Non Performing Loans, Moral Hazard & Supervisory Authority: the Italian Banking System

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Abstract

This paper aims to detect the existence of an opportunistic behaviour – i.e. moral hazard – within the Italian banking sector by investigating how banks face their challenges in lending relationships and they engage risky behaviour. In order to detect this opportunistic behaviour, we simply adopt a fixed effect panel analysis approach by investigating the role of Non Performing Loans (NPLs) in signalling moral hazard problems. Applying an unbalanced panel regression model to a dataset of 760 Italian commercial banks – composed of three different kinds of banks (S.p.A., popolari, mutual banks) – from 2006 to 2014, we investigate whether banks' lending behaviour is sensitive to withstand high level of NPLs and, more importantly, whether banks with higher NPLs ratio tend to adopt a more aggressive and riskier lending strategy. We also examine empirically the hypothesis that supervisor activity of Italian banking authority – through credit risk sanctions inflicted – is effective in providing incentives for banks to limit their risk lending strategy and in ensuring the stability of Italian banking system. The empirical results show that banks may be affected by moral hazard problems and that credit risk sanctions are considered essential tools for ensuring the stability of the system. Robustness analysis is also conducted.

Keywords: *Non-performing loans, Moral Hazard, Lending behaviour, Bank regulation*

JEL classification: G21, G30

1. Introduction

Bailouts within the financial context both in the US and, more recently, in Europe have emphasised a twofold scenario: restoration of confidence and social costs of moral hazard. The lively growth in the banking sector has led to a more pregnant and complicated regulation. Bad governance and excessive risk-taking may undermine the stability of a banking system and contribute to an economic downturn. The 2008 US sub-prime crisis – Bear-Stern *ad versus* Lehman – and the reaction of European governments to sovereign debt problems in Greece, Cyprus, Portugal and Spain are

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good examples. To avoid widespread economic collapse, governments throughout the Europe and USA felt compelled to intervene with public guarantees and recapitalisation to bail out financial institutions considered "*too big to fail*". In order to restore confidence and prevent further collapses in the financial system, bailouts appear as the *extrema ratio* and, in the meanwhile, encourage excessive risk taking.

Conflict of interest and moral hazard in the banking industry are serious threats to the stability of a banking system as a whole. Recently, the issue of excessive bank risk taking has come up again in terms of national public debt on the Southern periphery of the Eurozone.

Banks, as special firms, play a pivotal role in the functioning of the real economy. A shock occurred in a banking system could reflect its severe consequences to the real economy and could undermine the functioning of bank services on a systemic scale. In addition, banks, by the nature of their business, are highly exposed to maturity mismatch and liquidity risk which could lead to a forced sale of their assets (Diamond and Rajan, 2011)

This paper aims to detect the existence of an opportunistic behaviour – i.e. moral hazard – within the Italian banking sector by investigating how banks face their challenges in lending relationships and they engage risky behaviour. In order to detect this opportunistic behaviour, we simply adopt a fixed effect panel analysis approach by investigating the role of Non Performing Loans (NPLs) in signalling moral hazard problems. We apply this model to the Italian commercial banks in order to test the hypothesis in that troubled banks have incentives to take excessive risks. Our proposed methodology and empirical findings suggest important implications for Italian regulators facing high NPLs and potential moral hazard problems in the domestic banking sector.

In addition, inspired by a few academic contributions (Coffee, 2007; Jackson, 2007; Jackson and Roe, 2009; Delis and Staikouras, 2011; Delis *et al.*, 2013), we aim to investigate the supervisory effectiveness in containing bank risk through information on credit risk sanctions obtained by examining the Supervisory Bulletin published monthly by the Bank of Italy during the time period 2006 – 2014.[3] These kind of

[3] According to the second pillar of Basel II, credit risk sanctions come from on-site inspections. The latter is an essential component of supervisory review with the application of appropriate sanctions where breaches of law are revealed (Basel Committee on Banking Supervision, 2006c).

inspections enable the detection of management deficiencies and the verification of both the quality of the internal control systems and the reliability of information produced by banks (Basel Committee on Banking Supervision, 2002).

This particular aspect is important, *in primis*, because other authors have already studied (Zhang *et al.*, 2016) the moral hazard hypothesis, suggesting that an increase in the NPLs ratio raises riskier lending and, on the other hand, because of the presence of a third party (i.e. "banking authority") who by its actions defines the general set of rules and regulations regarding bank risk taking.

Based on these considerations, applying an unbalanced panel regression model to a dataset of 760 Italian commercial banks – composed of three different kinds of banks ("S.p.A.", "popolari", "mutual banks") – from 2006 to 2014, we investigate whether banks' lending behaviour could be sensitive to a specific level of NPLs and, more importantly, whether banks with higher NPLs ratio tend to adopt a more aggressive and riskier lending strategy. Afterwards, we examine empirically the hypothesis that supervisor activity of the Italian banking authority (i.e. "Bank of Italy") – through credit risk sanctions inflicted – is effective in providing incentives for banks to limit their risk lending strategy and in ensuring the stability of Italian banking system.

We hypothesise that banks with higher NPLs ratio take more risks in order to offset the losses associated with NPLs and hence NPLs increase further as a result of higher loan growth. Moreover, we also suppose that an effective supervisor activity of Italian banking authority could both provide incentives for banks to limit their risk lending strategy and to ensure the stability of Italian banking system as a whole, confirming that on-site examinations and sanctions are considered essential tools for ensuring the stability of the system (Quintyn and Taylor, 2002).

In this context, our study is based on a large and national micro dataset, including the Italian banking system as well as supervisory activity by the Bank of Italy in terms of risk credit sanctions.

The rest of the paper is organised as follows: section 2 presents a literature review split up into the relationship between moral hazard problems and non-performing loans and the supervisory activity; section 3 introduces the methodology adopted; section 4 provides data and descriptive statistics; section 5 provides the empirical results; section 6 presents robustness analysis and section 7 concludes.

2. Literature Review

2.1 Moral hazard problems and non-performing loans

Although information asymmetries origin comes from the corporate finance literature (Galai and Masulis, 1976; Jensen and Meckling, 1976; Merton, 1974) and is not focused on banking sector, the issue is likely to play a pivotal role in financial intermediaries. Since Galai and Masulis (1976), Jensen and Meckling (1976) and Merton (1974) introduced the risk-shifting problem, as one of the major conflicts of interest between shareholders and bondholders, many studies analyse the relation between the potential costs of risk shifting and a firm' characteristics.

According to Jensens and Meckling (1976), bank managers may have incentives to take riskier lending over the optimal level. The authors outline two kinds of moral hazard problems: a) managerial rent – seeking, which takes place when managers pursue their private benefits by investing in "pet projects" or through insufficient monitoring of loans; b) conflict of interest between shareholders and creditors. Shareholders may want to originate risky loans but eventually reverberate the risk to the depositors. Jensen and Meckling's (1976) theory implicitly suggests that both of these moral hazard problems lead to a higher loan growth rate and a larger number of NPLs.

In addition, Acharya *et al.* (2015) emphasise a trade-off between two types of moral hazard. If leverage is too low, debt holders lack incentives to monitor the manager behaviour because of debt is safe; otherwise, if leverage is too high, managers will probably substitute safer assets for riskier ones at the expense of debt holders. Laeven and Levine (2009) analyse the relationship of risk taking, ownership structure and national bank regulations using a dataset of 270 banks across 48 countries. They find that banks with more powerful owners tend to take greater risks. Foos *et al.* (2010), analysing more than 16,000 individual banks from 16 major countries during 1997 – 2007, find that loan growth represents a determinant of loan losses, bank profitability and bank solvency. In particular, they point out that loan growth leads to an increase in loan loss provisions during the next three subsequent years, to a decrease in relative interest income and to lower capital ratios.

A substantial number of academic contributions investigate the relationship between loan growth, NPLs and the risk taking of banks (Demirgüç-Kunt, 1989; Barr *et al.*, 1994; Berger and Udell, 1994; Gorton and Rosen, 1995; Shrieves and Dahl, 2003). Following this path, Saunders *et al.* (1990), by investigating the relationship between bank ownership structure and risk taking, show that stockholder banks exhibit significantly higher risk taking behaviour than managerially controlled banks in periods of deregulation relative to periods of regulation. In addition, they argue that, unlike non-banking firms, the presence of regulators may either accentuate or mitigate bank risk taking incentives. Bernanke and Gertler (1986) argue that the impaired loans of banks may induce different bank behaviour according to banks' risk preference. Prudential banks tend to be more cautious when they face increasing level of impaired loans and when the NPLs ratio is too high, both the shareholders and bank managers have clear incentive to shift risks.

When a firm is in financial distress, risk-shifting incentives also play a role in the investment-volatility relation. Eisdorfer (2008), analysing the relation between investment and volatility in a sample of 52,112 firms traded on the NYSE, AMEX and Nasdaq over the period 1963 to 2002, provides empirical evidence that expected volatility for distressed firms has a positive effect on investment and that risk-shifting behaviour is affected by various factors associated with the incentive and ability of shareholders to shift additional firm risk to bondholders. Other authors argue that banks, after Lehman Brothers collapse, might have saved themselves by holding on to risk assets even though selling them (Bruche and Lobet, 2011; Diamond and Rajan, 2011). Koudstaal and Wijnbergen (2012), collecting data on US banks between 1993 and 2010, find that higher loan-loss reserves are associated with a more troubled loan portfolio. Zhang *et al.* (2016) examine the impact of NPLs on bank behaviour in the Chinese banking system by estimating a NPLs threshold value.

2.2 *Measuring supervisory activity*

In this paper, a second current of the academic literature relies on the relationship between banking regulation and supervision.[4] A substantial number of academic contribution analyses the relationship between bank stability and financial regulation pointing out that banking regulation play a pivotal role in risk taking (Barth *et al.*, 2002, 2004, 2006, 2008; Quintyn *et al.*, 2011; Cihàk *et al.*, 2012). Few papers show empirical evidence about the relationship among bank risk-taking, supervisory activity and supervisors' enforcement actions (Delis and Staikouras, 2011; Delis *et al.*, 2013). Computing a sort of backward induction, Wu (1969) is the first to note the accuracy of bank examiners in business loans providing a valid *ex ante* measure of loan quality. Subsequently, other studies focus on the predictive skills of bank examinations regarding the quality of loans (Berger *et al.*, 2000; DeYoung *et al.*, 2001; Bhattacharya *et al.*, 2002; Kick *et al.*, 2010; Delis and Staikouras, 2011; Delis *et al.*, 2013). These authors feel compelled that on-site audits play a disciplinary power. Moreover, other empirical studies argue that on-site audits enhance banking discipline and provide remedial measures on imprudent banks, thus constraining excessive risk-taking (Swindle, 1995; Berger and Davies, 1998; DeYoung *et al.*, 2001; Kick *et al.*, 2010). Based on these assumptions, the number of on-site audits and the supervisory sanctions should be positively correlated with banking discipline and that an increased transparency in concert with an enhanced market discipline contribute significantly to banking stability.[5] A common assumption, underlying the academic literature and this research, relies on the ability of supervisors to enforce capital regulation. In this way, we argue that effective enforcement of capital requirements may represent the key incentive mechanism for banks to reduce both their portfolio (by increasing the loans quality) and leverage risk (Flannery, 1989). In the meanwhile, supervisory forbearance may be interpreted as a government subsidy, inducing banks to increase their risky assets (Allen and Rai, 1996; Galloway *et al.*, 1997; Cukierman and Izhakian, 2015).

[4] According to Basel Committee on Banking Supervision (2002), banking supervision and banking regulation have to be considered separately. Regulation encompasses formal rules that are adopted by an official public authority. On the other hand, banking supervision comprises the on-going monitoring of law and the imposition of remedial measures in case of violations.

[5] Other authors confirm this view by arguing that the stability of a banking system is strengthened by: (i) limiting informational asymmetries; (ii) boosting private monitoring; (iii) facilitating supervisory oversight; (iv) forcing banks to adopt more prudent risk-taking behaviour (Beck *et al.*, 2006; Demirgüç-Kunt *et al.*, 2008). On the other hand, different views offer a twofold reason for which information disclosure may undermine banking system stability. First, an increased disclosure of information may cause depositors to overreact to adverse information about other banks and start to run on their bank (Chen and Hasan, 2006). Second, information disclosure regulation may lead to pervasive "*free riding*" of monitoring information and to reduced profit margin (Hyytinen and Takalo, 2002).

3. Methodology

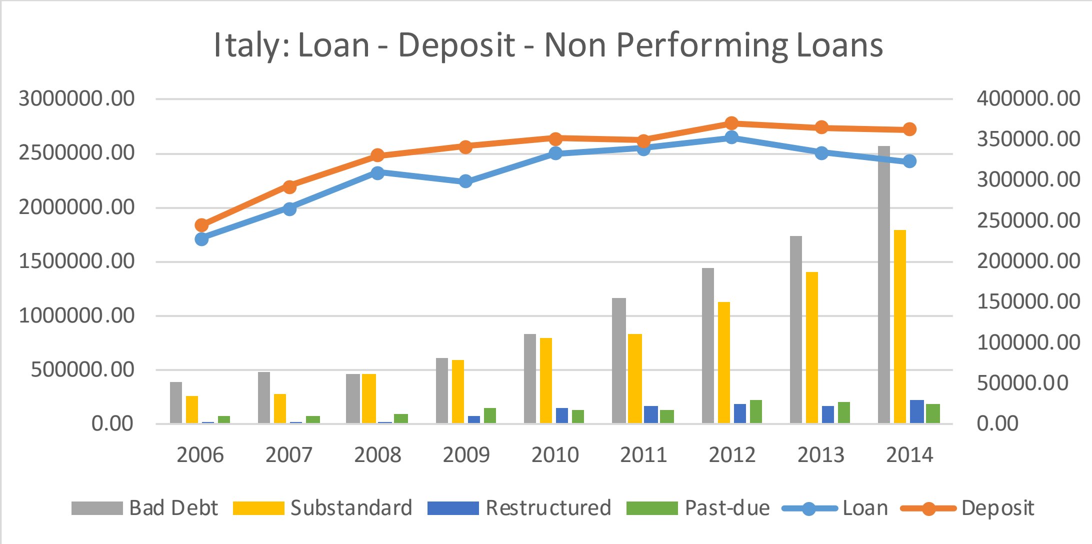
The problem of moral hazard arises in sampling theory for quality control. Whittle (1954) and Hill (1960) understand that the distributions of quality were endogenous and dependent on the care taken in the production process. They study how to take into account this "*noncontrollable*" effort level in their analysis of quality from a sample.

Attempting to shed light on the primary cause of problem loans and bank failures, Berger and DeYoung (1997) circumscribe the banks challenge in managing their NPLs ratios in terms of "*bad luck*", "*bad management*", "*skimping*" and "*moral hazard*".

In Italy, since 2007, NPLs have tripled growing at around 20% annually since 2008, reaching € 333 billion in June 2014 – 24% of GDP or 16.8% of total loans – (Jassaud and Kang, 2015). In the Italian banking system, NPLs cover four categories[6]: "*bad debt*" (i.e. loans in a state of insolvency), "*substandard*", "*past due*" and "*restructured*" loans (Figure 1).

[6] Since January 2015, Bank of Italy has aligned the Italian definition of NPLs to the non-performing exposure (NPE) and forbearance notion provided by the EU regulation on supervisory reportings.

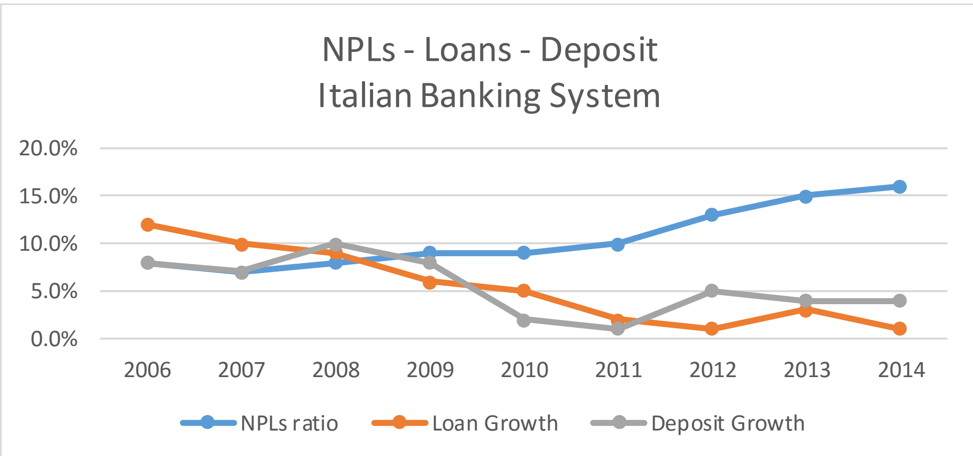
Figure 1 – Italy: Loan – Deposit – Non Performing Loans



More than 80% of bank NPLs are in the corporate sector reaching nearly 30% on average in 2014 with a significant percent in the South (Bank of Italy, 2014).[7] The high corporate NPLs ratio reflects the heavy indebtedness of many Italian SMEs.

NPLs growth ratio shows a substantial increase in comparison with loans and deposits growth ratio (Figure 2).

Figure 2 – NPLs – Loans – Deposit – Italian banking system



In keeping this picture, banks management may observe their NPLs ratios to increase as a result of bad luck or bad management (Berger and DeYoung, 1997). In case of bad luck, banks management will face the process by reducing lending and the NPLs ratio will fall. On the other hand, if the reason is bad management, banks management,

[7] As reported by Bank of Italy (2014), corporate loans amount to € 1,037 billion (52% of total bank loans in Italy), of which corporate NPLs account for almost €300 billion.

by expecting a rise in the NPLs ratio, will face this process by taking additional risk in order to reduce losses through higher level of lending. This additional risk identifies a particular banks management behaviour, captured by moral hazard, such that, an additional risk-taking level, in terms of an increase in loan growth ratio, follows a worsen in the NPL ratio. Moral hazard can induce both excessive risk-taking – lowering asset quality – and takes place when managers (agents) endeavour to optimise their own benefits which are not consistent with the interests of the owners (principles). Therefore, a high level of NPLs ratio depresses profitability and constrains new lending. On the revenue hand, NPLs generate a "*negative carry*" as they do not produce cash interest revenues. *Vice versa*, on the other hand, NPLs pushes up interest rates on performing loans to compensate for the lost revenue. In addition, NPLs can increase human and operational resources, involve legal and administrative costs and require valuable bank capital, which if released, could support fresh lending.[8] Furthermore, a high level of NPLs lowers bank valuations and increases the cost of funding. A weak asset quality may be an important determinant in explaining Italian banks' higher CDS spreads. Due to the high correlation between probabilities of default and loss given default, higher NPLs in an economic downturn lead to lower recovery values and larger credit losses. Moreover, banks with worse asset quality are more sensitive to sovereign distress, increasing risk *premia* in the real economy; high levels of NPLs exacerbate this sensitivity by raising the range surrounding possible future losses (CGFS, 2011).

This paper uses a panel regression model to identify moral hazard problems. Given an unbalanced panel data (*i* for cross-sectional index and *t* for the time series part), the structural equation can be written as:

$$y_{i,t}=\alpha_i+\beta_1 x_{i,t}+\varepsilon_{i,t} \tag{1}$$

Based on this basic model, the estimation equation can be written as:

[8] In large Italian banks, NPLs, even if adequately provisioned, absorb valuable bank capital. The cost of capital, for holding NPLs, depends on the credit risk approach: a) for banks using *standardised methods*, the capital charge for NPLs amounts to 12% or RWA but only applies to NPLs that are inadequately provisioned or not collateralised. Most mid-sized and all small Italian banks follow standardised method; b) under the *internal ratings – based models*, the capital charges on NPLs depend on the risk approach: for banks under the Basel II *IRB Advanced (IRBA)* approach, the capital cost for NPLs is twofold: (i) a capital deduction for the provision shortfall between Basel II expected losses and IFRS accounting provision. This capital deduction is known as the "IRB shortfall", and (ii) a capital charge for gross NPLs based on banks' internal models. All large Italian banks are under the *IRBA approach*. On the other hand, banks under the *IRB foundation (IRBF)* approach are only required to deduct the "IRB shortfall". There is no other capital charge on NPLs. In Italy, only two mid-sized banks follow IRBF methods. (Basel Committee on Banking Supervision, December 2014).

$$NPL_{i,t} = \alpha_i + \beta_1 LGR_{i,t} + \beta_2 LGR_{i,t-1} + \beta_3 DGR_{i,t} + \beta_4 CAR_{i,t} + \beta_5 Size_{i,t} + \beta_6 TimeDummy_t + \varepsilon_{i,t} \qquad (2)$$

where, $NPL_{i,t}$, the dependent variable, is the ratio between non-performing loans and total outstanding loans for bank i at time t; $LGR_{i,t}$ is our first explanatory variable expressed in terms of loan growth rate for bank i at time t; $LGR_{i,t-1}$ is our second explanatory variable expressed in terms of loan growth rate lagged one period backwards for bank i at time t. Based on the assumption before outlined, we expect a negative and significant relationship between banks' loan growth rate and level of NPLs ratio in Italy. Normal loan growth associated with standard banking operations may reduce the NPLs ratio, but an abnormal growth rate would indicate a moral hazard problem causing subsequent further losses. $DGR_{i,t}$ is our third explanatory variable expressed by the deposit growth rate for bank i at time t. Deposits are an important factor in bank balance sheets influencing the bank behaviour and loan quality; we expect that deposit growth ratio can be considered as an indicator of bank's objective function (Lepetit *et al.*, 2008).

Regarding control variables, $CAR_{i,t}$ is the risk-weighted assets ratio between tier 1 capital and tier 2 capital and dividing the total by the total risk-weighted assets for bank i at time t. Since CAR are an important part of both the micro and macro prudential framework,[9] they can provide a common measure for a bank's risks, ensure that capital allocated to assets is commensurate with the risks and that potentially highlight where destabilising asset class bubbles are arising (Leslé and Avramova, 2012). Due to these arguments, we can expect an ambiguous relationship between CAR and NPLs due to the lack of prudence and excessive management discretion in pushing capital down may result in aggressive risk-taking and could potentially lead to bank failure, with significant related social and economic costs. In so doing, banks management may "control" the system by under-estimating risks to optimise their capital beyond what prudence requires.

[9] The Basel Committee's regulatory solvency measures (Tier 1, Tier 2 and Total Capital, Common Equity Tier 1, Additional Tier 1 and Total Capital under Basel III, as well as other key solvency measures, such as Core Tier 1 or Tier 1 Common) are currently all defined in terms of risk-weighted assets (RWAs). However, Basel III will gradually introduce a new solvency measure, the leverage ratio, initially defined as Tier 1 capital over total unweighted on and off-balance sheet assets. Due to the holding period taking into account, this paper considers RWAs ratio (Leslé and Avramova, 2012).

Our second control variable is the bank size. The size of banks, expressed in terms of natural logarithm of total assets for bank *i* at time *t*, has often been considered as an important factor for NPLs. Large banks have more diversification opportunities and they can reduce the level of troubled loans (Salas and Saurina, 2002; Rajan and Dhal, 2003). In addition, large banks could evaluate loan quality better due to their richer resources (Hu *et al.*, 2004). Therefore, the bank size is negatively associated with the level of NPLs. However, due to the "*too big to fail*" arguments, we expect a positive relationship between the bank size and level of NPLs (Zhang *et al.*, 2016).
Finally, we introduce macroeconomic conditions or business cycles in order to understand how they could contribute to the level of NPLs. According to Carey (1998), a change in economic conditions could be an important factor affecting bank losses. Quagliarello (2007), analysing an Italian banking dataset, shows evidence that business cycles affect NPLs. Therefore, in order to control the 2008 global financial crisis, we introduce a time trend into the regressions.
In order to investigate the supervisor activity of the Italian banking Authority, the equation (2) can be written as:

$$NPL_{i,t}=\alpha_i+\beta_1 LGR_{i,t}+\beta_2 LGR_{i,t-1}+\beta_3 Anomalies_{i,t}+\beta_4 Anomalies_{i,t}*LGR_{i,t}+\beta_5 CAR_{i,t}+\beta_6 Size_{i,t}+\beta_7 TimeDummy_t+\varepsilon_{i,t}\ldots\ldots(3)$$

where, $Anomalies_{i,t}$ is a dummy variable which takes value 1 if a bank *i* has received at time *t* a credit risk sanction (i.e. anomalies occurred *ex ante* and along loan screening process not disclosed to the Supervisory Authority) and 0 otherwise; $Anomalies_{i,t}*LGR_{i,t}$ is an interactive variable between anomalies and loan growth ratio for bank *i* at time *t*. The aim of this interactive variable is to capture supervisory effectiveness in containing bank risk through information on credit risk sanctions. A positive relationship, therefore, should be interpreted as the effective role play by Bank of Italy in detecting timing anomalies and reduce excessive risk-taking by bank. We expect, therefore, a positive relationship with NPLs ratio.

4. Data and descriptive statistics

A first data base section contains data obtained from ABI Banking data base,[10] the data set which provides all micro data coming from bank balance sheet and income statement of all Italian commercial banks. Our dataset includes 760 Italian commercial banks, along the time period 2006 – 2014, composed of three different kinds of banks (S.p.A., popolari, mutual banks). In particular, the dataset includes 264 banks "S.p.A.", 46 banks "popolari", 450 "mutual banks" with a total number of 6,031 observations. Due to the data availability problems, although we have cancelled out few banks, the subsample of commercial banks represents an important part of our dataset in terms of asset value.[11]

The largest banks, in the Italian banking system, are "S.p.A." followed by "popolari" and "mutual banks" respectively. In terms of loan growth rate, the average rate is 4.7%, while the largest growth rate has 99.4%. The deposit growth rate exhibits a higher value in our sample period; in particular, "popolari" banks show, on average, a 6.7% deposit growth rate rather than "S.p.A." 5.1% and "mutual banks" 5.5% respectively. The level of risk-weighted assets in these commercial banks is reasonably high (56.7% on average) with significant heterogeneity among kinds of banks: "mutual banks" show a remarkable level of risk-weighted assets at 61.7%. In terms of NPLs ratio, the average rate is 10.4% and, specifically, with significant variations regarding "S.p.A." banks 8.5%, "popolari" 10% and "mutual banks" 11.4%.

Table 1 – Descriptive statistics of key variables

Sample Description	Variables	N. Obs.	Minimum	Maximum	Mean	Standard Deviation
Full sample	NPL	6,031	0.000	0.831	0.104	0.088
	Loans growth	6,031	-1.000	0.994	0.047	0.197
	Deposits growth	6,031	-0.972	0.995	0.055	0.148
	CAR	6,031	0.000	0.997	0.567	0.261
	Size	6,031	0.000	19.898	12.609	3.212
S.p.A. Banks	NPL	1,885	0.000	0.831	0.085	0.098
	Loans growth	1,885	-1.000	0.994	0.047	0.261
	Deposits growth	1,885	-0.972	0.988	0.051	0.218
	CAR	1,885	0.000	0.997	0.476	0.286
	Size	1,885	0.000	19.898	13.601	3.815

[10] ABI Banking data base belongs to Italian Banking Association (ABI).
[11] In order inference problems caused by outliers, we further drop banks with loans growth and deposits growth ratio more and less than 100%. Moreover, we drop banks with just three observations in the holding period.

Popolari Banks	NPL	369	0.000	0.489	0.100	0.090
	Loans growth	369	-1.000	0.962	0.046	0.227
	Deposits growth	369	-0.928	0.721	0.067	0.136
	CAR	369	0.000	0.966	0.525	0.279
	Size	369	0.000	18.616	13.070	4.987
Mutual Banks	NPL	3,777	0.000	0.644	0.114	0.081
	Loans growth	3,777	-1.000	0.983	0.047	0.152
	Deposits growth	3,777	-0.917	0.995	0.055	0.096
	CAR	3,777	0.000	0.996	0.617	0.232
	Size	3,777	0.000	16.170	12.069	2.448

Descriptive statistics of key variables – Note: the variables are in abbreviation, representatively standing for: NPL= NPLs ratio (non-performing loans divided by total outstanding loans); Loans growth= loan growth rate; Deposit growth= deposit growth rate; CAR= CAR ratio (is the ratio between Tier 1 capital and Tier 2 capital and dividing the total by the total risk-weighted assets); Size= end of year total assets (in log term) respectively.

A second data set section encompasses information on sanctions and on-site bank examinations for the Italian banking system obtained by examining the Supervisory Bulletin[12] published monthly by the Bank of Italy over the period 2006 – 2014. Starting from the sample of all Italian commercial banks, we matched hard information (coming from ABI Banking data base) with soft information (coming from monthly Supervisory Bulletin). In order to answer our research question, we considered only credit risk sanctions captured by anomalies occurred *ex ante* and along loan screening process not disclosed to the Supervisory Authority.[13]

[12] The monthly Supervisory Bulletin contains the general measures adopted by the credit authorities and other significant measures concerning person subject to supervision (https://www.bancaditalia.it/pubblicazioni/bollettino-vigilanza/index.html?com.dotmarketing.htmlpage.language=1).

[13] The monthly Supervisory Bulletin provides, in this context, three different kinds of credit risk sanctions: (i) lack of information *ex ante* loan screening process "*carenze di informazione nell'istrutturia di affidamento*"; (ii) anomalies occurred *ex ante* and along screening process not disclosed to the Supervisory Authority "*mancata segnalazione dell'andamento anomalo all'Autorità di Vigilanza*"; (iii) lack of managing other credit risks "*carenze nella gestione del rischio di credito*".

Table 2 – Descriptive statistics of credit risk sanctions

Type of bank	Type of sanction - Description	N. Sanctions	Amount of Sanctions	
			Max.	Mean
Full sample	Anomalies occurred *ex ante* and along screening process not disclosed to the Supervisory Authority	116	587,500	2,130.42
	Lack of information *ex ante* loan screening process	175	1,534,000	3,507.97
	Lack of managing other credit risks	253	1,045,000	1,644.76
S.p.A. Banks	Anomalies occurred *ex ante* and along screening process not disclosed to the Supervisory Authority	22	587,500	2,305.83
	Lack of information *ex ante* loan screening process	29	1,443,110	3,697.46
	Lack of managing other credit risks	62	315,000	1,136.87
Popolari Banks	Anomalies occurred *ex ante* and along screening process not disclosed to the Supervisory Authority	8	418,000	3,313.00
	Lack of information *ex ante* loan screening process	14	1,534,000	10,849.27
	Lack of managing other credit risks	23	293,500	2,860.43
Mutual Banks	Anomalies occurred *ex ante* and along screening process not disclosed to the Supervisory Authority	86	374,500	1,927.35
	Lack of information *ex ante* loan screening process	132	334,000	2,696.18
	Lack of managing other credit risks	168	1,045,000	1,779.47

Descriptive statistics of credit risk sanctions – Note: the amount of credit risk sanctions is expressed in thousands of Euros. Source: Bank of Italy Supervisory Bulletin.

5. Empirical results

Before estimating equation (2) and (3), we investigated the correlation among explanatory variables and independent variable and, in the meanwhile, the only correlation among explanatory variables in order to detect multicollinearity issues. Table 3 and 4 report correlation coefficients between the independent variable (NPLs) used in the empirical analysis.

Table 3 – Matrix correlation first equation

Panel A	NPLs	LGR	LGR_{t-1}	DGR	CAR	Size
NPLs	**1**					
LGR	-0.0793	**1**				
LGR_{t-1}	-0.1081	0.1880	**1**			
DGR	-0.1254	0.3258	0.1657	**1**		
CAR	0.1368	0.1935	0.1706	-0.0038	**1**	
Size	0.2164	0.3163	0.2211	0.0337	0.4001	**1**

Matrix correlation first equation – Note: matrix correlation of variables estimated into first regression. The variables are in abbreviation, representatively standing for: NPL= NPLs ratio (non-performing loans divided by total outstanding loans); LGR= loan growth rate; LGR_{t-1}= loan growth rate lagged one period backwards; DGR= deposit growth rate; CAR= Capital Adequacy Ratio (is the ratio between Tier 1 capital and Tier 2 capital and dividing the total by the total risk-weighted assets); Size= end of year total assets (in log term) respectively.

Moderate correlation indices, among explanatory variables, avoid few issues such as the increase in the variance of the coefficients estimated and lead more stable coefficient estimates.

Table 4 – Matrix correlation second equation

Panel B	NPLs	LGR	LGR_{t-1}	Anomalies	Anomalies*LGR_t	DGR	CAR	Size
NPLs	**1**							
LGR	-0.0793	**1**						
LGR_{t-1}	-0.1081	0.1880	**1**					
Anomalies	0.0125	-0.0127	-0.0469	**1**				
Anomalies*LGR_t	0.0158	0.1703	0.0540	0.0808	**1**			
DGR	-0.1254	0.3258	0.1657	-0.0111	0.0522	**1**		
CAR	0.1368	0.1935	0.1706	-0.0028	0.0504	-0.0038	**1**	
Size	0.2164	0.3163	0.2211	-0.0731	0.0682	0.0337	0.4001	**1**

Matrix correlation second equation – Note: matrix correlation of variables estimated into first regression. The variables are in abbreviation, representatively standing for: NPL= NPLs ratio (non-performing loans divided by total outstanding loans); LGR= loan growth rate; LGR_{t-1}= loan growth rate lagged one period backwards; DGR= deposit growth rate; ANOMALIES= dummy variable which takes value 1 if bank *i* has received a credit risk sanction for anomalies occurred *ex ante* and along screening process not disclosed to the Supervisory Authority at time *t*, 0 otherwise; ANOMALIES*LGR_t= interactive variable between credit risk sanctions for anomalies occurred *ex ante* and along screening process not disclosed to the Supervisory Authority and loan growth rate at time *t*; CAR= Capital Adequacy Ratio (is the ratio between Tier 1 capital and Tier 2 capital and dividing the total by the total risk-weighted assets); Size= end of year total assets (in log term) respectively.

The first step of our empirical analysis is to identify the existence of moral hazard through the evaluation of the behaviour of banks. The possibility of moral hazard could be captured by examining bank behaviour. As discuss earlier, losses in one bank can generate incentives for bank managers to take excessive risks, only if they have a large negative impact on bank performance due to a relatively large level of NPLs.

Table 5 reports estimation results for equations (2) and (3). On first and second column are reported the estimation results for equation (2); third and fourth column reports regression results for the equation (3). Model (2) and model (4) includes control variables for each equation estimated. Dependent variable in all equations are expressed in current NPLs ratios. In order to run a fixed or random effects model, we perform a *Hausman* test: the statistic is 215.72 and p-value= 0.000 which favours the fixed effects model.

The inclusion of lags of LGR ratio in the models is crucial. According to Clair (1992) and Zhang *et al.* (2016), the impact of a higher LGR is a deterioration in the quality of loans. However, this deterioration, in quality loans, occurs with some delay. The contemporaneous relationship between LGR and NPLs ratio should be negative. Banks with significant previous losses or with significant level of NPLs, by making additional loans (i.e. higher loan growth ratio) can reduce NPLs ratio temporarily, due to the dilution effect. Therefore, in order to achieve higher loan growth, banks managers may have to accept riskier positions, potentially originating higher future losses. However, also considering one lag backwards in LGR, the relationship between LGR_{t-1} and NPLs ratio keeps negative and highly significant. Furthermore, this relationship is kept constant in all equations regressed. This is consistent with what we expect: banks may be affected by moral hazard problems. Coefficients on the time trend dummies show a downward trend due to the negative and significant impact of 2007 – 2008 financial crisis on the Italian banking sector.

An interesting aspect, is the relationship between credit risk sanctions – $Anomalies*LGR_t$ – due to the anomalies occurred *ex ante* and along loans screening process not disclosed to the Supervisory Authority and current NPLs ratio. A positive and statistical significant (at 5% level) relation emphasises the supervisory effectiveness on excessive risk-taking by banks.

Table 5 – Regression results with NPLs ratio as dependent variable

Dependent Variable NPLs	**Model (1)**	**Model (2)**	**Model (3)**	**Model (4)**
LGR_t	-0.0357***	-0.0767***	-0.0389***	-0.0788***
	(0.0086)	(0.0089)	(0.0087)	(0.0089)
LGR_{t-1}	-0.0546***	-0.0748***	-0.0558***	-0.0755***
	(0.0096)	(0.0085)	(0.0096)	(0.0085)
Anomalies			-0.0082	-0.0033
			(0.0098)	(0.0082)
Anomalies*LGR_t			0.1169**	0.0857**
			(0.0363)	(0.0324)
DGR		-0.0321***		-0.0319**
		(0.0097)		(0.0097)
CAR		-0.0416***		-0.0418***
		(0.0083)		(0.0083)
Size		0.0152***		0.0151***
		(0.0012)		(0.0012)
Time Trend		0.0020***		0.0020***
		(0.0004)		(0.0004)
Constant	0.1124***	-0.0578***	0.1127***	-0.0568***
	(0.0008)	(0.0138)	(0.0008)	(0.0138)
N. Obs	5,249	5,249	5,249	5,249
R^2	3.47%	18.87%	3.80%	19.04%
R^2 Adjusted	3.43%	18.78%	3.72%	18.92%

Regression results with NPLs ratio as dependent variable – Note: the table presents estimation results (coefficients and robust standard errors in parentheses) on the relationship between NPLs ratio, bank risk and credit risk sanctions. Estimation method is a fixed effect, static and unbalanced panel data (with bank fixed effects) for all models. The variables are in abbreviation, representatively standing for: NPL= NPLs ratio (non-performing loans divided by total outstanding loans); LGR= loan growth rate; LGR_{t-1}= loan growth rate lagged one period backwards; DGR= deposit growth rate; ANOMALIES= dummy variable which takes value 1 if bank *i* has received a credit risk sanction for anomalies occurred *ex ante* and along screening process not disclosed to the Supervisory Authority at time *t*, 0 otherwise; ANOMALIES*LGR_t= interactive variable between credit risk sanctions for anomalies occurred *ex ante* and along screening process not disclosed to the Supervisory Authority and loan growth rate at time *t*; CAR= Capital Adequacy Ratio (is the ratio between Tier 1 capital and Tier 2 capital and dividing the total by the total risk-weighted assets); Size= end of year total assets (in log term) respectively; Time Trend is a control variable which takes value 1, 2, 3, 4, 5, 6, 7, 8, 9 for each year taking into account.

*** Denotes statistical significance at 1% level.

** Denotes statistical significance at 5% level.

* Denotes statistical significance at 10% level.

6. Robustness analysis

In order to overcome endogeneity issues, we do some additional robustness analysis allowing for endogeneity. In particular, we shed light on the role played by loan growth rate, as a key explanatory variable and potentially endogenous as it might be affected by the current NPLs ratio.

As first step, we run equation (2) and (3) by adding interactive variable for each different kinds of banks (e.g. "S.p.A.", "popolari", "mutual banks"). Table (6), (7) and (8) show regression results. The coefficients shown by the LGR_t ratio and the interactive variable Anomalies*LGR_t. In all equations, the two coefficients show the same relationship (as earlier discussed) and still remain significant.

As second step, we introduce instrumental variables and use 2SLS method to estimate the slope coefficients. As instrumental variable, we use the number of cars in each country where each bank has its headquarter. Table (9) reports the 2SLS regression results. In all equations, the results are qualitatively similar, which means that banks facing previous significant losses have the incentive to take higher risk, which will then result in further significant losses. All in all, when endogeneity is accounted for, our core conclusion remains valid.

Table 6 – Regression results with NPLs ratio as dependent variable

Dependent Variable NPLs	**Model (1)**	**Model (2)**	**Model (3)**	**Model (4)**
LGR_t	-0.0502**	-0.0960***	-0.0550***	-0.0997***
	(0.0165)	(0.0129)	(0.0166)	(0.0129)
LGR_t S.p.A.&Popolari	0.0354	0.0369*	0.0376	0.0386*
	(0.0195)	(0.0158)	(0.0193)	(0.0157)
LGR_t Mutual	0	0	0	0
	(.)	(.)	(.)	(.)
LGR_{t-1}	-0.0864***	-0.1062***	-0.0889***	-0.1079***
	(0.0171)	(0.0133)	(0.0173)	(0.0133)
LGR_{t-1} S.p.A.&Popolari	0.0574**	0.0524**	0.0591**	0.0536**
	(0.0210)	(0.0172)	(0.0211)	(0.0173)
LGR_{t-1} Mutual	-0.2047	-0.0547	-0.1853	-0.0406
	(0.1357)	(0.0803)	(0.1337)	(0.0784)
Anomalies			-0.0078	-0.0038
			(0.0103)	(0.0085)
Anomalies*LGR_t			0.1153**	0.0908*
			(0.0389)	(0.0357)
DGR		-0.0307**		-0.0305**
		(0.0097)		(0.0097)
CAR		-0.0377***		-0.0378***
		(0.0083)		(0.0083)
Size		0.0149***		0.0149***
		(0.0012)		(0.0012)
Time Trend		0.0019***		0.0019***
		(0.0004)		(0.0004)
Constant	0.1140***	-0.0555***	0.1143***	-0.0547***
	(0.0010)	(0.0145)	(0.0010)	(0.0145)
N. Obs	5,249	5,249	5,249	5,249
R^2	5.07%	19.78%	5.39%	19.97%
R^2 Adjusted	4.98%	19.64%	5.26%	19.80%

Table 7 – Regression results with NPLs ratio as dependent variable

Dependent Variable NPLs	**Model (1)**	**Model (2)**	**Model (3)**	**Model (4)**
LGR_t	-0.0613***	-0.0991***	-0.0654***	-0.1020***
	(0.0152)	(0.0115)	(0.0152)	(0.0115)
LGR_t S.p.A.&Popolari	0.0465*	0.0398**	0.0477**	0.0408**
	(0.0184)	(0.0148)	(0.0182)	(0.0147)
LGR_{t-1}	-0.0946***	-0.1085***	-0.0965***	-0.1097***
	(0.0170)	(0.0130)	(0.0171)	(0.0130)
LGR_{t-1} S.p.A.&Popolari	0.0656**	0.0546**	0.0667**	0.0553**
	(0.0209)	(0.0171)	(0.0209)	(0.0171)
Anomalies			-0.009	-0.0041
			(0.0104)	(0.0085)
Anomalies*LGR_t			0.1253**	0.0928*
			(0.0424)	(0.0362)
DGR		-0.0310**		-0.0306**
		(0.0096)		(0.0097)
CAR		-0.0376***		-0.0377***
		(0.0083)		(0.0083)
Size		0.0150***		0.0149***
		(0.0012)		(0.0012)
Time Trend		0.0019***		0.0019***
		(0.0004)		(0.0004)
Constant	0.1137***	-0.0564***	0.1140***	-0.0553***
	-0.0009	-0.0145	-0.001	-0.0145
N. Obs	5,249	5,249	5,249	5,249
R^2	4.74%	19.76%	5.12%	19.96%
R^2 Adjusted	4.67%	19.64%	5.01%	19.81%

Table 8 – Regression results with NPLs ratio as dependent variable

Dependent Variable NPLs	**Model (1)**	**Model (2)**	**Model (3)**	**Model (4)**
LGR_t	-0.0156	-0.0601***	-0.0181	-0.0619***
	(0.0103)	(0.0110)	(0.0103)	(0.0109)
LGR_t Mutual	-0.036	-0.0372*	-0.0381*	-0.0389*
	(0.0195)	(0.0159)	(0.0194)	(0.0158)
LGR_{t-1}	-0.0489***	-0.0719***	-0.0502***	-0.0727***
	(0.0096)	(0.0087)	(0.0097)	(0.0087)
LGR_{t-1} Mutual	-0.2563	-0.1018	-0.2397	-0.0898
	(0.1407)	(0.0847)	(0.1390)	(0.0834)
Anomalies			-0.006	-0.0022
			(0.0099)	(0.0082)
Anomalies*LGR			0.1096**	0.0857*
			(0.0368)	(0.0343)
DGR		-0.0299**		-0.0296**
		(0.0097)		(0.0097)
CAR		-0.0393***		-0.0394***
		(0.0083)		(0.0083)
Size		0.0150***		0.0150***
		(0.0012)		(0.0012)
Time Trend		0.0019***		0.0019***
		(0.0004)		(0.0004)
Constant	0.1134***	-0.0563***	0.1136***	-0.0556***
	(0.0009)	(0.0142)	(0.0009)	(0.0142)
N. Obs	5,249	5,249	5,249	5,249
R^2	4.50%	19.30%	4.78%	19.47%
R^2 Adjusted	4.42%	19.18%	4.67%	19.32%

Table 9 – Regression results with NPLs ratio as dependent variable – Instrumental variables (IV)

Dependent Variable NPLs	**Model (1)**	**Model (2)**	**Model (3)**	**Model (4)**
LGR	-0.4418***	-0.7837***	-0.4760***	-0.8304***
	(0.1325)	(0.1824)	(0.1408)	(0.1908)
LGR_{t-1}	-0.0458***	-0.1439***	-0.0499***	-0.1511***
	(0.0113)	(0.0235)	(0.0116)	(0.0247)
Anomalies			-0.012	-0.008
			(0.0115)	(0.0108)
Anomalies*LGR			0.5224***	0.5846***
			(0.1398)	(0.1388)
DGR		0.1742**		0.1854**
		(0.0618)		(0.0645)
CAR		0.0358		0.0376
		(0.0245)		(0.0251)
Size		0,0384***		0.0391***
		(0.0066)		(0.0069)
Time Trend		-0.0042*		-0.0046*
		(0.0017)		(0.0018)
Constant	0.1273***	-0.3522***	0.1289***	-0.3593***
	(0.0050)	(0.0840)	(0.0053)	(0.0868)
N. Obs	5,249	5,249	5,249	5,249
R^2	0.78%	5.95%	0.85%	5.93%
Chi_squared	31,9303	90,9551	36,6059	88,3171
Correlation	26.28%	54.8%	27.24%	54.52%
F_f	2.7277***	1.5446***	2.5427***	1.4186***

7. Conclusions

Conflict of interest and moral hazard in the banking industry are serious threats to the stability of a banking system as a whole. Recently, the issue of excessive bank risk taking has come up again in terms of national public debt on the Southern periphery of the Eurozone.

In Italy, since 2007, NPLs have tripled growing at around 20% annually since 2008, reaching € 333 billion in June 2014 – 24% of GDP or 16.8% of total loans – (Jassaud and Kang, 2015). In the Italian banking system, NPLs cover four categories: "*bad debt*" (i.e. loans in a state of insolvency), "*substandard*", "*past due*" and "*restructured*" loans. More than 80% of bank NPLs are in the corporate sector reaching nearly 30% on average in 2014 with a significant percent in the South (Bank of Italy, 2014). The high corporate NPLs ratio reflects the heavy indebtedness of many Italian SMEs.

NPLs growth ratio shows a substantial increase in comparison with loans and deposits growth ratio. In keeping this picture, banks management may observe their NPLs ratios to increase as a result of bad luck or bad management (Berger and DeYoung, 1997).

This paper aims to detect the existence of an opportunistic behaviour – i.e. moral hazard – within the Italian banking sector by investigating how banks face their challenges in lending relationships and they engage risky behaviour. In order to detect this opportunistic behaviour, we simply adopt a fixed effect panel analysis approach by investigating the role of Non Performing Loans (NPLs) in signalling moral hazard problems. We apply this model to the Italian commercial banks in order to test the hypothesis in that troubled banks have incentives to take excessive risks. Our proposed methodology and empirical findings suggest important implications for Italian regulators facing high NPLs and potential moral hazard problems in the domestic banking sector.

Based on these considerations, applying an unbalanced panel regression model to a dataset of 760 Italian commercial banks – composed of three different kinds of banks ("S.p.A.", "popolari", "mutual banks") – from 2006 to 2014, we investigate whether banks' lending behaviour could be sensitive to a specific level of NPLs and, more importantly, whether banks with higher NPLs ratio tend to adopt a more aggressive and riskier lending strategy. Afterwards, we examine empirically the hypothesis that supervisor activity of the Italian banking authority (i.e. "Bank of Italy") – through credit risk sanctions inflicted – is effective in providing incentives for banks to limit their risk lending strategy and in ensuring the stability of Italian banking system.

Banks with significant previous losses or with significant level of NPLs, by making additional loans (i.e. higher loan growth ratio) can reduce NPLs ratio temporarily, due to the dilution effect. Therefore, in order to achieve higher loan growth, banks managers may have to accept riskier positions, potentially originating higher future losses. However, also considering one lag backwards in LGR, the relationship between LGR_{t-1} and NPLs ratio keeps negative and highly significant. Furthermore, this relationship is kept constant in all equations regressed. This is consistent with what we expect: banks may be affected by moral hazard problems.

Relationship between credit risk sanctions – $Anomalies*LGR_t$ – due to the anomalies occurred *ex ante* and along loans screening process not disclosed to the Supervisory Authority and current NPLs ratio is positive and statistical significant (at 5% level) emphasising the supervisory effectiveness on excessive risk-taking by banks. We also introduce instrumental variables and use 2SLS method to estimate the slope coefficients. In all equations, the results are qualitatively similar, which means that banks facing previous significant losses have the incentive to take higher risk, which will then result in further significant losses. All in all, when endogeneity is accounted for, our core conclusion remains valid.

In order to provide a comprehensive analysis of the NPL problem in Italy, a next step relies on the detection of a particular threshold value of NPLs ratio, such that above the threshold level risk-taking by banks rises and hence the NPLs ratio worsens. Therefore, monitoring banks, with NPLs higher than the threshold value, is particularly important for regulators to avoid further deterioration of already troubled banks.

Italian regulators should consider NPLs ratio as a useful indicator for detecting potential bank moral hazard problem and design transparent policy goals and monitor banks closely.

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