The Origins of Italian NPLs

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Abstract

What caused Italian banks' gross nonperforming loans (NPLs) to balloon to €360bn at the end of 2015? By using a detailed bank-firm dataset we try to identify what fraction of NPLs was "unavoidable", due to the economic recession, and which one was caused by poor ex-ante lending decisions by banks. The analysis using aggregated data suggests that macroeconomic conditions explain almost 90% of the NPLs flows observed in the period 2008-16. A micro analysis focusing on the non-financial corporate sector (where most of NPLs originated) relying on a simple counterfactual exercise suggests that at least 50% of defaults were "unavoidable". A combination between a weak corporate sector at the onset of the recession and a weak ability of banks to select borrowers played a role in the rest. Actual or potential criminal behavior by bank managers seems to account for 4% to 8% of total defaults observed among non-financial corporations.

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1. Introduction

The large stock of non-performing loans (NPLs) among EU banks, which at the end of 2016 stood at about €1trillion gross of provisions, has been (and continues to be) the subject of an intense debate among policymakers. While Italy is not the EU country with the highest NPLs/total loans ratio, it stands out as the country with the largest stock in nominal terms, a stock that grew from €94bn to €360bn in gross terms (from 50 to 200bn in net terms[1]) between the end of 2007 and the end of 2015.

Both the sheer level and the potential impact of Italian NPLs raise a question. Why did NPLs grow so much in Italy? Is this just the effect of the severe double-recession that hit Italy between 2008 and 2014? Or is instead the result of some problems specific to Italy (be it on the industrial side or on the banking side)? More broadly, what can be learnt about the bank-specific or firm-specific factors that may help reduce defaults, and hence NPLs? The interest for the answers goes beyond Italy and even beyond the Eurozone, as they have implications for bank managers, supervisors as well as for macroeconomic modeling. In this paper we try to answer these questions.

To do so, we will focus on NPLs flow over the crisis period. The NPLs stock can be affected by sales and resolution: a bank with poor lending standards can display a very low stock of NPLs simply because it sells them. By contrast, the integral of NPLs flows over a certain period fully captures the quality of the lending decision. While the literature on NPLs is in its infancy, if we are concerned about the negative impact of NPLs on lending, Figure 1 seems to suggest that this impact is driven by the flows, not the stock.

We start by comparing the 2008 Italian crisis with previous Italian crises and with other post-2008 European crises. Then, we conduct a micro analysis of the variations of NPLs across Italian banks. From a micro point of view, a loan can become an NPL for a host of reasons, which ultimately boil down to three broad, non-mutually exclusive categories: bad luck (materialization of credit risks), high ex-ante risk taking, or poor lending. An unexpected, exceptional recession can be a good example for the first category; the concentration of lending in high-z-score borrowers, of the second. The third category may include various sub-categories:

[1] Note that the figure that matters for banks' balance sheets is the net one. The gross figure reflects losses, due to provisions or write-offs, reported in previous income statements.

the decision to ignore or misuse soft information on borrowers; poor screening or monitoring¸ incompetent lending, outright fraud.

Whatever its causes, each individual NPL originates in a credit decision typically made years before, based on the information set available at that time. Hence, we try to look at the environment in which credit decisions were made, and then track the loan over time.

We first conduct an analysis based on aggregated data. Given the severity of the crisis, the dynamics of post-2008 NPLs is not unusual in the Italian historical context. Adjusting for the severity of the downturn, the flow of NPLs experienced in the last 9 years is largely consistent with that experienced in previous recessions: macroeconomic fundaments explain almost 90% of the cumulated flow of bad loans. If we compare Italy with other countries that experienced similar GDP losses, or declines in real estate prices, Italy does stand out. In a multiple regression, where we control for changes in real estate prices and changes in GDP, Italy appears to have significantly higher NPLs than the rest of the sample. However, the regression is run on few observations and must be interpreted with caution. Furthermore, the stock of NPLs is proportional to the length of credit recovery procedures (a given new NPL inflow will yield a stock twice as large if credit recovery process is twice as long). The current specification does not control for this potentially important variable, which will be added in a next draft.

Based on stocks data, in the recent Italian crisis NPLs are concentrated in the non-financial corporate sector (72%). This is the result of Italian banks' lending primarily to this sector (at the end of 2016 it accounted for 44% of total loans, vs. 31 for the household sector and 11 for financial corporations) and of the high default rates of corporate loans (see Figure 3). For all these reasons, in trying to explain the rise in NPLs we will focus on the non-financial corporate sector. Within this sector, the hardest hit was Constructions, which in Italy represents 17% of corporate lending. In Constructions the NPL ratio (the ratio between NPLs and total loans) reached 54%. The manufacturing and services sectors were also hit hard, with NPL ratios that reached 24 and 29%, respectively.

NPLs stocks build up due to NPLs flows but are also affected both by NPLs sales and by the speed of credit recovery in court, which is particularly slow in Italy (Djankov et al., 2003) and characterized by a significant variation across regions (Banca d'Italia, 2017). We therefore consider NPLs flows, reducing the magnitude of these problems. We look at the integral of NPL flows in three non-overlapping periods: 2008-2010, 2011-2013, 2014-2016. Thanks to a highly detailed micro-level dataset, comprising observations at the bank-firm level, we can study bank-specific determinants of NPLs, controlling for borrower-specific characteristics and geographic diversity (which absorbs the effect of the speed of the local courts).

First, we analyze bank lending on the basis of ex ante criteria. Of the loans outstanding at the end of 2007, 28% were with borrowers classified as "sound" (z-score from 1 to 4 when the loan was granted).[2] In the three following years, these loans defaulted at an annual rate of 5.6%, roughly half of the overall average. Thus, even if banks had lent to the safest borrowers, they would not have been able to bring the average default rate below that level. The same year, 29% of non-financial corporate loans were classified as "risky" (i.e., with a z-score of 7 and above), with an average ex-post default rate of 19.4%. These loans are responsible for 38% of the amount of loans defaulted in the three following years.

To determine the causes of NPLs we decompose the deviation of each bank's NPL ratio from the national average into four components. The first, which we label "exogenous factors", is the difference in defaults due to the dimensional and geographic characteristics of the pool of clients of a bank. The second, which we label "sector allocation", is the difference in defaults due to the different weights banks put in the lending to the five major sectors (Manufacturing, Construction, Energy, Services, and Others). The third, which we label "risk attitude", is the difference in defaults due to a bank choosing firms in higher/lower z-score categories than the average. The last component is the difference between a bank default rate and the system one, controlling for z-score, province, sector, and dimensional class. We label it "bank residual". It reflects bank-specific random factors not captured by the previous components, as well as factors under the "poor/good lending" category discussed above. The "bank residual" is affected by the decision to ignore or misuse soft information on borrowers; by poor screening or monitoring¸ incompetent lending, etc.. In the analysis we try to distinguish the potential impact of some such causes by using proxies.

The geographical location, firm size characteristics and ex ante riskiness of the borrowers explain a relatively small portion of the overall cross sectional variability in banks' default. This can be due to two causes: either the geographical (say) characteristics do not matter for defaults, or all provinces are hit by the roughly similar shocks (e.g. the exceptional recession). We do not

[2] The classification of z-score in sound, vulnerable and risky is the standard one adopted by the Bank of Italy in its publications (see, for example, Financial Stability Report No. 2 / 2016).

investigate this issue in the current draft; the result of the NPL forecast exercise using aggregated data, illustrated above, is consistent with the latter hypothesis.

The asset allocation and the “bank residual” account for a larger share of the cross-sectional variance of the default rate distribution. The interquartile range of the “bank residual” is by far the largest (7.4 percentage point in the first period, 8.9 pp in the second, 6.6 in the third). Considering that this component captures potentially important elements of a bank lending policy, we study its determinants.

In the first period, four percent of the variability in the “bank residual” is explained by banks’ conditions: more profitable and better capitalized banks seem to select their borrowers better, even after accounting for the different z-scores. A measure of a bank’s overall ability to manage lending accounts for another 5% of the variability of the “bank residual”. Six per cent more is explained by proxies of misconduct and potential crime. We find that banks whose managers have been deferred by the Bank of Italy to the judiciary for criminal prosecution or have been indicted by a judge for a crime different from “usury”, have significantly higher defaults. Banks whose managers were deferred to the prosecutor experienced in the first period a default rate 6pp higher than average. Similarly banks whose manager were indicted for criminal charges had a default rate 3pp higher than average. Overall, given the frequency of misconduct and crime in the sample (8.2 and 7.2%, respectively), these phenomena account for 8% of all defaults. By contrast, the proportion of politicians on boards does not appear to have any effect on a bank’s rate of defaults. The R squares of the regressions over the three periods suggest that 80% to 90% of the variance of the “bank residual” remains unexplained, a result that is rather typical of cross-sectional analysis.

Based on a simple counterfactual exercise relying on the micro data, we reckon that at least 50% of NPLs were unavoidable, because made to firms that were ex-ante very safe. A role in the rest was played by the fragility of the Italian non-financial firms sector coming into the crisis, and by banks’ ability at selecting and monitoring borrowers. A disproportionate concentration in the construction sector was responsible for a 30-40% increase in default in the two latter periods. Banks in the 25th percentile of the “bank residual” distribution experienced a default rate from 30 to 40% lower than the national average, depending on the period. The correlation of the “bank residuals” across contiguous periods is about 30% and about 20% between the first and the third.

The rest of the paper proceeds as follows. Section 2 describes the Italian NPLs in historical and international context. Section 3 presents the data. In Section 4 we analyze the ex-post default based on ax-ante lending criteria. In section 5 we decompose a bank's default into four components: exogenous factors, sectorial allocation, risk policy, and "bank residual". Section 6 concludes.

2. **The Italian NPLs: historical context and cross-country comparison**

To understand Italian NPLs we start from a historical and international comparison.

2.1 The dimension of the phenomenon

The gross stock of NPLs of Italian banks began to increase with the global recession, in 2008-09. Figure 2.a shows that at the end of 2015, when the phenomenon was at its peak, 18% of all loans were non-performing. While there is some discretion in this classification, these figures are computed after the European Asset Quality Review test performed by the European Central Bank, which included the largest banks in Italy. Thus, we can be fairly sure these numbers are representative.

In 2016 the gross stock of NPLs declined by around one point as a share of total outstanding loans. At the end of 2016 the annualized flow of new NPLs fell close to 2 percent of performing loans, the lowest level recorded since 2008 (Figure 2.b). The latest available estimates indicate that the downward trend should continue.

Table 1A breaks down the stock of Italian NPLs at the end of 2016 by type of borrower and by category of non-performing. In Italy NPLs are differentiated in bad debt ("sofferenze") and others. Bad debt, which refers to credit to bankrupt or patently insolvent borrowers, reached 195bn in 2016.

The NPL phenomenon hides considerable heterogeneity across type of borrower. Loans to the public administration and to financial firms have very low level of default (respectively 2,5% and 4.4%). Households default at a much lower rate than firms (see Figure 3). The percentage of NPLs among loans extended to the household sector is only 10.8% vs. the 31% of the loans extended to non-financial corporations and the 25.3% of loans extended to small family firms ("famiglie produttrici"). One reason is that mortgages in Italy are full recourse. Another is that the Italian household sector is much less indebted at aggregate level[3] and the debt is concentrated among the more affluent households (see, XX). Unfortunately, data allowing cross-country separate comparisons for the households and nonfinancial firms sectors are currently unavailable.

Figure 2.B also shows that the emergence of NPLs took place continuously over the crisis; the new NPL rate displays two peaks: 2008-2009 and 2012-14, in concomitance with the two recessions. Focusing on the non-financial corporate sector, the percentage of NPLs at the end of 2016 was 31% (Table 1.B) with an increase of 26 percentage points vis-à-vis the level in 2007. This increase is particularly pronounced in the construction sector, where NPLs reached 55% of the loans, but it is present also in the manufacturing sector (24%) and in the service sector (29%).

Table 1.C shows the distribution of NPL stocks by institutional bank category. We consider joint stock companies (the bulk of the banking system), credit cooperatives (over 300 institutions, typically very small), "popolari" banks (a different form of cooperative banks), and subsidiaries of foreign banks.[4] Except for foreign subsidiaries the NPL ratios are very similar across institutional categories.

Table 1.D shows the geographical distribution of NPLs. The NPL ratios are higher in the South of Italy (26%), much lower for foreign loans (6%), and very similar for the North and the Center (18.9% and 18.5%).

2.2 Are Italian NPLs extraordinarily high?

Italy lost 6.8% of GDP in the biennium 2008-2009. After a short and shallow recovery in 2010 (1.1%), Italy was hit by the euro crisis, which led to an additional 4.8% drop in GDP and a much larger drop in nominal house prices (-19%). There is an obvious endogeneity problem between financial and economic crises. Yet, it is pretty uncontroversial that in the Italian case the initial shocks did not come from the financial sector. The first came from a large drop in international trade following the 2008 financial crisis and the second from the sovereign spread crisis, which forced Italy to a severe contractionary fiscal adjustment. The sovereign spread crisis also jeopardized bank funding, curtailing the ability of banks to lend. Thus, it is possible that

[3] https://data.oecd.org/hha/household-debt.htm

[4] A 2015 law required ten "popolari" banks with total assets greater than €8bn to transform into joint stock companies and eight out of ten did during 2016. For the purpose of this paper we treat them still as "popolari".

bank lending (or lack thereof) might have exacerbated the crisis, but it certainly did not start it. Thus, it is legitimate to ask whether the level of NPLs that materialized in Italy during the 9-year period between 2008 and 2016 was largely driven by the economic downturn.

We try to answer this question in two ways. First, we look within the Italian historical context. This can only be done for the category 'bad debt", for which a sufficiently long time series is available. We estimate the following relationship based on Bofondi and Ropele (2011):

$$BD_t = \beta_0 + \beta_1 BD_{t-1} + \beta_2 g_{t-1} + \beta_3 u_t + \beta_4 GOM_{t-1} + \beta_5 HP_{t-1} + \varepsilon_t,$$

where BD_t is the ratio of the flow of new bad debt in quarter t divided by performing loans at t-1, g_t is the real GDP growth, u_t is the unemployment rate, GOM_t the gross operating margin of nonfinancial corporations, and HP_t Is the annual growth rate of house prices. We estimate the equation over the 1991:1-2007:4 period and then use these estimated coefficients and the actual ex post realization of g_t, u_t, GOM_t, and HP_t to predict NPLs.[5] Note that in predicting BD_t we use the predicted and not actual BD_{t-1}. Figure 4 shows the actual and predicted BD_t.

The two flows are very similar up until 2012, then the model under-predicts the actual flows. To get a summary measure of this under-prediction we back out the cumulated predicted flow of bad debts over the 2007-2016 period, and compare it with the actual one. The ratio between the predicted and the actual flow is close to 90%. This suggests that the surge in Italian bad debt in the 2008-2016 period is largely (although not entirely) explained by the dynamics of macroeconomic fundamentals, under the assumption that elasticities are the same as in the previous big downturn (i.e., the period 1992-1997). Note that in that period a large number of banks were still state-owned. There is evidence that political considerations influenced the way these banks priced credit (Sapienza, 2004).

A complementary exercise is performed by Notarpietro and Rodano (2016). They estimate the bad debt during the crisis period under the counterfactual hypothesis that the crisis would not have occurred. They reach broadly similar results.

The second approach conducts an international comparison. Defining a comparison sample is not easy. What matters is not just the severity of the crisis, but also its length. The decline in house prices also matters, since so much of bank lending is directly or indirectly

[5] The lags of the right-hand side variables are those in Bofondi and Ropele (2011), who estimate the equation over the 1991:1-2011:4. We checked that these lags are adequate also over our estimation period.

linked to real estate prices. Furthermore, the availability of comparable NPLs data is a relatively recent phenomenon. The World Bank (http://data.worldbank.org/indicator/FB.AST.NPER.ZS) collects information on the ratio of the stock of non-performing loans to total loans starting from 1997-1998. From that date, we search all OECD countries that have data on real estate prices in the OECD "Residential Property Prices Indices (RPPIs) (https://stats.oecd.org/Index.aspx?DataSetCode=HOUSE_PRICES) and experienced either a drop of least a 5% in real GDP[6] or of at least 10% in nominal house prices.

We end up with the 22 observations contained in Table 2, all following the 2008 financial crisis. On the one hand, the number of observations is very limited. On the other hand, the sample is relatively homogenous, both for type of shock and for type of country.

Figure 5.A plots the increase in the stock of NPLs during a crisis against the maximum drop in real GDP during the same crisis. Italy is above the linear fit, although it does not stand out. Figure 5.B plots the increase in NPLs during the crisis on the maximum nominal decline in house prices during the same episode. In this case as well, Italy does not stand out but it is above the fitted line.

In Table 3 we estimate a simple linear regression. The left-hand side variable is the peak level in the NPLs ratio (constructed as the gross stock divided by total loans) during each crisis or, alternatively, the difference between this value and its level as of 2007. As explanatory variables we use the change in real GDP and in nominal house prices during the same crisis. When we use the NPLs ratio as a left-hand side variable, the drop in house prices is statistically significant at the 1% level, while the change in GDP is not. When we use the changes in the NPL ratio, both of these variables are statistically significant and explain 55% of the variance. If we insert a dummy for Italy, in both specifications we find that this is positive and statistically significant. The stock of NPLs in Italy seems to be 8 percentage points above than warranted by its economic conditions. Looking at the change in the stock, the effect is reduced to 4 percentage points. The difference between the two estimates is due to the relatively high level of NPLs in Italy before the crisis. The pre-existing level of NPLs can be partly explained by the length of the judiciary credit recovery in Italy, which is high in the international comparison (Djankov et al., 2003).

[6] As computed by the IMF International Financial Statistics (http://data.imf.org/?sk=5DABAFF2-C5AD-4D27-A175-1253419C02D1&sId=1390030341854).

Since Italy had a 12 percentage point increase in NPLs during the crisis, these estimates suggest that at least 2/3 of the increase in NPLs is due to economic conditions. Some of this difference may be explained by the slow courts. The current specification in Table 3 does not control for this potentially important variable, which will be added in a next draft.

This estimate is based on only 22 observations and should be taken with extreme caution. Nevertheless, the similarity between the estimate obtained with the international comparison and the historical one is reassuring and suggests that the vast majority of the surge in the NPLs stock in Italy was due to the macroeconomic conditions.

3. Data

The bulk of the paper focuses on micro data, which we describe in the following section.

3.1 Micro Data on Italy

We have three main data sources. The first is the Credit Register (CR) housed at the Bank of Italy, which contains information on the loan contracts granted by Italian banks. All banks report information on the credit granted and utilized for all loans exceeding a minimum threshold (75,000 euros until December 2008, 30,000 euros afterwards). This data also reports when a loan is past due (payment delay exceeding 90 days) and when it is classified as bad ("sofferenza"). The types of loans include credit lines, credit receivables, and fixed-term loans.

Our second main source is the Company Accounts Data System (CADS), managed by the Cerved Group, which includes balance sheet data covering all Italian limited liability companies. Besides the accounting items, CADS also includes some indicators such as Altman's Z-score (a measure of credit risk).

The third main source is the supervisory reports sent by banks to the Bank of Italy, from which we extract banks balance sheet data.

Table 4 describes our sample. The total amount of loans extended to the 1,241,075 non-financial corporations present in Italy at the end of 2007 was 780.7bn, comprised of 724.9bn of performing loans and 55.8bn non-performing. 29% of the performing loans were extended to non-financial corporation without any financial information in CADS. As we can see from Table 4, the loans extended to these firms tend to be smaller and to default more (18% vs.12.4% in the first period). This is consistent with a priori, as firms that are not required to produce a balance sheet are typically small. Yet, we begin by restricting our analysis to loans for which we have balance sheet data, because only for those we can control for the intrinsic risk of the borrowers.

We exclude from this sample the branches of foreign banks, which tend to make occasional very large loans, and banks specialized in other activities (such as asset management).

We use several additional data sources. To obtain information on bank boards we use the ORgani SOciali (ORSO) dataset. ORSO, managed by the Bank of Italy, contains exhaustive current and historical information on the members of the governing bodies of banks and financial intermediaries (e.g. president, executive director, members of the boards of directors, members of supervisory boards, etc.).

We intersect this dataset with the list of all elected officials from the "Anagrafe degli Amministratori Locali e Regionali from the Interior Ministry web site (www.amministratori.interno.it).

The Bank of Italy is also the source of data on sanctions and referrals to the prosecutor. In the course of its supervisory activity, mainly during on-site inspections, the Bank of Italy may discover potential or actual violations of laws and of secondary regulations, or of laws. In this case e first case, a process is initiated which whereby the violations may give rise to sanctions against the bank or its administrators, statutory auditors and directors. Sanctions are generally of pecuniary nature, but can also cause representatives administrators to temporarily or permanently lose their fit-and-proper status. The sanctions are proposed by the Banking Supervision and regulation directorate and administered by the Board of the Bank of Italy. The sanctioned subjects have a right to be heard during the procedure. They may appeal to a court against the final decision made by the Bank of Italy. The sanctioning measures are published on the Bank of Italy's website.

In case of actual or potential violations of criminal state laws, the Bank of Italy alerts the competent prosecutors, who have judiciary powers and may autonomously decide to start an investigation. These cases are a subset of the sanctioning cases. The relevant data are not published, but they are available to the Bank of Italy so we can use them in the analysis. Unfortunately, we do not have information on the final outcome of these procedures, i.e. whether these referrals do or do not end up in actual convictions. Finally, we used web searches to assemble data on indictments of bank administrators.

3.2 Stock vs. flows

The stock of NPLs on the balance sheet is not a good measure to compare the quality of the lending policy across banks. First, the NPL stock is the result of inflows (when debtors run into difficulties) and outflows, which can be due to the debtor recovering, to a restructuring of the debt, to the conclusion of the internal recovery procedures, or to the bank selling the debt off. Thus, in principle a bank can be a very poor lender, and yet have a very low NPL stock because it succeeded in selling them. Controlling for NPL sales is feasible in principle but hard to do in practice, because consistent data are not available.

Second, the stock is affected by the efficiency of the judicial system. Two otherwise identical banks can display very different NPL stocks if they operate in jurisdictions characterized by a different speed of credit recovery. Assume for example that in area A insolvency procedures take 1 year and in area B they take 5 years, then, the steady state stock of NPLs of banks operating in area A will be five times larger than those in area B. In principle, it is possible to control for the speed of credit recovery procedures. In practice, however, it is complicated. Data are not readily available, either in the international cross-section or at a sub-national level in Italy; furthermore, the speed of execution is also a function of the number of non-performing loans.

For these reasons, in this paper we focus on the gross flow of NPLs. Even this variable entails a set of discretionary choices. For instance, it is necessary to make assumptions about loans that enter the NPL status but exit it after a limited time. Our methodological choices are documented in the data appendix (to be drafted).

4. Ex ante lending policy

In this section we look at key patterns in lending and subsequent defaults based on the information available to the banks at the moment the lending decision was made.

As discussed in paragraph 3.1 above, we focus on the subset of companies that are present in CADS, for which we have financial information and a measure of risk (Altman's z-score). These companies represent 72% of all bank loans in 2007 and 65% of all defaults during the 2008-2010 period.

To analyze the evolution of defaults, we divide the 9 years between the end of 2007 and the end of 2016 into three non-overlapping periods, each with a length of 3 years. In each of these periods of analysis (which we label ex post) we analyze default rates based on variables measured in a preceding two-year window (ax ante). For instance, the defaults between Jan 2008 and Dec 2010 are analyzed on the basis of the z-score measured in December 2005 or on the basis of the credit expansion between December 2005 and December 2007.

Figure 6 helps understand how the preceding two-year windows of later periods overlap with previous periods of analysis. It is important to stress that there is never an overlapping between the three periods of analysis, or between periods of analysis and periods in which the sorting variables are measured. The other two periods are designed in an identical fashion.

4.1 Lending dynamics

In Table 4 we group firms based on the dynamics of their bank credit during the ex-ante period. For example, in Panel A, which covers the period 2008-2010, we sort firms based on the credit expansion in the biennium 2006-2007.

In this period, roughly half of the firms saw an increase in their loans, while the remaining half saw their loans stable or declining. The ex post default of the two groups suggests that firms that received more loans experienced a higher default rate (13.7% vs. 10.6%). Thus, in the two years before the crisis the active lending policy was increasing risk.

This pattern disappears in the 2011-13 period (Panel B), where ex-post default rates among firms that experienced an increase or a decrease in loans becomes equal (17.3% vs. 17.2%). This phenomenon is taking place within the context of no-growth in aggregate lending.

The original pattern inverts in the 2014-16 period (Panel C), where the ex-post default rate among firms that experienced an increase in loans drops to 11.9% vs. 15.6% for those experiencing a decrease.

This is a very reduced form analysis. The increase/decrease in loans is driven both by demand and supply. Firms experiencing a loan reduction can be both firms that are doing so well that they do not need loans any more, and firms so in trouble that their lines of credit have been reduced. A better way to identify an active lending policy is to look at new clients, i.e. firms that were not borrowing from a bank at the beginning of the ex-ante period (i.e., January 2006), but had a bank debt at the end (i.e., December 2007). These new clients are reported in the first line of the table.

This analysis of new clients broadly confirms the previous results. In the first period, the new clients have a higher frequency of defaults. It is only in the third period that they do better than the rest, a sign of a more prudent lending policy. It is important to keep in mind that new clients differ on many dimensions from existing ones. In particular, their average loan size is much smaller than average (in the 2008-2010 period, 0.6mln vs. an average of 2.3mln).

4.2 Z-score

To gain further insight into these patterns, we look at key firms' characteristics at the time these lending/borrowing decisions were made. In Table 5 we rank firms based on their ex ante z-score. Consider the top panel (z-score measured at end 2005; defaults observed over the Jan. 2008 - Dec 2010 window). First of all, z-scores are highly predictive of future defaults. The frequency of ex-post defaults increases almost homogenously with the z-scores of firms.

Aggregating loans extended to firms in the "sound" category (z-scores from 1 to 4), we find that the average default rate was 6%, vs the 15% for firms in the "vulnerable" category (z-scores 5 and 6) and 22% for firms in the "high risk" category (z-scores from 7 to 9).

In this period the credit to "vulnerable" firms grew at a rate 15 to 20%. Thus, it is legitimate to ask whether a more prudent lending policy could have substantially reduced the flow of new NPLs.

To this end we conduct the following counterfactual exercise: we assume that in the biennium 2006-2007 banks refused to extend additional credit to firms that were in the "vulnerable" and "high risk" categories. To compute the counterfactual, we assume that the default rate in these categories remains the same as that observed in reality.[7] In this scenario, there would have been 40bn less loans and 6.2bn less NPLs. Thus, the flow of NPLs during this period would have dropped by 10%.

Overall, the patterns identified in 2007 seem to repeat themselves in the two subsequent periods, with a few important differences. First, the pattern linking credit extension and z-score is broadly confirmed across the three sub-periods (Figure 8), but with a large shift in the mean. While credit was growing at a 16% rate during the biennium 2006-7, it was shrinking at 1.5% during the biennium 2008-2010, and at 13% in 2012-3.

A second difference is that the overall level of defaults seems to increase, especially in the "sound" category. While in the first triennium only 6% of the sound firms at the beginning of

[7] Of course, this is an arbitrary assumption, as a credit squeeze such as the one hypothesized might have caused a larger number of defaults.

the period defaulted during the following three years, in the second triennium 10% defaulted, and in the third 8% did.

If we accept the z-score as a measure of risk in lending, it is safe to say that defaults incurred on loans made to "sound" firms are due to "bad luck" (i.e., the recession) and not to risky lending. The opposite is not necessarily true. If we sum the default across the three periods (weighting it by the size of the loans) we obtain that 18% of the total default occurring across the three periods happened in firms with "sound" ex-ante credit conditions; 46% of defaults come from the "vulnerable" category and 36% from the "risky strategy." These percentages are misleading if not related to the fraction of lending in the various categories: 35%, 39%, and 26%. A better way to interpret these results is through the following counterfactual. If banks had extended loans only to firms in the sound category (assuming enough such firms existed in the system), the average rate of default over the three periods would have been 7.9% instead of the actual 15.1%. Since it is inconceivable to have a more prudent lending policy, we can conclude that at least half of the defaults are due to bad luck.

We replicated the above counterfactual with an alternative measure of ex-ante riskiness of the firms, leverage (debt over debt plus equity). The results are very similar. If banks had made loans only to low leverage firms (those with leverage below…), the average rate of default over the entire period would have dropped to 9.7%.

4.3 Size of loans

It is also important to break down default rates by size of loans. There is a fixed cost in credit screening. Thus, we should expect less discretionary screening for smaller loans and thus a higher rate of default. As Table 6 shows, this is true, but only up to a point.

During the first period, small loans (<100K) have an average rate of default equal to 16%, higher than the 11.6% average. In the immediate next category (between 100K and 500K) the average rate of default drops to 12.4% and in the category 500K to 1M, drops even further to 11.8%. After that, however, in all the bigger categories except the last one, the rate of default remains flat. This pattern is not specific to the first period. In fact, in the two subsequent periods the minimum default rate is reached in the 100K to 1M category, and then the default rate increases up to the category between 2.5 and 5M, before declining again for the higher categories.

As bigger loans should be subjected to the scrutiny and the discretion of senior bankers, the observed pattern casts doubts on the value added of this discretionary lending policy applied by banks.

5. Determinants of ex-post defaults

5.1 Decomposition of banks' defaults

A loan can become an NPL due to a host of reasons, which ultimately boil down to three broad categories: idiosyncratic (materialization of credit risks), high ex-ante risk taking, or bad lending. To make inference on these determinants, we assign firms to "cells", identified based on the province of location of each non-financial firm, its sector of activity, size, and level of risk (measured by the z-score). We compute the bank-specific default rate in each "cell", in deviation from the (weighted) average of the cell. We then aggregate the various cells to end up with a single figure for each bank, which can be below or above the mean. In a similar vein, we compute the average default rate in each "cell" across in deviation from the national average.

We define as "exogenous" the component driven by operating in a given geographical area, characterized by a certain distribution of potential borrowers with a given size and sectorial distribution. For instance, an idiosyncratic economic shock affecting a province or region will hit hard a small bank operating in that province or region. In this case, there is little that the bank can do avert the shock. In a similar vein, each region will be characterized by a certain distribution of firm size and sector, which in the short-term is given, and therefore can be viewed as an exogenous variable from the small bank's viewpoint. Of course, these environmental constraints are not truly "exogenous", as a bank can always decide not to lend, e.g. to a given sector. However, this will tend to be more difficult if that sector is predominant in a given region.

We define as "risk attitude" the choice by the bank to lend to a given distribution of borrowers by z-score. We define as "banks residual" the rest. Formally, let $Def_{b,\mathrm{a},z}$ be the default rate of bank *b* in the z-score category *z*, in "area" *a*, where we group into "area" not only the geography, but also the distribution by size and sector of the firms in the area. Then we have:

(1)

$$\sum_{a,z} w_{b,a,z} Def_{b,\mathrm{a},z} - Def_{\bullet,\bullet,\bullet} \equiv \sum_{a,z} \underbrace{w_{b,a,z}[Def_{\bullet,\mathrm{a},\bullet} - Def_{\bullet,\bullet,\bullet}]} + \sum_{a,z} \underbrace{w_{b,a,z}[Def_{\bullet,\mathrm{a},z} - Def_{\bullet,\mathrm{a},\bullet}]} + \sum_{a,z} \underbrace{w_{b,a,z}[Def_{b,\mathrm{a},z} - Def_{\bullet,\mathrm{a},z}]}$$

"Exogenous" "Risk Attitude" "Bank Residual"

where $w_{b,a,z}$ is the proportion of loans by bank *b* to firms in area *a* with z-score *z*, and $\bullet$ indicates the average with respect to that index. Thus, we can label the first term in brackets, which represents the contribution to default given by the fact to be in a bad or a good "area", as "exogenous". As argued above, this component cannot be considered truly exogenous from the bank's viewpoint.

The second term in brackets reflects the z-score composition of a bank portfolio with respect to the average z-score of the bank system. Thus, this is the difference in defaults due to the risk policy adopted by a bank. Note that we do not take any position on whether this risk policy is optimal or not. To answer this question we would need to know at least the interest rates at which this lending took place and the recovery rate in case of default. The third term in brackets, the "bank residual", is a component which includes random noise, not captured by the previous two components. For instance, in a finite population of firms affected by random shocks, two identical banks lending to identical firms may end up with different default rates. The residual includes such noise. However, it should also include the host of factors that we grouped above under the "poor/good lending" label. For instance, a strongly positive residual can result from a bank's poor ability to screen ex-ante borrowers, or to monitor them, or by corrupt lending. In what follows we try to disentangle the potential impact of some such causes by using proxies.

We have labelled the term $\sum_{a,z} w_{b,a,z}[Def_{\bullet,\mathrm{a},\bullet} - Def_{\bullet,\bullet,\bullet}]$ as "exogenous". This term is composed of two elements: the sheer good (bad) luck to be lending in an area with good (bad) firms and the strategic choice of lending more or less in some sectors. Since we know that the construction sector has been particularly devastated, much of what we call idiosyncratic may be driven by the weight of the construction sector in a particular bank. To account for these differences we further decompose this term into two terms in the following way:

$$(2)\quad \sum_{a,z} w_{b,a,z}[Def_{\bullet,\mathrm{a},\bullet} - Def_{\bullet,\bullet,\bullet}] \equiv \sum_{a,z} w_{\bullet,a,z}[Def_{\bullet,\mathrm{a},\bullet} - Def_{\bullet,\bullet,\bullet}] + \sum_{a,z} (w_{\mathrm{b},a,z} - w_{\bullet,a,z})[Def_{\bullet,\mathrm{a},\bullet} - Def_{\bullet,\bullet,\bullet}]\ ,$$

where $w_{\bullet,a,z}$ is the average weight the sector *a* with z-score *z* across all banks. In this way, the first term on the right hand side of (2) is sheer luck and the second one is the impact on default of the strategic choice of in which sectors a bank lends.

In the "area" components we consider 110 provinces, five dimensional classes (micro, small, medium, big, top), and five sectors (manufacturing, constructions, services, energy, and others). We then group the z-score in three categories (stable, vulnerable, and risky). We consider as bank any lending institution with a separate board of directors, so we might have multiple banks from the same banking group.

In Table 8 we report the summary statistics of the three components of default: the composition of borrowers in the region (including region, firm size, and sector), the ex-ante risk (Z-score) and the bank-specific component. In the first period (Panel A), the standard deviation of the first component amounts to 1.8%, of the second to 1.5%, and of the third 9.4%. Thus, the bank-specific component accounts for the big part of the cross sectional variability of loans defaults. The numbers are almost identical in the third period (Panel C), while they are almost double in the second one (Panel B). The ranking, however, is the same: the bank component represents the bigger component.

5.2 A Graphical Illustration

Figure 8 presents box plot illustration of the above decomposition for the three periods considered in this paper. The rectangular boxes represent the inter-quartile distribution, with the median marked by the middle line. The whisker bars represent the adjacent value to 1.5 times the interquartile range. The "bank residual" component is represented in blue, the risk policy in red, the sectorial allocation in green, and the exogenous factor component in yellow.

As the figure show very clearly, variation in the exogenous factors or in risk taking have very little explanatory power in the first period. The banks with the better sectorial allocation (25% of the distribution) have a default rate that is 1 percentage point below the national average. The same is true for the safer banks (25% of the distribution). This impact increases a bit in the subsequent periods, in particular the third one.

The bulk of the variation is in the "bank residual". In the first period, better lenders (25% of the distribution) have 5.6 percentage points less defaults, i.e., experience only 60% of the default rate experienced by the system, in the second period 70%, and in the third period 60%.

5.3 Determinants of the risk attitude

In Table 9 we explore the determinants of a bank's risk policy. The dependent variable is the component of defaults during a certain period that is due to the ex-ante choice of the composition of Z-score of borrowers (i.e., the second term in brackets in equation (1)). As explanatory variables we use bank level information, mostly financial variables.

When we look at the first two columns, concerning the period 2008-2010, we notice that a higher return on equity preceding the sample period is associated with lower level of risk taking, but the effect is small: one standard deviation increase in return on equity is associated with only 46 basis point more of defaults (4% more). A higher cost-to-income ratio has a negative and statistically significant coefficient on defaults due to risk taking: one standard deviation increase in the cost-to-income ratio is associated with only 25 basis point more of defaults (2% more).

When we look at the bank-size categories, we see that top and small banks (the omitted category) have fewer defaults due to an ex-ante choice of high z-score firms, with big banks having 1.5 pp more defaults, and medium banks .8pp more.

Accounting variables are a proxy of bank's lending policy, but only a very rough one. Ideally, we would like to have a direct measure of the quality and sophistication of the lending policy of each bank. One indicator of sophistication is the use of standardized procedures for lending, especially for household lending. For this reason, we compute the "bank residual" on household defaults in the same way in which we have computed the left hand side measure for corporate loans. When we insert this variable in the specification (column 2) appears to have a positive, but not statistically significant effect.

The results are similar in the subsequent periods, with the only difference that Tier-1 ratio becomes statistically significant in the third period. During 2014-16 more capitalized banks tend to have 39 basis points fewer defaults due to risk taking (3.4% less). Thus, we do find some evidence of moral hazard, but quantitatively small.

5.3 Determinants of the "bank residual"

In Table 10 we repeat the same exercise with the component of defaults that is due to the ex-ante choice of the borrowers per given z-score and geographical, sectorial, and dimensional characteristics of a client (i.e., the third term in brackets in equation (1)).

In column 1 of Table 9 the specification relates this measure on some financial characteristics of the banks. We find that better capitalized banks appear to experience less defaults. One standard deviation increase in Tier-1 ratio is associated with a 76 basis point decline in defaults. A similar effect has a bank's return on equity preceding the sample period, but one standard deviation increase in ROE has twice the impact in term of reduced default of a one-standard deviation increase in Tier-1 ratio. All these coefficients are statistically different from zero at the 5% level.

Interestingly, the cost-to-income ratio has a negative and statistically significant coefficient. One standard deviation increase in the cost-to-income ratio is associated with a 1.3 percentage point decline in defaults. A possible interpretation of this result is that selecting good borrowers is expensive and thus banks need to pay to obtain certain results. Finally, medium banks appear to have 2.5 percentage points more defaults than the average. The overall explanatory power of the regression is relatively modest (4%).

In column 2, we insert the component of household defaults due to a bank's choice of borrowers. Banks with a worse record of defaults among households tend to have also a worse record in corporate loans. One standard deviation increase in households' defaults is associated with a two percentage point increase in corporate defaults. The other coefficients are fairly unchanged, except for the dummy variables for bank size, where the coefficients drop by a third, suggesting that these bank dimensional variables were partially capturing the sophistication of banks.[8] Now a small bank that was a one-standard deviation better on all the dimensions (including the household defaults) would have experienced a default rate 57% below the mean, a large bank 70% below the mean.

In column 3 we insert another possible proxy for the quality of a bank. We use a bank's delay in recognizing bad loans. In the Italian credit registry system, a bank classifying a debt as bad ("sofferenza") is required to communicate this to all of the other banks. The other banks are not forced to classify the debt in the same way, yet it is generally a good idea to do so. We use the percentage of bad loans not yet classified by a bank as such as a proxy of the quality of a bank internal control system. On average, just 10% of loans are misclassified, but for some banks

[8] All the specifications in Table 9 have been estimated both with and without the measure of excess household defaults. The results are substantially the same.

this number is as high as 60%. When we insert this variable in the specification used in column 2, it exhibits a positive coefficient, marginally statistically significant.

In column 4 we introduce the number of sanctions imposed by the Bank of Italy on each bank during this period (see Section 3.1 for a description of the sanctioning process). During this period 16% of the banks received a sanction; a few received two. These sanctions tend to be grouped into two categories: weak internal controls and failure to communicate relevant information to the Bank of Italy. In some cases, sanctions may be the consequence of violations of norms that have no bearing with the credit process. The coefficient of this variable (positive and statistically significant at the 1% level) seems consistent with the view that sanctions reflect real problems in the credit allocation mechanism. The default rate of sanctioned banks is 3.4 percentage points higher than average (29% above the mean).

This result is only strengthened when we look (column 5) at the cases in which the Bank of Italy referred bank managers to the judicial authority for possible prosecution. These referrals are much less frequent than the fines (roughly half) and they are not in the public domain. Banks whose management was referred for prosecution exhibit 6.8 percentage point higher defaults (57% above the mean). This coefficient is statistically different from zero at the 1% level.

Bank of Italy referrals for prosecutions are not the only source of prosecutions bank managers faced. To identify the others, we looked at the CEO and general directors of all of the banks in the sample for the period 2007-2009 and searched the Internet for the combination of the manager's name, the name of the bank, and the word "indicted" ("rinviato a giudizio," note that at the time only 1% of the managers were women). We then manually look at the first 25 search results in order to see whether there was any news of indictment. We ignore those results where the manager is only under investigation and focus solely on actual indictments ("rinvio a giudizio") decided by a judge. Based on this measure, 10% of the managers in our sample received an indictment. Yet, 25% of those are for "usury," a crime difficult to define and not necessarily related to bad lending. Thus, we drop these results and focus on the other indictments, mostly for fraud, money laundering, or racketeering.

Default at banks with indicted managers is 4.0 percentage points higher (34% more than the mean). This coefficient is statistically different from zero at the 1% level. When we combine both the Bank of Italy referral and the actual indictments (Column 8), both variables have a positive and statistically significant coefficient. If we multiply the in-sample frequency of referrals and indictment by their estimated coefficient, we obtain the result that roughly 8% of the defaults during the triennium 2008-2010 are associated with actual or potential criminal behavior.

Historically, the Italian banking system has been heavily affected by political intervention (Sapienza (2004)). Even after the 1990s privatizations, many current and former politicians have remained on the boards of banks, especially smaller ones. Since one possible reason for bad lending might be political pressure, we compute the fraction of bankers who ever held a political position by merging the ORSO database with the dataset of local administrators. On average, 27% of the board members have political experience, with a huge variation, from 0 to 77%.

In column 7 we insert this proportion into our basic specification. The coefficient is positive, but statistically insignificant, suggesting that politicians on boards do not seem to be responsible for bad lending.

Thus far, we have only looked at Panel A, which analyzes the defaults in the triennium 2008-2010, i.e. the default following the big decline in international trade caused by the 2008 financial crisis. During this period house prices are still fairly stable.

Panel B analyzes the defaults in the triennium 2011-2013, i.e. during the euro crisis. The main difference in this panel is the household defaults have a much smaller coefficient not statistically significant. The other difference is that Big and medium banks have roughly three percentage point more defaults than the rest. For the rest, the results are very similar, with sanctions and referrals having a smaller effect and indictment having an insignificant effect on the percentage of defaults.

By contrast, Panel C, which analyzes the defaults in the triennium 2014-2016, present quite a different picture. First of all, past lending growth has a *negative* and statistically significant effect on corporate defaults. It seems to suggest that firms are defaulting because they do not receive enough credit. However, it may also capture banks' attempt at cutting credit to firms that they expect to be non-viable.

Referrals of bank managers for criminal prosecution maintains their impact on default, while indictments are not statistically significant. One possibility is that the nature of later defaults is very different from earlier ones, the other is that there is not enough time for the criminal indictment to go through.

As we saw above, banks in the 25th percentile of the “bank residual” distribution experienced a default rate from 30 to 40% lower than the national average, depending on the period. To gauge the level of persistence of this performance we look at the rank correlation of the “bank residuals” across the three periods. Table 12 shows that banks are not consistently under-or over-performers: the rank correlation is relatively low. This confirms that the random component of the “bank residual” plays an important part.

5.4 Determinants of the Sectorial Allocation

In Table 11 we estimate the determinants of the components of default due to the sectorial composition of a bank’s portfolio vis-à-vis the national average. Banks that experienced a higher growth in lending have a higher default due to their sectorial composition in the first period, the opposite is true in the third period.

Banks with a worse record of defaults among households tend to have also a worse record in non-financial corporate loans.

5.5 What Caused Bank’s Failures?

Thus far, we have tried to explain the rate of loan defaults experienced by all banks. Clearly, it is of special interest to understand what caused some banks to be so distressed to require regulatory intervention. Confidentiality rules prohibit us from undertaking this analysis at the bank level. We can, however, explore how the banks in trouble collectively fared in the three dimensions we decomposed defaults into. We define a bank as “in trouble” if it is under strict supervision of the Single Supervisor, if it is a large bank, or of the bank of Italy, if it is small.

We compute the “exogenous factors”, “sector allocation”, risk attitude”, and “bank residual” components for this group of banks. During the 2008-10 period, this group of banks had no more defaults due to exogenous factors, 2.5 percentage points more defaults do to sectorial allocation, 0.05 pp more defaults due to risk attitudes, and 4.4 pp more defaults due to the “bank residual”. During the 2011-13 period, this group of banks had 0.1 pp more defaults due to exogenous factor, 4 pp due to sector allocation, 1.1 risk attitudes, and 4.5 pp due to the “bank residual”. During the 2011-13 period, this group of banks had 0.20 pp more defaults due to exogenous factors, 4.2 percentage points due to sector allocation, 1.1 pp due to risk attitudes, and 3.2 pp “bank residual”.

Thus, banks' troubles seem to be only marginally due to aggressive risk taking ex-ante. Throughout the three periods, the "bank residual" accounts for a large fraction of the difference of the default rate of these banks and the national one, with the wrong sectorial allocation a close second in the last two periods. This decomposition does not emphasize a potential link between the quality of screening and the sectorial allocation in construction. One hypothesis is that constructions may be more difficult to screen according to standard balance sheet information. Thus, there is more arbitrariness in lending. As Figure 9 shows, the more loans are made to the construction sectors the bigger is the variance in the "bank residual".

7. Conclusions

We try to uncover the causes of the surge in Italian NPLs following the 2008 financial crisis and the 2011 eurozone crisis. From a macro perspective this surge is not abnormal in the Italian historical context: macroeconomic conditions explain almost 90% of the NPLs flows observed in the period 2008-16.

From a micro perspective, we find that at least 50% of the defaults were inevitable: good ex-ante lending turned sour. It is more difficult to allocate precisely the responsibility for the remaining half. One important factor is the fragility of the Italian private sector coming into the crisis: 35% of corporations, representing 39% of the credit granted, had a leverage above 75%. A disproportionate concentration in the construction sector was responsible for a 30-40% in default in the two latter periods. The ex-ante choice of risk, based on z-scores, cannot explain much of the variation in actual defaults. The better banks were able to cut the defaults by 30 to 40% depending on the period.

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Table 1: Italian Non Performing Loans: Gross Exposures as of Dec 31st 2016

(bn euro and percentage points)

Panel A: By Type of Borrowers

	Total	Public Administration	Financial Corp	Households	Family firms	Non Financial Corporations	Foreign residents and other
Loans	1,616.4	45.5	190.8	493.8	85.1	719.0	82.2
Bad Loans	190.6	0.4	3.2	35.1	15.2	134.7	1.9
Other	120.9	0.7	5.2	18.1	6.3	87.1	3.5
Total NPLs	311.6	1.1	8.5	53.2	21.5	221.8	5.4
NPLs ratio	19.3%	2.5%	4.4%	10.8%	25.3%	30.8%	6.6%

Panel B: By Economic Sector

	Manufacturing	Construction	Services	Other	Non Financial Corporations
Loans	188.2	116.1	364.2	50.6	719.0
Bad Loans	29.9	38.7	61.4	4.7	134.7
Other	14.6	24.1	43.8	4.6	87.1
Total NPLs	44.5	62.8	105.2	9.3	221.8
NPLs ratio	23.6%	54.1%	28.9%	18.3%	30.8%

Panel C: By Bank Institutional Category

	Total	Joint stock companies	Popolari	Cooperative credit banks	Subsidiaries of foreign banks
Loans	1,616.4	922.3	394.6	132.7	166.9
Bad Loans	190.6	116.8	45.5	14.6	13.7
Other	120.9	66.3	36.6	10.8	7.2
Total NPLs	311.6	183.0	82.1	25.5	20.9
NPLs ratio	19.3%	19.8%	20.8%	19.2%	12.5%

Panel D: By Geographical area

	Total	North	Center	South and islands	Foreign
Loans	1,616.4	887.1	404.8	251.8	72.6
Bad Loans	190.6	99.7	46.5	43.1	1.3
Other	120.9	68.3	27.8	21.9	2.9
Total NPLs	311.6	168.0	74.4	65.0	4.2
NPLs ratio	19.3%	18.9%	18.4%	25.8%	5.8%

Source: Individual Supervisory Reports.

Table 2: International Comparison

The table selects the OECD countries that have data on real estate prices in the OECD “Residential Property Prices Indices (RPPIs) (https://stats.oecd.org/Index.aspx?DataSetCode=HOUSE_PRICES) and experienced either a drop of least a 5% in real GDP (as computed by the IMF International Financial Statistics (http://data.imf.org/?sk=5DABAFF2-C5AD-4D27-A175-1253419C02D1&sId=1390030341854) or of at least 10% in nominal house prices.

Country	Last year	Real GDP growth	Real estate Prices	NPLs pre crisis	Max NPLs	Change in NPLs
Denmark	2016	-0.05	-0.18	0.01	0.06	0.05
Estonia	2016	-0.17	-0.43	0.01	0.05	0.05
Finland	2015	-0.08	0.00	0.00	0.01	0.00
Germany	2010	-0.06	0.01	0.03	0.03	0.00
Greece	2015	-0.27	-0.42	0.05	0.37	0.32
Hungary	2015	-0.07	-0.16	0.03	0.17	0.14
Iceland	2014	-0.10	-0.12	0.00	0.18	0.18
Ireland	2016	-0.09	-0.53	0.01	0.26	0.25
Israel	2008	0.09	-0.10	0.09	0.08	-0.01
Italy	2015	-0.09	-0.19	0.06	0.18	0.12
Japan	2012	-0.06	-0.05	0.02	0.02	0.01
Latvia	2015	-0.19	-0.44	0.01	0.16	0.15
Lithuania	2016	-0.15	-0.35	0.06	0.24	0.18
Luxembourg	2010	-0.06	0.02	0.00	0.01	0.00
Netherlands	2016	-0.04	-0.19	0.02	0.03	0.02
Portugal	2016	-0.08	-0.18	0.03	0.12	0.09
Slovak Republic	2016	-0.05	-0.20	0.02	0.06	0.03
Slovenia	2016	-0.10	-0.23	0.04	0.15	0.11
Spain	2016	-0.08	-0.35	0.01	0.09	0.08
Sweden	2010	-0.06	0.01	0.00	0.01	0.01
United Kingdom	2013	-0.05	-0.13	0.01	0.04	0.03
United States	2015	-0.03	-0.19	0.01	0.05	0.04

Table 3: Determinants of NPLs in the cross-section

The dependent variable "Level of NPLs at the peak" is the stock of NPLs at the peak during the crisis period divided by total loans. The variable "Changes in NPLs" is the difference between the previous variable and its value in 2007. "Change in real GDP" is the maximum drop in real GDP during the same crisis; "Change in house prices" is the maximum nominal decline in house prices during the crisis period. Robust standard errors are in brackets.

	Level of NPLs at the peak		**Changes in NPLs from trough to peak**	
Change in real GDP	-0.44	-0.43*	-0.55**	-0.54*
	(0.35)	(0.31)	(0.25)	(0.26)
Change in house prices	-0.29***	-0.30**	-0.25**	-0.26**
	(0.10)	(0.10)	(0.10)	(0.10)
Italy dummy		0.08***		0.04***
		(0.02)		(0.01)
Constant	0.01	0.01	0.01	-0.01
	(0.02)	(0.03)	(0.02)	(0.02)
R-squared	0.52	0.55	0.58	0.63
N	22	22	22	22

Table 4: From Universe of Non-Financial Corporations to Our Sample

In each period we start from the total loans granted by banks to non-financial corporations (i.e., 781bn). This figure is the 2007 equivalent of the 719bn of Table 1.A. Then we exclude the non-performing loans. Then we exclude the loans made by branches of foreign banks and by banks specialized in other activities (such as asset management). “Firms without bs data” are firms not belonging to CADS, and thus firms for which we do not have balance sheet information.

Panel A: First period: Loans as of 2007 and defaults in the following three years

	Number	**Loans 2007 (€mln)**	**Av loan size (€mln)**	**Credit growth 2005-07 (%)**	**Flow of defaulted loans (€mln)**	**Def rate (%)**
			Including non-performing loans			
Firms without bs data	839,333	234,863	0.3	39.1	36,888	
Firms with bs data	401,742	545,827	1.4	15.5	64,666	
Total	1,241,075	780,690	0.6	22.0	101,554	
			Excluding non-performing loans			
Firms without bs data	691,836	204,602	0.3	53.4	36,888	18.0
Firms with bs data	370,736	520,308	1.4	17.8	64,666	12.4
Total	1,062,572	724,909	0.7	26.6	101,554	14.0
			Excluding non-performing loans and specialized banks			
Firms without bs data	682,998	190,744	0.3	52.1	34,135	17.9
Firms with bs data	368,243	481,311	1.3	17.9	62,267	12.9
Total	1,051,241	672,055	0.6	26.5	96,402	14.3

Panel B: Second period: Loans as of 2010 and defaults in the following three years

	Number	**Loans 2010 (€mln)**	**Av loan size (€mln)**	**Credit growth 2005-07 (%)**	**Flow of defaulted loans (€mln)**	**Def rate (%)**
			Including non-performing loans			
Firms without bs data	811,591	228,495	0.3	19.6	36,201	
Firms with bs data	457,065	614,096	1.3	-3.8	92,584	
Total	1,268,656	842,591	0.7	2.0	128,784	
			Excluding non-performing loans			
Firms without bs data	627,804	175,379	0.3	28.1	36,201	20.6
Firms with bs data	408,649	539,715	1.3	-1.7	92,584	17.2
Total	1,036,453	715,093	0.7	4.8	128,784	18.0
			Excluding non-performing loans and specialized banks			
Firms without bs data	619,990	168,235	0.3	29.4	34,882	20.7
Firms with bs data	405,556	501,837	1.2	2.3	88,100	17.6
Total	1,025,546	670,073	0.7	8.4	122,982	18.4

Panel C: Third period: Loans as of 2013 and defaults in the following three years

	Number	Loans 2013 (€mln)	Av loan size (€mln)	Credit growth 2005-07 (%)	Flow of defaulted loans (€mln)	Def rate (%)
			Including non-performing loans			
Firms without bs data	820,856	201,236	0.2	-8.4	21,734	
Firms with bs data	486,808	557,941	1.1	-17.8	60,128	
Total	1,307,664	759,177	0.6	-15.4	81,862	
			Excluding non-performing loans			
Firms without bs data	568,124	110,105	0.2	-3.7	21,734	19.7
Firms with bs data	420,356	431,463	1.0	-18.4	60,128	13.9
Total	988,480	541,568	0.5	-15.5	81,862	15.1
			Excluding non-performing loans and specialized banks			
Firms without bs data	551,027	103,926	0.2	-4.1	20,895	20.1
Firms with bs data	413,373	401,083	1.0	-16.6	57,972	14.5
Total	964,400	505,009	0.5	-14.1	78,868	15.6

Table 5: Defaults of Non-Financial Firms as a Function of their initial credit dynamics

Panel A: NPLs flows in 2008 - 2009 -2010

Granted credit growth	Firms	Loans 2007 (mil)	Average loan size 2007 (mln)	Granted credit growth 2005-07 %	Leverage 2005	Change Leverage 2005-07	Z score 2005	NPLS at default (mln)	Default rate (%)
No loans in 2005, but loans in 2007	33,189	19,360	0.6	.	45.6	13.0	.	2,643	22.8
Increasing loans	127,051	575,959	4.5	47.0	50.0	7.7	5.0	44,591	13.7
Stable loans	31,958	60,047	1.9	0.2	50.1	-3.3	4.8	3,275	10.6
Decreasing loans	85,573	190,797	2.2	-35.2	59.2	-3.1	5.2	10,914	9.8
Loans in 2005 but not in 2007	27,602	0	0.0	.	58.5	-8.0	5.4	.	.
Loans <75.000€ in 2005	5,024	1,206	0.2	146.2	46.0	3.7	5.2	130	18.6
No loans in 2005 and 2007 but loans in 2008-10	57,846	0	0.0	.	56.9	-5.5	.	629	.
Total	368,243	847,368	2.3	16.2	54.1	1.9	5.1	62,181	12.9

Panel B: NPLs flows in 2011 - 2012 -2013

Granted credit growth	Firms	Loans 2010 (mil)	Average loan size 2010 (mln)	Granted credit growth 2008-10 %	Leverage 2008	Change Leverage 2008-10	Z score 2008	NPLS at default (mln)	Default rate (%)
No loans in 2008, but loans in 2009	71,839	16,884	0.2	.	55.5	1.5	.	2,661	25.2
Increasing loans	113,361	392,805	3.5	32.9	49.1	4.8	4.9	39,989	17.3
Stable loans	35,577	78,238	2.2	-0.2	60.2	-1.3	5.2	8,083	18.0
Decreasing loans	131,666	342,310	2.6	-28.8	56.2	-2.7	5.3	36,750	17.2
Loans in 2008 but not in 2009	20,583	0	0.0	.	61.4	-6.8	5.4	.	.
Loans <75.000€ in 2008	6,078	934	0.2	102.8	39.2	1.0	5.2	140	24.3
No loans in 2008 and 2009 but loans in 2011-13	25,475	0	0.0	.	49.2	-1.2	.	286	.
Total	404,579	831,171	2.1	-1.5	54.4	-0.4	5.2	87,909	17.6

Panel C: NPLs flows in 2014 - 2015 -2016

Granted credit growth	Firms	Loans 2013 (mil)	Average loan size 2013 (mln)	Granted credit growth 2011-13 %	Leverage 2011	Change Leverage 2011-13	Z score 2011	NPLS at default (mln)	Default rate (%)
No loans in 2011, but loans in 2012	19,996	11,927	0.6	.	58.3	1.7	.	717	10.4
Increasing loans	71,902	229,269	3.2	27.4	55.9	1.7	4.7	16,217	11.9
Stable loans	35,312	56,418	1.6	-0.7	45.7	-2.6	4.8	5,299	16.2
Decreasing loans	165,275	348,764	2.1	-32.8	56.3	-1.5	5.1	34,632	15.6
Loans in 2011 but not in 2012	45,572	0	0.0	.	49.9	-11.5	5.6	.	.
Loans <75.000€ in 2011	44,231	3,678	0.1	54.8	41.6	-0.4	4.9	379	17.8
No loans in 2011 and 20013 but loans in 2014-16	31,085	0	0.0	.	51.6	-0.1	.	443	.
Total	413,373	650,055	1.6	-13.0	55.0	-0.8	5.0	57,686	14.5

Table 6: Defaults of Non-Financial Firms as a Function of their Z-score

Panel A: NPLs flows in 2008 - 2009 -2010

Z score	**Level of risk**	**Firms**	**Loans 2007 (mil)**	**Average loan size 2007 (mln)**	**Granted credit growth 2005-07 %**	**Leverage 2005**	**Change Leverage 2005-07**	**NPLS at default (mln)**	**Default rate (%)**
1	Sound	13,226	12409.4	0.9	62.9	17.4	8.7	245	2.0
2	Sound	16,697	14550.8	0.9	14.5	25.9	3.3	567	3.9
3	Sound	31,620	30404.3	1.0	15.3	36.6	8.2	1,790	5.9
4	Sound	78,204	105589.2	1.4	16.4	47.0	2.7	6,589	6.2
5	Vulnerable	68,169	112054.7	1.6	19.6	65.6	3.7	12,512	11.2
6	Vulnerable	53,407	84205.4	1.6	16.2	57.9	1.7	16,899	20.1
7	Risky	73,712	102754.5	1.4	9.8	65.8	-2.3	19,210	18.7
8	Risky	27,800	16878.8	0.6	2.5	85.8	-11.3	3,534	20.9
9	Risky	5,408	2463.6	0.5	-44.9	88.5	3.3	921	37.4
Total		368,243	481310.8	1.3	16.2	54.1	1.9	62,267	12.9

Panel B: NPLs flows in 2011 - 2012 -2013

Z score	Level of risk	Firms	Loans 2010 (mil)	Average loan size 2010 (mln)	Granted credit growth 2008-10 %	Leverage 2008	Change Leverage 2008-10	NPLS at default (mln)	Default rate (%)
1	Sound	18,237	6437.6	0.4	2.9	10.4	2.1	262	4.1
2	Sound	20,672	20198.6	1.0	3.6	28.5	10.4	600	3.0
3	Sound	38,588	31627.2	0.8	5.3	31.0	0.6	4,024	12.7
4	Sound	85,711	106394.6	1.2	1.2	47.9	0.8	11,322	10.6
5	Vulnerable	67,962	101393.3	1.5	-0.1	65.6	-0.1	17,329	17.1
6	Vulnerable	56,411	93427.7	1.7	-4.4	58.7	0.2	22,133	23.7
7	Risky	78,375	115291.0	1.5	-2.7	67.1	-2.4	25,366	22.0
8	Risky	32,112	23677.9	0.7	-19.6	81.4	-5.9	6,250	26.4
9	Risky	6,511	3257.0	0.5	-38.5	93.7	-21.5	812	24.9
Total		404,579	501704.8	1.2	-1.5	54.4	-0.4	88,097	17.6

Panel C: NPLs flows in 2014 - 2015 -2016

Z score	Level of risk	Firms	Loans 2013 (mil)	Average loan size 2013 (mln)	Granted credit growth 2011-13 %	Leverage 2011	Change Leverage 2011-13	NPLS at default (mln)	Default rate (%)
1	Sound	20,113	6256.7	0.3	-7.2	8.8	1.5	272	4.3
2	Sound	22,286	12922.4	0.6	-13.7	27.1	-2.4	473	3.7
3	Sound	42,177	30855.3	0.7	-10.4	32.9	-1.7	2,328	7.5
4	Sound	93,768	102214.1	1.1	-8.7	53.1	0.4	9,278	9.1
5	Vulnerable	72,562	90996.9	1.3	-10.4	67.1	-1.2	12,867	14.1
6	Vulnerable	56,471	60543.3	1.1	-16.8	68.0	0.1	14,346	23.7
7	Risky	69,655	79462.8	1.1	-15.6	65.0	0.4	14,479	18.2
8	Risky	29,909	15724.4	0.5	-36.7	77.1	-2.4	3,468	22.1
9	Risky	6,432	2107.0	0.3	-31.5	110.1	-35.0	462	21.9
Total		413,373	401082.8	1.0	-13.0	55.0	-0.8	57,973	14.5

Table 7: Defaults of Non-Financial Firms as a Function of the Size of the Loans Granted

	Loans in 2007	**Default 2008-10 %**	**Loans in 2010**	**Default 2011-13 %**	**Loans in 2013**	**Default 2014-16 %**
Less then 100K	9,552	16.4	13,632	19.4	13,093	16.0
Btw 100K & 500K	68,289	12.4	68,409	16.8	59,042	13.8
Btw 500K & 1ML	55,488	11.8	54,706	16.8	43,516	13.8
Btw 1ML & 2.5ML	88,034	11.6	90,326	17.7	69,648	15.0
Btw 2.5 & 5ML	64,287	11.7	67,197	19.3	53,586	15.1
Btw 5ML & 25ML	102,541	12.0	112,223	18.8	92,075	14.8
Over 25ML	93,436	9.8	95,392	11.3	70,151	9.5
Total	**481,628**	**11.6**	**501,885**	**16.8**	**401,112**	**13.7**

Table 8: Summary Statistics

Panel A: NPLs flows in 2008 - 2009 -2010

Variable	Mean	Median	St Dev	1%	99%	N
Default system	0.114	0.114	0.000	0.114	0.114	572
Default bank	0.119	0.105	0.094	0.000	0.459	572
"Bank residual"	-0.001	-0.008	0.083	-0.194	0.292	572
Component due to risk attitude	0.002	0.003	0.021	-0.057	0.063	572
Component due to sector allocation	0.004	0.002	0.031	-0.063	0.094	572
Component due to luck	0.000	0.000	0.001	-0.006	0.004	572
Value loss HH loans	0.042	0.017	0.107	-0.047	0.452	572
Bank's credit growth prev 2y	0.366	0.326	0.339	-0.165	1.882	572
ROE beginning	0.008	0.008	0.006	-0.013	0.023	572
Tier 1 ratio beginning	0.155	0.133	0.084	0.061	0.466	572
Cost-to-income ratio beginning	0.624	0.611	0.137	0.308	1.006	572
Misclassified NPLs	0.123	0.094	0.122	0.000	0.665	572
Number of fines	0.166	0.000	0.408	0.000	2.000	572
Number of referrals to prosecutors	0.082	0.000	0.299	0.000	1.000	572
Number of CEO or DG indicted	0.072	0.000	0.271	0.000	1.000	572
% politicians in the board	0.193	0.154	0.170	0.000	0.727	572

Panel B: NPLs flows in 2011 - 2012 -2013

Variable	Mean	Median	St Dev	1%	99%	N
Default system	0.161	0.161	0.000	0.161	0.161	534
Default bank	0.186	0.172	0.119	0.000	0.549	534
"Bank residual"	-0.001	-0.011	0.096	-0.244	0.272	534
Component due to risk attitude	0.004	0.003	0.026	-0.057	0.082	534
Component due to sector allocation	0.020	0.016	0.055	-0.116	0.172	534
Component due to luck	0.000	0.000	0.002	-0.006	0.006	534
Value loss HH loans	0.052	0.024	0.128	-0.073	0.663	534
Bank's credit growth prev 2y	0.324	0.254	0.315	-0.206	1.609	534
ROE beginning	0.002	0.003	0.007	-0.021	0.016	534
Tier 1 ratio beginning	0.165	0.144	0.079	0.067	0.452	534
Cost-to-income ratio beginning	0.766	0.746	0.169	0.369	1.360	534
Misclassified NPLs	0.146	0.112	0.138	0.000	0.823	534
Number of fines	0.208	0.000	0.450	0.000	2.000	534
Number of referrals to prosecutors	0.125	0.000	0.343	0.000	1.000	534
Number of CEO or DG indicted	0.069	0.000	0.269	0.000	1.000	534
% politicians in the board	0.189	0.143	0.175	0.000	0.667	534

Panel C: NPLs flows in 2014 - 2015 -2016

Variable	Mean	Median	St Dev	1%	99%	N
Default system	0.126	0.126	0.000	0.126	0.126	466
Default bank	0.141	0.137	0.090	0.000	0.435	466
“Bank residual”	-0.014	-0.015	0.068	-0.178	0.203	466
Component due to risk attitude	0.001	0.004	0.023	-0.064	0.056	466
Component due to sector allocation	0.027	0.029	0.047	-0.096	0.167	466
Component due to luck	0.001	0.001	0.002	-0.005	0.006	466
Value loss HH loans	0.061	0.046	0.098	-0.056	0.478	466
Bank's credit growth prev 2y	0.079	0.032	0.275	-0.273	0.994	466
ROE beginning	0.001	0.002	0.008	-0.032	0.015	466
Tier 1 ratio beginning	0.172	0.155	0.075	0.065	0.474	466
Cost-to-income ratio beginning	0.656	0.650	0.206	0.298	1.210	466
Misclassified NPLs	0.105	0.079	0.101	0.000	0.459	466
Number of fines	0.148	0.000	0.442	0.000	2.000	466
Number of referrals to prosecutors	0.092	0.000	0.325	0.000	2.000	466
Number of CEO or DG indicted	0.064	0.000	0.263	0.000	1.000	466
% politicians in the board	0.179	0.143	0.166	0.000	0.667	463

Table 9: Determinants of Banks' Ex-Ante Risk Levels

The dependent variable is the level of defaults due to the z-score composition of a bank's clients, keeping the location, the sectoral composition, and the size distribution of its clients constant. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

	1st period		2nd period		3rd period	
VARIABLES						
Value loss on HH loans - av prev 2y		0.011		0.037***		0.025**
		(0.018)		(0.013)		(0.012)
Bank's credit growth prev 2y	0.003	0.003	0.000	-0.003	0.003	0.001
	(0.003)	(0.003)	(0.005)	(0.005)	(0.004)	(0.004)
Tier 1 ratio beginning	0.001	0.002	-0.004	-0.002	-0.052***	-0.047***
	(0.010)	(0.010)	(0.023)	(0.022)	(0.013)	(0.013)
ROE beginning	-0.761***	-0.739***	-0.671**	-0.509*	-0.550***	-0.476***
	(0.175)	(0.178)	(0.277)	(0.270)	(0.135)	(0.130)
Cost-to-income ratio beginning	-0.026***	-0.026***	-0.004	0.001	-0.013***	-0.010***
	(0.008)	(0.008)	(0.014)	(0.014)	(0.004)	(0.004)
Top	0.001	0.001	0.006	0.007	-0.004	-0.005
	(0.002)	(0.002)	(0.007)	(0.007)	(0.005)	(0.005)
Big	0.015***	0.014***	0.013***	0.013***	0.001	-0.000
	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)
Medium	0.008***	0.008***	0.014***	0.014***	0.007*	0.005
	(0.002)	(0.002)	(0.004)	(0.004)	(0.003)	(0.003)
Constant	0.016***	0.016***	-0.002	-0.008	0.014***	0.011**
	(0.005)	(0.005)	(0.011)	(0.011)	(0.005)	(0.005)
Observations	572	572	534	534	466	466
R-squared	0.051	0.054	0.054	0.085	0.080	0.089

Table 10: Determinants of the "Bank residual"

The dependent variable is the additional defaults due to a bank's choice of borrowers, keeping the location, the sectoral composition, size dimension, and riskiness of the borrowers constant. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Panel A: NPLs flows in 2008 - 2009 -2010

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Share of misclass NPLs 2006-07			0.051*					
			(0.028)					
# of fines 2008-10				0.034***				
				(0.012)				
# of refer to pros 2008-10					0.068***			0.064***
					(0.018)			(0.019)
# of CEO or DG indicted						0.040***		0.030**
						(0.014)		(0.014)
Share of politician in the Board							0.009	
							(0.019)	
Value loss on HH loans - av prev 2y		0.177**	0.175**	0.152**	0.161**	0.181**	0.178**	0.165**
		(0.074)	(0.075)	(0.068)	(0.065)	(0.074)	(0.074)	(0.065)
Bank's credit growth prev 2y	0.018	0.019	0.014	0.020*	0.017	0.017	0.019*	0.016
	(0.012)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Tier 1 ratio beginning	-0.089*	-0.083*	-0.080	-0.093*	-0.097*	-0.073	-0.082	-0.088*
	(0.050)	(0.050)	(0.050)	(0.051)	(0.051)	(0.050)	(0.051)	(0.051)
ROE beginning	-2.309***	-1.971***	-1.871***	-1.212*	-0.910	-1.897***	-1.982***	-0.916
	(0.540)	(0.538)	(0.528)	(0.692)	(0.849)	(0.588)	(0.537)	(0.890)
Cost-to-income ratio	-0.093***	-0.085**	-0.082**	-0.060	-0.044	-0.082**	-0.086***	-0.044
	(0.035)	(0.033)	(0.033)	(0.038)	(0.047)	(0.035)	(0.033)	(0.049)
Top	0.001	0.001	0.001	-0.006	-0.010	0.004	0.001	-0.007
	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.007)	(0.007)	(0.008)
Big	0.027**	0.021*	0.020	0.014	0.014	0.018	0.021*	0.013
	(0.013)	(0.012)	(0.013)	(0.013)	(0.012)	(0.012)	(0.013)	(0.012)
Medium	0.028***	0.021***	0.022***	0.015**	0.015**	0.027***	0.021***	0.020***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)	(0.007)	(0.007)	(0.007)
Constant	0.059***	0.049**	0.040**	0.029	0.018	0.038*	0.047**	0.012
	(0.020)	(0.020)	(0.020)	(0.024)	(0.030)	(0.021)	(0.020)	(0.031)
Observations	572	572	572	572	572	572	572	572
R-squared	0.039	0.090	0.095	0.115	0.145	0.106	0.090	0.154

Panel B: NPLs flows in 2011 - 2012 -2013

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Share of misclass NPLs av 2009-10			-0.016					
			(0.038)					
# of fines 2011-13				0.023**				
				(0.009)				
# of refer to pros 2011-13					0.028**			0.024*
					(0.013)			(0.013)
# of CEO or DG indicted						0.029		0.024
						(0.019)		(0.020)
Share of politician in the Board							-0.008	
							(0.026)	
Value loss on HH loans - av prev 2y		0.037	0.037	0.025	0.029	0.036	0.036	0.029
		(0.043)	(0.043)	(0.042)	(0.043)	(0.042)	(0.043)	(0.042)
Bank's credit growth prev 2y	0.028*	0.025	0.028*	0.023	0.022	0.024	0.024	0.022
	(0.016)	(0.016)	(0.016)	(0.016)	(0.015)	(0.016)	(0.016)	(0.015)
Tier 1 ratio beginning	-0.138**	-0.135**	-0.135**	-0.119**	-0.121**	-0.137**	-0.136**	-0.124**
	(0.058)	(0.058)	(0.058)	(0.057)	(0.058)	(0.058)	(0.059)	(0.058)
ROE beginning	-2.826***	-2.665***	-2.658***	-2.364**	-2.449***	-2.637***	-2.668***	-2.451***
	(0.861)	(0.885)	(0.891)	(0.920)	(0.900)	(0.885)	(0.885)	(0.898)
Cost-to-income ratio beginning	-0.090**	-0.085**	-0.085**	-0.085**	-0.085**	-0.084**	-0.086**	-0.084**
	(0.039)	(0.041)	(0.041)	(0.040)	(0.041)	(0.040)	(0.041)	(0.041)
Top	-0.001	0.000	0.001	-0.001	-0.002	0.003	0.000	0.000
	(0.018)	(0.018)	(0.018)	(0.017)	(0.018)	(0.018)	(0.018)	(0.017)
Big	0.032**	0.032**	0.033**	0.033**	0.031**	0.029*	0.032**	0.029*
	(0.016)	(0.016)	(0.015)	(0.015)	(0.015)	(0.016)	(0.016)	(0.016)
Medium	0.028***	0.028***	0.028***	0.028***	0.029***	0.033***	0.029***	0.033***
	(0.011)	(0.011)	(0.011)	(0.010)	(0.010)	(0.011)	(0.011)	(0.011)
Constant	0.063**	0.057*	0.058*	0.050*	0.052*	0.051*	0.059*	0.047
	(0.029)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.031)	(0.031)
Observations	534	534	534	534	534	534	534	534
R-squared	0.055	0.057	0.057	0.067	0.066	0.063	0.057	0.070

Panel C: NPLs flows in 2014 - 2015 -2016

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Share of misclass NPLs av 2012-13			0.022					
			(0.039)					
# of fines 2014-16				0.018**				
				(0.009)				
# of refer to pros 2014-16					0.017*			0.016*
					(0.009)			(0.009)
# of CEO or DG indicted						0.010		0.008
						(0.009)		(0.009)
Share of politician in the Board							0.022	
							(0.020)	
Value loss on HH loans - av prev 2y		0.116**	0.113**	0.106**	0.114**	0.116**	0.117**	0.115**
		(0.048)	(0.050)	(0.051)	(0.048)	(0.048)	(0.048)	(0.049)
Bank's credit growth prev 2y	-0.018	-0.027**	-0.029**	-0.030**	-0.026**	-0.027**	-0.025**	-0.027**
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Tier 1 ratio	-0.116**	-0.090*	-0.090*	-0.079	-0.083	-0.090	-0.088	-0.083
	(0.053)	(0.055)	(0.055)	(0.055)	(0.055)	(0.055)	(0.054)	(0.055)
ROE beginning	-1.537***	-1.195***	-1.210***	-0.875*	-0.987**	-1.159***	-1.227***	-0.971**
	(0.419)	(0.439)	(0.442)	(0.458)	(0.460)	(0.441)	(0.447)	(0.460)
Cost-to-income ratio	-0.038**	-0.025*	-0.025*	-0.025*	-0.024*	-0.024*	-0.023*	-0.024*
	(0.017)	(0.013)	(0.013)	(0.014)	(0.013)	(0.013)	(0.013)	(0.013)
Top	0.015	0.013	0.013	0.011	0.010	0.015	0.013	0.012
	(0.016)	(0.015)	(0.015)	(0.015)	(0.016)	(0.015)	(0.016)	(0.016)
Big	0.025*	0.020	0.021	0.016	0.016	0.020	0.021	0.016
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Medium	0.024*	0.016	0.015	0.014	0.014	0.018	0.014	0.016
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)
Constant	0.011	-0.001	-0.003	-0.003	-0.003	-0.005	-0.005	-0.005
	(0.016)	(0.015)	(0.016)	(0.016)	(0.015)	(0.016)	(0.016)	(0.016)
Observations	466	466	466	466	466	466	463	466
R-squared	0.076	0.100	0.100	0.111	0.105	0.101	0.101	0.106

Table 11: Determinants of Sectorial Composition of Lending

The dependent variable is the additional defaults due to a bank's choice of sectors where to lend, keeping the location, the sectoral composition, size dimension, and riskiness of the borrowers constant. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Panel A: NPLs flows in 2008 - 2009 -2010

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Share of misclass NPLs 2006-07			0.017					
			(0.011)					
# of fines 2008-10				0.006*				
				(0.004)				
# of refer to pros 2008-10					0.015***		0.013**	
					(0.005)		(0.005)	
# of CEO or DG indicted						0.011**	0.009*	
						(0.005)	(0.005)	
Share of politician in the Board								-0.007
								(0.009)
Value loss on HH loans - av prev 2y		0.066***	0.065***	0.062***	0.063***	0.067***	0.064***	0.066***
		(0.016)	(0.016)	(0.017)	(0.015)	(0.016)	(0.015)	(0.016)
Bank's credit growth prev 2y	0.009*	0.009**	0.007*	0.009**	0.009**	0.008*	0.008*	0.008*
	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Tier 1 ratio beginning	-0.032**	-0.030*	-0.029*	-0.032*	-0.033*	-0.027	-0.030*	-0.031*
	(0.016)	(0.017)	(0.017)	(0.018)	(0.018)	(0.017)	(0.017)	(0.017)
ROE beginning	0.208	0.334	0.367	0.471	0.560*	0.356	0.558*	0.342
	(0.317)	(0.338)	(0.349)	(0.329)	(0.299)	(0.318)	(0.298)	(0.335)
Cost-to-income ratio beginning	0.020	0.023	0.024	0.027*	0.032**	0.024	0.032**	0.023
	(0.016)	(0.016)	(0.017)	(0.015)	(0.013)	(0.015)	(0.013)	(0.016)
Top	-0.001	-0.001	-0.001	-0.003	-0.004	-0.000	-0.003	-0.002
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Big	-0.001	-0.004	-0.004	-0.005	-0.005	-0.005	-0.006	-0.004
	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
Medium	-0.003	-0.005*	-0.005	-0.006**	-0.006**	-0.004	-0.005	-0.005
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Constant	-0.007	-0.010	-0.013	-0.014	-0.017*	-0.013	-0.019**	-0.009
	(0.010)	(0.011)	(0.011)	(0.010)	(0.009)	(0.010)	(0.009)	(0.011)
Observations	572	572	572	572	572	572	572	572
R-squared	0.022	0.074	0.078	0.079	0.092	0.083	0.098	0.075

Panel B: NPLs flows in 2011 - 2012 -2013

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Share of misclass NPLs 2009-10			0.031*					
			(0.018)					
# of fines 2011-13				0.012***				
				(0.004)				
# of refer to pros 2011-13					0.013**		0.012**	
					(0.006)		(0.006)	
# of CEO or DG indicted						0.007	0.004	
						(0.007)	(0.007)	
Share of politician in the Board								-0.018
								(0.014)
Value loss on HH loans - av prev 2y		0.127***	0.127***	0.121***	0.123***	0.127***	0.123***	0.126***
		(0.027)	(0.027)	(0.026)	(0.026)	(0.026)	(0.026)	(0.027)
Bank's credit growth prev 2y	0.018**	0.008	0.002	0.007	0.006	0.007	0.006	0.006
	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Tier 1 ratio beginning	0.016	0.026	0.025	0.035	0.032	0.025	0.032	0.024
	(0.042)	(0.038)	(0.039)	(0.039)	(0.038)	(0.038)	(0.038)	(0.038)
ROE beginning	-0.650	-0.096	-0.110	0.069	0.005	-0.090	0.005	-0.102
	(0.541)	(0.531)	(0.532)	(0.524)	(0.512)	(0.530)	(0.512)	(0.537)
Cost-to-income ratio beginning	0.006	0.023	0.021	0.023	0.023	0.023	0.023	0.021
	(0.020)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Top	0.019**	0.025***	0.023**	0.024**	0.024**	0.026***	0.024**	0.024**
	(0.010)	(0.010)	(0.010)	(0.010)	(0.009)	(0.010)	(0.010)	(0.010)
Big	0.005	0.006	0.005	0.007	0.006	0.006	0.005	0.006
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Medium	0.011	0.011	0.010	0.011	0.011	0.012*	0.012*	0.013*
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Constant	-0.001	-0.021	-0.022	-0.025	-0.024	-0.022	-0.024	-0.017
	(0.017)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Observations	534	534	534	534	534	534	534	534
R-squared	0.027	0.107	0.112	0.116	0.113	0.108	0.113	0.110

Panel C: NPLs flows in 2014 - 2015 -2016

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Share of misclass NPLs 2012-13			0.072***					
			(0.022)					
# of fines 2014-16				0.005				
				(0.004)				
# of refer to pros 2014-16					0.008*		0.007*	
					(0.004)		(0.004)	
# of CEO or DG indicted						0.005	0.004	
						(0.007)	(0.007)	
Share of politician in the Board								-0.013
								(0.013)
Value loss on HH loans - av prev 2y		0.130***	0.120***	0.127***	0.129***	0.130***	0.129***	0.129***
		(0.035)	(0.034)	(0.036)	(0.035)	(0.035)	(0.035)	(0.035)
Bank's credit growth prev 2y	-0.010	-0.020**	-0.026***	-0.020**	-0.019**	-0.020**	-0.020**	-0.021**
	(0.009)	(0.008)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Tier 1 ratio beginning	0.017	0.046	0.046	0.049	0.049	0.046	0.049	0.044
	(0.035)	(0.033)	(0.033)	(0.034)	(0.033)	(0.033)	(0.033)	(0.034)
ROE beginning	-0.637***	-0.255	-0.302	-0.173	-0.157	-0.237	-0.149	-0.251
	(0.243)	(0.251)	(0.251)	(0.264)	(0.260)	(0.251)	(0.259)	(0.253)
Cost-to-income ratio beginning	-0.008	0.007	0.006	0.007	0.007	0.007	0.007	0.006
	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Top	0.014	0.011	0.011	0.011	0.010	0.012	0.011	0.011
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Big	0.004	-0.001	0.000	-0.002	-0.003	-0.001	-0.003	-0.000
	(0.009)	(0.009)	(0.010)	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)
Medium	0.022***	0.014*	0.013*	0.013*	0.013*	0.015*	0.014*	0.015*
	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Constant	0.011	-0.003	-0.009	-0.004	-0.004	-0.005	-0.005	-0.001
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)	(0.011)
Observations	466	466	466	466	466	466	466	463
R-squared	0.027	0.088	0.110	0.090	0.091	0.089	0.091	0.090

Table 12: Correlations for the “bank residual” across the three sub-periods

(computed on the dependent variable of the regressions in Table 11)

	Spearman			Pair wise		
	2008-10	*2011-13*	*2014-16*	*2008-10*	*2011-13*	*2014-16*
2008-10	1			1		
2011-13	0.28	1		0.32	1	
2014-16	0.17	0.28	1	0.16	0.27	1

Note: all statistics are significant at least at the 5% level.

Figure1: NPLs and difficulty of accessing bank credit by non-financial firms

(percentage points)

The curve "Difficulty of accessing credit" is an indicator of the difficulty of accessing credit among non-financial firms. It is computed on survey data, as the number of firms that declare increasing difficulties of accessing bank credit minus the number of those perceiving easier conditions, as a percentage of the overall number of firms in the sample. The new NPL rate is computed as the ratio between the value of new total loans entering the NPL status in a given quarter and the stock of loans at the beginning of the quarter, annualized. The Gross NPL ratio is computed as the stock of gross NPLs divided by total loans. Source: ISTAT for the indicator of difficulty of accessing bank credit. Bank of Italy for the new NPL rate and for the gross NPL ratio.

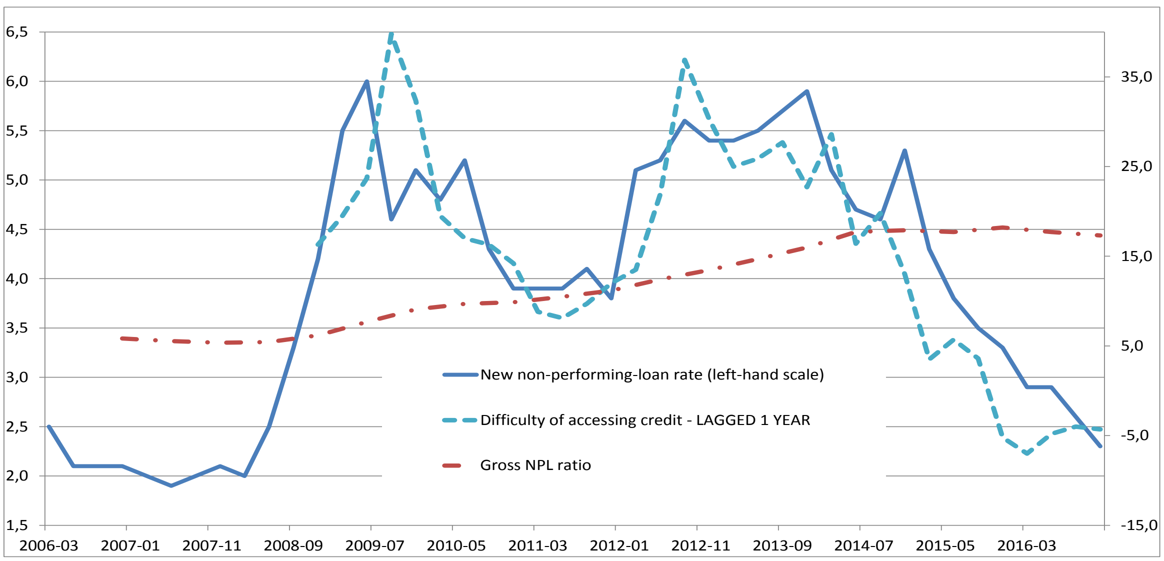


Figure2: NPLs in Italy

(percentage points)

(a) Outstanding stocks/ total loans *(b) Flows/total loans vs GDP growth*

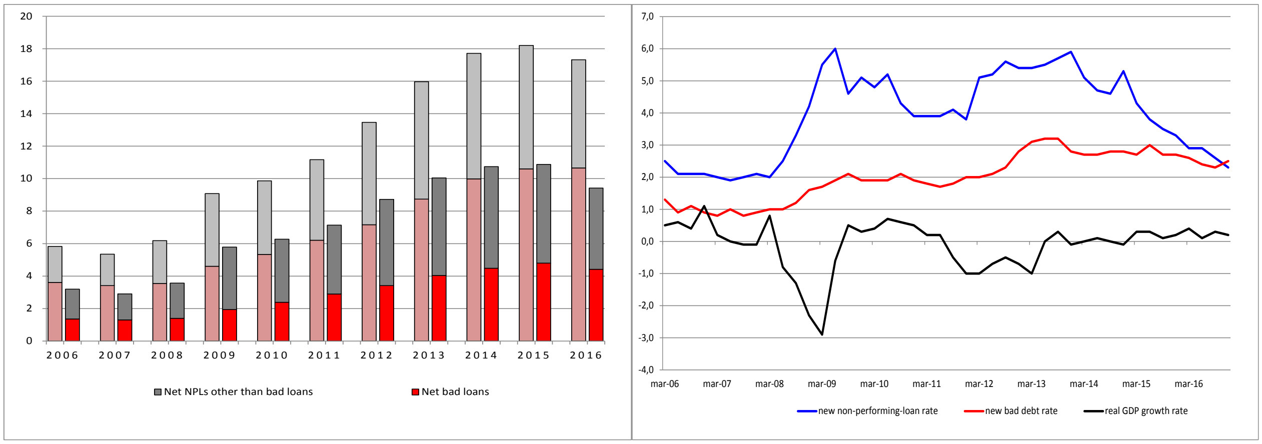


Figure 3: NPL flows as a ratio of performing loans: firms vs households

(quarterly data, annualized and seasonally adjusted; per cent)

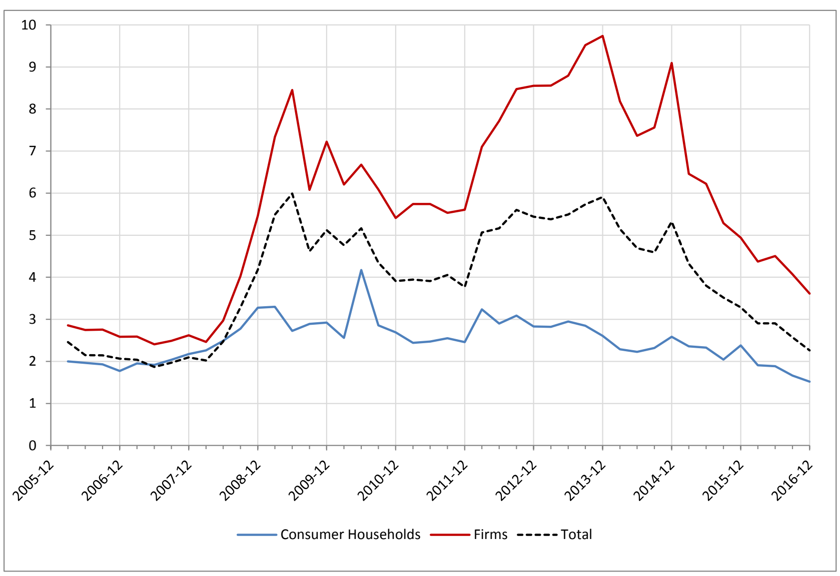


Figure 4: Predicting Deafults Based on Italian History

We estimate the following relationship based on (Bofondi and Ropele, 2011)

$$BD_t = \frac{1.895}{(1.087)} + \frac{0.361}{(0.103)} BD_{t-1} + \frac{-8.178}{(3.025)} g_{t-1} + \frac{18.655}{4.459} u_t + \frac{4.693}{(0.777)} GOM_{t-1} + \frac{-2.981}{(1.007)} HP_{t-1} + \varepsilon_t$$

where BD_t is the ratio of the flow of new bad debt in quarter t divided by performing loans at t-1, g is the real GDP growth rate in quarter t, u is the unemployment rate in quarter t, and *GOP is* the gross operating margin of nonfinancial corporations in quarter t-2. We estimate the coefficients over the 1991:1-2007:4 period and then use these estimated coefficients and the actual ex post realization of g, u ,and GOP to predict NPLs. Figure 4 shows the actual and predicted . Note that in predicting we use the predicted and not actual BD_{t-1}.

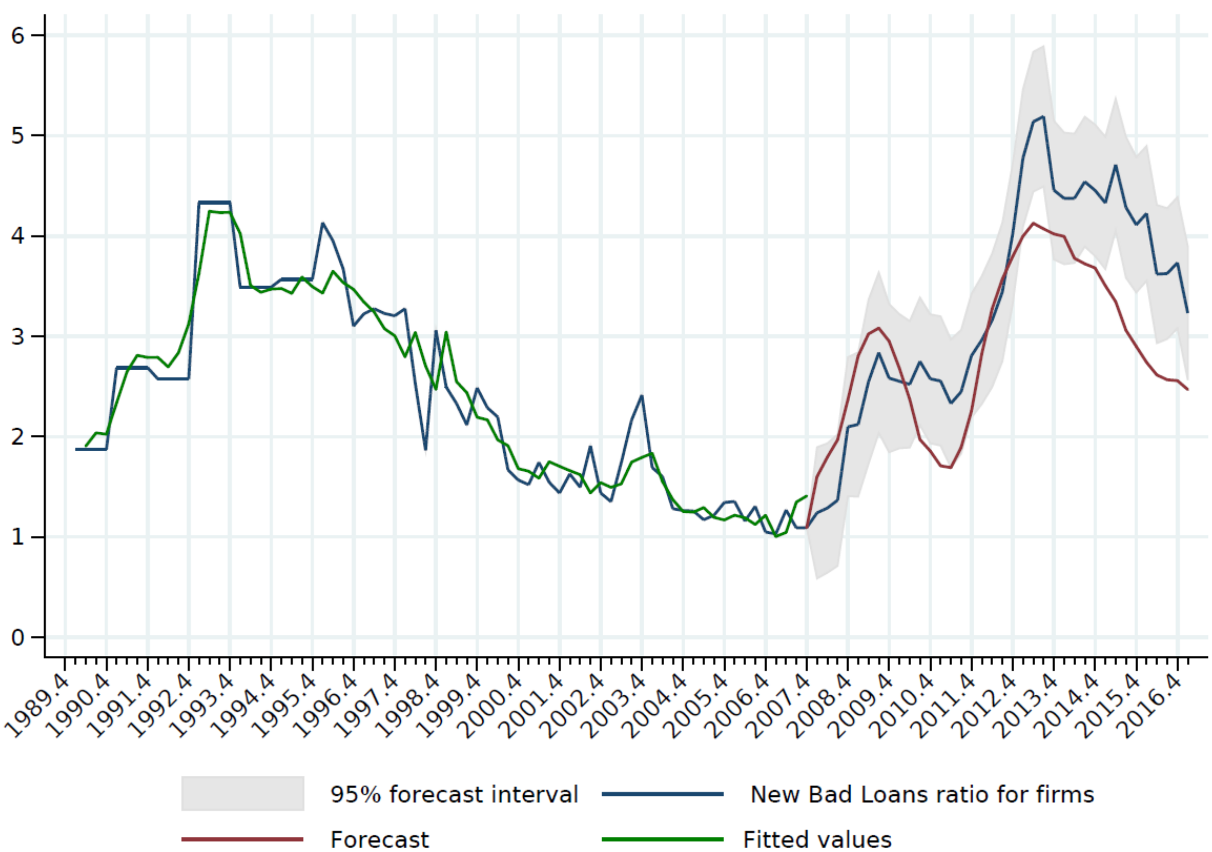
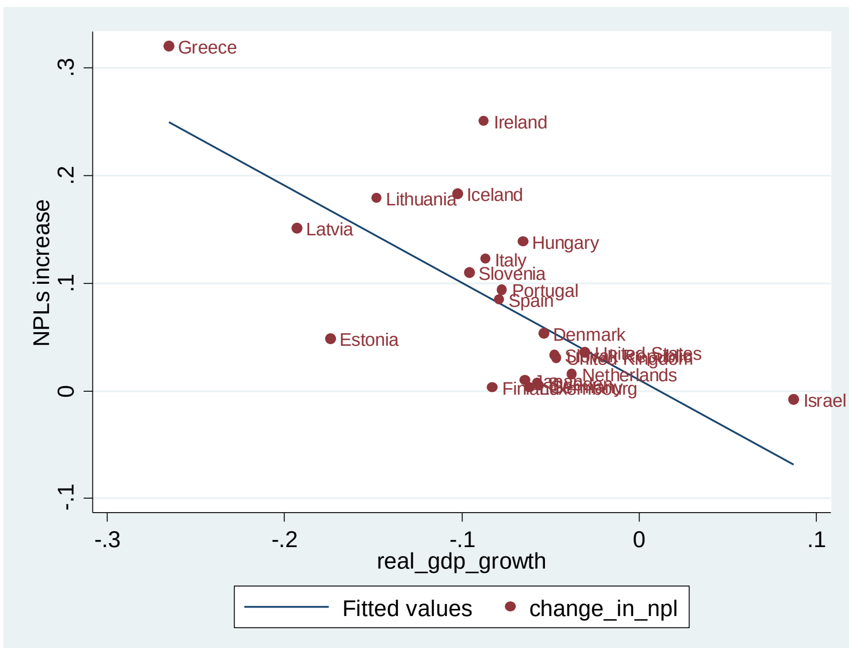


Figure 5: GDP and NPLs in the EU

The sample is composed of all OECD countries that have data house prices in "Residential Property Prices Indices" (https://stats.oecd.org/Index.aspx?DataSetCode=HOUSE_PRICES) and experienced either a drop of least a 5% in real GDP or of at least 10% in nominal house prices. NPL increase is the change between the 2007 level of the NPLs ratio and the peak leavel after the crisis (source: http://data.worldbank.org/indicator/FB.AST.NPER.ZS). Real GDP growth is the worst contiguous drop in real GDP after 2007 (source: http://data.worldbank.org/indicator/FB.AST.NPER.ZS). Real estate prices is the worst contiguouos drop in real estate prices after 2007.

Panel A: NPLs on GDP changes



Panel B: NPLs on Ral Estate Prices

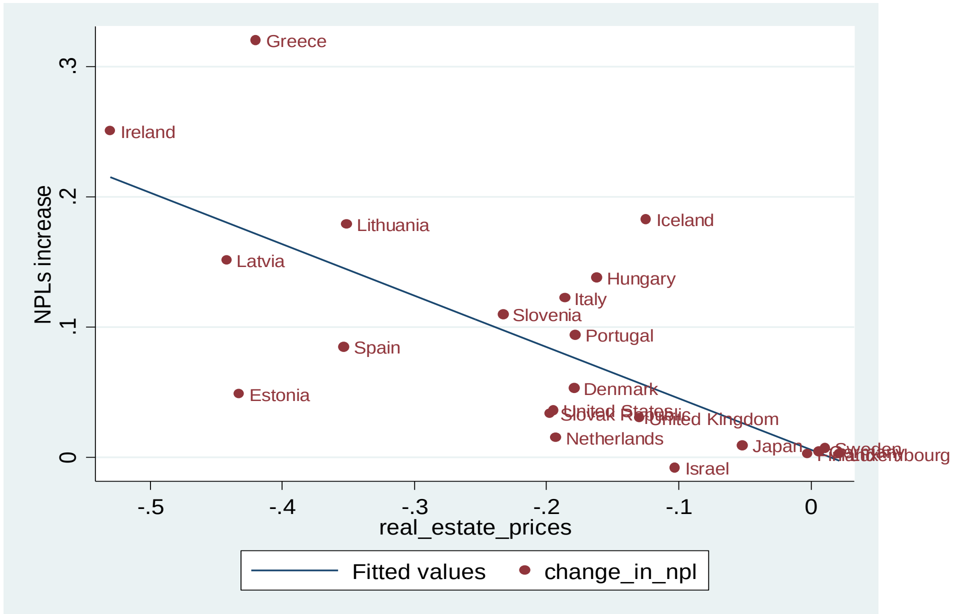


Figure 6: Structure of the dataset

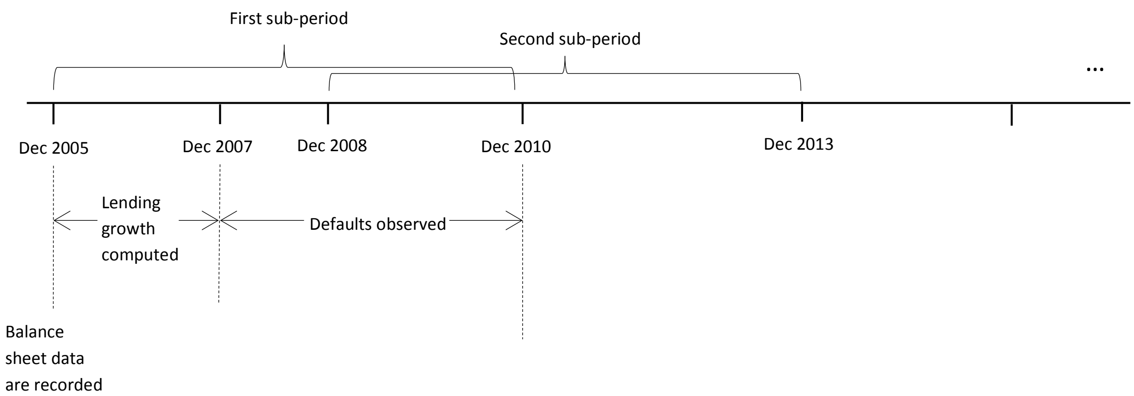


Figure 7: Lending to non-financial firms: credit growth and z-scores

z-score is an Altman's z-score computed by CADS. Higher values of the z-score signal lower creditworthiness of the non-financial firms. Conventionally, firms with z-scores 1 to 4 are labelled "sound", those with z-score 5 to 6 "vulnerable", those with z-score 7 to 9 "risky". The credit growth is computed over the two years "ex-ante" period, for the three samples.

Figure 8: Bank-Specific Factors and Common Factors in Defaults

We divide all the borrowers in a region into 8,250 cells: one for each of the 110 provinces, one for each of the five dimensional classes for non-financial firms (micro, small, medium, big, top), one each for the five sectors (manufacturing, constructions, services, energy, and others), and one each for the three levels of z-score (stable, vulnerable, and risky).

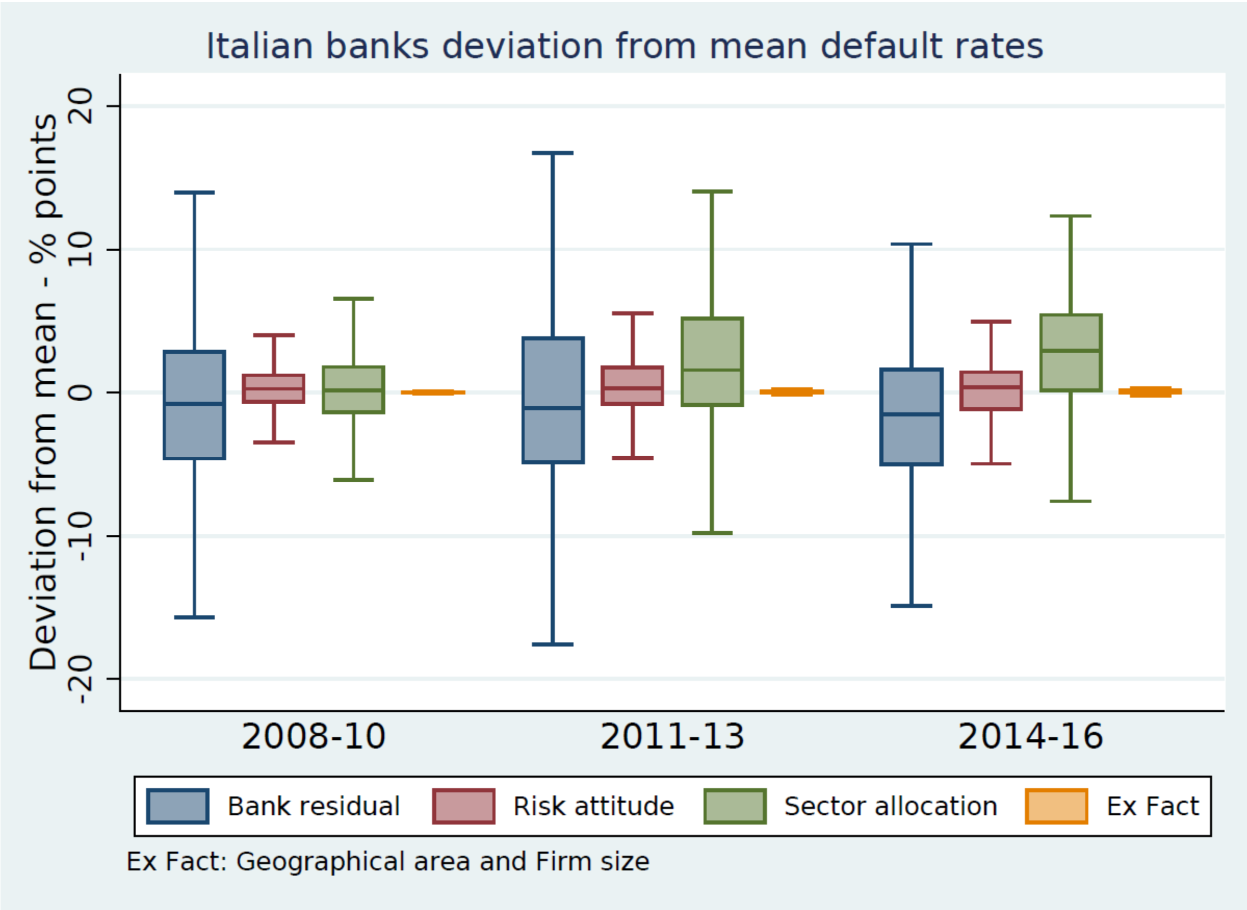


Figure 9: "Bank residual" and Sectorial Allocation of Loans

The x variable is the rate of additional defaults of a bank due to the sectoral allocation. The y-variable is the rate of additional defaults of a bank due to bank's selection of customers.