ALMA MATER STUDIORUM
UNIVERSITÀ DI BOLOGNA

ARCHIVIO ISTITUZIONALE
DELLA RICERCA

Alma Mater Studiorum Università di Bologna
Archivio istituzionale della ricerca

Do capital buffers matter? Evidence from the stocks and flows of nonperforming loans

This is the final peer-reviewed author's accepted manuscript (postprint) of the following publication:

Published Version:
Cicchiello, A.F., Cotugno, M., Perdichizzi, S., Torluccio, G. (2022). Do capital buffers matter? Evidence from the stocks and flows of nonperforming loans. INTERNATIONAL REVIEW OF FINANCIAL ANALYSIS, 84, 1-14 [10.1016/j.irfa.2022.102369].

Availability:
This version is available at: https://hdl.handle.net/11585/894003 since: 2022-09-13

Published:
DOI: http://doi.org/10.1016/j.irfa.2022.102369

Terms of use:

Some rights reserved. The terms and conditions for the reuse of this version of the manuscript are specified in the publishing policy. For all terms of use and more information see the publisher's website.

This item was downloaded from IRIS Università di Bologna (https://cris.unibo.it/).
When citing, please refer to the published version.

(Article begins on next page)

19 October 2024

This is the final peer-reviewed accepted manuscript of:

Cicchiello, A. F., Cotugno, M., Perdichizzi, S., & Torluccio, G. (2022). Do capital buffers matter? Evidence from the stocks and flows of nonperforming loans. International Review of Financial Analysis, 84, 102369.

The final published version is available online at:

https://doi.org/10.1016/j.irfa.2022.102369

Terms of use:

Some rights reserved. The terms and conditions for the reuse of this version of the manuscript are specified in the publishing policy. For all terms of use and more information see the publisher's website.

This item was downloaded from IRIS Università di Bologna (https://cris.unibo.it/)

When citing, please refer to the published version.

Do capital buffers matter? Evidence from the stocks and flows of nonperforming loans

July 4, 2022

Abstract

This paper investigates the determinants of the stocks and flows (both in- and outflows) of nonperforming loans (NPLs) by considering a bank-specific factor that is not adequately analysed in the literature, namely, bank capital buffers. Using unbalanced panel data with 6,087 bank-year observations for the 2006-2018 period and a two-step system generalised method of moments (GMM) estimation, we find that banks with higher levels of capital buffers (both in terms of Tier 1 and total capital) have fewer NPL stocks and generate fewer NPL inflows. When we control for the characteristics of the loan portfolio, real guarantees collected by the bank increase the stocks and flows of new, impaired loans, while personal guarantees favour the outflow of bad loans.

JEL Classification: G20; G21; G32

Keywords: NPLs, Capital buffer, Collateral, Bank risk-taking

1 Introduction

The subprime crisis and the subsequent European Sovereign Debt Crisis strongly attracted the attention of the European Supervisory Authorities to the issuance of nonperforming loans (hereafter, NPLs). The sharp increase in NPLs–due to harsh economic situations, incompetent loan administration, and a deficient understanding of loan conditions–increased banks' failures and financial system instability (Duran & Lozano-Vivas 2015). Moreover, the deterioration of loan quality restricted the ability of the banking system to grant new loans to businesses and consumers, slowing economic growth (Serrano 2021).

In the aftermath of the financial crisis, supervisory authorities–especially the European Central Bank (ECB)–started to closely monitor the level of NPLs across the European banking sector. The ECB also began to implement measures to assess banks' ability to adequately manage the riskiness of their loans and implement appropriate governance strategies, structures and processes.[1] Since then, banks have made significant efforts to restructure their business models and reduce NPLs. According to the European Banking Authority report on NPLs (European Banking Authority, 2019), a comparison of NPL ratios reported as of June 2019 with those reported as of June 2015 highlights that most European countries have experienced an improvement. However, the economic consequences of the COVID-19 crisis and related challenges to financial resilience have renewed concerns about banks' accumulation of higher levels of NPLs on their balance sheets. Furthermore, the ECB expects an

[1] https://www.eba.europa.eu/regulation-and-policy/credit-risk/guidelines-on-loanoriginationand-monitoring

economic downturn due to the Russian invasion of Ukraine and related sanctions, with a subsequent asset quality deterioration and credit valuation adjustments by the end of 2022 (ECB, 2022).

A member of the Supervisory Board of the ECB, Elizabeth McCaul, during her speech at the NPL Summit 2021 stated: "*As government and other support measures (i.e., direct transfers to households and businesses, loan moratoria and guarantee schemes) are phased out and the economic shock continues to reverberate across Europe, SME [small and medium-sized enterprise] and corporate insolvencies are likely to increase and bank customers may find it more difficult to repay their loans. This is likely to lead to a higher share of NPLs on bank balance sheets, which, in turn, will require higher provisions, generate losses and put pressure on banks' lending capacity and their already structurally low profitability.*"[2]

According to ECB Banking Supervision, material deficiencies in credit risk management frameworks represent one of the main vulnerabilities faced by the significant institutions under its direct supervision. Strategic priorities for the next three years include improving the credit risk management practices of supervised institutions, particularly with regard to the timely identification, forward-looking measurements of, and mitigation of credit risks.[3]

In this unprecedented context, understanding the key determinants of loan portfolio quality is of the utmost importance from a supervisory perspective to ensure financial system stability and guarantee the safety and soundness of banking management

[2]https://www.bankingsupervision.europa.eu/press/speeches/date/2021/html/ssm.sp210318\{}~{}a0a512f98b.en.html

[3]https://www.bankingsupervision.europa.eu/banking/priorities/html/ssm.supervisory_priorities2022~0f890c6b70.en.html

(ECB 2018). Reducing the stock of nonperforming assets on the balance sheets of EU-area banks is fundamental to addressing the consequences of COVID-19 and will be an important issue of financial stability following the Russian–Ukrainian war shock. Asset quality deterioration is a leading cause of bank failure, and a high level of NPLs influences lending capacities, with adverse effects on profitability, capital ratios, and economic development (Casu et al. 2015).

Therefore, we examine the relationship between capital buffers (measured both in terms of Tier 1 and total capital) and the stocks and flows (both in- and outflows) of NPLs divided into three credit risk categories, namely, past due, unlikely to pay (UTP), and bad loans. Using an all-encompassing dataset on Italian banks from the Italian Banking Association (ABI) database (770 banks), we conduct a two-step system, generalised method of moments (GMM) estimation for the period 2006 to 2018 (a period strongly characterised by the global financial crisis, the European Sovereign Debt Crisis, and the severe economic recession that followed in some countries). A GMM estimation is suitable for capturing the dependent variable's dynamic properties, is robust to the presence of unit roots and is widely employed in the literature for empirical analysis on this topic (Cucinelli et al. 2021, Ghosh 2015, Vithessonthi 2016). We also control the characteristics of the loan portfolio in terms of the real and personal guarantees collected by the banks.

We focus on the Italian case for three reasons. First, at the end of 2015, the total amount of NPLs in European banks reached its maximum, with a volume of 1,089 billion euros, of which 341 billion related to the Italian banking system. Excluding the three countries that receive financial assistance from the EU (i.e., Greece, Cyprus, and

Portugal), Italy showed the highest NPL ratio in Europe, reaching an all-time high of 17.1%.[4] Second, the NPL amounts declined, favouring the banks' derisking but making it more challenging to analyse banks' risk-taking behaviours. The Italian banking system makes a highly consistent contribution to the secondary loans market (in 2017, 72 billion euros were sold through both asset sales and securitisation transactions).[5] Third, the banking literature recognises NPLs, commonly used as a proxy for credit risk, as sound indicators of banks' risk-taking levels. In fact, NPLs tend to deteriorate before banks fail (Jokipii & Milne 2011, Shim 2013). In the case of Italy, credit risk is one of the main risk-taking drivers in the banking industry, given that bank loans are the largest source of corporate financing and the main earning assets for banks. Therefore, the analysis of NPL flows is essential to understanding Italian banks' risk-taking choices and their derisking strategies.

As discussed in detail below, the results reveal that capital buffers (both in terms of Tier 1 and total capital) negatively affect NPL stocks and inflows, which are divided into three risk categories. Moreover, when we control for the loan portfolio characteristics, we find evidence that real guarantees collected by the bank increase the stocks and flows (in and out) of new, impaired loans, while personal guarantees favour the outflows of bad loans. A range of robustness tests shows that our findings are consistent. This paper contributes to the empirical literature investigating the possible NPL determinants in several ways. First, we analyse the impact of capital buffers on the dynamics of the stock and flow of NPLs. The relationship between

[4]https://www.eba.europa.eu/regulation-and-policy/credit-risk/guidelines-on-the-applicationof-the-definition-of-default

[5]https://www.bancaifis.it/en/press-releases/npl-meeting-the-non-performing-loan-stock-willrise-to-385-billion-euro/

NPLs and bank-specific variables has been extensively analysed in the literature using several explanatory variables. However, while the literature concerning the capital ratio is large, studies are relatively scarce considering capital buffers as a possible NPL determinant (Manz 2019).

Because of the nature of risk under which banks operate, capital requirements may serve both as a cushion during adverse economic conditions and as an ex ante mechanism for preventing excessive risk-taking (Couaillier et al. 2022, Jokipii & Milne 2011). A high capital buffer, measured by the difference between the capital endowment and the minimum capital requirement over time, should leave banks better able to absorb any adverse shocks with their own resources without becoming insolvent or necessitating bailout funds (VanHoose 2007, Berger et al. 1995). In addition, by forcing bank owners to "put their own skin in the game", a high capital buffer should induce prudent behaviour and curb the incentives for excessive risk-taking created by limited liability and amplified by the establishment of deposit insurance and the expectation of public intervention (Demirguc-Kunt et al. 2013).

Second, this paper contributes to the literature by analysing the flows (both in- and outflows) of NPLs. The banking literature has extensively investigated NPL determinants, focussing on country- and bank-specific factors (Karadima & Louri 2020, Boumparis et al. 2019, Ghosh 2015, Vithessonthi 2016, Jiménez et al. 2009, Berger & DeYoung 1997). However, the literature has focussed on studying the determinants of NPL stocks, (Cerulli et al. 2020, Jiang et al. 2020, Cucinelli et al. 2018, Ghosh 2015), and only in a few cases has an depth analysis been performed based on the flows of impaired loans (Cucinelli et al. 2021, Baldini & Causi 2020,

Marcucci & Quagliariello 2009, Bofondi & Gobbi 2006). An analysis of the flows (in- and outflows) of NPLs is essential to understanding the dynamics of banks' credit risk and asset management strategies (Marcucci & Quagliariello 2009). The number of gross NPLs is influenced by the new NPLs generated during the year and by the disposals (towards specialised operators or through securitisation transactions), write-offs and recovery activities (outflow of NPLs) (Cucinelli et al. 2021, Marcucci & Quagliariello 2009). Furthermore, the judicial system's inefficiencies could facilitate the accumulation of NPLs, making it difficult to identify whether this phenomenon is due to the ineffectiveness of banking management or to the inefficiencies of the institutional environment (Cerulli et al. 2020, Jappelli et al. 2005). Unlike NPL stocks, new NPL inflows are insensitive (or less influenced by) to the inefficiencies of the judicial system. Therefore, an increase in NPL inflows could be attributed only to the banks' capacity to properly screen and monitor borrowers.

Third, to the best of our knowledge, this is the first study to investigate the determinants of the three NPL risk categories: past due, UTP, and bad loans.[6]

Specifically, we analyse the determinant of the inflows and outflows of these three risk categories. The previous empirical literature focussed on the relationship between the default rate and economic cycle or has investigated the determinants of new UTP exposures, omitting the analysis of past due and bad loan flows (Cucinelli et al. 2021,

[6]According to current supervisory regulations, the loan portfolio' quality is classifiable in three aggregates characterised by increasing credit risk levels: past due, UTP, and bad loans. Past due exposures (aside from those classified among bad loans and UTP exposures) are those that are past due by more than 90 days and for above a predefined amount. UTP exposures (aside from those included among bad loans) are those with respect to which banks believe the debtors are unlikely to meet their contractual obligations in full unless action such as the enforcement of guarantees is taken. Bad loans are exposures to debtors who are insolvent or in substantially similar circumstances.

Marcucci & Quagliariello 2009, Bofondi & Gobbi 2006).

Finally, we contribute to the literature by considering the guarantees collected by the bank, both real (mortgage and pledge) and personal, as NPL flow determinants. The limited research conducted thus far has shown that collateralised loans have a higher probability of default (Jiménez & Saurina 2004, Berger et al. 2011). The role of real and personal guarantees collected by banks as determinants of NPLs remains unexplored in the literature.

This paper proceeds as follows. In the next section, we discuss the related literature. In Section 3, we describe the methodology, and in Section 4, we present our data and summary statistics. In Section 5, we show the baseline results. In Section 6, we add some robustness tests to the main outcomes. Section 7 concludes the paper.

2 Literature Review

The well-established literature concerning NPL determinants has focussed mainly on the role of macroeconomic and external factors underlining the close relationship between the economic cycle and the credit portfolio quality of banks (Bofondi & Ropele 2011, Jiménez et al. 2009, Berger & DeYoung 1997). According to Ghosh (2015), a common finding is that NPLs are countercyclical to overall country-specific macroeconomic conditions. In contrast, only a limited number of theoretical and empirical works have examined the impact of bank-specific factors, which appear to exert a powerful influence on the NPL rate.

In the empirical studies, researchers have adopted different variables to measure

banks' propensity for excessive risk-taking in lending and to explain problem loans Salas & Saurina (2002). An important strand of the literature focusses on bank capitalisation and its effect on the level of NPLs in credit portfolios, given the relative risk-taking incentive in accordance with the capital strength of the bank.

The relationship between capital buffers and NPLs–used as a measure of banks' risk-taking behaviours (Shim 2013)–can be explained with the support of three theories. The motivation underlying the current capital regulation and supported by Jensen & Meckling (1976) assumes a moral hazard behaviour of banks arising from a conflict of interest between bank shareholders–who enjoy limited liability–and depositors. Moral hazard theory predicts that the implementation of explicit deposit insurance induces banks to operate with lower capital levels (Keeley 1990) and to increase asset risk-taking (Hoque et al. 2015, Anginer et al. 2014). Therefore, in the risk distribution between shareholders and depositors, a low-capitalised bank can exploit deposit insurance schemes, assuming greater risk and generating higher NPLs. Empirical studies have tested the moral hazard hypothesis, confirming the existence of a negative relationship between bank capitalisation and NPLs (Keeton & Morris 1987, Berger & DeYoung 1997, Salas & Saurina 2002, Louzis et al. 2012, Klein 2013, Chaibi et al. 2016).

However, theory asserts that risk-based capital requirements may reduce moral hazard incentives by forcing banks to operate with a sufficient amount of capital and choose less risky asset portfolios (Merton 1977, Furlong & Keeley 1989, Freixas & Rochet 2008). At the same time, the banking literature suggests that, under the assumption of a risk-averse bank utility function (Acharya 2009), stringent capital

requirements may lead banks to increase the overall asset portfolio risk (Koehn & Santomero 1980, Kim & Santomero 1988, Rochet 1992, Lundtofte & Nielsen 2019). Thus, in well-capitalised banks, risk-taking might actually increase in the long term in response to greater bank capital (Calem & Rob 1999).

Additionally, managers in highly capitalised banks may engage in more risky activities to seek higher returns on assets that can compensate their shareholders for the increased risk to their investments. The high-risk profile for such banks leads to a positive relationship between capital and NPLs, which is confirmed in the literature. Ghosh (2015), for example, analysed the banking-industry specific and regional economic determinants of NPLs for US banks using a dynamic GMM estimation and found that greater capitalisation increased NPLs. Similarly, Cucinelli et al. (2021) found a positive relationship between banks' regulatory capital, proxied by the Tier 1 ratio, and NPLs.

The relationship between bank capital and risk-taking can also be explained by charter value theory (Marcus 1984, Diamond & Rajan 2000). Also referred to as franchise value, charter value is the value that would be lost in the case of bankruptcy; hence, it represents the bank's private cost of failure. In contrast to the predictions of moral hazard theory, charter value theory argues that banks may be deterred from adopting excessive risk-taking behaviours to protect their charter value. Conversely, banks with low charter values have little to lose and therefore may adopt riskier strategies (Demsetz et al. 1996). Similarly, charter values act as a self-disciplining mechanism with regard to risk-taking, restraining banks' moral hazard behaviours and making supervisors' jobs easier (Keeley 1990). As stated by Acharya (1996), "the

larger the charter value of a bank, the less severe is the moral hazard by which a bank may take a higher risk after the deposit insurance premium is determined. This is because increasing the portfolio risk can raise the value of the default option (gain from moral hazard), but it also increases the probability of losing the charter value."

A large body of the empirical literature has found evidence in favour of the charter value hypothesis and that high charter value banks are less risky, whether in terms of default, asset, or leverage risk. Demsetz et al. (1996), for example, found that US high- (vs. low-) franchise-value banks operate more safely when they hold more capital and take on less portfolio risk, primarily by diversifying their lending activities. Within the banking literature, attention has more recently shifted towards capital buffer theory (VanHoose 2007, Jokipii & Milne 2011).

According to capital buffer theory, banks maintain a level of capital above the required minimum (i.e., a capital buffer) to avoid the high cost of capital adjustment and the costly supervisory actions activated in case the regulatory minimum capital requirements are violated. Imposing conservative capital buffers on banks is also important because it avoids costly capital-raising activities during difficult times and reduces risk by liquidating risky assets such as commercial loans. In line with the predictions of capital buffer theory, Heid et al. (2003) found evidence that capital and risk adjustments depend on the amount of capital the bank holds in excess of the regulations. Specifically, banks with lower capital buffers try to rebuild appropriate buffers by increasing capital and reducing risk. In contrast, banks with large buffers try to maintain their capital buffers by increasing risk when capital stocks increase. In contrast, Stolz & Wedow (2011) found evidence that low-capitalised banks do not

catch up with their well-capitalised peers and they do not decrease risk-weighted assets during a recession. This finding suggests that their low capitalisation does not force them to retreat from lending. Using a sample of publicly traded US bank holding companies (BHCs), Jokipii & Milne (2011) investigated the relationship between short-term capital buffers and portfolio risk adjustments. Their results revealed that banks with capital buffers approaching the minimum requirement increase their buffers either by reducing their risk or by gambling for relief by adopting more risk as a means of rebuilding the buffers. Alternatively, they maintain their target capital levels by increasing (decreasing) risk when capital increases (decreases). Well-capitalised banks, conversely, maintain their target capital levels by increasing (decreasing) risk when capital increases (decreases). Bui et al. (2017) used a sample of Australian banks to analyse the dynamics of loan loss rates and the interactions of such dynamics on banks' capital buffers and system resilience. Their results reveal that a moderate increase in bank capital buffers is sufficient to maintain financial system resilience, even during economic downturns. Furthermore, the authors found that higher loan loss rates led to higher funding costs faced by banks, while the funding costs decreased as banks' capital buffers increased. In a recent study, Jiang et al. (2020) verified the relationship between bank risk-taking (measured with the Z score and the NPL ratio) and capital buffers in a sample of 135 Chinese banks. The authors found a nonlinear U-shaped relationship that was more significant in high-risk than it was in low-risk banks. In only a certain range did banks with higher capital buffers take lower risks; beyond that range, additional capital buffers may induce excessive risk-taking.

Evidence concerning the relationship between capital buffers and bank risk-taking

remains limited and requires more attention (VanHoose 2007). We contribute to the aforementioned literature by focussing on the influence of bank capital buffers on impaired loans both in a static analysis (NPL stock) and from a dynamic perspective (NPL inflows and outflows). In particular, we respond to the following research question: *Do capital buffers influence bank NPL inflows and outflows?*

In the context of the aforementioned literature, we expect that due to the effect of prudential regulations, high regulatory capital will be negatively associated with the NPL rate and a further increase in NPL stock. Thus, highly capitalised banks will have a higher credit portfolio quality.

3 Econometric methodology and variables

The empirical literature shows that NPLs and their components are typically persistent (Cerulli et al. 2020, Cucinelli et al. 2021, Ghosh 2015, Klein 2013). In the presence of the dependent variable's significant persistence, the panel fixed effects estimates will be biased and inconsistent since the error term is correlated with the lagged dependent variable (Ghosh 2015). Moreover, the banking-specific variables are most likely to be endogenous with the NPLs and their components. A further deterioration in the bank portfolio quality would probably induce banks to lower their leverage and reduce profit. To overcome this obstacle and the aforementioned endogeneity concern, we employed a two-step system GMM estimation design (Arellano & Bover 1995, Blundell & Bond 1998, Roodman 2009). The two-step system GMM is commonly used in the banking literature (Conlon et al. 2020, Hessou et al.

2017, Jokipii & Milne 2011) and provides several benefits; for example, it accounts for the dependent variable dynamics, and it is robust to the presence of unit roots. The two-step system GMM method allows us to address the endogeneity problem arising from both the risk of reverse causality in the econometric specification and the correlations between the lagged dependent variable and the error term. Hence, as is common in the literature (Cerulli et al. 2020, Cucinelli et al. 2021, Ghosh 2015), we included as instruments for the lagged dependent variables the second and third lags of the dependent variables in each econometric specification. We also included year fixed effects in the regression as an alternative for macroeconomic variables to capture and control time-based differences, e.g., the banking and sovereign debt crises. We focussed on the period from 2006 to 2018, and we estimated the following equation:

$$\begin{aligned} y_{i,t} = \beta_0 + \beta_1 y_{i,t-n} + \beta_2 Buffer_{i,t-1} + \beta_3 ROA_{i,t-1} + \\ \beta_4 Size_{i,t-1} + \beta_5 Cost\ Income_{i,t-1} + \beta_6 Loan\ TA_{i,t-1} + \\ \beta_7 Loan\ growth_{i,t-1} + \beta_8 Coverage\ Ratio_{i,t-1} + \\ \beta_9 Secured\ Loans\ by\ real\ guarantee_{i,t-1} + \\ \beta_{10} Secured\ Loans\ by\ personal\ guarantee_{i,t-1} + \\ \beta_{11} Time_t + \epsilon_{i,t} \end{aligned} \tag{1}$$

where $y_{i,t}$ is the indicator of the portfolio quality for bank i at time t (*Past due ratio*, *UTP ratio*, or *Bad loan ratio*). Following the convention in the NPL literature (Cerulli et al. 2020, Ghosh 2015, Klein 2013), we expressed our dependent variables

as their logit transformations.[7] $Buffer_{i,t-1}$ is our variable of interest and is equal to the Tier 1 capital or total capital that banks hold above the different minimum requirement from the Basel II and Basel III regulations (see Table 1 for definitions). This proxy measures the excess capital (in terms of Tier 1 or total capital) that banks hold to protect against different risks (Milne & Jokipii 2008, Jokipii & Milne 2011).

As bank-specific factors, in line with the literature (Cerulli et al. 2020, Cucinelli et al. 2021, Ghosh 2015, Klein 2013, Foos et al. 2010, Berger & DeYoung 1997), we considered the following variables.

Bank profitability (ROA). Highly profitable banks have fewer incentives to engage in high-risk credit, while inefficient banks are more likely to be involved in risky activities to defend their profitability and meet prudential rules imposed by monetary authorities (Ghosh 2015, Leung et al. 2015). However, according to Rajan (1994), even in highly profitable banks, managers may set liberal credit policies to increase their short-term reputation by inflating current earnings at the expense of increasing their NPLs in the future.

Bank Size. Previous studies have shown that the effect of bank size on NPLs can be ambiguous. On the one hand, large banks may increase their leverage too much and extend loans to lower-quality borrowers, expecting to be supported by governments in the case of failures. The "too big to fail" hypothesis (Stern & Feldman 2004, Louzis et al. 2012) implies a positive relationship between bank size and NPL level. On the other hand, large banks have more diversification opportunities (Salas & Saurina 2002), have more resources and are more experienced in dealing better

[7] More precisely, $y_{i,t} = \ln[y_{i,t}/(1\text{-}y_{i,t})]$.

with bad borrowers (Hu et al. 2004). Thus, they can evaluate loan quality better, reducing the level of troubled loans (Rajan & Dhal 2003, Wang 2014).

Cost to income ratio. According to Berger & DeYoung (1997), efficient banks risk employing fewer resources in monitoring activities that report higher NPL amounts. In contrast, under the "bad management hypothesis", a cost-inefficient bank has poor management skills and credit risk management qualities, and reports a larger NPL amount (Louzis et al. 2012).

Bank diversification. Greater diversification in the bank's asset portfolio reduces risk-taking, as the potential losses on the loan activity may be overcome by noninterest revenue sources (i.e., financial revenues and capital gains) (Hu et al. 2004). NPLs should be lower for well-diversified banks, where noninterest revenues are important, than for less (poorly) diversified financial institutions (Salas & Saurina 2002, Huynh & Dang 2021).

Loan growth. The sustainable growth of banks' credit activities–characterised by a low to moderate growth rate–may reflect a level of management quality under which a smaller number of problem loans is more likely. However, as interest revenues are the main source of return creation in banks, managers may decide to excessively expand loan growth to maximise their short-term gains (Jensen 1986). To increase their loan supply, bank managers reduce the interest rates charged on loans or lower their credit standards, discarding the necessary credit quality assessment of borrowers (Kwan & Eisenbeis 1997, Keeton 1999, Klein 2013). These phenomena lead, through adverse selection reasoning, to an increase in problem loans.

Collateral and personal guarantees. Collateral can be associated with lower

credit risk Salas & Saurina (2002). Indeed, low-risk borrowers are not only willing to pledge more collateral to signal their creditworthiness but also less likely to adopt moral hazard behaviours because they pledged collateral. However, the collateral pledge could reduce banks' incentives to properly screen and monitor borrowers (i.e., the bank relies simply on the collateral) and give banks a false sense of optimism that increases along with the collateral value. This situation may increase the probability of loan default (Jiménez & Saurina 2004, Berger et al. 2011).

Loan loss provisions reflect the credit quality of banks and their overall attitude to control expected loan losses. Theoretically, higher NPL levels should be associated with high rates of lagged provisioning (Hasan & Wall 2004). However, according to the "moral hazard" hypothesis (Keeton & Morris 1987), banks with poor credit quality have higher moral hazard incentives. Therefore, they are more likely to increase the riskiness of their loan portfolio, causing an increase in NPLs. Therefore, we control for the loan loss reserve ratio by dividing the amount of the past due, UTP and bad loans by the amount of the loan loss reserves of each NPL category of nonperforming loans ($Coverage\ Ratio_{i,t-1}$). $Time_t$ represents the time fixed effects, and the term $\epsilon_{i,t}$ is an independent and identically distributed error term. Table 1 shows all the variables employed in the estimation model. Finally, following the empirical literature (Cerulli et al. 2020, Cucinelli et al. 2021) and as recommended by Arellano & Bond (1991), we used the Windmeijer-corrected standard error (Windmeijer 2005). In the second part of our analysis, we study the dynamics of the inflows and outflows of the different NPL risk categories. We ran another regression, employing a two-step system GMM regression with the Windmeijer-corrected standard error. The dependent variables

for the second part of the analysis are the inflows and outflows of the different risk categories of NPLs. We relate the flows (in and out) of the various risk categories at time *t* over the gross loan amount at time *t-1*, obtaining six other dependent variables: (*inflow of past due*, *inflow of UTP*, *inflow of bad loans*, *outflow of past due*, *outflow of UTP*, and *outflow of bad loans*). As a control variable, we used the same set of variables as in the previous analysis.

4 Data and Sample

4.1 Data

This paper contributes to the literature regarding both the research questions and the variables employed as well as the extension of the database used. Most of the previous studies have used databases such as BankFocus by Bureau Van Dijk, which cover commercial banks widely but cooperative banks sparsely. Using data from the ABI, we covered the entire Italian banking system.

Our dataset comprises all the Italian banks from the ABI database (770 banks) for the period 2006-2018. We applied selection filters to the initial dataset to remove outliers. First, following Cerulli et al. (2020) and Cubillas et al. (2017), we selected all the banks for which information was available on total assets or total equity for at least two years in the sample period. We were left with 722 banks. Second, following Cucinelli et al. (2021) and Cerulli et al. (2020), we dropped the banks with very small *net loans to nonfinancial institutions/assets* ($< 5\%$) to avoid those banks whose core business was not commercial banking. We also excluded banks whose total assets

increased by more than 50% in absolute terms over the sample period. The final sample consisted of 691 banks (6,087 bank-year observations) and covered almost the whole population of Italian banks. We also winsorised all the variables at the 1% and 99% levels to further reduce the outlier influence. The sample size varied across regression specifications because not all the variables were available for all the bank-year observations.

4.2 Summary Statistics

Tables 2 and 3 display the summary statistics and correlation matrix, respectively. As expected, our dependent variables were negatively correlated with loan growth and the Tier 1 (total capital) buffer. Simultaneously, they were positively related to profitability (*ROA*), secured loans (with either real or personal guarantees) and the coverage ratio (i.e., past due, UTP, and bad loans). Overall, the correlations among our variables of interest were low.

In terms of NPL deterioration, the *past due ratio* had a mean of 1.1% (and a standard deviation (SD) of 1.2%), the *UTP ratio* had a mean of 5.7% (4.1%), and the *bad loan ratio* had a mean of 7.1% (6.3%). In terms of the NPL inflows, those of the *inflow of past due* averaged 1.7% (1.9%), those of the*inflow of UTP* averaged 4.1% (3.7%), and those of the *inflow of bad loans* averaged 2.4% (2.4%). Then, in terms of the outflow of NPLs, those of the past due, UTP and bad loans averaged 1.6%, 2.9%, and 1.3% (1.8%, 2.2%, and 2.1%), respectively. Considering our main test variables, the mean value of the Tier 1 (total capital) buffer was 13.2% (10.9%). Regarding the personal and real guarantees, the *secured loans by real guarantees* equalled 75.1%,

and the *secured loans by personal guarantees* equalled 37.5%.

Finally, Table 4 shows the stationarity test of the variables used in the multivariate analysis. Specifically, we performed Fisher–ADF tests that assume individual unit root processes, which is useful for unbalanced panels, as in our case. We can reject the null hypothesis (nonstationarity) for all the variables used.

5 Empirical Analysis

5.1 Baseline Results

Table 5 shows the main results for the loan portfolio deterioration. In Columns 1-2, we present the results for the *past due ratio*. In Columns 3-4, we tabulate the results for the *UTP ratio*, and in Columns 5-6, we show the results for the *bad loans ratio*. Regarding our principal variable of interest (*Tier 1 buffer* or *total capital buffer*), we found a negative and statistically significant influence on both the UTP and bad loans ratio. In contrast, for the *past due ratio*, we found weak evidence at the 10% level for the capital buffer in terms of Tier 1 and no evidence for total capital. Our finding is consistent with Salas & Saurina (2002), Louzis et al. (2012), Klein (2013), Chaibi et al. (2016), who showed a negative relationship between bank capitalisation and NPL levels.

Specifically, an increase of 1% SD in the Tier 1 (total capital) buffer led to an average decrease in the UTP ratio of 3.18% (2.926%) and in the bad loan ratio of 12.14% (12.45%).[8]

[8]We calculated the economic magnitude as the product of the Tier 1 (total capital) buffer

These results are consistent with the view that capital buffers serve to absorb future adverse shocks, and they confirm the effect of prudential regulations that aim to curb moral hazard incentives by imposing risk-sensitive capital requirements (Bui et al. 2017, Guidara et al. 2013, Drehmann & Gambacorta 2012, VanHoose 2007, Berger et al. 1995). Interestingly, we found a positive and statistically significant relationship between the secured loan levels, both real and personal, on the *past due ratio* and the *UTP ratio* levels. An SD increase of 1% in the loans secured by real (personal) guarantees led to an increase of 9.98% in the *Past due ratio* and 4.62% (2.79%) in the *UTP ratio*. In contrast, for neither the real nor the personal guarantees did we find any statistical evidence for the *Bad loans ratio*. The results support the view that collateralised loans have a higher probability of default, consistent with ex post theory (Jiménez & Saurina 2004, Berger et al. 2011).

Concerning our bank-specific controls, the estimated coefficients were barely significant for the different types of portfolio deterioration variables. For example, the estimated coefficients for profitability (*ROA*) were positive (Cucinelli et al. 2021, Poghosyan & Čihak 2011) but statistically significant only for the *UTP ratio*. In summary, these results suggest that capital buffers in terms of Tier 1 or total capital are generally associated with less loan portfolio deterioration (past due or UTP or bad loans ratio). In contrast, a higher level of secured loans is usually associated with a higher *past due ratio* (real guarantees only) and *UTP ratio* (both real and personal guarantees). Interestingly, the value of the coefficient of the *secured loans by*

coefficient and the SD of the Tier 1 (total capital) buffer. As an example, for the per UTP ratio, we obtained -0.308*0.105=-0.0323. Since the UTP ratio was a logit transformation, we used the exponential of -0.0323 minus 1, which is equivalent to -3.18%.

real guarantees was lower in magnitude than that reported for the *past due ratio*.

Table 6 shows the main results for the inflow of NPLs. In Columns 1-2, we present the results for the *inflow of past due*. In Columns 3-4, we tabulate the results for the *inflow of UTP*. Furthermore, in Columns 5-6, we show the results for the *inflow of bad loans*. In this case, we again found a negative and statistically significant influence of the Tier 1 (total capital) buffer on the inflow of past due, UTP and bad loans. Compared to the deteriorated loan portfolio stocks, we also found a negative and statistically significant relationship between the Tier 1 (total capital) buffer and past inflows. Specifically, an SD increase of 1% in the Tier 1 (total capital) buffer led to a decrease of 6.891% (5.686%) in the *inflow of past due*, of 8.250% (7.611%) in the *inflow of UTP*, and of 7.164% (5.838%) in the *inflow of bad loans*. This result offers an overview of the relationship between capital buffers and loan portfolio quality. An analysis based only on the past due ratio highlights an unsatisfactory conclusion, suggesting that the capital buffer could prevent the origination of higher risk impaired loans (UTP and bad loans) but was ineffective in preventing lower risk loans (past due loans). Conversely, considering the past due inflows, our evidence suggests that capital buffers can reduce all the impaired loan categories. Moreover, the Tier 1 ratio capital buffer had a higher effect than did the capital ratio on reducing the impaired loans.

Regarding the secured loan level, we found a positive and statistically significant relationship only between the *secured loans by real guarantees* and the *inflow of past due* . In contrast, when we examined the *secured loans by personal guarantees*, we found a positive and significant relationship between the *inflow of UTP*. Furthermore,

we did not find any statistically significant effect of either the real or the personal guarantees on the *inflow of bad loans*. These results suggest that the capital buffer negatively affected all the types of impaired loan inflows. More interestingly, having loans secured by guarantees negatively affected the inflows of past due and UTP loans but not those of the bad loans.

Finally, in Table 7, we show the main results for the NPL outflows. In Columns 1-2, we present the results for the *outflow of past due*. In Columns 3-4, we tabulate the results for the *outflow of UTP*. Moreover, in Columns 5-6, we show the results for the *outflow of bad loans*. We did not find any significant difference between the levels of the Tier 1 (total capital) buffer and those of any of the dependent variables. We highlight that the capital buffer positively affected loan origination but was ineffective in helping to reduce risky exposures. As the empirical banking literature suggests, the link between recovery rates and the decline of an impaired portfolio is driven by the guarantees collected. Indeed, we found that the *secured loans by real guarantees* positively and significantly correlated with the outflows of past due and UTP loans. In contrast, the *secured loans by personal guarantees* were positively associated with the outflows of UTP and bad loans. This evidence implies that the presence of a real guarantee, which is generally more liquid with an easily monitored market value and eligible from a regulatory capital perspective, facilitated the outflows only from low-risk categories (past due and UTP loans). In contrast, personal guarantees, which are generally illiquid and eligible only under certain conditions for standardised banks and FIRB (Foundation Internal Ratings-based) adopters, facilitated the NPL outflows from higher-risk categories. This in-depth analysis is essential since the supervisory

regulations treat collateral from personal guarantees differently.[9] In detail, personal guarantees in the standard and FIRB approaches are eligible only under certain conditions (i.e., pledged by states, companies or supervised financial intermediaries with an external rating better than that guaranteed), unlike banks that adopt an advanced internal rating-based (AIRB) approach to credit risk measurement.

In summary, we find that capital buffers are generally associated with lower loan portfolio deterioration and lower inflows of impaired loans; in contrast, the buffers did not affect the outflows of impaired loans. Conversely, collateral favoured the new past due flows but did not influence the inflows of the other risk categories. Conversely, personal guarantees generated an increase in the UTP loans but did not affect the different types. Finally, regarding the outflows, collateral had a high impact on the outflows of the past due and UTP loans, unlike collateral, which facilitated outflows only for the UTP loans and the highest risk category (bad loans). Arellano–Bond AR(1) and Arellano–Bond AR(2) are the tests for the first- and second-order autocorrelation of the residuals. In all of the specifications (except for the *Past due ratio*) we can reject the null hypothesis of no first (second)-order serial correlation of the residuals. The Hansen test of overidentifying the restrictions suggested that our instruments were appropriate. These tests imply that our two-step system GMM results were consistent.

[9] https://www.bis.org/basel framework/chapter/CRE/20.htm

5.2 Additional analysis: Subsample, propensity score matching (PSM) and macroeconomic factors

In this section, we highlight some additional analyses. First, the sample period (2006-2018) covered both the global financial crisis (2007-2009) and the sovereign debt crisis (2012-2013). Therefore, our main results could be different before and after both crises. For this reason, we divided our sample into two subsamples: 2006-2012 (Table 8, Panels A and B) and 2013-2018 (Table 8, Panels C and D). The estimates presented in Table 8 corroborated our previous findings only for the second subsample (2013-2018, Table 8, Panels C and D). These findings show that banks with higher capital buffers were less risky after a downturn. Nevertheless, in the subsample that considered the global financial and European Sovereign Debt crises (Table 8, Panels A and B), we did not find a negative association between banks with higher capital buffers and the past due, UTP and bad loan ratios. In contrast, the capital buffer reduced the inflows of UTPs and bad loans, even in times of financial crisis.

Although we used the two-step GMM estimation technique, our analysis could suffer from endogeneity concerns. Nevertheless, the two-step system GMM is robust to the presence of the unit root of the dependent variable and alleviates endogeneity concerns. However, using only the GMM setup is not enough to address all the possible endogeneity concerns. For example, banks with higher capital buffers may generate a low NPL level, which could affect our results. Therefore, using PSM techniques, we matched banks based on bank size (Danisewicz et al. 2018). We first divided banks based on a dummy variable (Treatment) equal to one if the *Tier 1 capital buffer* was higher than the median and 0 otherwise. Then, we estimated a

probit model as follows:

$$Treatment = \beta_0 + \beta_1 Size + \epsilon \tag{2}$$

We computed the propensity score, and we matched a sample of comparable banks in size terms. The results with the matched sample estimates reinforced the previous results (Table 9 Panels A and B). In particular, we showed a negative and statistically significant relationship for all the risk categories in terms of stocks. The association was negative and statistically significant for the inflows of UTPs and bad loans.[10]

Finally, in the last analysis, instead of using the year fixed effects, we controlled for macroeconomic variables, such as gross domestic product (GDP) growth, inflation (proxied by the consumer price index, CPI), and M2 growth (a measure of the money supply). Since the econometric setup is based on a single country, the macroeconomic variables capture the business cycle trend. Shown in Table 9, Panels C and D, the results corroborated our previous findings.

6 Robustness Tests

In this section, we provide various robustness tests. To mitigate the potential omitted variable bias, we added to our regression two sets of dummies as control variables. To preserve space, these tests are relegated to Tables A.1 and A.2 in the

[10]In the text, we show only the PSM matched sample using size, while when we considered a measure of bank profitability (ROA) to generate the matching sample, the results were quite similar. For the sake of brevity, the results are not reported here but are available upon request.

Appendix. First, we divided the banks into three groups based on their asset size according to the Bank of Italy's definition:[11] small banks with total assets less than or equal to €3.6 billion, medium banks with total assets between €3.6 billion and €21 billion, and large banks with total assets higher than €21 billion. We found that bank size did not add explanatory power to our preferred specification, and our main findings were in line with the baseline results (Table A.1).[12]

Second, we added three dummies for bank specialisation, following the definition of Beccalli & Girardone (2016): (i) commercial banks (Banche SpA, limited company banks accepting short-term funds), (ii) cooperative mutual banks (Banche di Credito Cooperativo), and (iii) cooperative banks (Banche Popolari). Interestingly, the dummy variable representing commercial banks indicates that they have a higher bad loan ratio; more inflows of past due, UTP and bad loans; and more outflows of UTP loans. In contrast, cooperative banks have higher past due ratios; more inflows of past due, UTP and bad loans; and more outflows of UTP and bad loans. Nevertheless, our main findings remained substantially the same (Table A.2).

Third, we verified whether bank-specific variables could alter the results. Specifically, we used another variable for bank profitability (return on equity (ROE) instead of ROA) and bank earnings volatility (which was measured as the year ROA SD, *SD*

[11] https://www.bancaditalia.it/footer/glossario/index.html?letter=b

[12] We also controlled for global and other systemically important institutions buffers (https://www.esrb.europa.eu/national_policy/systemically/html/index.en.html). For this reason, we constructed another variable for Tier 1 and common equity capital buffers considering the additional amount for other and globally systematically important institutions (O-SIIs and G-SIIs, Banca Monte dei Paschi di Siena (0.25%), Banco Popolare di Milano (BPM) (0,25%), Intesa SanPaolo (0,75%), and Unicredit SPA (2%)). The results confirmed our previous findings and are available upon request.

ROA) in our base model.[13] These bank-specific variables did not change our main findings, which were reiterated (Tables A.3 and A.4).

For our final robustness tests, we used a static fixed-effects model to control the time-invariant unobserved heterogeneity across banks (Klein 2013, Cucinelli et al. 2021, Cerulli et al. 2020, Ghosh 2015). Moreover, the use of both bank and time fixed effects helped to address the omitted-variables bias problem. However, this approach could suffer from possible endogeneity, and the system GMM estimation remains the best statistical method in the case of dynamic panel data (Arellano & Bover 1995, Blundell & Bond 1998). Table A.5 in the Appendix presents the results. The Tier 1 and total capital buffer coefficients showed the same negative signs and explanatory powers as did the baseline results.[14]

7 Concluding Remarks

In this study, we used a two-step system GMM approach to shed light on the impact of capital buffers on bank risk-taking. While other papers have evaluated NPL determinants, focussing on country- and bank-specific factors (Cerulli et al. 2020, Jiang et al. 2020, Ghosh 2015, Jiménez et al. 2009, Berger & DeYoung 1997), only a few have focussed on the flow of impaired loans(Cucinelli et al. 2021, Baldini & Causi 2020, Marcucci & Quagliariello 2009, Bofondi & Gobbi 2006). We fill the gap in this literature, showing the effects of capital buffers on the stocks and flows of the three NPL risk categories, namely, past due, UTP and bad loans.

[13]To preserve space, these tests are relegated to Tables A.3 and A.4 in the Appendix.

[14]A simple OLS estimation provided similar conclusions. The results are available upon request.

We choose as a natural laboratory the Italian case since Italian banks have the highest NPL ratio in the EU, and NPL management in Italy is particularly significant (Baldini & Causi 2020, Cucinelli et al. 2021). We adopt a standard two-step system GMM approach linking capital buffers to the stocks and flows (in and out) of different NPL categories. We respond to the following research question: Do capital buffers influence bank NPL inflows and outflows? The answer to this question, according to the results of this study, is yes.

Overall, our results suggest that the average stocks of past due, UTP and bad loans are lower. Moreover, the inflows of past due, UTP and bad loans decrease for banks with higher capital buffers, while for the outflows, there is no impact. Finally, the Tier 1 capital buffer has a greater ability to mitigate NPLs (stocks and flows) than does the total capital buffer, highlighting how the highest quality capital buffer–more closely related to shareholder capital–can reduce the bank's risk-taking level. From a policy perspective, our results endorse a macroprudential approach to financial stability. Regulatory capital acts favourably towards lower bank risk-taking and a better asset quality, curbing moral hazard incentives and favouring the banking system's stability.

The banking literature reveals that there is still no clear consensus on the relationship between the capitalisation level and the NPL ratio. Following the moral hazard hypothesis, some studies have revealed a positive relationship between the two variables (Ghosh 2015, Cucinelli et al. 2018), while others have found a negative one (Louzis et al. 2012, Klein 2013, Chaibi et al. 2016). These ambiguous results may be due to the nature of the NPL ratio, which represents an ex post measure

of risk-taking, as well as to the role of regulatory capital. According to our results, banks with higher capitalisation levels experience lower NPL levels, probably due to the effect of prudential regulations that aim to curb moral hazard incentives by imposing risk-sensitive capital requirements.

These results are consistent with the view that capital buffers serve as a tool to prevent banks from becoming insolvent, as the buffers allow banks to absorb future adverse shocks from the credit market (Bui et al. 2017, Guidara et al. 2013, Drehmann & Gambacorta 2012, Berger et al. 1995). The capital buffers that banks hold in addition to the required minimum capital can play a crucial role in mitigating the impact of the volatility of capital requirements due to changes in risk. This phenomenon means that even a moderate increase in bank capital buffers can be sufficient to maintain the resilience of the financial system, especially during times of economic recession.

Interestingly, the collateral and personal guarantees collected by the bank affect loan portfolio quality, in terms of either stocks or flows (both inflows and outflows). In particular, the results show that personal guarantees positively influenced the outflows of the highest NPL risk category (i.e., bad loans). This evidence suggests that the supervisory authority must consider the role of personal guarantees in its risk mitigation models.

Going forward, there are multiple directions for research. First, since we used data on the Italian banking system, future studies could expand the experimental setting of our study by analysing the impact of capital buffers on NPLs in the European banking system to determine whether our results hold in different contexts. Second,

the economic consequences of the coronavirus crisis and related challenges for the resilience of the EU banking sector have raised concerns about banks' accumulation of higher levels of NPLs on their balance sheets. Despite the significant decline in NPLs since 2016, the COVID-19 pandemic and recent war could have caused a new wave of NPLs in Europe, which could undermine banks' ability to provide intermediate credit and support economic recovery in the post-COVID world. The empirical findings of this study may provide a good measure for future studies investigating resolution strategies for NPL stock reduction in the case of economic shock.

References

Acharya, S. (1996), 'Charter value, minimum bank capital requirement and deposit insurance pricing in equilibrium', *Journal of Banking & Finance* **20**(2), 351–375.

Acharya, V. V. (2009), 'A theory of systemic risk and design of prudential bank regulation', *Journal of Financial Stability* **5**(3), 224–255.

Anginer, D., Demirguc-Kunt, A. & Zhu, M. (2014), 'How does deposit insurance affect bank risk? evidence from the recent crisis', *Journal of Banking & Finance* **48**, 312–321.

Arellano, M. & Bond, S. (1991), 'Some tests of specification for panel data: Monte carlo evidence and an application to employment equations', *The Review of Economic Studies* **58**(2), 277–297.

Arellano, M. & Bover, O. (1995), 'Another look at the instrumental variable estimation of error-components models', *Journal of Econometrics* **68**(1), 29–51.

Baldini, A. & Causi, M. (2020), 'Restoring credit market stability conditions in italy: evidences on loan and bad loan dynamics', *The European Journal of Finance* **26**(7-8), 746–773.

Beccalli, E. & Girardone, C. (2016), 'Banking in italy', *The Palgrave Handbook of European Banking* pp. 521–540.

Berger, A. N. & DeYoung, R. (1997), 'Problem loans and cost efficiency in commercial banks', *Journal of Banking & Finance* **21**(6), 849–870.

Berger, A. N., Espinosa-Vega, M. A., Frame, W. S. & Miller, N. H. (2011), 'Why do borrowers pledge collateral? new empirical evidence on the role of asymmetric information', *Journal of Financial Intermediation* **20**(1), 55–70.

Berger, A. N., Herring, R. J. & Szegö, G. P. (1995), 'The role of capital in financial institutions', *Journal of Banking & Finance* **19**(3-4), 393–430.

Blundell, R. & Bond, S. (1998), 'Initial conditions and moment restrictions in dynamic panel data models', *Journal of Econometrics* **87**(1), 115–143.

Bofondi, M. & Gobbi, G. (2006), 'Informational barriers to entry into credit markets', *Review of Finance* **10**(1), 39–67.

Bofondi, M. & Ropele, T. (2011), 'Macroeconomic determinants of bad loans: evidence from italian banks', *Bank of Italy Occasional Paper* (89).

Boumparis, P., Milas, C. & Panagiotidis, T. (2019), 'Non-performing loans and sovereign credit ratings', *International Review of Financial Analysis* **64**, 301–314.

Bui, C., Scheule, H. & Wu, E. (2017), 'The value of bank capital buffers in maintaining financial system resilience', *Journal of Financial Stability* **33**, 23–40.

Calem, P. & Rob, R. (1999), 'The impact of capital-based regulation on bank risk-taking', *Journal of Financial Intermediation* **8**(4), 317–352.

Casu, B., Girardone, C. & Molyneux, P. (2015), 'Introduction to banking', *Pearson* .

Cerulli, G., D'Apice, V., Fiordelisi, F. & Masala, F. (2020), 'Benchmarking non-performing loans', *The European Journal of Finance* **26**(16), 1591–1605.

Chaibi, H. et al. (2016), 'Determinants of problem loans: Non-performing loans vs. loan quality deterioration', *International Business Research* **9**(10), 86–93.

Conlon, T., Cotter, J. & Molyneux, P. (2020), 'Beyond common equity: The influence of secondary capital on bank insolvency risk', *Journal of Financial Stability* **47**, 100732.

Couaillier, C., Lo Duca, M., Reghezza, A. & d'Acri, C. R. (2022), 'Caution: do not cross! capital buffers and lending in covid-19 times', *ECB Working Paper* .

Cubillas, E., Fernández, A. I. & González, F. (2017), 'How credible is a too-big-to-fail policy? international evidence from market discipline', *Journal of Financial Intermediation* **29**, 46–67.

Cucinelli, D., Di Battista, M. L., Marchese, M. & Nieri, L. (2018), 'Credit risk in european banks: The bright side of the internal ratings based approach', *Journal of Banking & Finance* **93**, 213–229.

Cucinelli, D., Gai, L., Ielasi, F. & Patarnello, A. (2021), 'Preventing the deterioration of bank loan portfolio quality: a focus on unlikely-to-pay loans', *The European Journal of Finance* **27**(7), 613–634.

Danisewicz, P., McGowan, D., Onali, E. & Schaeck, K. (2018), 'Debt priority structure, market discipline, and bank conduct', *The Review of Financial Studies* **31**(11), 4493–4555.

Demirguc-Kunt, A., Detragiache, E. & Merrouche, O. (2013), 'Bank capital: Lessons from the financial crisis', *Journal of Money, Credit and Banking* **45**(6), 1147–1164.

Demsetz, R. S., Saidenberg, M. R. & Strahan, P. E. (1996), 'Banks with something to lose: The disciplinary role of franchise value', *Economic Policy Review* **2**(2).

Diamond, D. W. & Rajan, R. G. (2000), 'A theory of bank capital', *Journal of Finance* **55**(6), 2431–2465.

Drehmann, M. & Gambacorta, L. (2012), 'The effects of countercyclical capital buffers on bank lending', *Applied Economics Letters* **19**(7), 603–608.

Duran, M. A. & Lozano-Vivas, A. (2015), 'Moral hazard and the financial structure of banks', *Journal of International Financial Markets, Institutions and Money* **34**, 28–40.

ECB (2018), 'Addendum to the ecb guidance to banks on non-performing loans: supervisory expectations for prudential provisioning of non-performing exposures'.

Foos, D., Norden, L. & Weber, M. (2010), 'Loan growth and riskiness of banks', *Journal of Banking & Finance* **34**(12), 2929–2940.

Freixas, X. & Rochet, J.-C. (2008), *Microeconomics of Banking*, MIT press.

Furlong, F. T. & Keeley, M. C. (1989), 'Capital regulation and bank risk-taking: A note', *Journal of Banking & Finance* **13**(6), 883–891.

Ghosh, A. (2015), 'Banking-industry specific and regional economic determinants of non-performing loans: Evidence from us states', *Journal of Financial Stability* **20**, 93–104.

Guidara, A., Soumaré, I., Tchana, F. T. et al. (2013), 'Banks' capital buffer, risk and performance in the canadian banking system: Impact of business cycles and regulatory changes', *Journal of Banking & Finance* **37**(9), 3373–3387.

Hasan, I. & Wall, L. D. (2004), 'Determinants of the loan loss allowance: Some cross-country comparisons', *Financial Review* **39**(1), 129–152.

Heid, F., Porath, D. & Stolz, S. (2003), Does capital regulation matter for bank behavior? evidence for german savings banks, Technical report, Kiel Working Paper.

Hessou, H. et al. (2017), 'Basel iii capital buffer requirements and credit union prudential regulation: Canadian evidence', *Journal of Financial Stability* **30**, 92–110.

Hoque, H., Andriosopoulos, D., Andriosopoulos, K. & Douady, R. (2015), 'Bank regulation, risk and return: Evidence from the credit and sovereign debt crises', *Journal of Banking & Finance* **50**, 455–474.

Hu, J.-L., Li, Y. & Chiu, Y.-H. (2004), 'Ownership and nonperforming loans: Evidence from taiwan's banks', *The Developing Economies* **42**(3), 405–420.

Huynh, J. & Dang, V. D. (2021), 'Loan portfolio diversification and bank returns: Do business models and market power matter?', *Cogent Economics & Finance* **9**(1), 1891709.

Jappelli, T., Pagano, M. & Bianco, M. (2005), 'Courts and banks: Effects of judicial enforcement on credit markets', *Journal of Money, Credit and Banking* pp. 223–244.

Jensen, M. C. (1986), 'Agency costs of free cash flow, corporate finance, and takeovers', *The American Economic Review* **76**(2), 323–329.

Jensen, M. C. & Meckling, W. H. (1976), 'Theory of the firm: Managerial behavior, agency costs and ownership structure', *Journal of Financial Economics* **3**(4), 305–360.

Jiang, H., Zhang, J. & Sun, C. (2020), 'How does capital buffer affect bank risk-taking? new evidence from china using quantile regression', *China Economic Review* **60**.

Jiménez, G., Salas, V. & Saurina, J. (2009), 'Organizational distance and use of collateral for business loans', *Journal of Banking & Finance* **33**(2), 234–243.

Jiménez, G. & Saurina, J. (2004), 'Collateral, type of lender and relationship banking as determinants of credit risk', *Journal of Banking & Finance* **28**(9), 2191–2212.

Jokipii, T. & Milne, A. (2011), 'Bank capital buffer and risk adjustment decisions', *Journal of Financial Stability* **7**(3), 165–178.

Karadima, M. & Louri, H. (2020), 'Non-performing loans in the euro area: Does bank market power matter?', *International Review of Financial Analysis* **72**, 101593.

Keeley, M. C. (1990), 'Deposit insurance, risk, and market power in banking', *American Economic Review* pp. 1183–1200.

Keeton, W. R. (1999), 'Does faster loan growth lead to higher loan losses?', *Economic Review* **84**(2), 57.

Keeton, W. R. & Morris, C. S. (1987), 'Why do banks' loan losses differ', *Economic Review* **72**(5), 3–21.

Kim, D. & Santomero, A. M. (1988), 'Risk in banking and capital regulation', *The Journal of Finance* **43**(5), 1219–1233.

Klein, N. (2013), 'Non-performing loans in cesee: Determinants and impact on macroeconomic performance', *International Monetary Fund* .

Koehn, M. & Santomero, A. M. (1980), 'Regulation of bank capital and portfolio risk', *The Journal of Finance* **35**(5), 1235–1244.

Kwan, S. & Eisenbeis, R. A. (1997), 'Bank risk, capitalization, and operating efficiency', *Journal of Financial Services Research* **12**(2), 117–131.

Leung, W. S., Taylor, N. & Evans, K. (2015), 'The determinants of bank risks: Evidence from the recent financial crisis', *Journal of International Financial Markets, Institutions and Money* **34**, 277–293.

Louzis, D. P., Vouldis, A. T. & 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 & Finance* **36**(4), 1012–1027.

Lundtofte, F. & Nielsen, C. Y. (2019), 'The effect of stricter capital regulation on banks' risk-taking: Theory and evidence', *European Financial Management* **25**(5), 1229–1248.

Manz, F. (2019), 'Determinants of non-performing loans: What do we know? a systematic review and avenues for future research', *Management Review Quarterly* **69**(4), 351–389.

Marcucci, J. & Quagliariello, M. (2009), 'Asymmetric effects of the business cycle on bank credit risk', *Journal of Banking & Finance* **33**(9), 1624–1635.

Marcus, A. J. (1984), 'Deregulation and bank financial policy', *Journal of Banking & Finance* **8**(4), 557–565.

Merton, R. C. (1977), 'An analytic derivation of the cost of deposit insurance and loan guarantees an application of modern option pricing theory', *Journal of Banking & Finance* **1**(1), 3–11.

Milne, A. & Jokipii, T. (2008), 'The cyclical behaviour of european bank capital buffers', *Journal of Banking & Finance* **32**(1).

Poghosyan, T. & Čihak, M. (2011), 'Determinants of bank distress in europe: Evidence from a new data set', *Journal of Financial Services Research* **40**(3), 163–184.

Rajan, R. & Dhal, S. C. (2003), 'Non-performing loans and terms of credit of public sector banks in india: An empirical assessment', *Reserve Bank of India Occasional Papers* **24**(3), 81–121.

Rajan, R. G. (1994), 'Why bank credit policies fluctuate: A theory and some evidence', *The Quarterly Journal of Economics* **109**(2), 399–441.

Rochet, J.-C. (1992), 'Capital requirements and the behaviour of commercial banks', *European Economic Review* **36**(5), 1137–1170.

Roodman, D. (2009), 'How to do xtabond2: An introduction to difference and system gmm in stata', *The Stata Journal* **9**(1), 86–136.

Salas, V. & Saurina, J. (2002), 'Credit risk in two institutional regimes: Spanish commercial and savings banks', *Journal of Financial Services Research* **22**(3), 203–224.

Serrano, A. S. (2021), 'The impact of non-performing loans on bank lending in europe: an empirical analysis', *The North American Journal of Economics and Finance* **55**, 101312.

Shim, J. (2013), 'Bank capital buffer and portfolio risk: The influence of business cycle and revenue diversification', *Journal of Banking & Finance* **37**(3), 761–772.

Stern, G. H. & Feldman, R. J. (2004), 'Too big to fail: The hazards of bank bailouts', *Brookings Institution Press* .

Stolz, S. & Wedow, M. (2011), 'Banks' regulatory capital buffer and the business cycle: Evidence for germany', *Journal of Financial Stability* **7**(2), 98–110.

VanHoose, D. (2007), 'Theories of bank behavior under capital regulation', *Journal of Banking & Finance* **31**(12), 3680–3697.

Vithessonthi, C. (2016), 'Deflation, bank credit growth, and non-performing loans: Evidence from japan', *International Review of Financial Analysis* **45**, 295–305.

Wang, M.-S. (2014), 'Financial innovation, basel accord iii, and bank value', *Emerging Markets Finance and Trade* **50**(sup2), 23–42.

Windmeijer, F. (2005), 'A finite sample correction for the variance of linear efficient two-step gmm estimators', *Journal of Econometrics* **126**(1), 25–51.

Table 1: Data description. Data definitions for the Tier 1 buffer, the total capital buffer, and the control variables applied in the study. The data were sourced from the ABI database (ABI Banking Data) on an annual basis.

Variable	Definition
Tier 1 buffer	The Tier 1 buffer is defined as the additional Tier 1 capital that banks hold above the different minimum requirement from Basel II (4% before 2013) and Basel III (from 4.5% to 6%). https://www.bis.org/bcbs/basel3/basel3_phase_in_arrangements.pdf
Total capital buffer	The total capital buffer is the additional total capital ratio plus the conservation buffer that banks hold above the different minimum requirements from Basel II (8% before 2013) and Basel III (from 8% to 10.5%). https://www.bis.org/bcbs/basel3/basel3_phase_in_arrangements.pdf
Past due ratio	The past due ratio is defined as the bank past due loans over the gross loans. A higher past due ratio indicates a lower asset quality.
UTP ratio	The UTP ratio is defined as the UTP loans over the gross loans. A higher UTP ratio indicates a lower asset quality.
Bad loans ratio	The bad loans ratio is defined as the bank bad loans over the gross loans. A higher bad loans ratio indicates a lower asset quality.
Inflow of past due loans	The inflow of past due loans is defined as the flow of the new past due loans at time t over (the gross loans at time t-1 - the past due loan stock at time t-1).
Inflow of UTP loans	The inflow of UTP loans is defined as the flow of new UTP loans at time t over (the gross loans at time t-1 - the UTP loan stock at time t-1).
Inflow of bad loans	The inflow of bad loans is defined as the flow of the new bad loans at time t over (the gross loans at time t-1 - the bad loan stock at time t-1).
Outflow of past due loans	The outflow of past due loans is defined as the decreases in the past due loans at time t over the gross loans at time t-1.
Outflow of UTP loans	The outflow of UTP loans is defined as the decreases in the UTP loans at time t over the gross loans at time t-1.
Outflow of bad loans	The outflow of bad loans is defined as the decreases in the bad loans at time t over the gross loans at time t-1.
ROA	The ROA is calculated as the ratio of the annualised pre-tax income to the total assets.
Size	The bank size is the log value of the total assets.
Cost-Income	The cost-income is defined as the ratio between the operating costs (administrative and fixed costs, such as salaries and property expenses) and operating income.
Loan growth	The loan growth is the difference between the log value of the loans at time t minus the log value of the loans at time t-1.
Loan to total assets	Total loans over total assets.
Loans secured by real guarantees	The loans secured by real guarantees are defined as the ratio between the amount of the loans secured by the real guarantees and the gross loans.
Loans secured by personal guarantees	The loans secured by personal guarantees are defined as the ratio between the amount of the loans secured by personal guarantees and the gross loans.
Past due coverage ratio	Loan loss reserve specific for past due over the stock of total past due.
UTP coverage ratio	Loan loss reserve specific for UTP over the stock of total UTP.
Bad loans coverage ratio	Loan loss reserve specific for bad loans over the stock of total bad loans.

Table 2: Summary statistics: Capital buffers and control variables.

Table 2 displays the summary statistics calculated from 2006 to 2018. All the variables are defined in Table 1. In each case, the descriptive statistics relating to the mean, SD, minimum, maximum, 25th percentile, 50th percentile, 75th percentile, minimum, maximum, and number of observations are displayed.

	Observations	Mean	Median	SD	p25	p75	Min	Max
Tier 1 buffer	5788	0.132	0.106	0.105	0.073	0.155	0.006	0.743
Total capital buffer	5788	0.109	0.080	0.108	0.050	0.129	0.012	0.765
Past due ratio	6087	0.011	0.006	0.012	0.002	0.015	0.000	0.060
UTP ratio	6087	0.057	0.048	0.041	0.026	0.078	0.000	0.198
Bad loans ratio	6087	0.071	0.053	0.063	0.025	0.098	0.000	0.299
Inflow of past due	5920	0.017	0.010	0.019	0.004	0.023	0.000	0.102
Inflow of UTP	5957	0.041	0.031	0.037	0.017	0.052	0.000	0.212
Inflow of bad loans	5957	0.024	0.017	0.024	0.008	0.031	0.000	0.142
Outflow of past due	5920	0.016	0.010	0.018	0.004	0.022	0.000	0.094
Outflow of UTP	5920	0.029	0.025	0.022	0.014	0.039	0.000	0.115
Outflow of bad loans	5920	0.013	0.007	0.021	0.003	0.013	0.000	0.127
ROA	6087	-0.001	-0.001	0.003	-0.002	0.000	-0.009	0.012
Size	6087	13.373	13.156	1.649	12.194	14.291	10.442	18.347
Cost-Income	6087	0.692	0.674	0.208	0.587	0.763	0.233	1.772
Loan growth	5957	0.064	0.031	0.164	-0.020	0.096	-0.267	0.871
Loan to total assets	6087	0.622	0.639	0.169	0.530	0.741	0.104	0.941
Secured loans by real guarantees	6087	0.751	0.812	0.211	0.711	0.876	0.000	0.987
Secured loans by personal guarantees	6087	0.375	0.241	0.393	0.152	0.426	0.000	0.874
Past due coverage ratio	5894	0.070	0.042	0.088	0.011	0.095	0.000	0.537
UTP coverage ratio	5995	0.189	0.169	0.137	0.086	0.269	0.000	0.674
Bad loans coverage ratio	5979	0.551	0.548	0.170	0.444	0.646	0.086	1.000

Table 3: Correlation matrix between the variables (2006–2018).

Table 3 presents the Pearson correlation coefficients between all the variables reported for 2006–2018. * Indicates statistical significance at the 1% level.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Tier 1 buffer	(1)	1									
Total capital buffer	(2)	0.975*	1								
Past due ratio	(3)	-0.056*	-0.050*	1							
UTP ratio	(4)	-0.091*	-0.078*	0.254*	1						
Bad loans ratio	(5)	-0.056*	-0.031	0.315*	0.545*	1					
Inflow of past due	(6)	-0.059*	-0.047	0.773*	0.205*	0.240*	1				
Inflow of UTP	(7)	-0.080*	-0.066*	0.248*	0.688*	0.405*	0.376*	1			
Inflow of bad loans	(8)	-0.103*	-0.078*	0.277*	0.433*	0.656*	0.328*	0.568*	1		
Outflow of past due	(9)	-0.061*	-0.048	0.572*	0.287*	0.320*	0.836*	0.416*	0.365*	1	
Outflow of UTP	(10)	-0.069*	-0.056*	0.221*	0.574*	0.515*	0.313*	0.597*	0.626*	0.372*	1
Outflow of bad loans	(11)	0.004	0.026	0.043	0.170*	0.281*	0.049	0.132*	0.364*	0.070*	0.290*
ROA	(12)	0.011	0.035	0.099*	0.375*	0.361*	0.087*	0.314*	0.366*	0.137*	0.317*
Size	(13)	-0.269*	-0.207*	-0.113*	-0.062*	0.036	-0.015	-0.019	0.070*	0.009	-0.038
Cost-Income	(14)	0.118*	0.119*	0.016	-0.007	0.075*	0.009	0.002	0.068*	0.002	0.059*
Loan growth	(15)	0.066*	0.061*	-0.110*	-0.311*	-0.265*	-0.005	-0.039	0.057*	-0.083*	-0.145*
Loan to total assets	(16)	-0.404*	-0.411*	-0.038	-0.013	-0.159*	0.032	0.003	-0.040	0.010	0.018
Secured loans by real guarantees	(17)	-0.009	-0.032	0.164*	0.234*	0.236*	0.098*	0.166*	0.113*	0.101*	0.136*
Secured loans by personal guarantees	(18)	0.036	0.015	0.154*	0.120*	0.076*	0.129*	0.087*	0.052*	0.127*	0.072*
Past due coverage ratio	(19)	0.066*	0.084*	-0.066*	-0.005	0.154*	-0.073*	-0.041	0.082*	-0.022	0.018
UTP coverage ratio	(20)	0.039	0.065*	-0.052*	0.059*	0.212*	-0.068*	-0.029	0.136*	-0.019	0.041
Bad loans coverage ratio	(21)	0.150*	0.153*	-0.077*	-0.061*	0.047	-0.109*	-0.081*	-0.057*	-0.089*	-0.095*

		(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
Outflow of bad loans	(11)	1									
ROA	(12)	0.156*	1								
Size	(13)	0.082*	-0.036	1							
Cost-Income	(14)	0.117*	0.443*	-0.239*	1						
Loan growth	(15)	0.134*	-0.102*	-0.032	0.109*	1					
Loan to total assets	(16)	-0.018	-0.028	0.111*	-0.051*	0.0272	1				
Secured loans by real guarantees	(17)	-0.081*	0.059*	-0.235*	-0.002	-0.251*	-0.083*	1			
Secured loans by personal guarantees	(18)	-0.098*	-0.011	-0.193*	-0.044	-0.123*	-0.025	0.323*	1		
Past due coverage ratio	(19)	0.200*	0.066*	0.192*	0.029	0.076*	-0.159*	-0.202*	-0.138*	1	
UTP coverage ratio	(20)	0.250*	0.133*	0.285*	-0.011	0.049	-0.228*	-0.220*	-0.163*	0.543*	1
Bad loans coverage ratio	(21)	0.072*	-0.044	0.061*	-0.012	0.088*	-0.278*	-0.162*	-0.122*	0.301*	0.419*

Table 4: Panel unit root test results. This table shows the results of the Fisher–ADF tests that assume individual unit root processes. All the variables are defined in Table 1

Variable	ADF-Fisher chi-square	P-value	Variable	ADF-Fisher chi-square	P-value
Tier 1 buffer	3500.5763	0.000	ROA	2614.751	0.000
Total capital buffer	3494.7067	0.000	Size	2742.4508	0.000
Past due ratio	2974.2987	0.000	Cost-Income	2837.1	0.000
UTP ratio	2327.4458	0.000	Loan growth	3131.2146	0.000
Bad loans ratio	2125.1381	0.000	Loan to total assets	1627.7466	0.000
Inflow of past due	3717.9739	0.000	Secured loans by real guarantees	3508.9302	0.000
Inflow of UTP	3842.7889	0.000	Secured loans by personal guarantees	4600.5351	0.000
Inflow of bad loans	3380.9189	0.000	Past due Coverage ratio	2852.5928	0.000
Outflow of past due	3442.4362	0.000	UTP Coverage ratio	2150.7189	0.000
Outflow of UTP	3444.2049	0.000	Bad loans Coverage ratio	2526.8755	0.000
Outflow of bad loans	3745.2774	0.000			

Table 5: Effect of the Tier 1 and total capital buffers on loan portfolio deterioration. This table shows the results of two-step system GMM regressions that examine the effect of the Tier 1 and total capital buffers on the loan portfolio deterioration proxies (stock variables). In Columns 1-2, the dependent variable is the past due ratio. In Columns 3-4, the dependent variable is the UTP ratio. In Columns 4-5, the dependent variable is the ratio of the bad loan. All explanatory variables are as defined in Table 1. All bank-level variables are winsorised at the 1st and 99th percentiles. All models include time-fixed effects, and we use Windmeijer standard error corrections. The estimation results are for the 2006-2018 period. The t-statistics are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Past due ratio	Past due ratio	UTP ratio	UTP ratio	Bad loans ratio	Bad loans ratio
Tier 1 buffer	-0.401*		-0.308**		-1.233**	
	(-1.857)		(-2.549)		(-2.507)	
Total capital buffer		-0.276		-0.275**		-1.232**
		(-1.375)		(-2.358)		(-2.488)
ROA	0.226	0.230	0.351***	0.354***	0.152	0.165
	(1.140)	(1.160)	(5.123)	(5.159)	(1.473)	(1.614)
Size	-0.005	-0.002	0.012	0.013*	0.014	0.020
	(-0.347)	(-0.168)	(1.469)	(1.646)	(0.408)	(0.617)
Cost-Income	0.013	0.015	-0.194**	-0.193**	-0.018	-0.008
	(0.112)	(0.130)	(-2.338)	(-2.319)	(-0.108)	(-0.045)
Loan growth	0.137	0.142	-0.060	-0.060	-1.751*	-1.716*
	(0.574)	(0.597)	(-0.577)	(-0.580)	(-1.814)	(-1.783)
Loan to total assets	-0.187	-0.161	0.255**	0.260**	-1.648	-1.685
	(-0.853)	(-0.739)	(2.511)	(2.548)	(-1.512)	(-1.556)
Secured loans by real guarantees	0.473**	0.476**	0.219**	0.218**	-0.794	-0.749
	(2.480)	(2.487)	(2.413)	(2.412)	(-0.912)	(-0.857)
Secured loans by personal guarantees	-0.014	-0.015	0.071***	0.071***	0.274	0.264
	(-0.291)	(-0.293)	(3.248)	(3.241)	(0.464)	(0.449)
Past due coverage ratio	0.394	0.382				
	(1.068)	(1.040)				
UTP coverage ratio			-0.059	-0.061		
			(-0.442)	(-0.461)		
Bad loans coverage ratio					-0.415	-0.391
					(-0.701)	(-0.677)
Dependent variable (t-1)	0.436*	0.437*	0.613***	0.613***	0.966***	0.967***
	(1.834)	(1.848)	(13.230)	(13.207)	(16.207)	(16.262)
Intercept	YES	YES	YES	YES	YES	YES
Observations	5,163	5,163	5,386	5,386	5,318	5,318
Number of banks	680	680	691	691	691	691
Year FE	YES	YES	YES	YES	YES	YES
Arellano-Bond AR(1) test p-value	0.137	0.135	0.000	0.000	0.000	0.000
Arellano-Bond AR(2) test p-value	0.537	0.542	0.371	0.371	0.350	0.362
Hansen test p-value	0.172	0.172	0.278	0.276	0.271	0.279

Table 6: Effect of the Tier 1 and total capital buffers on the NPL inflows. This table shows the results of two-step system GMM regressions that examine the effect of Tier 1 and total capital buffers on the loan portfolio deterioration proxies (flow variables). In Columns 1-2, the dependent variable is the inflow of past due loans. In Columns 3-4, the dependent variable is the inflow of UTP loans. In Columns 4-5, the dependent variable is the inflow of bad loans. All explanatory variables are as defined in Table 1. All bank-level variables are winsorised at the 1st and 99th percentiles. All models include time-fixed effects, and we use Windmeijer standard error corrections. The estimation results are for the 2006-2018 period. The t-statistics are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1) Inflow of past due	(2) Inflow of past due	(3) Inflow of UTP	(4) Inflow of UTP	(5) Inflow of bad loans	(6) Inflow of bad loans
Tier 1 buffer	-0.680**		-0.820***		-0.708***	
	(-2.333)		(-3.232)		(-2.727)	
Total capital buffer		-0.542**		-0.733***		-0.557**
		(-2.004)		(-2.863)		(-2.114)
ROA	-0.156*	-0.146*	0.456***	0.464***	0.335	0.346
	(-1.780)	(-1.661)	(4.770)	(4.872)	(1.202)	(1.233)
Size	0.023	0.026	0.002	0.006	0.020	0.024
	(1.261)	(1.439)	(0.150)	(0.425)	(0.775)	(0.911)
Cost-Income	0.154	0.155	-0.279**	-0.275**	-0.275	-0.278
	(1.094)	(1.101)	(-2.087)	(-2.055)	(-1.511)	(-1.525)
Loan growth	-0.375	-0.365	-0.425**	-0.420**	-1.126***	-1.120***
	(-1.539)	(-1.497)	(-2.502)	(-2.477)	(-3.366)	(-3.347)
Loan to total assets	-0.196	-0.169	0.335**	0.347**	0.033	0.052
	(-0.935)	(-0.803)	(1.968)	(2.029)	(0.148)	(0.239)
Secured loans by real guarantees	0.445**	0.445**	0.202	0.204	0.295	0.294
	(2.192)	(2.193)	(1.412)	(1.433)	(1.558)	(1.559)
Secured loans by personal guarantees	0.007	0.008	0.234***	0.233***	0.068	0.068
	(0.123)	(0.133)	(6.505)	(6.475)	(1.248)	(1.239)
Past due coverage ratio	-0.363	-0.380				
	(-1.070)	(-1.122)				
UTP coverage ratio			0.132	0.127		
			(0.633)	(0.611)		
Bad loans coverage ratio					0.013	0.003
					(0.046)	(0.009)
Dependent variable (t-1)	0.420***	0.418***	0.261***	0.262***	0.524***	0.523***
	(2.686)	(2.659)	(7.009)	(7.021)	(2.735)	(2.721)
Dependent variable (t-2)	0.180***	0.181***	0.195***	0.195***	0.101**	0.102**
	(3.372)	(3.389)	(5.793)	(5.800)	(2.195)	(2.197)
Intercept	YES	YES	YES	YES	YES	YES
Observations	4,536	4,536	4,730	4,730	4,586	4,586
Number of banks	659	659	668	668	658	658
Year FE	YES	YES	YES	YES	YES	YES
Arellano-Bond AR(1) test p-value	0.003	0.003	0.000	0.000	0.000	0.000
Arellano-Bond AR(2) test p-value	0.240	0.236	0.346	0.343	0.703	0.708
Hansen test p-value	0.222	0.222	0.590	0.584	0.160	0.161

Table 7: Effect of the Tier 1 and total capital buffers on the NPL outflows. This table shows the results of two-step system GMM regressions that examine the effect of the Tier 1 and total capital buffers on the loan portfolio deterioration proxies (flow variables). In Columns 1-2, the dependent variable is the outflow of past due. In Columns 3-4, the dependent variable is the outflow of UTP. In Columns 4-5, the dependent variable is the outflow of bad loans. All explanatory variables are as defined in Table 1. All bank-level variables are winsorised at the 1st and 99th percentiles. All models include time fixed effects, and we use Windmeijer standard error corrections. The estimation results are for the 2006-2018 period. The t-statistics are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1) Outflow of past due	(2) Outflow of past due	(3) Outflow of UTP	(4) Outflow of UTP	(5) Outflow of bad loans	(6) Outflow of bad loans
Tier 1 buffer	-0.312		-0.219		0.219	
	(-0.156)		(-1.237)		(0.748)	
Total capital buffer		-0.372		-0.195		0.410
		(-0.194)		(-1.116)		(1.474)
ROA	0.877	0.929	0.511***	0.513***	0.377***	0.377***
	(1.032)	(1.093)	(7.007)	(7.061)	(3.506)	(3.504)
Size	-0.032	-0.029	0.003	0.004	0.060***	0.061***
	(-0.326)	(-0.300)	(0.266)	(0.360)	(3.015)	(3.041)
Cost-Income	-3.429	-3.506	-0.322***	-0.320***	0.216	0.211
	(-1.437)	(-1.465)	(-3.530)	(-3.512)	(1.317)	(1.285)
Loan growth	-1.681	-1.761	-0.888***	-0.885***	-0.747***	-0.743***
	(-0.908)	(-0.944)	(-5.279)	(-5.289)	(-3.208)	(-3.198)
Loan to total assets	0.789	0.358	0.347**	0.350**	0.084	0.126
	(0.256)	(0.120)	(2.534)	(2.550)	(0.347)	(0.522)
Secured loans by real guarantees	3.770*	3.729*	0.264**	0.264**	0.190	0.195
	(1.804)	(1.767)	(2.016)	(2.018)	(0.929)	(0.947)
Secured loans by personal guarantees	-0.721	-0.723	0.118***	0.118***	0.162***	0.164***
	(-0.900)	(-0.904)	(3.796)	(3.786)	(3.538)	(3.560)
Past due coverage ratio	6.865*	7.247*				
	(1.781)	(1.884)				
UTP coverage ratio			0.098	0.096		
			(0.591)	(0.582)		
Bad loans coverage ratio					-0.272	-0.290
					(-1.192)	(-1.263)
Dependent variable (t-1)	0.280***	0.285***	0.335***	0.335***	0.169***	0.169***
	(4.441)	(4.566)	(8.999)	(9.004)	(3.806)	(3.804)
Dependent variable (t-2)	0.123***	0.125***	0.111***	0.111***	0.033*	0.033*
	(3.075)	(3.134)	(3.820)	(3.835)	(1.760)	(1.760)
Intercept	YES	YES	YES	YES	YES	YES
Observations	4,514	4,514	4,676	4,676	4,526	4,526
Number of banks	656	656	662	662	658	658
Year FE	YES	YES	YES	YES	YES	YES
Arellano-Bond AR(1) test p-value	0.000	0.000	0.000	0.000	0.000	0.000
Arellano-Bond AR(2) test p-value	0.275	0.267	0.466	0.464	0.471	0.473
Hansen test p-value	0.264	0.262	0.296	0.296	0.212	0.208

Table 8: Subsample analysis.

Table 8 shows the results of the subsample analysis. Panels A and B are estimated from 2006-to 2012, and Panels C and D from 2013-to 2018. All bank-level variables are winsorised at the 1st and 99th percentiles. We use Windmeijer standard error corrections for all models that include time-fixed effects. The t-statistics are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A	(1) Past due ratio	(2) Past due ratio	(3) UTP ratio	(4) UTP ratio	(5) Bad loans ratio	(6) Bad loans ratio	(7) Inflow of past due	(8) Inflow of past due	(9) Inflow of UTP
Tier 1 buffer	-0.260		-0.177		-0.740		-0.663		-0.877**
	(-0.386)		(-1.127)		(-0.787)		(-1.545)		(-2.501)
Total capital buffer		-0.168		-0.173		-0.749		-0.327	
		(-0.344)		(-1.124)		(-0.825)		(-0.850)	
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	2,736	2,736	2,876	2,876	2,832	2,832	2,14	2,14	2,259
Number of banks	650	650	662	662	657	657	619	619	635
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Arellano-Bond AR(1) test p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Arellano-Bond AR(2) test p-value	0.833	0.836	0.133	0.131	0.194	0.200	0.127	0.124	0.775
Hansen test p-value	0.625	0.624	0.448	0.447	0.586	0.585	0.853	0.850	0.669
Panel B	(1) Inflow of UTP	(2) Inflow of bad loans	(3) Inflow of bad loans	(4) Outflow of past due	(5) Outflow of past due	(6) Outflow of UTP	(7) Outflow of UTP	(8) Outflow of bad loans	(9) Outflow of bad loans
Tier 1 buffer		-0.840**		0.605		-0.261		0.020	
		(-2.270)		(-1.038)		(-0.902)		(0.051)	
Total capital buffer	-0.781**		-0.582		0.643		-0.227		0.222
	(-2.121)		(-1.503)		(-1.124)		(-0.807)		(0.573)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	2,259	2,191	2,191	2,109	2,109	2,215	2,215	2,148	2,148
Number of banks	635	623	623	610	610	620	620	611	611
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Arellano-Bond AR(1) test p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Arellano-Bond AR(2) test p-value	0.758	0.651	0.641	0.868	0.850	0.810	0.812	0.424	0.431
Hansen test p-value	0.665	0.766	0.765	0.104	0.113	0.147	0.145	0.320	0.312
Panel C	(1) Past due ratio	(2) Past due ratio	(3) UTP ratio	(4) UTP ratio	(5) Bad loans ratio	(6) Bad loans ratio	(7) Inflow of past due	(8) Inflow of past due	(9) Inflow of UTP
Tier 1 buffer	-0.613*		-0.441**		-0.477*		-0.681*		-1.054***
	(-1.818)		(-2.227)		(-1.694)		(-1.898)		(-2.943)
Total capital buffer		-0.626		-0.383**		-0.473*		-0.748**	
		(-1.017)		(-2.061)		(-1.916)		(-2.137)	
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	1,914	1,914	1,982	1,982	1,960	1,960	1,889	1,889	1,952
Number of banks	533	533	542	542	540	540	527	527	536
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Arellano-Bond AR(1) test p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Arellano-Bond AR(2) test p-value	0.754	0.766	0.368	0.353	0.573	0.582	0.347	0.340	0.151
Hansen test p-value	0.333	0.331	0.196	0.191	0.356	0.356	0.331	0.333	0.652
Panel D	(1) Inflow of UTP	(2) Inflow of bad loans	(3) Inflow of bad loans	(4) Outflow of past due	(5) Outflow of past due	(6) Outflow of UTP	(7) Outflow of UTP	(8) Outflow of bad loans	(9) Outflow of bad loans
Tier 1 buffer		-0.732**		-1.095		-0.447*		0.282	
		(-2.313)		(-1.364)		(-1.854)		(0.788)	
Total capital buffer	-0.995***		-0.659**		-1.275		-0.394*		0.459
	(-2.871)		(-2.116)		(-1.533)		(-1.750)		(1.335)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	1,952	1,886	1,886	1,902	1,902	1,947	1,947	1,884	1,884
Number of banks	536	523	523	530	530	532	532	524	524
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Arellano-Bond AR(1) test p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Arellano-Bond AR(2) test p-value	0.147	0.217	0.328	0.167	0.273	0.656	0.458	0.350	0.353
Hansen test p-value	0.244	0.230	0.226	0.513	0.437	0.233	0.433	0.210	0.316

Table 9: PSM and macroeconomic analyses.

Table 9 shows the results of the PSM and macroeconomic analyses. Panels A and B use a propensity score-matched sample as described in Section 5.2, Equation 2. Panels C and D uses a matched sample controlling for the macroeconomic variables GDP growth, CPI and M2 growth. All bank-level variables are winsorised at the 1st and 99th percentiles. We use Windmeijer standard error corrections. The t-statistics are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Past due ratio	Past due ratio	UTP ratio	UTP ratio	Bad loans ratio	Bad loans ratio	Inflow of past due	Inflow of past due	Inflow of UTP
Tier 1 buffer	-0.306*		-0.329*		-0.484**		-0.577		-1.001***
	(-1.910)		(-1.715)		(-2.169)		(-1.232)		(-2.763)
Total capital buffer		-0.368*		-0.303*		-0.457**		-0.621	
		(-1.924)		(-1.753)		(-2.295)		(-1.467)	
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	5,246	5,246	5,414	5,414	5,398	5,398	4,497	4,497	4,688
R-squared	0.185	0.185	0.448	0.448	0.662	0.662	0.215	0.215	0.156
Number of banks	689	689	696	696	695	695	658	658	668
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Panel B	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Inflow of UTP	Inflow of bad loans	Inflow of bad loans	Outflow of past due	Outflow of past due	Outflow of UTP	Outflow of UTP	Outflow of bad loans	Outflow of bad loans
Tier 1 buffer		-1.274***		0.073		-0.621**		0.175	
		(-2.776)		(0.152)		(-1.966)		(0.441)	
Total capital buffer	-0.993***		-1.136***		0.010		-0.538*		0.321
	(-2.836)		(-2.799)		(0.022)		(-1.900)		(0.938)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	4,688	4,561	4,561	4,474	4,474	4,635	4,635	4,497	4,497
Number of banks	0.157	0.124	0.124	0.184	0.184	0.133	0.133	0.221	0.221
Number of id	668	657	657	655	655	661	661	657	657
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Panel C	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Past due ratio	Past due ratio	UTP ratio	UTP ratio	Bad loans ratio	Bad loans ratio	Inflow of past due	Inflow of past due	Inflow of UTP
Tier 1 buffer	-0.034		-0.311*		-0.530*		-0.176		-0.883***
	(-0.088)		(-1.918)		(-1.719)		(-0.495)		(-2.862)
Total capital buffer		-0.029		-0.258*		-0.475*		-0.150	
		(-0.081)		(-1.823)		(-1.658)		(-0.459)	
GDP growth	-0.146***	-0.146***	-0.001	-0.000	0.046***	0.046***	-0.178***	-0.178***	-0.078***
	(-10.465)	(-10.457)	(-0.063)	(-0.038)	(4.650)	(4.680)	(-12.982)	(-12.941)	(-6.974)
CPI	0.027*	0.027*	-0.068***	-0.069***	-0.114***	-0.115***	0.039**	0.039**	-0.028**
	(1.792)	(1.786)	(-6.206)	(-6.252)	(-9.662)	(-9.665)	(2.539)	(2.494)	(-2.069)
M2 growth	-0.040***	-0.040***	-0.003	-0.003	0.021***	0.021***	-0.067***	-0.066***	-0.050***
	(-4.132)	(-4.128)	(-0.508)	(-0.492)	(3.007)	(3.031)	(-7.087)	(-7.074)	(-6.659)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	5,255	5,255	5,414	5,414	5,400	5,400	5,278	5,278	5,412
R-squared	0.083	0.083	0.245	0.245	0.384	0.383	0.098	0.098	0.103
Number of banks	689	689	696	696	695	695	691	691	697
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Panel D	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Inflow of UTP	Inflow of bad loans	Inflow of bad loans	Outflow of past due	Outflow of past due	Outflow of UTP	Outflow of UTP	Outflow of bad loans	Outflow of bad loans
Tier 1 buffer		-1.196***		0.003		-0.441		0.020	
		(-2.836)		(0.009)		(-1.615)		(0.057)	
Total capital buffer	-0.790***		-1.134***		-0.039		-0.366		-0.007
	(-2.757)		(-2.794)		(-0.129)		(-1.482)		(-0.020)
GDP growth	-0.077***	-0.018	-0.017	-0.109***	-0.109***	-0.041***	-0.040***	0.123***	0.123***
	(-6.900)	(-1.343)	(-1.290)	(-8.411)	(-8.388)	(-3.767)	(-3.730)	(8.834)	(8.814)
CPI	-0.030**	-0.061***	-0.064***	-0.049***	-0.049***	-0.008	-0.009	-0.060***	-0.060***
	(-2.182)	(-3.979)	(-4.092)	(-3.102)	(-3.088)	(-0.571)	(-0.633)	(-3.231)	(-3.207)
M2 growth	-0.050***	-0.005	-0.005	-0.076***	-0.076***	-0.037***	-0.037***	0.080***	0.080***
	(-6.620)	(-0.490)	(-0.471)	(-8.715)	(-8.709)	(-5.115)	(-5.094)	(8.521)	(8.520)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	5,412	5,326	5,326	5,305	5,305	5,416	5,416	5,319	5,319
R-squared	0.103	0.108	0.109	0.083	0.083	0.128	0.128	0.126	0.126
Number of banks	697	694	694	694	694	698	698	691	691
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Appendix

Table A.1: Robustness checks.

Table A.1 shows the results of the robustness testing for the role of bank size. All explanatory variables are as defined in Table 1. All bank-level variables are winsorised at the 1st and 99th percentiles. All models include time-fixed effects, and we use Windmeijer standard error corrections. The estimation results are for the 2006-2018 period. The t-statistics are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1) Past due ratio	(2) Past due ratio	(3) UTP ratio	(4) UTP ratio	(5) Bad loans ratio	(6) Bad loans ratio	(7) Inflow of past due	(8) Inflow of past due	(9) Inflow of UTP
Tier 1 buffer	-0.383*		-0.292**		-1.356**		-0.694**		-0.809***
	(-1.775)		(-2.337)		(-1.970)		(-2.402)		(-3.171)
Total capital buffer		-0.250		-0.258**		-1.272*		-0.556**	
		(-1.253)		(-2.139)		(-1.799)		(-2.081)	
ROA	0.227	0.229	0.350***	0.352***	0.352*	0.361*	-0.143	-0.133	0.462***
	(1.109)	(1.123)	(5.117)	(5.148)	(1.780)	(1.805)	(-1.611)	(-1.495)	(4.868)
Size	0.017	0.020	0.020*	0.021**	0.109	0.113	0.008	0.011	0.008
	(0.741)	(0.861)	(1.843)	(1.972)	(0.683)	(0.709)	(0.280)	(0.408)	(0.391)
Cost-Income	0.026	0.027	-0.191**	-0.190**	-0.020	-0.009	0.140	0.140	-0.276**
	(0.220)	(0.233)	(-2.312)	(-2.296)	(-0.086)	(-0.040)	(0.992)	(0.998)	(-2.043)
Loan growth	0.142	0.149	-0.060	-0.060	-2.038**	-2.058**	-0.377	-0.368	-0.421**
	(0.602)	(0.630)	(-0.575)	(-0.578)	(-2.180)	(-2.195)	(-1.514)	(-1.475)	(-2.446)
Loan to total assets	-0.207	-0.179	0.253**	0.259**	-2.777**	-2.784**	-0.208	-0.181	0.328*
	(-0.894)	(-0.780)	(2.374)	(2.426)	(-2.020)	(-2.020)	(-0.984)	(-0.852)	(1.873)
Secured loans by real guarantees	0.458**	0.460**	0.210**	0.210**	-0.733	-0.710	0.467**	0.468**	0.198
	(2.401)	(2.404)	(2.293)	(2.292)	(-0.730)	(-0.705)	(2.292)	(2.291)	(1.383)
Secured loans by personal guarantees	-0.013	-0.013	0.071***	0.071***	0.289	0.285	0.004	0.005	0.236***
	(-0.254)	(-0.256)	(3.208)	(3.201)	(0.496)	(0.487)	(0.077)	(0.087)	(6.572)
Past due coverage ratio	0.407	0.393					-0.372	-0.389	
	(1.100)	(1.068)					(-1.104)	(-1.157)	
UTP coverage ratio			-0.065	-0.067					0.127
			(-0.486)	(-0.502)					(0.606)
Bad loans coverage ratio					-0.875	-0.866			
					(-1.249)	(-1.248)			
Large banks	-0.174	-0.176	-0.054	-0.051	-1.780	-1.741	0.030	0.033	-0.059
	(-1.497)	(-1.516)	(-0.801)	(-0.756)	(-1.383)	(-1.357)	(0.228)	(0.255)	(-0.478)
Medium banks	0.069	0.069	0.008	0.005	2.174*	2.141	0.097	0.091	0.044
	(0.712)	(0.712)	(0.127)	(0.079)	(1.649)	(1.635)	(0.898)	(0.857)	(0.399)
Dependent variable (t-1)	0.433*	0.434*	0.614***	0.614***	0.941***	0.943***	0.428***	0.427***	0.260***
	(1.831)	(1.842)	(13.394)	(13.370)	(14.265)	(14.252)	(2.728)	(2.700)	(6.950)
Dependent variable (t-2)							0.179***	0.180***	0.195***
							(3.309)	(3.325)	(5.795)
Intercept	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	5,163	5,163	5,386	5,386	5,318	5,318	4,536	4,536	4,730
Number of banks	680	680	691	691	691	691	659	659	668
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Arellano-Bond AR(1) test p-value	0.135	0.133	0.000	0.000	0.000	0.000	0.003	0.003	0.000
Arellano-Bond AR(2) test p-value	0.542	0.548	0.383	0.383	0.180	0.187	0.259	0.255	0.344
Hansen test p-value	0.183	0.182	0.289	0.286	0.267	0.273	0.216	0.217	0.590

Table A.1 continued from previous page

	(10) Inflow of UTP	(11) Inflow of bad loans	(12) Inflow of bad loans	(13) Outflow of past due	(14) Outflow of past due	(15) Outflow of UTP	(16) Outflow of UTP	(17) Outflow of bad loans	(18) Outflow of bad loans
Tier 1 buffer		-0.704***		1.128		-0.201		0.234	
		(-2.709)		(0.484)		(-1.122)		(0.781)	
Total capital buffer	-0.721***		-0.558**		0.836		-0.173		0.442
	(-2.802)		(-2.119)		(0.377)		(-0.980)		(1.539)
ROA	0.470***	0.327	0.337	0.319	0.310	0.511***	0.512***	0.392***	0.392***
	(4.966)	(1.165)	(1.195)	(0.279)	(0.269)	(7.155)	(7.209)	(3.661)	(3.662)
Size	0.011	0.008	0.011	0.276	0.232	0.016	0.017	0.070**	0.072***
	(0.543)	(0.211)	(0.305)	(0.800)	(0.693)	(1.030)	(1.102)	(2.502)	(2.582)
Cost-Income	-0.272**	-0.280	-0.283	-2.743	-2.725	-0.314***	-0.313***	0.217	0.211
	(-2.015)	(-1.535)	(-1.552)	(-1.118)	(-1.092)	(-3.426)	(-3.413)	(1.308)	(1.276)
Loan growth	-0.417**	-1.146***	-1.141***	-1.463	-1.528	-0.883***	-0.880***	-0.726***	-0.722***
	(-2.426)	(-3.398)	(-3.379)	(-0.765)	(-0.788)	(-5.200)	(-5.207)	(-3.093)	(-3.077)
Loan to total assets	0.342*	0.062	0.082	2.240	1.803	0.325**	0.330**	0.035	0.077
	(1.955)	(0.280)	(0.370)	(0.655)	(0.545)	(2.261)	(2.292)	(0.146)	(0.320)
Secured loans by real guarantees	0.200	0.296	0.295	3.103	3.190	0.251*	0.250*	0.192	0.196
	(1.403)	(1.566)	(1.566)	(1.279)	(1.322)	(1.901)	(1.903)	(0.958)	(0.972)
Secured loans by personal guarantees	0.235***	0.068	0.068	-0.462	-0.498	0.117***	0.117***	0.162***	0.164***
	(6.546)	(1.244)	(1.234)	(-0.552)	(-0.596)	(3.769)	(3.761)	(3.516)	(3.539)
Past due Coverage ratio				4.621	4.989				
				(1.146)	(1.239)				
UTP Coverage ratio	0.122					0.086	0.084		
	(0.585)					(0.512)	(0.501)		
Bad loans Coverage ratio		0.012	0.002					-0.281	-0.298
		(0.042)	(0.006)					(-1.236)	(-1.306)
Large Banks	-0.051	0.117	0.123	0.288	0.654	-0.106	-0.105	-0.178	-0.195
	(-0.409)	(0.805)	(0.846)	(0.072)	(0.170)	(-1.105)	(-1.094)	(-1.078)	(-1.171)
Medium Banks	0.037	-0.085	-0.092	-3.278	-3.460	0.052	0.050	0.219	0.229*
	(0.333)	(-0.715)	(-0.782)	(-0.752)	(-0.814)	(0.577)	(0.560)	(1.588)	(1.658)
Dependent variable (t-1)	0.261***	0.531***	0.530***	0.286***	0.292***	0.335***	0.336***	0.169***	0.168***
	(6.968)	(2.780)	(2.763)	(4.408)	(4.632)	(8.972)	(8.978)	(3.800)	(3.798)
Dependent variable (t-2)	0.195***	0.099**	0.100**	0.124***	0.127***	0.111***	0.112***	0.034*	0.034*
	(5.805)	(2.153)	(2.155)	(3.104)	(3.198)	(3.845)	(3.862)	(1.950)	(1.980)
Intercept	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	4,730	4,586	4,586	4,514	4,514	4,676	4,676	4,526	4,526
Number of banks	668	658	658	656	656	662	662	658	658
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Arellano-Bond AR(1) test p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Arellano-Bond AR(2) test p-value	0.341	0.674	0.680	0.176	0.176	0.460	0.458	0.454	0.455
Hansen test p-value	0.585	0.158	0.159	0.298	0.280	0.292	0.292	0.218	0.213

Table A.2: Robustness checks.

Table A.1 shows the results of the robustness testing for the role of bank specialisation. All explanatory variables are as defined in Table 1. All bank-level variables are winsorised at the 1st and 99th percentiles. All models include time fixed effects, and we use Windmeijer standard error corrections. The estimation results are for the 2006-2018 period. The t-statistics are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1) Past due ratio	(2) Past due ratio	(3) UTP ratio	(4) UTP ratio	(5) Bad loans ratio	(6) Bad loans ratio	(7) Inflow of past due	(8) Inflow of past due	(9) Inflow of UTP
Tier 1 buffer	-0.422*		-0.313**		-1.101**		-0.747**		-0.844***
	(-1.931)		(-2.562)		(-2.357)		(-2.563)		(-3.349)
Total capital buffer		-0.300		-0.280**		-1.074**		-0.623**	
		(-1.476)		(-2.384)		(-2.344)		(-2.301)	
ROA	0.240	0.244	0.355***	0.358***	0.489***	0.498***	-0.106	-0.096	0.470***
	(1.206)	(1.228)	(5.398)	(5.437)	(2.837)	(2.899)	(-1.196)	(-1.078)	(5.077)
Size	-0.015	-0.012	0.008	0.009	-0.127**	-0.122*	-0.025	-0.021	-0.019
	(-0.945)	(-0.769)	(0.922)	(1.104)	(-1.975)	(-1.845)	(-1.400)	(-1.191)	(-1.196)
Cost-Income	-0.005	-0.002	-0.208***	-0.207***	-0.678**	-0.668**	-0.010	-0.007	-0.334**
	(-0.043)	(-0.015)	(-2.604)	(-2.585)	(-2.185)	(-2.152)	(-0.066)	(-0.051)	(-2.479)
Loan growth	0.116	0.121	-0.059	-0.059	-0.884	-0.860	-0.422*	-0.413*	-0.447***
	(0.483)	(0.504)	(-0.574)	(-0.577)	(-0.810)	(-0.789)	(-1.759)	(-1.719)	(-2.652)
Loan to total assets	-0.187	-0.162	0.251**	0.256**	-1.313	-1.316	-0.244	-0.221	0.338**
	(-0.856)	(-0.747)	(2.478)	(2.515)	(-1.327)	(-1.319)	(-1.226)	(-1.103)	(2.009)
Secured loans by real guarantees	0.493**	0.496**	0.230**	0.229**	0.320	0.336	0.566***	0.564***	0.245*
	(2.502)	(2.507)	(2.505)	(2.502)	(0.271)	(0.285)	(2.647)	(2.640)	(1.680)
Secured loans by personal guarantees	-0.012	-0.012	0.072***	0.072***	0.374	0.362	0.015	0.016	0.245***
	(-0.233)	(-0.235)	(3.383)	(3.376)	(0.597)	(0.575)	(0.255)	(0.262)	(6.940)
Past due coverage ratio	0.396	0.385					-0.406	-0.421	
	(1.076)	(1.050)					(-1.264)	(-1.314)	
UTP coverage ratio			-0.065	-0.067					0.107
			(-0.494)	(-0.511)					(0.520)
Bad loans coverage ratio					-0.850	-0.838			
					(-1.543)	(-1.530)			
Cooperative banks	0.207**	0.207**	0.035	0.036	0.725	0.718	0.412***	0.413***	0.243***
	(2.253)	(2.256)	(1.038)	(1.064)	(0.820)	(0.808)	(3.040)	(3.036)	(4.194)
Commercial banks	0.030	0.028	0.021	0.021	0.902***	0.898***	0.233**	0.231**	0.089*
	(0.581)	(0.551)	(0.745)	(0.736)	(2.758)	(2.739)	(2.522)	(2.512)	(1.731)
Dependent variable (t-1)	0.436*	0.437*	0.614***	0.614***	0.812***	0.813***	0.456***	0.454***	0.260***
	(1.832)	(1.845)	(13.445)	(13.422)	(7.348)	(7.344)	(3.067)	(3.041)	(7.075)
Dependent variable (t-2)							0.170***	0.171***	0.196***
							(3.138)	(3.157)	(5.828)
Intercept	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	5,163	5,163	5,386	5,386	5,318	5,318	4,536	4,536	4,730
Number of banks	680	680	691	691	691	691	659	659	668
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Arellano-Bond AR(1) test p-value	0.135	0.133	0.000	0.000	0.000	0.000	0.001	0.001	0.000
Arellano-Bond AR(2) test p-value	0.543	0.548	0.362	0.362	0.119	0.125	0.327	0.321	0.333
Hansen test p-value	0.175	0.176	0.293	0.291	0.154	0.152	0.221	0.221	0.605

Table A.2 continued from previous page

	(10) Inflow of UTP	(11) Inflow of bad loans	(12) Inflow of bad loans	(13) Outflow of past due	(14) Outflow of past due	(15) Outflow of UTP	(16) Outflow of UTP	(17) Outflow of bad loans	(18) Outflow of bad loans
Tier 1 buffer		-0.719***		-0.005		-0.258		0.215	
		(-2.746)		(-0.002)		(-1.483)		(0.728)	
Total capital buffer	-0.759***		-0.573**		-0.046		-0.241		0.401
	(-2.981)		(-2.163)		(-0.023)		(-1.396)		(1.433)
ROA	0.478***	0.356	0.366	0.849	0.932	0.527***	0.530***	0.386***	0.385***
	(5.176)	(1.262)	(1.290)	(0.708)	(0.752)	(7.244)	(7.301)	(3.644)	(3.638)
Size	-0.014	0.001	0.005	0.054	0.046	-0.017	-0.016	0.051**	0.051**
	(-0.923)	(0.056)	(0.213)	(0.207)	(0.174)	(-1.354)	(-1.276)	(2.410)	(2.448)
Cost-Income	-0.328**	-0.329*	-0.331*	-3.316	-3.476	-0.387***	-0.384***	0.201	0.197
	(-2.438)	(-1.723)	(-1.733)	(-1.006)	(-1.020)	(-3.959)	(-3.942)	(1.194)	(1.172)
Loan growth	-0.443***	-1.134***	-1.129***	-1.877	-1.914	-0.889***	-0.886***	-0.749***	-0.746***
	(-2.628)	(-3.410)	(-3.397)	(-0.921)	(-0.930)	(-5.272)	(-5.282)	(-3.197)	(-3.190)
Loan to total assets	0.349**	0.019	0.038	1.095	0.661	0.335**	0.336**	0.081	0.123
	(2.068)	(0.086)	(0.173)	(0.346)	(0.214)	(2.453)	(2.454)	(0.335)	(0.505)
Secured loans by real guarantees	0.247*	0.343*	0.341*	3.495	3.477	0.305**	0.304**	0.212	0.215
	(1.696)	(1.691)	(1.689)	(1.581)	(1.559)	(2.336)	(2.340)	(1.000)	(1.012)
Secured loans by personal guarantees	0.243***	0.077	0.077	-0.785	-0.773	0.128***	0.127***	0.166***	0.167***
	(6.909)	(1.378)	(1.367)	(-0.881)	(-0.859)	(4.138)	(4.127)	(3.664)	(3.683)
Past due coverage ratio				7.071	7.389				
				(1.389)	(1.426)				
UTP coverage ratio	0.103					0.063	0.062		
	(0.503)					(0.379)	(0.373)		
Bad loans coverage ratio		-0.020	-0.029					-0.287	-0.303
		(-0.068)	(-0.100)					(-1.235)	(-1.300)
Cooperative banks	0.245***	0.263***	0.267***	-1.351	-1.277	0.190***	0.191***	0.183*	0.184*
	(4.229)	(2.876)	(2.912)	(-0.582)	(-0.549)	(3.915)	(3.961)	(1.817)	(1.817)
Commercial banks	0.087*	0.084	0.083	-0.370	-0.318	0.101**	0.101**	0.028	0.026
	(1.704)	(1.252)	(1.243)	(-0.287)	(-0.246)	(2.554)	(2.563)	(0.425)	(0.388)
Dependent variable (t-1)	0.261***	0.519***	0.518***	0.277***	0.281***	0.335***	0.336***	0.170***	0.170***
	(7.088)	(2.721)	(2.708)	-4.11	(4.203)	(8.889)	(8.892)	(3.866)	(3.862)
Dependent variable (t-2)	0.197***	0.105**	0.105**	0.117***	0.120***	0.112***	0.112***	0.034*	0.034*
	(5.836)	(2.249)	(2.249)	(2.735)	(2.787)	(3.861)	(3.874)	(1.890)	(1.880)
Intercept	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	4,730	4,586	4,586	4,514	4,514	4,676	4,676	4,526	4,526
Number of banks	668	658	658	656	656	662	662	658	658
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Arellano-Bond AR(1) test p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Arellano-Bond AR(2) test p-value	0.329	0.743	0.747	0.407	0.385	0.446	0.445	0.448	0.450
Hansen test p-value	0.599	0.150	0.151	0.218	0.217	0.307	0.307	0.217	0.212

Table A.3: Robustness checks.

Table A.3 shows the results of the robustness tests using different proxies of profitability (ROE instead of ROA). All explanatory variables are as defined in Table 1. All bank-level variables are winsorised at the 1st and 99th percentiles. All models include time fixed effects, and we use Windmeijer standard error corrections. The estimation results are for the 2006-2018 period. The t-statistics are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1) Past due ratio	(2) Past due ratio	(3) UTP ratio	(4) UTP ratio	(5) Bad loans ratio	(6) Bad loans ratio	(7) Inflow of past due	(8) Inflow of past due	(9) Inflow of UTP
Tier 1 Buffer	-0.442*		-0.388***		-1.255**		-0.639**		-0.915***
	(-1.939)		(-3.140)		(-2.511)		(-2.183)		(-3.680)
Total Capital Buffer		-0.317		-0.352***		-1.260**		-0.499*	
		(-1.494)		(-2.954)		(-2.495)		(-1.838)	
Size	-0.004	-0.001	0.015*	0.016**	0.013	0.019	0.022	0.025	0.007
	(-0.229)	(-0.046)	(1.763)	(1.993)	(0.380)	(0.594)	(1.201)	(1.377)	(0.477)
Cost-Income	0.063	0.069	-0.146*	-0.143*	-0.013	-0.002	0.174	0.178	-0.224*
	(0.509)	(0.556)	(-1.794)	(-1.762)	(-0.074)	(-0.010)	(1.221)	(1.252)	(-1.699)
Loan growth	0.147	0.150	-0.055	-0.055	-1.748*	-1.709*	-0.395	-0.387	-0.423**
	(0.612)	(0.625)	(-0.529)	(-0.530)	(-1.807)	(-1.777)	(-1.614)	(-1.577)	(-2.451)
Loan to total assets	-0.184	-0.159	0.241**	0.245**	-1.637	-1.681	-0.169	-0.141	0.303*
	(-0.828)	(-0.718)	(2.314)	(2.338)	(-1.498)	(-1.549)	(-0.815)	(-0.675)	(1.776)
Secured loans by real guarantees	0.459**	0.463**	0.209**	0.208**	-0.884	-0.845	0.458**	0.460**	0.183
	(2.458)	(2.469)	(2.283)	(2.282)	(-1.035)	(-0.988)	(2.282)	(2.288)	(1.271)
Secured loans by personal guarantees	-0.016	-0.016	0.072***	0.072***	0.292	0.282	0.009	0.010	0.235***
	(-0.331)	(-0.329)	(3.246)	(3.233)	(0.501)	(0.484)	(0.153)	(0.165)	(6.518)
Past due coverage ratio	0.370	0.358					-0.365	-0.382	
	(1.025)	(0.996)					(-1.075)	(-1.129)	
UTP coverage ratio			-0.053	-0.055					0.136
			(-0.399)	(-0.419)					(0.657)
Bad loans coverage ratio					-0.439	-0.417			
					(-0.740)	(-0.721)			
ROE	0.013	0.013	0.026***	0.026***	0.013	0.014	-0.017**	-0.017**	0.034***
	(0.977)	(0.982)	(4.871)	(4.911)	(1.380)	(1.521)	(-2.535)	(-2.491)	(4.680)
Dependent variable (t-1)	0.441*	0.443*	0.616***	0.616***	0.966***	0.968***	0.418***	0.417***	0.261***
	(1.838)	(1.853)	(13.764)	(13.726)	(16.348)	(16.442)	(2.669)	(2.642)	(6.908)
Dependent variable (t-2)							0.181***	0.182***	0.194***
							(3.368)	(3.384)	(5.764)
Intercept	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	5,163	5,163	5,386	5,386	5,318	5,318	4,536	4,536	4,730
Number of banks	680	680	691	691	691	691	659	659	668
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Arellano-Bond AR(1) test p-value	0.141	0.137	0.000	0.000	0.000	0.000	0.003	0.003	0.000
Arellano-Bond AR(2) test p-value	0.544	0.550	0.421	0.421	0.359	0.375	0.244	0.240	0.337
Hansen test p-value	0.171	0.171	0.272	0.272	0.271	0.281	0.220	0.219	0.572

Table A.3 continued from previous page

	(10) Inflow of UTP	(11) Inflow of bad loans	(12) Inflow of bad loans	(13) Outflow of past due	(14) Outflow of past due	(15) Outflow of UTP	(16) Outflow of UTP	(17) Outflow of bad loans	(18) Outflow of bad loans
Tier 1 buffer		-0.760***		-0.369		-0.352**		0.146	
		(-2.896)		(-0.181)		(-2.009)		(0.492)	
Total capital buffer	-0.829***		-0.609**		-0.470		-0.328*		0.339
	(-3.278)		(-2.335)		(-0.242)		(-1.894)		(1.206)
ROE	0.035***	0.019	0.020	0.061	0.067	0.039***	0.039***	0.029***	0.029***
	(4.774)	(0.978)	(1.004)	(0.877)	(0.974)	(6.564)	(6.621)	(3.420)	(3.361)
Size	0.011	0.022	0.026	-0.015	-0.012	0.007	0.008	0.064***	0.064***
	(0.782)	(0.813)	(0.947)	(-0.159)	(-0.132)	(0.592)	(0.738)	(3.164)	(3.209)
Cost-Income	-0.218*	-0.197	-0.196	-2.960	-3.087	-0.275***	-0.271***	0.250	0.249
	(-1.650)	(-1.199)	(-1.207)	(-1.308)	(-1.367)	(-2.927)	(-2.903)	(1.534)	(1.534)
Loan growth	-0.418**	-1.149***	-1.143***	-1.629	-1.701	-0.875***	-0.872***	-0.742***	-0.740***
	(-2.423)	(-3.443)	(-3.426)	(-0.871)	(-0.904)	(-5.245)	(-5.249)	(-3.230)	(-3.229)
Loan to total assets	0.314*	0.032	0.051	0.999	0.520	0.323**	0.324**	0.062	0.106
	(1.827)	(0.144)	(0.233)	(0.331)	(0.179)	(2.344)	(2.347)	(0.260)	(0.441)
Secured loans by real guarantees	0.185	0.288	0.287	3.784*	3.736*	0.250*	0.249*	0.177	0.181
	(1.285)	(1.571)	(1.572)	(1.843)	(1.805)	(1.913)	(1.913)	(0.869)	(0.889)
Secured loans by personal guarantees	0.234***	0.068	0.068	-0.667	-0.675	0.118***	0.117***	0.163***	0.165***
	(6.483)	(1.248)	(1.239)	(-0.837)	(-0.847)	(3.766)	(3.746)	(3.525)	(3.547)
Past due coverage ratio				6.674*	7.060*				
				(1.761)	(1.859)				
UTP coverage ratio	0.131					0.094	0.092		
	(0.636)					(0.569)	(0.560)		
Bad loans coverage ratio		0.018	0.008					-0.281	-0.299
		(0.063)	(0.028)					(-1.240)	(-1.313)
ROE	0.035***	0.019	0.020	0.061	0.067	0.039***	0.039***	0.029***	0.029***
	(4.774)	(0.978)	(1.004)	(0.877)	(0.974)	(6.564)	(6.621)	(3.420)	(3.361)
Dependent variable (t-1)	0.261***	0.532***	0.531***	0.282***	0.287***	0.336***	0.337***	0.167***	0.167***
	(6.913)	(2.814)	(2.804)	(4.554)	(4.683)	(8.867)	(8.873)	(3.773)	(3.771)
Dependent variable (t-2)	0.194***	0.101**	0.102**	0.121***	0.122***	0.110***	0.110***	0.031*	0.031*
	(5.768)	(2.191)	(2.194)	(3.017)	(3.054)	(3.782)	(3.799)	(1.730)	(1.750)
Intercept	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	4,730	4,586	4,586	4,514	4,514	4,676	4,676	4,526	4,526
Number of banks	668	658	658	656	656	662	662	658	658
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Arellano-Bond AR(1) test p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Arellano-Bond AR(2) test p-value	0.335	0.675	0.679	0.300	0.296	0.466	0.465	0.477	0.480
Hansen test p-value	0.567	0.157	0.158	0.260	0.262	0.301	0.301	0.237	0.232

Table A.4: Robustness checks.

Table A.4 shows the results of the robustness testing controlling for bank profit variability (proxied by the ROA standard deviations). All explanatory variables are as defined in Table 1. All bank-level variables are winsorised at the 1st and 99th percentiles. All models include time-fixed effects, and we use Windmeijer standard error corrections. The estimation results are for the 2006-2018 period. The t-statistics are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1) Past due ratio	(2) Past due ratio	(3) UTP ratio	(4) UTP ratio	(5) Bad loans ratio	(6) Bad loans ratio	(7) Inflow of past due	(8) Inflow of past due	(9) Inflow of UTP
Tier 1 buffer	-0.425*		-0.370***		-1.018**		-0.647**		-0.912***
	(-1.921)		(-3.045)		(-2.029)		(-2.211)		(-3.666)
Total capital buffer		-0.294		-0.320***		-1.005**		-0.527*	
		(-1.438)		(-2.755)		(-2.026)		(-1.928)	
Size	-0.007	-0.004	0.011	0.013	0.004	0.009	0.015	0.019	0.004
	(-0.451)	(-0.265)	(1.355)	(1.587)	(0.139)	(0.313)	(0.900)	(1.089)	(0.275)
Cost-Income	0.077	0.082	-0.113	-0.109	-0.224	-0.214	-0.059	-0.054	-0.087
	(0.476)	(0.505)	(-1.396)	(-1.347)	(-1.316)	(-1.272)	(-0.445)	(-0.411)	(-0.629)
Loan growth	0.099	0.104	-0.103	-0.104	-1.428*	-1.442*	-0.310	-0.303	-0.516***
	(0.369)	(0.390)	(-0.951)	(-0.957)	(-1.658)	(-1.707)	(-1.290)	(-1.261)	(-2.893)
Loan to total assets	-0.135	-0.108	0.298***	0.306***	-1.112	-1.141	-0.200	-0.176	0.400**
	(-0.681)	(-0.546)	(2.891)	(2.957)	(-1.086)	(-1.122)	(-0.963)	(-0.840)	(2.298)
Secured loans by real guarantees	0.509**	0.511**	0.266***	0.266***	-0.811	-0.781	0.460**	0.462**	0.250*
	(2.543)	(2.547)	(2.942)	(2.943)	(-0.998)	(-0.960)	(2.241)	(2.246)	(1.777)
Secured loans by personal guarantees	-0.013	-0.013	0.072***	0.072***	0.562	0.554	0.007	0.007	0.239***
	(-0.259)	(-0.260)	(3.251)	(3.243)	(1.210)	(1.197)	(0.118)	(0.128)	(6.439)
Past due coverage ratio	0.301	0.286					-0.387	-0.404	
	(0.860)	(0.824)					(-1.161)	(-1.214)	
UTP coverage ratio			-0.152	-0.155					0.094
			(-1.064)	(-1.086)					(0.442)
Bad loans coverage ratio					-0.535	-0.531			
					(-1.019)	(-1.036)			
SD ROA	0.224**	0.224**	0.261***	0.261***	0.771**	0.789**	0.297**	0.300**	0.246*
	(1.973)	(1.962)	(3.681)	(3.667)	(2.346)	(2.421)	(2.034)	(2.050)	(1.843)
Dependent variable (t-1)	0.432*	0.433*	0.620***	0.620***	0.910***	0.910***	0.410***	0.409***	0.272***
	(1.826)	(1.839)	(13.668)	(13.653)	(12.133)	(12.124)	(2.776)	(2.749)	(7.347)
Dependent variable (t-2)							0.180***	0.181***	0.195***
							(3.516)	(3.531)	(5.863)
Intercept	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	5,163	5,163	5,386	5,386	5,318	5,318	4,536	4,536	4,730
Number of banks	680	680	691	691	691	691	659	659	668
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Arellano-Bond AR(1) test p-value	0.137	0.135	0.000	0.000	0.000	0.000	0.002	0.002	0.000
Arellano-Bond AR(2) test p-value	0.517	0.522	0.395	0.394	0.125	0.128	0.209	0.206	0.330
Hansen test p-value	0.177	0.177	0.331	0.326	0.287	0.306	0.291	0.292	0.549

Table A.4 continued from previous page

	(10) Inflow of UTP	(11) Inflow of bad loans	(12) Inflow of bad loans	(13) Outflow of past due	(14) Outflow of past due	(15) Outflow of UTP	(16) Outflow of UTP	(17) Outflow of bad loans	(18) Outflow of bad loans
Tier 1 buffer		-0.755***		0.252		-0.356**		0.136	
		(-2.864)		(0.127)		(-2.008)		(0.444)	
Total capital buffer	-0.800***		-0.597**		0.064		-0.311*		0.349
	(-3.186)		(-2.262)		(0.033)		(-1.789)		(1.210)
Size	0.008	0.015	0.019	-0.012	-0.008	0.001	0.002	0.049**	0.050**
	(0.584)	(0.583)	(0.728)	(-0.125)	(-0.082)	(0.044)	(0.204)	(2.492)	(2.543)
Cost-Income	-0.076	-0.217	-0.214	-2.632	-2.622	-0.209**	-0.204**	0.233	0.230
	(-0.547)	(-1.479)	(-1.475)	(-1.285)	(-1.262)	(-2.160)	(-2.120)	(1.486)	(1.463)
Loan growth	-0.514***	-1.167***	-1.163***	-1.983	-2.079	-0.967***	-0.963***	-0.692***	-0.690***
	(-2.884)	(-3.756)	(-3.746)	(-0.988)	(-1.022)	(-5.331)	(-5.339)	(-2.911)	(-2.907)
Loan to total assets	0.418**	0.094	0.117	2.200	1.622	0.431***	0.437***	0.182	0.228
	(2.393)	(0.430)	(0.537)	(0.760)	(0.589)	(3.035)	(3.077)	(0.763)	(0.952)
Secured loans by real guarantees	0.251*	0.353*	0.354*	3.922*	3.888*	0.338***	0.337***	0.265	0.268
	(1.790)	(1.774)	(1.781)	(1.833)	(1.785)	(2.685)	(2.692)	(1.309)	(1.324)
Secured loans by personal guarantees	0.238***	0.072	0.073	-0.215	-0.193	0.123***	0.122***	0.162***	0.163***
	(6.415)	(1.244)	(1.238)	(-0.270)	(-0.241)	(3.840)	(3.828)	(3.452)	(3.477)
Past due coverage ratio				5.917	6.351				
				(1.515)	(1.589)				
UTP coverage ratio	0.089					-0.037	-0.041		
	(0.420)					(-0.221)	(-0.244)		
Bad loans coverage ratio		-0.043	-0.055					-0.410*	-0.428*
		(-0.139)	(-0.175)					(-1.754)	(-1.826)
SD ROA	0.243*	0.420*	0.424*	1.370	1.450	0.506***	0.506***	0.623***	0.617***
	(1.813)	(1.752)	(1.763)	(0.757)	(0.786)	(5.255)	(5.259)	(6.184)	(6.071)
Dependent variable (t-1)	0.273***	0.530***	0.528***	0.272***	0.279***	0.343***	0.343***	0.163***	0.162***
	(7.385)	(2.706)	(2.693)	(4.298)	(4.465)	(9.019)	(9.048)	(3.600)	(3.598)
Dependent variable (t-2)	0.196***	0.102**	0.103**	0.115***	0.117***	0.109***	0.110***	0.033*	0.033*
	(5.876)	(2.117)	(2.121)	(2.828)	(2.879)	(3.802)	(3.830)	(1.780)	(1.800)
Intercept	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	4,730	4,586	4,586	4,514	4,514	4,676	4,676	4,526	4,526
Number of banks	668	658	658	656	656	662	662	658	658
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Arellano-Bond AR(1) test p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Arellano-Bond AR(2) test p-value	0.327	0.708	0.715	0.213	0.211	0.494	0.491	0.444	0.447
Hansen test p-value	0.545	0.144	0.145	0.224	0.211	0.292	0.291	0.200	0.195

Table A.5: Robustness checks.

Table A.5 shows the results of the robustness testing using fixed-effects models. All explanatory variables are as defined in Table 1. All bank-level variables are winsorised at the 1st and 99th percentiles. All models include time fixed effects, and we use robust standard error. The estimation results are for the 2006-2018 period. The t-statistics are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1) Past due ratio	(2) Past due ratio	(3) UTP ratio	(4) UTP ratio	(5) Bad loans ratio	(6) Bad loans ratio	(7) Inflow of past due	(8) Inflow of past due	(9) Inflow of UTP
Tier 1 buffer	-0.308		-0.371**		-0.511**		-0.675		-1.088***
	(-0.941)		(-1.972)		(-2.357)		(-1.481)		(-3.026)
Total capital buffer		-0.366		-0.335**		-0.479**		-0.707*	
		(-1.245)		(-1.976)		(-2.476)		(-1.715)	
ROA	-0.035	-0.035	0.302***	0.302***	0.249***	0.249***	-0.196*	-0.195*	0.327***
	(-0.388)	(-0.390)	(5.196)	(5.197)	(4.676)	(4.680)	(-1.918)	(-1.914)	(4.155)
Size	0.302***	0.299***	-0.018	-0.017	-0.019	-0.018	-0.136	-0.137	-0.309
	(2.767)	(2.771)	(-0.192)	(-0.180)	(-0.397)	(-0.373)	(-0.543)	(-0.552)	(-1.437)
Cost-Income	-0.146	-0.143	-0.107	-0.105	-0.218**	-0.214**	-0.295	-0.287	-0.598***
	(-0.825)	(-0.810)	(-1.103)	(-1.081)	(-2.224)	(-2.188)	(-1.399)	(-1.372)	(-2.969)
Loan growth	-0.453***	-0.453***	-0.215**	-0.218**	-0.239***	-0.243***	-0.704***	-0.705***	-0.351**
	(-2.930)	(-2.941)	(-2.376)	(-2.411)	(-2.721)	(-2.768)	(-3.876)	(-3.899)	(-2.302)
Loan to total assets	0.324	0.314	-0.038	-0.039	-0.457**	-0.462**	-0.369	-0.377	-0.878***
	(1.021)	(0.992)	(-0.255)	(-0.259)	(-2.339)	(-2.360)	(-1.067)	(-1.095)	(-2.829)
Secured loans by real guarantees	0.106	0.106	-0.076	-0.078	0.047	0.045	0.208	0.207	-0.156
	(0.704)	(0.703)	(-0.663)	(-0.676)	(0.562)	(0.533)	(0.890)	(0.887)	(-1.288)
Secured loans by personal guarantees	-0.201***	-0.201***	0.021	0.021	0.008	0.008	-0.253***	-0.253***	0.102**
	(-4.083)	(-4.100)	(0.907)	(0.921)	(0.361)	(0.366)	(-5.717)	(-5.739)	(2.583)
Past due coverage ratio	0.070	0.068					-0.881*	-0.886*	
	(0.177)	(0.171)					(-1.919)	(-1.929)	
UTP coverage ratio			-0.363*	-0.362*					0.245
			(-1.730)	(-1.727)					(1.015)
Bad loans coverage ratio					-0.117	-0.114			
					(-0.968)	(-0.947)			
Intercept	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	5,287	5,287	5,459	5,459	5,437	5,437	4,536	4,536	4,730
R-squared	0.184	0.184	0.433	0.433	0.648	0.648	0.214	0.214	0.156
Number of id	689	689	696	696	695	695	659	659	668
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table A.5 continued from previous page

	(10) Inflow of UTP	(11) Inflow of bad loans	(12) Inflow of bad loans	(13) Outflow of past due	(14) Outflow of past due	(15) Outflow of UTP	(16) Outflow of UTP	(17) Outflow of bad loans	(18) Outflow of bad loans
Tier 1 buffer		-1.262***		0.054		-0.607**		0.312	
		(-2.865)		(0.118)		(-1.988)		(0.750)	
Total capital buffer	-1.078***		-1.126***		-0.010		-0.529*		0.441
	(-3.114)		(-2.885)		(-0.025)		(-1.931)		(1.225)
ROA	0.328***	0.398***	0.400***	-0.126	-0.127	0.365***	0.366***	0.450***	0.450***
	(4.157)	(4.702)	(4.731)	(-1.263)	(-1.270)	(5.392)	(5.405)	(4.467)	(4.477)
Size	-0.310	-0.421*	-0.419*	-0.165	-0.167	-0.345*	-0.342*	-0.581***	-0.576***
	(-1.456)	(-1.782)	(-1.772)	(-0.656)	(-0.665)	(-1.701)	(-1.688)	(-2.716)	(-2.669)
Cost-Income	-0.586***	-0.739***	-0.724***	-0.596***	-0.596***	-0.423***	-0.416***	-0.059	-0.063
	(-2.938)	(-4.067)	(-3.994)	(-3.028)	(-3.038)	(-2.623)	(-2.587)	(-0.298)	(-0.317)
Loan growth	-0.357**	-0.692***	-0.699***	-0.767***	-0.766***	-0.668***	-0.672***	-0.014	-0.016
	(-2.356)	(-4.183)	(-4.252)	(-4.186)	(-4.183)	(-4.730)	(-4.777)	(-0.067)	(-0.079)
Loan to total assets	-0.885***	-1.052***	-1.056***	-0.242	-0.247	-0.945***	-0.941***	-1.526***	-1.510***
	(-2.890)	(-2.913)	(-2.925)	(-0.696)	(-0.712)	(-3.672)	(-3.657)	(-3.787)	(-3.739)
Secured loans by real guarantees	-0.158	-0.145	-0.148	0.142	0.143	-0.081	-0.083	-0.233	-0.233
	(-1.304)	(-1.068)	(-1.097)	(0.881)	(0.887)	(-0.685)	(-0.697)	(-1.218)	(-1.230)
Secured loans by personal guarantees	0.102**	-0.046	-0.045	-0.095**	-0.095**	-0.015	-0.014	0.100**	0.102**
	(2.578)	(-1.147)	(-1.116)	(-2.138)	(-2.155)	(-0.438)	(-0.414)	(2.182)	(2.221)
Past due coverage ratio		-1.277***	-1.279***						
		(-2.702)	(-2.704)						
UTP coverage ratio	0.250					0.170	0.174		
	(1.041)					(1.012)	(1.033)		
Bad loans coverage ratio		0.022	0.031					-0.123	-0.126
		(0.099)	(0.138)					(-0.468)	(-0.479)
Intercept	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	4,730	4,586	4,586	4,514	4,514	4,676	4,676	4,526	4,526
R-squared	0.157	0.124	0.124	0.180	0.180	0.130	0.130	0.217	0.217
Number of id	668	658	658	656	656	662	662	658	658
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES