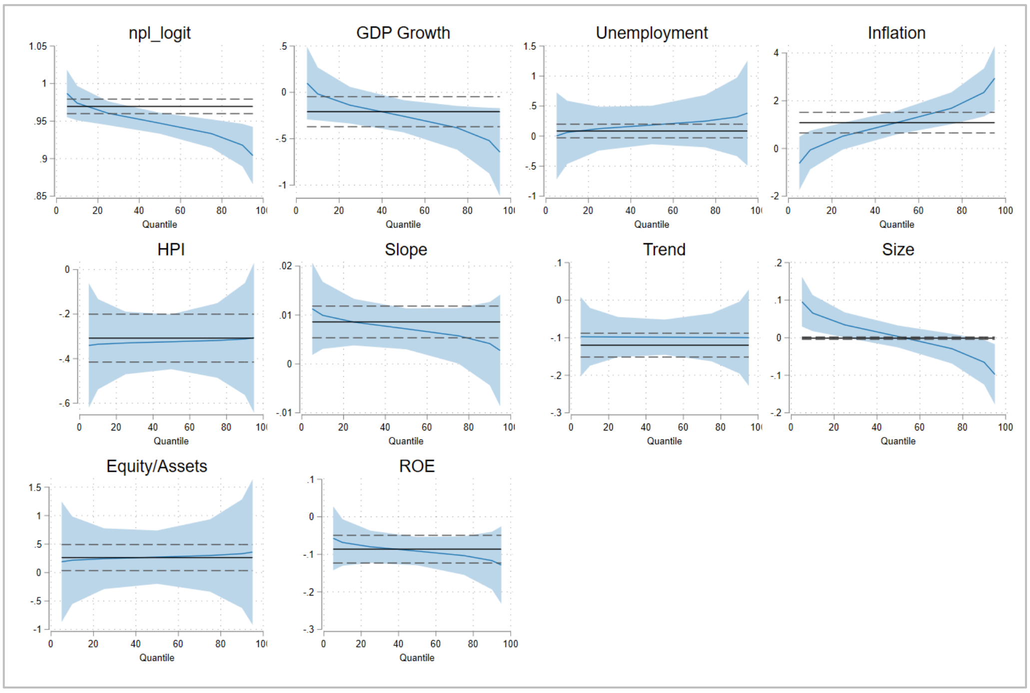
	(1) **OLS**	(2) **0.05**	(3) **0.10**	(4) **0.25**	(5) **0.50**	(6) **0.75**	(7) **0.90**	(8) **0.95**
$npls\_logit_{i,t-1}$	0.9472***	0.9869***	0.9739***	0.9605***	0.9472***	0.9333***	0.9179***	0.9041***
	(0.0063)	(0.0161)	(0.0117)	(0.0081)	(0.0071)	(0.0096)	(0.0145)	(0.0195)
$size_{i,t-1}$	0.0032	0.0961***	0.0657***	0.0342**	0.0032	-0.0292	-0.0652**	-0.0976**
	(0.0133)	(0.0338)	(0.0245)	(0.0170)	(0.0149)	(0.0202)	(0.0304)	(0.0410)
$equity/asset_{i,t-1}$	0.2711	0.1897	0.2163	0.2440	0.2712	0.2996	0.3311	0.3595
	(0.2630)	(0.5395)	(0.3925)	(0.2721)	(0.2391)	(0.3244)	(0.4871)	(0.6530)
$ROE_{i,t-1}$	-0.0914***	-0.0571	-0.0683**	-0.0799***	-0.0914***	-0.1033***	-0.1166***	-0.1285**
	(0.0204)	(0.0435)	(0.0316)	(0.0219)	(0.0193)	(0.0261)	(0.0393)	(0.0526)
$gdp\_growth_{j,t-1}$	-0.2569***	0.1004	-0.0164	-0.1376	-0.2570***	-0.3817***	-0.5202***	-0.6447***
	(0.0853)	(0.2002)	(0.1454)	(0.1008)	(0.0886)	(0.1201)	(0.1805)	(0.2424)
$unemployment_{j,t-1}$	0.1855	0.0033	0.0629	0.1247	0.1856	0.2492	0.3198	0.3833
	(0.1967)	(0.3689)	(0.2683)	(0.1860)	(0.1635)	(0.2218)	(0.3331)	(0.4466)
$inflation_{j,t-1}$	1.0870***	-0.6225	-0.0638	0.5162*	1.0876***	1.6838***	2.3468***	2.9419***
	(0.3913)	(0.5696)	(0.4127)	(0.2856)	(0.2512)	(0.3405)	(0.5123)	(0.6896)
$hpi_{j,t-1}$	-0.3240***	-0.3405**	-0.3351***	-0.3295***	-0.3240***	-0.3182***	-0.3118**	-0.3060*
	(0.0684)	(0.1422)	(0.1034)	(0.0717)	(0.0630)	(0.0855)	(0.1284)	(0.1721)
$slope_{j,t}$	0.0072***	0.0113**	0.0099***	0.0085***	0.0072***	0.0057**	0.0042	0.0027
	(0.0018)	(0.0048)	(0.0035)	(0.0024)	(0.0021)	(0.0029)	(0.0043)	(0.0058)
$trend_t$	-0.0985***	-0.0972*	-0.0976**	-0.0981***	-0.0985***	-0.0990***	-0.0995**	-0.1000
	(0.0284)	(0.0540)	(0.0393)	(0.0272)	(0.0239)	(0.0325)	(0.0488)	(0.0654)
N	5003	5003	5003	5003	5003	5003	5003	5003
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Figure 11. Coefficient Plots of Quantile Regressions

Panel A. Model 1 – without bank controls



Panel B. Model 2 with bank controls



2.4.2 Individual contribution of explanatory variables to the NPL model

As a further analysis, we investigate the economic significance of our results. Specifically, we report the historical decomposition of the contribution from each explanatory macroeconomic variable to the evolution of loan quality for each of the euro area countries. In this way, it is possible to assess the driving forces behind the developments in NPLs throughout the sample period (Bofondi and Ropele, 2011). To conserve space, we focus on the results of Model 1 estimated at the 50th percentile.[83] Additionally, we report in the main text the graphs for the four largest economies of the euro area (i.e., Germany, France, Italy and Spain) (Figure 12), while the graphs for the remaining countries are reported in Appendix B (Figure B2). The contribution of each explanatory variable is calculated by multiplying the observed value of each regressor (for each country and quarter) by the corresponding estimated coefficient from Table 27. For the purpose of this analysis, we focus on the macroeconomic determinants and statistically significant coefficients, and as such, we exclude from the graphs unemployment and trend.

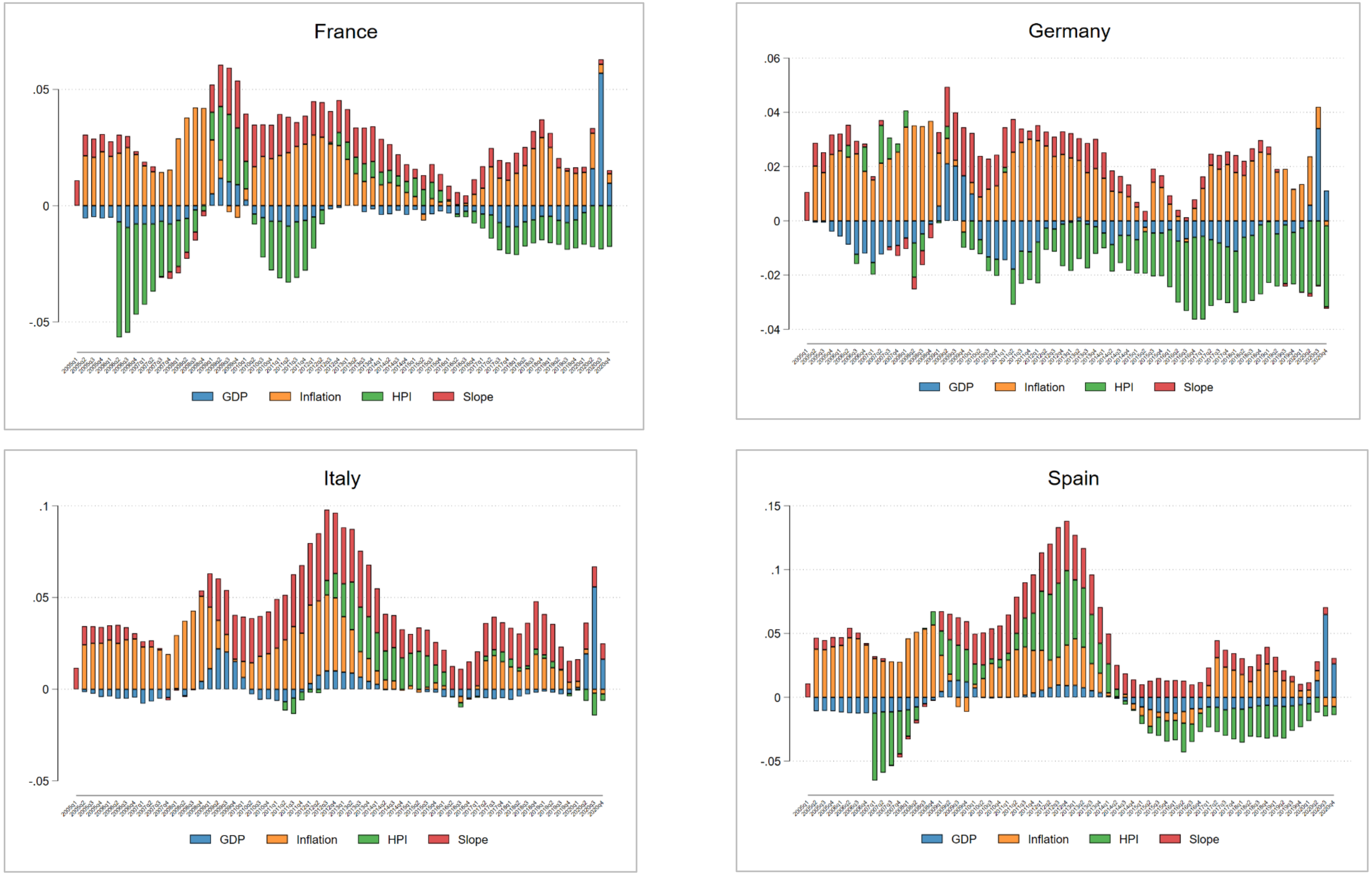
Looking at Figure 12, the first striking feature is that the contribution of gdp_growth, $inflation$, hpi and $slope$ are remarkably volatile over time. None of these variables stably contribute to NPLs, but rather they display a cyclical behaviour. Overall, the two variables that negatively affect loan quality the most are inflation (orange bar) and the slope of the yield curve (red bar). With the exception of a few quarters pre-financial crisis, the steepness of the yield curve is a major driver of NPLs for those banks at the median of the distribution of NPLs located in these four countries. It is interesting to notice how hpi has different effects across countries. For instance, the price of houses displays a stable negative contribution to NPLs in Germany (with the exclusion of a few quarters at the beginning of our sample), whereas it is a major driver of NPLs in Spain, Italy and France between 2012 and 2015, approximately. Gdp_growth also shows country-specific patterns. While it reduced NPLS in France and Germany starting in 2010, it has the opposite effect in Spain and Italy between 2012 and 2014.

Figure 12 is also useful to compare the drivers in NPLs during the financial crisis (2008-2009) with those during the sovereign crisis (2010-2012). For example,

[83] We could also produce these graphs for Model 2. However, given that Model 2 includes bank-specific variables, this would involve producing 106 different graphs as we need to multiply the coefficients of the controls for each bank balance sheet value.

in France, gdp_growth and hpi contribute to an increase in NPLs during the financial crisis whereas they have the opposite effect during the sovereign crisis.

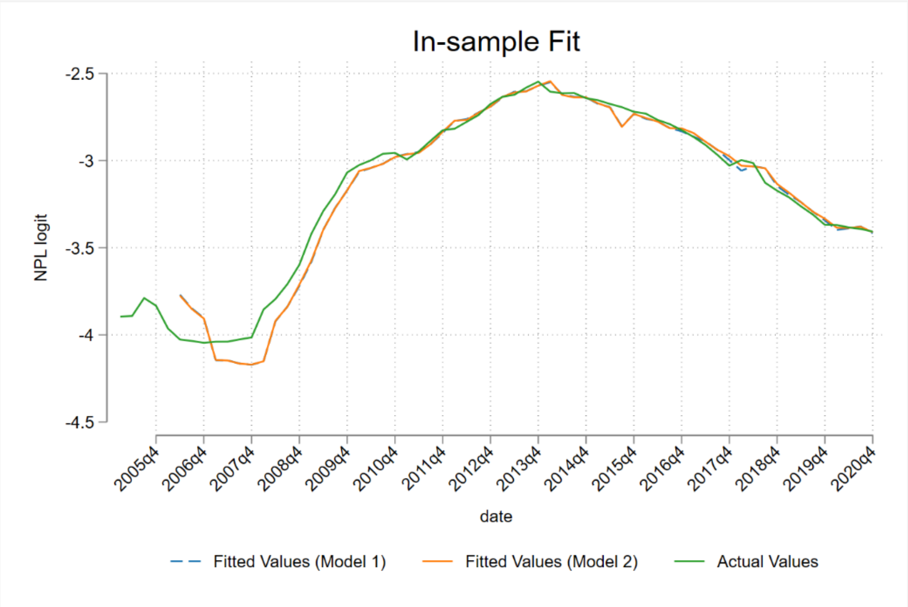
Figure 12 Contribution of macroeconomic variables to Model 1



2.4.3 In-sample fit of the models

After showing the drivers of NPLs and their contribution over time, we move to show the goodness of the models. Specifically, following Bofondi and Ropele (2011), we use Figure 13 below to graphically illustrate the in-sample fit (i.e., the comparison between observed and fitted values) of the models presented in Table 27 (Model 1) and Table 28 (Model 2). We can draw two conclusions from the visual inspection of the graphs. First, the in-sample fit of the models, with and without bank controls, is overall satisfactory. While the in-sample fit is relatively poor at the beginning of our sample (potentially due to many missing data), it becomes particularly accurate after 2010. Both models are able to track the steep rise in NPLs following the sovereign debt crisis until they peak in 2013. The models also manage to capture the downward trend of NPLs thereafter. Secondly, it is worth pointing out how Model 2 does not significantly improve the in-sample fit of the more parsimonious Model 1. Indeed, differences in the fitted values are only visible from 2016 onwards. This is not surprising given the small coefficients of the bank-specific variables reported in Table 28.

Figure 13. In-sample Fit of Model 1 and Model 2



2.4.4 In-sample forecasting performance

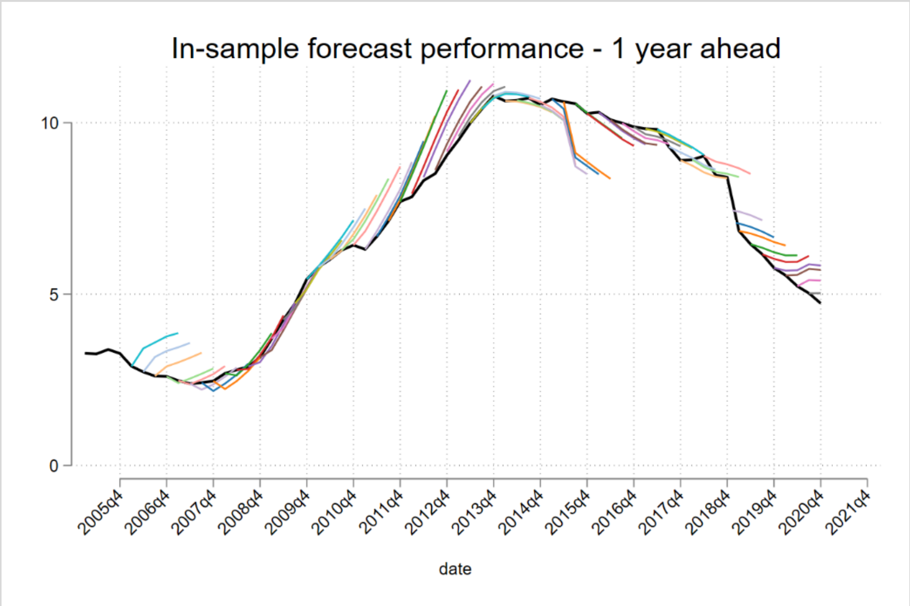
In the previous Section, we show how the models have a good in-sample fit. However, in the context of forecasting models, good in-sample fit does not necessarily imply good out-of-sample performance. In this section, we propose an analysis of the in-sample forecasting performance of our model. For brevity, we focus exclusively on Model 1 (without the bank controls) but the results are quantitatively and qualitatively the same for Model 2.

We assess the in-sample performance by simulating from a specific starting point *t* of the historical data the 1-year and 3-years ahead projections using the observed macro-financial variables and the elasticities estimated through Eq. (2.1) and reported in Table 27. This method allows us to compare the model's predictions against the historical evolution of the NPLs ratio. Specifically, for each bank, the starting point of the forecast is represented by the realized value of the NPLs ratio in time *t*. We then compute the 1-year and 3-year ahead forecasts of NPL ratios by multiplying the coefficients coming from Eq. (2.1) with the observed values of the macroeconomic variables. For brevity, we do not report the in-sample performance bank-by-bank, but we average the predictions across the sample and we compare them with the historical evolution of the NPLs ratio across our sample.

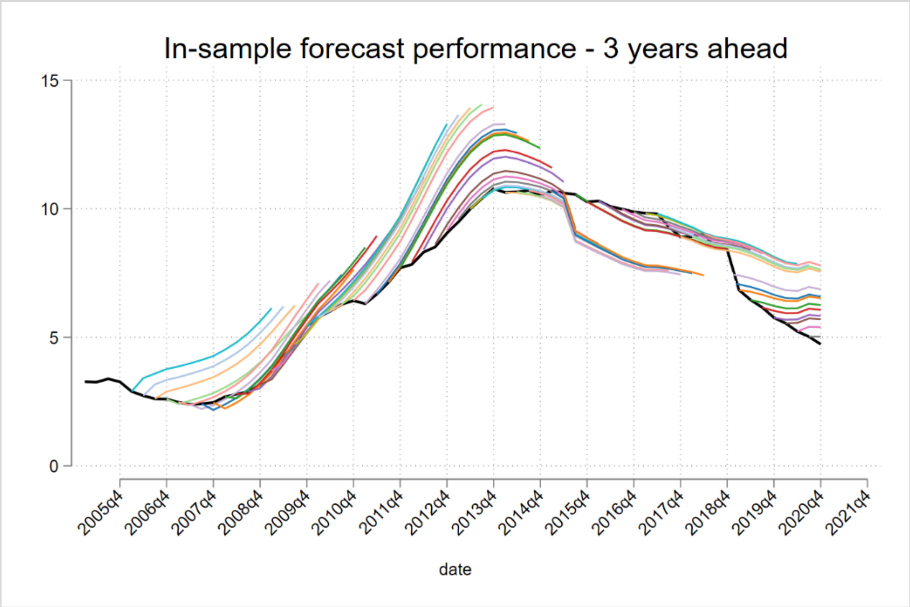
In Figure 14 below, the black solid line represents the mean NPLs ratio in our sample while the other lines show the in-sample forecast performance 1-year (Panel A) and 3-years ahead (Panel B) given the starting point in time *t*. Overall, the model predicts well the path of NPL ratios. Focusing on the predictions between 2007 and 2012, our model would forecast a steep deterioration in credit quality, which is in line with what happened in those years. The 1-year ahead predictions are particularly accurate for this period, capturing almost perfectly the increase in NPLs. It is also interesting to notice how the model is able to capture the turning point around 2013 when the NPLs ratio across the euro area starts decreasing. The model performs particularly well also between 2015 and 2017, predicting an improvement in loan quality. However, not surprisingly, the model underperforms after 2017. This is because it is not able to capture the acceleration in the pace of NPLs reduction that occurred in the euro area and that resulted in sudden drops of NPLs ratios as a result of a wave of NPLs disposals (such as the one observable towards the end of 2017).

Figure 14. In-sample forecast performance

Panel A. 1 Year ahead in-sample forecast



Panel B. 3 Years ahead in-sample forecast



2.4.5 Out-of-sample forecasts

As a final step of this Chapter, we conduct a scenario analysis, and we produce out-of-sample forecasts of the evolution of NPL ratios. For this exercise, we used as input for the forecasts the scenario prepared by the ESRB for the 2021 EU-wide banking sector stress test. The scenario is constituted by a baseline and an adverse scenario and it covers a three-year horizon spanning from 2021 to 2023.[84] As mentioned above, the purpose of a stress test exercise is to assess the resilience of the banks to severe but plausible adverse conditions. For the 2021 exercise conducted by the EBA, the adverse scenario depicted the paths for the key macro-financial variables in a hypothetical adverse condition, triggered by the materialisation of specific risks to which the EU banking system is exposed. Specifically, the narrative adopted for the adverse scenario reflected a prolonged COVID-19 scenario in a "lower for longer" interest rate environment and a strong drop in confidence.[85]

To give a better understanding of the scenario envisaged for the 2021 Stress Test, we report in Table 29 the path of our key macroeconomic variables at the euro area level. These figures allow us to understand the severity and the narrative behind the stress test scenario, but to produce our forecasts, we rely on country-level figures. Over the scenario horizon, GDP contracts by 3.6% in the euro area. As a consequence of the economic slowdown, unemployment rises sharply to a substantial cumulative rise of 4.5 percentage points in the euro area. A slowdown in residential property market activity leads to significant price corrections, with real estate prices declining by 15.7%. The slowdown in the economy and global economy weakens countries' fiscal positions. with resurfacing concerns about the sustainability of public debt. As a consequence, there is an increase in credit risk premia on sovereign

[84] While the baseline scenario is based on the December 2020 projections of national central banks, the adverse scenario is designed by the ESRB's Task Force on Stress Testing in collaboration with the European Central Bank. See Annex 3 to "Macro-financial scenario for the 2020 EU-wide banking sector stress test", ESRB, January 2020 for further details.

[85] More in details, "*The narrative depicts an adverse scenario related to the ongoing concerns about the possible evolution of the COVID-19 pandemic coupled with a strong drop in confidence leading to a prolongation of the worldwide economic contraction. The worsening of economic prospects is reflected in a global decline of long-term risk-free rates from an already historically low level and results in a sustained drop in GDP and an increase in unemployment. Slowing growth momentum would cause a drop in corporate earnings leading, together with a re-assessment of market participants' expectations, to an abrupt and sizeable adjustment of financial asset valuations as well as a significant drop in residential and commercial real estate prices. A decline in economic growth and rising risk premia could further challenge debt sustainability in the public and private sectors across the EU" (European Banking Authority, 2021)*.

bonds (long-term rate), especially in high-spread economies.[86] It is interesting to point out that the scenario of the 2021 EU-wide banking sector stress test has been the most severe among the EBA exercises carried out to date.

Table 29. Macroeconomic scenario at euro area level for the 2021 EBA Stress Test

	Historical growth (%)	Baseline growth (%)			Adverse growth (%)			Cumulative growth from the starting point (%)
	2020	2021	2022	2023	2021	2022	2023	
GDP Growth	-7.3	3.9	4.2	2.1	-1.5	-1.9	-0.2	-3.6
Inflation	0.2	1.0	1.1	1.4	0.8	0.7	0.5	2.1
Unemployment	8.0	9.3	8.2	7.5	10.4	11.5	12.4	4.5
House Price	4.7	2.1	2.1	2.8	-3.9	-8.2	-4.5	-15.7
Long-term Rate	0.04	-0.11	0.01	0.13	0.02	0.17	0.18	-

Source: European Banking Authority (2021)

Using this scenario, our models would inform on how the loan quality of euro area banks would evolve given the assumed evolution of the macroeconomic conditions reported in Table 29. To produce the forecasts of NPL ratios, we multiply the elasticities obtained from the quantile regression models (see Table 27 and Table 28) with the forecasts of the macro-determinants entering the regressions. Specifically, we use the coefficients estimated at the 50th and 75th to produce the forecast for the baseline and the adverse scenarios, respectively. Additionally, we propose an analysis of NPLs under a "disaster scenario", for which we rely on the coefficients estimated at the 90th while applying the evolution of the macroeconomic variables according to the adverse scenario produced by the ESRB.

Table 30 and Figure 15 below show the forecasted NPL ratios aggregated at the euro area according to Model 1 and Model 2 under a baseline, adverse and disaster scenario. Specifically, Panel A reports the not-weighted results, while Panel B shows the NPLs ratios after they have been weighted by the volume of gross loans of each bank in each country.[87] In Appendix B (see Figure B3), we report the results at the country level when looking at the weighted-average NPLs ratio. It is not

[86] The ESRB does not provide a scenario for the short-term rate (Euribor). We use the 3months Euribor forward curve (Bloomberg), which represents the market's expectation of future interest rates derived from readily observable trade data.

[87] The weighted average is calculated at bank-level, by weighting the NPL ratios of each bank by the bank' share in the volume of gross loans in each country. In the second step, we calculate the average at euro area level by averaging the weighted averages at country level.

surprising that the models perform similarly, with the model without bank controls producing slightly lower forecasted values in the baseline scenario and higher in the adverse scenario.

From a macroprudential perspective, the results of this exercise are useful to provide an assessment of the resilience of the banking sector as a whole - given the assumed evolution of the macroeconomic conditions. Given the severity of the scenario of this 2021 Stress Test, the results depict a positive outcome. Focusing on the weighted NPLs ratio, under a baseline scenario, our models suggest that the NPLs would continue decreasing, reaching by the end of 2023, the same level seen in 2006, before the outbreak of the financial crisis. As concerns the adverse scenario, our model forecasts that NPLs would increase by slightly more than 2pp in 3 years, moving from 3.6% to 5.7% by the end of 2023, but remains below the peak reached in 2013. Lastly, the disaster scenario depicts an extremely severe evolution of NPLs, with the ratio moving from 3.6% to above 8% at the euro area level, which is slightly above the peak reached in 2013. Nonetheless, it is important to remember that this result comes from the combination of an extremely adverse macroeconomic scenario with elasticities estimated at the 90th percentile, where, recalling Table 26, the NPLs ratio is 18%.[88]

As a final consideration, while it is not the focus of this chapter, our model is also able to identify individual financial institutions that would suffer from above-than-average NPLs increases since the forecasted NPLs ratios are bank-specific. This is pivotal from a micro-prudential perspective. Indeed, the next step in a supervisory Stress Test would be to assess how the NPLs increase is translated into P&L impact via the booking of loan loss provisions. This assessment, together with the results from the satellite models used to predict net interest income and other income sources (e.g., trading income, fees and commission income) (recall the blocks of a Stress Test framework, Figure 10 in Section 2.2), inform on the losses that banks' capital would need to absorb in an adverse scenario, thus informing on the solvency position of banks.

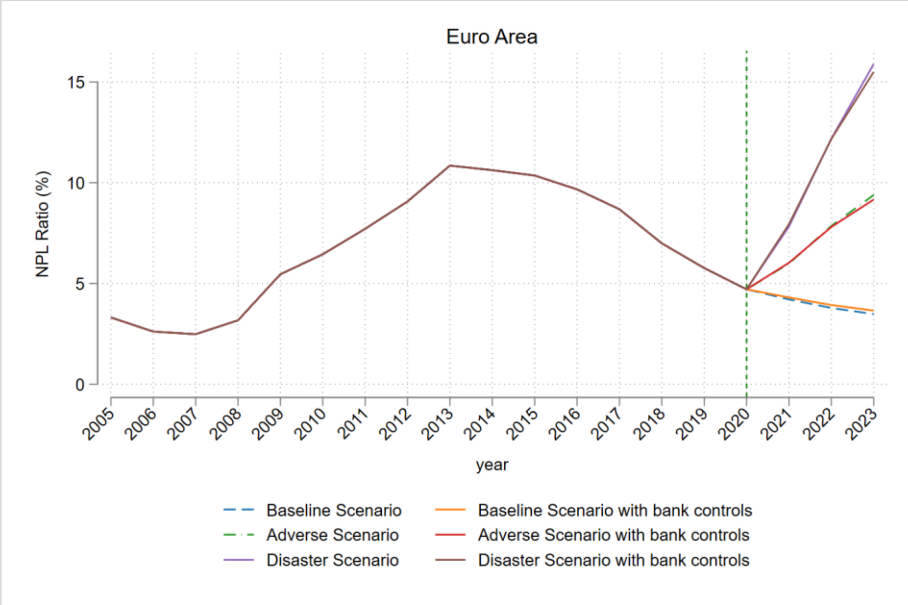
[88] It would be natural to assess the predictive power of the model against the observed values during 2021 and 2022. Nonetheless, the enormous amount of government interventions that were put into place during the COVID-19 pandemic to support borrowers and banks (e.g., moratoria, government guarantees) have naturally affected the evolution of NPLs that otherwise we would have seen if these measures were not active. As such, we argue that it would be misleading to perform such an exercise.

Table 30. Forecasted NPL Ratios at the euro area level with and without bank-specific controls

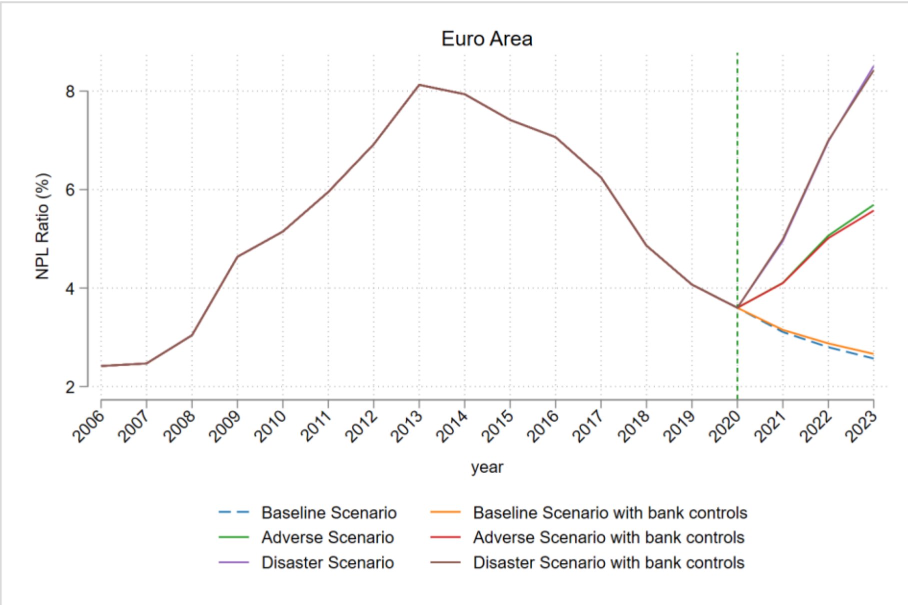
		2020	**2021**	**2022**	**2023**
Model 1 (without bank controls)	Baseline	4.7%	4.2%	3.8%	3.5%
	Adverse	4.7%	6%	7.8%	9.4%
	Disaster	4.7%	7.8%	12.2%	15.9%
Model 2 (with bank controls)	Baseline	4.7%	4.3%	3.9%	3.6%
	Adverse	4.7%	6%	7.8%	9.1%
	Disaster	4.7%	7.9%	12.2%	15.5%
Model 1 - Weighted (without bank controls)	Baseline	3.6%	3.1%	2.8%	2.5%
	Adverse	3.6%	4.1%	5%	5.7%
	Disaster	3.6%	4.9%	7%	8.5%
Model 2 - Weighted (with bank controls)	Baseline	3.6%	3.1%	2.9%	2.6%
	Adverse	3.6%	4%	5%	5.6%
	Disaster	3.6%	5%	7%	8.4%

Figure 15. Forecasted NPL ratios with and without controls

Panel A. Forecasted NPL ratios with and without controls



Panel B. Forecasted NPL ratios with and without controls – Weighted Average



Note: the aggregation at the euro area level of bank-specific forecasts has been obtained by weighting the NPL ratio by gross loans to assign more importance to larger banks.

2.5 Conclusions

Non-performing loans represent a long-standing policy issue in the euro area. Over the last decade, non-performing loans have been under the close scrutiny of both banks and policymakers because they have micro- and macroprudential implications. On the one hand, a high volume of NPLs creates a "vicious circle" between profitability, capital, and lending, whereby the provision for credit losses depress banks' profits, ultimately hindering banks' capacity to build up capital buffers to absorb losses and extend loans. On the other hand, NPLs create macroprudential and financial stability problems by weakening the banking sector's resilience to further shocks and by affecting banks' ability and willingness to provide credit to the economy. Ultimately, the lack of bank credit could impair economic recovery, especially in European countries that are characterised by bank-centred economies. Following the global financial crisis and the sovereign debt crisis, the stock of NPLs in banks' balance sheets increased exponentially, reaching an all-time-high record of €1 trillion at the end-2016. Following the COVID-19 pandemic and the global economic slowdown triggered by the Russia-Ukraine war, non-performing loans are likely to become once again an important problem.

In light of this pressing issue, models aimed at informing in a forward-looking manner on the performance of banks, such as stress test exercises, have become an integral part of prudential and supervisory authorities' toolkits. This chapter presented a credit risk model aimed at i) detecting non-linear dynamics between NPLs and macro-financial variables and ii) conditionally forecasting the evolution of banks' non-performing loans under a baseline and an adverse scenario.

First, we use novel non-linear techniques to gain a deeper and more nuanced understanding of the drivers behind the build-up of NPLs in euro area banks. By using dynamic fixed effects quantile models, we document novel evidence that our selected macroeconomic variables have heterogenous explanatory powers at different quantiles of the distribution of NPLs. This is in stark contrast with prior studies, that by using linear regression models, fail to shed light on the dynamics at the tails of the distributions of NPLs. This is a severe limitation since the distribution of credit risk variables is often skewed and non-linearities tend to arise during periods of macroeconomic distress, which are the ones of interest to prudential and supervisory authorities.

In the second step of our analysis, we exploit the scenario of the 2021 EBA Stress Test, and we produce bank-specific forecasts of NPLs under a baseline, adverse and disaster scenario. By using quantile regressions, we are able to produce conditional forecasts using various sets of coefficients estimated at different percentiles.

From a macroprudential perspective, our results provide an assessment of the resilience of the banking sector as a whole. Given the severity of the scenario of the 2021 stress test, the results depict a positive outcome, where, in an adverse scenario, NPLs would increase from 3.6% to 5.7% by the end of 2023, while remaining below the 2013 peak. However, the disaster scenario depicts an extremely severe evolution of NPLs, with the weighted ratio moving from 3.6% to above 8% at the euro area level. Nonetheless, it is important to remember that this result comes from the combination of an extremely adverse macroeconomic scenario with elasticities estimated at the 90th percentile, where the NPLs ratio is 18%. From a micro-prudential perspective, our model is also able to identify individual financial institutions that would suffer from above-than-average NPLs increases, as the NPLs forecasts are bank-specific. The results can then be used to provide an assessment of the P&L impact, ultimately informing on the solvency position of banks.

To conclude, compared to prior studies, our model is better equipped to detect dynamics between non-performing loans and macro-financial variables that materialise at the tails of the distribution of NPLs. This is of particular relevance because the focus of prudential authorities is on periods of macroeconomic distress when high levels of NPLs can emerge. Additionally, the state-of-the-art empirical approach we use entails the estimation of bank fixed effects, which are pivotal to providing bank-specific paths for the evolution of NPLs. By failing to control for non-linearities or bank-specific characteristics, other models might result in severe underestimation of the evolution of NPLs under an adverse scenario.

Chapter 3

The relationship between capital and credit supply in the Eurozone: a model uncertainty approach

3.1 Introduction

The relationship between bank capital and lending has been the topic of investigation in a multitude of theoretical and empirical studies. The literature on this topic has grown particularly fast during the last decade. This is because the global financial crisis has exposed a number of weaknesses in the financial systems of developed countries including inadequate bank capital buffers to absorb unexpected losses (Basel Committee on Banking Supervision, BCBS, 2018). The regulatory response to the crisis included the introduction of the new Basel III framework with enhanced risk-weighted capital requirements as a key new feature. To comply with the Basel regulation, banks are expected to significantly adjust the structure and the size of their balance sheets. However, modifying the composition of their assets and liabilities is likely to affect the core activity of banks, including their role as credit providers, that is, their lending activity (Roulet, 2018).

On the one hand, banks may decide to meet their risk-based capital requirements by *de-risking* their balance sheet, that is, by substituting assets absorbing more capital, such as loans to Non-Financial Corporations (NFCs), with assets absorbing lower regulatory capital, such as government securities. Banks may also decide to comply with Basel III by *deleveraging*, that is, by reducing the overall size of their balance sheet. It follows that the introduction of higher regulatory capital requirements may lead to a reduction of the credit supply to the economy (Berger et al., 1995; Ben Naucer et al., 2018). However, on the other hand, banks may respond to higher capital requirements by raising equity, either internally via retained earnings, or externally, by raising funds on the capital markets. A stronger capital position could enhance banks' risk absorption capacity, ultimately strengthening their ability to fund more credit (Allen and Santomero, 1997; Berger and Bouwman, 2009). In other words, introducing higher capital requirements can have social benefits in the form of financial stability and higher economic output. Nevertheless, policymakers and regulators need to appraise potential economic costs associated with banks meeting the capital requirements by lending less (Berrospide and Edge, 2010; Martín-Oliver, Ruano and Salas-Fumás, 2012).

The relationship between bank capital and lending has been investigated in many studies (Gambacorta and Mistrulli, 2004; Berrospide and Edge, 2010; Aiyar, et al., 2016; Ben Naucer et al., 2018; Chu et al., 2018; Fraisse et al., 2020) with several contrasting findings being reported. For example, Berrospide and Edge (2010) and Carlson et al. (2013) find a positive link between capital position and bank credit supply, whereas a reduction in lending following higher capital requirements is reported, for instance, by Kanngiesser et al. (2017a) and Gropp et al. (2019). In this chapter, we argue that this inconclusive evidence on the link between regulatory capital and bank credit is the outcome of the fact that, while economic theories predict such a relationship, it remains less clear how to empirically test for it. That is, by not having a clear a priori knowledge of it, researchers are left with a large amount of *uncertainty* on how to model this relationship, being faced with a multitude of choices concerning the model specifications. In other words, researchers have to deal with *model uncertainty* related, for example, to the choice of the estimation methodology, control variables to include in the specification, and operational definitions of the control variables.

Model uncertainty is pervasive in social sciences. There exist many different theories and many different ways in which these theories can be implemented in empirical models (Steel, 2020). Ignoring the problem of model uncertainty by selecting a few specific models and ignoring all the alternative – yet plausible – specifications might result in overconfident results and a distorted representation of the phenomenon one wants to investigate. In the literature, model uncertainty has been dealt with by employing *model averaging* techniques, such as Bayesian Model Averaging (BMA) and Frequentist Model Averaging (FMA). These methods aim at estimating a large number of regressions and computing a weighted average where the weights are chosen by means of probabilistic calculus (for BMA) or according to specific properties of the estimator (in the case of FMA).

In this chapter, we contribute to the literature on the relationship between capital requirements and lending by acknowledging model uncertainty in this research area and by dealing with it using the *model uncertainty framework* (MUF hereafter) proposed by Young and Holsteen (2017) and Muñoz and Young (2018a). Using the MUF, we do not restrict our analysis to a few model specifications, but rather we explore the relationship between regulatory capital and lending across all the theoretically possible specifications. Specifically, we focus on euro area banks operating under the supervision of the Single Supervisory Mechanism between 2006 and 2020 and we examine the *significance* and *sign* stability of the estimated coefficient of interest (i.e., regulatory capital) across all possible combinations and multiple operational definitions of the control variables (overall 20,000 regressions). To the best of the authors' knowledge, this is the first empirical study in the banking literature to adopt this methodology.

In contrast to BMA and FMA methods, which aim at presenting a final "best estimate", MUF aims at showing the modelling distribution of the relationship under investigation. In particular, the MUF allows i) the exploration of the critical model assumptions to the results and ii) decide which assumptions can be relaxed without overturning the conclusion from that estimate. In the BMA and FMA frameworks, there is no space for an analysis of the critical modelling assumptions and the merit of different modelling choices. Additionally, the MUF takes a broader approach to model uncertainty by investigating the role of several "model ingredients", such as functional forms, standard error calculations, and variable definitions. This is in stark contrast with BMA and FMA, where the model uncertainty is investigated exclusively in terms of control variables.

We start by running baseline model specifications using a selection of control variables borrowed from the literature. This first set of results suggests that, on average, there is a negative – albeit insignificant - relationship between the amount of regulatory capital held by euro area banks and their lending behaviour. Then, we show how changing some of the control variables in the regression can lead to dramatically different findings. First, we account for potential model selection bias and relax some of the assumptions concerning the control variables to include in the specification. In this case, out of the almost 16 thousand possible combinations of variables, capital has a positive coefficient in 35% of the cases, while in the remaining cases, it is negative. Additionally, among the model with negative coefficients, 25% are also statistically significant. Then, we further assess the sensitivity of our results by testing for functional form robustness, that is, how the estimates of the coefficient of capital are influenced by the use of multiple operational definitions of the same explanatory variable (e.g., return on equity vs return on assets). In this analysis, we observe that in 98% of the models (out of the 4320 regressions), the coefficient of capital is negative and, in 27% of the cases, capital is also statistically significant.

Overall, the findings from the use of the model uncertainty computational framework have implications for both researchers and policymakers. Model uncertainty is pervasive and intrinsic in social science studies, and ignoring it might lead to an overconfident representation of reality because the results do not take into account the array of other possible models that could have been tested (Steel, 2020). From a broader perspective, model uncertainty leads to a problem of asymmetric information between the researcher and the reader. By often presenting only a fraction of the theoretically plausible models, researchers "know much more about the sensitivity of their results than do readers" (Young, 2018a). These reported results are often the outcome of very *curated* model specifications where the coefficients of interest are *statistically significant*. This is because researchers have often incentives to find *significant* results as it increases their likelihood of publication (Brodeur et al. 2019; Andrews and Kasy 2019). Model uncertainty techniques can shed light on the presence of *"false positives"* – "parameter estimates that are statistically significant even when there is no real relationship in the data (Muñoz and Young, 2018, p.2)"- ultimately reducing the issue of *p-hacking* by increasing research transparency.

The rest of the chapter proceeds as follows. In Section 3.2, we present stylised facts about the evolution of the relationship between regulatory capital and lending in euro area banks and we review the existing theories and literature. Section 3.3 introduces the model uncertainty problem and the relative framework used in the Chapter. In Section 3.4, we introduce the empirical approach and the data used. In Section 3.5, we report the results of the baseline regressions and the application of the model uncertainty framework. Section 3.6 concludes.

3.2 The relationship between bank regulatory capital and lending

In this section, we explain why understanding the relationship between regulatory capital and lending is important from a policymaker's perspective, especially in the euro area. We do so by briefly introducing the regulatory framework that governs the capital requirements and then showing how this relationship has evolved between 2006 - before the Global Financial Crisis - and 2020. Additionally, we present the theories explaining the links between capital and credit supply and we conclude the section by reviewing the most important studies that have empirically tested this relationship.

3.2.1 Stylised facts on the relationship between regulatory capital and lending in the euro area

The examination of the dynamics of European bank lending is particularly relevant from a policymaker's perspective. Euro area countries are primarily characterised by bank-based financial systems, implying that bank loans play a critical role in financing SMEs as well as households. Over the period 2008-2018, bank loans have accounted for approximately 80% of the debt financing of SMEs whereas they represent by far the main component of household financing (see Köhler-Ulbrich et al., 2016). Therefore, bank loans play two crucial roles. On the one hand, by often representing the only source of household and SMEs financing, bank loans are vital for European countries' economic growth. On the other hand, loans act as the main channel for monetary policy transmission, that is, they are pivotal in reconciling the shift in the monetary strategy of the ECB (Matousek and Sarantis, 2009; Ciccarelli et al., 2015).

The ability of banks to provide credit crucially depends on their balance sheet characteristics. In this chapter, we focus on examining how the level of *regulatory* capital influences bank lending decisions. The international regulatory standards for bank capital are set out by the Basel Committee. The proposal for the first Basel accord dates back to 1988. As a result of the Latin American debt crisis that occurred in the early 1980s, international regulators grew concerned over the low level of capital ratios of internationally active banks. "Basel I" introduced the notion of risk-based capital requirements by calling for a minimum ratio of capital to risk-weighted assets of 8%. Under Basel I, banks followed a simplistic approach whereby assets were classified into five risk categories (0%, 10%, 20%, 50%, and 100%) according to the nature of the debtor. In June 1999, the Committee issued a proposal for a new capital adequacy framework to replace the 1988 Accord, resulting in a revised capital framework in June 2004 (known as "Basel II").[89] Following the

[89] Basel II was a historical change in bank regulation. While Basel I envisaged a "one-size-fits-all" approach, the Basel II and successive amendments granted banks the possibility of using either the Standardised Approach (SA) or the Internal Ratings-Based (IRB) approach to calculate their minimum capital requirements. The SA approach is a simplistic methodology, whereby fixed risk-weights (i.e., pre-determined by the regulatory authorities) are assigned to different categories of borrowers (e.g., financial institutions, corporations, retail, etc) so that the applied risk-weights are consistent across all banks. By contrast, the IRB approach relies on banks' own (internal) models to calculate their own risk-weights. Banks are allowed to use their own models, which have been ex-ante scrutinized and

global financial crisis (2007-2009), the Basel Committee introduced more stringent capital requirements with the goal of increasing the *quality* as well as the *level* of capital held by financial institutions. Under "Basel III", the minimum regulatory capital (Tier 1 + Tier 2) remains at 8%, whereas the composition of the different capital instruments has been changed. Banks are asked to increase the amount of Common Equity Tier 1 (CET1) capital- the highest quality of capital comprising common shares and retained earnings- from 2% to 4.5% of RWA. The minimum Tier 1 has been set at 6%, up to the 4% requirement under Basel II, leading to a reduction of Tier 2 requirements from 4% to 2% under Basel III.

In addition, Basel III envisages the introduction of a series of capital buffers that sit on top of minimum regulatory capital. Banks are required to hold a Capital Conservation Buffer (CCoB) (2.5%), which is intended to preserve banks' minimum loss-absorbing capacity during periods of stress. To address pro-cyclicality concerns, Basel III introduced a Countercyclical Capital Buffer (CCyB) (0-2.5%), which banks have to build up during periods of economic upswing and draw-down during macroeconomic distress. On top of this, Global Systemically Important Institutions (G-SIIs) and Other Systemically Important Institutions (O-SIIs) are subjected to the implementation of an additional capital buffer (1-2.5%), depending on the level of interlinkages and common exposures of the bank- that intends to address systemic risk concerns. Finally, an institution-specific or exposures-specific Systemic Risk Buffer (SyRB) was also introduced to address systemic risks that are not covered by the CCyB or the G-SII/O-SII buffers. These buffers are required to be met using Common Equity Tier 1, yielding to a minimum Tier 1 ratio between 8.5% and 13.5% depending on whether the CCyB and the SIBs buffers are implemented.[90]

Figure 16 displays the trend in the growth rate of net loans and Tier 1 capital ratios in our sample of euro area banks.[91] We observe a collapse in lending between

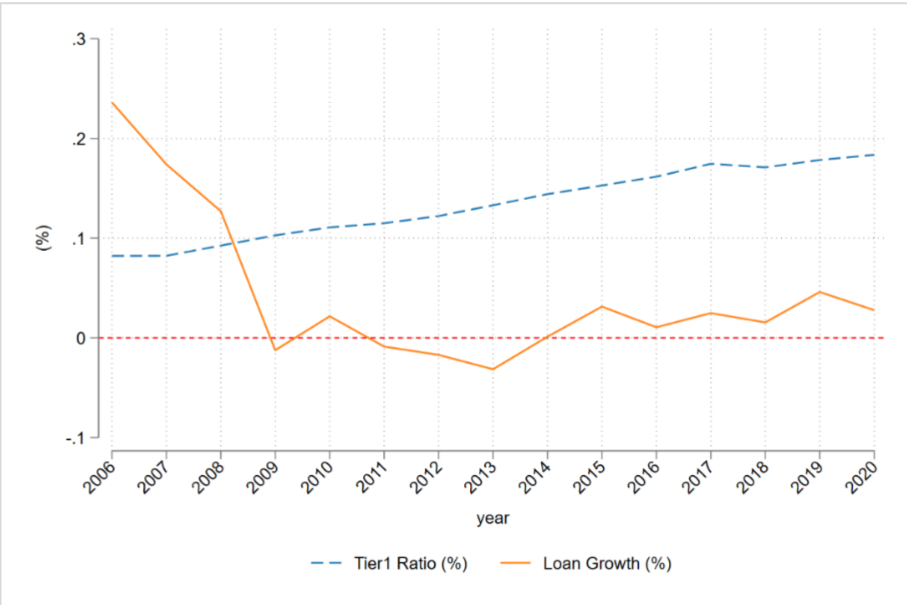
authorized by the supervisory authority, to estimate the credit risk parameters (such as probability of default and loss given default) that feed the regulatory formulas used to calculate risk weights and thus the minimum level of regulatory capital.

[90] Additionally, Basel III introduced the Leverage Ratio, a minimum amount of most absorbing capital relative to all of a bank's asset and off balance sheet exposure regardless of risk weighting, and liquidity requirements, among which the Liquidity Coverage Ratio (LCR), intended to provide enough cash to cover funding needs over a 30 day period of stress and the longer term ratio, the Net Stable Funding Ratio (NSFR), intended to address maturity mismatches over the entire balance sheet.

[91] We focus on Tier 1 ration instead of Common Equity Tier 1 Ratio because of data availability from Fitch Connect.

2006 and 2009 as a consequence of the outbreak of the financial crisis. After a brief period of recovery, we distinctively observe a “credit crunch” from 2011 until 2013 due to the sovereign crisis. Bank lending started recovering approximately around 2014 when presumably the effects of the launch of the first round of the Targeted-Long Term Refinancing Operations (TLTROs-I) in June 2014 began having positive effects on bank lending behaviour.[92] While lending has been sluggish, European banks have considerably strengthened their capital levels, moving from an average Tier 1 ratio of 8.2% in 2006 to approximately 18.3% in 2020. Overall, as noted by Kanngiesser et al. (2017) the reason for the sharp increase in capital, especially in the early stages of the crisis, could be attributable to the intense market pressure to rebuild capital (see also de Bandt et al., 2018) whereas, from 2011, capital increases could have been the outcome of regulatory pressure. Nonetheless, higher capital may be the result of banks de-risking or deleveraging their banking books.

Figure 16. Net Loans Growth and Tier 1 Ratio of selected European Banks



Note: Loan Growth refers to the year-on-year growth rate of net loans of an unbalanced sample of 90 banks

[92] This unconventional monetary policy aimed at providing credit to banks at attractive conditions, thus easing banks marginal funding costs and improving credit conditions for Euro Area households and SMEs (see ECB Economic Bulletin, 2017).

3.2.2 Theories explaining the relationship between capital and lending

As explained in the previous section, Basel regulation governs the capital framework that banks have to comply with. After the GFC, the framework has been extensively revised, resulting in significantly higher regulatory requirements. Thus, it is not surprising that the relationship between regulatory capital and bank lending behaviour has been the subject of several theoretical and empirical studies since the implementation of the 1988 Basel accord (see, for example, Peek and Rosengren, 1995, 1997; Thakor, 1996; Diamond and Rajan, 2001; Gambacorta and Mistrulli, 2004; Berger and Bouwman, 2009; Gorton and Winton, 2017; Kanngiesser et al., 2017; Ben Naceur et al., 2018). Several theories have produced contradicting predictions concerning the relationship between credit growth and bank capital.

The first set of theories can be explained through the conceptual framework of the Modigliani-Miller (hereafter MM) (1958) theorem. The MM theorem suggests that in a frictionless world of full information and complete markets, a firm's capital structure does not affect its investment policies (Chu, Zhang and Zhao, 2018). Economists have challenged the MM theorem as they started investigating the implications arising from the introduction of market imperfections, such as asymmetric information and tax shields (de Bandt et al., 2018). One market imperfection that can invalidate the postulate of neutrality of bank capital is the presence of bankruptcy costs. Indeed, the costs associated with financial distress depend on the amount of bank capital, thus implying that there is an optimal leverage ratio minimising the cost of funds (Martín-Oliver, Ruano and Salas-Fumás, 2012). In other words, the MM theorem may hold only partially in the case of banks as the cost of debt and equity is dependent on the firm's debt structure. Holding higher levels of capital enables banks to reduce their leverage and enjoy lower funding costs. In turn, this allows banks to support more lending as they can earn higher profits arising from the lower yield spread over their funding costs. (Chu, Zhang and Zhao, 2018).

A second theory that links positively bank lending and capital refers to the higher risk-absorption capacity associated with higher levels of bank equity ("*risk absorption hypothesis*"). According to the modern theory of financial intermediations, banks perform two central roles in the economy: they transform risk and create liquidity (by funding illiquid, long-maturity assets with liquid, short-maturity liabilities) (see Berger and Bouwman, 2009). Higher capital levels enhance bank risk-bearing capacity - especially when hit by a shock, and thus improve their ability to create liquidity and fund loans. This is because a stronger capital position increases banks' resilience, for instance, by allowing them to raise debt more favourably on the market compared to less capitalised banks, ultimately supporting their capacity to generate loans (Kapan and Minoiu, 2018). Furthermore, higher capital levels could incentivise higher levels of borrowing monitoring as bank shareholders are the first to bear the loss in the event of a bank's insolvency. Enhanced bank monitoring reduces the probability of bank defaults, which in turn helps improve firms' expected payoff and encourages banks to extend loans (Holmstrom and Tirole, 1997, Mehran and Thakor, 2011, Allen et al., 2011).

In contrast, and maybe more intuitively, the second set of theories suggests that introducing higher capital requirements may result in a downward shift in loan supply if, contrary to the Modigliani-Miller (1958) theorem, financial markets are imperfect and there is a net cost of raising capital, that is, there are differences in the cost of debt (e.g., deposits) and equity financing. Indeed, raising bank capital is more expensive than raising deposits. In this scenario, banks could respond to capital requirements by de-risking their balance sheet, either by reducing the amount of risky loans or by shifting their investment strategy towards liquid securities. That is, risk-based capital requirements could encourage banks to substitute assets bearing higher risk, such as loans to NFCs, with assets with lower risk-weights, such as mortgage loans, ultimately leading to a reduction of the credit supply towards the productive sectors of the economy. In other cases, banks may also opt to reduce loans in favour of securities holding, especially government securities as they bear a 0% risk-weight, meaning that banks do not have to set aside capital when investing in these instruments.[93] Lastly, banks could decide to comply with the requirements by shrinking the volume of loans granted, that is, by *deleveraging* (Berger et al., 1995; Ben Naucer et al., 2018; Chu et al., 2018).

In line with this, Diamond and Rajan (2000, 2001) argue that higher capital reduces lending by making a bank's capital structure less fragile ("*financial fragility structure"* hypothesis). Having a fragile capital structure incentives banks to commit to monitoring and collecting repayments from their borrowers, hence allowing the

[93] This behaviour could heightened the risk of a sovereign-bank nexus (Dell'Ariccia et al., 2018).

bank to extend more credit. Contrary to this, high levels of capital render it harder for the less-fragile bank to commit to monitoring, in turn increasing the probability of bank defaults and hampering the bank's liquidity creation

From this discussion, it emerges that it is of great importance for policymakers to weigh the benefits and costs associated with capital requirements. Benefits in terms of a more stable and sound financial system may be counterbalanced with a loss in economic output in the case banks respond to regulatory requirements by de-risking or deleveraging their balance sheets (Berrospide and Edge, 2010).

3.2.3 Related empirical literature

As presented in the previous section, several studies have tried to formalise with theories the potential dynamics that one can observe between capital and credit origination. However, several theories that have been put forward posit contrasting effects of capital on lending. More importantly, these theoretical studies do not provide guidance on how to empirically test for the presence of the hypothesised relationships. Thus, researchers interested in investigating this topic are faced with significant degrees of freedom in choosing how to model the relationship. In this section, we provide a review of the most relevant empirical studies focusing on capital and lending and we show how the findings are often contradicting.

The empirical literature investigating the relationship between regulatory capital and credit supply is vast and heterogeneous in terms of findings and modelling choices. Several studies have examined the lending decisions of European banks, generally reporting a negative or insignificant role of bank capital. In the context of the Czech banking system, Horváth et al. (2014) show a reverse causality relationship between capital (measured as equity-to-asset ratio) and liquidity creation.[94] Higher capital hampers lending but, at the same time, higher liquidity weakens banks' solvency, thus suggesting a trade-off between the benefits of financial stability induced by stronger capital requirements and the benefits of increased liquidity creation. In another study, Kanngiesser et al. (2017) observe that, between 2003Q4 and 2016Q3, the pressure on banks to comply with the new

[94] In this paper, the concept of liquidity creation is a rather comprehensive measure of a bank's overall ability to transform maturity in the economy (Berger and Bouwman 2009), and it comprises not only on-balance-sheet activities but also off-balance-sheet activities.

regulatory framework resulted in banks de-risking their balance sheet and curtailing lending. Interestingly, a counter-factual exercise shows that an increase in capital ratios before the start of the global financial crisis could have helped to prevent, or at least soften, the boom-bust cycle and economic crisis in the euro area. Likewise, in two recent studies, Ben Naucer et al. (2018) and Roulet (2018) noticed that higher Basel III regulatory capital levels are associated with lower retail lending of European banks but not lower commercial lending. Gropp et al. (2019) show that European banks responded to the EBA capital exercise – which required banks to increase their regulatory capital – by reducing their exposures to corporate and retail clients.[95] Focusing on the French banking sector between 2008 and 2011, Fraisse et al. (2020) estimate that a 1 percentage point increase in capital requirements reduces lending by 2.3%–4.5%.

Interestingly, contrasting findings are generally found in those studies focusing on the US market. For example, Berrospide and Edge (2010) estimate that a 1% increase in the capital ratios corresponds to an increase of approximately 0.7-1.2% in the credit supply of US Bank Holding Companies (BHCs) over the period 1990Q3-2008Q3. They also provide evidence that BHCs whose capital exceeds 1% of their target level tend to increase the annualised loan growth by 0.25%. Likewise, Carlson et al. (2013), using a matched bank approach to control for differences in loan demand across the US, show that loan growth is positively linked to stronger capital positions. However, the magnitude of these effects is rather small, as a one percentage point increase in the capital ratio raises lending by a modest 0.05–0.2 percentage points. In addition, they notice that this relationship becomes positive only in 2008-2010, being insignificant before the crisis.

Karmakar and Mok (2015) report a strong positive relationship between regulatory capital and business lending for small US banks between 1996 and 2010, whereas for larger banks the results are mixed. In line with this, Kim and Sohn (2017) show that capital affects bank lending of small and medium US commercial banks positively whereas no relationship is observed in the case of large banks. In addition, they show that the effect of bank capital on lending is positively associated with the liquidity level of large banks, suggesting that the effect of an increase in the

[95] The objective of the EBA exercise was to restore confidence in the EU banking sector by ensuring that banks had sufficient capital to against unexpected losses. To achieve this objective, the EBA required 61 banks to build additional capital buffers to reach a 9% CET1 ratio by the end of June 2012 (Gropp et al. 2019).

capital ratio on credit growth is significantly negative for low liquidity ratios. Other studies have considered the US context of syndicated loans. Chu et al. (2018) show that a bank with a 1% higher total capital ratio contributes, on average, 0.5% more funding to a loan than another bank participating in the same loan. Moreover, they demonstrate that the impact of capital on lending is stronger for banks more reliant on unsecured wholesale funding. Similar conclusions are reached by the recent empirical investigation of Ben Naucer et al. (2018) who find that both commercial and retail bank-lending growths benefitted from higher risk-weighted capital ratios during the period 2008-2015.

Outside the US context, Mora and Logan (2012) find that, between 1990 and 2004, a fall in the capital of UK banks was associated with a significant drop in lending in particular, to non-financial corporations whereas households lending increased. In line with these findings, Bridges et al. (2014) report that in the year following the introduction of more stringent capital requirements, UK banks tend to cut lending for commercial real estate, other corporates and household secured lending. Similarly, Aiyar et al. (2014) find a negative and statistically significant effect of changes to banks' capital requirements on cross-border bank loan supply of UK banks from 1999Q1 to 2006Q4. On average, a 100 basis points increase in the requirement is associated with a reduction in the growth rate of cross-border credit by 5.5 percentage points. The authors show that banks tend to favour their most important country relationships so that the negative cross-border credit supply response in “core” countries is significantly less than in others. Also, banks tend to cut back cross-border credit to other banks more than to firms and households. A later study by Aiyar et al. (2016) also highlights the adverse effects of a tightening in capital requirements on the credit supply of UK institutions over the period 1998-2007. Exploiting credit registry data from Latin America, Cantú et al. (2020) report that well-capitalised banks generally supply more credit and tend to adjust less their credit supply following a monetary policy shock. A positive effect of capital ratio on bank loan growth is reported by Košak et al. (2015) for a global sample between 2000 and 2010. This effect is particularly pronounced during the financial crisis, for small banks and banks in the non-OECD and BRIC countries. Finally, in a different setting, Louhichi and Boujelbene (2017) assess to what extent Islamic and non-Islamic banks’ different capital structures could affect their lending decisions. They discover Tier 1 capital to be positively associated with the bank's credit growth and that this association increases in magnitude in the aftermath of the financial crisis.

As shown in this section, the literature on bank capital on loan growth is extensive and the findings on their relationship are mixed. We recognise that the inconsistent results are likely the outcome of the multitude of different samples, periods examined and econometric methodology employed by these studies (e.g., difference-in-difference approaches vs linear fixed effects models). However, we also point out that these studies adopt very different approaches to the modelling of the relationship between capital and lending, especially with respect to the variables included in the models and the operational definition of these controls. More importantly, these papers all report a limited set of results, when, in reality, many other models could have been run with likely remarkably different results. In other words, these studies have ignored the presence of *model uncertainty*. In the next section, we introduce the model uncertainty framework adopted in this chapter.

3.3 The Problem of model uncertainty

Model uncertainty is a pervasive problem in economics. Model uncertainty refers to a situation where

> "social theory provides empirically testable ideas but by its nature does not give concrete direction on how the testing should be done (Young and Holsteen, 2017, p. 4)"

In other words,

> "social theory rarely says which control variables should be in the model, how to operationally define the variables, what the functional form should be, or how to specify the standard errors. When the ''true'' model is unknown, it is hard to say which imperfect approximation is best. As a result, theory can be tested in many different ways and modest differences in methods may have large influence on the results (Young and Holsteen, 2017, p. 4)".

Model uncertainty derives from the 'fact' that the optimal or appropriate model specification to address a specific research question will never be known, and what we then see happening is a form of herd behaviour towards a conventional approach (or wisdom) that takes hold and is replicated, sometimes without question, until a certain model becomes dominant to examine a certain issue. However, we must remain cognisant that for any given study, in any given area, there is a tremendous variety of statistical methods, potential explanatory variables, variable definitions, standard errors (e.g., homoscedastic versus heteroskedastic standard error) and functional forms (e.g., ordinary least square regression versus fixed-effects regression) that could be applied (Sala-i-Martin et al., 2004; Young, 2018).

Limiting the analyses to a narrow set of selected, previously touted as the "best" models, means that we may fail to capture explanatory aspects of reality, which is intrinsically characterised by uncertainty (Steel, 2020). More importantly, it renders hard to predicate if the empirical findings are data-driven or are simply the outcome of the preferred model specification and empirical methodology used by the author(s) (Young, 2018). Ignoring uncertainty can lead to over-confident inferences and predictions, and a distorted representation of reality (Fletcher, 2019). In the context of our study, model uncertainty arises because the existing theories and models in this area, which concern the relationship between regulatory capital and credit supply, do not provide any strict guidance either on which control variables should be included in the model specification, on which operational definitions to use or which econometric technique to employ.

In the literature, one of the most common solutions to the problem of model uncertainty is *model averaging*, where two main strands of studies can be distinguished: Bayesian Model Averaging and Frequentist Model Averaging. These methods aim at estimating a large number of regressions and computing a weighted average where the weights are chosen by means of probabilistic calculus (for BMA) or according to specific properties of the estimator (in the case of FMA).

The Bayesian framework focuses on obtaining a model-averaged *posterior* for any parameter of interest. This is achieved by estimating the *posterior model probability*, which describes the plausibility that the model is true after the data are observed. Then, BMA calculates a weighted combination of the posterior distributions from the different models, the weights being the posterior model probabilities (see, for a few examples of BMA applications in finance, Giannone et al., 2011; Ho, 2015; Gross and Población García, 2015; Devereux and Dwyer, 2016; Zigraiova and Havranek, 2016). By contrast, the frequentist approach involves calculating a weighted mean of the estimates obtained from each of the candidate models, with the weights reflecting a measure of the potential value of that model for estimation. The weights are usually obtained via Akaike's information criterion, cross-validation, or the mean squared error of the estimate of the parameter of interest. (Fletcher, 2019).

3.3.1 The Model Uncertainty Framework

For the purpose of this study, we employ the model uncertainty framework developed by Young and Holsteen (2017). This model uncertainty framework relies on computational power to systemically estimate an entire model space that is defined by all the possible combinations of "model ingredients" (i.e., possible control variables, alternative proxies of the same variable, estimation commands, functional forms, standards errors) (Young and Holsteen, 2017).

By adopting this computational framework, we address the problem of asymmetric information between the authors (i.e., the researchers) and readers of the empirical studies. Published papers tend to report only a small set of curated model specifications - almost always reporting statistically significant results - while, in reality, researchers may have run many plausible models with contrasting findings. That is, there may be strong incentives for researchers to engage in *p-hacking* by selectively reporting only those results that produce statistically significant results (Andrews and Kasy, 2019; Brodeur et al., 2019). This is aggravated by the common habit to provide circumstantial evidence of robust results by referencing unreported analyses that confirm the main findings in footnotes (Young and Holsteen, 2017). Not surprisingly, it is rare to find footnotes where authors explicitly mention the non-robustness of their findings to alternative model specifications. As a consequence, empirical studies could be filled with statistically significant findings as a result of arbitrary model selections as opposed to true relationships in the data. These findings can be referred to as "*false positives*", meaning "parameter estimates that are statistically significant even when there is no real relationship in the data (Muñoz and Young, 2018, p.2)". Often, these "false positives" are the outcome of "arbitrary refinements to model specification" (Muñoz and Young, 2018, p.2).

To elaborate on this, suppose we are interested in assessing the effect of X on y (estimated via β_1, see Eq. 3.1). Examining the literature, we find that X_2 is used by the vast majority of empirical studies as a control variable whereas the variables X_3 and X_4 are employed alternatively to explain the relationship between X and y. That is, certain studies only add to the model X_3, others include only X_4 whereas other studies incorporate both X_3 and X_4 as control variables. Thus, model uncertainty is represented in the following set of four possible models:

$$y_i = \beta_1 X_{1i} + \beta_2 X_{2i} + \varepsilon_i \qquad 3.1$$

$$y_i = \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \varepsilon_i \qquad 3.2$$

$$y_i = \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{4i} + \varepsilon_i \qquad 3.3$$

$$y_i = \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \beta_3 X_{4i} + \varepsilon_i \qquad 3.4$$

These four equations all represent different but theoretically informed ways of specifying the model and they all give plausible estimates of β_1. In this context, "*false positives*" could arise if the authors decide to present solely the findings from a subset of the potential model specifications that support the main hypothesis of the study. This can be the case when researchers have incentives in reporting statistically significant effects as significant results are more likely to be published (Young, 2018b; Andrews and Kasy, 2019; Brodeur et al., 2019). Thus, the problem associated with the presence of model uncertainty is that arbitrary modelling choices can determine the results of the empirical analysis (Muñoz and Young, 2018). Therefore, we argue that researchers should question the robustness of their empirical findings because if there are p possible control variables, there are 2^p unique combinations of those variables that should be tested (Young and Holsteen, 2017).[96] As such, it is important to clarify that the aim of this study is not to provide a final answer to the question "does capital influence bank lending behaviour?" Rather, our goal is to show how sensitive the results from empirical estimations can be, and thus, how researchers should report a larger set of robustness analyses compared to those we currently see in the published papers.

The appealing feature of model robustness analysis, as related to the topic under investigation, is that the outcome informs us of the stability of estimates of our variable of main interest (i.e., $Tier$ 1 capital) across all the unique combinations of

[96] For example, consider a model investigating the relationship between capital and lending and that it includes among the control variables: $NPL, ROA, Liquidity, Deposits, Size$. With five control avriables, there are 2^5= 32 unique possible models. If we also consider different estimation methodologies (e.g., POLS and FE), the number of combinations rises to 64 (32 $\times$ 2). Note that Tier 1 is considered as our variables of main interest rather than a control variable.

"model ingredients". That is, we aim at examining whether the findings on the relationship between $Tier\ 1$ and lending growth obtained in our baseline specification (see Section 3.5.1 below) are the outcome of our model specification or if it is due to real underlying relationships in the data. If the results are due to the underlying relationships, they will not be very sensitive to arbitrary changes in the model specifications. If the significant results are determined by the use of an *ad hoc* combination of "model ingredients", they will tend to fall in and out of significance with trivial changes to the model specifications (Muñoz and Young, 2018). Specifically, this computational framework enables us to investigate

- the *sign stability* of the coefficient estimates (i.e., the percentage of estimates of $Tier\ 1$ that have the same sign); and
- the *significance rate* (i.e., the percentage of models that report a statistically significant coefficient of $Tier\ 1$).

Further, the model uncertainty computational framework allows us to perform *model influence analysis*. Model influence analysis focuses on how the introduction of a "model ingredient" changes the coefficient of interest. In this respect, Young and Holsteen (2017) argue that if Z_i is truly a control variable, researchers should *not* focus on the effect of Z_i on the dependent variable (y_i) but rather on how the inclusion of Z_i influences the coefficient of interest (X_i). For example, consider the following two nested models:

$$y_i = \alpha + \beta X_i + \varepsilon_1 \tag{3.5}$$

$$y_i = \alpha + \beta^* X_i + \delta Z_i + \varepsilon_1 \tag{3.6}$$

Our focus is on how changes in X_i affects the outcome y_i, so β is the coefficient of interest. In Eq. (3.63.6), the relationship between the control variable Z_i and the outcome y_i is given by δ. It is conventional in empirical analysis to report and comment on the δ estimate. Nonetheless, the focus should be on the changes in β (i.e., $\Delta\beta = \beta^* - \beta$) caused by the inclusion of the control variable. We refer to $\Delta\beta$ as the *model influence* of Z_i. In other words, model influence analysis enables us to examine which are the control variables required to sustain particular conclusions or, contrary, which assumptions are non-influential and do not affect the findings.

3.3.2 Comparison between model averaging and the model uncertainty framework

The model uncertainty framework of Young and Holsteen (2017) builds directly on the work related to model averaging. However, while model averaging is concerned with presenting a final "best estimate", MUF aims at showing the modelling distribution of the relationship under investigation. More importantly, the framework of Young and Holsteen (2017) focuses on answering two main questions: how many model assumptions can be relaxed without overturning the conclusion from that estimate? and which model assumptions are most critical to the results? In the model averaging literature, there is no space for a conversation on critical modelling assumptions and the merit of different modelling choices, whereas these topics play a central role in the MUF of Young and Holsteen (2017).

Additionally, by not relying on weights, MUF does not suffer from the flaws that can be attributed to model averaging techniques. That is, model averaging approaches typically weight the estimates either by model fit or by Bayesian priors. High model fit can be the result of the presence of endogenous regressors, implying that, for their validity, these metrics of model fit need to assume strict exogeneity of the regressors. Likewise, weights based on Bayesian priors (representing a researcher's beliefs about model validity) privilege a given set of model assumptions whereas robustness analysis should focus on showing how the estimates change under *different* beliefs. By contrast, Young and Holsteen's (2017) approach focuses on the raw (unweighted) distribution of estimates "as a way of revealing, not what is the best estimate, but rather what estimates can be obtained from the data (Young and Holsteen's, 2017, p.30)". The model uncertainty framework does not make any assumptions and treats all the possibilities as open questions.

Lastly, MUF takes a broader approach to the problem of model uncertainty compared to model averaging methods. The latter mainly focuses on uncertainty related to which control variables should be included in the regressions, thus overlooking uncertainty stemming from the remaining "model ingredients", such as functional forms, standard error calculations, and variable definitions (Young and Holsteen, 2017).

3.4 Econometric Methodology

To empirically model the relationship between regulatory capital and bank lending, we begin by specifying the following linear regression model:

$$\Delta Loans_{i,t,j} = \beta_0 + \beta_1 Tier1_{i,t-1,j} + \beta_2 X'_{i,t-1,j} + \beta_3 Z'_{t-1,j} + \alpha_i + \varepsilon_{i,t,j}; \qquad 3.7$$

The dependent variable $\Delta Loans_{i,t,j}$ denotes the year-on-year change in the volume of net loans of bank *i*, in quarter *t*, in country *j*. $Tier1_{i,t-1,j}$ refers to the variables of main interest, that is Tier 1 capital ratio.[97] X' represents a vector of bank-specific balance sheet characteristics, Z' denotes country-level indicators, α_i are bank fixed effects and $\varepsilon_{i,t,j}$ is the random error. Bank-specific and country-level variables are lagged once $(t-1)$ to mitigate possible endogeneity problems (Berrospide and Edge, 2010; Ben Naucer et al., 2018). The model is estimated using fixed effects (FE) to control for unobserved bank heterogeneity

3.4.1 Data

The sample employed in this study focuses on the banks directly supervised by the Single Supervisory Mechanism, which is the supervisory arm of the European Central Bank (see also Section 2.3.3 in Chapter 2).[98] We collect annual balance sheet and income statement data from Fitch Connect. We exclude institutions with missing observations in at least one of our variables of interest (see Table 33 below) and banks that appear in the sample for less than four consecutive years. These data treatments leave us with a sample of 90 banks across 18 jurisdictions (see Table 31 below). The final sample consists of an unbalanced panel dataset of 987 yearly observations ranging from 2006 to 2020. Finally, we retrieve macroeconomic and country-level indicators from the ECB Statistical Data Warehouse and the Word Bank.

[97] Unfortunately, data on Common Equity Tier 1 are scarce as they are usually being consistently reported in Fitch Connect from 2013. Therefore, we focus on Tier 1 ratio.
[98] See https://www.bankingsupervision.europa.eu/banking/list/html/index.en.html

Table 31 Sample Composition

Country	Number of Banks	Country	Number of Banks
Austria	6	Italy	12
Belgium	4	Latvia	4
Cyprus	3	Lithuania	3
Estonia	2	Luxembourg	3
Finland	2	Malta	3
France	7	Netherlands	5
Germany	13	Portugal	4
Greece	4	Slovenia	2
Ireland	3	Spain	10

3.4.2 Bank-specific and country-level control variables

When exploring the effect of capital on lending, the literature reviewed in Section 3.2.3 tends to control for the role played by bank-specific as well as country-specific factors in determining this relationship. However, we notice that these studies are significantly heterogeneous with respect to i) which explanatory variables are included and ii) the operational definition of the control variables. Thus, we leverage on this heterogeneity to construct the model uncertainty framework adopted in this Chapter.

Bank-specific controls

Following the studies reported in Section 3.2.3, we identify several dimensions of a bank's balance sheet that one needs to control for when exploring the effect of capital on lending. These dimensions are size, asset quality, liquidity, profitability, funding, diversification, and cost structure.

Size. The relationship between bank size (proxied by the natural logarithm of total assets) and credit growth is ambiguous. On the one hand, large banks, being perceived as Too-Big-to-Fail, could have funding cost advantages over smaller banks, thus enabling these banks to fund more loans. Likewise, TBTF banks could have incentives to take on greater risks amid expectations of government bailouts to prevent systemic risk, thereby supplying more credit. Moreover, large banks could enjoy economies of scale in the screening and monitoring of borrowers, or could have greater incentives in monitoring because they have more capital at risk.

Enhanced monitoring means a lower probability of defaults. As a result of lower credit risk, larger and safer banks will report higher lending (see Holmstrom and Tirole, 1997, Allen et al., 2011). On the other hand, large banks benefit from portfolio diversification advantages over smaller institutions, which tend to pursed traditional lending activities. As such, the tightening of capital requirements and the costs associated with the non-compliance could have led to large banks shifting the composition of their balance sheets towards securities and liquid assets (i.e., de-risking the balance sheet), ultimately decreasing lending (Kim and Sohn, 2017). Almost all the reviewed studies include size as a control variable (for example, (Gambacorta and Mistrulli, 2004; Louhichi and Boujelbene, 2017; Ben Naucer et al., 2018).

Loan Quality. Accounting for bank asset quality is of particular importance when studying European banks as the post-financial crisis decade has seen a rapid increase in non-performing loans. Poor asset quality could indirectly affect lending rates via a reduction in bank equity as capital levels are likely to be eroded by loan write-offs. It follows that to comply with capital regulations, capital-constrained banks will be forced to deleverage or de-risk the banking book by reducing bank loans to firms and households or by favouring liquid assets over loans, respectively (Behn et al., 2016; Kanngiesser et al., 2017b). Furthermore, poor asset quality could affect banks' ability to supply credit through an increase in their funding costs as investors will demand higher risk premia (Bredl, 2018). In the literature, asset quality has been proxied by non-performing loans (Ben Naucer et al., 2018), loan loss reserves (e.g., Kim and Sohn, 2017) or loan loss provisions over gross loans (e.g., Distinguin et al., 2013; Cantú et al., 2020), loan loss provisions over assets (Košak et al., 2015). Finally, other studies do not control for banks' risk profile (e.g., Brei and Schclarek, 2015; Gambacorta and Shin, 2018).

Liquidity. The measure of liquidity is intended to capture to what extent banks employ their stock of securities to adjust their credit supply. Banks with higher liquidity ratios are better able to shield their lending activities against shocks to external finance (e.g., deposits) by recurring to their stock of liquid assets (Gambacorta and Mistrulli, 2004). That is, banks might decide to hold liquid assets to meet the uncertain liquidity needs of depositors and borrowers. Papers that have used the ratio of liquid assets (securities plus cash & cash equivalent) to totals assets include Aiyar et al. (2014b), Ferri et al., (2014) and Khan et al. (2016) while other studies use the ratio of securities over assets (e.g., Berrospide and Edge, 2010)

Profitability. We include a measure of bank profitability to test the hypothesis that bank capital is sensitive to the evolution of profits as a source of retained earnings (see Martín-Oliver et al., 2012). As aforementioned, if raising equity from the market is too costly, banks may resort to internal resources (i.e., retained earnings) to reach capital targets. Therefore, in the presence of binding capital constraints, we expect more profitable banks to be better able to increase their capital level, thus supporting lending (Peek and Rosengren, 1995; Chu et al., 2018; Kim and Sohn, 2017). Several proxies for profitability appear in the literature, such as return on assets (Berrospide and Edge, 2010), return on average assets (Košak et al., 2015), return on equity (Ben Naucer et al., 2018), and net interest margin. Other studies do not control for profitability (e.g., Karmakar and Mok, 2015).

Cost Structure. Banks' cost efficiency is a widely used measure of banks' performance, capturing the ability of a bank to operate at low costs compared to its revenues. In this study, whereby it is often categorised among the indicators of profitability, we consider cost efficiency as a dimension of banks' balance sheet that needs to be investigated in isolation. Banks operating with low costs could indirectly capture banks that are able to extend more productive loans, thus suffering from lower NPLs (Berger and DeYoung, 1997) and higher returns, ultimately leading to greater loan growth. In the literature, the cost structure of banks is proxied by the cost-to-income ratio (non-interest expenses/ non-interest income plus net interest income) (as in Cantú et al., 2020) or as the ratio of operating expenses over total assets.

Funding. A high stock of stable funding (i.e., deposits) could enable banks to fund more loans. That is, the reliance on deposits could shield banks from an unexpected increase in wholesale funding costs following economic shocks, thus ensuring the supply of credit to the economy. Likewise, Pennacchi (2006) argues that the presence of a deposit insurance scheme could help banks address liquidity risk. Banks that enjoy a significant portion of deposit funding will be able to better withstand periods of financial distress and would respond with a lower decline in bank lending (see also Louhichi and Boujelbene, 2017). On the other hand, following the introduction of a negative Deposit Facility Rate (DFR) by the ECB, the reliance on deposit funding could have hampered the ability of banks to supply credit. In fact, a negative policy rate is unlikely to be transmitted to lower deposit rates (as in the case of a lower (positive) rate) because banks may be reluctant to charge negative rates to depositors. As a consequence, the ultra-low interest rate environment might have led to more risk-taking and less lending by euro-area banks with a greater reliance on deposit funding, as found by Heider et al. (2018). In the empirical literature, the proxies used for the funding structure of banks include deposits over assets (Chu et al., 2018; Gropp et al., 2019)**,** deposits over liabilities (Gambacorta and Marques-Ibanez, 2011; Cappelletti et al., 2022), wholesale funding (Kim and Sohn, 2017). Interestingly, other studies do not account for this dimension (see Horváth et al., 2014)**.**

Diversification. Diversification in the revenue sources (interest vs non-interest revenues) can foster banks' overall income and support lending during periods of distress, when traditional sources of revenue (i.e., net interest income) may suffer from stronger contraction. In the literature, we find this dimension is proxied by the ratio of non-interest income (trading, investment banking and higher brokerage fees and commissions) to total revenues (see Gambacorta and Marques-Ibanez, 2011; Cantú et al., 2020, Cappelletti et al., 2022).

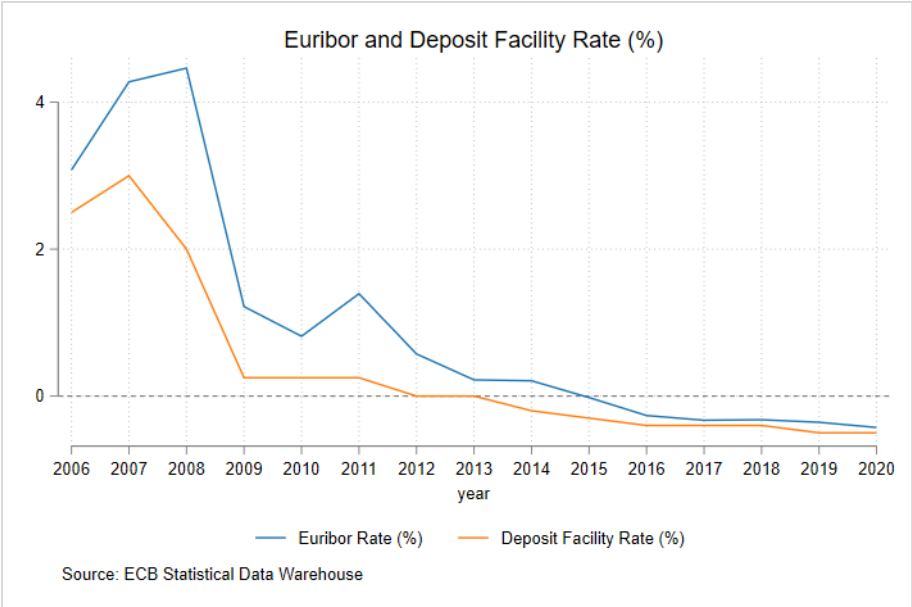
Country-specific controls

Interest Rate. The interest rate environment is a key factor for banks when making a lending decision. A decrease in the interest rate improves the ability of banks to support credit via the so-called *bank lending channel* (see Bernanke and Gertler, 1995). A lower (positive) policy rate reduces (increases) bank funding costs, and thereby supports banks' capacity to generate profits (i.e., stemming from the maturity mismatch between short-term volatile deposits and long-term stable loans' interest rates fixation periods) and increases bank net worth, ultimately affecting their capacity to supply credit to the real economy. Nevertheless, as aforementioned, one needs to consider the unprecedented developments in the monetary policy stance of the European Central Bank that happened during the last decade. Looking at the DFR and the Euro Interbank Offered (Euribor) rate, we observe their first significant drop in correspondence to the collapse of Lehman Brothers (2008Q3) (see Figure

17).[99] After two years of moderate fluctuations, we notice another progressive decrease in the rates in correspondence with the European Sovereign Debt Crisis. Since June and November 2014, the DFR and the Euribor have been in the negative territory, respectively, following the decision of the ECB to lower – first the first time in history - the DFR to -0.10% in June 2014.

The introduction of negative monetary policy rates might have hampered the transmission of monetary policy via the standard *bank lending channel* as negative rates could affect the cost of deposit funding. For instance, Heider et al., (2018) argue that “negative policy rates do not transmit to lower deposit rates because banks appear reluctant to charge negative rates to their depositors. […] (pp, 14-15)”. As a consequence, negative rates might have resulted in a negative shock to banks’ net worth and their lending capacity. In light of this discussion, we could expect either a positive or negative link between lending growth and the interest rate environment. As a proxy for the monetary policy stance, we can employ the Euribor rate, the DFR (Heider et al., 2019; Altavilla et al., 2021) and the change in the Euribor (similar to Ben Naucer et al., 2018).

Figure 17. Evolution of Euribor and DFR (2006-2020)



[99] The DFR is the rate at which banks make overnight deposits with the Eurosystem, while the Euribor represents the average interest rate at which banks in the Eurozone lend unsecured funds to other banks in the euro wholesale money market.

Demand Factors. Bank lending dynamics are often jointly determined by supply and demand factors. In other words, a decrease in loan growth may be the result of a lack of demand from borrowers rather than banks' unwillingness to supply credit. To control for this possibility, we include in our model three macroeconomic variables, namely GDP growth (e.g., Bridges et al., 2014; Cubillas and Suárez, 2018), unemployment (e.g., Horváth et al., 2014; Altavilla et al., 2019) and inflation rate (e.g., Cappelletti et al., 2022), which aim at capturing the economic environment that can drive the demand for credit.

Institutional Environment. A lengthy and inefficient judicial system can play a key role in banks' lending decisions. Banks operating in countries where the judicial system is inefficient might show lower growth rates as banks may fear that they would struggle to recover their investments in case of a borrower default. Indirectly, the institutional environment may also negatively affect lending via higher NPLs that traditionally are present in those countries with higher judicial inefficiency (Garrido et al., 2016; Cerulli et al., 2020). To capture this aspect, we include in our regression two indices from the World Bank Doing Business Surveys, namely the resolving insolvency score and the enforcing contracts score. The resolving insolvency index captures the recovery rate of insolvency proceedings involving domestic entities, as well as the strength of the legal framework applicable to judicial liquidation and reorganization proceedings. The enforcing contract score captures the time and cost of resolving a commercial dispute through a local first-instance court, as well as the quality of judicial processes that promotes quality and efficiency in the court system.

The summary statistics and the definition and sources of the variables used in the model uncertainty framework and reviewed in this section are presented in Table 32 and Table 33, respectively.

Table 32. Summary Statistics

	Obs	Mean	Median	Min	Max
$\Delta Loans$	987	0.024	0.014	-0.308	0.51
$Tier1$	987	0.142	0.135	0.055	0.388
$Size$	987	25.272	25.2	21.432	28.33
$Diversification$	987	0.355	0.358	-0.444	0.891
NPL_GL	987	0.076	0.043	0.003	0.461
NPL_TA	987	0.05	0.023	0.001	0.384
LLR_GL	987	0.042	0.026	0.001	0.254
LLR_TA	987	0.027	0.014	0.001	0.197
LLP_GL	987	0.009	0.005	-0.007	0.078
LLP_TA	987	0.006	0.003	-0.004	0.064
ROA	987	0.001	0.003	-0.068	0.024
$ROAA$	987	0.001	0.003	-0.062	0.025
ROE	987	0.02	0.058	-0.905	0.306
$ROAE$	987	0.019	0.058	-1.024	0.294
NIM	987	0.016	0.015	0.002	0.037
$NIMEA$	987	0.016	0.015	0.002	0.036
$Liquidity$	987	0.184	0.159	0.02	0.72
$Securities\_assets$	987	0.184	0.176	0.014	0.48
$Deposits\_Liabilities$	987	0.485	0.487	0.039	0.87
$Deposits\_TotFunding$	987	0.6	0.614	0.048	0.982
$STFunding\_TotFunding$	987	0.22	0.196	0.001	0.814
$WholesaleFund\_TotFunding$	987	0.224	0.213	0.002	0.749
$Cost-to-Income$	987	0.651	0.63	0.235	10.618
$OpExp\_assets$	987	0.02	0.018	0.002	0.079
$Euribor$	987	0.006	0.002	-0.004	0.045
DFR	987	0.085	-0.2	-0.5	3
$Euribor\_chg$	987	-0.261	-0.07	-3.245	1.199
$GDP\ Growth$	987	0.006	0.013	-0.148	0.252
$Inflation$	987	0.014	0.012	-0.045	0.154
$Unemployment$	987	0.095	0.08	0.031	0.275
$Resolving\ Insolvency$	987	0.736	0.77	0.366	0.939
$Enforcing\ Contracts$	987	0.661	0.704	0.38	0.86

Table 33. Variable Definitions and Data Sources

	Variable Name	Database Definition	Source
	$\Delta Loans$	Net Loan Growth measured as Year-on-Year growth rate	Fitch Connect
	$Tier1$	Tier 1 Capital Ratio calculated as Tier 1 over risk-weighted assets:	Fitch Connect
	$Size$	Logarithmic value of total assets	Fitch Connect
	$Diversification$	Non-interest income divided by total operating income	Fitch Connect
Asset Quality	NPL_GL	The ratio of nonperforming loans to total gross loans	Fitch Connect
	NPL_TA	The ratio of nonperforming loans to total assets	Fitch Connect
	LLR_GL	The ratio of loan loss reserves loans to total gross loans	Fitch Connect
	LLR_TA	The ratio of loan loss reserves loans to total assets	Fitch Connect
	LLP_GL	The ratio of loan loss provisions loans to total gross loans	Fitch Connect
	LLP_TA	The ratio of loan loss provisions loans to total assets	Fitch Connect
Profitability	ROA	Return on assets calculated as net income divided by total assets	Fitch Connect
	$ROAA$	Return on assets calculated as net income divided by average total assets	Fitch Connect
	ROE	Return on equity calculated as net income divided by total equity	Fitch Connect
	$ROAE$	Return on equity calculated as net income divided by average total equity	Fitch Connect
	NIM	Net interest margin calculated as net interest income divided by average earning assets	Fitch Connect
	$NIMEA$	Net interest margin calculated as net interest income divided total earning assets	Fitch Connect
Liquidity	$Liquidity$	The ratio of liquid assets (cash and near cash items, interbank assets and securities) to total assets	Fitch Connect
	$Securities\_assets$	The ratio of securities to total assets	Fitch Connect
Funding	$Deposits\_Assets$	The ratio of customer deposits over total assets	Fitch Connect
	$Deposits\_Liabilities$	The ratio of customer deposits over total liabilities	Fitch Connect
	$Deposits\_TotFunding$	The ratio of customer deposits over total funding sources	Fitch Connect
	$STFunding\_TotFunding$	The ratio of short-term funding over total funding sources	Fitch Connect
	$WholesaleFund\_TotFunding$	The ratio of wholesale funding over total funding sources	Fitch Connect
Cost Structure	$Cost-to-Income$	The ratio of operating expenses over total revenues	Fitch Connect
	$OpExp\_assets$	The ratio of operating expenses over total assets	Fitch Connect
Interest Rate	$Euribor$	3-months Euribor rate	Statistical data Warehouse
	DFR	Deposit Facility Rate. The rate on the deposit facility, which banks may use to make overnight deposits with the Eurosystem	Statistical data Warehouse
	$Euribor\_chg$	Year-on-Year change in 3-months Euribor rate	Calculation
Demand Factor	$GDP\ Growth$	Year-on-Year change in gross domestic product	Word Bank
	$Inflation$	Inflation rate	Word Bank
	$Unemployment$	Unemployment Rate	Word Bank

Institutional Environment	*Resolving Insolvency*	The resolving insolvency index captures the recovery rate of insolvency proceedings involving domestic entities, as well as the strength of the legal framework applicable to judicial liquidation and reorganization proceedings	Word Bank
	Enforcing Contracts	The enforcing contract score captures the time and cost for resolving a commercial dispute through a local first-instance court, as well as the quality of judicial processes that promotes quality and efficiency in the court system	Word Bank

3.5 Results

In this section, we first present and briefly discuss the finding from running the baseline model specification presented in Eq. (3.7). After this, we show how these results compare to the larger set of findings coming from employing the model uncertainty framework. Lastly, we show how statistically significant results can often be the outcome of "knife-edge" specifications, and as such, they do not represent real relationships in the data but are simply the outcome of the modelling choices of the researcher.

3.5.1 Determinants of bank lending – baseline specification

To show how empirical results are often model-dependent and *not* data-driven, we begin by reporting the results of the estimation of a baseline model (Eq. 3.7) in Table 34.[100] In this model specification, we include a set of bank-specific variables taken from the aforementioned dimensions found in the literature and reported in Table 33 above, specifically: size, non-performing loans over gross loans, return on assets, liquid assets, diversification, deposit ratio and cost-to-income ratio. The first column of Table 34 shows the results from the FE estimator when only bank-specific controls are included while in the second column, we control for additional forms of unobserved heterogeneity that might affect bank credit supply via the inclusion of *time fixed-effects*, which control for any variation due to macroeconomic developments in any given period. In columns 3 and 4, we saturate the model with additional factors that capture the macroeconomic environment (demand factors, i.e., GDP growth, unemployment, inflation), the institutional environment (the resolving insolvency score, the enforcing contract score) and the monetary policy stance (Euribor). Column 4 includes time-fixed effects.

Focusing on our variable of primary interest, $Tier$ 1 capital is found to be negative and statistically *insignificant* in all our model specifications. Between 2006 and 2020, on average, there is no relationship between the amount of regulatory capital and the credit supply of SSM banks.[101] Concerning the other bank-specific drivers of lending, in line with our expectations, we find a negative and significant

[100] For completeness, we also estimated a dynamic model (results reported in Appendix C, Table C1). We noticed that the lagged dependent variable is insignificant, thus providing support for the use of a static model.
[101] Not surprisingly, it is not possible to make reference to the literature, because, as mentioned before, only papers that report statistically significant result tend to be published.

relationship between asset quality and credit growth. The deterioration of the loan portfolios that occurred in many financial systems across Europe could have weakened banks' capital positions, likely affecting their willingness to provide credit (as also reported by Horváth et al., 2014; Kim and Sohn, 2017). Furthermore, a high stock of $NPLs$ might have impacted banks' funding costs via the higher risk premia demanded by investors, further depressing bank lending to the economy. These results are consistent with findings from the previous literature (Berrospide and Edge, 2010; Kim and Sohn, 2017; Ben Naucer et al., 2018; Cappelletti et al., 2022). Concerning bank profitability, ROA and credit supply are found to share a positive and significant relationship, potentially reflecting the capacity of banks to use internally generated funds to strengthen their capital position and increase lending. Larger banks ($Size$) are also observed to have lower growth rate of lending. This interesting finding seems to suggest that larger banks have adopted an investment strategy focused on securities. As aforementioned, this may be the outcome of one of the features of the Basel regulation, whereby, loans, especially towards NFCs and SMEs are very costly in terms of risks weights and thus capital requirements. However, given the ultra-low interest rate environment, it could also denote a more general tendency of large banks to "search-for-yield" by investing in high-return stocks rather than extending risky loans.

Our findings provide mixed evidence of the relationship between liquidity and lending as the coefficient ($Liquidity$) loses statistical significance when both macroeconomic conditions and time-fixed effects are accounted for. Surprisingly, we do not find evidence that the funding structure ($Deposits$) of listed European banks affects their ability to lend, but the findings are in line with Ben Naucer et al., (2018) and Degryse et al. (2019). Likewise, $Diversification$ and $Cost-to-income$ are found insignificant in the majority of the models.

Focusing on the set of macroeconomic indicators, GDP growth suggests a pro-cyclical behaviour of banks, whereby they expand credit during the upswing of the business cycle and reduce it during recessions. This result is in line with Heryán and Tzeremes (2017), Kim and Sohn (2017), and Roulet (2018). Inflation is found to be negative and strongly significant, whereas, surprisingly, the level of unemployment does not affect lending – in contrast with, for instance, Horváth et al. (2014) and Ghosh (2015). In line with our expectation, we find that the interest rate environment (Euribor) is positively linked to credit supply. It is worth noticing that Euribor is present only in column 3 since this variable is absorbed by the time fixed effects in column 4. Finally, on average, the institutional environment in which banks operate does not have explanatory power.

Overall, this first set of results does not provide evidence of a statistically significant relationship between capital and lending behaviour of euro area banks between 2006 and 2020. However, these conclusions are based on a very limited set of regressions where specific modelling choices have been made. Would the result change if some of our choices would have been different? For instance, another researcher may not think that the cost structure is an important driver of lending, and she/he would have not included it in the model. In that case, would the coefficient of $Tier$ 1 still be insignificant? Additionally, another researcher may believe that asset quality is better captured via loan loss provisions. Would we have reached the same outcome? In other words, how many model assumptions can be relaxed without overturning the conclusion from that estimate? And which model assumptions are most critical to the results? All these questions can be answered using a model uncertainty framework.

Table 34. Determinants of Bank Lending

	(1)	(2)	(3)	(4)
	$\Delta Loans$	$\Delta Loans$	$\Delta Loans$	$\Delta Loans$
$\boldsymbol{Tier\ 1\ Ratio}$	**-0.1775**	**-0.0498**	**-0.1947**	**-0.0500**
	(0.1252)	**(0.1656)**	**(0.1432)**	**(0.1846)**
$Size$	-0.1144^{***}	-0.0782^{***}	-0.1077^{***}	-0.0859^{***}
	(0.0324)	(0.0261)	(0.0309)	(0.0276)
ROA	1.8424^{***}	1.1233^{***}	0.8975^{***}	0.8859^{***}
	(0.3583)	(0.3105)	(0.3232)	(0.3187)
NPL	-0.4037^{***}	-0.3806^{***}	-0.5631^{***}	-0.5070^{***}
	(0.0731)	(0.0767)	(0.0975)	(0.0938)
$Liquid\ Assets$	0.2342^{***}	0.1206^{*}	0.1695^{**}	0.0876
	(0.0732)	(0.0664)	(0.0690)	(0.0685)
$Deposit\ Ratio$	-0.0683	-0.0870	-0.1158^{*}	-0.1237^{*}
	(0.0609)	(0.0755)	(0.0586)	(0.0720)
$Diversification$	0.0270	-0.0249	0.0074	-0.0281
	(0.0399)	(0.0316)	(0.0356)	(0.0304)
$Cost-to-income$	-0.0221	-0.0309	-0.0345	-0.0440^{*}
	(0.0268)	(0.0238)	(0.0244)	(0.0234)
$GDP\ Growth$			0.6203^{***}	0.3605^{**}
			(0.1330)	(0.1528)
$Inflation$			-1.9949^{***}	-1.4356^{***}
			(0.2970)	(0.3722)
$Unemployment$			-0.0799	0.1271
			(0.2075)	(0.2532)
$Euribor$			0.8295^{**}	
			(0.3477)	
$Resolving\ Insolvency$			0.1466^{*}	0.0603
			(0.0791)	(0.0834)
$Enforcing\ Contracts$			0.0564	0.0901
			(0.0696)	(0.0650)
Adj R-square	0.1796	0.2795	0.2401	0.2964
Obs	987	987	987	987
Bank FE	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes
No of firms	90	90	90	90

Note: The table displays the estimates of the coefficients of Eq. (3.7). The dependent variable is the year-on-year growth rate of net loans during the period 2006-2020. All the explanatory variables are lagged by one year. The standard errors are clustered at the bank level and are reported in parentheses. "YES" indicates that the set of fixed effects is included. ***, **, and * denote that estimates are statistically significant at the 1%, 5% and 10% levels.

3.5.2 Model uncertainty results

After presenting the results of the baseline specifications, we now adopt the model uncertainty framework and present the results of the sensitivity analyses. In the first step, we relax the assumptions about possible control variables. In our study, we are interested in estimating the effect of capital (our variable of interest) in a setting with a large number of potential control variables (*n*). In this context, there are up to 2^n possible combinations of control variables that the researcher could run. *P-hacking* may occur if the research selectively reports only the regressions where the variable of interest is statistically significant. In the second step, we assess the robustness of our findings with the use of alternative definitions of the control variables.

As a first robustness analysis, we start by considering the set of controls used in Column 4 of Table 34 and we assess the sensitivity of the coefficient of $Tier$ 1 ratio to the inclusion/exclusion of these control variables. In this setting with 14 control variables, there are 16384 possible combinations of these variables.[102] In this model space, we show in Table 35 below, that the average estimate of $Tier$ 1 ratio across all the models is -0.0945. The average sampling standard error (SE) is 0.1693, whereas the modelling standard error is 0.1683. These statistics indicate that i) the mean estimate is statistically insignificant (i.e., 0.1693 /0.1683=1.006, analogous to a *t-statistics*) and ii) uncertainty about the estimates derives more from the sample of data rather than from the model.[103] Finally, the combined total standard error is 0.2387, leading to a *robustness ratio* of -0.3958 (i.e., -0. 0945/0.2387=-0.3958).[104] The value of the robustness ratio provides evidence of the weak robustness of the results. Following Young and Holsteen (2017), a variable is considered to have a robust statistical relationship with the dependent variable if the *robustness ratio* is above the critical value of 2 (analogous to the *t-statistics*).

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[102] The 14 variables include: $Size, ROA, NPL\_GL, Liquid\_Assets, Deposits\_Assets$, $Diversification$, $Cost-to-income, GDP\_Growth, Unemployment$, $Inflation, Euribor$, $Resolving\_Insolvency, Enforcing\_Contracts$, and time-fixed effects (2^{14}=16384). Note that Euribor, which is the only variable not country-specific, will be absorbed by the time-fixed effects in those model combinations where the two variables enter together in the regression.

[103] The sampling SE indicates how much an estimate is expected to change if we draw a new sample while the modelling SE refers to how much the estimate is expected to change if we draw a new randomly selected model.

[104] The total standard error is the square root of the sum of the squares the sampling and modelling standard errors, so that $\sqrt{0.1793^2 + 0.1683^2} = 0.2387$.

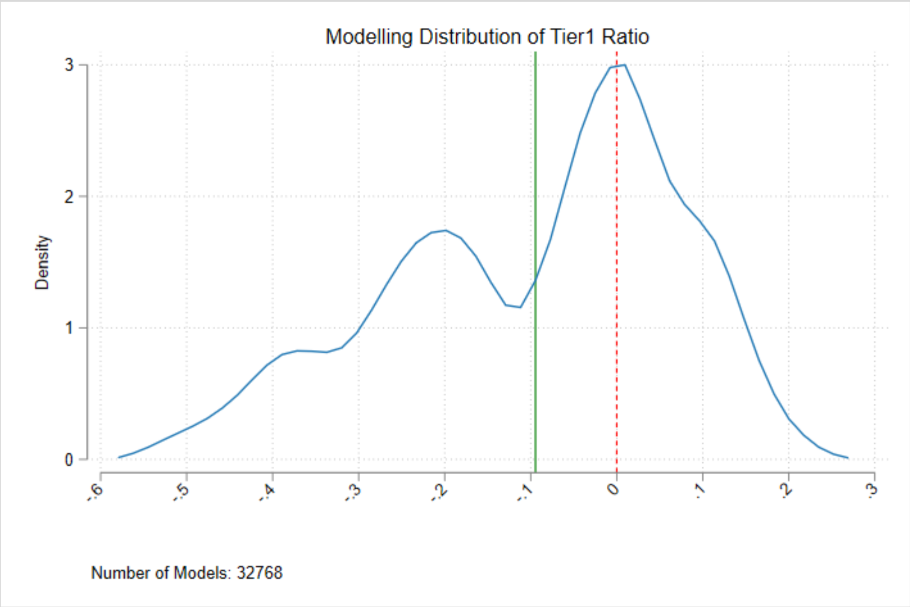
Zooming into the values and significance rate of $Tier\ 1$, we first observe that across all the possible combinations, the coefficient is found to be negative 65% of the time and positive 35% of the time. In those models where the coefficient is negative, we observe that 25% of the models report a statistically significant coefficient of $Tier\ 1$ (at least at the 10% level). As before, we follow Young and Holsteen (2017) and adopt the 50% significance rate as the lower bound for "weak" robustness (i.e., only 50% of plausible models have significant results) whereas a 95% or higher significance rate suggests "strong" robustness of our estimates. The ratio of significant coefficients over the entire model spaces decreases to 19% and 12% when looking at the 5% and 1% significance levels (results not reported).

Table 35. Model Robustness of the effect of Tier 1 ratio on Lending

Fixed-effects (within) regression			
Variable of Interest:	$\boldsymbol{Tier1\ Ratio}$		
Outcome Variable:	$\Delta Loans$	Number of Observations	9787
Possible Control Terms:	14	Mean R^2	0.11
Number of Models	16384	Multicollinearity	0.44
Model robustness Statistics:		**Significance Testing**	
Mean(b)	-0.0945	Sign Stability	65%
Sampling SE	0.1693	Significance Rate	25%
Modelling SE	0.1683		
Total SE	0.2387	Positive	35%
		Positive and Sign	0%
Robustness Ratio	-0.3958	Negative	65%
		Negative and Sig	25%

The distribution of the coefficient of our variable of interest across the 16384 models is displayed in Figure 18. The vertical solid line represents the mean estimates (-0.0945) while the dotted line marks zero. The modelling distribution appears to be multimodal with clusters of estimates around -0.4, -0.2, and zero. It seems hard to draw conclusions from this evidence without knowing more about the modelling distribution. Figure 18 leaves us with many more questions: why do these estimates vary so much? Why is the distribution so non-normal? What combinations of control variables are critical to finding a negative and significant result? These questions lead us to the next stage in our analysis: understanding model influence.

Figure 18. Modelling Distribution of the coefficient of Tier 1 Ratio



Note: the solid vertical line represents the mean value of the coefficient of Tier 1 Ratio across the entire model space (-0.0945)

<u>*Model Influence*</u>

Model influence analysis shows which control variables are critical to the results, by focusing on how the introduction of a control variable changes the coefficient of the variable of interest. The results from the *model influence analysis* are reported in Table 36. Column 1 reports the marginal effect of including each control variable in the models. That is, it shows the expected change in the coefficient of interest ($Tier\ 1$) if that specific control variable is included. In addition, column 2 shows the percentage change in the coefficient of $Tier\ 1$ associated with including each control variable.

From our analysis, it emerges that the most influential control is $time\ fixed\ effect$, followed by ROA and $Euribor$, as their inclusion leads to an average change of the mean coefficient greater than 50%. All else being equal, including $time\ fixed\ effect$ reduces, on average, the coefficient of $Tier\ 1$ by 274%. This is not surprising. Looking at the results from the baseline specification (Table 34), the coefficient of $Tier\ 1$ is -0.17 in column 3 and it becomes significantly smaller (-0.05) in column 4 when time-fixed effects are included. Similarly, we find that the introduction in the model space of ROA and $Euribor$ causes, on average, the mean coefficient of *Tier 1* to more than double and to be reduced by 95%, respectively. One explanation for the strong influence of time fixed effects is that they capture factors affecting equally all banks at the same time in each year of our sample and that are not captured by the other control variables included in our model. This set of fixed effects can significantly reduce omitted variable bias caused by excluding unobserved variables that evolve over time but are constant across banks.[105]

One final observation concerning the results of Table 36 highlights the critical difference between the significance of a control variable and its model influence. The variables most significant in the main regression are $Size, ROA, NPL\_GL$ and $Inflation$ (see Table 34). While ROA has a very high influence on the coefficient of $Tier$ 1, $Size$ and $Inflation$ have a considerable minor model influence (less than 50%). More strikingly, despite being always significant at 1% in Table 34, NPL_GL have very little model influence and has almost no real bearing on the conclusions about $Tier$ 1 ratio. NPL_GL has a lower model influence than $cost - to - income$ and $liquid\ assets$, which in Table 34 do not appear among the main drivers of lending growth of euro area banks. As pointed out by Young and Holsteen (2017), these findings call attention to the fact that:

> "Influential variables may be nonsignificant, and significant variables may well be noninfluential. Insight into which control variables are critical to the analysis is not visible in a conventional regression table. This is a transparent flaw in conventional regression tables that can be readily corrected with multimodel influence analysis (p. 23)".

[105] The problem of omitted variable bias arises when relevant control variables are omitted from the regression and it causes the coefficients to be bias.

Table 36. Model Influence Results for the effect of Tier 1 on Lending

	(1)	(2)
	Marginal Effect of Variable Inclusion	Percent Change From Mean(b)
Time Fixed Effects	0.2597	-274.9%
ROA	-0.1077	114%
Euribor	0.0899	-95.2%
GDP Growth	-0.0435	46%
Inflation	-0.0377	39.9%
Size	-0.0338	35.8%
Cost-to-Income	0.0244	-25.8%
Liquid_assets	-0.0194	20.5%
Unemployment	-0.0170	18%
Deposits_assets	0.0078	-8.3%
Resolving_Insolvency	-0.0059	6.2%
NPL_GL	0.0058	-6.2%
Enforcing_Contracts	0.0037	-4%
Diversification	-0.0002	0.2%
Constant	-0.1577	
R-Squared	0.8214	

3.5.3 Functional form robustness analysis

Alternative Operational Definition of Control Variables

In the previous section on model robustness analysis, we showed how the coefficient of $Tier\ 1$ ratio is sensitive to the combination of control variables included. However, one could argue that across the 16384, there are several models that researchers may not consider *"theoretically informed"* as the exclusion of key variables leads to a problem of *"omitted variable bias"*. Thus, we continue our study by showing how model robustness might also depend on different functional forms such as different estimation commands and variable constructions (Young and Holsteen, 2017). In light of this, we further explore the sensitivity of our findings by examining the stability of $Tier\ 1$ estimates across multiple plausible operational definitions of the control variables we have previously adopted (see Table 33). The rationale for this is that, by increasing exponentially the model space, the presence of such a wide array of possible control variables increases the uncertainty regarding the robustness of our initial findings.

We start our analysis by focusing on the models estimated in Columns 3 and 4 of Table 4. In these specifications, model uncertainty comes from the presence of multiple operational definitions of the bank-specific controls, monetary policy stance, and the inclusion/exclusion of time fixed effects. Table 33 above shows the different proxies used to test model robustness across different functional forms.

First, it is worth mentioning that we did not find a suitable alternative variable to proxy for bank $Size$, and, as such, banks' dimension is always proxied by the natural logarithm of Total Assets. Likewise, $Diversification$ does not have any alternative operational definition. Demand factors are always accounted for via the inclusion of GDP Growth, Unemployment and Inflation. By contrast, the remaining explanatory variables are controlled for using different definitions. For example, we find six different proxies that can be theoretically used to control for the asset quality of banks (see Table 33 above).

The results from the functional form robustness analysis are presented in Table 37 and graphically displayed in Figure 19. The model space is constituted of 4320 models. In contrast with the previous analysis (see Table 35) where the model space was constituted by all the possible combinations of control variables, all the 4320 models resemble Columns 3 and 4 of Table 34. That is, this functional form robustness analysis tests the stability of results across the alternative measurements (e.g., ROA or ROE) and *not* across the combination of controls. In other words, the 4320 models estimated for this analysis include *always* 14 controls, which alternatively assume the different definitions and where models that include both versions of the control variable (e.g., ROA or ROE) are excluded. The only control that is allowed to be included or excluded all together is time fixed effects. This approach ensures that all the 4320 regressions come from plausible and *"theoretically informed"* model specifications.

This set of results is particularly interesting (see Table 37). We start by examining the sign stability (the percentage of estimates that have the same sign) of our variable of main interest. In this model space, 98% of the estimates of Tier 1 are negative, which is a significantly higher rate than the previously observed 67% in Table 35. Moving to the significance rate (the percentage of models that report a statistically significant coefficient), Table 37 shows that 27% of the models are statistically significant at least at the 10% level (the rate decrease to 23% and 14% when considering the 5% and the 1% significance level, results not reported). Overall, these findings confirm again the presence of a weak relationship between the level of $Tier\,1$ capital of European banks and their lending growth as the robustness ratio is significantly below the threshold of 2 and the significance rate is below 50%. As previously observed, the sampling standard error is greater than the model standard error, suggesting that uncertainty stems from the sample data rather than from the models.

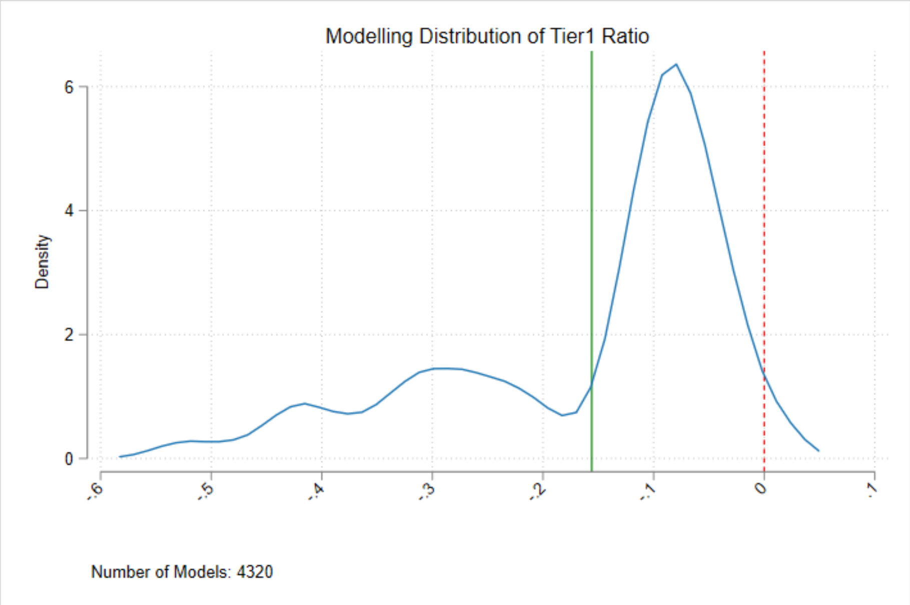
At this point, it is important to remember that all 4320 models are *“theoretically informed”* specifications that replicate Columns 3 and 4 of Table 34. There are approximately 1166 (27% of 4320) models in which $Tier\ 1$ enters the regression negative and statistically significant. This number is exponentially larger than any set of robustness analyses that will be ever reported in any published papers. However, it represents only one-quarter of the *“theoretically informed”* models. In the remaining models, $Tier\ 1$ tends to be negative and insignificant, with 86 plausible models (2% of 4320) reporting a positive (albeit insignificant) coefficient of the relationship between Tier 1 and net loan growth.

As concerns the modelling distribution of $Tier\ 1$, Figure 19 shows that the estimates are concentrated around -0.1, despite overall being characterised by a great dispersion, ranging from -0.5614 to 0.0279. Our last observation concerns the model influence analysis (see Table 38). As aforementioned, for this exercise, the only control variable that is allowed to be alternatively included/excluded is time-fixed effects. As observed before, this control has a very strong model influence, changing the coefficient of $Tier\ 1$ by almost 105% with its inclusion (see Table 38).

Table 37. Functional Form Model Robustness

Fixed-effects (within) regression			
Variable of Interest:	$\boldsymbol{Tier\ 1\ Ratio_{(t-1)}}$		
Outcome Variable:	$\Delta Loans$	Number of Observations	987
Possible Control Terms:	1	Mean R^2	0.09
Number of Models	4320	Multicollinearity	0.58
Model robustness Statistics:		**Significance Testing**	
Mean(b)	-0.1559	Sign Stability	98%
Sampling SE	0.1574	Significance Rate	27%
Modelling SE	0.1297		
Total SE	0.2040	Positive	2%
		Positive and Sign	0%
Robustness Ratio	-0.7646	Negative	98%
		Negative and Sig	27%

Figure 19. Modelling Distribution of Tier 1 Ratio (Functional Form Robustness)



Note: the solid vertical line represents the mean value of the coefficient of Tier 1 ratio across the entire model space (-0.1559)

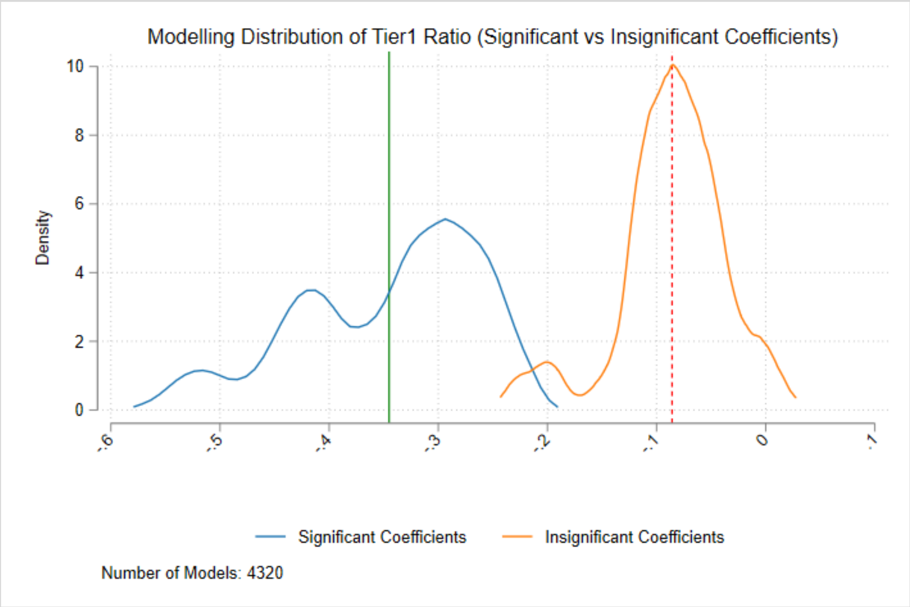
Table 38. Model Influence (Functional Form Robustness)

	(1)	(2)
	Marginal Effect of Variable Inclusion	Percent Change From Mean(b)
Time Fixed Effects	0.1630	-104.5%
Constant	-0.2347	
$\boldsymbol{R-squared}$	0.3947	

Further Analyses

In this section, we further explore our results to investigate common patterns in the control variables that may drive the result for $Tier\ 1$ reported in Table 37. Plotting the distribution of $Tier\ 1$ according to the significance of the coefficients (Figure 20), we observe that those coefficients concentrated across -0.1 are all statistically insignificant, while the statistically significant coefficients are skewed towards the left, ranging from -0.5614 to -0.2082. Are there specific control variables or a set of control variables that make $Tier\ 1$ become significant (or insignificant)?

Figure 20. Modelling Distribution of Significant vs Insignificant Coefficients of Tier 1 Ratio



When analysing the role played by any specific control variable in driving the significance and the distribution of Tier 1 coefficients, one can think about four possible cases to take into consideration, as displayed in the matrix in Table 39. For instance, it may be that the inclusion of a specific variable is associated with Tier 1 always being significant (case 1), or vice versa, that Tier 1 is statistically significant only when a specific variable is excluded (case 2).

Table 39. Matrix for analysing the role played by control variables.

Case 1	Tier 1 Coefficient Significant & Control Variable Included	**Case 2**	Tier 1 Coefficient Significant & Control Variable Excluded
Case 3	Tier 1 Coefficient Insignificant & Control Variable Included	**Case 4**	Tier 1 Coefficient Insignificant & Control Variable Excluded

Taking into consideration Table 39, we observe that the inclusion of time-fixed effects and DFR results in the coefficient of Tier 1 ratio being always insignificant (see Figure 21 and Figure 22). In both the figures, we are missing the plot referring to case 1 of Table 39, where the control is included and the coefficient of Tier 1 is significant. Nonetheless, when the variables are excluded, Tier 1 is found both significant and insignificant across the model space. None of the other control variables displays such a pattern, always resulting in all four possible cases. From this simple exercise appears clear that often results are the outcome of the modelling choices of the researchers rather than representing real underlying relationships in the data.

Figure 21. When Year fixed effects are included, Tier 1 is always insignificant

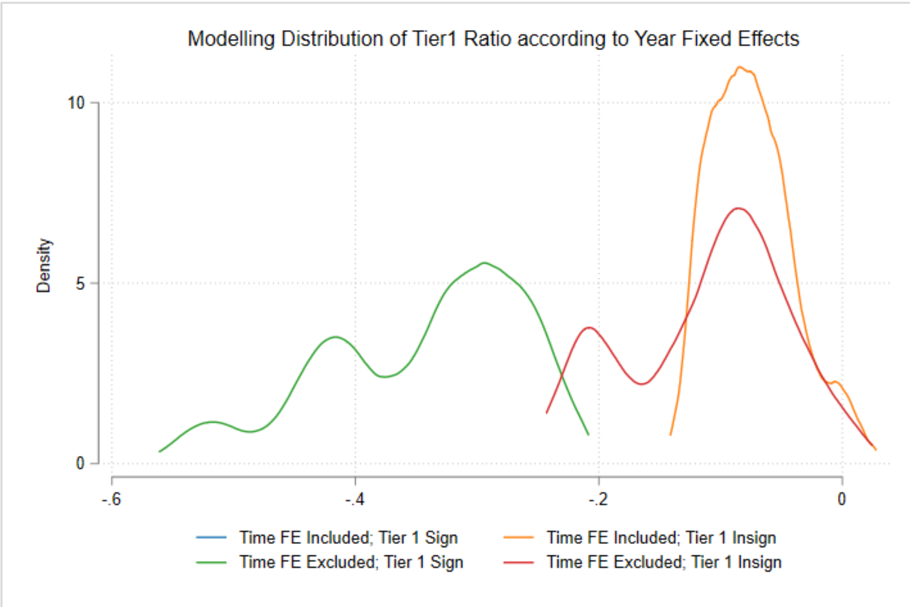
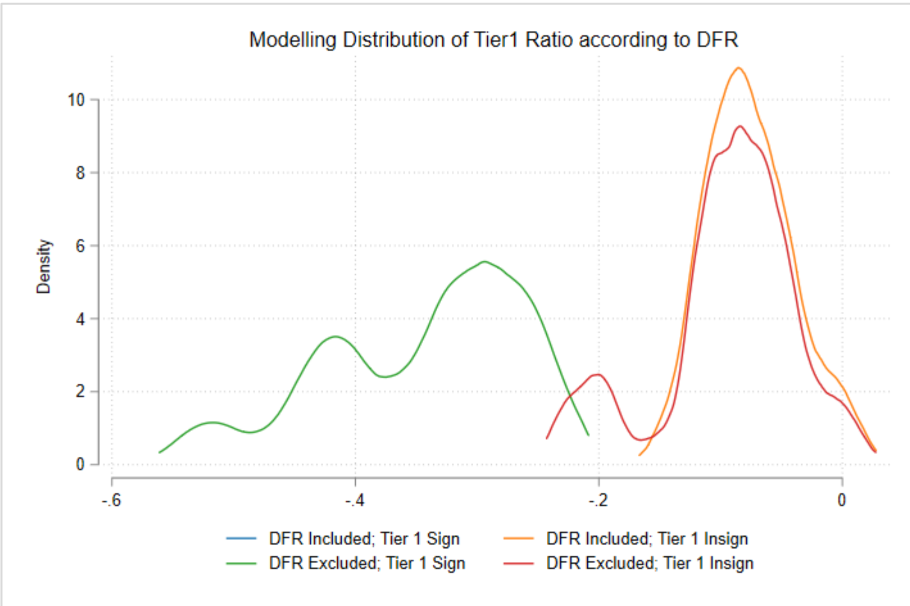


Figure 22. When DFR is included, Tier 1 is always insignificant



We conclude our analysis by showing how small modifications of our baseline models (Table 34) may lead to different conclusions on the relationship between regulatory capital and lending growth. We learnt that across the entire model space, models that include time fixed effects always report an insignificant coefficient of Tier 1. Thus, for this exercise, we ignore columns 2 and 4 of Table 34, while we focus on columns 1 and 3 and explore which variables should be changed to observe a dramatic change in the significance rate of our variable of interest.

We start by relaxing the assumption that NPL_GL is the best proxy for credit quality, while keeping all the remaining controls fixed. In other words, we re-run our baseline specification including, alternatively, LLR_GL, LLR_TA, LLP_GL, and LLP_TA. The result as reported in Table 40. For simplicity, in columns (1) and (2) of Table 40 we report the results from the baseline specification (columns 1 and 3 of Table 34). It is worth noticing that the regressions reported in this table are a small subset of the model space presented above in Table 37. All else being equal to the baseline specification, the use of LLP (columns 7 to 10) as a proxy for credit quality leads to a negative and strong significant coefficient of Tier 1. What if another researcher had started its project with LLP_GL as the main indicator of credit risk and a different proxy for profitability? The results are shown in Table 41. In all these 12 cases, Tier 1 is found to have a significant and negative impact on the credit supply of euro area banks. As before, these 12 models are part of the 4320 regression presented in the MUF of Table 37.

The objective of these further analyses has been to show how very small changes to the model specification lead to different outcomes in the coefficient of Tier 1. Thus, we argue that researchers should not report a limited set of results, but they should offer an overview of the model space and the possible sources of model uncertainty. The models presented in Table 40 and Table 41 can be considered as circumstantial evidence resulting from "knife-edge" model specifications, that is "[models] carefully selected to report statistically significant results, and remarkably unrepresentative of the overall modelling distribution (Young and Holsteen, 2017, p.26). Through the adoption of the model uncertainty framework, researchers are able to address concerns related to p-hacking and/or the presence of "knife-edge" model specifications by i) accounting for potential model selection bias and relaxing some of the assumptions concerning the control variables to include in the specification (Section 3.5.2) and ii) investigating functional form robustness using multiple operational definitions of the same control variable (Section 3.5.3). Ultimately, the model uncertainty framework increases the transparency of the research outputs.

Table 40. Robustness analysis to a change in the proxy for loan quality

	(1) $\Delta Loans$	(2)	(3) $\Delta Loans$	(4) $\Delta Loans$	(5) $\Delta Loans$	(6) $\Delta Loans$	(7) $\Delta Loans$	(8) $\Delta Loans$	(9) $\Delta Loans$	(10) $\Delta Loans$
Tier 1 Ratio	-0.1775	-0.1947	-0.1878	-0.1911	-0.1915	-0.1908	**-0.3166*****	**-0.2751****	**-0.3128*****	**-0.2645****
	(0.1252)	(0.1432)	(0.1219)	(0.1438)	(0.1181)	(0.1332)	**(0.1132)**	**(0.1246)**	**(0.1143)**	**(0.1234)**
NPL_GL	-0.1144***	-0.1077***								
	(0.0324)	(0.0309)								
LLR_GL			-0.7461***	-1.0914***						
			(0.1261)	(0.1613)						
LLR_TA					-1.0801***	-1.5311***				
					(0.1940)	(0.2370)				
LLP_GL							-2.5641***	-2.2498***		
							(0.5781)	(0.6488)		
LLP_TA									-2.8971***	-2.4029***
									(0.7379)	(0.8276)
$Size$	1.8424***	0.8975***	-0.1169***	-0.1110***	-0.1159***	-0.1079***	-0.1115***	-0.0878***	-0.1106***	-0.0857**
	(0.3583)	(0.3232)	(0.0333)	(0.0317)	(0.0337)	(0.0321)	(0.0321)	(0.0311)	(0.0341)	(0.0327)
ROA	-0.4037***	-0.5631***	1.7785***	0.6872**	1.6754***	0.5691*	0.4870	-0.1096	0.7670	0.1588
	(0.0731)	(0.0975)	(0.3744)	(0.3296)	(0.3685)	(0.3421)	(0.5590)	(0.5594)	(0.5640)	(0.5610)
$Liquid\ Assets$	0.2342***	0.1695**	0.2448***	0.1798***	0.2210***	0.1449**	0.2894***	0.1931***	0.2721***	0.1760**
	(0.0732)	(0.0690)	(0.0718)	(0.0642)	(0.0706)	(0.0640)	(0.0767)	(0.0720)	(0.0796)	(0.0740)
$Deposit\ Ratio$	-0.0683	-0.1158*	-0.0640	-0.1052*	-0.0598	-0.0935*	-0.0815	-0.0969	-0.0749	-0.0896
	(0.0609)	(0.0586)	(0.0593)	(0.0567)	(0.0582)	(0.0561)	(0.0609)	(0.0638)	(0.0607)	(0.0634)
$Diversification$	0.0270	0.0074	0.0225	0.0011	0.0233	0.0023	0.0081	-0.0033	0.0092	-0.0021
	(0.0399)	(0.0356)	(0.0421)	(0.0386)	(0.0425)	(0.0392)	(0.0418)	(0.0407)	(0.0424)	(0.0413)
$Cost-to-income$	-0.0221	-0.0345	-0.0305	-0.0482*	-0.0345	-0.0540**	-0.0583*	-0.0615**	-0.0540*	-0.0572*
	(0.0268)	(0.0244)	(0.0272)	(0.0250)	(0.0276)	(0.0257)	(0.0301)	(0.0304)	(0.0296)	(0.0297)
$GDP\ Growth$		0.6203***		0.6622***		0.6671***		0.3576***		0.3820***
		(0.1330)		(0.1274)		(0.1258)		(0.1320)		(0.1332)
$Inflation$		-1.9949***		-2.0226***		-2.0365***		-1.9431***		-1.9104***
		(0.2970)		(0.2904)		(0.2898)		(0.2901)		(0.2883)
$Unemployment$		-0.0799		-0.0527		-0.0381		-0.5433**		-0.5673**
		(0.2075)		(0.2035)		(0.2007)		(0.2195)		(0.2180)
$Euribor$		0.8295**		0.9411***		1.0249***		1.1408***		1.1561***
		(0.3477)		(0.3524)		(0.3419)		(0.3573)		(0.3554)
$Resolving\ Insolvency$		0.1466*		0.1594**		0.1554**		0.1263		0.1263
		(0.0791)		(0.0739)		(0.0766)		(0.0915)		(0.0953)
$Enforcing\ Contracts$		0.0564		0.0565		0.0454		0.0292		0.0264
		(0.0696)		(0.0681)		(0.0694)		(0.0726)		(0.0732)
Adj R-square			0.1785	0.2424	0.1844	0.2494	0.1599	0.2058	0.1550	0.2017
Obs			987	987	987	987	987	987	987	987
Bank FE			Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE			No	No	No	No	No	No	No	No
No of firms			90	90	90	90	90	90	90	90

Robust standard errors in parenetheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 41. Robustness analysis to a change in the asset quality proxy and profitability

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	$\Delta Loans$	$\Delta Loans$	$\Delta Loans$	$\Delta Loans$	$\Delta Loans$	$\Delta Loans$	$\Delta Loans$	$\Delta Loans$	$\Delta Loans$	$\Delta Loans$	$\Delta Loans$	$\Delta Loans$
Tier 1 Ratio	**-0.3166*****	**-0.2751****	**-0.3117*****	**-0.2906****	**-0.3167*****	**-0.2806****	**-0.3120*****	**-0.2817****	**-0.3008*****	**-0.2779****	**-0.3109*****	**-0.2731****
	(0.1132)	**(0.1246)**	**(0.1111)**	**(0.1210)**	**(0.1127)**	**(0.1244)**	**(0.1122)**	**(0.1230)**	**(0.1122)**	**(0.1262)**	**(0.1130)**	**(0.1246)**
LLP_GL	-2.5641***	-2.2498***	-1.9085***	-1.3309***	-2.0958***	-1.8940***	-2.2103***	-1.7908***	-2.8407***	-2.1624***	-2.9631***	-2.1493***
	(0.5781)	(0.6488)	(0.4552)	(0.4869)	(0.6142)	(0.6763)	(0.6070)	(0.6671)	(0.3838)	(0.3978)	(0.3672)	(0.4107)
ROA	0.4870	-0.1096										
	(0.5590)	(0.5594)										
ROE			0.1024***	0.0875***								
			(0.0282)	(0.0292)								
$ROAA$					1.1138*	0.3735						
					(0.6393)	(0.6373)						
$ROAE$							0.0662	0.0357				
							(0.0435)	(0.0452)				
NIM									2.0929	2.2357		
									(2.0078)	(1.9817)		
$NIMEA$											-1.0692	-0.6104
											(1.9818)	(1.9376)
$Size$	-0.1115***	-0.0878***	-0.1059***	-0.0843***	-0.1101***	-0.0875***	-0.1082***	-0.0865***	-0.1067***	-0.0852***	-0.1157***	-0.0891***
	(0.0321)	(0.0311)	(0.0320)	(0.0314)	(0.0324)	(0.0314)	(0.0321)	(0.0314)	(0.0316)	(0.0311)	(0.0327)	(0.0319)
$Liquid\ Assets$	0.2894***	0.1931***	0.2980***	0.2021***	0.2842***	0.1906***	0.2960***	0.1967***	0.2942***	0.1998***	0.2935***	0.1911***
	(0.0767)	(0.0720)	(0.0768)	(0.0723)	(0.0766)	(0.0723)	(0.0768)	(0.0717)	(0.0781)	(0.0746)	(0.0765)	(0.0723)
$Deposit\ Ratio$	-0.0815	-0.0969	-0.0744	-0.0964	-0.0804	-0.0976	-0.0751	-0.0952	-0.0930	-0.1137*	-0.0754	-0.0926
	(0.0609)	(0.0638)	(0.0587)	(0.0618)	(0.0606)	(0.0636)	(0.0605)	(0.0637)	(0.0610)	(0.0660)	(0.0602)	(0.0633)
$Diversification$	0.0081	-0.0033	0.0080	-0.0021	0.0097	-0.0018	0.0064	-0.0031	0.0329	0.0238	-0.0067	-0.0101
	(0.0418)	(0.0407)	(0.0401)	(0.0389)	(0.0419)	(0.0407)	(0.0406)	(0.0397)	(0.0526)	(0.0496)	(0.0489)	(0.0466)
$Cost-to-income$	-0.0583*	-0.0615**	-0.0425	-0.0405	-0.0493	-0.0545*	-0.0516*	-0.0526*	-0.0433	-0.0378	-0.0762**	-0.0658*
	(0.0301)	(0.0304)	(0.0314)	(0.0313)	(0.0311)	(0.0311)	(0.0304)	(0.0302)	(0.0379)	(0.0357)	(0.0360)	(0.0341)
$GDP\ Growth$		0.3576***		0.3344**		0.3483***		0.3460**		0.3348**		0.3581***
		(0.1320)		(0.1336)		(0.1315)		(0.1323)		(0.1304)		(0.1312)
$Inflation$		-1.9431***		-1.9033***		-1.9220***		-1.9067***		-1.9782***		-1.9222***
		(0.2901)		(0.2830)		(0.2881)		(0.2847)		(0.2952)		(0.2963)
$Unemployment$		-0.5433**		-0.5373**		-0.5402**		-0.5349**		-0.4940**		-0.5521**
		(0.2195)		(0.2178)		(0.2179)		(0.2180)		(0.2017)		(0.2148)
$Euribor$		1.1408***		1.0293***		1.1072***		1.0884***		1.1054***		1.1334***
		(0.3573)		(0.3557)		(0.3562)		(0.3546)		(0.3621)		(0.3589)
$Resolving\ Insolvency$		0.1263		0.1291		0.1247		0.1269		0.1424		0.1228
		(0.0915)		(0.0940)		(0.0927)		(0.0932)		(0.0910)		(0.0919)
$Enforcing\ Contracts$		0.0292		0.0352		0.0302		0.0308		0.0494		0.0246
		(0.0726)		(0.0725)		(0.0727)		(0.0723)		(0.0756)		(0.0755)
Adj R-square	0.1599	0.2058	0.1694	0.2130	0.1618	0.2060	0.1631	0.2068	0.1618	0.2082	0.1600	0.2059
Obs	987	987	987	987	987	987	987	987	987	987	987	987
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	No	No	No	No	No	No	No	No	No	No	No
No of firms	90	90	90	90	90	90	90	90	90	90	90	90

Robust standard errors in parenetheses, * p < 0.10, ** p < 0.05, *** p < 0.01

3.6 Conclusions and policy implications

Following the financial crisis, banks are expected to significantly adjust their balance sheet structure to comply with the enhanced risk-weighted capital requirements introduced under the Basel III regulatory framework. Depending on the banks' compliance strategy, these adjustments could affect the credit supply to the economy. It follows that investigating the costs and benefits of more stringent capital requirements on credit developments is of particular importance from a policymakers' perspective.

Several theories can explain the relationship between capital and credit growth in banking. However, these theories say little as regards the best approach to empirically model this relationship. As a consequence, researchers face a large amount of uncertainty, as they can choose from a multitude of model specifications (e.g., estimation methodology, control variables, and operational definitions of the control variables …). *Model uncertainty* is pervasive and intrinsic in social science studies, and ignoring it might lead to an overconfident representation of reality because the results do not take into account the array of other possible models that could have been tested (Steel, 2020). This issue is particularly relevant in the context of the literature on bank capital and lending because, as we have seen in Section 3.4.2, empirical studies have used a multitude of different model specifications and control variables when trying to answer this research question.

In light of this, this study contributes to the literature by investigating the relationship between capital requirements and lending growth of euro area banks between 2006 and 2020 using the model uncertainty framework of Young and Holsteen (2017). Employing this approach, we do not restrict our analysis to a few model specifications, but rather we report the modelling distribution of our coefficient estimates across the entire model space.

In the first step of our analysis, we run a baseline specification where the included control variables have been selected drawing from the existing broad literature review on this topic. This first set of results suggests that, on average, there is a negative – albeit insignificant - relationship between the amount of regulatory capital held by euro area banks and their lending behaviour.

However, in the second step of the chapter, we show how changing some of the control variables in the regression can lead to dramatically different findings. By relaxing the assumptions on the control variables to include in the specification, we find that out of the almost 16 thousand possible combinations of variables, Tier 1 ratio has a positive coefficient in 35% of the cases, while in the remaining cases it is negative. On top of this, out of the 65% of models where the coefficient is negative, in 25% of the cases, the coefficient is also statistically significant, in contrast with our baseline specification.

We continue our analysis by further assessing the sensitivity of our results to the use of multiple operational definitions of the same explanatory variable (e.g., ROE vs ROA). To this end, we run 4320 regressions, which constitute a model space where all the regressions are "theoretically informed" as they include always all the control variables identified as the most relevant, but with different definitions. In this case, we observe that in 98% of the models, the coefficient of Tier 1 is negative and, in 27% (1166 regressions) of the cases, capital is also statistically significant. Overall, the model uncertainty framework's results suggest a non-robust relationship between regulatory capital and lending of SSM banks between 2006 and 2020. As a final step, we should how a trivial change in the baseline specification, that is, substituting the NPLs ratio with the LLP ratio, would have led to a statistically significant coefficient of Tier 1.

In this Chapter, we aimed to show how the presence of model uncertainty, coupled with the incentives researchers faced when trying to publish, leave significant room to engage in *p-hacking* and present circumstantial evidence of robust results. Taking as an example our findings, a researcher could have chosen to present a subset of the 1166 regressions where Tier 1 enters the model statistically significant, concluding that regulatory capital reduces the loan supply of euro area banks. However, we show how these 1166 models represent only a small subset (27%) of the possible theoretically informed models that could have been tested.

By showing the results across the entire model space, we contribute to addressing the severe problem of asymmetric information between the researcher and readers that often occurs in published papers. The lack of transparency of modelling choices in addition to the strong incentives for researchers to publish statistically significant coefficients can result in *"false positives",* that is, results that are often the outcome of very *curated* model specifications where the coefficients of interest are *statistically significant*, while, in reality, there is no real relationship in the data. Additionally, it is important to remain aware that the optimal or appropriate model specification to address a specific research question will never be known. Thus, intuitively, providing the inference and the conclusions based on a limited set of models is an oversimplification of reality which can result in severe mistakes being made.

To conclude, the findings from the use of the model uncertainty computational framework bear implications for both researchers and policymakers. Specifically, we advocate that researchers should consider adopting a computational robustness framework to support the credibility of their analyses by providing evidence of the stability of the sign and significant rate of the variable of interest across all the possible model combinations and operational definitions. Indeed, as shown in this study, trivial changes in some of the operational definitions or neglecting certain variables matter as they yield significantly different outcomes and thus, different inference and policy implications. Finally, we argue that regulators should base the implementation of policies and regulations on studies that provide exhaustive evidence of robust results across all the unique combinations of possible (theoretically informed) “model ingredients”, thus avoiding studies that present only a few carefully selected models.

Conclusions

This Thesis has focused on three different, yet interlinked, topics related to the European banking industry. First, we studied the relationship between bank cost efficiency and non-performing loans in Italian banks using a state-of-the-art Stochastic Frontier Analysis empirical specification. Second, we presented a model aimed at forecasting non-performing loans in the presence of non-linear effects and we show how NPLs in the euro area would evolve following a shock. Third, we explored one of the most debated research questions in the banking literature, that is, the dynamics between regulatory capital and bank lending.

The Chapters of this Thesis stand out for two reasons. Firstly, the Chapters cover three research areas that are highly policy relevant, and where the findings furnish timely and greatly important implications for both banks and policymakers alike, while also providing interesting avenues for future research. Secondly, the three Chapters employ novel and at-the-forefront econometric approaches and research designs.

In the first Chapter, to investigate the relationship between cost efficiency and non-performing loans, we employ the latest advancement in the Stochastic Frontier Analysis literature (i.e., the four-error decomposition model by Badunenko and Kumbhakar 2018) and we disentangle cost efficiency into its transient and persistent components. In doing so, we expand the current literature that has relied on a single measure of overall efficiency and thus might have overlooked important aspects of the cost minimization behaviour of banks. Our findings have several implications in terms of regulation and policy. Firstly, we observe that higher persistent efficiency is associated with higher volumes of NPLs, potentially denoting a problem of resource misallocation. Therefore, the primary objective of regulators should relate to the removal of the structural inefficiencies, which we report are related to the geographical location and the legal form of banks. Furthermore, we observe a negative intertemporal relationship between transient efficiency and asset quality, suggesting that it is within the control of the senior management to remove short-term inefficiencies, thus preventing the increase of that part of NPLs that stem because of banks' lax practices in loan underwriting, monitoring and control. Thus, we argue that policymakers should consider intensifying the regulatory framework for individual accountability.

In Chapter 2, we propose a model to inform in a forward-looking manner about the evolution of non-performing loans by addressing non-linear dynamics that can arise during periods of crisis. By using the novel dynamic fixed effects quantile models by Machado and Santos Silva (2019), our model is better equipped to detect dynamics between non-performing loans and macro-financial variables that materialise at the tail of the distribution of NPLs. This is of particular relevance because the focus of prudential authorities is on periods of macroeconomic distress when high levels of NPLs can emerge. Additionally, the state-of-the-art empirical approach employed entails the estimation of bank fixed effects, which are pivotal to providing bank-specific paths for the evolution of NPLs. By failing to control for non-linearities or bank-specific characteristics, other models might result in severe underestimation of the evolution of NPLs under an adverse scenario.

The Thesis concludes with the third Chapter, where we employ a novel research design to investigate one of the most debated issues in the banking literature, that is, whether regulatory capital affects bank lending decisions. Despite the several theories that explain this relationship, they say little as regards the best approach to *empirically* model it. For instance, we identify more than twenty thousand possible models that could be used to answer this research question. As a consequence, researchers are faced with *model uncertainty*, which coupled with the incentives they encounter when trying to publish, leaves significant room to engage in *p-hacking* and present circumstantial evidence of robust results. We advocate that researchers should consider adopting a computational robustness framework to support the credibility of their analyses by providing evidence of the stability of the sign and significant rate of the variable of interest across all the possible model combinations and operational definitions. Finally, we argue that regulators should base the implementation of policies and regulations on studies that provide exhaustive evidence of robust results across all the unique combinations of possible (theoretically informed) “model ingredients”, thus avoiding studies that present only a few carefully selected models.

References

Accornero, M. et al. (2017) Non-Performing Loans and the Supply of Bank Credit: Evidence from Italy, *Questioni di Economia e Finanza* (Occasional Papers). doi: 10.2139/ssrn.2954995.

Aiello, F. and Bonanno, G. (2013) ‘Profit and cost efficiency in the Italian banking industry (2006-2011)’, Munich Personal RePEc Archive, (29506).

Aiello, F. and Bonanno, G. (2016) ‘Looking at the determinants of efficiency in banking: evidence from Italian mutual-cooperatives’, *International Review of Applied Economics*, 30(4), pp. 507–526. doi: 10.1080/02692171.2015.1122747.

Aigner, D., Lovell, C. A. K. and Schmidt, P. (1977) ‘Formulation And Estimation Of Stochastic Frontier Production Function Models’, *Journal of Econometrics*, 6, pp. 21–37.

Aiyar, S. et al. (2014) ‘The international transmission of bank capital requirements: Evidence from the UK’, *Journal of Financial Economics*, 113(3), pp. 368–382. doi: 10.1016/j.jfineco.2014.05.003.

Aiyar, S. et al. (2015) A Strategy for Resolving Europe’s Problem Loans International Monetary Fund Staff Discussion Note

Aiyar, S., Calomiris, C. W. and Wieladek, T. (2016) ‘How does credit supply respond to monetary policy and bank minimum capital requirements?’, *European Economic Review*, 82, pp. 142–165. doi: 10.1016/j.euroecorev.2015.07.021.

Akhigbe, A. and McNulty, J. E. (2003) ‘The Profit Effiiency of Small US Commercial Banks’, *Journal of Banking and Finance*, 27, pp. 307–325.

Albertazzi, U. et al. (2014) ‘The impact of the sovereign debt crisis on the activity of Italian banks’, *Journal of Banking and Finance*, 46(1), pp. 387–402. doi: 10.1016/j.jbankfin.2014.05.005.

Allen, F. and Santomero, A. M. (1997) ‘The theory of financial intermediation’, *Journal of Banking and Finance*, 21(11–12), pp. 1461–1485. doi: 10.1016/S0378-4266(97)00032-0.

Allen, F., Carletti, E. and Marquez, R. (2011) ‘Credit market competition and capital regulation’, *Review of Financial Studies*, 24(4), pp. 983–1018. doi: 10.1093/rfs/hhp089.

Altavilla, C., Boucinha, M., Holton, S. and Ongena, S., (2021). Credit supply and demand in unconventional times. *Journal of Money, Credit and Banking*, 53(8), pp.2071-2098.

Altavilla, C., Canova, F. and Ciccarelli, M. (2019) ‘Mending the broken link: Heterogeneous bank lending rates and monetary policy pass-through’, *Journal of Monetary Economics*. doi: 10.1016/j.jmoneco.2019.01.001.

Altunbas, Y. et al. (2000) ‘Efficiency and risk in Japanese banking’, *Journal of Banking and Finance*, 24(10), pp. 1605–1628. doi: 10.1016/S0378-4266(99)00095-3.

Altunbas, Y. et al. (2001) ‘Efficiency in European banking’, *European Economic Review*, 45, pp. 1931–1955.

Altunbas, Y. et al. (2007) ‘Examining the Relationships between Capital , Risk and Efficiency in European Banking’, *European Financial Management*, 13(1), pp. 49–70.

Altunbas, Y., Evans, L. and Molyneux, P. (2001) ‘Bank Ownership and Efficiency’, *Journal Of Money Credit And Banking*, 33(4), pp. 926–954.

Andreou, P.C., Philip, D. and Robejsek, P., (2016). Bank liquidity creation and risk-taking: Does managerial ability matter? *Journal of Business Finance & Accounting*, 43(1-2), pp.226-259.

Andreou, P.C., Karasamani, I., Louca, C. and Ehrlich, D., (2017). The impact of managerial ability on crisis-period corporate investment. *Journal of Business Research*, 79, pp.107-122.

Andrews, I. and Kasy, M. (2019) ‘Identification of and Correction for Publication Bias’, *American Economic Review*, 109(8), pp. 2766–2794. doi: 10.1257/aer.20180310.

Angelini, P. (2018) ‘Do high levels of NPLs impair banks’ credit allocation?1’, Notes on Financial Stability and Supervision, Bank of Italy, (12), pp. 1–6.

Assaf, A. G. et al. (2019) ‘Does efficiency help banks survive and thrive during financial crises?’, *Journal of Banking and Finance*, 106, pp. 445–470. doi: 10.1016/j.jbankfin.2019.07.013.

Badunenko, O. and Kumbhakar, S. C. (2017) ‘Economies of scale, technical change and persistent and time-varying cost efficiency in Indian banking: Do ownership, regulation and heterogeneity matter?’, *European Journal of Operational Research*, 260(2), pp. 789–803. doi: 10.1016/j.ejor.2017.01.025.

Badunenko, O. et al. (2021) ‘The impact of efficiency on asset quality in banking’, *European Journal of Finance*. doi: 10.1080/1351847X.2021.1946117.

Baldini, A. and Causi, M. (2020) ‘Restoring credit market stability conditions in Italy: evidences on Loan and Bad Loan dynamics’, *European Journal of Finance*, 26(7–8), pp. 746–773. doi: 10.1080/1351847X.2019.1663229.

Balgova, M., Nies, M. and Plekhanov, A. (2016) ‘The economic impact of reducing non- performing loans’, EBRD Working Paper, (193), pp. 1–45.

Bank of Italy (2013) 'The recent Asset quality review on non-performing loans conducted by the Bank of Italy: Main features and results'.

Basel Committee on Banking Supervision (2018) Structural changes in banking after the crisis, CGFS Papers.

Battaglia, F. et al. (2010) 'The efficiency of cooperative banks : the impact of environmental economic conditions', *Applied Economics*, pp. 1363–1376. doi: 10.1080/09603107.2010.491442.

Beaton, K., Myrvoda, A. and Thompson, S. (2016) 'Non-Performing Loans in the ECCU : Determinants and Macroeconomic Impact', *IMF Working Paper*, pp. 1–33. doi: 10.5089/9781475555714.001.

Beccalli, E. and Frantz, P. (2009) 'M&A operations and performance in banking', *Journal of Financial Services Research*, 36(2), pp. 203–226. doi: 10.1007/s10693-008-0051-6.

Becchetti, L., Ciciretti, R. and Paolantonio, A. (2016) 'The cooperative bank difference before and after the global financial crisis', *Journal of International Money and Finance*, 69, pp. 224–246. doi: 10.1016/j.jimonfin.2016.06.016.

Beck, R., Jakubik, P. and Piloiu, A. (2015) 'Key Determinants of Non-performing Loans: New Evidence from a Global Sample', *Open Economies Review*, 26(3), pp. 525–550. doi: 10.1007/s11079-015-9358-8.

Behn, M., Haselmann, R. and Wachtel, P. (2016) 'Procyclical Capital Regulation and Lending', *Journal of Finance*, 71(2), pp. 919–956. doi: 10.1111/jofi.12368.

Ben Naucer, S., Marton, K. and Roulet, C. (2018) 'Basel III and bank-lending: Evidence from the United States and Europe', *Journal of Financial Stability*, 39, pp. 1–27. doi: 10.1016/j.jfs.2018.08.002.

Benston, G. J. and Smith, C. W. (1976) 'A Transactions Cost Approach to the Theory of Financial Intermediation', The *Journal of Finance*, 31(2), pp. 215–231.

Berge, O. and Boye, K. G. (2007) 'An analysis of banks' problem loans', Norges Bank, *Economic Bulletin*, 78, pp. 65–76.

Berger, A. N. (2003) 'The economic effects of technological progress: {E}vidence from the banking industry', *Journal of Money, Credit, and Banking*, 27(2), pp. 404–431.

Berger, A. N. and Bouwman, C. H. S. (2009) 'Bank liquidity creation', *Review of Financial Studies*, 22(9), pp. 3779–3837. doi: 10.1093/rfs/hhn104.

Berger, A. N. and DeYoung, R. (1997) 'Problem loans and cost efficiency in commercial banks', *Journal of Banking and Finance*, 21(6), pp. 849–870. doi: 10.1016/S0378-4266(97)00003-4.

Berger, A. N. and Mester, L. J. (1997) 'Inside the black box : What explains differences in the efficiencies of financial institutions?', *Journal of Banking and Finance*, 21, pp. 895–947.

Berger, A. N., Hasan, I. and Zhou, M. (2009) 'Bank ownership and efficiency in China: What will happen in the world's largest nation?', *Journal of Banking and Finance*, 33(1), pp. 113–130. doi: 10.1016/j.jbankfin.2007.05.016.

Berger, A. N., Herring, R. J. and Szegö, G. P. (1995) 'The role of capital in financial institutions', *Journal of Banking and Finance*, 19(3), pp. 393–430. doi: 10.1016/0378-4266(95)00002-X.

Berger, A. N., Leusner, J. H. and Mingo, J. J. (1997) 'The efficiency of bank branches', *Journal of Monetary Economics*, 40(1), pp. 141–162. doi: 10.1016/S0304-3932(97)00035-4.

Berrospide, J. M. et al. (2010) 'The Effects of Bank Capital on Lending: What Do We Know, and What Does It Mean?', *International Journal of Central Banking*.

Bertay, A. C., Demirguc-Kunt, A. and Huizinga, H. (2013) 'Do we need big banks? Evidence on performance, strategy and market discipline', *Journal of Financial Intermediation*, 22(4), pp. 532–558. doi: 10.1016/j.jfi.2013.02.002.

Bertrand, M. and Schoar, A., (2003). Managing with style: The effect of managers on firm policies. *The Quarterly Journal of Economics*, 118(4), pp.1169-1208.

Bholat, D. M. et al. (2016) 'Non-Performing Loans: Regulatory and Accounting Treatments of Assets', Staff Working Papers, The Bank of England. doi: 10.2139/ssrn.2768865.

Blasch, J. et al. (2017) 'Explaining electricity demand and the role of energy and investment literacy on end-use efficiency of Swiss households', *Energy Economics*, 1 October, pp. 89–102. doi: 10.1016/j.eneco.2017.12.004.

Bloom, N., Bond, S. and Reenen, J. V (2007) 'Uncertainty and Investment Dynamics', *The review of Economic Studies*, 74(2), pp. 391–415. doi: 10.3386/w12383.

Bofondi, M. and Ropele, T. (2011) 'Macroeconomic determinants of bad loans: evidence from Italian banks', Questioni di Economia e Finanza, Occasional Papers, Bank of Italy, 89, pp. 1–40. doi: 10.1016/j.econlet.2016.06.031.

Bonaccorsi Di Patti, E. and Cascarino, G. (2020) 'Modelling the dynamics of nonperforming loans in Italy', Notes on Financial Stability and Supervision, Bank of Italy, 20(19), pp. 1–6.

Boss, M., Fenz, G., Pann, J., Puhr, C., Schneider, M. and Ubl, E., (2009). Modeling credit risk through the Austrian business cycle: An update of the OeNb model.*Financial Stability Report*,*17*, pp.85-101.

Bredl, S. (2018) ‘The role of non-performing loans for bank lending rates’, Discussion Paper, Deutsche Bundesbank, (52).

Brei, M. and Schclarek, A. (2015) ‘A theoretical model of bank lending: Does ownership matter in times of crisis?’, *Journal of Banking and Finance,* 50, pp. 298–307. doi: 10.1016/j.jbankfin.2014.03.038.

Bridges, J. and et al. (2014) ‘The impact of capital requirements on bank lending’, Working Paper, Bank of England, 486, pp. 1–36.

Brodeur, A., Cook, N. and Heyes, A., (2020), May. A proposed specification check for p-hacking, *AEA Papers and Proceedings* (Vol. 110, pp. 66-69).

Budnik, K. (2020) ‘Banking euro area stress test model’, European Central Bank, (2469).

Calligaris, S. et al. (2016) ‘Italy’s Productivity Conundrum A Study on Resource Misallocation in Italy’, *European Economy Discussion Paper*, pp. 1–89.

Cantú, C., Claessens, S. and Gambacorta, L. (2020) ‘How do bank-specific characteristics affect lending? New evidence based on credit registry data from Latin America’, *Journal of Banking and Finance*, (798). doi: 10.1016/j.jbankfin.2020.105818.

Cappelletti, G. et al. (2022) ‘Compositional Effects of Bank Capital Buffers and Interactions with Monetary Policy’, *Journal of Banking and Finance*, p. 106530. doi: 10.1016/j.jbankfin.2022.106530.

Carlson, M., Shan, H. and Warusawitharana, M. (2013) ‘Capital ratios and bank lending: A matched bank approach’, *Journal of Financial Intermediation*, 22(4), pp. 663–687. doi: 10.1016/j.jfi.2013.06.003.

Carvallo, O. and Kasman, A., (2005). Cost efficiency in the Latin American and Caribbean banking systems. *Journal of International Financial Markets, Institutions and Money*, 15(1), pp.55-72.

Castro, V. (2013) ‘Macroeconomic determinants of the credit risk in the banking system: The case of the GIPSI’, *Economic Modelling*, 31(1), pp. 672–683. doi: 10.1016/j.econmod.2013.01.027.

Casu, B. and Girardone, C. (2002) ‘A Comparative Study of the cost Efficiency of Italian bank conglomerates’, *Managerial Finance*, 28(9), pp. 3–23.

Casu, B. and Girardone, C. (2009) ‘Testing the relationship between competition and efficiency in banking: A panel data analysis’, *Economics Letters*, 105(1), pp. 134–137. doi: 10.1016/j.econlet.2009.06.018.

Casu, B., Deng, B. and Ferrari, A. (2017) ‘Post-crisis regulatory reforms and bank performance: lessons from Asia’, *European Journal of Finance*, 23(15), pp. 1544–1571. doi: 10.1080/1351847X.2016.1177566.

Casu, B., Ferrari, A. and Zhao, T. (2013) 'Regulatory Reform and Productivity Change in Indian Banking', *Review of Economics and Statistics*, 95(3), pp. 1066–1077. doi: 10.1162/REST_a_00298.

Cerulli, G. et al. (2020) 'Benchmarking non-performing loans', *European Journal of Finance*, 26(16), pp. 1591–1605. doi: 10.1080/1351847X.2020.1794923.

Chaibi, H. and Ftiti, Z. (2015) 'Credit risk determinants: Evidence from a cross-country study', *Research in International Business and Finance*, 33, pp. 1–16. doi: 10.1016/j.ribaf.2014.06.001.

Chavleishvili, S. and Manganelli, S. (2020) Forecasting and stress testing with quantile vector autoregression. doi: 10.2866/589234.

Chemmanur, T.J. and Paeglis, I., (2005). Management quality, certification, and initial public offerings. *Journal of Financial Economics*, 76(2), pp.331-368.

Chemmanur, T.J., Paeglis, I. and Simonyan, K., (2009). Management quality, financial and investment policies, and asymmetric information. *Journal of Financial and Quantitative Analysis*, 44(5), pp.1045-1079.

Chu, Y., Zhang, D. and Zhao, Y. E. (2018) 'Bank Capital and Lending: Evidence from Syndicated Loans', *Journal of Financial and Quantitative Analysis*, pp. 1–28. doi: 10.1017/S0022109018000698.

Chuliá, H. et al. (2017) 'Impact of US uncertainties on emerging and mature markets: Evidence from a quantile-vector autoregressive approach', *Journal of International Financial Markets, Institutions and Money*, 48, pp. 178–191. doi: 10.1016/j.intfin.2016.12.003.

Ciccarelli, M., Maddaloni, A. and Peydró, J. L. (2015) 'Trusting the bankers: A new look at the credit channel of monetary policy', *Review of Economic Dynamics*, 18(4), pp. 979–1002. doi: 10.1016/j.red.2014.11.002.

Colombi, R. et al. (2014) 'Closed-skew normality in stochastic frontiers with individual effects and long/short-run efficiency', *Journal of Productivity Analysis*, 42(2), pp. 123–136. doi: 10.1007/s11123-014-0386-y.

Cosma, S., and Gualandri, E. (2012). The Italian banking system: Impact of the crisis and future perspectives. Springer.

Cotugno, M., Stefanelli, V. and Torluccio, G. (2013) 'Relationship lending, default rate and loan portfolio quality', *Applied Financial Economics*, 23(7), pp. 573–587. doi: 10.1080/09603107.2012.744133.

Covas, F. B., Rump, B. and Zakrajšek, E. (2014) 'Stress-testing US bank holding companies: A dynamic panel quantile regression approach', *International Journal of Forecasting*, 30(3), pp. 691–713. doi: 10.1016/j.ijforecast.2013.11.003.

Cubillas, E. and Suárez, N. (2018) 'Bank market power and lending during the global financial crisis', *Journal of International Money and Finance,* 89, pp. 1–22. doi: 10.1016/j.jimonfin.2018.08.003.

Cubillas, E., Fonseca, A. R. and González, F. (2012) 'Banking crises and market discipline: International evidence', *Journal of Banking and Finance,* 36(8), pp. 2285–2298. doi: 10.1016/j.jbankfin.2012.04.011.

Daniëls, T. et al. (2017) 'A top-down stress testing framework for the Dutch banking sector', 15.

Davies, R. and Tracey, B. (2014) 'Too big to be efficient ? The impact of implicit funding subsidies on scale economies in banking', *Journal of Money, Credit & Banking,* 46(February), pp. 219–253.

de Bandt, O. et al. (2018) 'Optimal capital, regulatory requirements and bank performance in times of crisis: Evidence from France', *Journal of Financial Stability,* 39, pp. 175–186. doi: 10.1016/j.jfs.2017.03.002.

De Mitri, S., Gobbi, G. and Sette, E. (2010) 'Relationship lending in a financial turmoil.', Banca d'Italia, Temi di discussione (Working papers), Number 772, pp. 1–27. doi: 10.2139/ssrn.1788037.

Debreu, G., (1951). The coefficient of resource utilization. *Econometrica: Journal of the Econometric Society,* pp.273-292.

Degryse, H. et al. (2019) 'Identifying credit supply shocks with bank-firm data: Methods and applications', *Journal of Financial Intermediation,* 40. doi: 10.1016/j.jfi.2019.01.004.

Del Giovane, P., Nobili, A. and Signoretti, F. M. (2013) Supply tightening or lack of demand? An analysis of credit developments during the Lehman Brothers and the sovereign debt crises, Banca d'Italia Termi di Discussione.

Delis, M. D. et al. (2009) 'Evaluating cost and profit efficiency: A comparison of parametric and nonparametric methodologies', *Applied Financial Economics,* 19(3), pp. 191–202. doi: 10.1080/09603100801935370.

Dell'Ariccia, G. et al. (2018) 'Managing the sovereign-bank nexus', *ECB Working Paper* Series, (2177).

Demerjian, P., Lev, B. and McVay, S. (2012) 'Quantifying managerial ability: A new measure and validity tests', *Management Science,* 58(7), pp. 1229–1248. doi: 10.1287/mnsc.1110.1487.

Devereux, J. and Dwyer, G. P. (2016) 'What determines output losses after banking crises?', *Journal of International Money and Finance,* 69, pp. 69–94. doi: 10.1016/j.jimonfin.2016.10.004.

Diamond, D. W. and Rajan, R. G. (2000) 'A Theory of Bank Capital', The *Journal of Finance,* LV(6), pp. 2431–2465. doi: 10.1111/0022-1082.00296.

Diamond, D. W. and Rajan, R. G. (2001) ‘Banks and Liquidity’, *American Economic Review*, 91(2), pp. 422–425. doi: 10.1257/aer.91.2.422.

Dietsch, M. and Lozano-Vivas, A. (2000) ‘How the environment determines banking efficiency : A comparison between French and Spanish industries’, *Journal of Banking and Finance*, 24, pp. 985–1004.

Dimitras, A.I., Gaganis, C. and Pasiouras, F., (2018). Financial reporting standards' change and the efficiency measures of EU banks. *International Review of Financial Analysis*, 59, pp.223-233.

Dimitrios, A., Helen, L. and Mike, T. (2016) ‘Determinants of non-performing loans: Evidence from Euro-area countries’, *Finance Research Letters*, 18, pp. 116–119. doi: 10.1016/j.frl.2016.04.008.

Distinguin, I., Roulet, C. and Tarazi, A. (2013) ‘Bank regulatory capital and liquidity: Evidence from US and European publicly traded banks’, *Journal of Banking and Finance*, 37(9), pp. 3295–3317. doi: 10.1016/j.jbankfin.2013.04.027.

Dong, Y., Girardone, C. and Kuo, J.M., (2017). Governance, efficiency and risk taking in Chinese banking. *The British Accounting Review*, 49(2), pp.211-229.

Dumitrescu, E. I. and Hurlin, C. (2012) ‘Testing for Granger non-causality in heterogeneous panels’, *Economic Modelling*, 29(4), pp. 1450–1460. doi: 10.1016/j.econmod.2012.02.014.

Duygun, M., Sena, V. and Shaban, M., (2013). Schumpeterian competition and efficiency among commercial banks. *Journal of Banking and Finance*, 37(12), pp.5176-5185.

Espinoza, R. and Prasad, A. (2010) ‘Nonperforming Loans in the GCC Banking System and their Macroeconomic Effects’, *IMF Working Paper*, 10(224), p. 1. doi: 10.5089/9781455208890.001.

European Commission (2015) ‘Country Report Italy 2015’.

European Commission (2016) ‘Country Report Italy 2016’.

European Commission (2017) ‘Country Report Italy 2017’.

European Systemic Risk Board (2017), ‘Resolving non-performing loans in Europe’

Faini, R., Giannini, C. and Ingrosso, F., (1992). Finance and development: the case of Southern Italy (No. 674). CEPR Discussion Papers.

Favero, C. A. and Papi, L. (1995) ‘Technical efficiency and scale efficiency in the Italian banking sector: A non-parametric approach’, *Applied Economics*, 27(4), pp. 385–395. doi: 10.1080/00036849500000123.

Farrell, M.J., (1957). The measurement of productive efficiency. *Journal of the Royal Statistical Society*: Series A (General), 120(3), pp.253-281.

Feldman, R. J. (2010) ‘Scale Economies in Banking’, The Region.

Feng, G. and Serletis, A. (2008) ‘Efficiency And Productivity Of The Us Banking Industry, 1998–2005: Evidence From The Fourier Cost Function Satisfying Global Regularity Conditions’, *Journal of Applied Econometrics*. doi: 10.1002/jae.

Ferri, G., Kalmi, P. and Kerola, E. (2014) ‘Does bank ownership affect lending behavior? Evidence from the Euro area’, *Journal of Banking and Finance*, 48, pp. 194–209. doi: 10.1016/j.jbankfin.2014.05.007.

Fethi, M. D. and Pasiouras, F. (2010) ‘Assessing bank efficiency and performance with operational research and artificial intelligence techniques: A survey’, *European Journal of Operational Research*, 204(2), pp. 189–198. doi: 10.1016/j.ejor.2009.08.003.

Filippini, M. and Greene, W. (2016) ‘Persistent and transient productive inefficiency: a maximum simulated likelihood approach’, *Journal of Productivity Analysis*, 45(2), pp. 187–196. doi: 10.1007/s11123-015-0446-y.

Filippini, M., Geissmann, T. and Greene, W. H. (2018) ‘Persistent and transient cost efficiency—an application to the Swiss hydropower sector’, *Journal of Productivity Analysis*, 49(1), pp. 65–77. doi: 10.1007/s11123-017-0522-6.

Fiordelisi, F., Marques-Ibanez, D. and Molyneux, P. (2011) ‘Efficiency and risk in European banking’, *Journal of Banking and Finance*, 35(5), pp. 1315–1326. doi: 10.1016/j.jbankfin.2010.10.005.

Fiordelisi, F. and Mare, D.S., (2014). Competition and financial stability in European cooperative banks. *Journal of International Money and Finance*, 45, pp.1-16.

Fiordelisi, F., Ricci, O. and Stentella Lopes, F. S. (2017) ‘The unintended consequences of the launch of the single supervisory mechanism in Europe’, *Journal of Financial and Quantitative Analysis*, 52(6), pp. 2809–2836. doi: 10.1017/S0022109017000886.

Fraisse, H., Lé, M. and Thesmar, D. (2020) ‘The real effects of bank capital requirements’, *Management Science*, 66(1), pp. 5–23. doi: 10.1287/mnsc.2018.3222.

Gallant, A. R. (1981) ‘On the Bias in Flexible Functional Forms and and Essentialy Unbiased Form’, *Journal of Econometrics*, 15, pp. 211–245.

Gambacorta, L. and Marques-Ibanez, D., (2011). The bank lending channel: lessons from the crisis. *Economic policy*, 26(66), pp.135-182.

Gambacorta, L. and Mistrulli, P. E. (2004) ‘Does bank capital affect lending behavior?’, *Journal of Financial Intermediation*, 13(4), pp. 436–457. doi: 10.1016/j.jfi.2004.06.001.

Gambacorta, L. and Shin, H. S. (2018) 'Why bank capital matters for monetary policy', *Journal of Financial Intermediation*, 35, pp. 17–29. doi: 10.1016/j.jfi.2016.09.005.

Garrido, J. (2016) 'Insolvency and Enforcement Reforms in Italy', *IMF Working Paper*.

Garrido, J., Kopp, E. and Weber, A. (2016) 'Cleaning-up Bank Balance Sheets: Economic, Legal, and Supervisory Measures for Italy', *IMF Working Paper*, 16(135), p. 1. doi: 10.5089/9781498357036.001.

Ghosh, A. (2015) 'Banking-industry specific and regional economic determinants of non-performing loans: Evidence from US states', *Journal of Financial Stability*, 20, pp. 93–104. doi: 10.1016/j.jfs.2015.08.004.

Ghosh, A. (2017) 'Sector-specific analysis of non-performing loans in the US banking system and their macroeconomic impact', *Journal of Economics and Business*, 93, pp. 29–45. doi: 10.1016/j.jeconbus.2017.06.002.

Giannone, D., Lenza, M. and Reichlin, L. (2011) 'Market freedom and the global recession', IMF Economic Review, 59(1), pp. 111–135. doi: 10.1057/imfer.2010.14.

Giglio, C. et al. (2021) 'Stress-Testing Net Trading Income: The Case of European Banks', *ECB Working Paper*, (2525). doi: 10.2139/ssrn.3717707.

Giordano, L. and Lopes, A. (2015) 'Competition versus Efficiency: What Drives Banks' Spreads in Italian Banking System?', *Academic Journal of Economic Studies*, 1(2), pp. 93–119. doi: 10.2139/ssrn.2640899.

Girardone, C., Molyneux, P. and Gardener, E. P. M. (2004) 'Analysing the determinants of bank efficiency : the case of Italian banks', *Applied Economics*, (February), pp. 215–227. doi: 10.1080/0003684042000175334.

Goddard, J., Molyneux, P. and Williams, J. (2014) 'Dealing with cross-firm heterogeneity in bank efficiency estimates: Some evidence from Latin America', *Journal of Banking and Finance*, 40(1), pp. 130–142. doi: 10.1016/j.jbankfin.2013.11.025.

Gorton, G. B. and Winton, A. (2017) 'Liquidity provision and the social cost of bank capital', *Journal of Money, Credit and Banking*, 49(1).

Granger, C. W. J. (1969) 'Investigating Causal Relations by Econometric Models and Cross-spectral Methods', *Econometrica*, 37(3), p. 424. doi: 10.2307/1912791.

Gropp, R. et al. (2019) 'Banks response to higher capital requirements: Evidence from a quasi-natural experiment', *Review of Financial Studies*, 32(1), pp. 266–299. doi: 10.1093/rfs/hhy052.

Gross, M., Georgescu, O.M., and Hilberg, B. (2017). Credit risk satellite models, in Dees, S., Henry, J. and Martin, R., 2017. STAMP€: Stress-Test Analytics for Macroprudential Purposes in the euro area. *European Central Bank*.

Guttormsen, A. G. and Roll, K. H. (2014) 'Production Risk in a Subsistence Agriculture', *Journal of Agricultural Education and Extension*, 20(1), pp. 133–145. doi: 10.1080/1389224X.2013.775953.

Haile, G., Srour, I. and Vivarelli, M. (2017) 'Imported technology and manufacturing employment in Ethiopia', *Eurasian Business Review*, 7(1), pp. 1–23. doi: 10.1007/s40821-016-0051-7.

Hauner, D. (2005) 'Explaining efficiency differences among large German and Austrian banks', *Applied Economics*, 37(9), pp. 969–980. doi: 10.1080/00036840500081820.

Heider, F., Saidi, F. and Schepens, G. (2019) 'Life below Zero: Bank Lending under Negative Policy Rates', The *Review of Financial Studies*, 32(10), pp. 3728–3761. doi: 10.1093/rfs/hhz016.

Heryán, T. and Tzeremes, P. G. (2017) 'The bank lending channel of monetary policy in EU countries during the global financial crisis', *Economic Modelling*, 67, pp. 10–22. doi: 10.1016/j.econmod.2016.07.017.

Ho, T. K. (2015) 'Looking for a Needle in a Haystack: Revisiting the Cross-country Causes of the 2008-9 Crisis by Bayesian Model Averaging', *Economica*, 82(328), pp. 813–840. doi: 10.1111/ecca.12125.

Holmstrom, B. and Tirole, J., (1997). Financial intermediation, loanable funds, and the real sector. T*he Quarterly Journal of economics*,*112*(3), pp.663-691.

Horváth, R., Seidler, J. and Weill, L. (2014) 'Bank Capital and Liquidity Creation: Granger-Causality Evidence', *Journal of Financial Services Research*, 45(3), pp. 341–361. doi: 10.1007/s10693-013-0164-4.

Huljak, I. et al. (2022) 'Do non-performing loans matter for bank lending and the business cycle in euro area countries?', *Journal of Applied Economics*, 25(1), pp. 1050–1080. doi: 10.1080/15140326.2022.2094668.

Hughes, J.P. and Mester, L.J., (1993). A quality and risk-adjusted cost function for banks: Evidence on the "too-big-to-fail" doctrine. *Journal of Productivity Analysis*, 4(3), pp.293-315.

Hunter, W. C. and Timme, S. G. (1991) 'Technological Change in Large U.S. Commercial Banks', *The Journal of Business*, 64(3), pp. 339–362.

Jaenicke, E. C., Frechette, D. L. and Larson, J. A. (2003) 'Estimating Production Risk and Inefficiency Simultaneously: An Application to Cotton Cropping Systems', *Journal of Agricultural and Resource Economics*, 28(3), pp. 540–557.

Jassaud, N. and Kang, K. (2015) ‘A Strategy for Developing a Market for Nonperforming Loans in Italy’, *IMF Working Paper*, 15(24), p. 1. doi: 10.5089/9781498337984.001.

Jeitschko, T. D. and Jeung, S. D. (2005) ‘Incentives for risk-taking in banking - A unified approach’, *Journal of Banking and Finance*, 29(3), pp. 759–777. doi: 10.1016/j.jbankfin.2004.05.028.

Jiménez, G. et al. (2017) ‘Macroprudential Policy, Countercyclical Bank Capital Buffers, and Credit Supply: Evidence from the Spanish Dynamic Provisioning Experiments’, *Journal of Political Economy*, 125(6), pp. 000–000. doi: 10.1086/694289.

Jobst, A. (Andy) and Weber, A. (2016) ‘Profitability and Balance Sheet Repair of Italian Banks’, *International Monetary Fund Working Paper*, pp. 1–34. doi: 10.5089/9781475527513.001.

Just, R. E. and Pope, R. D. (1978) ‘Stochastic specification of production functions and economic implications’, *Journal of Econometrics*, 7(1), pp. 67–86. doi: 10.1016/0304-4076(78)90006-4.

Kanas, A. and Molyneux, P. (2018) ‘Macro stress testing the U . S . banking system’, *Journal of International Financial Markets, Institutions & Money*, 54, pp. 204–227. doi: 10.1016/j.intfin.2017.12.006.

Kanngiesser, D. et al. (2017) ‘Estimating the impact of shocks to bank capital in the euro area’, Working Paper Series, European Central Bank. doi: 10.2866/688406.

Kapan, T. and Minoiu, C., (2018). Balance sheet strength and bank lending: Evidence from the global financial crisis. *Journal of Banking & Finance*,*92*, pp.35-50.

Karmakar, S. and Mok, J. (2015) ‘Bank capital and lending: An analysis of commercial banks in the United States’, *Economics Letters*, 128, pp. 21–24. doi: 10.1016/j.econlet.2015.01.002.

Keeton, W. R. (1999) ‘Does faster loan growth lead to higher loan losses?’, Federal Reserve Bank of Kansas, *Economic Review*, 84(2), pp. 57–75.

Kenjegalieva, K. et al. (2009) ‘Comparative analysis of banking production frameworks in eastern european financial markets’, *European Journal of Operational Research*, 198(1), pp. 326–340. doi: 10.1016/j.ejor.2008.09.002.

Khan, H. H., Ahmed, R. B. and Gee, C. S. (2016) ‘Bank competition and monetary policy transmission through the bank lending channel: Evidence from ASEAN’, International *Review of Economics and Finance*, 44, pp. 19–39. doi: 10.1016/j.iref.2016.03.003.

Kim, D. and Sohn, W. (2017) ‘The effect of bank capital on lending: Does liquidity matter?’, *Journal of Banking and Finance*, 77, pp. 95–107. doi: 10.1016/j.jbankfin.2017.01.011.

Klein, N. (2013) ‘Non-Performing Loans in CESEE: Determinants and Impact on Macroeconomic Performance’, *IMF Working Paper*, 13(72).

Köhler-Ulbrich, P., Hempell, H.S. and Scopel, S., (2016). The Euro Area Bank Lending survey: Role, Development and Use in Monetary Policy Preparation (No. 179). *ECB Occasional Paper.*

Koopmans, T.C., (1951). An Analysis of Production as an Efficient Combination of Activities. In: Koopmans, T.C. ed. Activity Analysis of Production and Allocation. New York: Wiley, pp.33.

Košak, M. et al. (2015) ‘Quality of bank capital and bank lending behavior during the global financial crisis’, *International Review of Financial Analysis*, 37, pp. 168–183. doi: 10.1016/J.IRFA.2014.11.008.

Koutsomanoli-Filippaki, A. and Mamatzakis, E. (2009) ‘Performance and Merton-type default risk of listed banks in the EU: A panel VAR approach’, *Journal of Banking and Finance*, 33(11), pp. 2050–2061. doi: 10.1016/j.jbankfin.2009.05.009.

Kumbhakar, S. C., Lien, G. and Hardaker, J. B. (2014) ‘Technical efficiency in competing panel data models: A study of Norwegian grain farming’, *Journal of Productivity Analysis*, 41(2), pp. 321–337. doi: 10.1007/s11123-012-0303-1.

Kwan, S. and Eisenbeis, R. A. (1997) ‘Bank Risk, Capitaliazation and Operating Efficiency’, *Journal of Financial Services Research*, 12(2–3), pp. 117–131. doi: 10.1023/A:1012464108248.

Lai, H.-P. and Kumbhakar, S. C. (2016) ‘Panel Data Stochastic Frontier Model with Determinants of Persistent and Transient Inefficiency’. Available at: https://feb.kuleuven.be/drc/Economics/misc/seminars/papers2016/paper-kumbhakar.pdf (Accessed: 4 June 2018).

Lane, P. R. (2012) ‘The European Sovereign Debt Crisis’, *Journal of Economic Perspectives*, 26(3), pp. 49–68. doi: 10.1257/jep.26.3.49.

Lien, G., Kumbhakar, S. C. and Alem, H. (2018) ‘Endogeneity, heterogeneity, and determinants of inefficiency in Norwegian crop-producing farms’, International *Journal of Production Economics*, 201(April), pp. 53–61. doi: 10.1016/j.ijpe.2018.04.023.

Louhichi, A. and Boujelbene, Y. (2017) ‘Bank capital, lending and financing behaviour of dual banking systems’, *Journal of Multinational Financial Management*, 41, pp. 61–79. doi: 10.1016/j.mulfin.2017.05.009.

Louzis, D. P., Vouldis, A. T. and Metaxas, V. L. (2012) 'Macroeconomic and bank-specific determinants of non-performing loans in Greece : A comparative study of mortgage, business and consumer loan portfolios', *Journal of Banking and Finance*, 36(4), pp. 1012–1027. doi: 10.1016/j.jbankfin.2011.10.012.

Luo, Y., Tanna, S. and De Vita, G. (2016) 'Financial openness, risk and bank efficiency: Cross-country evidence', *Journal of Financial Stability*, 24, pp. 132–148. doi: 10.1016/j.jfs.2016.05.003.

Machado, J. A. F. and Santos Silva, J. M. C. (2019) 'Quantiles via moments', *Journal of Econometrics*, 213(1), pp. 145–173. doi: 10.1016/j.jeconom.2019.04.009.

Makri, V., Tsagkanos, A. and Bellas, A. (2014) 'Determinants of non-performing loans: The case of Eurozone', *Panoeconomicus*, 61(2), pp. 193–206. doi: 10.2298/PAN1402193M.

Mamatzakis, E., Staikouras, C. and Koutsomanoli-Filippaki, A. (2008) 'Bank efficiency in the new European Union member states: Is there convergence?', *International Review of Financial Analysis*, 17(5), pp. 1156–1172. doi: 10.1016/j.irfa.2007.11.001.

Marcucci, J. and Quagliariello, M. (2008) 'Is bank portfolio riskiness procyclical?: Evidence from Italy using a vector autoregression', *Journal of International Financial Markets, Institutions and Money*, 18(1), pp. 46–63. doi: 10.1016/J.INTFIN.2006.05.002.

Martín-Oliver, A., Ruano, S. and Salas-Fumás, V. (2012) 'Effects of Equity Capital on the Interest Rate and the Demand for Credit: Empirical Evidence from Spanish Banks', Ssrn. doi: 10.2139/ssrn.2046923.

Matousek, R. and Sarantis, N. (2009) 'The bank lending channel and monetary transmission in Central and Eastern European countries', *Journal of Comparative Economics*, 37(2), pp. 321–334. doi: 10.1016/j.jce.2008.09.008.

Maudos, J. et al. (2002) 'Cost and profit efficiency in European banks', *Journal of International Financial Markets, Institutions and Money*, 12(1), pp. 33–58. doi: 10.1016/S1042-4431(01)00051-8.

Maudos, J., Pastor, J. M. and Pérez, F. (2002) 'Competition and efficiency in the Spanish banking sector: The importance of specialization', *Applied Financial Economics*, 12(7), pp. 505–516. doi: 10.1080/09603100010007977.

Mehran, H. and Thakor, A., (2011). Bank capital and value in the cross-section. *The Review of Financial Studies, 24*(4), pp.1019-1067.

Mitchell, K. and Onvural, N. M. (1996) 'Economies of scale and scope at large commercial banks: Evidence from the Fourier flexible functional form', *Journal Of Money Credit And Banking*, 28(2), pp. 178–199. doi: 10.2307/2078022.

Modigliani, F. and Miller, M.H., (1958). The cost of capital, corporation finance and the theory of investment. *The American Economic Review*, *48*(3), pp.261-297.

Montagnoli, A., Napolitano, O. and Siliverstovs, B. (2016) 'Regional Interest Rate Pass-Through in Italy', *Regional Studies,* 50(8), pp. 1404–1419. doi: 10.1080/00343404.2015.1022311.

Moosa, I. (2010) 'The myth of too big to fail', *Journal of Banking Regulation*, 11(4), pp. 319–333. doi: 10.1057/jbr.2010.15.

Mora, N. and Logan, A. (2012) 'Shocks to bank capital: Evidence from UK banks at home and away', *Applied Economics*, 44(9), pp. 1103–1119. doi: 10.1080/00036846.2010.537639.

Muñoz, J. and Young, C. (2018) 'We Ran 9 Billion Regressions: Eliminating False Positives through Computational Model Robustness', *Sociological Methodology,* pp. 1–33. doi: 10.1177/0081175018777988.

Mydland, Ø., Haugom, E. and Lien, G. (2018) 'Economies of scale in Norwegian electricity distribution: a quantile regression approach', *Applied Economics*, 50(40), pp. 4360–4372. doi: 10.1080/00036846.2018.1450481.

Nkusu, M. (2011) 'Nonperforming Loans and Macrofinancial Vulnerabilities in Advanced Economies', *IMF Working Paper*, 11(161), p. 1. doi: 10.5089/9781455297740.001.

Nurisso, G. C. and Prescott, E. S. (2017) 'The 1970s Origins of Too Big to Fail', Federal Reserve Bank of Cleveland.

OECD (2021) 'The COVID-19 crisis and banking system resilience: Simulation of losses on non- performing loans and policy implications', OECD Paris.

Osborne, M., Fuertes, A. M. and Milne, A. (2017) 'In good times and in bad: Bank capital ratios and lending rates', *International Review of Financial Analysis,* 51, pp. 102–112. doi: 10.1016/j.irfa.2016.02.005.

Peek, J. and Rosengren, E. S. (1995) 'The Capital Crunch: Neither a Borrower nor a Lender Be.', *Journal of Money, Credit and Banking*, 27(3), pp. 625–637. doi: 10.2307/2077739.

Pennacchi, G. (2006) 'Deposit insurance, bank regulation, and financial system risks', *Journal of Monetary Economics,* 53(1), pp. 1–30. doi: 10.1016/j.jmoneco.2005.10.007.

Perotti, R. (1996) 'Fiscal Consolidation in Europe: Composition Matters', *American Economic Review,* 86(2), pp. 105–110. doi: 10.2307/2118105.

Podpiera, J. and Weill, L. (2008) ‘Bad luck or bad management? Emerging banking market experience’, *Journal of Financial Stability*, 4(2), pp. 135–148. doi: 10.1016/j.jfs.2008.01.005.

Quagliariello, M. (2007) ‘Banks’ riskiness over the business cycle: A panel analysis on Italian intermediaries’, *Applied Financial Economics*, 17(2), pp. 119–138. doi: 10.1080/09603100500486501.

Radić, N., Fiordelisi, F. and Girardone, C., (2012). Efficiency and risk-taking in pre-crisis investment banks. *Journal of Financial Services Research,* 41(1), pp.81-101.

Reinhart, C. M. and Rogoff, K. S. (2011) ‘From financial crash to debt crisis’, *American Economic Review*, 101(5), pp. 1676–1706. doi: 10.1257/aer.101.5.1676.

Resti, A. (1997) ‘Evaluating the cost-efficiency of the Italian banking system: What can be learned from the joint application of parametric and non-parametric techniques’, *Journal of Banking and Finance*, 21(2), pp. 221–250. doi: 10.1016/S0378-4266(96)00036-2.

Rinaldi, L. and Sanchis-Arellano, A. (2006) Household Debt Sustainability: What Explains Household Nonperforming Loans? An Empirical Analysis, *ECB Working Paper*.

Roodman, D. (2009) ‘Practitioners’ corner: A note on the theme of too many instruments’, *Oxford Bulletin of Economics and Statistics*, 71(1), pp. 135–158. doi: 10.1111/j.1468-0084.2008.00542.x.

Rossi, S., Schwaiger, M. and Winkler, G. (2005) Managerial Behavior and Cost/Profit Efficiency in the Banking Sectors of Central and Eastern European Countries, Austrian National Bank. Oesterreichische Nationalbank (Austrian Central Bank). doi: 10.2139/ssrn.676365.

Roulet, C. (2018) ‘Basel III: Effects of capital and liquidity regulations on European bank lending’, *Journal of Economics and Business*, 95, pp. 26–46. doi: 10.1016/j.jeconbus.2017.10.001.

Saeed, M. and Izzeldin, M. (2016) ‘Examining the relationship between default risk and efficiency in Islamic and conventional banks’, *Journal of Economic Behavior & Organization*, 132, pp. 127–154. doi: 10.1016/j.jebo.2014.02.014.

Sala-I-Martin, B. X., Doppelhofer, G. and Miller, R. I. (2004) ‘Determinants of Long-Term Growth : A Bayesian Averaging of Classical Estimates (BACE) Approach’, *American Economic Review*, 94(4), pp. 813–835. doi: 10.1257/0002828042002570.

Salas, V. and Saurina, J. (2002) ‘Credit risk in two institutional regimes: Spanish commercial and savings banks’, *Journal of Financial Services Research*, pp. 203–224. doi: 10.1023/A:1019781109676.

Schaeck, K. (2008) ‘Bank liability structure, FDIC loss, and time to failure: A quantile regression approach’, *Journal of Financial Services Research*, 33(3), pp. 163–179. doi: 10.1007/s10693-008-0028-5.

Schechtman, R. and Gaglianone, W. P. (2012) ‘Macro stress testing of credit risk focused on the tails’, *Journal of Financial Stability*, 8(3), pp. 174–192. doi: 10.1016/j.jfs.2011.10.003.

Schivardi, F., Sette, E. and Tabellini, G. (2017) ‘Credit misallocation during the European financial crisis’, BIS Working Papers, pp. 1–68.

Sealey, C. W. and Lindley, J. T. (1977) ‘Inputs, Outputs, and a Theory of Production and Cost at Depository Financial Institutions’, *The Journal of Finance*, 32(4), pp. 1251–1266. doi: 10.2307/2326527.

Shephard, R. W., (1953). Cost and Production Functions. Princeton: Princeton University Press.

Staehr, K. and Uuskula, L. (2017) ‘Forecasting Models for Non-Performing Loans in the Eu Countries’, Eesti Pank, Working Paper Series. doi: 10.23656/25045520/102017/0149.

Steel, M. F. J. (2020) ‘Model Averaging and Its Use in Economics’, *Journal of Economic Literature*, 58(3), pp. 644–719. doi: 10.1257/JEL.20191385.

Stefani, M. . et al. (2016) ‘Le banche locali e il finanziamento dei territori: evidenze per l’Italia (2007-2014)’, Occasional Papers, Bank of Italy, 324, pp. 1–38. doi: 10.1016/j.econlet.2016.06.031.

Stern, G. H. and Feldman, R. (2009) ‘Addressing TBTF by Shrinking Financial Institutions : An Initial Assessment’, The Region, Federal Reserve Bank of Minneapolis, (June), pp. 8–13.

Stern, G. H. and Feldman, R. J. (2008) ‘Managing the Expanded Safety Net’, The Region, pp. 5–17.

Tan, Y. and Floros, C. (2013) ‘Risk, capital and efficiency in Chinese banking’, *Journal of International Financial Markets, Institutions and Money*, 26(1), pp. 378–393. doi: 10.1016/j.intfin.2013.07.009.

Thakor, a V (1996) ‘Capital requirements, monetary policy, and aggregate bank lending: Theory and empirical evidence’, *Journal of Finance*, 51(June), pp. 279–324. doi: 10.1111/j.1540-6261.1996.tb05210.x.

Tölö, E. and Virén, M. (2021) ‘How much do non-performing loans hinder loan growth in Europe?’, *European Economic Review*, 136, p. 103773. doi: 10.1016/j.euroecorev.2021.103773.

Tsionas, E. G. and Kumbhakar, S. C. (2014) 'Firm Heterogeneity, Persistent And Transient Technical Inefficiency: A Generalized True Random-Effects Model', *Journal of Applied Econometrics*, 29, pp. 110–132. doi: 10.1002/jae.

Usai, S. and Vannini, M., (2005). Banking structure and regional economic growth: lessons from Italy. *The Annals of Regional Science*, 39(4), pp.691-714.

Vithessonthi, C. (2016) 'Deflation, bank credit growth, and non-performing loans: Evidence from Japan', *International Review of Financial Analysis*, 45, pp. 295–305. doi: 10.1016/j.irfa.2016.04.003.

Wang, H. J. (2002) 'Heteroscedasticity and non-monotonic efficiency effects of a stochastic frontier model', *Journal of Productivity Analysis*, 18(3), pp. 241–253. doi: 10.1023/A:1020638827640.

Wang, H. J. and Schmidt, P. (2002) 'One-step and two-step estimation of the effects of exogenous variables on technical efficiency levels', *Journal of Productivity Analysis*, 18(2), pp. 129–144. doi: 10.1023/A:1016565719882.

Wezel, T., Canta, M. and Luy, M. (2014) 'A Practical Example of the Nonperforming Loans Projection Approach to Stress Testing'.

Wheelock, D. C. and Wilson, P. W. (2018) 'The evolution of scale economies in US banking', *Journal of Applied Econometrics*, 33(1), pp. 16–28. doi: 10.1002/jae.2579.

Williams, J. (2004) 'Determining management behaviour in European banking', *Journal of Banking and Finance*, 28(10), pp. 2427–2460. doi: 10.1016/j.jbankfin.2003.09.010.

Windmeijer, F. (2005). "A Finite Sample Correction for the Variance of Linear Efficient two-Step GMM Estimators." *Journal of Econometrics* 126 (1): 25–51. doi:10.1016/j.jeconom.2004.02.005.

Xiang, D., Shamsuddin, A. and Worthington, A. C. (2013) 'The differing efficiency experiences of banks leading up to the global financial crisis : A comparative empirical analysis from Australia , Canada and the UK', *Journal Economic Finance*. doi: 10.1007/s12197-013-9258-y.

Yildirim, H. S. and Philippatos, G. C. (2007) 'Efficiency of banks: Recent evidence from the transition economies of Europe, 1993-2000', *European Journal of Finance*, 13(2), pp. 123–143. doi: 10.1080/13518470600763687.

Young, C. (2018a) 'Model Uncertainty and the Crisis in Science', *Socius: Sociological Research for a Dynamic World*, 4, p. 237802311773720. doi: 10.1177/2378023117737206.

Young, C. (2018b) 'The Difference Between Causal Analysis and Predictive Models: Response to "Comment on Young and Holsteen (2017)"', *Sociological Methods and Research*. doi: 10.1177/0049124118782542.

Young, C. and Holsteen, K. (2017) ‘Model Uncertainty and Robustness: A Computational Framework for Multimodel Analysis’, *Sociological Methods and Research*, 46(1), pp. 3–40. doi: 10.1177/0049124115610347.

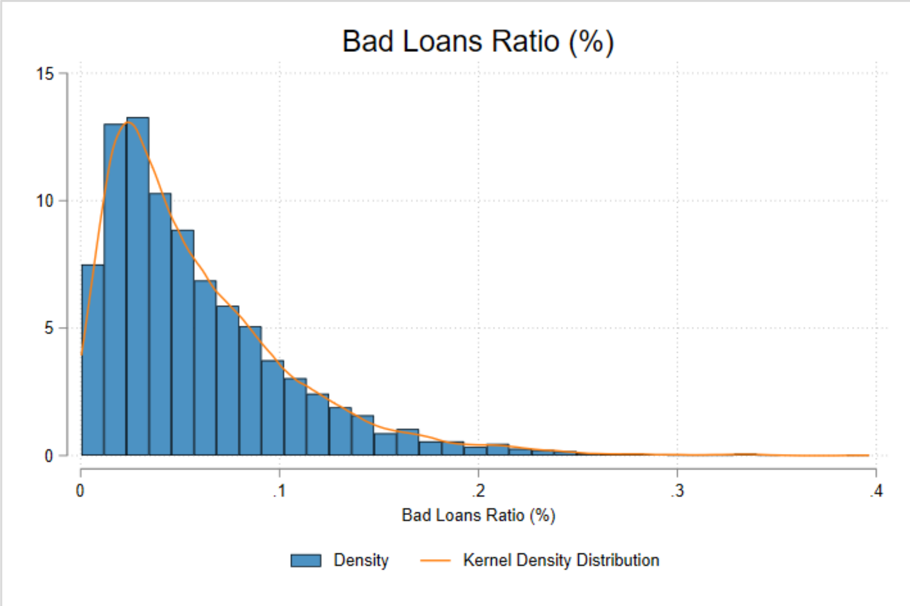
Zhang, D. et al. (2016) ‘Non-performing loans, moral hazard and regulation of the Chinese commercial banking system’, *Journal of Banking and Finance*, 63, pp. 48–60. doi: 10.1016/j.jbankfin.2015.11.010.

Zigraiova, D. and Havranek, T. (2016) ‘Bank Competition and Financial Stability: Much Ado About Nothing?’, *Journal of Economic Surveys*, 30(5), pp. 944–981. doi: 10.1111/joes.12131.

Appendix A – Chapter 1

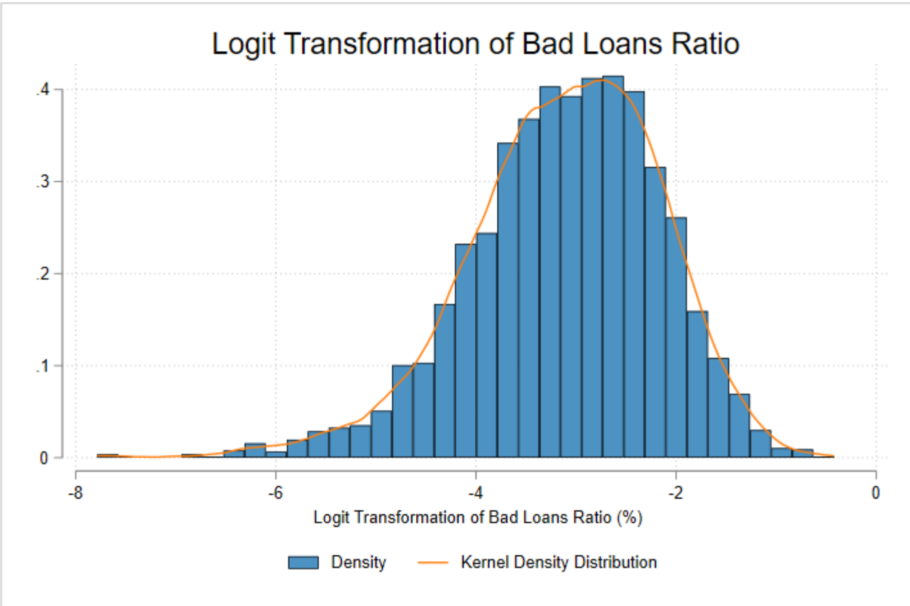
Appendix A1

Figure A1. Distribution of Bad Loans Ratio



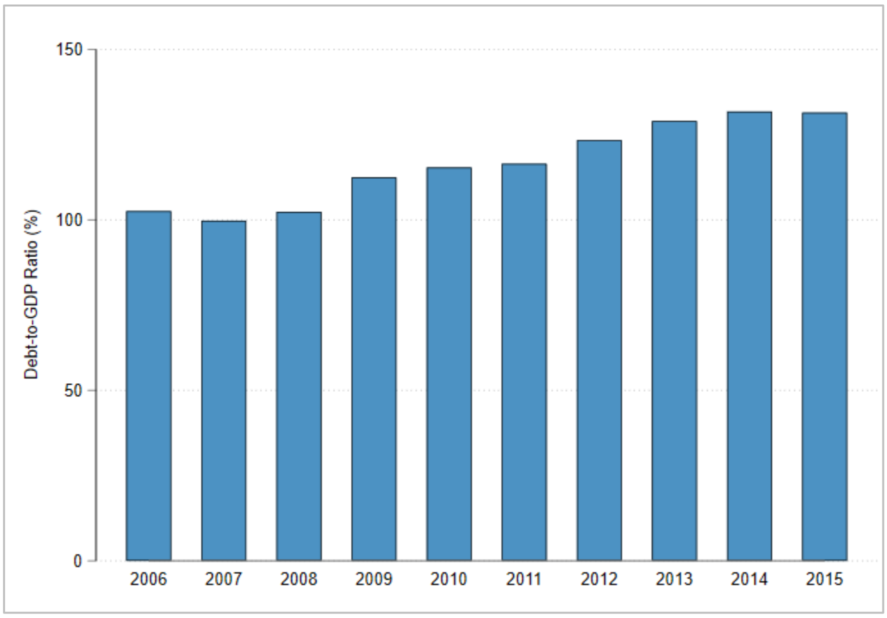
Source: Author's own calculations

Figure A2. Distribution of the Logit Transformation of Bad Loans Ratio



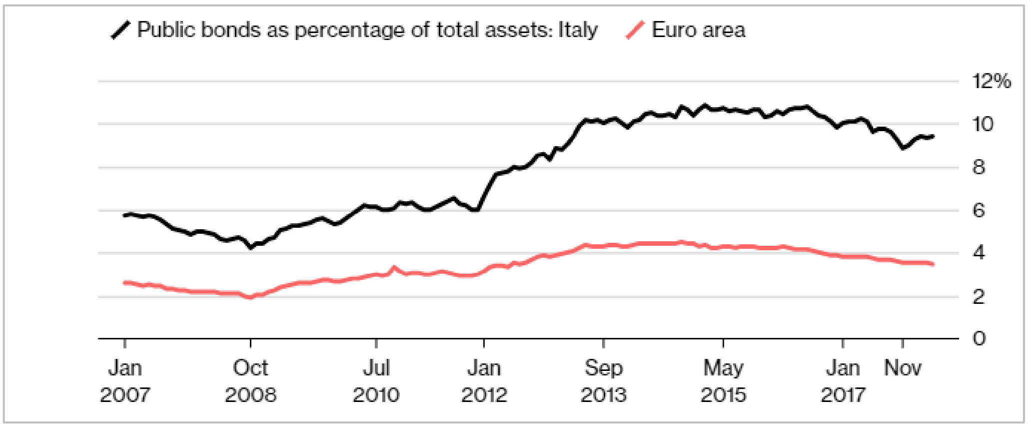
Source: Author's own calculations

Figure A3 Evolution of the Debt-to-GDP Ratio of Italy



Source: World Bank Open Data

Figure A4 Italian banks' holding of Government Bonds



Source: Bloomberg based on ECB data

Table A1 Number of Branches and Employees of Domestic Credit Institutions

	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Number of Branches	32,334	33,230	34,169	34,030	33,631	33,561	32,872	31,759	30,723	30,723
Number of Employees	339,091	340,443	338,035	323,407	320,327	316,360	309,478	306,607	299,684	299,684

Source: the data on the number of branches are from the 'EU Structural Financial Indicators' Report (2010, 2016). The data on the number of employees are from the 'Structural Indicators or the EU Banking Sector (2011, 2016).

Table A2. Parameters Estimates of the Fourier Cost Function

Parameter	Coefficients	Parameter	Coefficients
Intercept	1.388***	$cos\ (z_{lnY_2})$	0.338***
lnW_1	0.169***	$cos\ (z_{lnY_3})$	-0.156***
lnW_2	0.178***	$cos\ (z_{lnY_1} + z_{lnY_1})$	0.000
lnW_1^2	0.038***	$cos\ (z_{lnY_2} + z_{lnY_2})$	0.093***
lnW_2^2	0.009	$cos\ (z_{lnY_3} + z_{lnY_3})$	0.023
$lnW_1 \times lnW_2$	0.005	$cos\ (z_{lnY_1} + z_{lnY_2})$	0.035**
lnY_1	0.583***	$cos\ (z_{lnY_1} + z_{lnY_3})$	0.017
lnY_2	0.849***	$cos\ (z_{lnY_2} + z_{lnY_3})$	-0.089***
lnY_3	0.012	$sin\ (z_{lnY_1})$	0.075**
lnY_1^2	0.077***	$sin\ (z_{lnY_2})$	-0.014
lnY_2^2	0.027***	$sin\ (z_{lnY_3})$	0.028
lnY_3^2	0.019***	$sin(z_{lnY_1} + z_{lnY_1})$	-0.037**
$lnY_1 \times lnW_1$	-0.011*	$sin(z_{lnY_2} + z_{lnY_2})$	-0.000
$lnY_1 \times lnW_2$	-0.004	$sin(z_{lnY_3} + z_{lnY_3})$	0.057***
$lnY_1 \times lnY_2$	-0.141***	$sin(z_{lnY_1} + z_{lnY_2})$	0.082***
$lnY_1 \times lnY_3$	-0.017**	$sin(z_{lnY_1} + z_{lnY_3})$	0.019
$lnY_2 \times lnY_3$	0.010	$sin(z_{lnY_2} + z_{lnY_3})$	-0.078***
$lnY_2 \times lnW_1$	0.019***	t	-0.012***
$lnY_2 \times lnW_2$	0.025***	t^2	0.001***
$lnY_3 \times lnW_1$	0.005	lnE	-0.005
$lnY_3 \times lnW_1$	-0.022**	lnE^2	-0.002
$cos\ (z_{lnY_1})$	0.182***		

Note: ***, **, and * indicate the statistical significance at the 1, 5, and 10 %, respectively. The dependent variable is the natural log of total costs.

Appendix A2

A.2.1 The Generalized Method of Moments

In the above Eqs. (1.2) and (1.3) (Section 1.3.1), the introduction of the lagged dependent variable as a predictor renders the standard ordinary least squares and the within estimator inconsistent (see Nickell, 1981). Furthermore, it gives rise to endogeneity issues, thus making traditional panel data estimators (e.g., Ordinary Least Square, Fixed Effects) subject to econometric bias. Thus, we estimate them using the system generalised method of moments (SGMM) procedure proposed by Arellano and Bond (1991), Arellano and Bover (1995) and Blundell and Bond (1998).

We exemplify this methodology by rewriting the above Eqs. (1.2) and (1.3), in a reduced form and temporarily ignoring the lagged values of x for notational ease. A dynamic panel data model specification can be presented as Eq. (A.1)

$$y_{it} = \alpha_0 + \sum_p \gamma_p y_{it-p} + \beta X'_{it} + \eta_i + \varepsilon_{it} \quad i = 1, \dots, N, \quad p > 0, \tag{A.1}$$

Where the subscript i denotes the cross-sectional dimension of the panel, the subscript t refers to the time dimension, y is the dependent variable, X'_{it} is a vector of explanatory variables, η_i represents unobserved firms' specific effects and ε_{it} is the error term. One can identify two main sources of endogeneity that can arise when estimating the empirical model of Eq. (A.1):

- Simultaneity (Reverse Causality)
- Unobserved heterogeneity (Omitted Variable Bias)

Simultaneity

Econometrically, *simultaneity* exists when $E(\varepsilon_{it}|X_{it}) \neq 0$. Economically, it arises when there is reverse causality between the dependent variable and the explanatory variables. To exemplify this, consider the efficiency/NPLs relationship. As the *bad management* and the *skimping* hypotheses posit, the level of bank cost efficiency could determine the asset quality of banks. However, the reverse may also be true, as suggested by the *bad luck* hypothesis (see Section 1.5.3). That is, the level of NPLs, influencing the costs borne by financial intermediaries, may affect the observed cost efficiency. If this is the case, cost efficiency and NPLs are simultaneously determined and both OLS and fixed effects regression will be biased. In other words, in this setting, causality between risk and efficiency can run both ways, implying that they are endogenously determined (Delis et al., 2017).

As noted by Wintoki et al. (2012), one potential solution for the issue of reverse causality is estimating a system of equations. In the first equation, NPLs are allowed to depend on cost efficiency and other regressors whereas, in the second equation, efficiency is dependent on NPLs and other control variables. Nonetheless, Wintoki et al. (2012) point out the complexity of this strategy since one must identify strictly exogenous instruments, that is, there must be at least one variable in the NPLs equations that does not appear in the efficiency equation.

Unobserved Heterogeneity

Concerning the issue of unobservable heterogeneity, this exists if $E(\eta_i|X_{it},) \neq 0$. From an economic point of view, firms' heterogeneity is a source of endogeneity if there are factors (z), not explicitly modelled, that affect both NPLs and the explanatory variables. If this omitted variable is correlated with any of the independent variables (X_{it}), then the error term (ε_{it}) is correlated with the explanatory variables, thus violating the key OLS assumption of no correlation between right-hand side variables and the error term. A potential solution would be a fixed-effects or "within" estimation, which requires time-demeaning all variables in order to remove the firms' effects (i.e., it involves subtracting the individual's mean value of y and X from the respective variable). That is, consider the following model:

$$y_t = \beta x_t + \eta + \varepsilon_{it} \quad \text{A.2}$$

Where η refers to an unobserved fixed effect. By applying the within transformation, we obtain:

$$\ddot{y}_t = \beta \ddot{x}_t + \varepsilon_{it} \quad \text{A.3}$$

Where $\ddot{x} = x_{it} - \bar{x}_i$ and $\ddot{y} = y_{it} - \bar{y}_i$.

Although the within estimator addresses the issue of unobserved heterogeneity by eliminating firm-specific effects, it does not eliminate dynamic panel bias. In this respect, Nickell (1981) shows that the time-demeaning process creates a correlation between explanatory variables and the error term, also known as the Nickell bias. That is, employing the within estimators yields the following model (Eq. A.4):

$$(y_{it} - \bar{y}_i) = \alpha(y_{it-1} - \bar{y}_{i-1}) + \beta(x_{it} - \bar{x}_i) + (\varepsilon_{it} - \bar{\varepsilon}_i) = \qquad \text{A.4}$$

Where $\bar{y}_i = \frac{\sum_t y_{it}}{T_i}$, $\bar{y}_{i-1} = \sum_{t=2}^{T} \frac{y_{it-1}}{T} - 1$, $\bar{x}_i = \frac{\sum_t x_{it}}{T_i}$, and $\bar{v}_i = \frac{\sum_t v_{it}}{T_i}$.

In Eq. (A.4), y_{it-1} is still correlated with $\bar{v}_i$ as the latter average contains the term v_{it-1} which is correlated with y_{it-1}. In light of this limitation of the within estimator, Anderson and Hsiao (1981) propose an instrumental variable (IV) estimator based on the first-difference equation that takes the form of Eq. (A.5):

$$\Delta y_{it} = \alpha_0 + \gamma_p \sum_p \Delta y_{it-p} + \beta \Delta X'_{it} + \Delta\varepsilon_{it} \quad i = 1, \dots, N, \quad p > 0; \ |\alpha| < 1; \qquad \text{A.5}$$

Where Δ is the first difference operator (i.e., $\Delta y_{it} = y_{it} - y_{it-1}$). By first-differencing, we eliminate any potential bias that may arise from the presence of unobserved heterogeneity (fixed effects). In Eq. (A.5), the natural candidate instruments for the lagged dependent variable are the second and third lags of y_{it}, either in levels or in difference. Specifically, Anderson and Hsiao (1981) suggest using $\Delta y_{it-2} = (y_{it-2} - y_{it-3})$ or simply y_{it-2} as an instrument for $\Delta y_{it-1} = (y_{it-1} - y_{it-2})$. In this case, these instruments will not be correlated with $\Delta v_{it} = v_{it} - v_{it-1}$ as long as the v_{it} are not serially correlated (see for an extensive discussion Baltagi, 2005; and Roodman, 2009a). In this regard, it is worth noting that a key insight of the dynamic estimator is that we can rely on a set of "internal" instruments contained within the panel itself to assess current variations in the dependent variable, that is, y_{it-p}, X_{t-k} where $k > p$ (see Wintoki et al., 2012).

For these instruments to be valid, they need to meet two criteria: *relevance* and *exclusion*. The *relevance condition* requires that the instruments are correlated with the endogenous regressors, that is, they must provide a source of variation for current values of the endogenous explanatory variables. With respect to the *exclusion condition*, the past values must be exogenous, that is, uncorrelated, with the error term. In other words, they must provide an exogenous source of variation for the current values of these explanatory variables. If the exogeneity assumption is valid, then we can write the following orthogonality conditions:

$$E(x_{it-s}\Delta\varepsilon_{it}) = E(y_{it-s}\Delta\varepsilon_{it}) = 0, \forall s > p \qquad \text{A.6}$$

We now estimate Equation (A.6) together with the above orthogonality conditions by using historical values of the explanatory variables as instruments for current changes in these variables.

However, the first-differencing procedure suffers from several econometric shortcomings:

- First, Arellano and Bond (1991) argue that the instrumental variable (IV) estimator of Anderson and Hsiao (1981), despite providing consistent estimates, fails to exploit all the potential orthogonality conditions (zero correlation) that exist between lagged values of y_{it} and ε_{it}
- Second, Arellano and Bover (1995) note that variables in levels may be weak instruments for first-differenced equations if the variables are close to a random walk.
- Third, Beck et al. (2000) argue that if the original model is conceptually in levels, first-differencing may reduce the power of our test by reducing the variation in the explanatory variables.
- Finally, fist-differencing may exacerbate the impact of measurement errors on the dependent variable (Griliches and Hausman, 1986).

To mitigate the above-mentioned limitations arising from first-differencing, Arellano and Bover (1995) and Blundell and Bond (1998) suggest including in the estimation procedure also the equation in levels, producing a "system GMM" estimator that involves estimating the following system of equations:

$$\begin{bmatrix} y_{it} \\ \Delta y_{it} \end{bmatrix} = \alpha + \gamma \begin{bmatrix} y_{it-p} \\ \Delta y_{it-p} \end{bmatrix} + \beta \begin{bmatrix} X'_{it} \\ \Delta X'_{it} \end{bmatrix} + \varepsilon_{it} \qquad \text{A.7}$$

Estimating the system of equations allows us to use the first-differenced variables as instruments for the equation in levels in a "stacked" system of equations that incorporates the equations both in levels and differences. However, the level equation still includes unobserved heterogeneity. To address this issue, we assume that the correlation between the explanatory variables and heterogeneity is constant over time, which is a plausible assumption in short panels. This assumption leads to an additional set of orthogonality conditions:

$$E(\Delta x_{it-s}(\eta_i + \varepsilon_{it}) = E(\Delta y_{it-s}(\eta_i + \varepsilon_{it}) = 0, \forall s > p \qquad \text{A.8}$$

We can now carry out system GMM estimation by employing the orthogonality conditions (A.6) and (A.8) and by assuming no serial correlation in the error term ε_{it}. These orthogonality conditions imply that we can now exploit lagged levels of our explanatory variables as instruments in the differenced equation and lagged differences as instruments for the level equation, respectively.

A.2.2 Origins and development of Stochastic Frontier Analysis

The Stochastic Frontier Analysis finds its origin in the two papers of Aigner et al. (1977) and Meeusen and van den Broeck (1977).[106] These two original SFA models were developed using a production frontier context and share the composed error structure. These specifications can be expressed as:

$$y = f(x, \beta) \cdot \exp[v - u]. \qquad \text{A.9}$$

Where y is scalar output, x is a vector of inputs and β is a vector of technology parameters. The composed error $v \sim N(0, \sigma_v^2)$ capture the statistical noise whilst $u \geq 0$ is meant to capture the inefficiency effects.

The specification of Equation (A.9) can be converted to a stochastic cost frontier by changing the sign of the inefficiency error component u, as in Equation (B.10):

$$E = c(y, w, \beta) \cdot \exp[v + u]. \qquad \text{A.10}$$

Where E represents expenditure, $c(y, w, \beta) \cdot \exp[v]$ is the stochastic cost frontier and u is the inefficiency effect.

The key feature and the main advantage of the SFA methodology relate to the decomposition of the error term. By having two error components, SFA models can discriminate between deviations from the best-practice frontier due to institutions' inefficiency (e.g., poor management) and deviations attributable to random shocks. In other words, SFA models assume that deviations from the optimal frontier could be attributed to both managerial inefficiency and factors beyond the control of management. This is in contrast with nonparametric techniques (e.g., DEA), which assume that all deviations between actual costs and the minimum costs of the frontier are due to inefficient behaviour, that is, they do not permit random error (Maudos et al., 2002; Delis et al., 2009).

Concerning the developments of SFA specifications, the first generation of SFA models (see, for instance, the early specifications of Pitt and Lee, 1981; Schmidt and Sickles, 1984; Kumbhakar, 1987; and Battese and Coelli, 1988) is

[106] The literature that directly influenced the development of SFA was the theoretical literature on productive efficiency, which started in the 1950s with the work of Koopmans (1951), Debreu (1951) and Shepard (1953). (Kumbhakar and Lovell, 2003).

generally characterised by restrictive assumptions about the nature of the inefficiency term. For instance, these early specifications assume the inefficiency to be time-invariant, that is, constant over time (u_i). This assumption is rather restrictive and hard to justify if we consider the current widespread availability of long panels of data (Greene, 2008; Belotti et al., 2013). Furthermore, time-invariant models have ignored the potential role of firms' heterogeneity in the estimation of inefficiency while other model specifications interpreted firm-specific effects as time-invariant inefficiency (e.g., Schmidt and Sickles, 1984). Finally, early SFA models also failed to consider the potential heteroskedasticity of the two error terms, that is, they rely on the assumption that v_{it} and u_i are homoskedastic (i.e., σ_u^2 and σ_v^2 are constant). In this respect, Kumbhakar and Lovell (2000) point out that ignoring heteroskedasticity may lead to inconsistent parameter estimates. Specifically, ignoring heteroskedasticity in the one-sided error term u_i causes both the parameters to be estimated θ and the firm-specific efficiency scores to be biased. Similarly, ignoring heteroscedasticity in the noise term v_i produces biased efficiency scores and downward biased intercept α.

The restrictive nature of the above-mentioned assumptions and the availability of panel data have encouraged developments in the efficiency literature. To relax the assumption of homoskedasticity, Caudill and Ford (1993) and Caudill et al. (1995) suggest parametrizing the variance of the inefficiency term by a vector of observable variables and associated parameters (Eq. (A.11)):

$$u_{it} \sim N^+\left(0, \sigma_{uit}^2\right) \text{ where } \sigma_{uit}^2 = \exp(z_{it}'\psi). \qquad \text{A.11}$$

Where, z_i' is a vector of exogenous variables, that is, the variance is considered a function of some environmental exogenous factors that affect efficiency. For instance, Caudill et al. (1995) parametrize the variance of the inefficiency component in terms of the number of bank branches, an indicator for the regulatory environment of the state where the US bank is located, an indicator for the institution type (i.e., commercial banks, saving and loans banks, mutual banks).

This last specification was subsequently expanded by Hadri (1999) who also parametrizes the variance of the noise term, Eq. (A.12):

$$v_{it} \sim N\left(0, \sigma_{vit}^2\right) \text{ where } \sigma_{vit}^2 = \exp(h_{it}'\phi). \qquad \text{A.12}$$

Where h_{it}' is a vector of exogenous variables that do not appear necessarily in z_{it}'.[107]

By parametrizing the variance of the inefficiency and noise term, these models not only account for potential heteroskedasticity but also address the issue of exogenous determinants of inefficiency that could directly influence the efficiency estimates. Other model specifications that introduce exogenous variables into the estimation process are those of Kumbhakar et al. (1991), Huang and Liu (1994) and Battese and Coelli (1995), who, however, propose to parametrise the mean of the inefficiency term (see Eq. (A.13)):

$$u_{it} \sim N^{+}(\mu_{it}, \sigma_u^2) \text{ where } \mu_{it} = z_i'\psi. \qquad \text{A.13}$$

The model of Battese and Coelli (1995) is the most frequently used in empirical studies (see, for example, Pasiouras et al., 2009; Xiang et al., 2013; Casu et al., 2017)

Finally, Wang (2002) proposes to parametrise both the mean and the variance of the inefficiency term u_{it}, that is, the mean and the variance become a function of z_{it} and h_{it} exogenous variables. Wang proved that parametrizing both the mean and the variance of u_{it} allows for non-monotonic efficiency effects, which can better describe the data and are more informative for regulatory purposes (Wang, 2002; Kumbhakar et al., 2014).[108] It is interesting to point out that the specifications of Kumbhakar et al. (1991), Huang and Liu (1994) and Battese and Coelli (1995) in which variances are assumed to be constant are all special cases of the Wang (2002) model.

[107] Note that the Equations (A.11) and (A.12) differ in terms of the error components that has been parametrised. Indeed, in Equation (A.11) the variance of the *inefficiency* term is made a function of exogenous variables while in Equation (A.12) the variance of the *random* noise is parametrised.

[108] By non-monotonic effects, Wang (2002) means that the "z_{it} can have, within a sample, *both* positive and negative effects on the […] efficiency, and that the sign of the effect depends on values of z_{it} (p. 243). [That is] while a farmer's age could represent experiences helpful in improving production efficiency, an old farmer is nevertheless likely to have a deteriorated mental and physical capacity, resulting in a negative efficiency effect. In this example, a young farmer's efficiency may improve as he matures, but the age factor eventually becomes detrimental to efficiency in the farmer's later years. Ignoring the non-monotonicity in this aspect can render estimation results imprecise at best and misleading at worst (p. 242)".

As aforementioned, one of the limitations of early SFA specifications relates to the fact that they do not control for firm-specific effects. With respect to this issue, the models of Kumbhakar (1991), Kumbhakar and Heshmati (1995) and Kumbhakar and Hjalmarsson (1993, 1995) represent the first attempts to explicitly control for heterogeneity across firms. They treat firm-specific effects as time-invariant (persistent) inefficiency by claiming that firms' characteristics that are likely to remain fixed over a short time span could be captured by the persistent inefficiency error term. The model takes the form of Eq. (A.14):

$$lnTC_{it} = f(y_{it}, w_{it}, \theta) + v_{it} + \eta_i + u_{it} \qquad \text{A.14}$$

Where v_{it} is the standard noise, $\eta_i \geq 0$ represents the firm's persistent technical inefficiency and $u_{it} \geq 0$ is the time-varying inefficiency. The overall technical inefficiency is $\eta_i + u_{it}$. In other words, they disentangle firm-specific effects from time-varying inefficiency, by proposing a three-component model that can separate inefficiency into time-varying and time-invariant. Subsequently, Kumbhakar and Wang (2005) introduced a model specification with firm-specific intercept α_i, as in Eq. (A.15):

$$lnTC_{it} = \alpha_i + f(y_{it}, w_{it}, \theta) + v_{it} + u_{it} \qquad \text{A.15}$$

In this specification, firm effects α_i are not considered as part of the inefficiency term. That is, by assuming that firm-effects do not include inefficiency (without any explanation), this model can separate time-varying inefficiency from firm heterogeneity (Kumbhakar et al., 2014).

In addition, Greene (2005a,b) introduces two model specifications to disentangle firm heterogeneity from inefficiencies, the so-called "true" fixed-effect frontier and the "true" random-effect frontier model (see Eq. (A.16):

$$lnTC_{it} = (\alpha + \omega_i) + f(y_{it}, w_{it}, \theta) + v_{it} + u_{it} \qquad \text{A.16}$$

Nonetheless, one criticism of these two last model specifications (A.15 and A.16) is that they consider the producer-specific, time-invariant component as unobserved heterogeneity, that is, long-run (persistent) inefficiency is confounded with latent heterogeneity (see Kumbhakar et al., 2014).

Finally, with regard to the most recent advancements in the SFA literature, the specifications of Colombi et al. (2011), Kumbhakar et al. (2014) and Tsionas and Kumbhakar (2014) introduce a generalized SFA framework that disentangles the error term into four components in order to distinguish firm heterogeneity from time-varying and time-invariant inefficiency. (Eq. (A.17))**:**

$$lnTC_{it} = f(y_{it}, w_{it}, \theta) + v_{0i} + u_{0i} + v_{it} + u_{it} \qquad \text{A.17}$$

Where v_{it} is the standard noise that captures random shocks, v_{0i} denotes the firms' latent heterogeneity, u_{0i} represents the long-run/persistent/time-invariant inefficiency while the u_{it} term captures short-run/time-varying inefficiency. Indeed, prior stochastic frontier models either incorporated firm heterogeneity but failed to accommodate persistent inefficiency (e.g., Greene, 2005; Kumbhakar and Wang, 2005) or included persistent inefficiency without separating it from firm effects (e.g., Kumbhakar, 1991; Kumbhakar and Heshmati, 1995; Kumbhakar and Hjalmarsson, 1993,1995). As noted by Tsionas and Kumbhakar (2014), failing to accommodate these components is likely to give incorrect inefficiency estimates. Furthermore, previous studies have relied on the questionable assumption that inefficiency is either time-varying (e.g., Battese and Coelli, 1995; Wang, 2002) or time-invariant (e.g., Pitt and Lee, 1981; Schmidt and Sickles, 1984; Battese and Coelli, 1992). Nonetheless, both of these specifications have shortcomings. In fact, on the one hand,

> "time-varying inefficiency models treat inefficiency as a period-specific random variable without considering the possible presence of some elements leading to long-lasting (i.e., time-invariant) effects on firms' inefficiency (Colombi et al., 2011, p. 2)".

On the other hand, time-invariant stochastic specifications assume that inefficiency is constant over time and that firms are unable to remove in the short-term any sources of inefficiency. However,

> "it is more sensible to assume that the firm may recover part of its inefficiency by removing some sources having short-run effects, while some other sources of inefficiency stay with the firm over time (Colombi et al., 2011, p. 3)".

Overall, the four-error model in Eq. (A.17) improves over prior specifications by assuming that there could be unobserved time-invariant factors (i.e., firm effects) that are not related to inefficiency and by relaxing the restrictive assumption that efficiency is either transient or persistent (see Kumbhakar et al., 2014 and Badunenko and Kumbhakar, 2017). The model specification of Equation (A.17) has been labelled the "homoskedastic four-component model". Indeed, despite its appealing features, this model fails to accommodate determinants of inefficiency as v_{0i}, u_{0i}, v_{it}, u_{it} are assumed to be independently and identically distributed random variables (i.i.d.). To address this limitation, Badunenko and Kumbhakar (2017) have recently introduced the "heteroskedastic four-component model", which is the one employed in Chapter 1 of this Thesis.

References - Appendix A

Anderson, T.W. and Hsiao, C., (1981). Estimation of dynamic models with error components. *Journal of the American Statistical Association*, 76(375), pp.598-606.

Aigner, D., Lovell, C. A. K. and Schmidt, P. (1977) 'Formulation And Estimation Of Stochastic Frontier Production Function Models', *Journal of Econometrics*, 6, pp. 21–37.

Badunenko, O. and Kumbhakar, S. C. (2017) 'Economies of scale, technical change and persistent and time-varying cost efficiency in Indian banking: Do ownership, regulation and heterogeneity matter?', *European Journal of Operational Research*, 260(2), pp. 789–803. doi: 10.1016/j.ejor.2017.01.025.

Baltagi, B. H. (2005) *Econometric Analysis of Panel Data*. John Wiley & Sons Ltd.

Battese, G.E. and Coelli, T.J., (1988). Prediction of firm-level technical efficiencies with a generalized frontier production function and panel data. *Journal of econometrics*, 38(3), pp.387-399.

Battese, G. E. and Coelli, T. J. (1995) 'A model for technical inefficiency effects in a stochastic frontier production function for panel data', *Empirical Economics*, 20(2), pp. 325–332. doi: 10.1007/BF01205442.

Belotti, F., Daidone, S., Ilardi, G., & Atella, V. (2013). Stochastic Frontier Analysis using Stata. The Stata Journal, 13(4), 719–758. https://doi.org/10.1177/1536867X1301300404

Casu, B., Deng, B. and Ferrari, A. (2017) 'Post-crisis regulatory reforms and bank performance: lessons from Asia', *European Journal of Finance*, 23(15), pp. 1544–1571. doi: 10.1080/1351847X.2016.1177566.

Caudill, S. B. and Ford, J. M. (1993) 'Biases in frontier estimation due to heteroscedasticity', *Economics Letters*, 41(1), pp. 17–20. doi: 10.1016/0165-1765(93)90104-K.

Caudill, S. B., Ford, J. M. and Gropper, D. M. (1995) 'Frontier estimation and firm-specific inefficiency measures in the presence of heteroscedasticity', *Journal of Business and Economic Statistics*, 13(1), pp. 105–111. doi: 10.1080/07350015.1995.10524583.

Colombi, R., Martini, G. and Vittadini, G. (2011) 'A stochastic frontier model with short-run and long-run inefficiency random effects', *Department of Economics and Technology Management, University of Bergamo*.

Delis, M., Iosifidi, M. and Tsionas, M. G. (2017) 'Endogenous bank risk and efficiency', *European Journal of Operational Research*, 260(1), pp. 376–387. doi: 10.1016/j.ejor.2016.12.024.

Greene, William (2005) 'Fixed and Random Effects in Stochastic Frontier', *Journal* *of Productivity Analysis*, (1984), pp. 7–32.

Greene, W. (2005) ‘Reconsidering heterogeneity in panel data estimators of the stochastic frontier model’, *Journal of Econometrics*, 126, pp. 269–303. doi: 10.1016/j.jeconom.2004.05.003.

Greene, William H., (2008). 'The Econometric Approach to Efficiency Analysis', in Harold O. Fried, C. A. Knox Lovell, and Shelton S. Schmidt (eds) The Measurement of Productive Efficiency and Productivity Change. (New York, 2008; online edn, Oxford Academic, 1 Jan. 2008), https://doi.org/10.1093/acprof:oso/9780195183528.003.0002

Griliches, Z. and Hausman, J.A., (1986). Errors in variables in panel data. *Journal of econometrics*, 31(1), pp.93-118.

Hadri, K. (1999) ‘Estimation of a Doubly Heteroscedastic Stochastic Frontier Cost Function’, *Journal of Business & Economic Statistics*, 17(3), p. 359. doi: 10.2307/1392293.

Huang, C. J. and Liu, J. T. (1994) ‘Estimation of a non-neutral stochastic frontier production function’, *Journal of Productivity Analysis*, 5(2), pp. 171–180. doi: 10.1007/BF01073853.

Kumbhakar, S.C., (1987). The specification of technical and allocative inefficiency in stochastic production and profit frontiers. *Journal of econometrics*, 34(3), pp.335-348.

Kumbhakar, S. C. (1991) ‘Estimation of technical inefficiency in panel data models with firm- and time-specific effects’, *Economics Letters*, 36(1), pp. 43–48. doi: 10.1016/0165-1765(91)90053-N.

Kumbhakar, S. C. and Heshmati, A. (1995) ‘Efficiency Measurement in Swedish Dairy Farms: An Application of Rotating Panel Data, 1976-88’, *American Journal of Agricultural Economics. August*, 77(3), pp. 660–674. doi: 10.2307/1243233.

Kumbhakar, S. C. and Hjalmarsson, L. (1995) ‘Labour-Use Efficiency in Swedish Social Insurance Offices’, *Journal of Applied Econometrics*, 10(10), pp. 33–47.

Kumbhakar, S. C., Lien, G. and Hardaker, J. B. (2014) ‘Technical efficiency in competing panel data models: A study of Norwegian grain farming’, *Journal of Productivity Analysis*, 41(2), pp. 321–337. doi: 10.1007/s11123-012-0303-1.

Kumbhakar, S. C. and Wang, H. J. (2005) ‘Estimation of growth convergence using a stochastic production frontier approach’, *Economics Letters*, 88(3), pp. 300–305. doi: 10.1016/j.econlet.2005.01.023.

Nickell, S., (1981). Biases in dynamic models with fixed effects. *Econometrica: Journal of the econometric society*, pp.1417-1426.

Pasiouras, F., Tanna, S. and Zopounidis, C. (2009) 'The impact of banking regulations on banks' cost and profit efficiency: Cross-country evidence', *International Review of Financial Analysis*, 18(5), pp. 294–302. doi: 10.1016/j.irfa.2009.07.003.

Pitt, M.M. and Lee, L.F., (1981). The measurement and sources of technical inefficiency in the Indonesian weaving industry. *Journal of development economics*, 9(1), pp.43-64.

Roodman, D. (2009) 'How to do xtabond2: An introduction to difference and system GMM in Stata', *The Stata Journal*, 9(1), pp. 86–136.

Schmidt, P. and Sickles, R.C., (1984). Production frontiers and panel data. *Journal of Business & Economic Statistics*, 2(4), pp.367-374.

Tsionas, E. G. and Kumbhakar, S. C. (2014) 'Firm Heterogeneity, Persistent And Transient Technical Inefficiency: A Generalized True Random-Effects Model', *Journal of Applied Econometrics*, 29, pp. 110–132. doi: 10.1002/jae.

Wang, H. J. (2002) 'Heteroscedasticity and non-monotonic efficiency effects of a stochastic frontier model', *Journal of Productivity Analysis*, 18(3), pp. 241–253. doi: 10.1023/A:1020638827640.

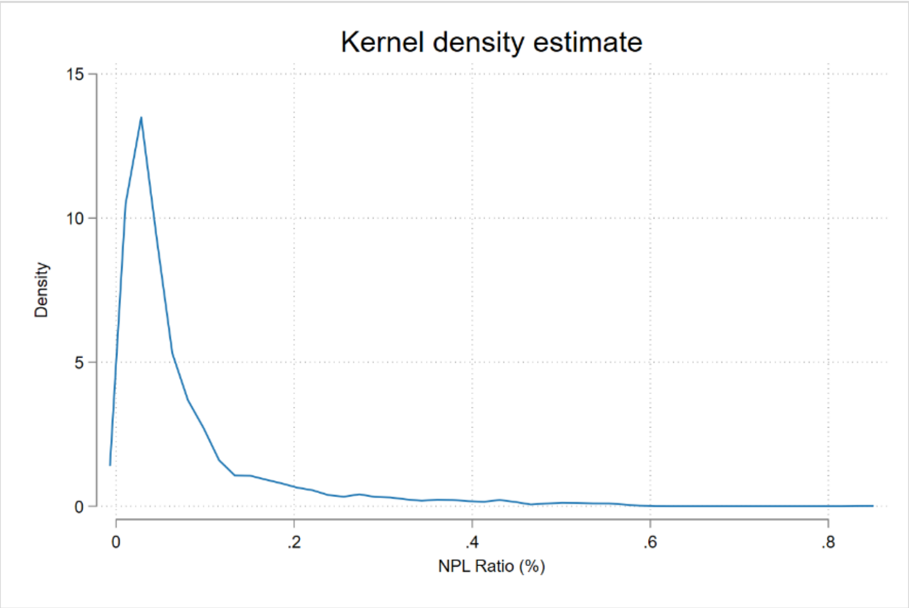
Wintoki, M. B., Linck, J. S. and Netter, J. M. (2012) 'Endogeneity and the dynamics of internal corporate governance', *Journal of Financial Economics*, 105(3), pp. 581–606. doi: 10.1016/j.jfineco.2012.03.005.

Xiang, D., Shamsuddin, A. and Worthington, A. C. (2013) 'The differing efficiency experiences of banks leading up to the global financial crisis : A comparative empirical analysis from Australia , Canada and the UK', *Journal Economic Finance*. doi: 10.1007/s12197-013-9258-y.

Appendix B – Chapter 2

Figure B1 Density Graphs of NPLs and NPLs Logit

Panel A. NPLs Ratio



Panel B. Logit Transformation

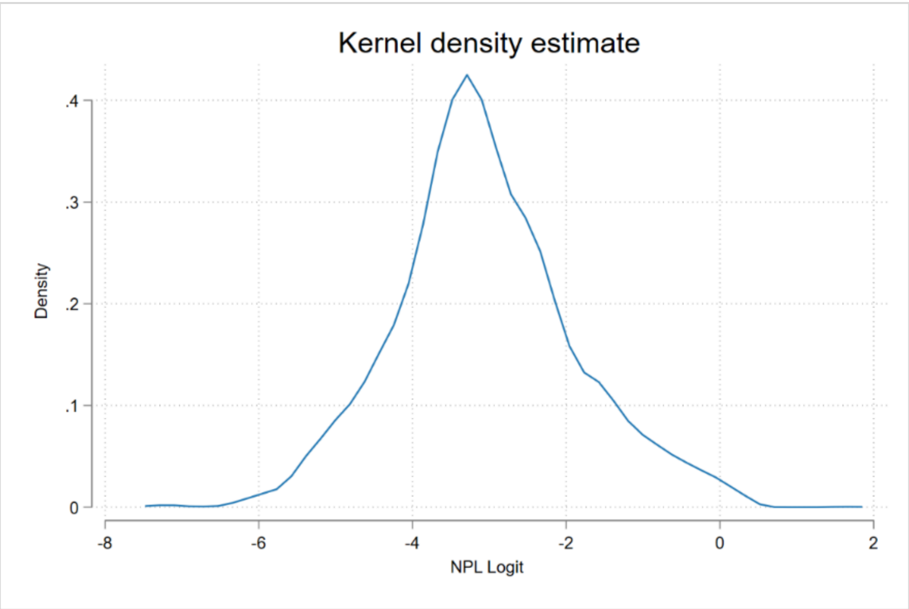
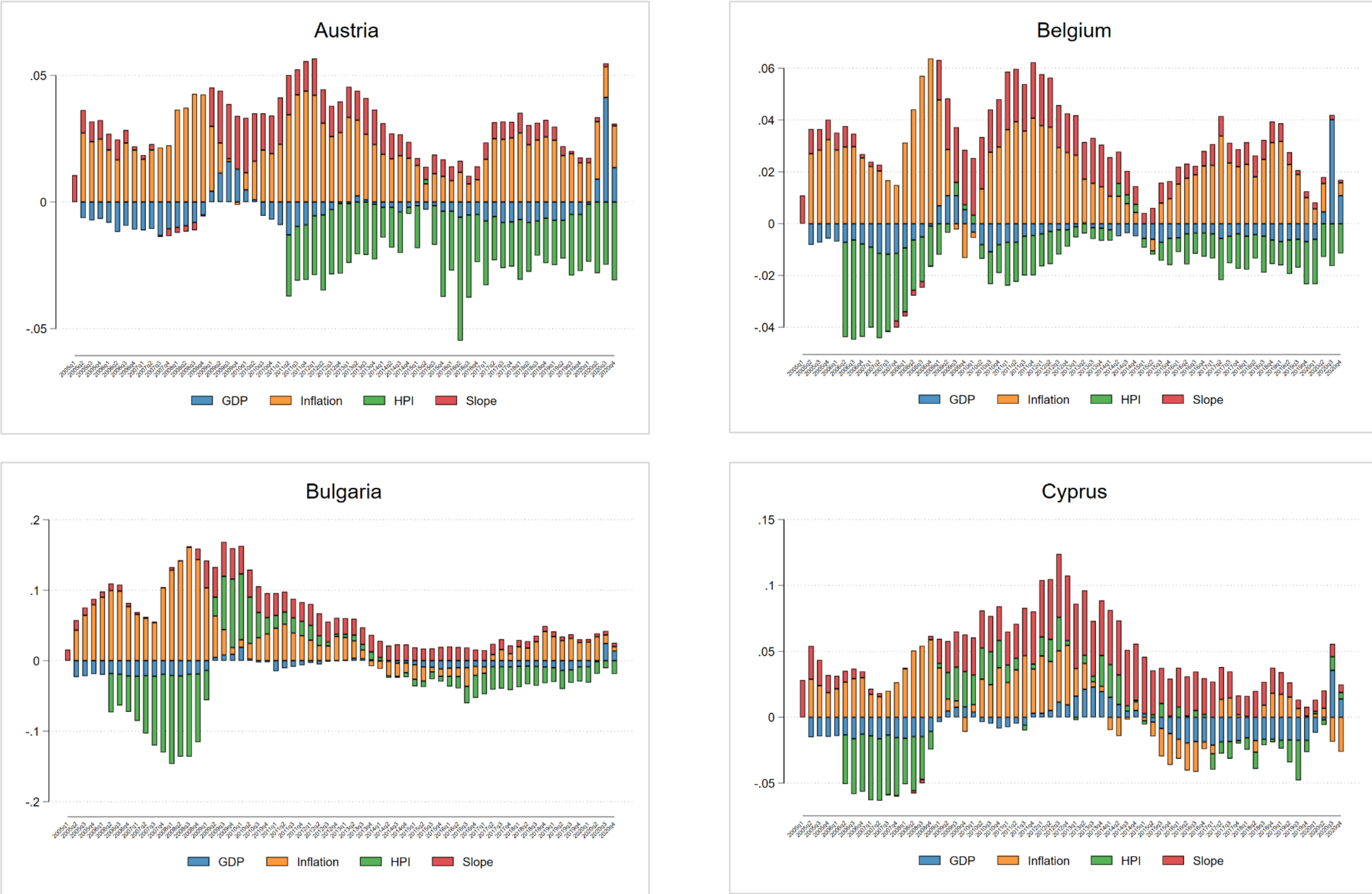
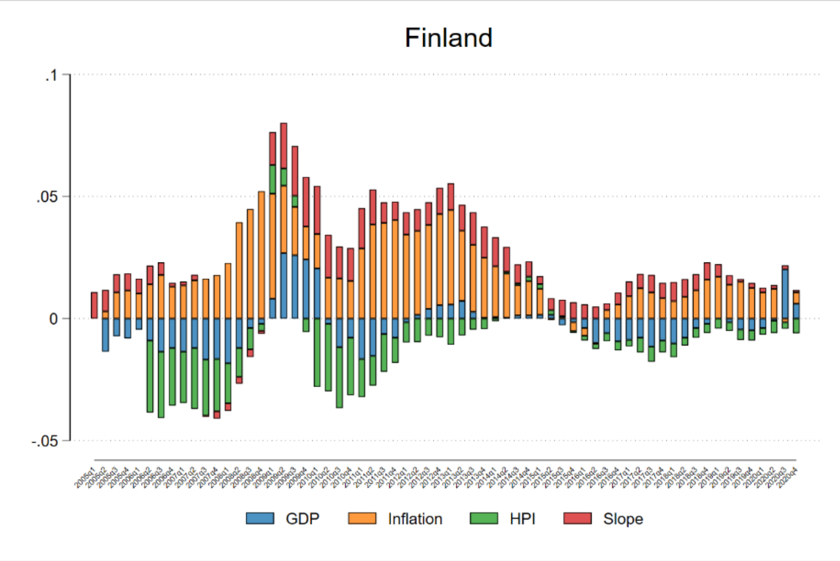


Figure B2 Contribution of macroeconomic variables to the NPL Model

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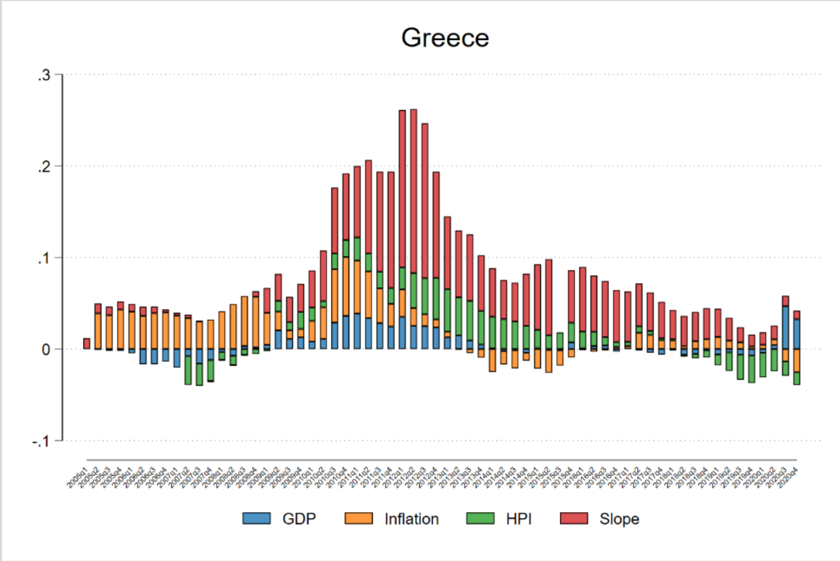
.1
.05
0
-.05
GDP
Inflation
HPI
Slope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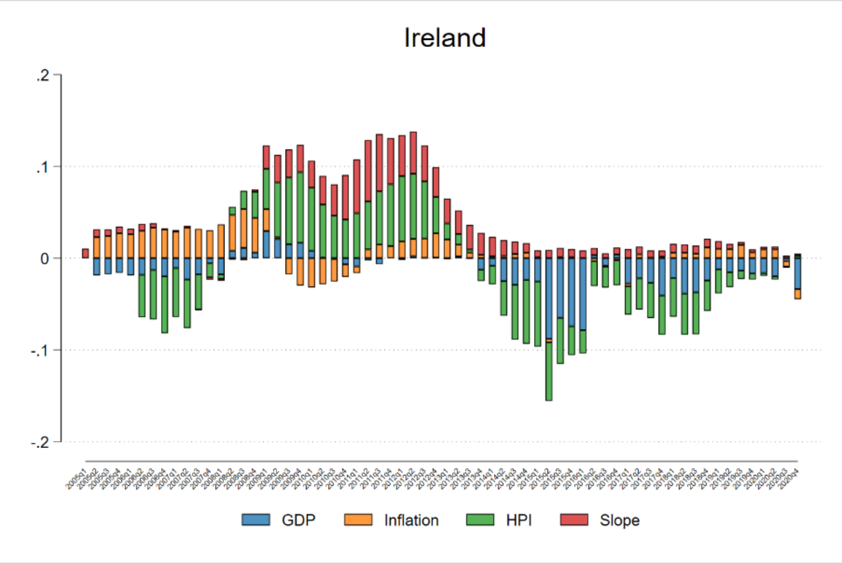
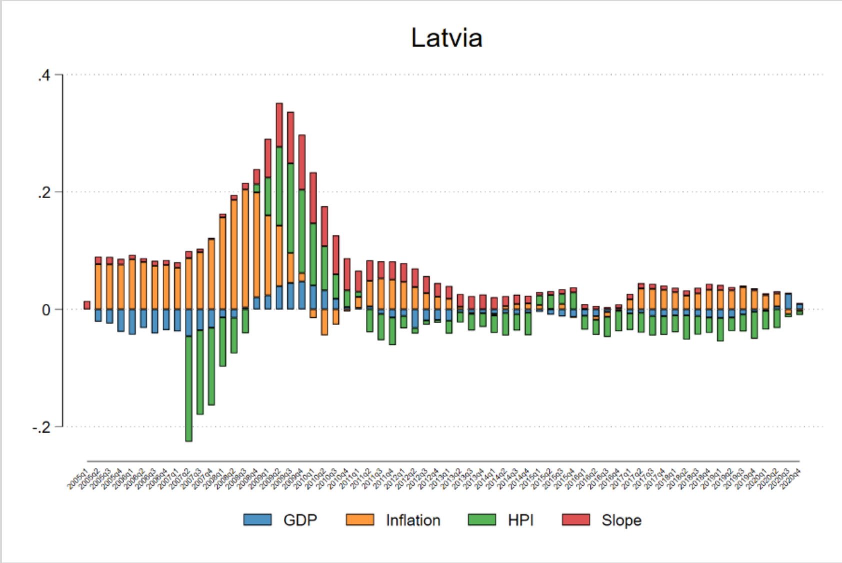
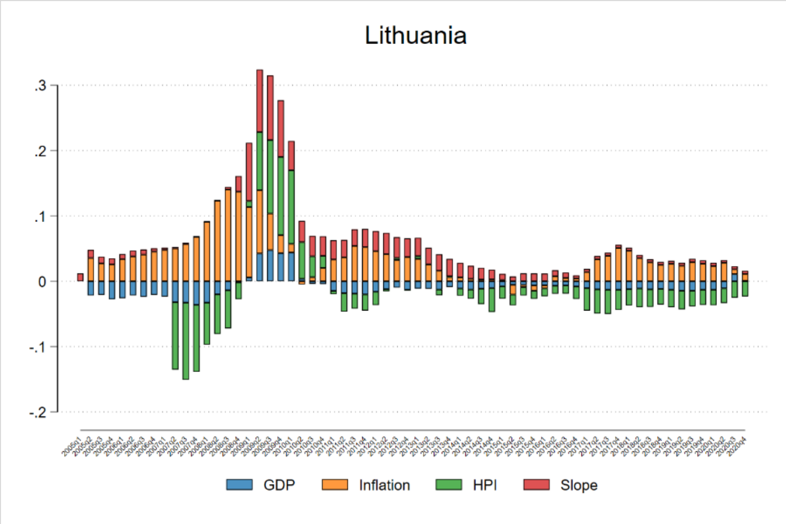
.2
.1
0
-.1
GDP
Inflation
HPI
Slope


Ireland
.2
.1
0
-.1
-.2
GDP
Inflation
HPI
Slope


Latvia
.4
.2
0
-.2
GDP
Inflation
HPI
Slope


Lithuania
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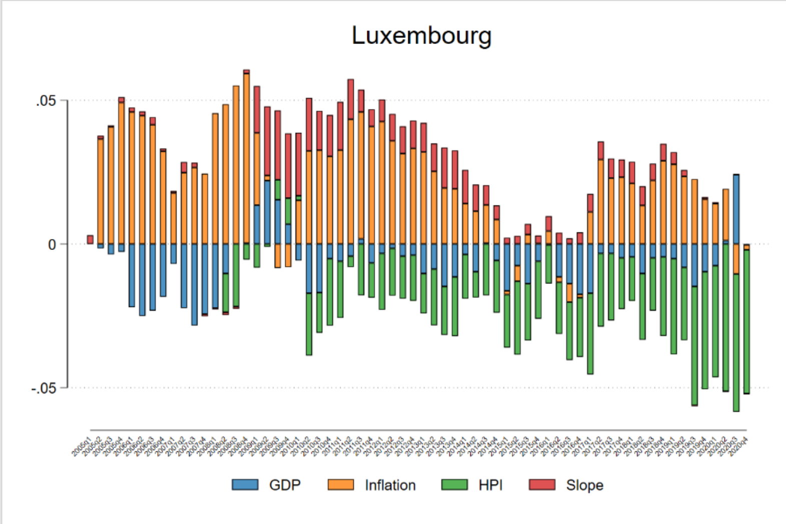
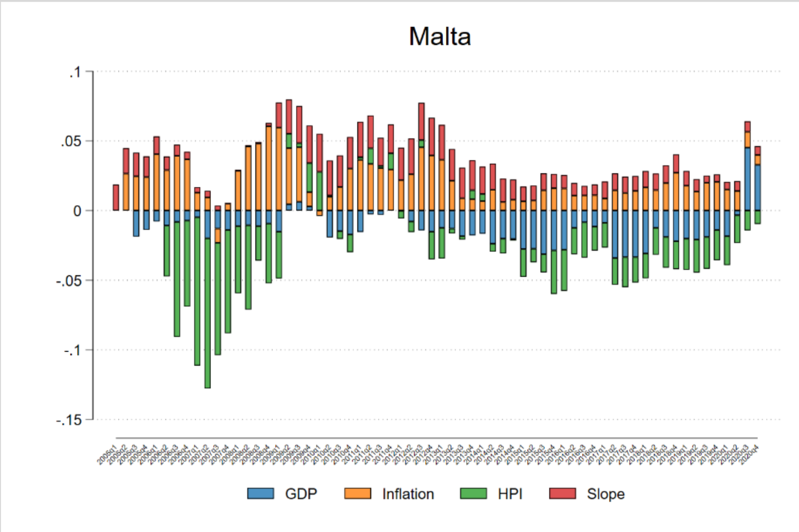
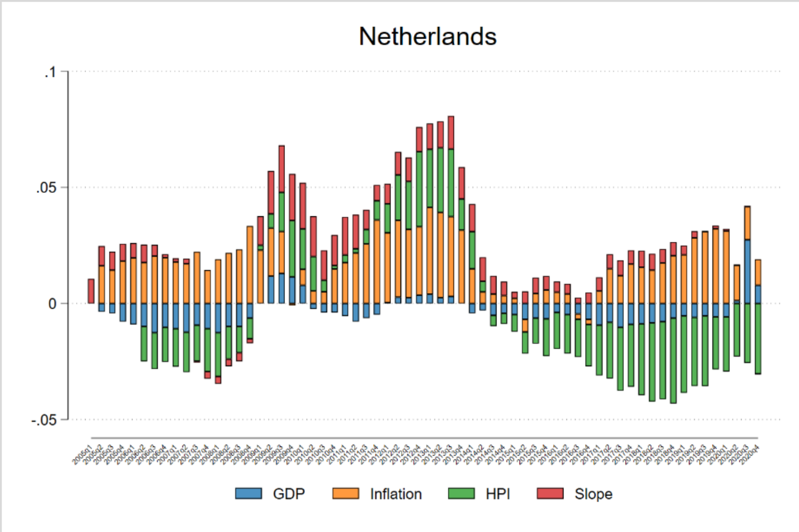
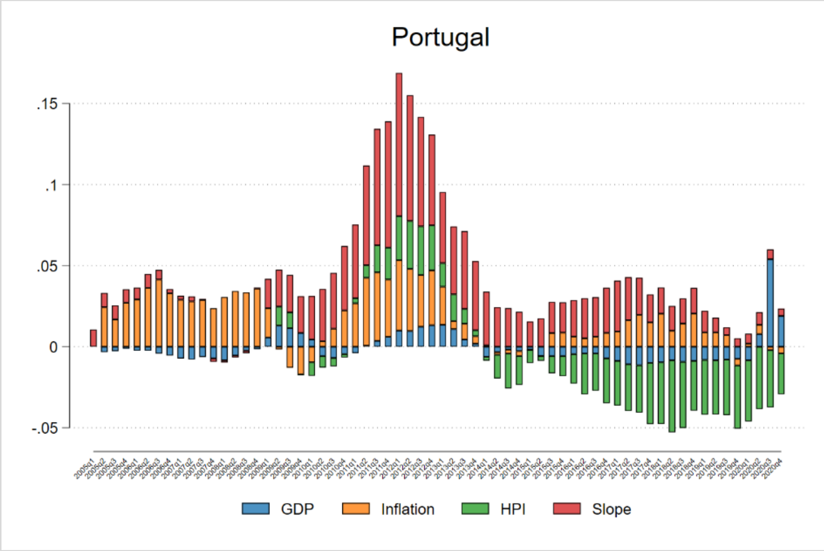
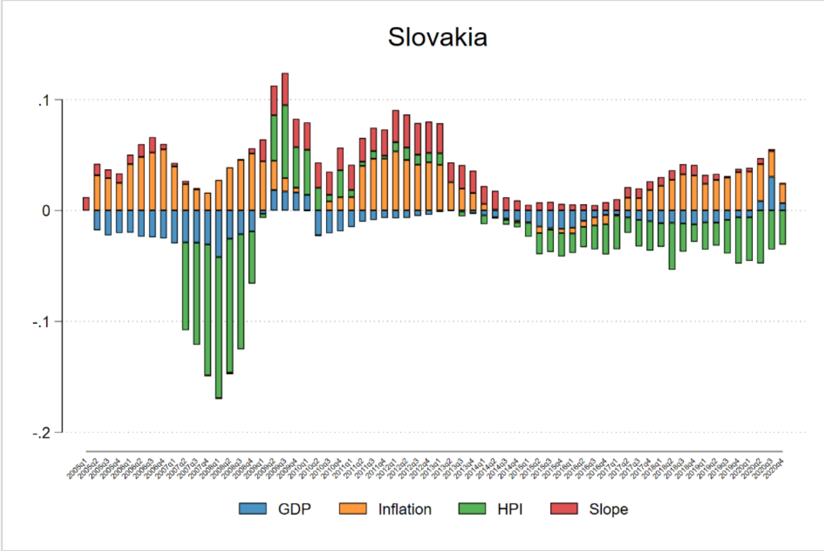
.2
.1
0
-.1
-.2
GDP
Inflation
HPI
Slope


Luxembourg
.05
0
-.05
GDP
Inflation
HPI
Slope


Malta
.1
.05
0
-.05
-.1
-.15
GDP
Inflation
HPI
Slope


Netherlands
.1
.05
0
-.05
GDP
Inflation
HPI
Slope


Portugal
.15
.1
.05
0
-.05
GDP
Inflation
HPI
Slope


Slovakia
.1
0
-.1
-.2
GDP
Inflation
HPI
Slope

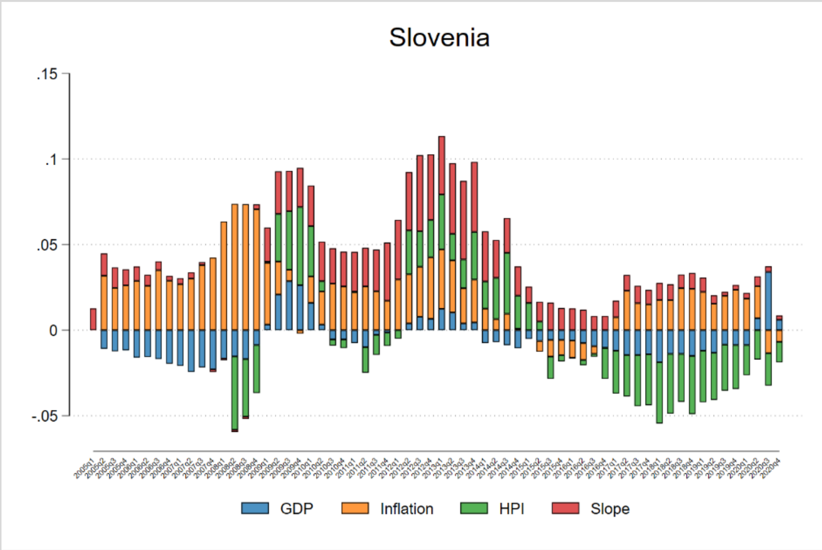
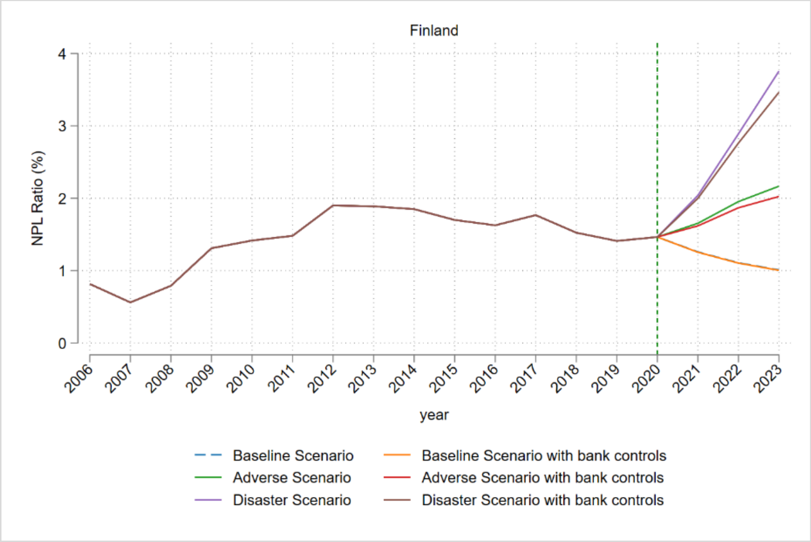
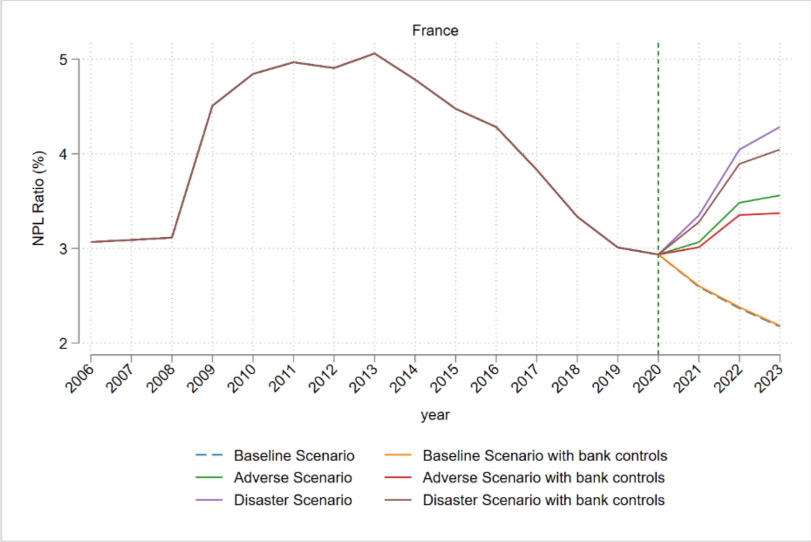

Slovenia
.15
.1
.05
0
-.05
GDP
Inflation
HPI
Slope

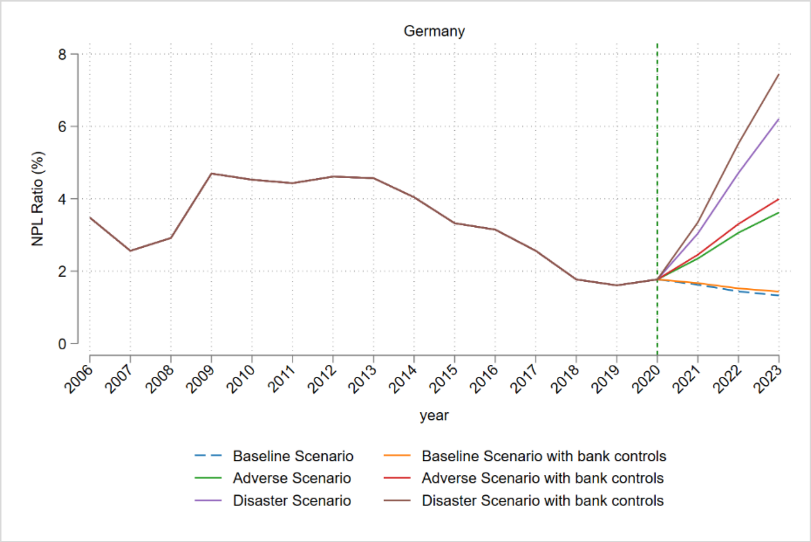
Figure B3 Weighted NPL Ratios at the country level



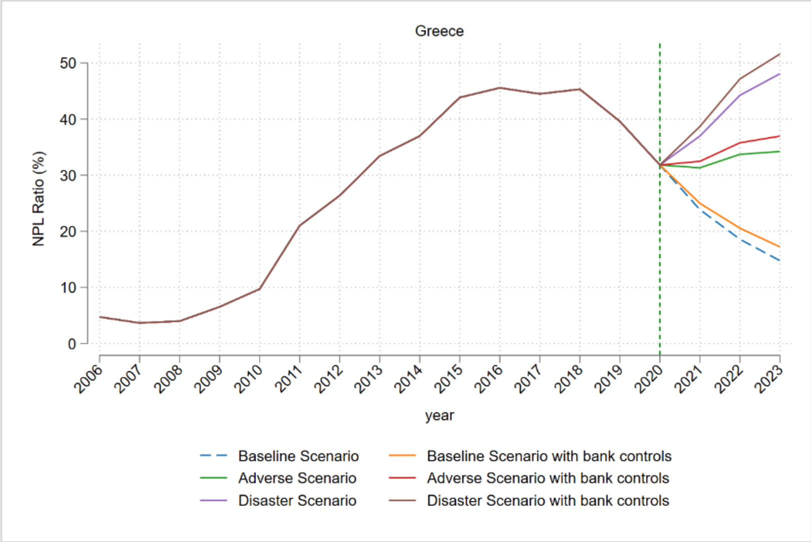
Finland
NPL Ratio (%)
0
1
2
3
4
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019
2020
2021
2022
2023
year
Baseline Scenario
Adverse Scenario
Disaster Scenario
Baseline Scenario with bank controls
Adverse Scenario with bank controls
Disaster Scenario with bank controls



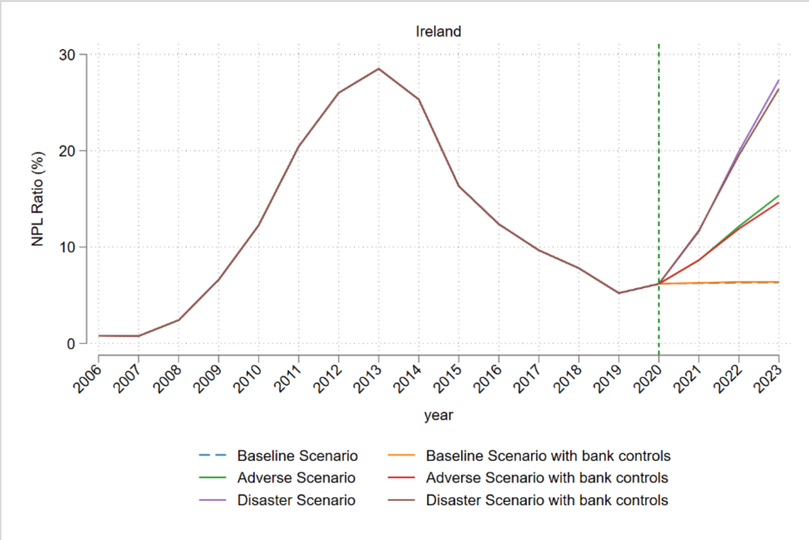
France
NPL Ratio (%)
2
3
4
5
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019
2020
2021
2022
2023
year
Baseline Scenario
Adverse Scenario
Disaster Scenario
Baseline Scenario with bank controls
Adverse Scenario with bank controls
Disaster Scenario with bank controls

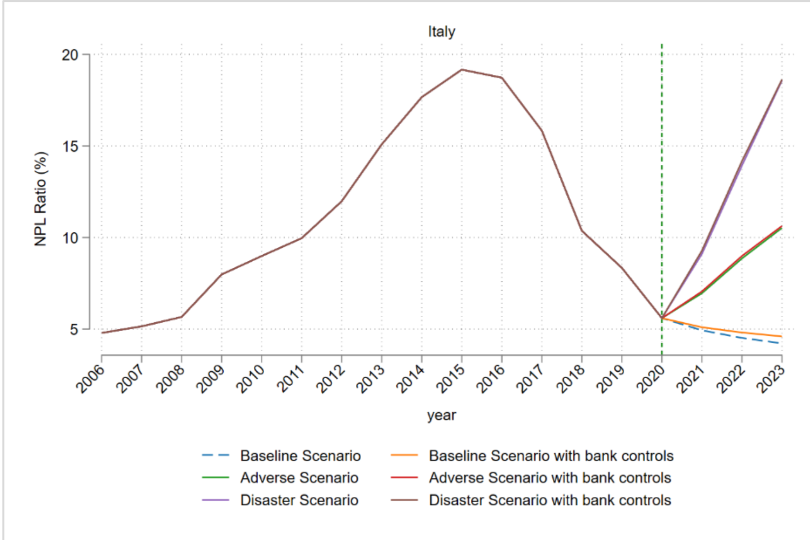


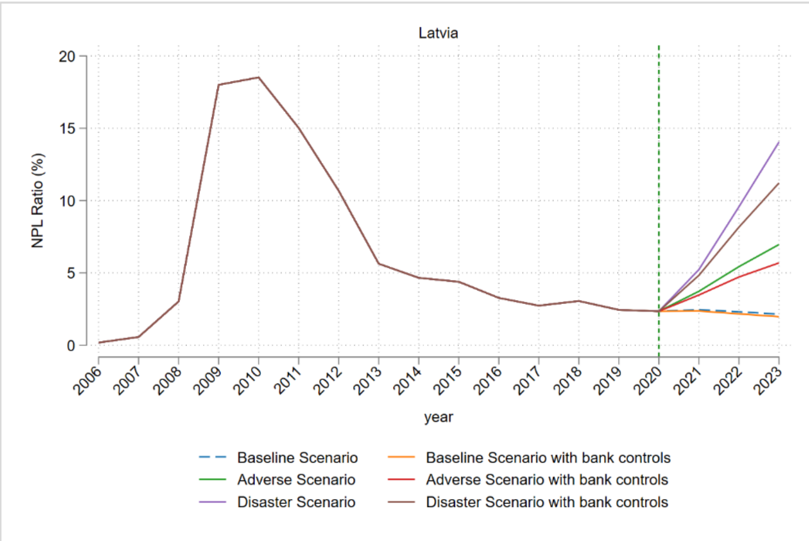
Germany
NPL Ratio (%)
0
2
4
6
8
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019
2020
2021
2022
2023
year
Baseline Scenario
Adverse Scenario
Disaster Scenario
Baseline Scenario with bank controls
Adverse Scenario with bank controls
Disaster Scenario with bank controls

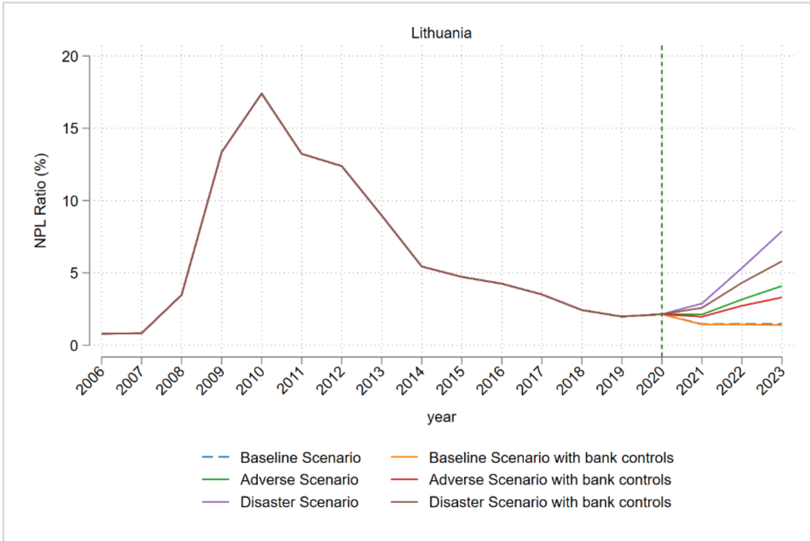


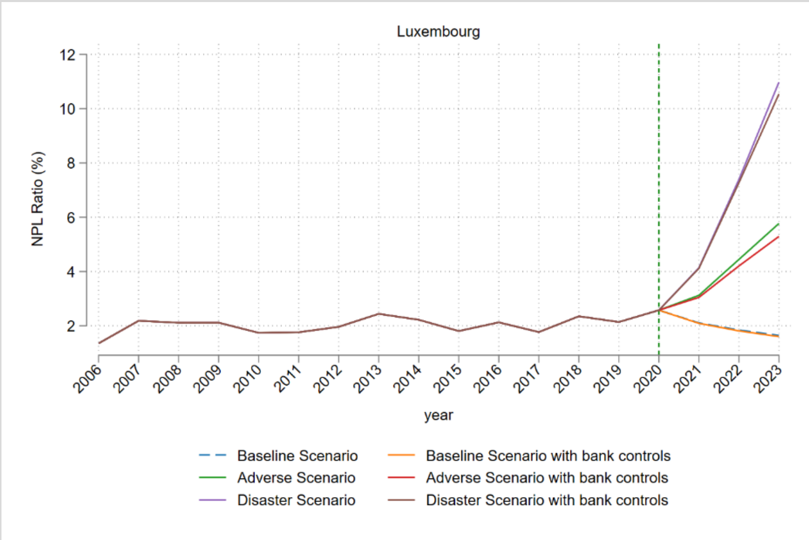
Greece
NPL Ratio (%)
0
10
20
30
40
50
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019
2020
2021
2022
2023
year
Baseline Scenario
Adverse Scenario
Disaster Scenario
Baseline Scenario with bank controls
Adverse Scenario with bank controls
Disaster Scenario with bank controls


Ireland
NPL Ratio (%)
year
Baseline Scenario
Adverse Scenario
Disaster Scenario
Baseline Scenario with bank controls
Adverse Scenario with bank controls
Disaster Scenario with bank controls

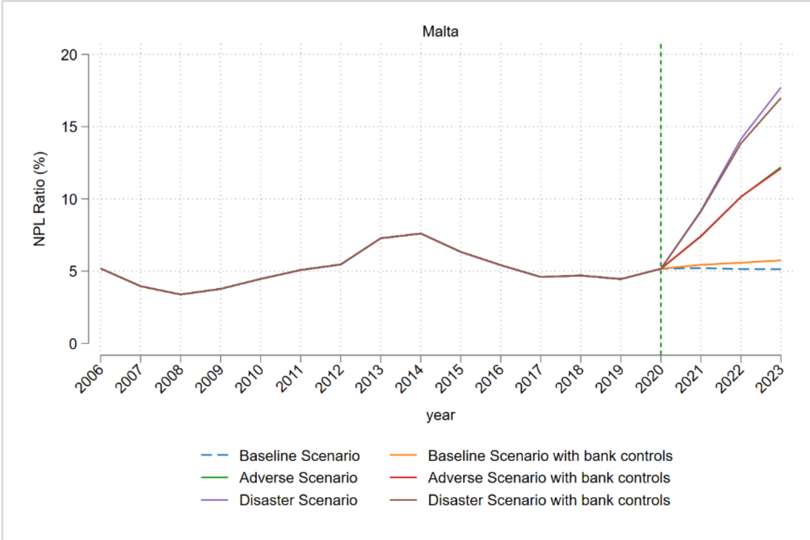

Italy
NPL Ratio (%)
year
Baseline Scenario
Adverse Scenario
Disaster Scenario
Baseline Scenario with bank controls
Adverse Scenario with bank controls
Disaster Scenario with bank controls


Latvia
NPL Ratio (%)
year
Baseline Scenario
Adverse Scenario
Disaster Scenario
Baseline Scenario with bank controls
Adverse Scenario with bank controls
Disaster Scenario with bank controls

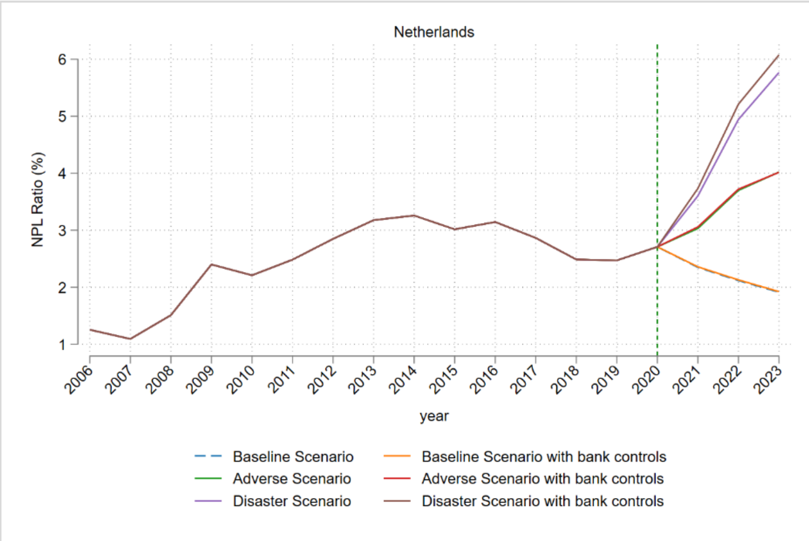

Lithuania
NPL Ratio (%)
year
Baseline Scenario
Adverse Scenario
Disaster Scenario
Baseline Scenario with bank controls
Adverse Scenario with bank controls
Disaster Scenario with bank controls



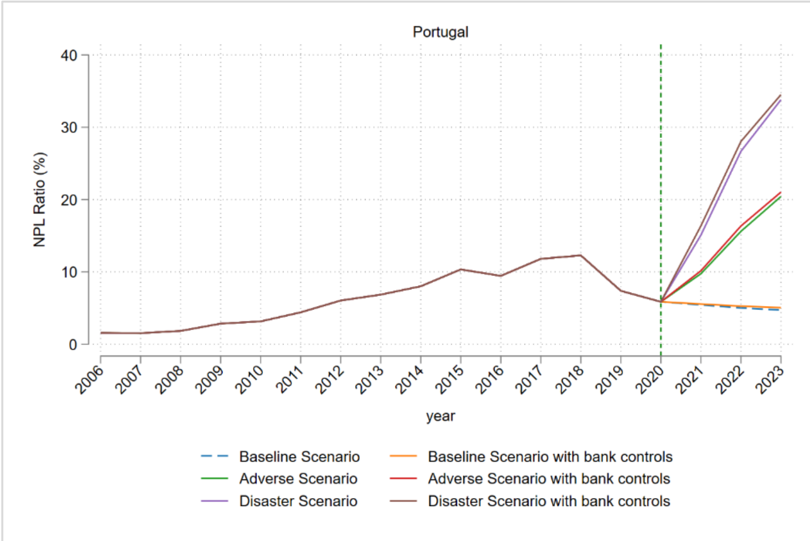
Luxembourg
NPL Ratio (%)
year
Baseline Scenario
Adverse Scenario
Disaster Scenario
Baseline Scenario with bank controls
Adverse Scenario with bank controls
Disaster Scenario with bank controls



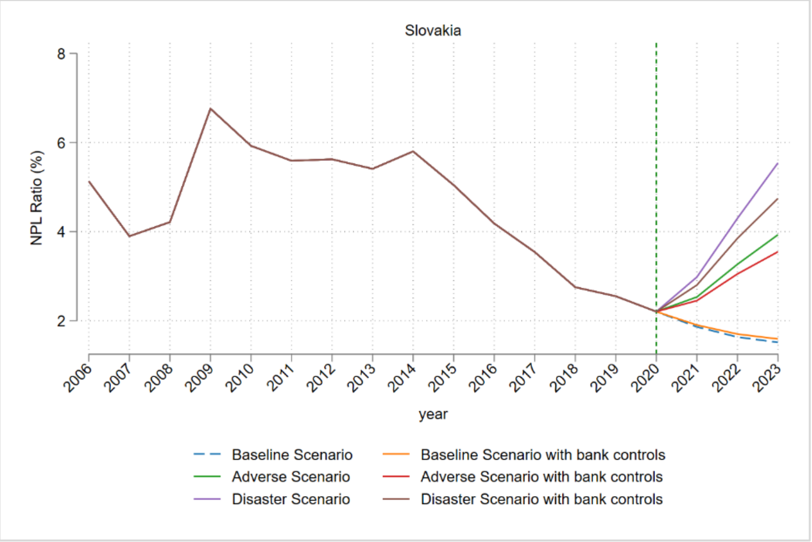
Malta
NPL Ratio (%)
year
Baseline Scenario
Adverse Scenario
Disaster Scenario
Baseline Scenario with bank controls
Adverse Scenario with bank controls
Disaster Scenario with bank controls

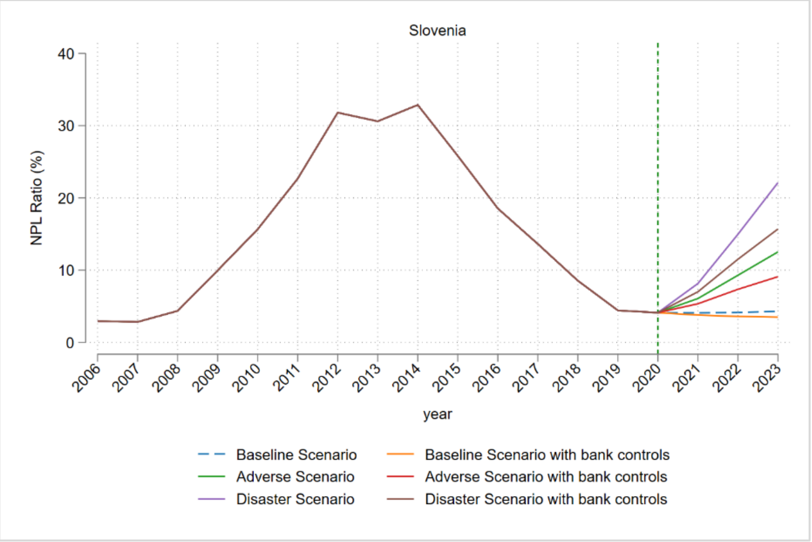


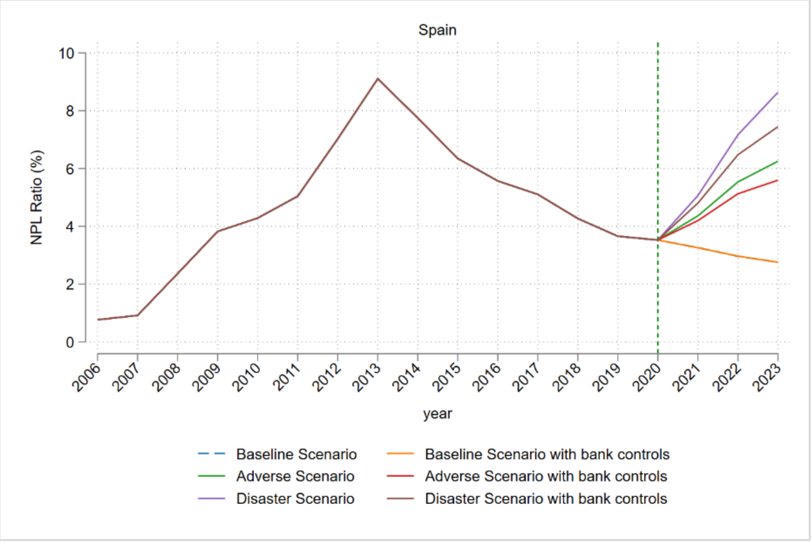
Netherlands
NPL Ratio (%)
year
Baseline Scenario
Adverse Scenario
Disaster Scenario
Baseline Scenario with bank controls
Adverse Scenario with bank controls
Disaster Scenario with bank controls



Portugal
NPL Ratio (%)
year
Baseline Scenario
Adverse Scenario
Disaster Scenario
Baseline Scenario with bank controls
Adverse Scenario with bank controls
Disaster Scenario with bank controls


Slovakia
NPL Ratio (%)
year
Baseline Scenario
Adverse Scenario
Disaster Scenario
Baseline Scenario with bank controls
Adverse Scenario with bank controls
Disaster Scenario with bank controls


Slovenia
NPL Ratio (%)
year
Baseline Scenario
Adverse Scenario
Disaster Scenario
Baseline Scenario with bank controls
Adverse Scenario with bank controls
Disaster Scenario with bank controls


Spain
NPL Ratio (%)
year
Baseline Scenario
Adverse Scenario
Disaster Scenario
Baseline Scenario with bank controls
Adverse Scenario with bank controls
Disaster Scenario with bank controls

Appendix C – Chapter 3

Table C1 Baseline Regressions - Dynamic Model

	(1) $\Delta Loans$	(2) $\Delta Loans$	(3) $\Delta Loans$	(4) $\Delta Loans$
$Net\ Loans\ Growth$	0.0832*	-0.0032	0.0339	-0.0239
	(0.0464)	(0.0402)	(0.0433)	(0.0400)
$\boldsymbol{Tier\ 1\ Ratio}$	**-0.1291**	**-0.0322**	**-0.1580**	**-0.0720**
	(0.1314)	**(0.1678)**	**(0.1363)**	**(0.1694)**
$Size$	-0.1150***	-0.0710***	-0.1000***	-0.0721**
	(0.0317)	(0.0257)	(0.0321)	(0.0274)
ROA	1.5677***	1.1341***	0.7719**	0.8767***
	(0.4030)	(0.3396)	(0.3411)	(0.3313)
NPL	-0.3868***	-0.3976***	-0.4785***	-0.4197***
	(0.0746)	(0.0795)	(0.1039)	(0.1028)
$Liquid\ Assets$	0.2424***	0.1077	0.1763**	0.0865
	(0.0728)	(0.0693)	(0.0707)	(0.0705)
$Deposit\ Ratio$	-0.0426	-0.0406	-0.0824	-0.0875
	(0.0585)	(0.0745)	(0.0580)	(0.0729)
$Diversification$	0.0258	-0.0331	-0.0047	-0.0497
	(0.0393)	(0.0307)	(0.0364)	(0.0300)
$Cost-to-income$	-0.0245	-0.0350	-0.0400	-0.0585**
	(0.0273)	(0.0241)	(0.0255)	(0.0252)
$GDP\ Growth$			0.0064***	0.0040**
			(0.0014)	(0.0017)
$Inflation$			-0.0203***	-0.0151***
			(0.0032)	(0.0044)
$Unemployment$			-0.0008	0.0011
			(0.0020)	(0.0025)
$Euribor$			0.0070*	
			(0.0037)	
$Resolving\ Insolvency$			-0.0386	-0.0519**
			(0.0235)	(0.0226)
Adj R-square	0.1980	0.2957	0.2379	0.2978
Obs	985	985	971	971
Bank FE	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes
No of firms	90	90	90	90

Note: The table displays the estimates of the coefficients of Eq. 3.7 with a lagged dependent variable. The dependent variable is the year-on-year growth rate of net loans during the period 2006-2020. All the explanatory variables are lagged by one year. The standard errors are clustered at the bank level and are reported in parentheses. "YES" indicates that the set of fixed effects is included. ***, **, and * denote that estimates are statistically significant at the 1%, 5% and 10% levels