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Incapability or Bad Luck? Testing the "Bad Management" Hypothesis in the Italian Banking System

Fabrizio Crespi and Mauro Aliano

4.1 Introduction

The pattern of growth of nonperforming loans (NPLs) in the banking sector of a country has always been considered an important issue in determining the onset of a banking crisis and the consequent instruments that should be used by authorities to prevent bank failures.

In this chapter, we add a contribution to the strand of literature starting with Berger and DeYoung (1997), by testing the "bad management hypothesis" in the Italian banking sector using a more detailed dataset about the composition of NPLs: That means that we can distinguish between substandard/past due loans and restructured exposures, on the one hand, and bad loans on the other. This possibility allows us to investigate if and how much the substandard/past due loans and restructured exposures translate into bad loans over time or, put in a

F. Crespi (✉) · M. Aliano
University of Cagliari, Cagliari, Italy
e-mail: Fabrizio.crespi@unicatt.it

G. Chesini et al. (eds.), *The Business of Banking*, Palgrave Macmillan Studies in Banking and Financial Institutions, DOI 10.1007/978-3-319-54894-4_4

different way, we can prove if credit managers are able to recover, at least partially, problematic credits. This part of the analysis is a novel in literature: Preceding studies have not investigated in this specific way the worsening in credit quality, which may indeed suggest the management incapability, *ceteris paribus,* to manage bad loans. In this regard, starting from our proprietary database, we insert a measure of bank credit health among the determinants of NPLs which acts as proxy of a worsening in the quality of credit.

We created a dataset composed of 48 banks of a single country (Italy) which cover about 82% of the market (measured as total assets in 2013), and we investigate a critical period for the Italian banking sector lasting four years (2010–2013): This stretch of time covers in fact the preceding period and the aftermath of the government debt crisis in Italy (2011–2012) and corresponds with a strong increase in NPLs for the entire banking system.

Considering that all banks in our sample operate mainly in Italy and are subject to the same economic conditions, we exclude macroeconomic explanatory variables from our analysis. We also prefer to investigate a group of banks of one single country, avoiding a comparison with other banking systems in which different economic conditions and accounting rules could alter the significance of results (see Barisitz, 2011). The choice of Italy as a laboratory for our analysis is due to the better information about NPLs that we could get from bank balance sheets and to the critical importance and enormous volume of NPLs in the Italian banking sector: just to have an idea, the ratio of NPLs on loans was about 18% at the end of 2015, compared with a 3% in France and a 2% in the USA.

The results of our study confirm the "bad management hypothesis" first introduced by Berger and DeYoung (1997). Indeed, we find that more specialized banks and more efficient banks tend to have a better quality of credit. More interesting, from our point of view, is the general relationship between substandard/past due loans, restructured exposures, and bad loans. Our results indicate that problematic loans tend to transform into bad loans, demonstrating that credit managers were not able to implement recovery strategies for these critical positions during the investigated period. We think our results can be considered an interesting contribution to the strand of the literature regarding NPLs and bad management.

The rest of the chapter is organized as follows. Section 4.2 presents an overview of the main strands of literature about the determinants of NPLs. Section 4.3 briefly presents the characteristics of our dataset. Section 4.4 describes the model and the variable used to investigate the relationships between bank-specific determinants and NPLs. Section 4.5 presents the results of our analysis, and finally, Sect. 4.6 summarizes our findings.

4.2 Determinants of NPLs: Main Strands of Literature

The literature on NPLs is extensive and covers different topics regarding the causes and effects of deterioration of credit quality. However, in the majority of studies that investigate the determinants of NPLs, three topics can be considered fundamentals. The first is related to a strand of literature that investigates macroeconomic explanatory variables. A second group of studies emphasize the effect of bank-specific characteristics on problem loans; in particular, researchers have long since investigated the relationship between NPLs and bank efficiency (usually measured through a cost frontier approach). A third strand of literature combines macroeconomic (country-specific factors) and microeconomic variables (bank-specific factors) to explain aggregate NPLs.

4.2.1 Macroeconomic Factors

Various papers about NPLs start from the evidence that behind every financial crisis there are macroeconomic factors (or systematic factors) which influence the creditworthiness of borrowers. These studies commonly compare data from different countries (see Beck et al. 2013; Klein 2013) over a long period of time with the aim to evaluate the impact of different phases of the economic cycle on the appearing of NPLs.

The main results of this part of literature can be summarized as follows. First of all, there is significant empirical evidence regarding the anti-cyclical behavior of the NPLs, where real GDP growth can be considered the main driver of NPLs, i.e., higher real GDP growth translates into more income which improves the debt-servicing capacity of borrowers. Conversely, when there is a slowdown in the economy, the level of NPLs is likely to increase as unemployment rises and borrowers face greater difficulties to repay their debt.

Beck et al. (2013), in a comprehensive study of 75 countries over a ten-year period, confirm that real GDP growth has a negative impact on NPLs when considered through a fixed effects model, but, using dynamic Arellano-Bond estimations, also appears that lagged GDP growth significantly affects NPLs with a positive sign; this finding suggests that bank asset quality deteriorates with a lag in response to positive growth due to loose credit standards applied during the boom period. In any case, the authors affirm that economic activity is not able to fully explain the evolution of nonperforming loans across countries and over time; additional factors may negatively affect asset quality in countries with specific vulnerabilities. For example, exchange rate depreciations lead to an increase of nonperforming loans in countries with a high degree of lending in foreign currencies to unhedged borrowers; further, an increase in lending interest rates tend to increase NPLs.

Other macroeconomic variables, which were found to affect bank's asset quality, include disposable income (Rinaldi and Sanchis-Arellano 2006), lending interest rate and unemployment (Berge and Boye 2007), and inflation (Klein 2013).

Rinaldi and Sanchis-Arellano (2006) try to understand what explains household NPLs in seven euro area countries; their results suggest that, in the long run, an increase in the ratio of indebtedness to income is associated with higher levels of arrears. However, if the rise in the debt ratio is accompanied by a rise in disposable income, the negative effect is more than offset.

Similarly, Berge and Boye (2007) indicate that households' debt-servicing capacity generally depends on developments in their income, debt, borrowing rate, and collateral values. Higher incomes are expected to contribute to reducing the volume of problem loans.

However, incomes may be unevenly distributed across households. When unemployment is rising, many households may experience a substantial reduction in income. Using an equilibrium correction model of the logarithm of the share of problem loans (to total loans) in the household sector in Norway, during the period 1993–2005, the authors find that the share of problem loans could be reduced by 1.2% in the long run if real disposable income increases by 1%. On the other hand, a rise in the unemployment rate from 3 to 4% could increase the share of problem loans by just over 11%.

4.2.2 Bank-Specific Factors

Even if macroeconomic factors are rightly considerable the main cause of the increase of NPLs during time, they are not able to explain everything. In the same country, and in the same phase of the economic cycle, banks do normally register different amounts of NPLs in their balance sheets: It should then be obvious to think that also bank-specific factors influence bad loans. And in fact, various researchers have tried to discover significant relationships between NPLs and endogenous variables. The starting point of this strand of literature (or at least one of the most important contributions in this regard) can be considered the paper of Berger and Deyoung (1997).

The authors draw attention to the links between bank-specific characteristics and NPLs; using a Granger-causality analysis, they test a set of hypotheses that describe the intertemporal relationship among problem loans, cost efficiency, and financial capital. Specifically, they indicate four possible mechanisms, namely "bad luck," "bad management," "skimping," and "moral hazard," to formulate predictions of the link between credit quality and efficiency.

Under the "bad luck" hypothesis, external events precipitate an increase in problem loans for the bank. The bank is then forced to increase managerial effort and expenses dealing with the increase in problem loans.[1] Thus, under the bad luck hypothesis, we should expect increases in NPLs to Granger-cause (i.e., temporally precede) decreases in measured cost efficiency. Conversely, under the "bad management" hypothesis, low cost efficiency Granger-causes larger amounts of problem loans (a deterioration in asset quality) because management's failure to control operating costs immediately produces low cost efficiency, suggesting that poor managerial practice causes an increase in problem loans after a lag. The basic idea is that bad managers do not sufficiently monitor and control their operating expense, which is reflected in low measured cost efficiency. Specifically, so-called bad managers exhibit the following tendencies. They are not adept at credit scoring and select a relatively high proportion of investments with low or negative net present values; collateral against loans is improperly valued; and customers are not sufficiently monitored in order to ensure compliance with the loan contract. It is important to note that "bad luck" hypothesis and "bad management" hypothesis have an opposite temporal order, but both predict that NPLs will be negatively associated with cost efficiency.[2]

Under the "skimping" hypothesis, it is implied that resources allocated to underwriting and monitoring of loans affect both loan quality and measured cost efficiency. Banks face a trade-off between short-term operating costs and future loan quality. Management may choose to minimize short-term operating costs by reducing expenditure on monitoring borrowers in an attempt to enhance long-term profitability. Therefore, management delays having to deal with deterioration in asset quality until an unspecified future date. Thus, under the skimping hypothesis, we should expect a positive Granger-causation from measured efficiency to problem loans (i.e., an opposite sign in comparison with the bad management hypothesis). Finally, the "moral hazard" hypothesis implies that low financial capital Granger-cause high NPLs; the idea behind this hypothesis is that banks' managers have moral hazard incentives to increase the riskiness of their loan portfolios when their banks are thinly capitalized. The "moral hazard" hypothesis is then based on the classical problem of excessive risk-taking when another party is bearing part of the risk and cannot easily charge for or prevent that risk-taking.

The results of the study of Berger and DeYoung suggest that the intertemporal relationships between loan quality and cost efficiency run in both directions. However, the data favor the bad management hypothesis over the bad luck hypothesis and the skimping hypothesis. Finally, decreases in bank capital ratios generally precede increases in NPLs for banks with low capital ratios (moral hazard hypothesis).

Following the methodology of Berger and DeYoung, Williams (2004) investigates management behavior in European saving banks from six European countries (Denmark, France, Germany, Italy, Spain, and the UK), between 1990 and 1998.[3] The results of Williams are mixed: Managers in German banks exhibit strong statistical evidence of bad management, while there is weaker statistical evidence of bad management in Danish and Italian banks.

Podpiera and Weill (2008) continue along this line of research and examine the relationship between efficiency and bad loans in the Czech banking industry from 1994 to 2005. They extend the Granger-causality model developed by Berger and DeYoung by applying GMM dynamic panel estimators. Their findings provide empirical evidence in favor of a negative relationship between decreased cost efficiency and future NPLs (i.e., the bad management hypothesis). Interestingly, Podpiera and Weil use two different measures to assess credit quality: the conventional ratio of NPLs on total loans and a so-called compensated risk taking measure, which account for the fact that a certain amount of NPLs is normally expected and accounted for in the interest required on such more risky loans. Thus, the actual (uncompensated) risk-taking measure of a particular bank (associated with unexpected events) might be smaller if the bank gets sufficiently compensated on interest revenues from the entire loan portfolio. Therefore, a second measure is introduced and formulated as the share of NPLs in total loans minus the share of interest revenues in total loans. Indeed, if bank managers choose consciously to increase the risk of the loans portfolio, we should expect immediately an increase in interest revenue, and later an increase in NPLs. In this case, the risk of NPLs could be considered well priced in the conditions of loans, and the management behavior riskier but justified.

Other studies in the same stream include Karim et al. (2010) and Louzis et al. (2012); the former investigates bank efficiency and NPLs in Malaysia and Singapore and reaches conclusions similar to those of Berger and DeYoung; the latter is a more complex analysis, in which both macroeconomic and bank-specific determinants are taken into account (see Sect. 4.2.3).

In most cases, these kinds of studies are run using data from single countries and not considering macroeconomic factors in connection with bank-specific determinants.

4.2.3 Micro and Macro Approach

As indicated above, explanations of the size and growth of NPLs can be traced back to macroeconomic factors or to bank internal characteristics; *ça va sans dire* that these two set of causes could be analyzed jointly.

There are indeed few studies which follow this approach; they include, for example, Salas and Saurina (2002) which compare determinants of problem loans of Spanish commercial and saving banks using both macroeconomic and individual bank-level variables; Williams (2004) which investigates management behavior at European saving banks located in six different countries; and Klein (2013) which uses four explanatory bank-level variables, three country (macroeconomic) specific variables, and two global (macroeconomic) variables. Interestingly, the results of this last study broadly confirm that both bank-level and macroeconomic factors play a role in affecting banks' asset quality, although the contribution of bank-level factors is relatively small.

Louzis et al. (2012) analyze macroeconomic and bank-specific determinants of NPLs in Greece, in a comparative study of mortgage, business, and consumer loans portfolios, using a panel of data spanning from 2003 to 2009[4]. In this study, nine different hypotheses are tested using dynamic panel estimators, and two of them regard bad management. Specifically, bad management hypothesis (I) refers to the link between cost efficiency and future NPLs as in the preceding papers (even if inefficiency is simply measured using the ratio between operating expenses and operating income), while bad management hypothesis (II) investigates the relationship between performance and future NPLs, following the idea that past performance (ROE) could be interpreted as a proxy for the quality of management, and should be negatively correlated with a later deterioration of asset quality.

For all macroeconomic variables, the results of this study are compatible with the theoretical arguments, even if their impact is different depending on the type of loans analyzed.[5] Bad management hypothesis (I) is confirmed by a positive and statistically significant coefficient of the inefficiency index for all NPLs categories; the ROE indicator is statistically significant and negatively related to the mortgage and consumer NPLs, supporting the bad management hypothesis (II) for these types of loans.[6] Moral hazard and diversification hypotheses are rejected.

Finally, Chiorazzo et al. (2016) analyze country-specific determinants of NPLs jointly to banking-industry-specific determinants for 124 large European banks located in 21 European countries: Their results highlight the strong influence of country-specific variables on NPLs, while the influence of bank-specific variables is rather limited.

The review of the literature reported above indicates, ultimately, that both macroeconomic and microeconomic factors influence NPLs increases in the course of time, with the first playing the most important role. In this chapter, we will focus on bank-specific determinants, following the strand of literature starting with the study of Berger and DeYoung (1997); the difference of our study relative to preceding analyses lies in the fact that we can better discern the development of NPLs during time using a unique dataset; in particular, our aim is to understand whether bank management is able to recover impaired loans before they become definitively bad loans or, put in a different way, whether the bad management hypothesis is demonstrated by the incapability of the bank management in doing that.

4.3 Data Description and Variables

In order to investigate the "bad management hypothesis" in the Italian banking sector, we created a dataset composed of 48 banks including data and variables in the period 2010–2013. Data about NPLs were manually extracted from the unconsolidated balance sheet of single banks and were then integrated with other data taken from Bankscope (Bureau Van Dijk) and ABI Banking data (a specific database for Italian banks created by the category Association). It is important to note that (in the period investigated) NPLs were accounted in banks' balance sheet following the accounting rules imposed by Bank of Italy (Rule 272/2008), which considered four different categories of bad loans/impaired loans, namely:

(i) substandard loans (loans to customers in temporary difficulties that can be expected to be cleared up in a reasonable time)
(ii) past due/overdrawn more than 90 days
(iii) bad loans (loans to insolvent customers, even when insolvency is not ascertained by court)
(iv) restructured exposures (loan for which a bank, upon granting a moratorium on repayment, renegotiates the loan at lower than market interest rates).

Information about bad loans and other impaired loans is manually collected from the notes to the accounts of balance sheets. In particular, we calculated the ratio between each different form of gross bad/impaired loans and the total amount of credit to clients.

The classification reported above permits a better understanding of the credit exposure of banks and give us the possibility to investigate the bad management hypothesis (also) by looking at if and how much the substandard/past due loans translate into bad loans over time. It is indeed reasonable to think that good managers should be able to recover (at least partially) these kinds of loans before they became definitively bad loans; on the other hand, if a great amount of substandard/past due loans became bad loans, we can assert that a poor management is positively correlated with an increase in NPLs. It is important to stress that the preceding literature (probably due to lack of data) normally considers the total amount of NPLs, that is bad loans, substandard or "weak" loans, and past due loans all together, making it impossible to discern the internal dynamics and relations among these different categories of impaired loans.

The selection of banks in our dataset started from the analysis of the entire banking system that is all the banks surveyed in the ABI Banking database (558 banks). We then considered independent and holding banks for which an unconsolidated balance sheet was available, while banks controlled by foreign companies were discarded. We then selected the largest 48 banks in terms of total assets (2013) for two reasons: (i) Our dataset represents numerically about 9% of the banks operating in 2013, but about 82% of the total assets of the sector, 65% of loans to domestic clients, and 66% of NPLs of the system; (ii) The detailed data for the smaller bank unfortunately do not always exist. Table 4.1 reports a first description of our dataset.

Table 4.1 shows that the majority of banks are located in the north of Italy (the most industrialized zone of the country) and are commercial banks operating as limited companies. Only seven banks operate as cooperative banks (the classification presented in Table 4.1 follows the classification used in ABI Banking database). To better investigate bad loans, two other banks were finally excluded because they specifically engaged in activities (such as private banking and asset management) which do not produce significant amounts of NPLs.

As indicated above, we choose a specific period of time to investigate NPLs in the Italian banking sector: Indeed, even if a deterioration of economic conditions in Italy can be traced back to the outburst of the financial crisis at the end of 2008, different studies (see Chiorazzo et al. 2016) indicate that a strong increase of NPLs in banks' balance sheet is temporarily linked to the government debt crisis (2011–2012). With respect to the banks in our dataset, Table 4.2 shows how the mean ratio of impaired loans (i.e., the four categories of bad loans described above) on credit to clients changed during the investigated period.

The increase of NPLs actually went on also in 2014 and 2015, reaching an astronomic value of over 300 billion euro for the entire system. However, we decided to limit our analysis to the period 2010–2013 because, from 2014, some banks in our dataset started to implement securitization processes which altered the accounting amounts of NPLs and, from 2015, the introduction of different accounting rules makes new data not comparable to the past ones.

Table 4.1 Dataset description

Geographical area	Dimension	Commercial banks (ltd.)		Cooperative banks		Total	
		Obs.	Total assets 2013 (EUR billion)	Obs.	Total assets 2013 (EUR billion)	Obs.	Total assets 2013 (EUR billion)
Center		**9**	**442.10**	**1**	**14.99**	**10**	**457.09**
	Large	1	36.34		–	1	**36.34**
	Major	2	275.21		–	2	275.21
	Medium-sized	5	87.56		–	5	87.56
	Small	1	42.99	1	14.99	2	57.99
Northeast		**11**	**558.79**	**3**	**90.90**	**14**	**649.68**
	Large		–	1	42.68	1	42.68
	Major	1	398.31		–	1	398.31
	Medium-sized	4	94.52	1	42.11	5	136.64
	Small	6	65.95	1	6.10	7	72.06
Northwest		**20**	**895.75**	**2**	**75.82**	**22**	**971.57**
	Large	4	297.62	1	45.36	5	342.98
	Major	1	393.16		–	1	393.16
	Medium-sized	8	130.68	1	30.46	9	161.15
	Small	7	74.29		–	7	74.29
South		**3**	**45.87**	**1**	**9.34**	**4**	**55.20**
	Medium-sized	3	45.87		–	3	45.87
	Small		–	1	9.34	1	9.34
Total		**43**	**1942.51**	**7**	**191.05**	**50**	**2133.55**
All commercial, cooperative and mutual banks in ABI banking database						*558*	*2610.71*
% of our dataset						*9%*	*82%*

Source ABI banking Data and BvD data provider

Table 4.2 Mean ratio of impaired loans on credit to clients for the banks in our dataset

Year	Mean 2010 (%)	Mean 2011 (%)	Mean 2012 (%)	Mean 2013 (%)
Commercial banks (ltd.)	*8.37*	*9.86*	*11.68*	*14.88*
Center	11.34	13.98	17.62	22.17
Northeast	10.69	12.33	14.50	17.40
Northwest	5.31	6.20	6.88	9.44
South	12.12	13.69	16.47	20.87
Cooperative banks	*9.20*	*10.73*	*14.67*	*18.96*
Center	14.71	20.29	30.02	37.45
Northeast	8.02	8.82	12.28	15.64
Northwest	6.43	7.34	9.87	15.02
South	12.73	13.72	16.09	18.34
Total	8.49	9.99	12.11	15.46

4.4 Model and Variables

In the first draft of our model, we employ a simple panel regression in order to examine the bank-specific determinants of the credit quality (cq). As indicator of credit quality (or ex post risk), we utilize the ratio between bad loans and accounts receivable (credit to clients). A higher (lower) value denotes a deteriorating (better) quality of credit quality ceteris paribus.

$$cq_{i,t} = \frac{Bad_{i,t}}{ARc_{i,t}} \tag{4.1}$$

where $cq_{i,t}$ is a measure of the credit quality for the i-th bank in the year t, while $Bad_{i,t}$ is the amount of bad loans for the i-th bank in the year t, and $ARc_{i,t}$ is the amount of accounts receivable from clients for the i-th bank in the year t.

It is important to note that our dependent variable does not consist of the total amount of NPLs, but only of loans to insolvent customers (even when insolvency is not ascertained by court) that can be considered no more restorable. The aim of our analysis is indeed to investigate whether other forms of impaired loans (still restorable) turn into bad loans after a lag or, put in a different way, whether credit managers are able to restore these kinds of impaired loans before they turn into bad loans.

As independent variables, we insert a set of indicators which describe the economic and financial structure of banks in our sample, the weight of loans in the balance sheet, the weight of other problematic loans (not again bad loans), and the operational area. The objective is to catch bank-specific determinants of bad loans. The specification of our model is contained in the following formula:

$$cq_t = \alpha + \sum_{j}^{n} \beta_j X_{j_{t-1}} \tag{4.2}$$

where β_j is the coefficient associated with the independent variables j-th (X_j) at the time t-1. Through a Pool Least Square Method each coefficient is estimated, without compute in fixed[7] and random effects.

In Table 4.3, descriptive statistics of variables used are reported.

Our results show that the mean value of the credit quality (cq) variable gets worse over the time, increasing from 4.5 to 8.5% in the period. That is in line with the persistence of negative real economic conditions in Italy, and this evidence justifies a high standard deviation value. For the Arc variable, *viceversa,* a negative trend is recorded, that is there was a decrease of loans to clients with respect to the total volume of business (and this aspect may partly capture the so-called credit crunch phenomenon).

The increasingly positive value for Exp and Ris variables suggests a possible transformation degree of exposure delayed in bad loans, meaning that over time critical exposures have become bad loans, both for the continuation of the economic crisis and for the failure to select (screening activities) and manage (controlling activities) credit.

The net interest income on total asset (Netinc) presents very low values that, on average, become negative in 2013 due to losses on credit and receivables. The ratio between total asset and equity (inversely captured by the variable Equity) decreases progressively, denoting an increase of capitalization requirement; however, this measure fails to take

Table 4.3 Descriptive statistics of variables used

	cq	Arc	Exp	Ris	Netinc	Equity	Efficiency	Struct
Mean	0.0626	0.0006	0.0088	0.0065	0.0009	7.5414	2.0403	0.5392
Median	0.0529	0.0007	0.0056	0.0050	0.0017	7.7205	1.8095	0.6720
Std. Dev.	0.0480	0.0003	0.0106	0.0060	0.0093	3.5147	1.7523	1.2925
Skewness	1.2851	−0.7712	2.7909	0.9364	−2.4219	0.5115	−1.3287	-10.7091
Kurtosis	5.4342	2.5418	13.5879	3.3610	17.3394	3.2971	24.5107	130.1650
Jarque-Bera	100.2458	20.7131	1146.0720	29.0992	1832.6470	9.0789	3758.1650	133,037.4000

The table shows the descriptive statistics of the variables used in the Panel Regression (OLS) for the period 2010–2013. Credit quality (cq) is the ratio between bad loans and accounts receivable to clients, Arc is the ratio between accounts receivable to client (ARC) and total asset, Exp is the ratio between exposure delayed and ARC, Ris represents the coefficient associated with restructured exposure to ARC, Netinc is the coefficient of the ratio between net interest income and total assets, Equity is the coefficient associated with the ratio between equity and total assets, Efficiency is the ratio between operating income and operating expenses, Struct is given by the ratio total noninterest expenses/ (net interest income + net fees and commissions) account of risk-weighted asset (RWA). For the Efficiency and Struct variables, an erratic pattern seems to emerge.

As indicated, one of the variables used in our model is given by the ratio between accounts receivable to clients and total asset. This variable (named Arc) refers to the percentage of asset invested in loans to clients and provides a proxy of credit specialization for the banks investigated. A positive relation between credit quality and Arc (i.e., when the β_j associated is positive) indicates that when the relative (to total assets) amount of receivables raises the quality of credit falls (or a positive movement for cq is showed). Vice versa, if β_j is negative, the rise in percentage of credit improves the quality of credit (i.e., cq ratio falls).

Another variable used to define the determinants of bad loans is the ratio between exposure delayed (Past due) and account receivable to clients. Following the classification of impaired loans reported above, the numerator of this ratio refers to a kind of problematic credit which is not yet a bad loan, but the credit presents a significant delay in payment. A positive coefficient indicates the attitude of problematic credit to transform itself into bad loans, or the (in) ability of credit manager to manage difficulty positions. A negative coefficient, on the other hand, suggests a positive skill of credit management to recover problematic receivables. This coefficient indicates the relation between the exposures delayed at time t-1 and bad debts at time t; if this relation is positive, it means that during the year the exposures delayed (less severe and precedent condition) have been transformed in bad debt (most serious and next condition). Since the macroeconomic and financial scenario is the same for the banks in the sample, one possible explanation may be provided by the (in) ability of management to manage exposures delayed.

Another type of impaired loans is restructured exposures, i.e., a problematic credit for which the bank and client make a deal in order to define a new payments program. This variable is also measured as a percentage of accounts receivable to clients, and the interpretation of the sign of the β_j is the same as for exposure delayed.

An indicator of economic structure is specified by the ratio between net interest income and total assets. A positive value of β_j indicates that the banks with high interest income (scaled on total assets) present a low quality of credit, and vice versa. This indicator could be then interpreted in two different and opposite ways. On the one hand, if β_j is negative, the relative rise in net interest income improves the quality of credit, and this result could be interpreted as a sort of specialization efficiency; on the other hand, if β_j is positive, the net interest income and the quality of credit are negatively correlated, and this result could suggest that conscious managers impose higher interest rate on more risky clients (as in Podpiera and Weill 2008, that could be interpreted as a right behavior, because the risk of bad loans could be considered well priced in the conditions of loans).

The role of capital is studied by the ratio between equity and total asset; this indicator highlights the effect of the capitalization on bad loans ratio. If the coefficient is positive, more capital means more troubles in loans. If the coefficient is negative, better capitalized banks show a low bad loans to credit ratio.

The bank's operative framework is captured by a dummy variable that displayed 1 if the bank has a regional operating zone, 0 elsewhere. Through this variable, we testify whether, for the Italian banks, the environment impacts on credit quality.

Finally, we use two variables to investigate operating efficiency/inefficiency. The operating efficiency is analyzed trough the ratio between operating income and operating expenses; a negative coefficient for this variable indicates the management's attitude to generate profit from business activity and can be used as a proxy of good/bad management.

The impact of the costs structure is captured by the following ratio: total noninterest expenses/ (net interest income + net fees and commissions). This ratio quantifies the impact of the costs structure on gross revenues and may be interpreted as an inefficiency indicator. A positive value (what we expect) suggests a positive relation between operative inefficiency and bad loans, an inefficiency that goes behind (deepening) bad management.

In a further version of the model, we inserted a dummy variable associated with the use of advanced IRB at the beginning of period (2010); our aim was to investigate whether the use of more sophisticated models to value the credit risk of a loan could reduce the following appearing of bad loans.

4.5 Results

In this section, we show the estimations of the model presented above using OLS panel regression without fixed and random effect. The results are presented in Table 4.4.

The negative value of the coefficient *Arc* means that banks with a high value of ARC on total assets present a better credit quality than the other banks (i.e., the ratio of bad loans on credit to clients decrease). This result suggests that a progressive specialization in credit can improve the quality of credit.

The positive value of *Exp* (Exposure delayed) indicates a vicious circle in which past due loans became nonperforming loans or, from a management perspective, the incapability of credit managers to recover problematic credit (a different proof of the bad management hypothesis). A similar interpretation is provided by the variable *Ris*; also in this case, the positive coefficient shows that restructured exposures usually translate in bad loans, demonstrating a failure in credit management.

The negative value for net interest income (*Netinc*) suggests that the banks in our panel which are overspecialized in credit are better positioned in the management of the credit quality, and this result is in line with that showed for *Arc* variable. Summarizing, banks with a greater

Table 4.4 Panel regression. Bank-specific determinants on credit quality

	Model A	Model B	Model C
α	0.003986	0.00672[c]	
Arc	−12.18002[b]	−11.67315[b]	−10.74555[b]
Exp	0.752817[a]	0.766854[a]	0.760051[a]
Ris	0.419537[c]	0.499378[b]	0.507247[b]
Netinc	−0.388602[b]	−0.354188[c]	−0.340694[c]
Bad loans (−1)	1.118938[a]	1.127141[a]	1.127228[a]
Equity	0.0000594		
Regional	0.007892[b]	0.007343[b]	0.00696[b]
Efficiency		−0.001806[c]	−0.002132[c]
Size			0.0191[c]
Struct			0.000872
R-square	0.907171	0.909137	0.909137

[a] significative at 99%

[b] significative at 95%

[c] significative at 90%. R-square: 0.91. Total panel (balanced) observations: 138

ratio of credit to total assets and a greater ratio of net interest income to total assets seem more capable to manage credit risk, imposing higher interest rates on clients.

The variable equity on total asset is not significant, and similarly the capitalization level seems not to impact on quality of credit. The dummy variable, positive and significant, indicates that the regional banks are more exposed to bad loans. With regard to efficiency, the negative value indicates a negative relation, as expected, between efficiency and bad loans; and this indication is partially confirmed by the value showed by the variable *Struct*.

Similarly to Chiorazzo et al. (2016), we also find a significant autocorrelation for the bad loans ratio, suggesting that an increase in bad loans in one year creates more bad loans in the next year. Finally, the control variable size (log total assets) has a negative and statistically significant impact on credit quality.

To what concern the use of IRB models to asses credit risk, contrary to other studies, we discovered that the coefficient related to this dummy is not significant, and also trying with a detailed analysis that considers only the credit quality and the use of Advanced IRB, give us back a negative relation, that is Advanced IRB determines falls in credit quality.

Considering that our model could be affected by multicollinearity, we use variance inflation factor[8] (VIF) to check whether there is correlation between independent variables employed in the models presented. Logically, we expect a certain degree of correlation, especially among loan quality variables, but this correlation should result in a lagged relation, and not in a cross-sectional relation (i.e., intuitively the exposures delayed at time t are not correlated with exposures restructured at time t, but eventually with the exposures restructured at time t + 1), and then could be considered a conversion factor of the progressive credit worsening.

As can be seen in Table 4.5, all the variables employed in the model are less than 4[9] showing no problematic with VIF values.

Moreover, to better explain the relations between dependent variable and independent variables, we run a simple redundant period fixed effects tests. The F-Statistics, and the relative Prob. values, contained in Table 4.6, lead us to reject the hypothesis that period fixed effects are significant (at least at the 95% level).

Table 4.5 VIF test results

	Model A	Model B	Model C
Arc	1.065	1.235	1.316
Exp	1.370	1.261	1.266
Ris	1.282	1.199	1.199
Netinc	1.114	1.131	1.136
Bad loans (−1)	1.565	1.435	1.449
Equity	1.282		
Regional	0.132	1.136	1.149
Efficency		1.111	1.366
Size			1.064
Struct			1.266

The table shows the VIF's values for the models displayed in the Table 4.4

Table 4.6 Redundant Fixed Effects Tests

	Model A	Model B	Model C
Period F	2.35	1.38	2.42
Period Chi-square	5.07*	2.91	5.18*

The table shows the F-Statistics (F) and Chi-square values for the redundant fixed effects tests. *** significative at 99%, ** significative at 95%, * significative at 90%

Table 4.7 Panel regression. Bank-specific determinants on credit quality. GMM

	Model A	Model B	Model C
Arc	−9.617761[c]	−5.63208[c]	−5.558272[c]
Exp	0.770208[a]	0.782203[a]	0.784275[a]
Ris	0.405222[c]	0.501241[c]	0.492964[c]
Netinc	−0.336999[b]	−0.263731	−0.259638
Bad loans (−1)	1.128687[a]	1.137686[a]	1.139673[a]
Equity	0.000238		
Regional	0.007417[a]	0.007325[a]	0.007224[b]
Efficency		−0.001189	−0.001423
Size			0.010226
Struct			0.000526

The table shows the estimations of the coefficients for the models given by a panel generalized method of moments (GMM); we added constant to instrument list.
[a] significative at 99%
[b] significative at 95%, [c] significative at 90%. R-square: 0.91

Further analyses are developed to check the persistence of the data; in order to do that, we used dynamic panel data (system GMM) technique proposed by Arellano and Bond (1991). Results displayed in Table 4.7

confirm the intensity and direction of the relationships identified in Table 4.4, for the variables Exp and Ris.

4.6 Conclusion

The results of our analysis, as reported in Sect. 4.5, confirm the "bad management hypothesis" first introduced by Berger and DeYoung (1997). Indeed, we discovered that more specialized banks (higher ratio of loans to clients on total assets and higher ratio of net interest income on total assets) and more efficient banks (higher ratio of operating income on operating expenses and lower ratio of total noninterest expenses on net interest income + net fees and commissions) tend to have a better quality of credit. Nevertheless, is rather surprising that the use of IRB models is not significant in reducing NPLs during time.

More interesting, from our point of view, is the general relationship between past due loans, restructured exposures, and bad loans. As our results indicate, problematic loans (past due and restructured) tend to transform into bad loans, demonstrating that credit managers were not able to implement recovery strategies for these critical positions during the investigated period. And even if part of these results could be attributed to the stressed macroeconomic conditions of the time, it is licit to affirm that bad management plays a part.

These last results are useful to better understand the present situation of the Italian banking system: Indeed, the total amount of impaired loans in the balance sheets of Italian banks is often much greater than bad loans alone, also nowadays. Just to have an idea, gross bad loans at the end of 2015 for the whole banking system amounted to about 200 billions (see Bank of Italy, Statistic Bulletin, I 2016), but the total amount of gross NPLs (bad loans and other impaired loans) was 338 billions.

If the same process of transformation of impaired loans into bad loans registered in the period investigated in our analysis should persist also in the future, it is then easy to forecast that the level of bad loans in the system will remain very high, preventing banks to increase significantly the amount of credit notwithstanding the nonconventional impulses of monetary policy that we have seen in the last years. Moreover, the solution to the problem of NPLs in Italy, through securitization and/or government guarantees, could take much more time than that requested by ECB to banks in problematic situations (such as Monte Paschi di Siena).

Finally, it is not inappropriate to suggest that better models to investigate the dynamics of credit quality during time (probably, the current IRB models used by banks are not able to forecast the deterioration of credit quality in a period of stress economic condition), and more efficient procedures to manage problematic credits (from the first moments of their appearance in the balance sheet) should be implemented.

Notes

1. Extra operating costs include, for example, additional monitoring of borrowers, the expense of analyzing and negotiating possible workouts arrangements, and the cost of disposing of collateral if default later occurs.
2. It must be stressed that these two assumptions are not mutually exclusive, as the relationship may be bidirectional.
3. Actually, Williams (2004) estimates two different measures of bank efficiency to test the hypotheses of Berger and Deyoung, namely operating cost efficiency and profit efficiency. Moreover, problem loans are measured using the ratio of loan loss provision-to-loans instead of other typical balance sheet measure such as the ratio NPLs/total loans or NPLs/total assets.
4. The dataset is created using supervisory data for only nine largest Greek banks, even if they accounted for 87.68% of the Greek banking system.
5. For example, the quantitative impact of GDP growth on mortgage NPLs is attenuated compared to the NPLs of other loan types. Moreover, for all NPLs categories, the estimation results indicate that the coefficients of the macroeconomic variables are fairly stable across different models with different bank-specific variables.
6. On the other hand, the ROE indicator for the business NPLs is insignificant. The authors suggest that this may signify that the effect of management quality is mainly reflected on the efficiency of households'

credit granting procedures, which are primarily based on the development of quantitative modeling techniques, while the quality of case-by-case assignment procedures, which characterize business loans granting, does not differ substantially among banks.

7. The redundant fixed effects tests present a Prob. a value higher than 0.10 for the three following models.
8. VIF is expressed as followed:

$$\mathrm{VIF}_{i,j} = \frac{1}{1 - R^2_{i,j}}$$

where, $R^2_{i,j}$ represents the R squared when the i-th explanatory variables is regressed to the j-th explanatory variable.

9. For the VIF's measure thresholds, see also O'Brien (2007): "We demonstrate that the rules of thumb associated with VIF (and tolerance) need to be interpreted in the context of other factors that influence the stability of the estimates of the i-th regression."

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