The Impact of Efficiency on Asset Quality in Banking

Oleg Badunenko [a], Aristeidis Dadoukis [b,*], Giulia Fusi [b], Richard Simper [b]

[a] Department of Economics and Finance, College of Business, Arts and Social Sciences, Brunel University London, Uxbridge, UB8 3PH, UK

[b] The Global Centre for Banking and Financial Innovation, Nottingham University Business School, University of Nottingham, NG8 1BB, UK

Abstract

We investigate the impact of banks' ability to minimise costs on asset quality, by assessing the temporal relationship between these variables in a sample of Italian banks over the period 2006-2015. We offer new insights into the channels through which bank efficiency affects non-performing loans by disentangling the short-term component of cost efficiency from its long-term component. We show that non-performing loans afflicting Italian banks can be explained by both efficiency components. A decrease in short-term cost efficiency precedes a worsening in banks' asset quality, implying that regulators should consider adopting short-term efficiency as an early warning indicator of a deterioration in asset quality. We also present evidence of a trade-off between long-term efficiency and bank non-performing loans, which suggests that the removal of exogenous hindrances that prevent banks from allocating optimal levels of resources to the management of their loan portfolio should be a main policymakers' objective.

Keywords: Banking; Non-performing Loans; Stochastic Frontier Analysis; Short-term Cost Efficiency; Long-term Cost Efficiency

JEL Classifications: C33; G01; G18; G21; G28

[*] Corresponding author: Tel.: +44 (0) 115 8466519
aristeidis.dadoukis@nottingham.ac.uk (A. Dadoukis). Nottingham University Business School, Jubilee Campus, Nottingham, NG8 1BB, UK.
E-mail addresses: oleg.badunenko@brunel.ac.uk (O. Badunenko), giulia.fusi@nottingham.ac.uk (G. Fusi), richard.simper@nottingham.ac.uk (R. Simper).

1. Introduction

The global financial crisis of 2007–2009 was marked by a rapid increase in non-performing loans (henceforth NPLs) in the financial systems of many developed countries. Particularly severe was the deterioration of bank asset quality in Europe, where NPLs reached around €1.0 trillion (5.1% of total outstanding gross loans) at the end of 2016 (European Systemic Risk Board 2017). NPLs represent a major concern for regulators and policymakers, as they ultimately hamper real economic growth (Fiordelisi et al. 2018). In particular, a high stock of NPLs triggers a vicious circle linking bank earnings, capital and lending; that is, NPLs depress bank profitability, in turn hindering the capacity of banks to strengthen their capital positions in order to support new lending. A high stock of NPLs also represents a threat to financial stability by weakening banking systems' resilience to shocks and/or further economic downturns (Cerulli et al., 2020). In addition, NPLs entail higher legal and administrative costs related to the managing, restructuring and disposal of bad loans, as well as higher staff costs and operational expenses. Finally, the low quality of assets casts doubts on banks' long-term viability, thus undermining its market valuation and increasing the cost of external financing (see Jassaud and Kang 2015).

Since the launch of the Comprehensive Assessment by the European Central Bank (ECB) in 2014, addressing asset-quality problems has become a supervisory priority (Fiordelisi et al. 2017).[1] In 2019, the Single Supervisory Mechanism (SSM) – the supervision arm of the ECB - identified credit risk in the EU banking industry as a high-level regulatory and supervisory priority (see 'ECB Banking Supervision: SSM Supervisory Priorities 2019').[2]

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

[2] https://www.bankingsupervision.europa.eu/banking/priorities/html/ssm.supervisory_priorities2019.en.html

In this context, the thorough and comprehensive understanding of the drivers of NPLs has become indispensable to ensure the design of effective policy responses. To this end, a number of recent empirical studies have focused on the identification of macroeconomic and bank-specific factors that contribute to the rise of impaired assets (see, for example, Louzis et al. 2012; Ghosh 2015; Beck et al. 2015; Baldini and Causi 2020). Among these, some have focused on exploring the presence of causal links between bank efficiency and risk (e.g., Williams 2004; Podpiera and Weill 2008; Fiordelisi et al. 2011; Luo et al. 2016;). This last group of studies builds on the seminal paper of Berger and DeYoung (1997), which hypothesise that three aspects of managerial behaviour ('bad management', 'skimping' and 'bad luck') could explain the temporal relationships occurring between NPLs and bank cost efficiency.

In this paper, we argue that an overlooked factor in the existing literature on the drivers of credit risk is the lack of consideration for latent, long-term bank inefficiencies due to regulatory constraints, sectorial rigidities and/or recurring factor misallocations as a source of problem loans. Indeed, the long-standing literature on bank efficiency is narrowed to the estimation of an overall, time-varying measure of profit/cost efficiency (for example, Radić et al. 2012; Fiordelisi and Mare 2014 and Casu et al. 2017). We overcome this limitation by exploiting the features of a state-of-the-art stochastic frontier (SF) model, developed by Badunenko and Kumbhakar (2017) and we disentangle efficiency in its short-term (time-varying) and long-term (time-invariant) components. Decomposing efficiency provides new insights into the channels through which bank cost efficiency - which measures the proximity of a bank's cost to that of a best practice bank that produces the same output bundle under the same environmental conditions - exerts an effect on credit risk. This implies that our approach is particularly relevant from a policymakers' perspective to ensure targeted policy responses.

To this end, we exploit a large sample of Italian banks over the period 2006 to 2015 and we investigate the relationship between short- and long-term cost efficiency and NPLs. Employing a Granger causality panel data generalised methods of moments (GMM) estimator, we are the first to document that Italian banks' NPLs are driven by both short- and long-term bank inefficiencies. More precisely, we find that deteriorations in short-term cost efficiency precede the worsening of banks' asset quality, suggesting that NPLs are the outcome of temporal behavioural shortcomings and 'non-systematic management mistakes'. From the point of view of managers and owners, this implies that banks may be in the position to prevent bad loans arising from lax practices through improved day-to-day practices related, for example, to loan underwriting, monitoring and control. From a policymakers' perspective, short-term efficiency could be regarded as a valuable early warning quantitative parameter for the future occurrence of NPLs and thus, our findings place emphasis on the necessity to monitor managerial performance in order to detect those banks that could suffer from problem loans. Furthermore, we show that a lower quality of bank assets can be explained by higher levels of long-term efficiency, which we argue is a result hinting at problems of misallocation of resources due to inefficient regulation, structural problems and systematic managerial failures. It follows that any policy response aimed at addressing NPLs needs to carefully consider that part of banks' NPLs that arise because of structural, latent weaknesses of the banking industry that affect banks' ability to devote sufficient resources to the loan portfolio.

We also propose to use the 'Granger-Sims causality' formulation to allay concerns of "reverse causality" between NPLs and cost efficiency. This allows us to overcome the severe limitations of a 'two-step' procedure in which cost efficiency is used as a dependent variable (see Wang and Schmidt 2002). Finally, we provide an up-to-date and comprehensive assessment of credit risk in Italian banks by covering the period that included the European sovereign debt crisis and by investigating the role of institutional features in driving increases in NPLs (to the best of our knowledge, the latest assessment of ex-post credit risk in Italian banks was Bofondi and Ropele (2011)).

The remainder of the paper is organised as follows. Section 2 presents the institutional background of the Italian banking system. Section 3 provides an overview of the theoretical and empirical literature investigating NPLs and formulates the main hypotheses linking short-term and long-term efficiency to NPLs. Section 4 describes the methodological framework, the control variables and the data employed. Section 5 reports the main findings, additional analyses and robustness checks. Finally, conclusions and policy implications are presented in Section 6.

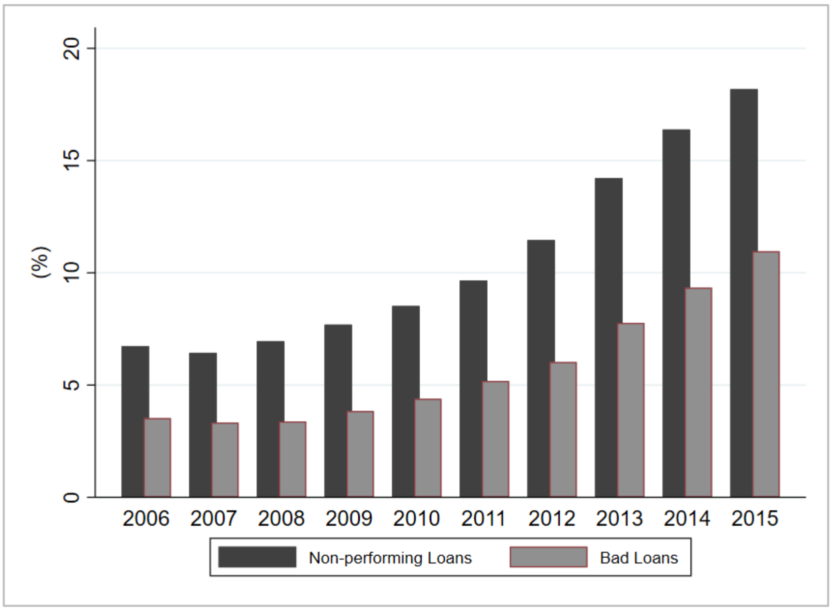
2. Institutional Background on the Italian Banking System

Italy represents an interesting setting for testing the importance of the inclusion of short- and long-term efficiency as drivers of credit risk for a twofold reason. First, among European countries suffering from a high stock of NPLs, Italy represents a noteworthy case as its volumes of impaired loans account for one-third (€360 billion at end of 2015) of all NPLs. Indeed, the Italian financial system has come under considerable strain during the last decade, first affected by the global financial crisis (2007-2009) and then by the European sovereign debt crisis (2010-2012). Particularly deleterious was the second crisis, when the 'doom loop' that ties Italian intermediaries to the Italian government began to weigh on banks' balance sheets.[3] Following the surge in Italy's 'country risk' evaluation, Italian banks' funding conditions and lending ability swiftly deteriorated. In addition, the prolonged economic recession exposed the vulnerabilities inherent in the strong bank–corporate nexus that characterises Italy' industrial fabric (European

[3] The Government's response to the global financial crisis included liquidity provisions, measures for the recapitalisation of distressed banks, schemes for strengthening and supporting the banking sector, and the extension of the depositor protection scheme. However, Italy's state was far better than that of other European counterparts. Only very modest amount of resources (0.3% of GDP) were deployed to sustained the banking system, in comparison to 55.8% in Belgium, 6.6% in France, 16.9% in Germany, 67.7% in the United Kingdom, 101.9% in Ireland, 24.5% in the Netherlands (Cosma and Gualandri, 2012). Concerning the sovereign crisis, Italy introduced in December 2011 the "Save Italy" decree, which included the provision of public guarantees on the liabilities of Italian banks by the Italian Ministry of Economy and Finance.

Commission, 2015). Thus, the poor economic performance over the study period (GDP collapsed by -5.5% and -2.8% in 2009 and 2012, respectively), was associated with steady deteriorations in banks' asset quality (see Figure 1). NPLs jumped from 6.8% in 2006 to 18.2 % in 2015, while bad loans – the most severe category of NPLs - triplicated from 3.5% to 11%, which translated into the volume of bad loans in the entire banking industry increasing from €6 billion to approximately €207 billion in 2015.

Figure 1. Evolution of Italy's bad loans ratio, 2006-2015



This figure shows the evolution of Italian bank non-performing loans and bad loans. Bad loans ratio refers to the most severe category of non-performing loans.

Overall, NPLs are the major concern for Italian and European regulators, as they fundamentally represent a drag on economic activity. By depressing bank profitability and pushing up funding costs, NPLs affect banks' ability to maintain adequate levels of capital and thus their willingness to extend credit, ultimately exacerbating the economic downturn. This is the result of Italy being fundamentally a bank-centred economy, with financial institutions being the primary, and most often the exclusive, source of credit for both firms and households (European Commission 2015).[4]

At this stage, it is worth mentioning that up until 2015, Italian banks classified NPLs in four sub-categories: past due exposures (*Crediti Scaduti*), restructured loans (*Crediti Ristrutturati*), substandard loans (*Incagli*) and bad loans (*Sofferenze*). These categories differ in terms of the likelihood of recovery, with the last group, 'bad loans' (hereafter BLs), identifying exposures to an insolvent counterparty.[5] Our study focuses on this category of impaired loans, in line with Quagliariello (2007) and Bofondi and Ropele (2011), as BLs represent a better proxy for the actual, realised bank credit risk as opposed to the aggregated measure of NPLs. Indeed, loans classified as 'restructured' or 'substandard' may still recover, and so they represent only a temporary situation, whereas bad loans capture defaulted borrowers.

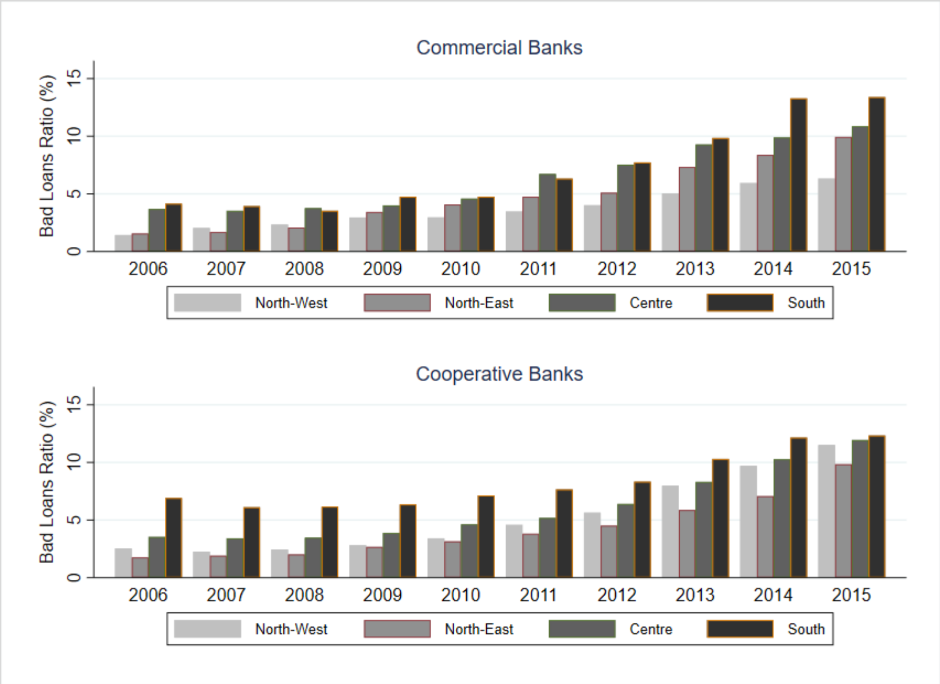
The second reason to focus on Italy relates to the presence of long-standing, persistent characteristics of the economic, regulatory and institutional environment in which they operate and that we argue may have latently affected the efficiency of banks. In particular, we draw our attention to the role of i) bank specialization (i.e., cooperative vs commercial banks) and ii) geographical location of banks (i.e., North-West, North-East, Centre and South) (see Section 4.2.1 for further details). In this respect, examining the evolution of Italian banks' BLs we notice that there is a pronounced geographical dimension, which does not significantly change over time (see Figure 2). The South and Centre areas have constantly suffered from worse asset

[4] For instance, in 2013, bank loans represented 64.7% of Italian firms' total financial debt, more than 20 percentage points higher than the euro area average, which stood at 42.9%. The only other country where firms were more dependent on bank credit was Greece, where bank loans accounted for approximately 70% of total firm financing. By way of comparison, bank loans represented 32.2% of total financial firm debt in France, 51.8% in Spain and 52.1% in Germany (European Commission, 2015).

[5] Bank of Italy (2013) defines 'bad loans' as *'exposures to an insolvent counterparty (even if insolvency is not legally ascertained) or in equivalent situations, regardless of any loss estimate made by the bank and irrespective of any possible collateral or guarantee'.*

quality than the North-West and North-East areas of Italy. However, the striking feature of Figure 2 is the volume of BLs already on Italian banks' balance sheets in the lead-up to the financial crisis (2006-2008), especially in the South, suggesting the presence of persistent, structural problems in the banking industry. To a lesser extent, divergences in bank asset quality are noticeable also across bank types.

Figure 2. Evolution of bad loans by bank specialisation and geographical area



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

3. Empirical Literature Review and Hypotheses Development

Management quality is measured by efficiency since at least Farrell (1957), who interprets the difference between actual and best-practice frontier as inefficiency due to bad management. In line with this, we interpret systematic deviations from the frontier as inefficiencies attributable to the lack of managerial skills/abilities in minimizing banks' costs while maintaining output levels (see also Demerjian et al., 2012; Assaf et al., 2019) and following the literature, we assume that these observed managerial inefficiencies have a direct impact on banks' risk. Management characteristics such as talent, quality and ability are key for firms' decision-making processes and outcomes. For example, Bertrand and Schoar (2003) report that heterogeneity in managerial corporate practices is systematically related to differences in corporate performance. Likewise, Chemmanur and Paeglis (2005) and Chemmanur et al. (2009), show that management quality positively influences firms' IPOs performance. Employing frontier estimation techniques, Demerjian et al. (2012) and Demerjian et al. (2013) demonstrate that managerial skills are positively associated with price reactions to management departures from the firm and earnings quality, respectively. In the same spirit, Andreou et al. (2017) document that higher managerial ability led to greater firms' investments during the financial crisis via the capacity of these firms to secure greater financing and resiliency. In a framework similar to this study, Andreou et al. (2016) provide evidence that managerial ability can explain bank performance, risk-taking (measured by risk-weighted assets over total assets) and liquidity creation.[6]

This study goes beyond existing research by exploiting the recent developments in the literature of stochastic frontier analysis (SFA) and decomposing overall cost efficiency into short-term (time-varying) and long-term (time-invariant) efficiency. It is restrictive, and potentially unrealistic, to consider inefficiency as either time-varying or time-invariant (see Badunenko and Kumbhakar 2017; Lien et al. 2018). Decomposing efficiency allows uncovering different aspects of managerial practices of a firm. Consider the case where inefficiency is

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[6] To estimate efficiency scores, Demerjian et al. (2012), Demerjian et al. (2013) and Andreou et al. (2017) use Data Envelopment Analysis whereas Andreou et al (2016) use Stochastic Frontier Analysis. In all cases, the authors use a two-step design where in the first step, efficiencies are estimated and in the second step they purge all firm specific effect from the efficiency component using tobit regressions. It is worth pointing out the two-step methodology employed by Andreou et al. (2016) has been amply criticised (see Wang and Schmidt, 2002).

associated with (unobserved) management. Assuming that management is time-invariant, inefficiency will also be time-invariant. More realistically, we can assume that management changes over time, although a part of it will remain constant. If management has a time-invariant and a time-varying component, it follows that the efficiency estimation needs to accommodate for the dual nature of management (see e.g., Tsionas and Kumbhakar, 2014).

In other words, it is plausible that banks are characterised by both short-term and long-term inefficiencies, which potentially have a distinct impact on the asset quality of banks. Short-term inefficiency captures 'non-systematic behavioural failures' of management and 'singular management mistakes' (Filippini et al. 2018, p. 75) and, as such, it relates to temporal behavioural aspects of the management that can be solved in the short term. For example, short-term inefficiency may denote the presence of failures in the day-to-day practices carried out by bank employees (e.g., lax practices in the loan underwriting, monitor and control by loan officers), which ultimately affect the risk profile of banks.

To test the link between short-term efficiency and credit risk, we exploit the widely used theoretical framework constituted by the 'bad management', 'skimping' and 'bad luck' hypotheses proposed by Berger and DeYoung (1997). Under the 'bad management' hypothesis, observed low short-term efficiency is seen as a signal of poor management practices: managers have inadequate control over operating costs, weak practices in the monitoring and controlling of borrowers and are not adept at appraising collaterals pledged against loans. This negligence in day-to-day activities is expected to cause an increase in the level of NPLs in the future since, as time passes, delinquencies begin to rise.[7] Thus, according to the 'bad management'

[7] The bad management hypothesis does not explicitly discuss the voluntary accumulation of risky loans by banks. That is, a bank may choose to take on more credit risk in a specific year which in turn may lead to higher monitoring costs, forcing this bank to depart from the cost frontier. This deliberate increase in credit risk will be therefore linked to lower levels of efficiency for different reasons than the bad luck hypothesis. We thank an anonymous referee for bringing this possible interpretation to our attention.

hypothesis, a decrease in short-term efficiency is expected to Granger-cause (i.e., temporally precede) an increase in the volume of NPLs.[8] On the other hand, under the 'skimping' hypothesis, bank managers might allocate fewer resources to loan underwriting, collateral appraisal, monitoring and control processes, thus showing immediately greater managerial efficiency and higher profits, but this is a short-term outcome: the temporary gains in efficiency will be offset by future reductions in the quality of the loan portfolio as borrowers start defaulting on their loans, revealing the previous oversights in the screening and monitoring of the loan allocation. Thus, according to the 'skimping' hypothesis, higher short-term cost efficiency is expected to Granger-cause an increase in the volume of NPLs. In light of this, we seek to test the following hypotheses that link cost efficiency to asset quality:

H_1: Bad Management Hypothesis. A decrease in the banks' short-term efficiency temporally precedes an increase in the level of bad loans.

H_2: Skimping Hypothesis. An increase in the banks' short-term efficiency temporally precedes an increase in the level of bad loans.

However, shocks to a bank's asset quality could also exert a negative effect on bank cost efficiency, as suggested by the 'bad luck' hypothesis. Exogenous events (e.g., economic downturns) could affect the creditworthiness of bank borrowers, resulting in higher credit risk in banks' balance sheets. It follows that banks will have to increase managerial efforts, incurring higher operating expenses from, for example, analysing and negotiating possible workout arrangements, monitoring delinquent borrowers and disposing of defaulted loans. The increased resources employed to deal with problem loans are expected to Granger-cause decreases in bank cost efficiency. Thus, the following hypothesis is formulated:

[8] A variable x is said to Granger-cause y if, given past values of y, past values of x are able to explain current values of y (Granger 1969).

H_3: Bad Luck Hypothesis. An increase in banks' bad loans temporally precedes a decrease in short-term efficiency.

Berger and DeYoung (1997) find evidence of a bi-directional causal link between cost efficiency and NPLs, as posited by the 'bad management' and the 'bad luck' hypotheses. Podpiera and Weill (2008) and Fiordelisi et al. (2011) also report the presence of 'bad management' behaviour in Czech and European banks, respectively, whereas they fail to observe an effect of NPLs on banks' cost efficiency. Recently, Assaf et al (2019) find that cost efficiency during normal times helps banks reduce the probability of default, decrease risk, and enhance profitability during subsequent financial crises, concluding that high bank cost efficiency reflects superior managerial abilities.

Other studies considering the drivers of NPLs include that of Louzis et al. (2012), who find that decreases in profitability and increases in cost-to-income (i.e., the ratio of operating expenses over operating income) temporally precede an increase in the volume of bad loans. They also document that real GDP growth rate, unemployment rate, lending rates and public debt have a strong effect on the level of NPLs. Interestingly, recent studies focusing on the US are more inconsistent. For instance, Ghosh (2015) reports an insignificant relationship between NPLs and operational efficiency (i.e., non-interest expenses divided by total assets) whereas, in a subsequent study, Ghosh (2017) finds support for the 'skimping' hypothesis. In both studies, a rise in unemployment is found to increase NPLs whereas a positive growth in GDP and house prices reduces credit risk.

Williams (2004) and Altunbas et al. (2007) employ loan loss provisions (LLPs) and loan loss reserves (LLRs), respectively, to examine European banks' risk-taking preferences during the 1990s, both finding evidence of 'bad management'. Similar conclusions are reached by Koutsomanoli-Filippaki and Mamatzakis (2009), who contribute to the debate concerning the dynamic interactions between risk and efficiency using a panel vector autoregressive (PVAR) model and defining bank risk in terms of Merton-type distance to default.

Among the studies exploring the determinants of NPL, Salas and Saurina (2002) report that credit risk in Spanish saving and commercial banks is explained by aggressive credit expansion policies, bank size and low capitalization. Finally, focusing on macro determinants of NPLs, Castro (2013) investigates credit risk in the GIPSI countries between 1997 and 2011 and reports strong correlations between NPLs and house prices, unemployment, and GDP growth rate. [9] Beck et al. (2015) also show that GDP growth, share prices, the exchange rate, and the lending interest rate are among the drivers of NPLs in 75 countries over 2005-2010. For the Italian case, Bofondi and Ropele (2011) distinguish between households and firms by considering the quarterly flow of new bad loans for the period 1990-2010. In both cases, new NPLs increase with the unemployment rate while household NPLs are also negatively related to real GDP growth and house prices.

We expand this literature by introducing the notion of long-term efficiency as a key driver of banks' credit risk. Specifically, long-term efficiency captures deviations from the cost frontier that could be attributed to structural problems of the industry, regulatory constraints, and 'systematic behavioural shortcomings' (Blasch et al. 2017, p. 92) of the management. Low measured long-term efficiency could capture embedded, latent negligence of Italian banks, lasting/recurring wasteful habits of the management or systematic inefficiencies (e.g., recurring mistakes in the managing of the loan portfolio due to 'systematic shortfalls in the managerial capabilities' - Filippini and Greene 2016, p. 187). It follows that banks characterised by low levels of long-term efficiency are potentially more likely to be associated with higher bad loans in future periods, which is the 'bad habits' hypothesis.

[9] GIPSI countries include Greece, Ireland, Portugal, Spain, Italy.

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

The previous discussion suggests testing the following hypotheses:[10]

H_4: Bad Habits Hypothesis. Long-term efficiency and bad loans are negatively related, that is, banks reporting a low level of long-term efficiency suffer from higher bad loans.[11]

H_5: Resources Misallocation Hypothesis. Long-term efficiency and bad loans are positively related, that is, banks reporting a high level of long-term efficiency suffer from higher bad loans.

4. Methodological Framework and Data

4.1. Econometric Methodology

Following Berger and DeYoung (1997) and Fiordelisi et al. (2011), we estimate an autoregressive distributed lag panel data model (ARDL) using Eqs. (1) and (2). We include two

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

[11] The use of the term 'habits' to identify recurring managerial behaviours as potential sources of structural inefficiency is widely accepted (see Blasch et al. 2017 and Filippini et al. 2018).

lags of the dependent variable to mitigate the effect of omitted explanatory variables and capture the persistence of BLs:[12]

$$BL_{it} = \alpha + \sum_{j=1}^{J} \beta_j BL_{it-j} + \sum_{j=1}^{J} \gamma_{1j} Short\_term_{it-j} + \gamma Long\_term_i + bank\_controls + \eta_i + \varepsilon_{it} \quad (1)$$

$$BL_{it} = \alpha + \sum_{j=1}^{J} \beta_j BL_{it-j} + \sum_{j=1}^{J} \gamma_{1j} Short\_term_{it-j} + \gamma Long\_term_i + bank\_controls + macro\_controls + \eta_i + \varepsilon_{it} \quad (2)$$

where $|\sum_j^J \beta_j| < 1$ and $J = 2$ in both equations specified above. BL_{it} denotes the logit transformation of bad loans ratio of bank i, in year t, $ln\left(\frac{BL_{it}}{1- BL_{it}}\right)$ (see Ghosh 2015).[13] In all the models, $bank\_controls$ denotes a vector of bank-specific control variables in lags and levels, $macro\_controls$ represents lagged macroeconomic controls (these sets of control variables are discussed in detail in Sections 4.2.2.), η_i are bank fixed effects and ε_{it} is the random error. The introduction of the lagged dependent variable as a predictor renders the standard ordinary least squares and the within estimator inconsistent (see Nickell 1981). Thus, we estimate Eqs. (1) and (2) using the system generalised method of moments (SGMM) procedure proposed by Arellano and Bond (1991), Arellano and Bover (1995) and Blundell and Bond (1998). Under the assumption of independent and homoscedastic residuals, consistent parameter estimates can be obtained, while controlling for time-invariant unobserved heterogeneity and simultaneity bias.

[12] We confirm the model specification with BIC information criteria, as suggested by Andrews and Lu (2001).

[13] The logit transformation ensures that the dependent variable spans over the interval [-∞;+∞] as opposed to the [0;1] interval and is distributed symmetrically (the untransformed distribution of BL is skewed to the right and we reject the null hypothesis of normality of the Shapiro-Francia W' test at the 1% level). Furthermore, the logit transformation prevents non-normality in the error term and accounts for non-linearities, for example if larger shocks to the explanatory variables cause a large, non-linear response in the transformed dependent variable (Ghosh 2015).

To examine the impact of efficiency on BLs, we use the two constituent components obtained by applying the Badunenko and Kumbhakar (2017) model ($Short\_term_{it}$ and $Long\_term_i$) This specification disentangles the effect of efficiency on impaired loans into its long- and short-run components. Further, we let efficiencies be determined by other variables, which we describe in Section 4.2.1. With respect to the tested hypotheses, our definition of causality is narrow and refers to a set of zero restrictions in Eqs. (1) and (2). More specifically, for each model, we test the null hypothesis of no Granger-causality: $H_0: \gamma_{1j} = \cdots = \gamma_{1J} = 0$ for $J = 1, 2$; a rejection of the null indicates that cost efficiency Granger-causes BLs, whereby the direction of Granger-causality is determined by the sum of the lagged coefficients. A positive (negative) sign implies that the relationship is positive (negative), confirming the skimping (bad management) hypothesis. Similarly, a positive (negative) γ coefficient for long-term efficiency will provide evidence in favour of the resource misallocation (bad habits) hypothesis.

This autoregressive distributed lag panel data model allows us to examine the impact of efficiency on BLs in two interrelated ways. First, by estimating the long-run multiplier ($\sum_{j=1}^{J} \gamma_{1j}$, for $J = 2$, Casu and Girardone, 2009) we can examine how a permanent decrease/increase in efficiency would affect BLs (for example, the impact of a decrease in efficiency in period t, which is also maintained in subsequent periods). In the absence of a long-run effect (if $\sum_{j=1}^{J} \gamma_{1j} = 0$), then efficiency has only a temporary effect and BLs depend on the change in the efficiency rather than its levels, an effect also known as "momentum". This can be seen by simplifying Eq. (1) and keeping only $Short\_term$, in which case our specification is equivalent to Eq. (A), $BL_{it} = a + \delta_1 Short\_term_{it-1} + \delta_2 (Short\_term_{it-1} - Short\_term_{it-2})$, where δ_2 is defined as the "momentum" coefficient, and $\delta_1 = \gamma_1 + \gamma_2$; $\delta_2 = -\gamma_2$. Substituting δ_1 and δ_2 into Eq. (A) we obtain our specification, $BL_{it} = a + \gamma_1 Short\_term_{it-1} + \gamma_2 Short\_term_{it-2}$, which suggest that the coefficient $-\gamma_2$ in Eq. (1) can be directly interpreted as the "momentum effect). The above would suggest that negative changes in the efficiency (even for high efficiency banks) would cause adverse changes in BLs. Finally, concerning the 'bad luck hypothesis', we discuss our empirical formulation in Section 5.2.2.

4.2. Explanatory Variables

4.2.1. Short-term and Long-term Cost Efficiency

Cost efficiency scores are estimated using the SFA method introduced by Aigner et al. (1977). We employ the heteroskedastic four-component error model of Badunenko and Kumbhakar (2017), where inefficiency and production risk are allowed to be systematically related to bank characteristics, as well as geographical and macro-economic factors:

$$lnTC_{it} = f(y_{it}, w_{it}, \theta) + v_{0i} + v_{it} + u_{0i} + u_{it} \tag{3}$$

Where $lnTC_{it}$ is the logarithm of the total costs of bank i for year t, y_{it} is a vector of outputs of the bank, w_{it} is a vector of input prices, θ refers to a vector of technology parameters to be estimated, v_{0i} denotes bank latent heterogeneity (i.e., bank fixed effects), v_{it} is the standard noise that captures random shocks, u_{0i} represents long-term/time-invariant inefficiency while the u_{it} term captures short term/time-varying inefficiency. We define the set of input prices and output quantities following the intermediation approach (Sealey and Lindley, 1977). Appendix A provides a detailed discussion into i) the SFA estimation, ii) the selection of inputs/outputs and iii) the determinants of each inefficiency component. We obtain short-term, long-term and overall cost efficiency ($CE = Short\_term \times Long\_term$) as in Badunenko and Kumbhakar (2017).[14]

[14] The advantages of cost efficiency over profit efficiency as a proxy for management quality with respect to risk have been well documented in the literature (for example, Williams 2004 and more recently Assaf et al. 2019).

This model specification allows for the parametrisation of the error components thereby modelling determinants of both types of efficiency. We exploit this key feature in the following way: we let short-term inefficiency (u_{it}) be determined by bank size, a post-2008 crisis dummy and a time trend variable in linear and quadratic form; long-term inefficiency (u_{i0}) is determined by bank specialization (i.e., cooperative vs commercial banks) and geographical location (i.e., North-West, North-East, Centre and South); production risk (v_{it}) is defined by GDP growth, unemployment and inflation; finally, we assume that v_{0i} is homoscedastic.[15] We stress how the heteroskedastic four-error component model represents a major improvement over prior researches that fail to disentangle long-term from short-term inefficiency. This is because understanding determinants of long-term inefficiency could help decision-makers to develop strategies addressing latent impediments, such as sectional rigidities and too restrictive regulations. On the other hand, bad luck and/or management mistakes can give rise to temporary inefficiency. Knowledge about the drivers of short-term inefficiency plays a key role in improving the efficiency of individual firms in the short-run (see Lien et al., 2018).

4.2.2. Bank-Specific and Macroeconomic Control Variables

In all models, we condition BLs on a number of bank-specific characteristics ($bank\_controls$). Following Berger and DeYoung (1997), we include the level of bank capital (CAP) to control for institutions facing moral hazard incentives, which may be the result of poorly capitalized banks being tempted to increase the riskiness of their loan portfolio as they have less "skin in the game".[16] Under-capitalization may also give rise to the phenomenon of "zombie

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[15] It is worth pointing out that the variables explaining persistent inefficiency should be *naturally* time-invariant as we aim to capture persistent characteristics of the Italian banking industry and operating environment that could have affected the cost-minimization behaviour of banks in the long-run (see Lien et al. 2018).

[16] Unlike Berger and DeYoung (1997), we do not test for this hypothesis only on a sub-sample of weakly capitalised banks but, in line with Fiordelisi et al. (2011) and Louzis et al. (2012), we rely on the entire sample. This approach

lending". Rather than writing-off loans and absorbing the losses, banks that are close to the minimum regulatory capital are more likely to keep "gambling for resurrection" of their borrowers that are close to or in default (the so-called *zombie firms*), keeping them "artificially" alive in the hope they will recover and service outstanding debt (Jiménez et al. 2017; Schivardi et al. 2017). Finally, the presence of information frictions and agency problems may lead to bank managers taking on greater risks when a bank has lower levels of capital (Jeitschko and Jeung (2005).

We include the ratio of net loans over total assets ($CreditGR$), as in Ghosh (2015), to capture increased loan delinquencies rates due to faster loan growth. High volumes of credit supply may be achieved by lowering interest rate charges and by the adoption of lax credit standards, increasing in the process the probability of future default. In addition, we use the natural logarithm of total assets ($Size$) to control for potential size effects. On the one hand, large banks may benefit from better opportunities for diversification, permitting them to spread their investments across different geographical areas or business sectors, thus reducing the risk of loan defaults (Salas and Saurina 2002). On the other hand, large banks may be driven by 'too-big-to-fail' (TBTF) considerations and engage in riskier activities due to moral hazard incentives and poor market discipline practices (see Stern and Feldman 2008). Likewise, to control for systemically important banks (SIBs), we add a dummy variable ($Supervised$) that takes the value of one if the bank is classified by the ECB as a 'significant supervised entity' and as such is directly supervised by the ECB rather than by Bank of Italy.[17] Finally, we condition BLs on

allows us to control for managers in highly capitalised banks who could resort to a liberal credit policy under the notion that their bank is 'too big to fail', thus implying a positive relationship between capital and asset quality (Rajan 1994).

[17] In our sample, the SIBs include UniCredit Spa, Banca Carige SpA, Veneto Banca, Unione di Banche Italiane (UBI), Intesa Sanpaolo, Mediobanca, Credito Emiliano, Banca Popolare di Vicenza, Banca Popolare di Sondrio, Banca Popolare di Milano, Banca Popolare dell'Emilia Romagna, Banco Popolare, Monte dei Paschi di Siena Spa (https://www.bankingsupervision.europa.eu/ecb/pub/pdf/list_of_supervised_entities_20160331.en.pdf).

bank type and we include a dummy variable ($Industry$) that takes a value of one if the bank is a cooperative bank and zero otherwise. One could expect to find cooperative banks suffering from lower rates of BLs due to *relationship lending* practices and their ability to collect *soft* information concerning their customers. Nonetheless, we recognise that the strong connections between cooperative banks and their borrowers (e.g. belonging to the same local community or personal connections) could lead to these financial institutions being reluctant to terminate long-standing client relationships, thus resulting in credit extended to borrowers even when the conditions are not sustainable (see Becchetti et al. 2016). An important consideration is also that cooperative banks may have fewer opportunities to dispose of their bad loans, as they lack the size and expertise to attract specialised investors in the secondary market.

Concerning the vector of macroeconomic variables ($macro\_controls$), we include three exogenous determinants. Gross domestic product growth ($GDPGR$) is used to capture the effect of the economic business cycle on the credit quality of banks (e.g., Castro 2013). As in Louzis et al. (2012), we incorporate a measure of government indebtedness ($SDEBT$) to control for the impact of rising sovereign tensions on banks' asset quality. Empirical studies have confirmed the link between banking and sovereign debt crises and found that the former most often either precede or coincide with the latter (see Reinhart and Rogoff 2011). Furthermore, we include the house price index (HPI) to capture the 'housing wealth' of Italian borrowers. A higher property value improves the financial wealth of the borrower, thus helping him/her to face unexpected financial shocks and facilitating debt renegotiation, ultimately limiting the risk of becoming an insolvent debtor. Similarly, rising home prices could ease access to credit by boosting the underlying value of the houses used as collateral, which in turn reduces the likelihood of default (see Beck et al. 2015; Ghosh 2015). Finally, we control for the impact of the financial crisis by including a dummy variable ($Crisis$) that takes the value of one for 2009-2015 and zero otherwise (Beaton et al. 2016).

4.3. Data

The dataset employed in this study consists of an unbalanced panel of 3,641 observations on Italian commercial and cooperative banks spanning the period 2006-2015 (before taking lags). Bank-specific data are collected from the Bureau van Dijk Bankscope Database and all macroeconomic indicators are obtained from the Statistical Data Warehouse of the ECB. To accommodate panel features in the efficiency estimation, only those banks for which at least three years of data were available have been included in the analysis. Table 1 presents the definitions of bank-specific and macroeconomic determinants of BL, while Table 2 reports the matrix of correlations among the variables. None of the bank-specific variables exhibits a very high correlation, mitigating any multicollinearity concerns. Concerning the macroeconomic variables, we observe that the highest correlation is between $SDEBT$ and HPI (-0.735). We also estimated the baseline models without HPI and the results remain unaltered. Table B1 in Appendix B shows the number of banks per specialization, per area and year.

Table 1. Definition of bank-specific and macroeconomic determinants of BL used for the Granger-causality models

	Description	Expected sign	Mean	Median	Std. Dev	Min	Max
$Short\_term$	The estimated level of short-term cost efficiency	+/-	0.973	0.980	0.027	0.691	0.999
$Long\_term$	The estimated level of long-term cost efficiency	+/-	0.926	0.939	0.046	0.669	0.980
CAP	The ratio of equity over total assets	-	0.105	0.100	0.362	0.011	0.371
$Size$	The logarithm of total assets	+/-	6.288	6.046	1.535	3.095	13.860
$CreditGR$	The ratio of net loans over total assets	+	0.636	0.653	0.148	0.030	0.961
$GDPGR$	Gross domestic product growth	-	-0.005	-0.002	0.021	-0.055	0.021
$SDEBT$	Government debt to gdp ratio	+	1.173	1.165	0.114	0.998	1.318
HPI	Housing price index	-	101.628	103.4	5.745	90.81	107.69

This table reports the variables used in Eqs. (1) and (2), their description and the summary statistics. The statistics are for the full sample (prior to taking the lags for the Granger-causality model).

Table 2. Matrix of correlations

	BL	$Short\_term$	$Long\_term$	CAP	$Size$	$CreditGR$	$GDPGR$	$SDEBT$	HPI
BL	1								
$Short\_term$	-0.030*	1							
$Long\_term$	-0.117***	0.024	1						
CAP	-0.170***	0.087***	0.195***	1					
$Size$	0.052***	-0.050***	-0.448***	-0.377***	1				
$CreditGR$	-0.321***	-0.009	0.293***	-0.034**	0.121***	1			
$GDPGR$	-0.031**	0.204***	-0.003	0.000	-0.012	0.024	1		
$SDEBT$	0.501***	-0.078***	-0.040**	-0.191***	0.130***	-0.324***	0.182***	1	
HPI	-0.429***	-0.172***	0.035**	0.130***	-0.096***	0.362***	-0.202***	-0.735***	1

This table reports the Spearman correlation coefficients of the variables in included in Eqs. (1) and (2). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5. Results

5.1. Overall, Short-Term and Long-Term Cost Efficiency Results

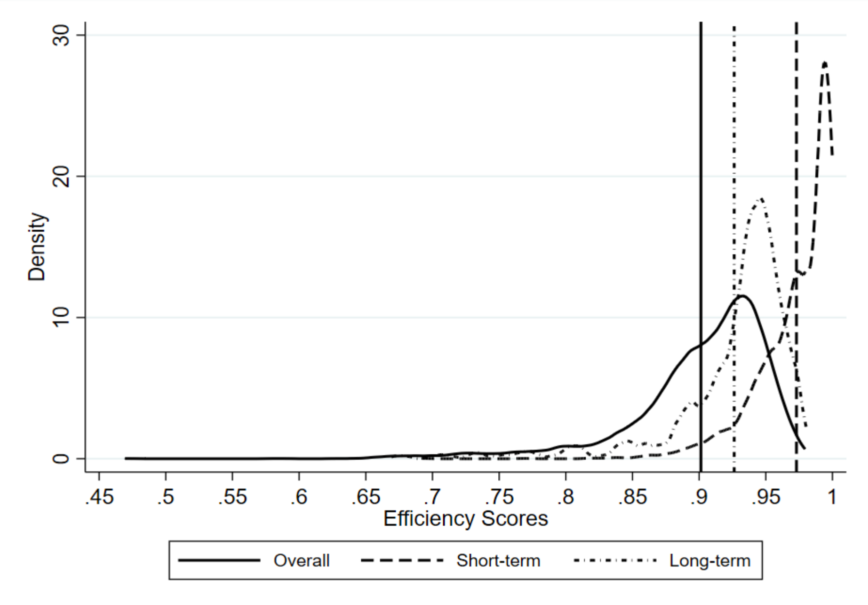
We first present the results of the SFA estimation in Table 3. We report an average level of overall efficiency of 90.1% (recall, $CE = Short\_term \times Long\_term$), which is the result of high short-term efficiency (mean value of approximately 97.3%) and lower long-term efficiency (mean value of approximately 92.6%) (see Table 3). That is, Italian banks could reduce their costs by approximately 2.8% and 7.4% if they were to reduce short-term and long-term inefficiencies, respectively. Figure 3 reports the kernel densities of the three efficiencies. While the distribution of short-term efficiency is remarkably skewed towards one, that of long-term efficiency, and thus of overall efficiency, is characterised by a greater dispersion. This negligible effect of short-term inefficiency suggests that the deviation from the optimal level of overall efficiency originates from long-term, permanent, structural effects, rather than temporal inefficiencies of the individual financial institutions.

Table 3. Summary Statistics of Short-term, Long-term and overall cost efficiency, 2006-2015

Variable	Obs.	Mean	Median	Std. Dev.	Min	Max
$Short-term\ Efficiency$	3,641	0.973	0.980	0.027	0.691	0.999
$Long-term\ Efficiency$	3,641	0.926	0.939	0.046	0.669	0.980
$Overall\ Efficiency$	3,641	0.901	0.913	0.052	0.469	0.979

This table reports the summary statistics of the estimated short-term, long-term and overall cost efficiency. The measure of overall efficiency is given by the product of short-term and long-term efficiency (see Section 4.2.1).

Figure 3. Kernel densities of efficiency estimates



The figure shows the distributions (estimated kernel densities) of overall, short-transient and long-term persistent efficiency. The vertical lines are the respective means.

Focusing on the sources of short-term inefficiency (Table 4, Panel A), there is no evidence that $Size$ explains time-varying efficiency of Italian banks while the significant concave relationship between time ((t) and (t^2)) and short-term inefficiencies suggests that technological advances increase inefficiencies at a decreasing rate over time. The crisis dummy ($Crisis$) indicates that short-term inefficiencies were lower in the period following the global financial crisis.

Moving to the determinants of time-invariant inefficiency (Table 4, Panel B), cooperative banks show lower levels of long-term inefficiency than their commercial counterparts (the coefficient of the $Industry$ dummy is negative and significant). A reason for this is that cooperative banks may constantly enjoy lower costs of funds and higher revenues due to their quasi-monopolistic power in certain local markets (see Girardone, Molyneux and Gardener, 2004).

Concerning the role of geographical location, banks located in the North-West and the South have higher levels of long-term inefficiencies than those in the Central region. Recall that banks in the South are marked by a larger proportion of bad loans (see Figure 2 above). Banks in the North-East that have the smallest proportion of bad loans show greater long-term efficiency than those in Central.

We stress that the identification of the two sources of inefficiency represents a major novelty in the literature for a twofold reason. First, estimating a model with only one inefficiency is likely to give incorrect estimates of inefficiency (Tsionas and Kumbhakar, 2014), implying that prior studies may have conveyed misleading results on both the levels and sources of the inefficiency of Italian banks. Secondly, by explicitly estimating and modelling the short and long-term parts of efficiency, we contribute to the understanding of where bank inefficiencies are stemming from. This allows firm's management and policymakers to respond with different improvement strategies, something that was not possible if the standard measure of overall efficiency were to be employed. For Italian banks, the long-term component of inefficiency is considerably larger than the short-term component, entailing that policy interventions aimed at addressing long-term inefficiency should be prioritized (Khumbakar et al., 2014). In particular, we are the first to show that the well-documented strong regional disparities (in terms of social, economic and demographic conditions) that characterised Italy and the bank type have a direct impact on the ability of banks to operate efficiently and to survive in the *long-run*. Finally, concerning production risk (Table 4, Panel C), we find that increases in GDP increase the time-varying production risk, whereas inflation and unemployment decrease it.

Table 4. Determinants of the error components

Error Component	Determinants	Determinants	Coefficients	Z-values
Panel A				
Short-term Inefficiency (u_{it})	Time trend	$t,$	8.277***	(8.93)
	Quadratic time trend	t^2	-0.568***	(-8.71)
	Log of total assets	$Size$	0.055	(1.30)
	Dummy=1 for the period 2009-2015	$Crisis\ Dummy$	-10.883***	(-9.59)
Panel B				
Long-term Inefficiency (u_{0i})	Dummy=1 if the bank is a cooperative bank	$Industry\ Dummy$	-1.434***	(-10.15)
	Dummy=1 if the bank's headquarters is located in that area	$North-West$	0.774***	(5.60)
		$North-East$	-0.508***	(-4.17)
		$South$	0.484***	(3.50)
Panel C				
Production Risk (v_{it})	Gross domestic product growth	$GDP\ Growth,$	0.133***	(7.99)
	Inflation rate	$Inflation$	-0.355***	(-6.51)
	Unemployment rate	$Unemployment$	-0.142***	(-6.09)

This table reports the parameter estimates for the determinants of short-term efficiency, long-term efficiency and production risk (random noise). Z-values are reported. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.2. Granger Causality Results

5.2.1. Main Results

Table 5 reports the results from the estimation of the temporal relationship between bank efficiency and BLs. In all specifications, we treat the macroeconomic variables as strictly exogenous, whereas the bank-specific determinants are assumed to be endogenous. In determining the validity of the SGMM regressions, we conduct two post estimation tests: the Hansen test of joint validity of the instruments and the Arellano-Bond test of serial correlation in the residuals. In all cases, we confirm the validity of the SGMM and the instruments used in the estimation.[18] Finally, we apply the finite sample correction proposed by Windmeijer (2005). The identification of coefficients of time-invariant variables in linear dynamic panel data models

[18] In all regressions, to avoid instrument proliferation and overfitting of the endogenous variables, we restrict the number of instruments in order not to exceed the number of cross-sections in the sample (Roodman, 2009). We further confirm the properties of the instruments used in the SGMM by estimating the constituent levels and differenced equations for our more inclusive models (columns 1 and 2, Table 6) and we assess the relevance of the instruments. In both cases, we reject the null of underidentification (Kleibergen and Paap, 2006). It should be noted that these tests serve only as an indication of the quality of the instruments used in the SGMM, as SGMM estimates require the joint estimation of the differenced and levels equations.

may be difficult. To check that the coefficient of long-term efficiency is identified in our model, we first follow the pre-test procedure proposed by Chatelain and Ralf (2021) and we select as internal Hausman-Taylor instruments the subset of variables that do not reject the null hypothesis of exogeneity. Then, we apply the Kripfganz and Schwarz (2019) estimator and test the joint validity of the instruments using the better sized second-stage Hansen test. The p-value of the test is 0.9367, implying that the overidentifying restrictions are not rejected and that the coefficient of long-term efficiency is identified. In what follows, we use the one-stage SGMM estimator.[19] All estimated regressions show high goodness of fit, confirming the model selection.

Our first interesting result concerns the coefficient of the lagged dependent variable, which is found positive and significant in all the regressions. The implication of this is that BLs are likely to increase when they have increased in the previous year and that banks with a high share of bad loans will need substantial time to remove them from their balance sheets. More specifically, our findings indicate high persistence of BLs, with the previous year's BLs affecting the present year's by 79-92% (columns 1 and 2). This persistence of NPLs can be in part explained by the stagnation of the Italian economy over the last decade. However, part of this persistence is likely attributable to obstacles to BLs resolutions: the heavy reliance on collaterals, lack of tax incentives to provision loans, low capital and coverage ratios, inefficiencies in the judicial system, divergences in the BLs' price expectations between banks and private investors, and lack of a secondary market for distressed debt – which delay banks' write-offs (see Jassaud and Kang 2015).

Moving to our key findings, we provide evidence that decreases in short-term efficiency Granger-cause higher BLs (i.e., the lagged coefficients of $Short\_term$ are jointly significant with negative coefficients, see columns 1 and 2, Table 5). This result supports H_1, the 'bad management' hypothesis, where lower managerial cost efficiency due to poor management

[19] We thank an anonymous referee for suggesting this test.

practices in the screening, monitoring and controlling of the loan portfolio precedes a worsening in banks' asset quality.

With respect to the long-term multiplier (recall, $\sum_{j=1}^{J} \gamma_{1j}$, for $J = 2$) we find that the positive marginal effect of the second lag is offset by the negative marginal effect of the shorter lag. That is, the long-term effect is not statistically different from zero, indicating that permanent changes in efficiency have temporary effects on BL, suggesting that BLs react to annual negative changes in efficiency over the last two years ($momentum$). Taken together, this would suggest that maintaining cost efficiency stability and reducing annual negative variation over the two-year horizon, would help minimize the negative impact of short-term efficiency on BLs.

Turning to long-term efficiency, the coefficient is positive and significant at the 5% level in both specifications. This indicates that banks that display higher levels of structural efficiency exhibit higher volumes of defaulted loans, in line with H_5, the 'resources misallocation' hypothesis. These findings concerning the dual effect of efficiency on credit risk are of particular interest from a regulators' perspective, for several reasons. First, we provide initial evidence that the asset quality of banks can be explained in terms of both short- and long-term efficiencies of the banking sector. This represents an improvement over prior studies that, by employing the standard measure of overall efficiency, ignore latent sectorial inefficiencies as a potential source of credit risk. Furthermore, failing to account for long-term inefficiency when investigating the determinants of credit risk could be a major shortcoming in the presence of banking sectors characterised by regulatory constraints (e.g., restrictions on voting rights, caps on ownership and membership requirements), structural problems and/or sector rigidities (e.g., limits to branch expansion).

In particular, the negative temporal relationship between short-term efficiency and bad loans bears substantial implications for both banks and regulators. On the institutions' side, this finding implies that there could be room for Italian banks to make improvements and prevent increases in bad loans, as short-term inefficiency denotes the presence of failures in the day-to-day practices carried out by bank employees. These management mistakes are characterised by their 'non-systematic' nature; that is, they stem from temporal behavioural aspects of the management and, as such, can be solved in the short term (Filippini and Greene, 2016; Filippini et al., 2018). In other words, our results suggest it is potentially within the control of senior management to remove these short-term inefficiencies, thus implying that Italian banks could at least prevent an increase in that part of bad loans that stem from banks' lax practices in loan underwriting, monitoring and control.

Concerning the remaining set of bank-specific control variables, we find strong evidence of moral hazard behaviour among Italian banks, as weakened capital positions (CAP) are found to temporally precede deteriorations in credit quality. These results hint at the presence of '*zombie lending*' practices. Under-capitalized banks may be reluctant to register losses in their balance sheet (i.e., writing-off loans) to avoid violations of the minimum capital requirements, and are more willing to extend additional credit to low-productivity firms to keep them from going bankrupt, following a 'gambling for resurrection' logic (Jiménez et al. 2017).[20] These conclusions are reinforced by the robust evidence that loan portfolios expansions ($CreditGr$) tend to be achieved at the expense of future credit quality.

We do not observe a significant relationship between bank size and BLs, thus rejecting our hypotheses that larger banks may benefit from greater asset diversification opportunities and from enhanced capabilities in managing impaired loans. However, interestingly, the dummy identifying SIBs ($Supervised$) is positive and statistically significant, supporting the 'too-big-

[20] Schivardi et al. (2017) observe that Italian banks with low levels of capitalisation were engaging in significant zombie lending between 2008 and 2013, and conclude that 'low capital banks may be particularly averse to absorb losses, especially during a recession, and may therefore be relatively more willing to keep lending to weak firms that otherwise would not be able to service their debt' (Schivardi et al., 2017, p.15).

to-fail' notion.[21] Anecdotal evidence provided by the noteworthy financial scandals involving Monte dei Paschi di Siena, Banca Carige, Banca Popolare di Vicenza and Veneto Banca seems to provide support for these results. Indeed, government intervention was necessary after these banks were hit by a series of scandals that revealed their extremely poor lending practices. At the end of 2015, these banks reported a level of NPLs (BLs) of 34% (20%), 28% (15%), 31% (15%) and 28% (14%). Concerning the relationship between bank specialisation and credit risk, we find that cooperative banks, on average, report lower NPLs than their commercial counterparts. This could relate to their reliance on 'relationship lending', which allows them to collect *soft information* on potential borrowers, thereby reducing the information asymmetry between the lender and the borrowers and improving overall credit quality (Becchetti et al. 2016). Finally, the crisis dummy ($Crisis$) is positive and statistically significant only in the models incorporating bank-specific characteristics, highlighting the negative effect of the exogenous shock on credit quality.

With respect to macroeconomic drivers, the coefficients of $GDPGR$ are positive and jointly significant, suggesting that during the expansionary phase of the economy, Italian banks extend credit to lower-quality borrowers, which leads to subsequent reductions in asset quality. Considering this finding together with the observed positive relationship between credit growth and BLs, we argue that regulators should consider strengthening the supervision process to ensure the enforcement of the prudential rules for the granting of loans, especially during economic upswings. For example, supervisory bodies might consider verifying that the risk premium charged by banks in each loan operation corresponds to the actual level of risk borne by the institutions. We find a negative effect of sovereign debt ($SDEBT$) on BLs, which is in

[21] Indeed, banks may be tempted to increase the riskiness of their loan portfolio if they are certain about government support in the event of financial troubles. At the same time, if investors recognise this implicit subsidy from the state, they tend to impose lower market discipline on the bank.

contrast to Louzis et al. (2012) and Ghosh (2015). One interpretation is that lower sovereign indebtedness implies eased funding conditions for banks, resulting in the greater supply of loans and thus increased credit risk, consistent with the findings concerning credit growth. Finally, we fail to observe a significant relationship between the 'house wealth' of borrower and banks' bad loans.

We perform sensitivity analyses on our findings by estimating four additional models where we alternatively include or exclude the measure of short-term and long-term efficiency (Table 5, columns 3-6). Specifically, we first include solely the index of short-term efficiency (column 3), and next, we saturate the model with macro determinants (column 4). Likewise, we estimate one regression incorporating only long-term efficiency (column 5), and finally, we augment the specification with macro variables (column 6). This set of findings reinforces the evidence of 'bad management' and 'resource misallocation' practices in Italian banks. Finally, following Ben Naceur et al. (2018), we perform robustness checks by replacing the set of macroeconomic variables with time-fixed effects (column 7). Overall, results on bank-specific features are robust across both ways of controlling for macroeconomic conditions, and we strongly confirm the presence of 'bad management' (H_1) and 'resources misallocation' (H_5).

Table 5. Granger-Sims causality results

Dependent variable: BL_{it}	(1) Short-term & Long-term Efficiency	(2) Short-term & Long-term Efficiency with $macro\_controls$	(3) Excluding Long-term Efficiency	(4) Excluding Long-term Efficiency with $macro\_controls$	(5) Excluding Short-term Efficiency	(6) Excluding Short-term Efficiency with $macro\_controls$	(7) Short-term & Long-term Efficiency and Time FE	(8) Sims Causality Short-term & Long-term Efficiency
BL_{it-1}	0.922***	0.790***	0.957***	0.911***	0.881***	0.793***	0.897***	0.692***
	(0.078)	(0.074)	(0.080)	(0.091)	(0.086)	(0.094)	(0.090)	(0.127)
BL_{it-2}	0.038	0.091	0.006	0.002	0.078	0.098	0.034	0.197
	(0.078)	(0.061)	(0.078)	(0.079)	(0.084)	(0.083)	(0.085)	(0.125)
$BL(Total)$	0.960***	0.880***	0.962***	0.913***	0.960***	0.892***	0.930***	0.889***
	(0.018)	(0.032)	(0.018)	(0.029)	(0.019)	(0.030)	(0.027)	(0.044)
$Short\_term_{it-1}$	-0.767***	-0.834**	-0.826***	-0.682			-1.357*	-1.363*
	(0.245)	(0.407)	(0.272)	(0.476)			(0.720)	(0.724)
$Short\_term_{it-2}$	0.566***	0.130	0.575***	0.549			0.512*	0.174
	(0.215)	(0.693)	(0.218)	(0.952)			(0.308)	(0.430)
$Short\_term$								-1.786*
								(0.965)
$Short\_term_{it+1}$								-0.952
								(0.985)
$Short\_term_{it+2}$								-1.315
								(1.316)
$Short\_term(Total - lags)$	-0.201	-0.705	-0.251	-0.133			-0.846	-1.189
	(0.357)	(0.969)	(0.352)	(1.313)			(0.700)	(1.037)
$Long\_term$	1.560**	1.835**			2.529***	3.271***	1.848***	0.891
	(0.727)	(0.803)			(0.836)	(1.114)	(0.664)	(1.219)
CAP_{it-1}	0.205	-2.004	0.069	-2.974**	-0.388	-0.765	-1.837	2.032
	(1.047)	(1.507)	(1.020)	(1.499)	(1.157)	(1.968)	(1.423)	(1.864)
CAP_{it-2}	-2.126*	0.287	-2.086**	0.938	-1.445	-0.840	0.524	-2.931
	(1.167)	(1.782)	(1.019)	(1.689)	(1.213)	(2.241)	(1.535)	(2.014)
$CAP(Total)$	-1.921***	-1.716**	-2.017***	-2.036**	-1.833***	-1.605**	-1.313**	-0.900
	(0.647)	(0.715)	(0.634)	(0.819)	(0.709)	(0.758)	(0.666)	1.070
$CreditGR_{it-1}$	-0.981***	-0.728	-0.864***	-0.362	-0.769***	-1.194***	0.017	-1.781***
	(0.226)	(0.463)	(0.223)	(0.518)	(0.199)	(0.403)	(0.443)	(0.453)
$CreditGR_{it-2}$	1.378***	1.039**	1.334***	0.848*	1.193***	1.477***	0.382	1.878***
	(0.227)	(0.466)	(0.207)	(0.515)	(0.201)	(0.405)	(0.456)	(0.464)
$CreditGR(Total)$	0.397***	0.311*	0.469***	0.486***	0.424***	0.284	0.399***	0.096
	(0.109)	(0.153)	(0.095)	(0.139)	(0.117)	(0.175)	(0.121)	(0.243)
$Size$	-0.048**	-0.038	-0.045**	-0.044**	-0.042	-0.048	-0.030	-0.036
	(0.023)	(0.025)	(0.020)	(0.022)	(0.028)	(0.038)	(0.022)	(0.040)
$Crisis$	0.077***	-0.036	0.072***	-0.018	0.093***	0.047	0.006	0.130
	(0.027)	(0.063)	(0.028)	(0.068)	(0.029)	(0.057)	(0.054)	(0.081)

$Supervised$	0.234**	0.235*	0.149	0.165*	0.237*	0.305	0.166	0.247
	(0.107)	(0.128)	(0.091)	(0.091)	(0.138)	(0.187)	(0.101)	(0.200)
$Industry$	-0.194**	-0.150*	-0.071	-0.024	-0.242***	-0.299**	-0.166**	-0.123
	(0.077)	(0.082)	(0.046)	(0.050)	(0.086)	(0.130)	(0.067)	(0.097)
$GDPGR_{it-1}$		9.384**		10.092**		9.377**		
		(4.486)		(4.823)		(4.447)		
$GDPGR_{it-2}$		3.008**		3.607**		3.027**		
		(1.504)		(1.558)		(1.524)		
$GDPGR(Total)$		12.39**		13.70**		12.40**		
		(5.954)		(6.326)		(5.949)		
$SDEBT_{it-1}$		6.599**		7.308**		5.993*		
		(3.096)		(3.205)		(3.087)		
$SDEBT_{it-2}$		-6.831**		-7.746**		-6.430*		
		(3.398)		(3.499)		(3.419)		
$SDEBT(Total)$		-0.231		-0.438		-0.437		
		(0.400)		(0.403)		(0.403)		
HPI_{it-1}		-0.013		-0.018**		-0.013		
		(0.008)		(0.008)		(0.008)		
$Constant$	-0.844	0.624	0.489	2.441	-1.965***	-0.940	-0.795	4.360
	(0.706)	(1.637)	(0.384)	(1.859)	(0.714)	(1.667)	(0.853)	(3.017)
$Wald\ Test\ (Short\_term - lags)$	0.000	0.041	0.000	0.048			0.0841	0.030
$Wald\ Test\ (Short\_term - leads)$								0.310
$Wald\ Test\ (CAP)$	0.010	0.011	0.003	0.007	0.034	0.076	0.071	0.333
$Wald\ Test\ (CreditGR)$	0.000	0.021	0.000	0.001	0.000	0.000	0.004	0.000
$Wald\ Test\ (GDPGR)$		0.112		0.063		0.099		
$Wald\ Test\ (SDEBT)$		0.037		0.058		0.110		
$Wald\ Test\ (Time\ Fixed\ Effects)$							0.089	
$AR(1)$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$AR(2)$	0.400	0.727	0.243	0.205	0.603	0.905	0.293	0.777
$Hansen\ Test\ of\ Overidentification$	0.526	0.429	0.564	0.601	0.289	0.220	0.534	0.149
$Goodness\ of\ fit$	0.870	0.870	0.877	0.879	0.862	0.851	0.873	0.852
$N\_of\ instruments\ (N\_groups)$	182 (426)	268 (426)	207 (426)	194 (426)	181 (426)	222 (426)	188 (426)	89 (426)
$N\_observations$	2,522	2,522	2,522	2,522	2,522	2,522	2,522	1,623

This table reports the results on the determinants of BLs estimated using the two-step system GMM estimator as specified in Eqs.(1) and (2). Windmeijer (2005) robust standard errors are reported in parentheses. The variables $BL(Total)$, $Short\_term\ (Total)$, $CAP(Total)$, $CreditGr(Total)$, $GDPGR(Total)$ and $SDEBT(Total)$ are the estimated coefficients for the test that the sum of the respective lagged terms are equal to zero (standard errors are obtained by the Delta method). In all cases, $BL(Total)$ is statistically different from one. The Wald test is the test for the joint significance of the coefficients of the lagged explanatory variables; we report the p-value. $AR(1)$, $AR(2)$ are tests of first- and second-order serial correlation in the first-differenced residuals, under the null of no serial correlation. The Hansen test of overidentification is under the null that all the instruments are valid. $Goodness\ of\ fit$ is the square correlated coefficient between actual and predicted values of the dependent variable (Bloom et al. 2007). Variables are defined as in Section 4.2. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.2.2. Testing for Bad Luck

We assess the presence of a bi-directional link between BLs and cost efficiency by testing for the 'bad luck hypothesis' (H_3), that is, whether exogenously driven increases in BLs exert an effect on the levels of efficiency. Testing the bad luck hypothesis would require estimating a panel ARDL model like Eq (1), with efficiency as the dependent variable, and a test of joint significance of the lagged BL coefficients. This estimation would effectively constitute a "two-step method", where in step 1, efficiency scores are estimated under some distributional assumption, and in step 2, the measure of efficiency is regressed on a set of explanatory variables. Such two-step procedures have been criticised on the basis of being subject to i) omitted variable bias, model misspecification and spuriously underdispersed efficiencies in step 1 and ii) understated effects in step 2 (see Wang and Schmidt, 2002 and Schmidt, 2011). To test for this hypothesis, and to avoid the pitfalls of a 'two-step' procedure, we augment our specification and we estimate the following regression:

$$\begin{aligned} BL_{it} = \alpha + \sum_{j=1}^{J} \beta_j BL_{i,t-j} + \sum_{j=1}^{J} \gamma_{1j} Short\_term_{i,t-j} + \gamma_2 Short\_term_{it} \\ + \sum_{k=1}^{K} \gamma_{3k} Short\_term_{i,t+k} + \gamma Long\_term_i + bank\_controls + \eta_i \\ + \varepsilon_{ti} \; for \; J = K = 2 \end{aligned} \tag{4}$$

In this augmented regression, we include the current and future values of short-term efficiency. Rejection of the restriction $H_0\colon \gamma_{31} = \cdots = \gamma_{3K} = 0$ would suggest a relationship between BLs and future levels of efficiency, providing evidence in favour of the 'bad luck hypothesis' (Eq. (4) is akin to a multivariate Granger – Sims (1972) specification). The above regression has two appealing properties. First, as stated above, it enables us to test for bad luck while overcoming the limitations of the two-step procedure. Second, given the disaggregated nature of efficiency used in our model, it permits us to include in the regression simultaneously both components of efficiency ($Short\_run$ and $Long\_run$), something that would not have been possible if we were to proceed with a second-stage regression of time-varying efficiency on BLs. It is important to highlight that, from the above regression, our focus is on the joint significance of the two lagged values of transient efficiency to confirm bad management/skimping and the joint significance of the lead values to confirm or reject the notion of 'bad luck'.

Column 8 of Table 5 presents the results of the augmented regression. We note that adding the current and lead values of cost efficiency ($Short\_term$) reduces the fraction of the variation in BLs explained by the other explanatory variables and only the two lags of $CreditGR$ remains jointly significant. Long-term efficiency maintains its positive sign; however, the effect becomes statistically insignificant. With respect to the coefficients of interest, we fail to reject the null hypothesis of joint significance for the lead values of efficiency (p-value = 0.310), thus confirming the absence of a bi-directional link and bad luck. This lack of intertemporal relationship between BLs and efficiency could be explained by the slow pace of resolution of impaired loans and therefore the lack of additional costs associated with disposing of bad loans or the need to monitor the existing performing loans more closely (Jassaud and Kang, 2015). Once again, we confirm the 'bad management' hypothesis, as the two lags of short-term efficiency remain jointly statistically significant (p-value =0.030), with a negative (but insignificant) long-run coefficient of -1.189.

5.3. Additional Analyses and Robustness Tests

The results presented in Section 5.2.1 provide support for industry-wide bad management and resource misallocation effects. In this section, to evaluate the robustness of our results to the data, we provide additional analyses conducted in subsamples of the bank population (Table 6). First, we examine size effects by splitting the sample between small and large banks; second, we analyse regional heterogeneity and we divide the sample into North and South, based on the location of banks' headquarters; third, we confirm that our findings are not driven by TBTF considerations by removing SIB form the sample; and finally we remove commercial banks from the estimation.[22] Concerning $Short\_term$, we strongly confirm H_1, bad management, with the exception of the sub-sample of banks located in the Southern regions. For these banks, the relationship between bad loans and $Short\_term$ is positive, suggesting the presence of a skimping behaviour, H_2. (Table 6, column 4). With respect to long-term efficiency, we broadly confirm H_5, the resource misallocation hypothesis, in all regressions except for small banks and banks in the South of Italy, where we report a negative, but insignificant coefficient for $Long\_term$ (columns 1 and 4 respectively). The remaining control variables maintain their signs and significance in all cases but for CAP when estimated for large banks, where we find no evidence of moral hazard.

We further evaluate the robustness of our results by thoroughly investigating the impact of outliers on our estimates (Table 7). We do so in three ways. First, we remove outliers identified as the largest prediction errors, after excluding the observations corresponding to the largest 1% of squared residuals (columns 1-3). Second, we control for outliers in the dependent variable using the Median Absolute Deviation method (MAD) (columns 4-6). This method is generally more effective than the standard deviation method, which may fail as outliers increase the standard deviation. Third, we winsorize all financial data at the top and bottom 1% (columns 7-9). In all these additional regressions, our main results remain unaffected, strongly confirming the effects of short- and long-term efficiency on BLs. As a final robustness exercise, we use an alternative specification of the dependent variable, that is the logarithmic transformation of bad loans ($lnBL$) and we re-estimate the baseline specifications (the results are reported in Appendix

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

C, Table C1).[23] All results remain qualitatively similar and confirm the 'bad management' and 'resources misallocation' hypotheses.

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

Table 6. Granger Causality Results – Different samples

Dependent variable: BL_{it}	(1) Small	(2) Large	(3) North	(4) South	(5) Excluding SIBs	(6) Cooperative Banks
BL_{it-1}	0.771***	1.085***	0.867***	1.055***	0.913***	0.798***
	(0.080)	(0.062)	(0.100)	(0.074)	(0.088)	(0.085)
BL_{it-2}	0.095	-0.105	0.048	-0.085	0.052	0.125
	(0.078)	(0.065)	(0.101)	(0.071)	(0.088)	(0.081)
$BL(Total)$	0.866***	0.980***	0.916***	0.970***	0.965***	0.924***
	(0.043)	(0.015)	(0.024)	(0.024)	(0.019)	(0.023)
$Short\_term_{it-1}$	-0.960*	-0.842***	-0.944**	-0.657	-0.796***	-0.625*
	(0.553)	(0.308)	(0.399)	(0.410)	(0.283)	(0.350)
$Short\_term_{it-2}$	0.756	0.631**	0.359	0.747*	0.585**	0.610**
	(0.490)	(0.259)	(0.294)	(0.383)	(0.233)	(0.265)
$Short\_term(Total - lags)$	-0.205	-0.211	-0.585	0.089	-0.210	-0.014
	(0.816)	(0.447)	(0.508)	(0.657)	(0.401)	(0.521)
$Long\_term$	-0.484	1.067**	1.959**	-1.176	1.438*	1.927*
	(1.439)	(0.499)	(0.943)	(0.731)	(0.771)	(0.993)
CAP_{it-1}	-0.192	1.081	-2.283	2.219*	0.198	-0.448
	(1.539)	(1.257)	(1.647)	(1.336)	(1.088)	(1.379)
CAP_{it-2}	-2.275	-1.367	-0.351	-2.966**	-2.064*	-2.376
	(1.415)	(1.176)	(1.728)	(1.364)	(1.223)	(1.448)
$CAP(Total)$	-2.467***	-0.286	-2.634**	-0.747	-1.865***	-2.824***
	(0.907)	(0.545)	(1.045)	(0.644)	(0.649)	(0.889)
$CreditGR_{it-1}$	-1.056***	-0.928***	-0.984***	-0.556*	-0.993***	-1.151***
	(0.396)	(0.267)	(0.319)	(0.332)	(0.240)	(0.301)
$CreditGR_{it-2}$	1.192***	1.260***	1.244***	1.052***	1.408***	1.453***
	(0.425)	(0.292)	(0.346)	(0.365)	(0.243)	(0.289)
$CreditGR(Total)$	0.136	0.332***	0.260	0.496***	0.415***	0.302**
	(0.198)	(0.117)	(0.179)	(0.121)	(0.116)	(0.126)
$Size$	-0.049	-0.032	-0.021	-0.041*	-0.046**	-0.030
	(0.062)	(0.026)	(0.031)	(0.023)	(0.023)	(0.029)
$Crisis$	0.132***	0.022	0.094*	0.094***	0.082***	0.108***
	(0.042)	(0.027)	(0.049)	(0.033)	(0.028)	(0.030)
$Supervised$		0.133	0.154	0.250		0.130
		(0.102)	(0.142)	(0.199)		(0.136)
$Industry$	-0.137	-0.120**	-0.141	0.013	-0.180**	
	(0.091)	(0.051)	(0.111)	(0.069)	(0.082)	
$Constant$	0.890	-0.550	-1.073	0.988	-0.753	-1.637*
	(1.406)	(0.632)	(0.902)	(0.860)	(0.747)	(0.984)
$Wald\ Test\ (Short\_term -\ lags)$	0.031	0.000	0.024	0.006	0.000	0.000
$Wald\ Test\ (CAP)$	0.012	0.462	0.030	0.079	0.014	0.005
$Wald\ Test\ (CreditGR)$	0.018	0.000	0.001	0.000	0.000	0.000
$AR(1)$	0.000	0.000	0.000	0.000	0.000	0.000

$AR(2)$	0.994	0.040	0.423	0.272	0.514	0.886
$Hansen\ Test\ of\ Overidentification$	0.272	0.596	0.355	0.385	0.331	0.270
$Goodness\ of\ fit$	0.839	0.917	0.852	0.889	0.869	0.863
$N\_of\ instruments\ (N\_groups)$	181 (217)	182 (209)	182 (229)	182 (197)	181 (413)	181 (367)
$N\_observations$	1,199	1,323	1,349	1,173	2,464	2,220

This table reports the results on the determinants of BLs estimated using the two-step system GMM estimator as specified in Eqs.(1) and (2) for different samples of banks: Small: Banks with average total assets below or equal to the sample median. Large: Banks with average total assets greater than the sample median. North: Banks located in the North East or North West. South: Banks located in the Central or South. Windmeijer (2005) robust standard errors are reported in parentheses. The variables $BL(Total)$, $Short\_term(Total)$, $CAP(Total)$, $CreditGr(Total)$, $GDPGR(Total)$ and $SDEBT(Total)$ are the estimated coefficients for the test that the sum of the respective lagged terms are equal to zero (standard errors are obtained by the Delta method). In all cases, $BL(Total)$ is statistically different from one. The Wald test is the test for the joint significance of the coefficients of the lagged explanatory variables; we report the p-value. $AR(1)$, $AR(2)$ are tests of first- and second-order serial correlation in the first-differenced residuals, under the null of no serial correlation. The Hansen test of overidentification is under the null that all the instruments are valid. $Goodness\ of\ fit$ is the square correlated coefficient between actual and predicted values of the dependent variable (Bloom et al. 2007). Variables are defined as in Section 4.2. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7. Granger Sims Causality – Controlling for Outliers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Trimmed Residuals			Median Absolute Deviation			Winsorised Variables		
Dependent variable: BL_{it}	Short-term & Long-term Efficiency	Short-term & Long-term Efficiency with $macro\_controls$	Sims Causality Short-term & Long-term Efficiency	Short-term & Long-term Efficiency	Short-term & Long-term Efficiency with $macro\_controls$	Sims Causality Short-term & Long-term Efficiency	Short-term & Long-term Efficiency	Short-term & Long-term Efficiency with $macro\_controls$	Sims Causality Short-term & Long-term Efficiency
BL_{it-1}	0.986***	0.852***	0.756***	0.913***	0.848***	0.661***	0.907***	0.800***	0.672***
	(0.069)	(0.063)	(0.117)	(0.085)	(0.065)	(0.111)	(0.080)	(0.066)	(0.123)
BL_{it-2}	-0.028	0.036	0.118	0.041	0.035	0.208**	0.043	0.087	0.196*
	(0.066)	(0.057)	(0.105)	(0.086)	(0.059)	(0.098)	(0.080)	(0.057)	(0.117)
$BL(Total)$	0.958***	0.887***	0.874***	0.954***	0.882***	0.870***	0.950***	0.887***	0.868***
	(0.017)	(0.024)	(0.040)	(0.016)	(0.025)	(0.042)	(0.017)	(0.028)	(0.043)
$Short\_term_{it-1}$	-0.558**	-0.585*	-1.498**	-0.718***	-0.565	-1.357*	-0.747***	-0.748**	-1.572**
	(0.246)	(0.355)	(0.720)	(0.235)	(0.384)	(0.729)	(0.231)	(0.380)	(0.696)
$Short\_term_{it-2}$	0.494**	0.542	0.152	0.546**	0.391	0.129	0.577***	0.279	0.095
	(0.214)	(0.608)	(0.423)	(0.216)	(0.577)	(0.396)	(0.217)	(0.654)	(0.434)
$Short\_term$			-2.005**			-2.297***			-2.006**
			(0.914)			(0.880)			(0.964)
$Short\_term_{it+1}$			-0.997			-0.677			-1.185
			(0.977)			(0.930)			(1.014)
$Short\_term_{it+2}$			-1.440			-1.574			-1.429
			(1.273)			(1.287)			(1.229)
$Short\_term(Total - lags)$	-0.063	-0.042	-1.346	-0.172	-0.174	-1.228	-0.170	-0.469	-1.477
	(0.364)	(0.867)	(1.026)	(0.355)	(0.844)	(1.020)	(0.352)	(0.884)	(1.021)
$Long\_term$	1.262*	1.636**	0.130	1.701**	1.842**	0.267	1.845**	2.058**	0.751
	(0.681)	(0.725)	(1.156)	(0.787)	(0.752)	(1.172)	(0.791)	(0.833)	(1.112)
CAP_{it-1}	0.066	-1.761	2.352	-0.079	-1.981	1.974	0.776	-1.623	2.129
	(1.028)	(1.251)	(1.761)	(0.975)	(1.300)	(1.753)	(1.106)	(1.513)	(1.799)
CAP_{it-2}	-1.628	-0.068	-3.103	-1.588	0.369	-2.871	-2.519**	-0.294	-2.633
	(1.097)	(1.418)	(1.993)	(1.066)	(1.446)	(2.005)	(1.254)	(1.718)	(1.951)
$CAP(Total)$	-1.562**	-1.829***	-0.751	-1.666***	-1.612***	-0.897	-1.744**	-1.917***	-0.504
	(0.636)	(0.608)	(1.017)	(0.575)	(0.618)	(0.956)	(0.682)	(0.687)	(1.006)
$CreditGR_{it-1}$	-0.970***	-0.790*	-1.739***	-1.001***	-0.704*	-1.813***	-0.976***	-0.649	-1.840***
	(0.222)	(0.412)	(0.447)	(0.228)	(0.385)	(0.427)	(0.223)	(0.443)	(0.452)
$CreditGR_{it-2}$	1.312***	1.044***	1.931***	1.347***	0.940**	1.983***	1.325***	0.926**	1.877***
	(0.220)	(0.403)	(0.456)	(0.227)	(0.376)	(0.446)	(0.221)	(0.441)	(0.468)
$CreditGR(Total)$	0.342***	0.254**	0.192	0.346	0.236	0.170	0.349***	0.277*	0.0363**
	(0.096)	(0.119)	(0.213)	(0.102)	(0.129)	(0.233)	(0.109)	(0.147)	(0.241)
$Size$	-0.027	-0.022	-0.060*	-0.043*	-0.028	-0.060	-0.040	-0.028	-0.016
	(0.021)	(0.021)	(0.036)	(0.022)	(0.021)	(0.039)	(0.025)	(0.025)	(0.041)
$Crisis$	0.072***	-0.015	0.123	0.084***	-0.020	0.165**	0.086***	-0.030	0.127
	(0.025)	(0.054)	(0.078)	(0.026)	(0.052)	(0.075)	(0.027)	(0.054)	(0.078)
$Supervised$	0.134	0.139	0.329*	0.229**	0.182*	0.337*	0.208*	0.182	0.139
	(0.096)	(0.104)	(0.186)	(0.109)	(0.103)	(0.199)	(0.115)	(0.111)	(0.176)
$Industry$	-0.131*	-0.107	-0.134	-0.200**	-0.139*	-0.141	-0.197**	-0.136	-0.077
	(0.070)	(0.072)	(0.093)	(0.082)	(0.078)	(0.099)	(0.088)	(0.086)	(0.100)
$GDPGR_{it-1}$		7.792*			8.721**			8.427**	
		(4.144)			(3.764)			(3.861)	

$GDPGR_{it-2}$		2.604*			2.918**			2.845**	
		(1.354)			(1.221)			(1.271)	
$GDPGR(Total)$		10.40*			11.64**			11.27**	
		(5.462)			(4.946)			(5.090)	
$SDEBT_{it-1}$		5.596**			6.164**			6.073**	
		(2.795)			(2.501)			(2.618)	
$SDEBT_{it-2}$		-5.785*			-6.385**			-6.250**	
		(3.075)			(2.761)			(2.889)	
$SDEBT(Total)$		-0.189			-0.221			-0.176	
		(0.358)			(0.353)			(0.375)	
HPI_{it-1}		-0.011			-0.012*			-0.011	
		(0.007)			(0.007)			(0.007)	
$Constant$	-0.909	-0.139	5.620*	-1.048	0.001	5.482*	-1.210*	-0.049	5.080*
	(0.631)	(1.497)	(2.995)	(0.731)	(1.466)	(3.077)	(0.707)	(1.463)	(2.929)
$Wald\ Test\ (Short\_term-\ lags)$	0.000	0.017	0.017	0.000	0.081	0.032	0.000	0.055	0.010
$Wald\ Test\ (Short\_term-\ leads)$			0.274			0.327			0.181
$Wald\ Test\ (CAP)$	0.041	0.003	0.298	0.014	0.010	0.345	0.025	0.008	0.402
$Wald\ Test\ (CreditGR)$	0.000	0.005	0.000	0.000	0.012	0.000	0.000	0.031	0.000
$Wald\ Test\ (GDPGR)$		0.157			0.057			0.080	
$Wald\ Test\ (SDEBT)$		0.042			0.013			0.020	
$AR(1)$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$AR(2)$	0.219	0.517	0.668	0.676	0.510	0.247	0.536	0.746	0.637
$Hansen\ Test\ of\ Overidentificationion$	0.318	0.384	0.144	0.454	0.415	0.199	0.467	0.438	0.190
$Goodndess\ of\ fit$	0.872	0.871	0.844	0.869	0.871	0.844	0.870	0.870	0.855
$N\_of\ instruments\ (N\_groups)$	182 (422)	268 (422)	89 (368)	182 (426)	268 (423)	89 (369)	182 (426)	268 (426)	89 (374)
$N\_observations$	2480	2480	1591	2,495	2,495	1,600	2,522	2,522	1,623

This table reports the results on the determinants of BLs estimated using the two-step system GMM estimator as specified in Eqs.(1) and (2) when controlling for outliers. Columns 1-3 report results excluding the observations corresponding to the largest 1% of squared residuals; columns 4-6 report results for using the Median Absolute Deviation method on BL; columns 7-9 report results from winsorizing all financial data at the top and bottom 1%. Windmeijer (2005) robust standard errors are reported in parentheses. The variables $BL(Total)$, $Short\_term(Total)$, $CAP(Total)$, $CreditGr(Total)$, $GDPGR(Total)$ and $SDEBT(Total)$ are the estimated coefficients for the test that the sum of the respective lagged terms are equal to zero (standard errors are obtained by the Delta method). In all cases, $BL(Total)$ is statistically different from one. The Wald test is the test for the joint significance of the coefficients of the lagged explanatory variables; we report the p-value. $AR(1)$, $AR(2)$ are tests of first- and second-order serial correlation in the first-differenced residuals, under the null of no serial correlation. The Hansen test of overidentification is under the null that all the instruments are valid. $Goodness\ of\ fit$ is the square correlated coefficient between actual and predicted values of the dependent variable (Bloom et al. 2007). Variables are defined as in Section 4.2. * p < 0.10, ** p < 0.05, *** p < 0.01

6. Conclusions and policy recommendations

In this study, we investigate the links between bank asset quality and bank managers' ability to minimise costs, by assessing the temporal relationships between bad loans and bank cost efficiency in a sample of Italian banks over the period 2006-2015 using Granger-causality tests. In doing so, we advance the literature by employing a new measure of cost efficiency, introduced by Badunenko and Kumbhakar (2017), which distinguishes between short- and long-term efficiency. Our analysis produces some interesting findings concerning the drivers of credit risk in Italian banks. In terms of Granger-causality, decreases in the short-term cost efficiency are found to precede a worsening in banks' asset quality (supporting the 'bad management' hypothesis) while we fail to observe an effect of bad loans on efficiency. Furthermore, we show that a weakening in the capital positions tends to be associated with portfolio deteriorations in the future and that credit risk builds up during expansionary phases of the economy. Finally, we observe a trade-off between long-term efficiency and bank asset quality (supporting the 'resources misallocation' hypothesis). These findings are confirmed by a series of sensitivity analyses.

From the policymakers' perspective, the evidence in favour of the 'bad management' argument places emphasis on the need for prudential regulators to monitor managerial performance in order to detect those financial institutions that could suffer from problematic loans. That is, the decreasing levels of managerial efficiency could act as an early warning of BLs getting larger. Additionally, European regulators could consider strengthening the regulatory framework for individual accountability, for example by introducing mandatory certification to ensure the fitness and propriety of people performing key roles in the bank, such as mortgage and retail investment advisers.[24] From a bank's perspective, 'bad management'

[24] Similar steps have been undertaken by UK regulators with the introduction of the Senior Managers and Certification Regime (SM&CR), aimed at strengthening the individual accountability of firms' management and

indicates that it is potentially within the control of the senior management to tackle that part of bad loans arising from lax credit practices.

We also show that the positive relationship between long-term efficiency and bad loans could be the outcome of a misallocation of resources driven by exogenous persistent hindrances related, for example, to each bank's geographical location and business model. Indeed, as previously shown in Figure.1 and Figure 2, there is a part of the stock of bad loans of Italian banks that is neither the outcome nor the legacy of the crises of the last decade, but rather a long-standing feature of these banks, suggesting the presence of latent inefficiencies affecting the industry. It follows that policy interventions should target those factors that give rise to these 'systematic minimisation problems', thus allowing banks to increase the resources they devote to the adequate management of the loan portfolio.

employees. With respect to the euro area, the SSM is in charge of assessing the suitability of new and re-appointed members of management bodies of banks since November 2014. As such, the 'fit and proper' assessment focuses only on the highest management positions.

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Appendix A: Efficiency Estimation

Rewriting Eq. (3) in full form, short-term and long-term efficiency are estimated using the following Fourier functional form (the likelihood (LR) statistic for testing the Translog against the Fourier is 103.72, which exceeds the critical value of a mixed χ^2_{18} distribution of 34.16, confirming our model specification):

$$\begin{aligned} lnTC = {} & \alpha_0 + \sum_{i=1}^{3} \alpha_i lnY_i + \sum_{j=1}^{2} \beta_j lnW_j + \tau_1 t + \lambda_1 lnE \\ & + \frac{1}{2}\left[\sum_{i=1}^{3}\sum_{m=1}^{3} \gamma_{im} lnY_i lnY_m + \sum_{j=1}^{2}\sum_{n=1}^{2} \delta_{jn} lnW_j lnW_n + \tau_{11} tt + \lambda_{11} lnElnE\right] \\ & + \sum_{i=1}^{3}\sum_{j=1}^{2} \rho_{ij} lnY_i lnW_j + \sum_{i=1}^{3}[a_i \cos(z_i) + b_i \sin(z_i)] \\ & + \sum_{i=1}^{3}\sum_{j=1}^{3}\left[a_{ij}\cos(z_i + z_j) + b_{ij}\sin(z_i + z_j)\right] + v_{0i} + u_{oi} + v_{it} + u_{it} \end{aligned} \quad \text{(A1)}$$

We follow the intermediation approach (Sealey & Lindley, 1977) and we define three outputs, namely net loans ($\mathrm{Y_1}$), total non-interest operating income ($\mathrm{Y_2}$) and other earning assets ($\mathrm{Y_3}$), and three bank input prices, namely the price of labour ($\mathrm{W_1}$), the price of borrowed funds ($\mathrm{W_2}$) and the price of physical capital ($\mathrm{W_3}$) and E as the level of equity for each bank. Banks' total costs (TC) are computed by summing the three input variables (i.e. $\mathrm{X_1}$=personnel expenses, $\mathrm{X_2}$= total interest expenses, $\mathrm{X_3}$=other operating expenses). Finally, z are the adjusted values of the log outputs and input prices such that they span the interval [0, 2π]. We impose homogeneity in input prices of the cost function by dividing TC, $\mathrm{W_1}$ and $\mathrm{W_2}$ by $\mathrm{W_3}$ and the usual symmetry restrictions by setting $\gamma_{\mathrm{im}} = \gamma_{\mathrm{mi}}$ and $\delta_{\mathrm{jn}} = \delta_{\mathrm{nj}}$. The definitions and summary statistics of the inputs and outputs used to model the efficiency of Italian financial institutions are available upon request.

The key feature of the model of Badunenko and Kumbhakar (2017) is the presence of four error components that can be parametrised in terms of exogenous variables, enabling us to investigate the drivers short-term and long-term efficiency. Specifically, these determinants are introduced in the pre-truncated variance of $\mathrm{u_{it}}$ and $\mathrm{u_{0i}}$. In detail, we assume:

$$u_{it} \sim N^{+}(0, \sigma_{uit}^{2}) \text{ where } \sigma_{uit}^{2} = \sigma_{u}^{2} \exp(z_{uit}\gamma_{u}), i = 1, \ldots, n \text{ and } t = 1, \ldots, T_{i} \tag{A2}$$

$$u_{0i} \sim N^{+}(0, \sigma_{u0i}^{2}) \text{ where } \sigma_{u0i}^{2} = \sigma_{u0}^{2} \exp(z_{u0i}\gamma_{u0}), i = 1, \ldots, n \tag{A3}$$

where z_{uit} is a vector of firm-specific and time-varying variables that explains time-varying inefficiency and z_{u0i} is a vector of *natural* time-invariant covariates that are outside banks' control and that define structural inefficiency (see Lien et al., 2018).

The model of Badunenko and Kumbhakar (2017) also accommodates heteroskedasticity in the firm-specific effects term (v_{0i}) and in the random noise (v_{it}). More specifically, one can assume:

$$v_{0i} \sim N(0, \sigma_{v0i}^{2}) \text{ where } \sigma_{v0i}^{2} = \sigma_{v0}^{2} \exp(z_{v0i}\gamma_{v0}), i = 1, \ldots, n \tag{A4}$$

$$v_{it} \sim N(0, \sigma_{vit}^{2}) \text{ where } \sigma_{vit}^{2} = \sigma_{v}^{2} \exp(z_{vit}\gamma_{v}),\ i = 1, \ldots, n \text{ and } t = 1, \ldots, T_{i} \tag{A5}$$

In Eq. (A4), z_{v0i} represents a vector of time-invariant covariates that determines persistent production risk, whereas in Eq. (A5), z_{vit} denotes a vector of covariates that define time-varying production risk. In our estimation, we assume that v_{0i} is homoscedastic in Eq. (A4). We also estimate a homoscedastic model with four error components; however, the likelihood ratio statistic of 579.9 exceeds the critical value (24.04) of a mixed χ_{11}^{2} distribution at the 1% significance level, implying that the heteroscedastic model is the preferred one.

Appendix B. The Sample

Table B1 shows the sample of banks across areas and specialization. Cooperative banks constitute the predominant type of banks operating in Italy, and their presence is particularly strong in the North-East, while they appear to be less widespread in North-West Italy. By contrast, the majority of commercial banks are located in the North-West while the presence of these types of intermediaries is less strong in remaining macro-areas. The sample includes fewer observations in the years at the endpoints mainly because of the lack of availability of data on BLs.

Table B1. Number of banks in the sample, per year/area/specialization

Area & Year	North West		North East		Central		South		Total	
	Comm	Coop	Comm	Coop	Comm	Coop	Comm	Coop	Comm	Coop
2008	10	29	5	81	5	53	6	61	26	224
2009	11	35	3	94	4	58	6	63	24	250
2010	13	38	5	107	4	63	6	54	28	262
2011	12	40	5	109	7	65	6	58	30	272
2012	16	41	8	117	7	67	6	69	37	294
2013	19	43	12	124	12	66	8	84	51	317
2014	19	46	13	126	13	67	10	86	55	325
2015	18	44	11	95	13	64	9	73	51	276

Appendix C. Robustness Analysis

Table C1. Granger-Sims Causality Results – logarithm of BL

Dependent variable: BL_{it}	(1) Short-term & Long-term Efficiency and Time FE	(2) Excluding Long-term Efficiency	(3) Excluding Long-term Efficiency with $macro\_controls$	(4) Excluding Short-term Efficiency	(5) Excluding Short-term Efficiency with $macro\_controls$	(6) Short-term & Long-term Efficiency	(7) Short-term & Long-term Efficiency with $macro\_controls$	(8) Sims Causality Short-term & Long-term Efficiency
BL_{it-1}	0.887***	0.946***	0.897***	0.869***	0.775***	0.912***	0.778***	0.695***
	(0.091)	(0.081)	(0.092)	(0.088)	(0.095)	(0.078)	(0.074)	(0.125)
BL_{it-2}	0.036	0.004	0.003	0.079	0.104	0.039	0.090	0.189
	(0.085)	(0.077)	(0.078)	(0.085)	(0.084)	(0.078)	(0.061)	(0.123)
$BL(Total)$	0.923***	0.951***	0.901***	0.948***	0.880***	0.951***	0.869***	0.884***
	(0.027)	(0.018)	(0.030)	(0.019)	(0.030)	(0.017)	(0.032)	(0.043)
$Short\_term_{it-1}$	-1.314*	-0.777***	-0.641			-0.731***	-0.750**	-1.284*
	(0.674)	(0.257)	(0.454)			(0.228)	(0.375)	(0.678)
$Short\_term_{it-2}$	0.460	0.553***	0.468			0.524***	0.121	0.162
	(0.287)	(0.204)	(0.909)			(0.200)	(0.637)	(0.408)
$Short\_term$								-1.594*
								(0.923)
$Short\_term_{it+1}$								-0.953
								(0.930)
$Short\_term_{it+2}$								-1.180
								(1.260)
$Short\_term(Total - lags)$	-0.854	-0.224	-0.173			-0.207	-0.629	-1.122
	(0.654)	(0.331)	(1.255)			(0.330)	(0.883)	(0.975)
$Long\_term$	1.771***			2.447***	3.127***	1.517**	1.755**	0.958
	(0.613)			(0.793)	(1.041)	(0.667)	(0.744)	(1.134)
CAP_{it-1}	-1.575	0.088	-2.674*	-0.346	-0.708	0.190	-1.763	1.883
	(1.358)	(0.976)	(1.406)	(1.101)	(1.826)	(0.995)	(1.435)	(1.706)
CAP_{it-2}	0.371	-1.979**	0.853	-1.357	-0.716	-1.958*	0.219	-2.703
	(1.459)	(0.968)	(1.575)	(1.156)	(2.053)	(1.109)	(1.701)	(1.869)
$CAP(Total)$	-1.204*	-1.892**	-1.820**	-1.703**	-1.424**	-1.768**	-1.544**	-0.820
	(0.626)	(0.598)	(0.756)	(0.675)	(0.704)	(0.610)	(0.677)	(1.008)
$CreditGR_{it-1}$	-0.009	-0.807***	-0.348	-0.706***	-1.138***	-0.890***	-0.699	-1.627***
	(0.420)	(0.208)	(0.482)	(0.191)	(0.387)	(0.208)	(0.428)	(0.426)
$CreditGR_{it-2}$	0.382	1.254***	0.799*	1.109***	1.395***	1.274***	0.982**	1.702***
	(0.434)	(0.193)	(0.479)	(0.189)	(0.390)	(0.209)	(0.435)	(0.437)
$CreditGR(Total)$	0.373***	0.448***	0.452***	0.402***	0.257	0.384*	0.282*	0.075
	(0.115)	(0.091)	(0.133)	(0.112)	(0.164)	(0.101)	(0.145)	(0.230)
$Size$	-0.028	-0.042**	-0.039*	-0.041	-0.043	-0.044**	-0.033	-0.030
	(0.021)	(0.018)	(0.020)	(0.026)	(0.035)	(0.021)	(0.023)	(0.038)
$Crisis$	0.005	0.071***	-0.011	0.092***	0.048	0.074***	-0.025	0.119
	(0.051)	(0.027)	(0.064)	(0.028)	(0.054)	(0.026)	(0.058)	(0.076)
$Supervised$	0.159*	0.140	0.147*	0.231*	0.278	0.221**	0.216*	0.218
	(0.096)	(0.086)	(0.084)	(0.131)	(0.178)	(0.101)	(0.120)	(0.189)
$Industry$	-0.160**	-0.065	-0.017	-0.234***	-0.280**	-0.185**	-0.139*	-0.115
	(0.063)	(0.043)	(0.046)	(0.082)	(0.122)	(0.072)	(0.077)	(0.091)
$GDPGR_{it-1}$			9.304**		8.588**		8.618**	

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

This table reports the results on the determinants of BLs estimated using the two-step system GMM estimator as specified in Eqs.(1) and (2) when using the logarithm of BL as dependent variable. Windmeijer (2005) robust standard errors are reported in parentheses. The variables $BL(Total)$, $Short\_term(Total)$, $CAP(Total)$, $CreditGr(Total)$, $GDPGR(Total)$ and $SDEBT(Total)$ are the estimated coefficients for the test that the sum of the respective lagged terms are equal to zero (standard errors are obtained by the Delta method). In all cases, $BL(Total)$ is statistically different from one. The Wald test is the test for the joint significance of the coefficients of the lagged explanatory variables; we report the p-value. $AR(1)$, $AR(2)$ are tests of first- and second-order serial correlation in the first-differenced residuals, under the null of no serial correlation. The Hansen test of overidentification is under the null that all the instruments are valid. $Goodness\ of\ fit$ is the square correlated coefficient between actual and predicted values of the dependent variable (Bloom et al. 2007). Variables are defined as in Section 4.2.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix References

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