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Credit Supply Response to Non-Performing Loans: Some Evidence From the Italian Banking System

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Abstract

Do high levels of NPLs depress credit supply? And, what are the implications of NPL buildups on banks' lending behaviour? To answer these questions we estimate impulse responses using [1] local projections on an unbalanced sample of Italian banks observed from 2009 to 2016. Our results provide fresh evidence on the negative association between NPLs and banks' loans supply. More specifically, we find that an unexpected shock to the level of NPL ratio is negatively associated to credit supply for at least two years after. Similarly, an unanticipated NPL ratio buildup is related to banks adopting a conservative lending behaviour in the following four years.

JEL classification numbers: E51, E58, G00, G21
Keywords: NPLs, Loan Supply, Local Projections Model

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1. Introduction

The soundness of the banking sector is key to securing banks' capacity to finance the real economy (households and firms) and ultimately to spur economic growth. The 2008 financial crisis, however, has adversely affected the banking system of most European countries, including that of Italy. Since the outburst of the crisis Italian banks have started to accumulate large stocks of non-performing loans (henceforth, NPLs), thus seriously deteriorating the quality of their balance sheets. Soon after, specifically from mid-2012, the supply of credit from Italian banks started to slow down, only to recover again at the beginning of 2016. The question is then what role did NPLs play in the observed decline of banks' credit supply. The issue is crucial not only because it raises concerns over a country's financial stability, but also because if not resolved it can trigger a vicious circle where higher NPLs depress credit growth leading to a slower recovery and thus a further deterioration of banks' balance sheet. The ultimate goal is to design policies contributing to the revival of banks' lending activity and, as a by product, prompt economic growth.

Research aimed at understanding the relationship between NPLs and banks' loan supply is thriving. Many contributions have found a significant negative association between the two [2,3]. Behind this result lies the fact that high levels of NPLs in banks' balance sheet generate a riskier asset side. Regulatory constraints to ensure the adequacy of asset valuations could therefore tie up bank capital that could be otherwise used to increase lending. Another line of reasoning is that growing NPLs translate in increasing loan loss provisions (LLPs) as the bank needs to protect itself against the risk associated to deteriorating credit worthiness. Higher provisions depress the banks' returns on assets, possibly leading to losses depleting the capital base and hence, credit contracts.

With this paper we contribute to this line of research. We focus on the Italian banking system as it was hit by a double-dip recession that was deeper and longer than that experienced by other Eurozone countries and also had a bigger impact on NPLs. Using detailed balance sheet information at the bank level collected by the Italian Bank Association (ABI), we explore the correlation between the level of NPLs, their buildup and the supply of credit. Our sample consists of an unbalanced panel data of individual banks operating in Italy and observed throughout the period 2009 to 2016. This represents our first contribution to the related literature since, as far as we know, we are the first to document the NPLs - credit supply nexus using this data. Another contribution of our work is represented by the empirical model we implement to explore our research question. In particular, we apply the local projection model (LPM) introduced by [1] in a micro-level setting, which to the best of our knowledge has never been done so far.

Before proceeding a few caveats are in order. The aim of this work is purely descriptive and does not uncover any casual relationship between NPL ratios and supply of credit. A key issue is identification. NPLs tend to rise during an economic downturn, when both supply and demand for credit contract. The major challenge, therefore, is to understand whether lower credit supply is driven by adverse economic conditions, or by the presence of excessive levels of NPLs impairing banks' ability to inject money into the economic system. Although we acknowledge attempts made in this direction, none of the existing empirical contributions have reached satisfactory conclusions yet [4]. Among the main reasons are data and methodological limitations that make it hard to solve the endogeneity bias affecting results. Although we are not able to isolate demand side effects, the LPM setup we employ does however allow us to estimate the response of credit supply to a NPL shock. More specifically, we define the shock as the deviation of the level of NPLs, first, and their growth, second, from their estimated path given a set of bank level characteristics. Clearly, the identified shock is correlated with the economic cycle and thus it does not represent an exogenous shock per se. Nevertheless, we feel that our methodology is able to bring fresh insights on the correlation between NPLs and credit supply to the current discussion.

Anticipating our findings, we find that an unexpected increase in the level of NPL ratios is negatively associated to credit supply. This piece of evidence corroborates previous findings and extends them to more recent years. The methodology we employ also allow us to uncover that this effect lasts up to two years after the initial shock. When we look at variations in NPL ratios, our results imply that an unanticipated NPL ratio buildup leads banks adopting a more conservative behaviour. We additionally find that this effect extends to four years thereafter.

The rest of the paper is structured as follows. The next Section discusses the related literature. Section 3 describes the data used, while Section 4 introduces the empirical model used to disentangle the relationship between NPLs and credit supply. Section 5 presents the results and Section 6 concludes.

2. Literature Review

This paper analyses the association between NPLs and the amount of credit supplied by banks to the economic system. The related literature spans from work at the aggregate level to research at the micro level.

At the macro level, economists have mainly looked at the likely impact of NPLs on economic growth. [5] suggest that a large increase in the NPL ratio serves as a reliable predictor of financial crises. Later contributions have explored the role of credit supply as the transmission channel between NPLs and economic growth. These include [6], who find that an increase in NPLs is associated with a sudden fall in private borrowing and a reduction in GDP growth using a sample of 26 developed countries that spans the period from 1998 to 2009. Similarly, [7] reports a negative impact of increases in NPL ratios on credit growth and employment in emerging Europe in the aftermath of the 2008-2009 financial crisis. Similar evidence is provided by [8], who using a panel of around 80 banks operating in the Gulf region over the period 1995 - 2008 conclude that NPLs in banks' balance sheets lead to a strong negative impact on the economy. More recently, [9] study the relationship between output growth and a rise in NPLs for a panel of countries between 1997 and 2014. They find that those countries that solve their NPL issue typically experience higher growth rates compared to those that ignore the issue. More importantly, this result is stronger when countries experience faster credit growth rather than just reducing their outstanding NPLs.

Overall, the macro literature documents well the negative association between NPLs and credit supply and this result has received large consensus among research circles, including work at the micro level. The latter has explored the relationship between NPLs and credit supply by using detailed bank level data. For example, [2] exploit dynamic regressions using balance sheet information for a sample of 42 banks in 16 European countries (excluding Italy) over the period 2004-2013. They find a significant negative impact of the level of NPLs and, although smaller, of changes in NPLs on corporate lending. Likewise, [3] estimates a dynamic fixed effect model. She focuses on a sample of Italian banks observed between 2007 and 2013 and finds that NPLs have a negative impact on the supply of bank loans. More recently, [10] develop a model whereby the relationship between NPLs and credit supply runs through the cost of issuing new equity. Their result confirm that holding NPLs increase the cost for capital for banks, which reduces credit supply as banks have restricted access to equity.[2]

Next to this literature, another line of research has been more interested in finding a causal relationship, rather than a simple correlation, between NPLs and credit supply. On one hand, the economic performance of the country where banks operate influences the amount of bad loans they buildup.[3] On the other hand, the economic environment influences demand for credit.

The challenge is therefore to dissect whether changes in banks' lending supply are driven by the stock and/or flow of NPLs or by fluctuations in demand for credit.

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[2] According to their model, poorly capitalized banks holding high levels of NPLs are riskier and lend less compared to healthier banks. Issuing new equity can encourage banks to loosen their lending behaviour. However, a riskier asset side implies higher issuing cost. Troubled banks may therefore find containing credit supply more convenient than raising capital. The authors test their prediction using a sample of Eurozone banks for the 2002-2016 period.

[3] This evidence is uncovered by [11], who use a dynamic panel of advanced and emerging economies observed over the period 2000-2010 to find that GDP growth is the most important determinant of banks' asset quality. Similar results are reached by [12] and [13]. In a similar vein, [14] focus on the Italian case. They find that the slowdown in GDP growth following the financial and sovereign debt crisis was one of the main contributors to the rise of bad debts in Italy. Similarly, [15] suggest that GDP growth rates above a certain threshold, if sustained for a number of years, allows banks to solve their NPL overhang. They estimate that for the Italian economy this threshold is equal to 1.2 percent.

There have been a number of attempts in this direction, although none have reached widely recognized conclusions yet.[4] Among the main reasons is the lack of data availability and an adequate methodological framework to dissect an exogenous change in NPLs and its impact on credit supply.

Although we acknowledge these efforts, our work is mostly concerned with providing novel evidence on the association between NPLs and credit supply. For this purpose we use detailed bank level data collected by ABI covering the period from 2009 to 2016. Also, we apply the LPM framework which allows us to unveil the credit supply response to an initial NPL shock. The dataset together with the empirical approach we exploit allow us to contribute to the related literature and bring further evidence on the negative association between NPLs and credit supply.

3. Data

3.1 Data Description

Our main source of data is ABI.[5] Banks disclose detailed balance sheet information to ABI twice a year on a voluntary basis. Data is collected at the individual level for each bank and at the consolidated level for banking groups.

For our analysis we employ the individual bank level data.[6] For each bank we retrieve data on its characteristics and main balance sheet items. In particular, we only employ end-of-the year data.[7] Using this information we build indicators employed in the subsequent analysis, such as the gross non-performing loans ratio (henceforth, NPL ratio). Table A1 provides a list of selected variables used in our analysis.

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[4] [16] resort to a matched bank-borrower level dataset for the Italian banking system over the period 2008-2015, which allows them to separate demand side from supply side effects when analyzing the relationship between the level of NPLs and credit supply. Moreover, to separately account for the implications of exogenous variations in NPLs, they resort to data on balance sheet adjustments originating from the Asset Quality Review (AQR), the in-depth supervisory activity carried out by the European Central Bank in 2014. They find that the observed negative correlation between NPL ratios and credit growth is mostly generated by contraction of firms' demand for credit. However, the emergence of new NPLs depresses credit by the associated increase in LLPs. [17] extend this analysis to euro area banks for the period 2010-2015 and uncover a strong direct negative effect of higher NPLs on banks' credit supply.

[5] We are most grateful to our colleagues at the Financial Markets and Intermediaries division of Prometeia for providing us with the data.

[6] [18] employ ABI data to build an annual unbalanced panel of Italian banks balance sheet and income statements from 2001 to 2015. Using this data they analyse the determinants of LLPs and find that Italian banks increase them mainly to cover expected future credit losses rather than for income smoothing motives.

[7] Mid-year information is only available for the largest banks thus significantly affecting the representativeness of the sample.

After some data cleaning we end up with an unbalanced panel of Italian banks covering the period from 2009 to 2016.[8] Overall, the dataset contains 3,440 observations.[9] Table 1 shows the sample coverage for the Italian banking system in each year both in terms of number of banks and total assets. We assess the representativeness of our data with information for the universe of banks available from the Bank of Italy. Overall, the coverage of our sample is good as it represents, on average, 60% and 53% of the Italian banking system in terms of number of banks and total assets, respectively.

Table 1: Individual bank level data: number of banks and sample coverage by year

Year	No. of banks	% on no. of total banks	% on total assets
	[1]	[2]	[3]
2009	452	57.4	45.4
2010	477	62.8	46.0
2011	477	64.5	53.7
2012	447	63.3	54.8
2013	432	63.2	54.9
2014	421	63.4	55.4
2015	395	61.4	55.9
2016	339	56.1	54.0

Note: Column [1] reports the number of banks observed in each year in our sample. Column [2] and [3] show the sample coverage in terms of number of banks and total assets with respect to data from the Bank of Italy, respectively.

Source: Author's own elaborations based on ABI and Bank of Italy.

[8] Data is available from 2005 to 2018. However, for each year from 2005 to 2008 the representitiveness of the sample is too low to be employed for the empirical analysis of this paper. Also, we limit our analysis to 2016 as from 2017 banks' lending picked up again and NPLs ceased to grow.

[9] At the outset we drop observations corresponding to bank types that we do not include in our analysis, namely foreign banks (1 observation) and banks specialized in factoring and leasing activities (902 observations). Then, we eliminate observations with negative values for selected variables, namely net worth and credit, which are most likely due to errors (23 observations). We retain end-of-the-year observations and drop the first observation for each bank as discussed in the next subsection. We consider only data from 2009 for reasons of sample representitiveness as already explained. We end up with an unbalanced panel data of 3,440 banks covering the period 2009-2016.

In terms of bank type, Table 2 shows that the sample covers well the number of existing cooperative credit banks (BCC) in the Italian banking system, less so the number of corporate banks (SPA). The representitiveness of banks falling under the category of POP (Banca Popolare) increases over time reaching 80% of the total POP banks operating in Italy in 2016.

Table 2: Individual bank level data: number of banks and sample coverage by year and bank type

Year	**BCC**		**POP**		**SPA**	
	No. of banks	**% on no. of total banks**	**No. of banks**	**% on no. of total banks**	**No. of banks**	**% on no. of total banks**
2009	331	78.6	18	48.6	103	41.5
2010	341	82.2	22	59.5	114	48.7
2011	342	83.2	26	70.3	109	50.7
2012	325	82.5	26	70.3	96	48.5
2013	316	82.1	27	73.0	89	48.6
2014	311	82.7	27	73.0	83	48.3
2015	295	80.8	26	78.8	74	44.8
2016	248	74.3	20	80.0	71	43.8

Note: The table shows the number of banks observed in each year by bank type and the sample coverage in terms of number of banks and total asset with respect to data from the Bank of Italy.

Source: Author's own elaborations based on ABI and Bank of Italy.

As an additional check on the level of representativeness of the data, Figure 1 plots average yearly growth rates calculated on the individual unbalanced panel dataset and compares them to those calculated on the data available from the Bank of Italy.[10]

[10] Banca d'Italia, Relazione Annuale, Issues from 2010 to 2017.

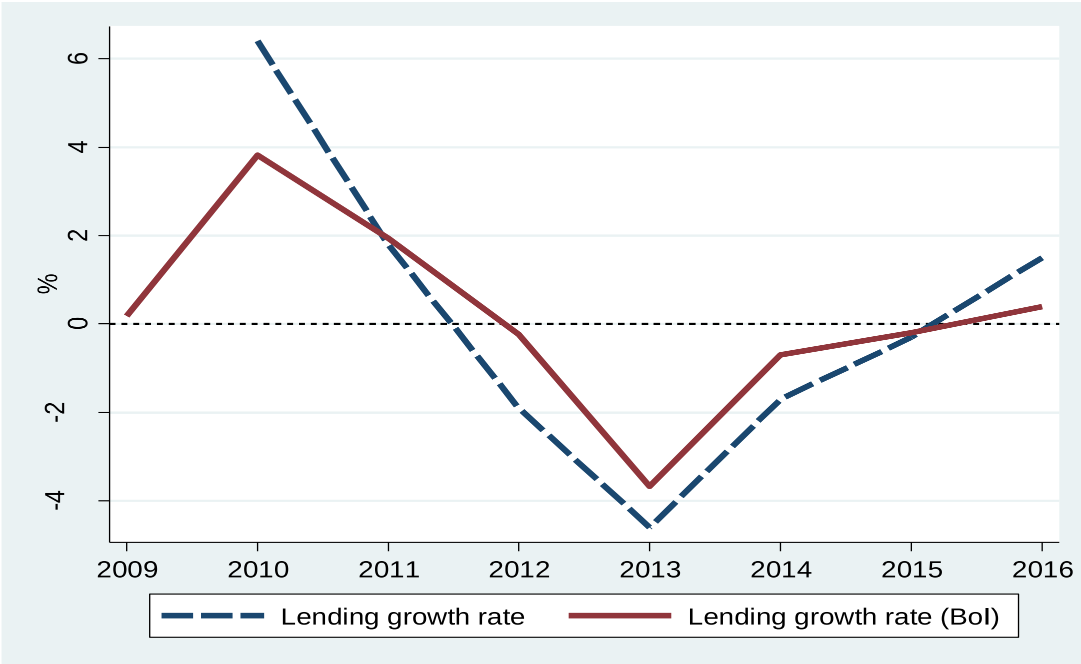

Figure 1: Average yearly lending growth rates: unbalanced panel vs. Bank of Italy

Source: Author's own calculations based on ABI and Bank of Italy.

Altogether, our data maps well the dynamics of credit growth in the Italian banking system over the period of analysis. As of 2010 lending growth rates start to drop and become negative in 2012. Only in 2016 they turn positive again.

We repeat the same exercise for the level of NPL ratio. Figure 2 compares the average level of NPL ratio calculated on our data to that available from the Bank of Italy. The ratio derived from our dataset is close to that available from the official source. Starting from 2009, we observe a significant and steady increase of the NPL ratio. It reaches its maximum in 2015 and drops in 2016 returning to a level similar to that reached in 2014.

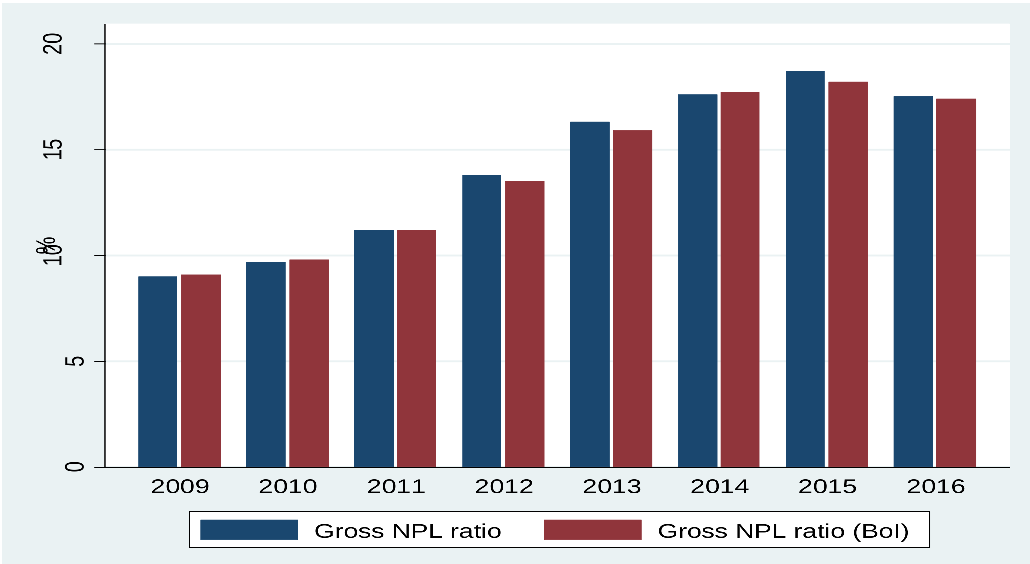

Figure 2: Average yearly NPL ratio: unbalanced panel data vs. Bank of Italy
Source: Author's own calculations based on ABI and Bank of Italy.

From this brief analysis, we are confident that the sample at our disposable covers well, and it is a good representation of the Italian banking system between 2009 and 2016.

3.2 Sample selection and attrition bias in the unbalanced panel

As mentioned above, when using the bank level data we end up with an unbalanced panel data, i.e. we do not follow all banks for the entire period of analysis. Unbalanced panel data may arise for several reasons. For example, the survey design may simply rotate banks out of the sample randomly. In this case, unbalanced panels do not cause any particular problem. Yet, if banks appear and disappear for non random reasons, unbalanced panels may generate a number of issues, most notably sample selection and attrition ([19]). Failing to properly rule out or address these problems may lead to biased results. For this reason, we need to assess whether our dataset is free of charges or, if not, how to tackle them.
In our unbalanced panel, sample selection may stem from the fact that banks convey balance sheet information on a voluntary basis. We may only observe healthier banks that are more willing to share their financial statements compared to distressed banks. If this is the case, we have a problem of sample selection. Nevertheless, balance sheet information is publicly available by law. ABI only provides the data collection service and makes information available to researchers and analysts in a more convenient fashion. Hence, banks' financial condition does not sufficiently motivate their appearance and disappearance in the ABI database. Their dimension, instead, could. Smaller banks might not have the capacity to pass

the relevant information in a timely manner. This suggests that we would only observe larger banks in our sample. However, as already shown in Table 2, BCC, which have a relatively smaller size, are the mostly covered type of banks in our sample. This line of reasoning makes us confident that in our analysis sample selection is not relevant.

Moreover, banks drop out of the sample because mergers and acquisitions (M&As) take place. This issue is known as attrition. A number of relevant M&As took place over the period we analyse. Thus, we cannot rule out the existence of attrition in our panel and proceed to address it in the following way. We retain all observations but we assign a different identification code to banks that have merged with other banks from the moment the merger has taken place. Thus, while the merged bank disappears from our dataset, we assume that the merger generates a new bank that we follow thereafter.[11] As such, there is no loss of information.

Finally, newly established banks appear in the dataset for the first time on the year of their creation when their activity is still at its early stages. For these banks lending growth rates for the second year they are observed are significantly large. This could bias our results as high lending growth rates in this case are not associated with changes in banks' lending behaviour but rather with the development of their activity. For this reason, we eliminate the first observation for each bank and only retain subsequent observations.

4. Empirical Strategy

Do high levels of NPLs depress credit supply? And what are the implications of NPL buildups on banks' lending behaviour? To answer these questions we estimate impulse responses using [1] local projections. Compared to using a VAR, impulse responses from local projections offer a number of advantages, namely they are more robust to misspecifications, they easily allow for the inclusion of control variables and their output is of straightforward interpretation ([20]).

[11] Alternatively, the merged bank can be dropped from the entire sample after aggregating its balance sheet items with that of the merger even in the years before the M&A took place.

We first uncover the relationship between the level of NPLs and credit supply by estimating impulse responses obtained by running the following sequence of fixed-effects panel regressions for bank *i* for horizons *h* = 1, ..., 4:

$$y_{i.t+h-1} = \alpha_i^h + \mu_t^h + \beta^h \mathbf{NPL}_{i,t} + \varepsilon_{i,t+h-1} \quad for \;\; i = 1, \dots, N; t = 1, \dots, T \qquad (1)$$

where α_i is the bank fixed effect, μ_t is the time fixed effect, y_i is the ratio of credit to the private sector on one period lagged total assets, $\mathbf{NPL}_{i,t}$ is the gross NPL ratio and ε_i is the error term. More specifically, we interpret $\mathbf{NPL}_{i,t}$ as the shock to the stock of NPLs.[12] It is calculated as the difference between the observed value of the NPL ratio ($NPL_{i,t}$) and the linear prediction ($\widehat{NPL_{\iota,t}}$) given its one-year lagged value ($NPL_{i,t-1}$) as follows:

$$\mathbf{NPL}_{i,t} = NPL_{i,t} - \widehat{NPL_{\iota,t}}$$

where:

$$\widehat{NPL_{\iota,t}} = \sigma_i + \tau_t + \delta NPL_{i,t-1} + \psi_{i,t} \qquad (2)$$

with σ_i, τ_t and $\psi_{i,t}$ indicating bank fixed effects, time fixed effects and the error term, respectively. Subsequently, we look at NPL buildups and assess to what extent they affect bank's lending policies by re-estimating Equation (1) in differences. More specifically, we recover a further set of impulse responses by estimating the following sequence of fixed-effects panel regressions for bank *i* and for horizons *h* = 1,..., 4:

$$\Delta_h y_{i,t+h-1} = \alpha_i^h + \mu_t^h + \beta^h \Delta\mathbf{NPL}_{i,t} + \varepsilon_{i,t+h-1}^h$$

$$for \; i = 1, \dots, N; t = 1, \dots, T \qquad (3)$$

where $\Delta_h y_i$ is the *h*-cumulated difference in the ratio of credit to the private sector on one period lagged total assets, $\Delta\mathbf{NPL}_i$ is the first difference in gross NPL ratio. α_i, μ_i and ε_i are defined above. The variable of interest $\Delta\mathbf{NPL}_i$ is the shock to the change in the NPL ratio. It is calculated as the difference between the observed first difference in gross NPL ratio ($\Delta NPL_{i,t}$) and its linear prediction ($\Delta\widehat{NPL_{\iota,t}}$) given its one-year lagged value ($\Delta NPL_{i,t-1}$) as follows:

$$\Delta\mathbf{NPL}_{i,t} = \Delta NPL_{i,t} - \Delta\widehat{NPL_{\iota,t-1}}$$

[12] In a similar vein, [21] include a measure of unanticipated government spending in their LPM setup to estimate government purchases multipliers for a number of OECD countries.

where:

$$\Delta\widehat{NPL}_{i,t} = \sigma_i + \tau_t + \delta\Delta NPL_{i,t-1} + \psi_{i,t} \tag{4}$$

where σ_i, τ_t and $\psi_{i,t}$ are defined above.

Before moving on, a few clarifications are in order. First, in Equation (1) to (4) standard errors are clustered at the bank level as a conservative fix for the leftover serial correlation typical of local projections ([1, 22]). Second, we normalize the credit variable by one-year-lagged total assets at the bank level to avoid capturing innovations to the banks' total assets in the credit equation. Finally, to check the robustness of our baseline results, we add to Equation (1) and (2) a set of control variables at the bank level taken at time *t* and to Equation (3) and (4) the first difference of a set of control variables between *t* and *t-1*.

5. Main Results

Our first question is whether high levels of NPL ratios depress banks' credit supply. We answer this question by estimating the sequence of regressions shown in Equation (1) and plot results in Figure 3. In particular, the left panel presents results from the baseline model, while the right panel plots projections controlling for a set of balance sheet items at the bank level. The latter include the value of the Tier1 ratio, risk-weighted assets, return on assets and total assets at time *t*. The solid lines represent the path followed by credit supply given a positive shock, i.e., increase, on the level of NPL ratio. The dashed lines represent 95% confidence intervals computed using standard errors clustered at the bank level. The corresponding estimation results are shown in Table 3 and 4 for the baseline and augmented model, respectively.[13]

The baseline estimates suggest that an increase in the level of NPL ratios is negatively associated with banks' loan supply. This negative association lasts three years after the initial shock as indicated by the negative coefficients associated with $NPL_{i,t}$ in Columns [1] to [3] of Table 3 and plotted in the left panel of Figure 3. The effect is, however, significant for the first two years only. Moreover, one year after the initial shock banks' loan supply slowly recovers as evidenced by the smaller coefficients in absolute value in Columns [2] and [3] as well as the change in direction of its mapped path. Meanwhile, the positive coefficient in Column [4] and [5] suggest that banks' credit supply fully recovers after four years from the initial shock, although this effect is not significant.

Table 4 and the right panel of Figure 3 show that the inclusion of control variables at the bank level does not significantly alter the baseline results. One year after the initial shock a riskier asset side exerts a negative effect on banks' loan supply as

[13] Column [1] and [2] of Table A2 show results from the estimation of the baseline and augmented version of Equation (2).

indicated by the negative coefficient associated with $RWA_{i,t}$ in Column [1] of Table 4. At the same time, higher capitalized banks and a higher return on assets positively affect the level of banks' credit supply as shown by the positive coefficient associated with $Tier1\ ratio_{i,t}$ and $ROA_{i,t}$, respectively. Moreover, a more robust asset side is associated with higher loan supply starting from three years after the initial shock as suggested by the positive coefficients associated with $Total\ Assets_{i,t}$ in Columns [3] to [5].

Overall, we find that the level of NPL ratios is negatively associated with credit supply. The evidence pointing to an inverse association between NPL and banks' loan supply is in line with previous work in this field. Noteworthy is that our methodology allows us to uncover that this effect lasts for at least two years after the initial shock.

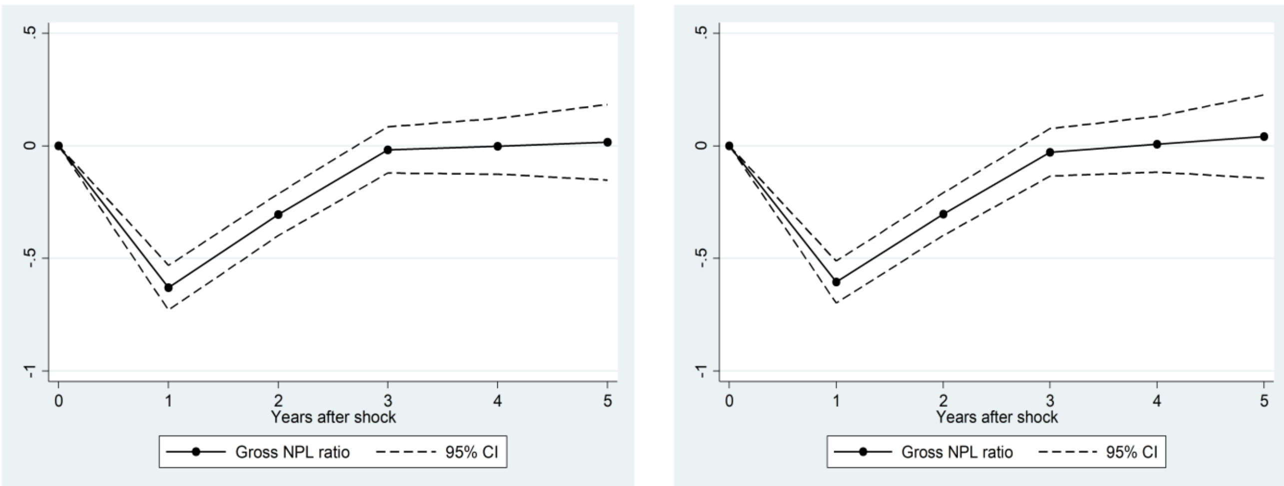

Figure 3: Local projection impulse responses, levels

Source: Author's own calculations based on ABI.

Note: This figure shows impulse responses from [1] local projections estimated in levels. The baseline results are plotted in the left panel and corresponds to estimates from Equation (1), which are reported in Table 3. The right panel plots results corresponding to estimates from an augmented version of Equation (1), which are reported in Table 4. Dashed lines represent 95% confidence intervals computed using standard errors clustered at the bank level.

Table 3: Local projections model, linear baseline

	[1]	[2]	[3]	[4]	[5]
	Horizon *h*				
	1	**2**	**3**	**4**	**5**
NPL$_{i,t}$	-0.606***	-0.304***	-0.029	0.007	0.0419
	(0.048)	(0.048)	(0.054)	(0.063)	(0.094)
Time trend	Yes	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes	Yes
No. of banks	490	446	420	396	354
No. obs.	2,402	1,912	1,466	1,046	650

Note: The Table shows results from the estimation of the sequence of regressions shown in Equation (1) and are plotted in the left panel of Figure 3. Robust standard errors in parentheses are clustered at the bank level. * Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level.

Source: Author's own elaborations based on ABI.

Table 4: Local projections model, linear robustness

	[1]	[2]	[3]	[4]	[5]
	Horizon *h*				
	1	**2**	**3**	**4**	**5**
NPL$_{i,t}$	-0.631***	-0.306***	-0.018	-0.002	0.015
	(0.051)	(0.047)	(0.052)	(0.063)	(0.086)
Tier1 ratio$_{i,t}$	0.011	-0.058	0.0208	-0.166**	-0.385***
	(0.043)	(0.044)	(0.089)	(0.078)	(0.131)
RWA$_{i,t}$	-3.371**	-8.908***	-4.500	-1.675	-8.227*
	(1.559)	(1.781)	(2.805)	(2.721)	(4.380)
ROA$_{i,t}$	0.755***	0.281	0.231	0.248	-0.738**
	(0.165)	(0.207)	(0.276)	(0.266)	(0.357)
Total Assets$_{i,t}$	-12.310***	-1.791	6.593***	6.337***	8.212**
	(1.624)	(1.564)	(1.617)	(2.181)	(4.117)
Time trend	Yes	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes	Yes
No. of banks	490	446	420	396	353
No. obs.	2,401	1,911	1,465	1,045	649

Note: The Table shows results from the estimation of an augmented version of Equation (1), where we add a set of control variables at the bank level, and are plotted in the right panel of Figure 3. Robust standard errors in parentheses are clustered at the bank level. * Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level.

Source: Author's own elaborations based on ABI.

The second theme we address is analysing the extent to which NPL buildups affect banks' lending policies. The strategy we follow to answer this question is estimating a sequence of regressions shown in Equation (3). We depict results in Figure 4, where the left panel shows estimates from the baseline model, while the right panel plots projections with the inclusion of a set of control variables at the bank level. The latter include the value of the first difference of the Tier1 ratio, risk-weighted assets, return on assets and total assets between *t* and *t-1*. The solid lines describe the reaction of changes in credit supply to an increase in NPL ratio. The dashed lines represent 95% confidence intervals computed using standard errors clustered at the bank level. The corresponding estimation results are shown in Table 5 and Table 6 for the baseline and augmented model, respectively.[14]

From the baseline model it emerges that an increase in NPL ratio buildups is related to lower credit growth. This effect lasts over the entire five-year horizon as emerging from the estimates shown in Table 5 and plotted in the left panel of Figure 4. Only in the last year this effect is not significant. Furthermore, the smaller coefficients in absolute value associated with $\Delta NPL_{i,t}$ in Column [3] to [5] compared to that in Column [1] suggest that credit growth slowly recovers from the third year on. The change in the direction of the plotted credit growth path clearly reflects this observation. Yet, credit growth never fully recovers its pre-shock levels over the five year horizon.

A similar, albeit slightly moderated, pattern emerges when adding a set of control variables to the baseline model. Estimates in Table 6 show that the coefficients associated with $\Delta NPL_{i,t}$ are very similar to those of Table 5. Consequently, the plot in the right panel of Figure 4 resembles the one of the left panel. With regards to the control variables, it is worth noticing that only a change in the return to assets significantly affects, albeit modestly, credit growth one year after the shock as indicated by the coefficient associated with $\Delta ROA_{i,t}$ in Column [1]. The other set of covariates turn significant starting from the second period onwards. In particular, a change in the value of the risk-weighted assets and return on assets is negatively correlated with credit growth as indicated by the negative coefficient associated with $\Delta RWA_{i,t}$ and $\Delta ROA_{i,t}$ in Columns [2] to [5]. Total assets is positively associated with credit growth as evidenced by the positive coefficient associated with $\Delta Total\ assets_{i,t}$. The Tier1 ratio, instead, is positively correlated to higher credit growth only in the fourth year after the initial shock ($\Delta Tier1\ ratio_{i,t}$).

[14] Column [1] and [2] of Table A3 show results from the estimation of the baseline and augmented version of Equation (4).

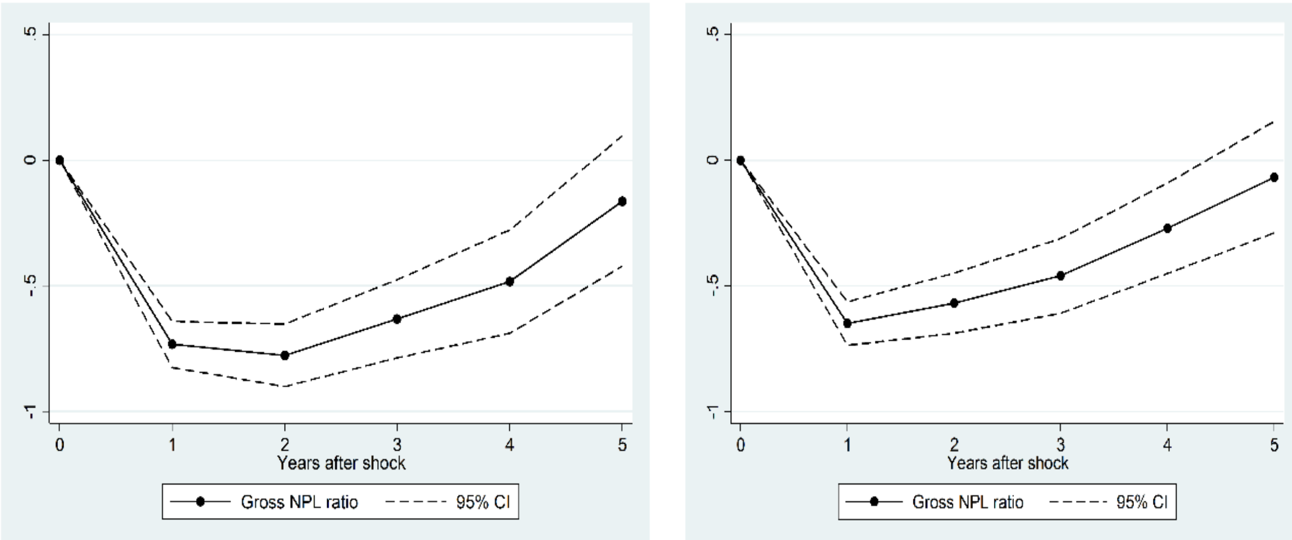

Figure 4: Local projection impulse responses, difference

Source: Author's own calculations based on ABI
Note: This figure shows impulse responses from [1] local projections estimated in levels. The baseline results are plotted in the left panel and corresponds to estimates from Equation (3), which are reported in Table 5. The right panel plots results corresponding to estimates from an augmented version of Equation (3), which are reported in Table 6. Dashed lines represent 95% confidence intervals computed using standard errors clustered at the bank level.

Table 5: Local projections model, delta baseline

	[1]	**[2]**	**[3]**	**[4]**	**[5]**
Horizon *h*					
	1	**2**	**3**	**4**	**5**
$\Delta \boldsymbol{NPL_{i,t}}$	-0.734***	-0.777***	-0.632***	-0.484***	-0.164
	(0.047)	(0.064)	(0.079)	(0.105)	(0.132)
Time trend	Yes	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes	Yes
No. of banks	490	446	420	396	354
No. obs.	2,402	1,912	1,466	1,046	650

Note: The Table shows results from the estimation of the sequence of regressions shown in Equation (3) and are plotted in the left panel of Figure 4. Robust standard errors in parentheses are clustered at the bank level. * Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level.

Source: Author's own elaborations based on ABI.

Table 6: Local projections model, delta robustness

	[1]	[2]	[3]	[4]	[5]
	Horizon h				
	1	**2**	**3**	**4**	**5**
$\Delta NPL_{i,t}$	-0.651***	-0.570***	-0.461***	-0.272***	-0.068
	(0.044)	(0.061)	(0.076)	(0.092)	(0.113)
$\Delta Tier1\ ratio_{i,t}$	0.035	0.036	0.088	0.277***	-0.020
	(0.035)	(0.046)	(0.063)	(0.083)	(0.085)
$\Delta RWA_{i,t}$	-1.561	-4.336**	-9.695***	-8.918***	-13.05***
	(1.217)	(1.701)	(3.470)	(3.396)	(4.024)
$\Delta ROA_{i,t}$	-0.195*	-0.353**	-0.716***	-0.792***	0.472*
	(0.106)	(0.147)	(0.220)	(0.246)	(0.279)
$\Delta Total\ assets_{i,t}$	1.420	6.605***	13.800***	27.770***	14.270***
	(1.491)	(2.528)	(3.300)	(4.018)	(4.192)
Time trend	Yes	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes	Yes
No. of banks	490	446	420	396	353
No. obs.	2,401	1,911	1,465	1,045	649

Note: The Table shows results from the estimation of the sequence of regressions shown in Equation (3), where we add a set of control variables at the bank level, and are plotted in the right panel of Figure 4. Robust standard errors in parentheses are clustered at the bank level. * Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level.

Source: Author's own elaborations based on ABI.

6. Conclusion

The high levels of NPLs reached by Italian banks in the aftermath of the financial crisis and the simultaneous drop in their supply of credit to the private sector have captured the attention of experts in the banking field. There have been various contributions seeking to understand the relationship between NPLs and banks' ability to supply money to the economic system. Most studies point to a negative association between the two, although no clear consensus has been reached yet.

With this paper we contribute to this line of research. In particular, we focus on two issues. First, the relationship between the *level* of NPL ratios and credit supply. Second, the implications of NPL *buildups* on banks' lending behaviour. To answer our research question we estimate impulse responses using [1] local projections on an unbalanced sample of Italian banks observed from 2009 to 2016 collected from ABI. As far as we know, we are the first to analyse the association between the level of NPLs, their buildup and banks' loan supply using ABI data. Furthermore, the application of the local projection model in a micro-level setting, to the best of our knowledge, has never been done so far.

The methodology we employ together with the data we use allow us to bring fresh evidence to the current discussion. Our findings suggest that the *level* of NPL ratios is negatively associated to credit supply. This result corroborates previous evidence (see [2] and [3], among others). We additionally find that an unexpected increase in the level of NPLs exerts a negative effect on banks' loans supply for at least the following two years. The second piece of evidence we provide is that an unanticipated *buildup* of NPL ratios leads banks to contain their lending activity. Similar evidence is found in [16], who indicate that "*the emergence of new NPLs and the associated increase in provisions causes a negative adjustment in credit supply*". We also uncover that this effect lasts up to four years after.

Some limitations of our work are worth emphasing as they mainly represent future avenues of research. Our work is purely descriptive and is not meant to uncover any casual relationship between NPL ratios and supply of credit. Attempts in this direction have been made but no satisfactory conclusion has been reached yet due to data availability and a sound methodology to resolve the endogeneity issue typically affecting the NPL-credit supply nexus. Moreover, our methodology is not intended to capture the transmission channels of NPLs on banks' lending supply, which can act either through a riskier asset side and/or an increase in losses. Further work to fill these gaps in the literature are warranted.

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Tables and figures

Table A1 lists selected variables and indicators used in the paper.

Table A1: Selected variables available from ABI

Class of information	Variable	Abbreviation	Description
Bank characteristics	Type	*Type*	Classifies banks according to their legal nature: i. Banca di Credito Cooperativo (BCC) ii. Banca Popolare (POP) iii. Società per Azioni (SPA)
Assets	Credit to the private sector	*Loans*	Sum of loans to the private sector (households and firms)
	Total assets	*Total assets*	Total amount of assets
	Risk weighted assets	*RWA*	Banks assets weighted according to risk under the Basel II framework
	Non-performing loans (gross and net)	*Gross NPL; Net NPL*	Credit to the private sector classified as non-performing under the harmonized definition of the BIS
Liabilities	Tier1 capital	*Tier1 capital*	Banks core equity capital defined by the Basel Committee on Banking Supervision
Expenses	Loan Loss Provisions	*LLPs*	Yearly allowance for uncollected loans and loan payments
Indicators	Tier1 ratio	*Tier1 ratio*	Ratio between *Tier1 capital* and *RWA*
	Gross Non-performing loans ratio	*NPL*	Ratio between gross *NPLs* and *Loans*

Source: Author's own elaborations.

Table A2 shows results from the estimation of Equation (2). Column [1] reports estimated coefficients from the baseline model. It indicates that the NPL ratio at time *t* is positively and significantly related to its one year lagged value ($NPL_{i,t-1}$). When we control for a set of balance sheet items in Column [2], the coefficient associated with $NPL_{i,t-1}$ shrinks, albeit moderately. Worthy of note is that higher capitalized banks are associated with lower levels of NPL ratios, as suggested by the coefficient associated with $Tier1\ ratio_{i,t-1}$. Also, more profitable banks are related to lower levels of NPL ratios as evidenced by the negative and statistically significant coefficient associated with $ROA_{i,t-1}$.

Table A3 shows results from the estimation of Equation (4). Column [1] reports estimated coefficients from the baseline model. It indicates that NPL buildups are negatively and significantly related to their one-year lagged value ($\Delta NPL_{i,t-1}$). After controlling for the first difference of an additional set of balance sheet items this association turns stronger as suggested by the higher coefficient in absolute value associated with $\Delta NPL_{i,t-1}$. None of the additional explanatory variables are statistically significant.

Table A2: NPL prediction, first stage estimates

	[1]	[2]
	$NPL_{i,t}$	$NPL_{i,t}$
$NPL_{i,t-1}$	0.747***	0.703***
	(0.025)	(0.023)
$Tier1\ ratio_{i,t-1}$		-0.056**
		(0.025)
$RWA_{i,t-1}$		0.365
		(0.911)
$ROA_{i,t-1}$		-0.474***
		(0.105)
$Total\ assets_{i,t-1}$		0.011
		(0.735)
Equation	OLS	OLS
R-squared	0.833	0.835
Time trend	Yes	Yes
FE	Yes	Yes
No. of banks	519	519
No. obs.	2,921	2,920

Note: The Table shows results from the estimation of Equation (2). Column [1] reports estimates from the baseline model, while Column [2] from its augmented version. All variables are defined in Table A1. Robust standard errors in parentheses are clustered at the bank level. * Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level.

Source: Author’s own elaborations based on ABI.

Table A3: ΔNPL prediction, first stage estimates

	[1]	[2]
	$\Delta\ NPL_{i,t}$	$\Delta\ NPL_{i,t}$
$\Delta NPL_{i,t-1}$	-0.073**	-0.278***
	(0.029)	(0.028)
$\Delta Tier1\ ratio_{i,t-1}$		-0.019
		(0.024)
$\Delta RWA_{i,t-1}$		0.151
		(0.882)
$\Delta ROA_{i,t-1}$		-0.232
		(0.145)
$\Delta Total\ assets_{i,t-1}$		0.732
		(0.807)
Equation	OLS	OLS
R-squared	0.014	0.012
Time trend	Yes	Yes
FE	Yes	Yes
No. of banks	490	490
No. obs.	2,402	2,402

Note: The Table shows results from the estimation of Equation (4). Column [1] reports estimates from the baseline model, while Column [2] from its augmented version. All variables are defined in Table A1. Robust standard errors in parentheses are clustered at the bank level. * Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level.

Source: Author's own elaborations based on ABI.