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ABSTRACT

We analyze the fate of 110 Italian banks that experienced abrupt drops in profitability, from which about 1/3 recover. Recovery depends primarily on post-shock adjustments made by the banks, particularly to their loan portfolios. Matched bank-borrower data shows that recovering banks are significantly more aggressive in managing their riskiest clients. The risk management differences are consistent with some banks cutting credit to very riskiest clients while others appear to be gambling for reclamation by continuing to extend credit to high risk borrowers.

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Introduction

Since the eruption of the global financial crisis, a large number of banks have faced sharp drops in profitability. When a bank becomes distressed, the problems need to be addressed in a timely fashion to minimize cost and to avoid disorderly resolution. The famous dictum by Bagehot, paraphrased by Tucker (2009), holds "to avert panic, central banks should lend early and freely (i.e. without limit), to solvent firms, against good collateral, and at 'high rates'." If a bank is no longer viable, it might need to be resolved. Often, however, determining solvency is very difficult, which complicates the usefulness of the dictum.

In the recent crisis authorities have in some cases nationalized the banks or they have provided capital injections;[1] in other cases banks have been allowed to operate without any public support, although under increased scrutiny by supervisors.

The consequences for the taxpayers of the different alternatives can be substantial. A key challenge is, therefore, to assess which banks can regain profitability and under which conditions. If banks can recover without support, then allowing them to do so is clearly the best option for all parties. But, delaying action can add to the eventual costs if later interventions are required. Even in the case when the decision to offer state financial support has been taken, the assistance may prove ineffective if no other actions that address the source of the problem are undertaken (Garcia and Nieto (2005)).

There are differences of opinion on how to prioritize these other potential actions. Qualitative evidence typically suggests that cleaning the portfolio and increasing the earning capability of banks is a key to rehabilitation (OCC (1988)). Another view is that limiting asset growth and increasing capital (the so-called "prompt corrective action" doctrine) is the most effective strategy for dealing with impaired banks.[2] While there is substantial evidence on the determinants of bank distress (e.g. Wheelock and Wilson (2000), King et al. (2005)) there is much less on the determinants of recovery and on how best to proceed once banks are seriously distressed.

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[1] For example, in the United Kingdom recently banks were nationalized and operated for an extended period while under government ownership. In other cases, such as Sweden in the early 1990s, Spain and Ireland during the recent crisis, non-performing assets were moved into separate asset management companies that were distinct from the banks. In the U.S. in 2009 the banks were recapitalized using private funds under the threat of a public capital injection.

[2] This doctrine was reflected in the U.S. legislation passed in response to the savings and loans crisis.

In this paper, we study how banks perform following sudden collapses in profitability, distinguishing between banks that recover within three years from the negative shock and those that do not. Looking over two or three years after the shock provides information on what adjustments have been undertaken and whether they have facilitated recovery. Our analysis covers all sharp profitability collapses that occurred in Italy from the early 1990s through the mid- 2000s, before the global financial crisis. This period, therefore, includes both the downturn and the subsequent economic recovery, allowing us to study banks all the way through a full cycle.

The Italian experience is interesting in several respects. On the one hand, the sample period includes the episode in the early 1990s when Italy suffered a major recession that led to spike defaults and an acute collapse in bank profits, the typical pattern observed during the post-2008 period in many advanced economies. We are able to follow the affected banks for enough time afterwards to see which ones recovered and which did not, as well to compare the timing of the recoveries to overall macroeconomic recovery. On the other hand, we also observe many idiosyncratic bank problems in subsequent years, where individual banks (including some large ones) get into trouble but the aggregate economy is not depressed. This allows us to contrast the fate of these banks to that of the banks which became distressed when the macro conditions were an important contributing factor.

Our empirical strategy is twofold. The first part of the analysis is descriptive. Here we attempt to offer a comprehensive picture of what happens to banks starting once profits collapse. We use some bank-level data to document observable differences between banks that do and do not regain profitability. We also establish some new facts about when the recovery depends on macro or regional conditions that are out of the hands of the individual banks.

The second part of the paper uses bank-firm relationship data to analyze banks' risk management policies. We show how the borrowers with different risk levels are treated by different banks. More specifically, we compare the lending practices of banks that regain profitability to those that do not, to isolate which factors that banks' can control matter.

The main finding from the descriptive analysis is that recovery depends on the adjustments made by banks in the wake of the shock of the level of risk contained in their loan portfolios. Banks that recover are able to reduce what we define as *idiosyncratic* risk of their portfolio, i.e. the component of credit risk that depends on their choices of who they to lend to.

Our main finding from the micro-level analysis is that the recovering banks are tougher in extending credit to riskier borrowers than banks that do not recover. We investigate two alternative explanations of the different behavior of recovering and non-recovering banks in terms of how they manage riskier borrowers. One possibility is that banks that are insolvent, or nearly so, may opt to gamble for reclamation by continuing to lend to the highest risk borrowers. If so, and if gambling fails on average, then we would expect to find that recovering banks have safer loan portfolios than non-recovering banks, consistent with the bank-level data. An alternative hypothesis is that banks that wind up chronically depressed are simply badly managed. Perhaps their managers are not actively choosing to gamble, but simply do not understand that risk reduction is critical for recovering, while some other better run banks do understand this. In this view, the competently run banks would take active steps to mitigate risks, while the other banks stand pat.

Under either of these accounts, the critical distinction between recovering and non-recovering banks would depend on how they handle their riskiest clients. We approach the problem analyzing how banks that are ex-ante more incentivized to be prudent or to gamble change their lending supply to clients with different ex-ante risk.

We find partial evidence that is consistent with both of the hypotheses about why credit risk matters. On the one hand, the banks that were the most impaired as of the time of the drop in profits do extend significantly more credit in the subsequent years to high risk borrowers (suggesting that some gambling is taking place). On the other, the banks which had relatively lower portfolio risk when their profits dropped cut lending to high risk borrowers (suggesting that some banks are actively reducing risk). Ultimately, we cannot decisively reject either hypothesis in favor of the other, but we can show that the handling of high risk customers is important.

Our empirical strategy aims at detecting observable characteristics under the control of banks that increased the chances of recovery, and which actions banks can take to improve with respect to such characteristics. Hence, by construction, we do not attempt to identify the different reasons why some banks experience the shock and others do not. Nor do we investigate why some banks choose strategies that are more likely to make them recover and others do not. The question we investigate is such that it would be very difficult to find an exogenous treatment that is administered to some of the distressed banks and not to others. All banks are likely to take some actions, possibly under supervisory pressure, but we can only ex-post attempt to detect which ones increased the chances of recovery.

Nevertheless, our results can still provide guidance on which intermediate objectives supervisors should target to improve the probability of recovery. This approach is akin to studying patients who become sick with a particular disease and asking what governs their survival. It would be useful for example to find that patients that adopt a particular diet have improved chances of survival. Moreover, in practice most banking crises have multiple causes. If we were to focus on banks that got into trouble for a particular, single reason there would be serious questions about whether inferences on such banks would generalize in way that would be externally valid.

Our work is indirectly related to three large literatures. One seeks to assess the effects of negative shocks to banks on their customers. The shocks include funding disruptions or capital losses, and most of the papers seek to identify changes in loan supply and knock-on effects to the real economy.[3] Another set of papers investigate the impact of a distressed banking industry on real variables or post-crisis economic recovery, but not on strategies that increase chances that the banking industry recovers.[4] Finally, a third body of research, on early warning models, analyzes the determinants of bank distress but does not investigate the fate of banks after they are hit by severe shocks.[5]

Perhaps the closest study to ours is Kick, Koetter and Poghosyan (2016). They study the effect of supervisory interventions for German banks between 1994 and 2008 on the probability that the banks repay capital injections. Banks are considered distressed if they received at least one capital injection during this period and recovery is full repayment of the capital. Even they do not analyze bank lending policies or profitability going forward.

[3] Jimenez, Ongena, Peydrò and Saurina (2017) analyze changes to capital requirements, while Gan (2007) and Santos (2011) study the effects on lending and interest rates from shocks that hit bank on the asset or liability side of the balance sheet. Iyer, Lopes,Peydrò and Schoar (2014) investigate the consequences of the unexpected European interbank borrowing freeze on credit supply in Portugal. Carvalho, Ferreira, and Matos (2015) analyze losses in borrowing firm valuations from bank shocks, like older studies such as Slovin, Sushka, and Polonchek (1993).

[4] Cingano, Manaresi, and Sette (2016) and Dell'Ariccia, Detragiache and Rajan (2008) are two examples of studies of the real effects of bank shocks; Reinhart and Rogoff (2009) provide cross-country evidence on the fact that the aftermath of banking crises is associated with persistent declines in output and employment.

[5] Early warning models are increasingly used for financial stability purposes, and are based either on bank-level data or aggregate cross-country data.

To show why we believe the questions we are asking are relevant, we replicate our descriptive calculations on recent data on banks in the four largest euro area countries. Table 1 shows how many banks (along with the percent of national banking assets are associated with the banks) experienced a drop by 50 per cent in return on assets (and as a result of the shock saw the return assets move to the bottom of the industry distribution). We refer to these banks as newly distressed banks. The details of the exact strategy used in the calculation are explained later in the paper and do not matter for our main motivating points.

The table yields several insights. First, in each of the four countries, many banks experience abrupt declines in profitability, over two thirds (by assets) in France, Italy and Germany. Second, the timing of the distress differs. In France and Germany, the big problems occurred between 2007 and 2009, whereas in Italy the losses materialized in 2011. This pattern is consistent with the different timing and sources of losses that hit the banks in each country. At the same time, the Spanish banking system looks much less distressed. This is because neither BBVA nor Santander, the two largest banks in the country, meet the exact definition of distress used in the calculation, despite having substantial profit declines in 2011 and 2012. In the other countries essentially all the major banks wound up in trouble.

Just based on these simple statistics, it seems clear that our profitability shock succeeds in identifying banking stresses that are undoubtedly policy-relevant. The premise of the paper is that understanding the recovery prospects for these banks is a critical issue. Given that the economic stresses in many of these countries are ongoing or have only recently abated, judging recovery at this point is challenging. We believe our historical investigation can provide useful guidance about what to expect.

The remainder of the paper is organized into six sections. The next section introduces our definition of distress and provides the requisite background on the banking industry in Italy to put the sample in context. Section 3 provides some simple comparisons of recovering and non-recovering banks. Section 4 presents bank-level regressions aimed at identifying the key determinants of recovery. Section 5 examines bank-borrower relationship data to further explore the adjustments that recovering banks make in the wake of a shock, and Section 6 provides some evidence on possible drivers of these adjustments. Section 7 concludes with some observations about how these findings bear on the ongoing banking troubles in Europe.

2. Background on the Italian banking industry and our sample

In this section we provide information on some of the underlying trends in the Italian banking system and economy during the relevant period, describe the data that are available and introduce the definition of bank distress that we use in the remainder of the paper.

2.1. Italian Macroeconomic Developments Since 1989

A brief summary of basic macroeconomic data is presented in Table 2. After a period of strong growth in the late 1980s, accompanied by a lending boom, the Italian economy started to slow down during the 1990-91 global recession.[6] In 1992, as the economy was starting to recover, the European exchange rate mechanism (ERM) began to unravel and there was strong pressure to devalue the Lira.[7] In the summer of 1992 there was a monetary tightening, and exchange rate tensions that led Italy to withdraw from ERM. Upon doing so there was a steep drop in the exchange rate. The economy slowed sharply and went into recession by the second half of the year. In 1993 real GDP growth was negative for the first time since 1975.

The stock of bad loans rose steadily between 1992 and 1996, topping out at 9.4 percent in 1996. The default rate was elevated from 1992 through 1996, which is not surprising because it takes some time before a loan can be determined to be bad and hence the flow of bad loans lags the business cycle.

In an international context, the Italian crisis is relatively modest. For instance, the World Bank's Caprio and Klingebiel dataset on "Episodes of Systemic and Borderline Financial Crises" calculates the peak share of insolvent bank assets to banking total system assets as 11 percent. [8] In the Swedish and Finnish banking crises, which occurred around the same time, the percentages were 22 and 33 percent respectively.

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[6] The information in this section is largely taken from the commentary on the Italian economy that is given each year in the annual report by the Banca d'Italia.

[7] Starting in June of 1992 the central bank began raising interest rates to defend the currency, with overnight interest rates exceeding 30 percent by the 11th of September 1992; inflation was running at about five percent at the time. On the 12th of September they sought to have the currency re-aligned and on the 17th of September they gave up the defense and withdrew from the ERM. The Lira dropped from 765 per Deutsch Mark (as of September 10) to 923 on October 6 (a 20 percent decline), before beginning to recover.

[8] Caprio and Klingebiel (2003) document 117 systemic banking crises around the world between the late 1970s and 2002, and 51 borderline and nonsystemic episodes in 45 countries during the same period.

By 1997 growth had resumed and interest rates had fallen noticeably. Between 1997 and 2000 lending started to grow rapidly, which led to an increase in the ratio of credit to GDP by 15 percentage points. Default rates and the NPL ratio remained low during this period. In 2001 another global recession began and Italian growth again decelerated. The slow growth continued through the end of our sample and during 2001-2003 a second wave of distress followed – although the aggregate default rate did not jump this time.

Table 3 provides some basic information on the Italian banking industry between 1987 and 2004. The top panel in the table highlights the consolidation that occurred as branching restrictions were progressively eliminated. The nearly 40 percent cumulative decline in the number of banks was also accompanied by a drop in profitability over the first ten years of the sample. The conventional view is that the dip in profit rates was a result of increased competition that was facilitated by the deregulation (Angelini and Cetorelli (2003)).

2.2. Distressed Banks

The banks we analyze are drawn from all banks operating in Italy excluding the cooperative banks and the foreign bank branches, due to lack of data on them for the earlier years. The sample we focus upon excludes very small banks, i.e. those with assets of less than 51 million euros as of 1995 (100 billion lira). We impose a size threshold because very small banks are not full service banks and tend to have specialized loan portfolios, leaving them unusually vulnerable to a particular sectoral or regional disturbance. To be included in our sample the bank's charter must be four years old. The age requirement is imposed because de novo banks have more volatile profitability (DeYoung (2003)).[9]

We identify distressed banks based on changes in profitability. A bank is considered distressed in year t if the following two conditions are met: i) its return on assets (ROA), measured by profits before tax divided by total assets, drops by at least half and ii) the drop in ROA is such that the bank moves from above to below the 25th percentile of the distribution. The first requirement isolates sharp drops in profitability because we are not trying to analyze chronically poor performing banks. The second condition compares the ROA decline relative to

[9] The age threshold also excludes some large banks that are so comprehensively restructured that they are re-chartered. In particular, Capitalia and Banca Intesa are eliminated by this screen. As we explain below we are trying to analyze banks that experience an abrupt change in circumstances so we do not want to pool them with banks that are chronically impaired and for which the timing of decisions could be much more ambiguous.

the distribution of profits, rather than a single absolute threshold. We opt for the relative benchmark because of the aforementioned trend in profitability and because banking profits are so cyclical.[10] In the 31 cases where a bank meets these conditions more than once, we count only the first episode.

The resulting sample of distressed banks is shown in the bottom panel of Table 3. In total 151 banks are identified as being distressed between 1987 and 2004, the summing across all the years indicates that about 50 percent of the industry assets were in banks that experienced distress at some point. To allow for sufficient leads and lags to study the behavior before and after the dip in profits, we analyze cases where the shock occurred after 1988 or before 2002. Therefore in the rest of the analysis we have a potential sample of 121 banks; one of these banks had incomplete data, so that our actual sample in what follows is 120 banks.

By construction the newly distressed banks have low ROA relative to the sample average and, not surprisingly, tend to have a high ratio of non-performing loans to total loans. Table 3 shows they also tend to have higher default rates (defined as newly non-performing loans relative to the stock of previously performing loans) in the year of their profit collapse. There do not seem to be systematic patterns regarding the average size of the banks that get in trouble, and their cost ratios are generally similar to those observed in the rest of the industry.

Overall, we read Tables 2 and 3 as suggesting that macroeconomic conditions are likely to be an important factor in the incidence and recovery of the distressed banks.

2.3. Regional Developments

Beneath the macro cycles, however, there is considerable heterogeneity amongst the distressed banks. One consideration is the profit collapses that sometimes occur even during years of high growth (such as 1988-89 and 2000). These cases appear to be due to purely idiosyncratic events. The data on the median size of the newly distressed banks, along with the small overall percentages of assets residing in newly impaired banks, shows that most of these cases involve smaller institutions.

A second source of variation comes from the particular nature of the 1992-93 slow down. With the floating of the Lira, even though the domestic economy was sinking, export oriented firms saw their competitiveness improve dramatically. In the southern part of Italy, where

[10] We used this same definition of default to identify the newly distressed banks in Table 1.

exports as of 1992 represented around 5 percent of production (versus 18 percent in the Center-North), the fall in domestic demand swamped the gains from the exchange rate depreciation. During this period the central government also reduced subsidies that had been granted to support infrastructure investment which disproportionately benefitted Southern firms. This policy switch led to a drop in construction and exacerbated the downturn in the South. Thus, the regions of the country performed very differently during this episode, with annual Southern growth in value added averaging only 0.3 between 1992 and 1996 and Northern value added growth averaging 1.6 percent.

Table 4 provides some basic data on the heterogeneity by comparing the incidence of distress across the North West, North East, Center and South of Italy.[11] As hinted at above, just under half of the banks in the South got into trouble at some point during our sample, while just over 20 percent of the banks in the Northern regions became distressed. We defer the discussion of the recovery rates until the next section, but the Table also shows that recovery rates vary across regions, especially during the 1992-1994 episode.

3. Basic characteristics of distressed and recovering banks

We next analyze the characteristics of the distressed banks. The first step is to identify the ones which recover after the initial decline in profits. We define recovery based on a combination of improved performance and persistence of the improvement. The persistence restriction is important to make sure that a single year of improvement followed by return to low profitability is not counted as a recovery. Because the mean level of industry profitability is time-varying, using a single cut off level of profitability to identify healthy banks would be misleading. Accordingly, we gauge recovery by looking at the level of profits *relative* to other banks in the sample. Specifically, a bank is considered to have recovered if any of the following conditions holds:

1) In year 1 its ROA is greater than the 25th percentile and in year 2 the ROA percentile is greater or equal to the percentile observed the year before the shock; or

2) In year 2 its ROA is greater than the 25th percentile and in year 3 the ROA percentile is greater or equal to the percentile observed in the year before the shock; or

3) In year 3 ROA is greater than the 25th percentile and in year 4 the ROA percentile is greater or equal to the percentile observed in the year before the shock.

Our view is that these conditions guarantee that, at least in a relative sense, a distressed bank has restored its profitability. So we dub this definition the "relative recovery" measure. As indicated in Table 4, 41 of the 120 distressed banks ultimately recover by this metric.

For robustness purposes, we also consider a stricter definition of recovery that requires that profitability makes it all the way back to the pre-shock level. In this case a bank is considered to have recovered if any of the following conditions holds:

1) At t = 1 its ROA is greater than the 25th percentile and at t=2 ROA is greater or equal to ROA the year before the shock; or

2) At t = 2 its ROA is greater than the 25th percentile and at t=3 ROA is greater or equal to ROA the year before the shock; or

3) At t = 3 ROA is greater than the 25th percentile and at t=4 ROA is greater or equal to ROA the year before the shock.

Based on this second, absolute definition of recovery, we have 31 recovering banks. We refer to this definition as the "absolute recovery" measure. To save space we concentrate on the relative recovery metric in the remainder of this section, but in the regression analysis of later sections we show results for both definitions.

Having defined recovery we can compare the distressed banks along several dimensions. We normalize the data by always comparing the distressed banks to other banks in the industry.[12] Table 5 presents the data in "event time" relative to the year in which the distress occurred so that we can compare outcomes across banks; for example, for a bank that got into trouble in 1998, we compare each of the indicators to the average value of those indicators for the industry average in 1998 and those deviations are the year 0 statistics for that bank. In the table, we offer two types of contrasts. First is a comparison of the distressed banks which recover to those which do not.

[11] The regional definitions we use follow the standard groupings used in the official Italian statistics. See the website of the Italian National Statistical Institute www.istat.it for more details.

[12] We also compared the distressed banks to other banks in their region of the same size and the important patterns in Table 5 are present with that adjustment too.

We also pool all the distressed banks and compare them to the entire universe of banks from which the distressed banks are selected.

Before discussing the specific findings in the table, one issue throughout the analysis is how to handle banks that disappear before year t+3. Potentially, they could disappear because of merger, acquisition or failure. Outright failure does not occur for any of the banks in our sample. Because we do not analyze the details surrounding each exit, it is not clear whether one would expect banks involved in mergers or acquisitions to be more or less likely to recover. Some of these banks would no doubt have failed had they been forced to continue to operate on their own. But some may have been acquired precisely because they were good bets for rehabilitation and had some value to the bank that took them over or merged.

In the comparisons in this section we base our contrasts at different points in time on the sample of banks that were currently operating. We proceed by keeping banks in the analysis for as long as we have data on them. As they disappear we classify them based on their status as of their last complete observation. Of the 120 banks in the sample, 10 disappear during year zero or before the end of year 1 and then another 17 drop out at some point prior to the end of year 3. Based on this approach, 1 bank recovers before year t+3 and all of the others do not. We will deal with this attrition problem in more detail in subsequent regression analysis.

The premise of our analysis is that the troubled banks are not chronic underperformers, but instead suffered from a shock that abruptly impaired their profitability. Our strategy for identifying banks fitting this kind of description allows us to concentrate on a point in time around which study the behavior of banks. The data in Table 5 on ROA suggest that we have succeeded in avoiding chronically impaired banks. In particular, for the full sample, prior to time 0 the distressed banks on average had slightly higher profits rates than others. These differences when compared to set of the universe of banks are statistically significant, and the average difference is between 10 and 20 basis points. At time 0, this pattern flips and the mean ROA falls below average and the magnitudes increase noticeably. From that point onwards the typical distressed bank is between 50 and 100 basis points less profitable than the average bank.

The table shows that the R and NR banks differ on several dimensions. The first critical difference relates to their relative profitability both before and after time 0. The NR banks have relatively high profitability prior to the shock, with significantly higher profits than the R banks in year -1. Starting in year 0 the NR banks underperform compared to the R banks for the following 3 years (with the differences being significant for years 2 and 3). The average gaps in years 2 and 3 are over 80 basis points which is large: recall from Table 2, between 1989 to 2002, average ROA fluctuated between 120 and 55 basis points.

This pattern can be interpreted in at least two ways. The less interesting explanation is a pure mean reversion story, where for some reason profits were abnormally high and then dropped and became abnormally low; essentially this hypothesis suggests that the shocks hitting the two sets of banks differed and that explains the relative performance.

A more interesting alternative would be that some choices made by the banks were responsible for differences in performance. Given the high/low pattern in the table, the most obvious possibility would be choices in the riskiness of the loan portfolio. For instance, if the NR banks were simply pursuing a strategy of lending to a riskier set of clients, then we might expect to find that their profits were abnormally high when the customers are doing well and then deteriorate sharply when customers underperform. But there are no doubt other potential explanations besides a risk-return that could explain the relative ROA patterns of the R and NR banks.

We decompose net income (the numerator of ROA) into sources of income, costs, and extraordinary items (consisting of write downs and provisions). Specifically,

Net income = Interest margin + Other revenues – Operating costs +
Net loan write-downs and provisions + Other write-downs and provisions

Table 5 shows the behavior of these components (normalized by assets so that they add to ROA). On the revenue side, all the important action appears to be coming from interest margin. In particular, for the other revenue category from year 0 onwards there are no important differences (either between the full sample of distressed banks relative to all banks, or between R and NR banks). For the interest margin, the distressed banks show consistently lower margins from year 0 onwards, and the NR banks are significantly below the R banks in years 2 to 3. The interest margin can vary because of differences in deposit costs, differences in interest rates on performing loans or difference on interest received on non-performing loans. This third consideration means that if there is essentially no interest received for bad loans, and the proportion of bad loans is much higher for NR banks, then this will cause the interest margin for the NR banks to be lower than for R banks. We explore this possibility below.

The operating costs for the distressed banks show no consistent patterns. The average costs of all distressed banks looks similar to other banks and neither the R or NR banks stand out relative to each other. While not reported in the table, the similarity in costs is also present when the data are further disaggregated to separate staff costs from other costs. Changes in costs have little to do with the onset or recovery from distress as we have defined it.

The data on write-offs, losses and provisions also point to differences in lending practices as being important. The distressed banks (compared to all others) show significantly less of these items in years -2 and -3, and then significantly higher charges in years 0 and 1. The difference is marginally higher in year 2, but at that point the gap is being driven by the NR banks. Hence for years 2 and 3 the non-recovering banks are showing significantly higher levels than the recovering banks. In contrast, there are no consistent patterns involving write-offs, losses and provisions on other assets.

The last panel in Table 5 provides further information on two aspects of lending behavior. The first entry shows data on the default rates. There are several suggestive patterns involving the default rates. First, both the R and NR banks have substantially higher default rates than other banks in year 0 and -1. This suggests that both seem to be lending to riskier clients. From year 1 onwards, the recovering banks have defaults rates that are if anything lower than the non-distressed banks, while the NR banks default rates remain elevated and about the same magnitude. The difference between the R and NR banks is significant throughout.

Comparisons involving the stock of non-performing loans exhibit the same pattern. The stock of non-performing loans is consistently higher for the distressed banks than for the other banks starting in year -1. Throughout the period the NR banks have significantly higher levels of NPLs than the R banks, which consistently have low levels of NPLs relative to others in the industry.

The last entry in the table shows data on capital levels, defined as book value of equity to gross total assets. The typical distressed bank has less capital than other banks. But interestingly, there are no significant differences between either the R and NR banks, or between the distressed banks on average and the universe of banks. The observation that capital levels are not very informative about bank health is a common finding. For instance, many of the large banks that required bailouts during 2008 were "well-capitalized" by the regulatory standard at the time of the assistance.

Overall, the data from Table 5 fit with the following simple story. The distressed banks tend to be lending to relatively high risk customers, the banks that ultimately do not recover seem to be especially well described by this characterization. The R banks have positive interest margins, but their default rate only becomes higher than average in year 1. Prior to year 0, their interest margins for both R and NR banks are high and default rates are also high. Up until year 0 the differences between the two are not terribly pronounced; ironically all the way up until year 0, the banks that will subsequently not recover have higher profits rates (significantly so in year -1). At time 0, the lending patterns and outcomes begin to diverge. The default rates for the NR banks remain high and become significantly different than for the R banks and bad loans begin piling up. There is little change in costs, so that deterioration in the loan portfolio leads to sharp differences in profit rates. Therefore, the profit rates for the non-recovering banks are consistently lower than for the recovering banks from year 0 onward.

Motivated by these statistics, we explore the source of the higher risk of distressed banks, and compare the R and NR banks. The distressed banks could have higher default rates because they are lending to customers in riskier sectors, or because they are selecting riskier clients, or because they are subject to a local macroeconomic shock. We decompose the deviation of the bank-level portfolio default rate with respect to the national average (i.e. the industry mean, shown in Table 5) into three components as follows:

Bank Specific Default Rate - National Default Rate ≡

Bank Specific Default Rate – Predicted Bank Specific Rate

+ (Predicted Bank Specific Rate - Predicted Regional Default Rate)

+ (Predicted Regional Default Rate – National Default Rate)

where the national default rate is the default rate of the national loan portfolio, i.e. the product of the average default rate for different types of customers and the shares of loans for the entire industry allocated to each type of customer.[13]

The *Predicted Bank Specific Rate* is the default that is implied for the given bank if the default rate on its loans defaulted at the national average for its customer mix; *Predicted Regional Default Rate* is the default that is implied for a bank in a given region assuming all its loans are made in the home region and default at the rate that is typical for each type of customer in that region. In these calculations we allow for six types of borrowers: households, manufacturing firms, construction firms, farmers, service sector firms, and all others. We allow for the possibility that the default experiences of these 6 types differs across the four regions. Thus, we have effectively 24 different types of customers.

The first term in this breakdown is naturally interpreted as the "idiosyncratic default risk" because it is due to the bank's customers defaulting more (or less) than the average customers throughout the economy, holding constant the portfolio composition of the bank. The third term, which we call the "regional risk", is also intuitive. It reflects the portion of the default rate that arises because the average loan portfolio varies across regions. Notice that by construction it abstracts from any bank specific customer characteristics and varies only because differences in regional loan risk (both across time and across regions).

The middle term, which we label "customer mix risk", is perhaps more subtle. The customer mix risk arises because the specific bank's lending shares differ from the lending share that would prevail for the typical bank in its region.

We believe tracking the importance of the three types of risk can shed light on why the default rates of NR and R banks are higher than the industry, and how they adjust after the shock. In particular, if the idiosyncratic default risk is the driving factor, then the banks' ability to screen individual borrowers would be important. In contrast, if the regional risk proves critical then the bank's own decisions would be inconsequential.

The data, reported in Table 6, show four intriguing patterns. First, there are no important differences in terms of their customer risks, all the action is in the idiosyncratic and regional risk. Second, the NR banks have systematically more regional risk. From years -1 onwards the

[13] Angelini, Bofondi and Zingales (2017) use a similar decomposition to analyze the origins of non-performing loans during the current Italian banking crisis. They find that idiosyncratic risk is very important for identifying

differences are significant. Third, both types of banks see a temporary spike in idiosyncratic risk in year zero, but the idiosyncratic risk for the NR banks is consistently higher than for the recovering banks. Finally, for the NR banks the levels of idiosyncratic risk before and after the spike are remarkably similar -- they seem to have neither increased nor cut back on risk. The R banks do seem to have lowered idiosyncratic risk a bit, relative to the pre-crisis period, but the differences are not statistically significant.

4. Logit regressions on bank data

To complete our descriptive analysis and better understand the patterns in Tables 5 and 6, we estimate a series of logit regressions in which the outcomes are coded as 0 if the bank charter survives but the bank does not recover, and 1 if the bank survives and recovers. Given our interest in simply documenting basic patterns, we do not attempt to model the exact dynamics of the banks recovery. Instead, we simply average some of the variables over the post-shock period.

The first hypothesis tested is that recovery is basically pre-determined and depends solely on external conditions (the macro-economy and the region). The second hypothesis is that recovery is influenced by bank-specific factors. We explore two alternatives: a) recovery is mainly driven by the size of the initial profit decline, and b) recovery is the result of factors that the bank can govern after the shock. In particular, the evidence from Table 5 suggested that recovering banks tended to have lower default rates during the years after the initial distress. This could be the result of the macroeconomic environment but also of choices the banks made in the wake of the shock.

The types of variables that we consider can be thought of as proxies for three different factors affecting recovery probabilities. We include indicator variables for region where the banks are headquartered: Northwest, Northeast, and South (so that the central region is the excluded category). We also construct an index of macro conditions which we approximate by the average growth rate of value added in the region over the three years after the bank gets in trouble. We include a dummy variable that identifies the crisis years of 1992 to 1994. Roughly 39% of the cases in our sample correspond to banks that fell into distress during this crisis

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which banks wound up with large levels of non-performing loans.

episode. This dummy variable will allow us to see whether this period stands out in terms of recovery.

The second consideration is the size of the shock hitting the bank. Obviously banks that experience bigger drops in profits will have to do more to regain profitability. The more interesting question is whether the size of the shock is a sufficient statistic for recovery. We use as a proxy of the size of the shock the difference between the return on assets for the afflicted bank and the average rate of return on assets for all banks (ROADEV) at the time of the shock; transforming the profits to be relative to the industry average is appropriate given the trend in profit rates and our definition of distress, which also measured ROA relative to the industry average.

Finally, we measure the riskiness of the loan portfolio after the bank becomes distressed using the difference between the bank's default rate and the national average (DEFAULTDEV), discussed previously, and its three components (IDRISK, REGRISK and CUSTRISK). We average these variables over years 1 to 3 to see how the default rate of the bank is behaving once industry average is accounted for.

When we follow the banks after the shock, we need to deal with the attrition due to banks that are not observed at t+3 because of mergers. Attrition could produce a selection bias if the determinants of exit, especially the unobservables, are correlated with the variables in the equation of interest. Ideally we would account for a potential selection issue in the econometric analysis. This would require some exclusion restrictions regarding factors that affect the chances of dropping out from the sample but not affect the likelihood of recovering from distress. It is hard *a priori* to conceive of any credible candidates that satisfy this restriction. In the absence of credible exclusion restrictions, a selection model would be inefficient (see Heckman et al. (1999), Puhani (2000)) and would not be properly identified.

Instead, we tackle the problem as follows. We first estimate a multinomial logit model with three outcome categories: merger, survival and recovery, survival and no recovery, as of year 3, controlling for the same regressors described above. We run Wald tests of the null hypothesis that two categories can be combined, for all combinations of outcome categories. If two outcomes are indistinguishable with respect to the variables in the model, the two outcomes can be combined to obtain more efficient estimates (see Long and Freese (2003)). The results show that the exiting firms are not systematically different from either the recovering or the non-recovering banks so they can be grouped with either category.[14] The model also confirms that the recovering and not recovering banks *do* differ from each other.[15]

This finding suggests that keeping the exiting banks that do not recover before exit and coding them as not recovered in the logit model should not distort our results. In practice all but one of the exiting banks are coded as not recovering because one bank makes it back to profitability by year t+2 and then exits.

To ensure robustness of results to this choice we estimate the model with two samples. The first sample includes all banks except for the 10 banks that disappear in the same year as the profit shock since we cannot compute post-shock bank variables for them. The post-shock variables for the other banks are the average over the years where data are available. The second sample includes only the 93 banks for which we have complete information until t+3. We find virtually identical regression results for both samples.[16]

Table 7 shows the summary statistics for the variables that will be used in the regressions. We report the statistics both for the 93 surviving banks and the sample of 110 banks for which data after year 0 exist. As a benchmark in what follows, note that 37 percent of the 110 banks recover in relative terms and 27 percent recover using our second stricter absolute definition; for the 93 bank sample for which we have complete information these percentages are 44 and 32, respectively.

4.1 Results

The results are shown over five panels. The first panel shows the estimates for the relative recovery definition with the 110 bank sample that includes the merged banks. The second panel shows the analogous results for the smaller sample of 93 banks with complete information. The next two panels present the results for the absolute recovery definition, based on the larger and smaller sample, respectively. Finally, the last panel shows some robustness checks where we

[14] The regression results are in appendix 2 which is an online appendix.

[15] Defining the three possible outcomes as exit, survive and not recover, survive and recover, the results of the test do not reject the null that exit can be combined either with survive and not recover, or survive and recover. The test does reject that recover and not recover can be combined. The test suggests that the coefficients associated the exit predictions are so noisy that they are totally uninformative.

[16] For robustness purposes we estimate a Cox survival model that allows banks that exit to have potentially recovered if the merger had not occurred, treating them as censored. We use fixed covariates (post-shock averages) and model the occurrence of recovery as the censored “failure” event. The results are fully consistent with the ones from our main specification.

include a number of additional covariates. In all the panels, we report coefficients after transforming them to represent the impact on the marginal probability of recovery from a one-unit change in each variable.

Since the main conclusions hold for either definition of recovery and with either sample, in this summary we will mostly refer to the coefficient estimates for the relative recovery definition in the sample that includes the merged banks. In cases, where the definition of recover or choice of sample matters we mention that explicitly.[17]

The first two columns in Table 8A and Table 8B show that controlling for only regional factors, the Southern banks are less likely to recover than the other banks. For instance, the marginal difference in the probability of recovery (evaluated at average regional GDP growth rate) is 39 percentage points higher for Northeastern banks relative to Southern banks. Regional growth has a positive coefficient but is never significant.

The indicator for banks that became distressed during the 1992 to 1994 banking crisis has a small and insignificantly different from zero coefficient.[18]

Judging by the absolute definition of recovery, it does appear that fewer banks regained profitability during this episode compared to others. However, the 1992-94 crisis dummy falls in magnitude and ceases to be significant once additional controls are included. Thus, this downturn does not seem to be unusual. Given the highly variable recovery rates shown in Table 4 this is not surprising. Perhaps the magnitude of the 1992-1994 crisis was not large enough to be deemed a systemic problem, but regardless of the reason we will not conduct separate analyses for this period.

Column 3 in both Tables 8A and 8B shows the results of adding the size of the initial profit decline to the initial specification. The banks whose ROA at the time of the shock was relatively higher have a greater chance of recovering. The estimated effect is marginally significant in contributing to a relative recovery, but far from significant for predicting absolute recovery (column 3 in Tables 8C and 8D). In both cases the magnitude of this effect is modest (in

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[17] The regressions with the regional dummy variables, the size of the initial profit decline and the 92-94 dummy were estimated also for the entire sample of 120 banks that experience the shock – which includes the 10 banks that disappear in year 0 .In this sample the measure of the size of the shock is statistically significant and positive indicating that banks that faced a smaller shock were more likely to recover, The regional dummies are insignificant except for the one for the South, that is negative.

[18] The 1992-1994 dummy is also insignificant in (unreported) specifications where there are only 2 region dummies and in specifications without the regional GDP control.

comparison to the others). A bank that underperformed the national average 102 basis points (which is the 25th percentile of the distribution) compared to one that underperformed by 57 basis points (the 75th percentile), would be 4.5 percentage points less likely to recover (in a relative sense).

In the next specification we add DEFAULTDEV (the average value of the default rate from the three years after the onset of distress relative to the national average default rate over the same period). The coefficient on this variable is negative and statistically significant at the 1 percent level. The magnitude of this effect is sizable. A bank that keeps default rates 0.45 percentage points below benchmark is at the 25th percentile of the distribution, while a bank with an average default rate 2.87 percentage points above the benchmark is at the 75th percentile of the distribution. The bank with the lower default rate would be about 15 percentage points more likely to recover. The inclusion of the default rate reduces the coefficient on the initial drop in profits. Thus, with the full set of controls, credit risk appears to be the quantitatively most important determinant of which banks recover. The result holds if we include the value of the same variable at the time of the shock, so the coefficient captures the extent to which the banks manages to reduce its default risk after t=0. The finding holds also for the absolute measure of recovery (Tables 8C and 8D).

To further explore the importance of the default rate we decompose it into idiosyncratic (IDRISK), customer mix (CUSTRISK) and regional risk (REGRISK) components defined above. The results, reported in the last column of Tables 8A and 8B, show that all three variables have negative coefficients. However, only the proxy for the idiosyncratic risk is highly statistically significant; the regional risk proxy is estimated to have a large effect but its impact is imprecisely estimated. An increase in the idiosyncratic risk from the 25th to the 75th percentile implies (all else equal) a reduction in the probability of recovery from 48 to 34 percent. The results hold if we include in the regressions also the three components of the default risk measured at the time of the shock. These variables are insignificant and our main result on idiosyncratic risk does not change, suggesting that the post-shock variable is not capturing differences in the initial size of the portfolio risk.

4.2. Robustness checks

Before concluding that the idiosyncratic risk is the key driver of recovery we consider several robustness checks. Our main concern is that there is some other omitted bank characteristic that is relevant for the recovery that is being picked up by the idiosyncratic risk variable. Prior work suggests two potential alternatives that we explore in Table 8E. The number of additional controls that can be included has to be parsimonious since we have a limited number of degrees of freedom.

One possibility is that national banks and regional banks might have different business models and lending practices. For instance, the law of large numbers might provide better loan diversification for banks with a broader geographic focus. In that case, we would like to control more directly for this characteristic. We constructed two proxies to measure the concentration of lending.

The first proxy, REGCONC, is a Herfindahl index based on the share of loans made by each bank in the four geographic regions. The sample mean of the index is 0.76, and it ranges between 0.29 and 1. As a second measure, we also constructed a variable, dubbed SAMEREG, that records the share of loans to clients in the same region as the bank's charter. This variable has a mean of 0.57 and a range between 0.1 and 0.95. So both these variables suggest that lending is highly geographically concentrated.

The first two columns of Table 8E show that adding either of these variables to the logit regression does not change our main results. Both proxies have statistically significant predictive content, but the sign of the effects are perhaps surprising. In each case, the estimated coefficients are *positive* implying that banks with more concentrated portfolios are more likely to recover. Perhaps this suggests that when very diversified banks get into trouble multiple things must have gone wrong, which makes recovery more difficult. Regardless of the explanation, more important for our analysis is the finding that the coefficient of IDRISK remains very significant and if anything slightly larger in magnitude, indicating that controlling for regional portfolio composition does not weaken the role played by idiosyncratic loan default rates.

A second possibility is that the ownership structure of the bank might influence management responses to problems. Sapienza (2004) shows that state-owned banks and private banks differ in their customer mixes and also in the interest rates they charge for similar borrowers (with the state-owned banks charging less). So we also investigate whether a bank's ownership structure influences the probability of recovery. As in Sapienza (2004) we consider two different definitions of bank type.[19] The simplest comparison is between private and different types of state-owned or local-government owned banks. Some of these banks are controlled by some public body, while others are technically controlled by foundations. These foundations were nonprofit entities created at the beginning of the privatization process to take ownership of newly created banking firms; during this period the foundations were controlled by local public authorities. We also include a dummy for the Savings and Loans (S&Ls), which were also controlled by local public authorities but had a different regulatory framework. The third specification in Table 8E shows that S&Ls were more likely to recover, than private banks which are the omitted category, but that the idiosyncratic risk remains highly significant (with a slightly larger magnitude).

In a last specification in Table 8E, we further separate the private banks based on their governance, to isolate the Mutual banks (Banche Popolari) from the other type of private banks. Mutual banks also have a higher probability of recovery than the other private banks. But, even with our full set of ownership controls included, the significance and magnitude of the IDRISK coefficient remains.

The importance of the idiosyncratic default rate suggests (at least) two potentially very different reasons why portfolio choices could be important. One possibility is that some banks are simply better run and are adept at finding high quality borrowers. If so, when a shock arrives, these banks would be expected to be able to manage risks and continue lending to deserving customers. Under this interpretation, low idiosyncratic risk would be a proxy for good management.

A very different hypothesis would be that high idiosyncratic risk is a signal that the bank is gambling for reclamation, while other banks may be doing nothing special. Provided that gambling fails on average, then we would still see that differences in idiosyncratic risk are important, but not because some banks are well-run.

To distinguish between these hypotheses we need to find out more about the specific lending choices that the banks are making. We turn to bank-firm relationship data to investigate the lending policies of banks after the shock.

[19] The bank type here is defined as of t=0. The banks do not switch types with the exception of two banks that were privatized between time 0 and time 3. The results we report are not affected by which way we classify these two

5. Evidence from Matched Lender-Borrower Regressions

5.1 Empirical Model

Given preceding descriptive findings, we concentrate on the lending to high risk borrowers, that are responsible for most loan losses after the profitability shock. One additional advantage of focusing on these clients is that we believe they are less likely to want to terminate a lending arrangement. A healthy borrower might decide to simply switch banks if the bank gets into trouble. For the high risk borrowers this seems less likely and so reductions in credit should be mainly driven by the lender's preference.

We compare credit growth at the different types of banks using a regression of the form:

$$\textit{Credit growth}_{ij} = f(\textit{Borrower Risk Proxy}_j, \textit{Borrower Risk Proxy}_j{*}\textit{RECOVER}_i, \textit{Borrower Controls}_j, \textit{Bank Fixed Effects}_i) \quad (1)$$

where credit growth refers to bank *i* loans to borrower *j*, and RECOVER is a dummy for recovering bank.

The presence of the bank fixed-effects in the regressions means that we make no attempt to directly estimate the direct effect of RECOVER on credit growth. The reason is that the recovery outcome is likely not to be independent from total credit growth, and both variables could be reflecting the existing customer mix of banks and differences in other bank balance sheet characteristics that affect both variables. The bank fixed effects absorb any average difference in lending between the NR and R banks. The coefficient of the interaction between RECOVER and borrower risk captures how the two types of banks treat differently borrowers with which they are affiliated. The advantage of estimating the model in this way is that we have controlled for other bank-level sources of variation such as the average capital level or lending standards that would arguably belong in the regression. So in what follows we focus on the interaction of the recovery dummy and variables measuring borrowers' quality. We do not attempt to identify a causal relationship between credit growth and recovery but instead follow the approach of Rajan and Zingales (1998) of analyzing patterns of differential effects to detect the channel through which the recovering banks manage to reduce credit risk.

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banks. In other words, the results are almost identical if we define the types as of t=3.

5.2. Data

The data employed in the analysis are constructed by merging firms' balance sheet and income statement data that are contained in the Company Accounts Data Set (CADS, "Centrale dei Bilanci" in Italian) with the data on loans in the Italian Central Credit Register.[20]

CADS is a proprietary data base containing financial data on a sample of around 25,000 Italian firms that is maintained by a group of banks for the purpose of credit risk analysis by the affiliated banks.[21] To this end, CADS contains a z score measuring the probability of default on a loan that is computed with linear discriminant analysis (see Altman, Marco and Varetto (1994) for the details of the method). More details on the z scores are given in Section 5.3 below.

The information on bank loans granted to the firms in CADS comes from the Central Credit Register of Italian Banks (Centrale dei Rischi, CR). The CR is managed by the Bank of Italy to track the credit exposures of the clients of resident banks. Banks can file inquiries to the CR about loan applicants to verify their creditworthiness, specifically regarding the total amount of borrowing outstanding and the applicants' default history. The minimum requirement for inclusion in the CR is that a borrower has either loan commitments or loans in place which exceed a specified threshold.[22] If the loan is in default the firm is automatically in the CR, even if the loan amount is below the usual threshold. In addition to reporting the size of the commitment, the banks also report the amount of credit actually dispersed, whether the loan is collateralized or guaranteed by a third party. By the nature of low thresholds that determine inclusion in the CR, the full CR by the end of our sample contained data on more than 800,000 borrowing firms.

The matched firm-bank data set is constructed as follows. We first identify all loans in the CR that are made to CADS firms and select any firm that borrowed at least once in the period 1986-2001 from our sample of distressed banks. We then shift the data to event time so that for each bank we have the CADS borrowers at year 0. The relationships between the banks and these borrowers are tracked back to year -3 and forward up to year 3.

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[20] A number of studies have used the matching between CADS and Credit Register data to analyze the dynamics of bank-firm relationships, for example see, Sapienza (2002), and Panetta, Schivardi and Schum (2009).

[21] CADS firms represent around 49 percent of total sales of nonfinancial firms in the national accounts.

[22] Until December of 1995 this cutoff value was 80 million Lire, about 40,000 euros, subsequently the cutoff became 150 million Lire (75,000 euros). Our sample of borrowers should not be affected by the cut-off change given their size.

The matching between CADS borrowers and the banks at the year of the shock yields around 90,000 observations. In the following section we restrict the analysis to relationships for which there is a minimum amount of credit outstanding of 10,000 euros at the time of the shock.[23] This reduces the number of observations to 64,198 because many bank-firm pairs have only commitments that have not yet been tapped at year 0 or have past loans that were granted that have subsequently been defaulted upon, but no active lending program in place. For a large share of the relationships we only have loan information and incomplete information on the borrower's balance sheet. The final data set with all firm-level variables includes 46,636 observations of credit relationships between 97 of our crisis banks and their clients. Descriptive statistics are reported in Table 9.

A limitation of the analysis is that we do not observe the entire portfolio of the banks. In addition, the analysis is necessarily conditional on following the borrowers that were affiliated at the time of the shock. Despite these shortcomings we still believe this exercise is useful for two reasons. First, corporate lending represents the largest component of banks' portfolios, particularly in the first half of the sample period. For instance, loans to households in Italy were 15 percent of lending in 1995 and are mainly in the form of mortgages, a component of lending that is both safer and stickier than others.[24] Second, CADS firms tend to be major bank clients: lending to CADS firms represents on average more than 30 percent of the loan portfolio for the banks in our sample. Accordingly, we would expect banks to give these customers higher priority than a typical borrower. Hence, if anything the presumption would be that these customers are insulated from credit reductions. If this is correct, it suggests that any effects that we do find understate what might occur for the smaller more typical bank customers.[25]

Our outcome variable is the average percentage increase of amount of credit granted by the bank to the customer in question, CREDITGROW, in the three years after the shock to the bank. If we have only one or two years of data on the relationship then we take the average growth over

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[23] Although the euro did not exist in most of our sample period we refer to euros as all values in the data were converted to the fixed parity that was adopted when the euro was introduced.

[24] See the Banca d'Italia Annual Report for 1995. Loans to non-financial companies were around half of the portfolio while credit to small businesses, defined as sole proprietorships and partnerships with up to 20 employees, were 13 percent. Small businesses defined in this way are not included in CADS because they are not incorporated.

[25] Of course, if we found no patterns in this sample the reason could be because of the special nature of the CADS sample. Fortunately, this does not appear to be a problem.

the shorter spell.[26] Average credit growth is about -5 percent per year, but the range across borrowers is very large.

We account for some borrower characteristics that could affect the firm specific credit supply and credit demand. To control for possible misspecification in our functional form we consider LOGCREDIT_0 which is the natural log of total credit in year 0. This control would be appropriate if the growth rate of credit granted differs depending on whether the borrower already has a large initial exposure to the lender.

Our second proxy, BANKSHARE, is the proportion of credit that the firm gets from the bank. We also consider the square of this variable. We include these variables to account for the possible outside options of the borrowers. In particular, for borrowers with many lenders it is possible that the switching costs of finding credit elsewhere could be sufficiently low that the borrower simply dumps the lender when the bank gets into trouble. The typical borrower is getting 23% percent of its credit from the bank that we are studying, but the variation is large so that cases where the percentage exceeds 50% are common.

We consider the length of the relationship (RELLENGTH), computed as the log of the number of years for which the relationship is observed.[27] This factor could be important if the banks view the distress as temporary and in adjusting credit give priority to their long standing customers. We also include firm size (log of total assets at time 0, FSIZE) as a catchall control to allow for the possibility that banks treat large and small customers differently.

We include also industry fixed effects (agriculture, manufacturing, construction, services) interacted with year dummies to control for credit demand and the industry-specific business cycles. Recall that because the observations are in event time, we are mixing years. We also include controls for provinces, based on the borrower headquarters, to pick up the regional differences that we found in the bank-level analysis.

In our setup we control for changes in credit demand by including the borrower characteristics and the industry*year and province fixed effects. To the extent that these variables

[26] One reason why we no longer observe outstanding credit could be that the firm has defaulted on its loans from a given bank. Our procedure in this case amounts to only computing the growth rate of credit over the period when the loans were considered to be performing. We believe this makes sense because upon becoming non-performing the loan amounts mechanically are increased to make up for unpaid interest. This convention also means that for the defaulting banks we overstate loan growth, because the cessation of lending that occurs when the default takes place is not included in the average.

adequately control for differences across borrowers in loan demand, the change in lending observed is driven primarily by choices by the banks.

Recent studies using bank-firm relationship data control for changes in loan demand by comparing credit growth of firms borrowing from multiple banks, some of which are affected by a shock (Khwaja and Mian (2008)), controlling for firm fixed effects. In our sample of 46,000+ credit relationships, only about 3% of cases involve a situation where the same borrower is borrowing from two banks that encounter distress in the same year. The borrowers that fit this description are unusual in several respects. For instance, they are four times larger than the rest of the sample and their profit shock at time 0 is bigger than for the typical firm. So we are hesitant to draw general conclusions from this selected set of firms. More importantly, however, is the fact that in the subsequent analysis we will show that the different ways in which banks handle their riskiest clients relative to their less risky ones is critical for recovery. Within the matched sample there are only about 80 of these high risk firms.[28] So there is simply not enough power to do the most obvious kind of test that would compare the outcomes of a common high-risk borrower that is attached to a recovering and non-recovering bank.

Furthermore, for our results to be driven by customers' demand for credit, one would have to argue that R and NR banks face differential shifts in the demand for credit by their borrowers that are systematically related to their relative credit risk (i.e. riskier borrowers at R banks contract their demand for loans more than at NR banks – low risk borrowers expand demand at R banks more than at NR). If this were the case, as Khwaja and Mian (2008) note, including the firm fixed effects would not uncover supply effects.[29]

5.3. Proxies for high risk borrowers

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[27] We cap the relationship variable to be 4 for any relationship that is at least 4 years old because of the truncation bias at the beginning of the sample.

[28] There are almost 400 cases where a firm is borrowing from two banks that become distressed in the same year and the firm has negative profits in the years after its lenders become distressed. For these firms we find that the recovering banks are significantly more aggressive in trimming lending than the non-recovering banks. This is consistent with all the evidence we find below for the full sample of borrowers.

[29] The identification of supply is based on the assumption that there is no bank-specific change in the demand for credit so all the change in loans of the bank-firm pair is driven by a supply shift, as the change in demand is absorbed by the firm fixed effect.

Because there is no single way to identify risky customers we consider three different candidates. The first focuses on the profitability of the borrowers. We flag any firm whose earnings before interest and taxes are negative (on average) between years 1 and 3. If we have incomplete information on profits we take the average over the years for which data exist.

Our second set of high risk borrowers are firms that had performing loans in year 0 but default at some point over the next three years. Default is only declared when the bank has become convinced that the borrower is not going to fully repay the loan. This involves a judgment decision which typically would only be declared after the client had missed payments and shown other indications of being impaired. Our first indicator picks firms that default on a loan to the distressed bank that is in our sample (DEFAULT).

We also identify firms that continue to make good on their payments to the bank which we are following, but default on a loan to some other bank that participates in the credit register (DEFAULTOTH). Usually once a firm has been recognized as defaulting with one bank it is only a matter of time before it will default with all its other lenders. The credit register is set up to make sure that these situations do not go undetected. Accordingly, the supervisors scrutinize these cases and continuously monitor the percentage of such loans at each bank. If the percentage of these types of loans at a given bank becomes too large, then the bank has to provide an explanation for why it is continuing to lend and, usually, has to present a plan on how it will reduce its exposure to borrowers that are in this condition.

Finally, the third measure of risk is given by a z score provided by CADS. This variable is an estimate computed by CADS to describe the probability that a particular borrower will default over the next year. This has the advantage of being a forward looking measure of risk. But, CADS does not compute anything for firms which are already in default. This means that the firms with a z score are higher quality (even than the average CADS customer, which themselves are bigger than average Italian firm and hence already less likely to default borrower than the typical firm in the economy).

The estimates of z are computed using discriminant analysis as pioneered by Altman (1968) and proposed for Italy by Altman, Marco and Varetto (1994). CADS assigns firms to 9 categories, with z's of 1 representing the lowest credit risk and 9 indicating the highest credit risk. CADS maps the score into four levels of risk: i) safe (scores equal to 1 or 2), solvent (3, 4), vulnerable (5, 6), risky (7, 8, 9).

The historical relationship between the z score in one year and the probability of default in the next year for CADS firms between 1986 and 2006 is:

Z score at year t	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**Total**
Average default rate at year t+1	0.10	0.11	0.14	0.20	0.49	0.89	1.94	5.22	15.69	**1.20**

Source: Centrale dei Bilanci.

In this context, default is defined as occurring when the firm is declared legally bankrupt or recorded as a non-performing borrower.

The z-scores appear to serve the purpose for which they were constructed, in that the default rates are monotonically increasing in the level of z. The levels of predicted defaults, however, are less than 0.9 percent for z's between 1 and 6, then rise to about two percent for z=7, and then climb much higher for z's above 7. Hence in what follows we isolate the borrowers as is suggested by the default probabilities. Firms with z's of one or two will be the control group. We then combine z's of 3 and 4 into one group, 5, 6 and 7 into a second group, and 8 and 9 into our high risk group.

While not shown in Table 9, the average values of the zscore are 5.15 and 5.25 for the R and NR banks respectively at time 0. Given the large number of loans in the sample the difference in the means is statistically significant. But we view the difference as economically small. To put this in perspective it implies that for every 100 borrowers, the distribution of the z's for the NR banks would have 10 borrowers with a rating of one grade worse than the for the R banks. Importantly, the share of borrowers with z scores of 7, 8 or 9 are very similar for the R and NR banks; tests comparing the equality of these shares cannot reject the hypothesis that they are equal. So the difference in the means is coming from a small difference in the lending to the relatively safe clients.

5.4. Results

The initial specifications shown in columns 1 to 3 of Table 10 present the results using our relative recovery definition. Firms with average negative operating profits in the years following the shock will experience about 15 percentage points lower credit growth (per year) at the NR banks[30]; the interaction term coefficient is -5.6 percentage points and highly statistically significant, suggesting that recovering banks perhaps reduce their lending by about one third more relative to the NR banks.

In column 2 we find that credit growth of firms that will default is 5.7 percentage points higher (per year) than other firms which likely reflects a scramble by these borrowers to tap as much credit as they can to stay in business. Ivashina and Scharfstein (2010) show that a similar credit-line draw-down by weak firms occurred in the United States immediately after the Lehman bankruptcy in September 2008. The recovering and non-recovering banks treat these borrowers similarly.

Firms that default at another bank tend to increase their borrowing by about 4.8 percentage points per year at a non-recovering bank where they are still considered as performing. In contrast, credit growth is estimated to be zero at the recovering banks (this is inferred from the sum of the coefficients on the other default variable and the interaction with recover).

The bank may not be able to shrink its credit exposure if it has long term loans that had been made to the customer, so the fact that the R do not succeed in significantly cutting credit is perhaps understandable. We see no good reason (other than forbearing to avoid recognizing losses) that the NR banks would be increasing lending to these customers. This type of behavior has been documented by Albertazzi and Marchetti (2010) who analyze lending relationship data for Italy after the Lehman Brothers bankruptcy and find that small and poorly capitalized banks tended to evergreen loans to riskier borrowers.

The results using the z scores as the risk proxy also show signs of more risk-taking by the NR banks. Recall that borrowers with z's of one and two are considered safe and because these are the omitted category they are the benchmark against which the estimates are made. Relative to the NR banks, the recovering banks are consistently more cautious in lending. The difference is most pronounced for the very risky borrowers, i.e. those with z scores of 8 or 9. The NR banks cut credit by about 4 percentage points per year, while the R banks cut it almost it by more than 13 percentage points per year. The remaining columns of the table show the estimates when we use the stricter absolute definition of recovery and the general patterns are very similar to what we found for the relative recovery definition.

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[30] In others words, if loans started at 100 they would fall 45 percentage points in three years to 55.

The additional controls in these regressions are almost all highly significant and the signs are intuitive. For example, customers with longer relationships have higher credit growth and larger firms get more credit. The main effect of including these controls is to reduce the standard errors of the coefficients on the high risk proxies.

To assess the robustness of these findings we considered a number of alternatives. In Table 11 we explore the consequences of dropping the three largest banks from the analysis. These three banks are responsible for about half of the observations in Table 10, so one might worry that all we learning from Table 10 is how these three banks behave. In fact, the results are somewhat sharper when we analyze the smaller sample. First, the distinction between how the firms with negative earnings are handled is more extreme, so that the recovering banks are substantially more aggressive in pruning credit to these firms. Second, the NR banks are much more prone to extend credit to firms that are in default to other banks. Finally, the difference between how the highest risk borrowers are treated also becomes more extreme. For instance, with the relative recovery metric, the NR banks hardly change their credit exposure to these borrowers (the coefficient estimate is not significantly different from zero), while the R banks cut credit to these firms by about 16 percentage points per year.

Other robustness tests were based on regressing the growth of credit granted, including the unused part of credit lines. Particularly in the case of revolving credit lines, firms hold a substantial share of unused credit they can resort to if needed. Banks can reduce the amount of granted credit and change pricing on short notice. In additional regressions, not reported, we find that recovering banks tend to cut commitments more aggressively than non-recovering banks to both firms with negative profitability after the shock and firms with the highest z-scores, consistent with our main results.

6. Exploring Hypotheses About Bank Types

Having identified differences in behavior, we now turn to the trickier question of whether the critical differences are coming from particularly wise choices by well-run banks or from bad choices by others banks.

Given the importance of borrower default rates in predicting recovery documented in the last section, we sort banks based on their default rates as of year 0; more specifically, splitting the sample based on banks whose default rates are above and below the median at the time of the shock. Loosely speaking, we think of the banks whose default rates were low as having been well-managed, although this could also reflect luck. Of the 60 low-default-rate banks, 45 percent recover, while only 23 percent of the high-default-rate banks recover. We can learn more about whether this is simply a matter of luck or we can also see if the bank is better capitalized than its peers (i.e. has a capital ratio above the median of the distressed banks). We dub those banks with relatively high capital and low percentages of customers in default “prudent”. The prudent banks have a recovery rate of 55 percent, compared to 27 percent for the other banks. We can see whether these prudent banks make different lending decisions than other less conservative banks.

The other interpretation of the importance of the default rates in predicting recovery is that it reflects gambles by insolvent or nearly insolvent banks. For these banks at risk of failing, it would rationally make sense to extend high risk loans that might offer high returns. To gauge solvency we require that banks have a combination of low capital and high portfolio default rate at the time of the shock; operationally we make this classification this by requiring banks to be below the sample median for the capital ratio and above the sample median for the default rate. This simple definition seems to capture what we have in mind: only 17 percent of the 29 banks that meet these conditions recover, as opposed to 40 percent of the other banks.[31] In what follows, we call the banks with high default rate and low capital “gamblers”.

To further explore these findings we now look at how the lending patterns for the banks that we expected to be prudent and those that seemed most likely to be gambling; recall the prudent banks have relatively low default rates at time 0 and are relatively well-capitalized and the gamblers are in the opposite situation. We estimate the regression of credit growth replacing the dummy RECOVER either with a dummy equal to 1 if the bank is PRUDENT, and 0 otherwise, or with a dummy for GAMBLING equal to 1, and 0 otherwise.

The results for the prudent banks are shown in columns 1 through 3 of Table 12. The prudent banks cut lending by around 20 percentage points per year to unprofitable borrowers, compared to other banks which reduce credit by 15 percentage points per year. The prudent banks shrink credit to borrowers which have defaulted to other lenders by 4 percentage points per year, while the other banks raise credit by 6.6 percentage points per year. The prudent banks are

[31] The difference in the percentage of recovering banks between prudent and not prudent, and gambling and not gambling are both statistically significant.

aggressive in trimming loans to borrowers with z scores of 8 or 9, cutting credit for them by 13 percentage points relative to other banks. Thus, based on each of our high risk proxies it appears that the banks with low defaults as of year zero are managing their lending risk aggressively in subsequent years.

Columns 4 to 6 of the table show the credit granted by the gambling banks. From column 4 we see that these banks cut credit to firms that are consistently unprofitable less than the other banks. The size of this effect, 7 percentage points per year, is large. The gamblers are also much more prone to continue lending to firms that have defaulted to other banks; the estimate here is also quite large, they are growing credit by about 14 percentage points per year to these firms relative to the rest of the sample (where loan growth is flat). Both these results are slightly surprising since the supervisors are likely checking to see if banks are engaged in anomalous lending patterns.

Column 6 shows that the gambling banks are also extending more credit to borrowers with high z scores; the gamblers keep credit roughly flat to the borrowers with z-scores of 8 and 9, while the other banks are shrinking loans by 10 percentage points per year.

Overall Tables 10, 11 and 12 paint a fairly consistent picture. There are important contrasts in the way different banks offer credit to risky customers. Focusing on the estimates using the z-scores, which provide an ex-ante assessment of the borrowers, we see that the banks that recover are substantially less generous with credit to riskiest borrowers. The firms with the most conservative loan book at the time of the profit drop are especially tough about contracting credit to these firms. In contrast, the firms whose solvency is in doubt don't reduce credit exposure for these same firms. Based on these comparisons, it seems that both conservative management by some banks and gambling by others are occurring.

7. Conclusions

Little is known about what governs recovery from large adverse profitability shocks. Our first pass at these data uncover several robust patterns. First, banks that get into trouble seem to have been lending to riskier clients than the average in the overall economy. Second, one important factor governing recovery is the size of the initial profit drop that occurs at the onset of distress. Third, the general business climate after the shock also matters. But we find no evidence that there was anything different about the banks that recovered from the 1992-1994 downturn when many banks were distressed than during other periods. Fourth, recovery also depends on factors that banks can control.

Among the factors that the bank can influence, the ability to adjust the loan portfolio is critical: recovering banks show consistently lower default rates on loans in the post-shock period because they are better able to reduce the risk of their portfolio with respect to the average bank with similar exogenous characteristics.

Matched bank-borrower data suggests that an important reason why the recovering banks manage defaults better is that they are tougher on extending credit to their riskiest customers. Banks that had relatively low default rates when their profits fall are tough on these same risky borrowers, while banks with an incentive to gamble for reclamation seem to be much more generous with credit to these firms.

Regulators tend to disclose relatively little about what steps are taken with respect to banks that require intervention. Our findings suggest paying close attention to whether the distressed banks are being particularly vigilant in containing credit to high risk borrowers. For countries that have credit registers and credit ratings that are readily available this would be easy to implement. Likewise, where supervisory assessments concentrate on a CAMELS (capital, assets, management, earnings, liquidity and sensitivity to market risk) rating system, it would be possible to closely monitor the riskiest assets and customers.

These findings also suggest that stress tests as currently practiced might not be as informative as is often believed. Currently, most tests around the world involve what amounts to an accounting calculation that looks at how bank earnings compare to potential loan losses, to judge the impact on capital. In these exercises little attention is paid to connections between stress scenarios and the implication for different types of bank customers (especially since the horizon of most tests is two years). Our analysis suggests that it might be useful to keep track of which customers loans would go bad during a crisis and to consider how readily a bank can manage these problems. In particular, indiscriminant reductions in lending seem to be less important than managing the credit extension to the riskiest borrowers.

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Table 1: Euro Area selected countries: Newly Distressed Banks (2007-2012)

The data are based on the sample of commercial, savings and cooperative banks that are reported by Bankscope. We identify the banks that become distressed applying the same criteria as the one used in Table 2, based on Bankscope's reported pre-tax profitability. The Bankscope sample of banks includes individual banks and banking groups; the balance sheet types reported here include those classified by Bankscope as C1, C2 and U1. Subsidiaries of groups included in the data were removed where ownership data were available. Assets are in million euros and are the sum of assets of the entities reported for each country, with no netting of interbank assets.

Country	Year	Bankscope Banks in the sample	Distressed banks	Share of sample assets	Sample Assets
France	2007	74	3	14.4	7,678.8
	2008	81	9	14.3	9,534.8
	2009	80	8	14.9	8,979.9
	2010	84	2	0.01	9,218.1
	2011	87	5	0.05	9,629.8
	2012	81	4	12.3	9,479.5
Germany	2007	1,464	118	2.51	5,408.2
	2008	1,467	163	60.8	5,829.9
	2009	1,511	24	2.54	5,557.4
	2010	1,555	23	1.86	5,960.3
	2011	1,593	41	7.18	6,235.3
	2012	1,586	28	0.59	6,138.7
Italy	2007	453	5	0.30	2,707.3
	2008	460	40	5.64	2,904.3
	2009	461	62	1.19	2,858.8
	2010	475	54	7.03	2,986.2
	2011	485	35	68.8	3,034.7
	2012	470	43	9.65	3,125.7
Spain	2007	84	0	0.00	2,319.2
	2008	95	7	4.31	2,952.4
	2009	99	3	10.9	3,071.2
	2010	104	7	0.61	3,297.0
	2011	109	13	2.66	3,367.8
	2012	105	13	10.7	3,550.7

Table 2: Italian Banking and Macroeconomic Trends

ROA is computed as profit before tax divided by total assets. The default rate is the ratio of loans to borrowers defaulting in year t divided by the stock of performing loans at the end of year t-1. Non-Performing loan ratio is the ratio of non-performing loans relative to the stock of performing and non-performing loans. Sources: Istat for GDP, Bank of Italy for the other data. Note the banking statistics are computed using individual banking data. The totals may differ from published statistics due to incomplete data and partial estimation of data for the special credit institutions before 1995. Lending growth is deflated using the GDP deflator.

Year	Real GDP growth	3-month interbank interest rate	Real lending growth	Return On Assets	NPL ratio	Default rate
1987	2.98	11.51	5.32	0.85	6.32	1.9
1988	3.95	11.29	11.38	0.93	5.81	1.5
1989	2.87	12.69	13.63	0.88	5.08	1.5
1990	1.97	12.30	9.31	0.95	4.76	1.5
1991	1.39	12.21	7.70	0.87	4.87	2.3
1992	0.76	14.02	5.97	0.67	5.05	2.2
1993	-0.88	10.20	-0.46	0.81	6.20	4.3
1994	2.21	8.51	-2.41	0.31	7.74	2.8
1995	2.92	10.46	-1.15	0.44	9.32	3.1
1996	1.09	8.82	-2.67	0.52	9.42	2.6
1997	2.03	6.88	5.78	0.36	8.75	2.3
1998	1.79	4.99	4.73	0.89	8.66	1.7
1999	1.66	2.95	8.99	0.95	7.36	1.4
2000	3.03	4.39	11.48	1.26	5.84	1.0
2001	1.76	4.26	4.90	0.95	4.66	1.0
2002	0.38	3.32	3.35	0.76	4.44	1.0
2003	0.25	2.33	3.15	0.69	4.64	1.2
2004	1.22	2.10	3.25	0.87	4.67	0.8

Table 3: Sample Descriptive Statistics and Newly Distressed Banks

The sample includes all banks operating in Italy excluding local cooperative banks (Banche di Credito Cooperativo), foreign banks, banks that are less than 4 years old or have assets below 100 billion Italian Lire (51 million euros). Median assets are reported in million euros and are deflated by the GDP deflator (1995=1). Values in Italian Lira before the introduction of the euro are converted at the fixed exchange rate of 1936.27. ROA is computed as profits before taxes divided by gross total assets. Non-Performing loan ratio is the ratio of non-performing loans relative to the stock of performing and non-performing loans. Default rate is the flow of new non-performing loans relative to the previous stock of performing loans. In panel B, a bank is considered distressed in year t if the following two conditions are met: i) its ROA drops by at least half and ii) the drop in ROA is such that the bank moves from above to below the 25th percentile of the distribution.

Panel A

			Banks in Sample*			
Year	Number of banks	Median Assets	Median ROA	Median NPL ratio	Default rate	Operating Cost/Assets
1987	326	649.84	1.20	7.03	2.09	3.24
1988	326	725.99	1.15	6.14	1.50	3.20
1989	312	835.65	1.20	5.44	1.46	3.08
1990	309	868.22	1.23	5.11	1.59	3.23
1991	296	963.91	1.15	5.02	2.15	3.21
1992	278	1046.29	1.01	4.85	2.34	3.22
1993	276	1085.27	1.17	6.10	3.93	3.16
1994	259	1090.21	0.55	7.45	2.70	3.10
1995	237	1135.52	0.98	7.95	2.50	3.12
1996	240	1150.40	0.91	7.33	2.31	3.05
1997	229	1200.15	0.77	6.69	1.81	2.94
1998	222	1211.24	0.94	6.25	1.42	2.80
1999	218	1271.28	0.82	4.82	1.05	2.65
2000	210	1276.98	0.98	3.45	0.94	2.62
2001	209	1409.30	0.93	3.08	0.94	2.57
2002	202	1336.00	0.78	2.57	0.83	2.46
2003	195	1570.46	0.79	2.67	0.95	2.38
2004	197	1612.55	0.86	2.69	0.79	2.33

Panel B

				Newly distressed banks			
Year	Number of banks	Total Assets (% of Sample)	Median Assets	Median ROA	Median NPL ratio	Default rate	Operating Cost/Assets
1987	11	8.83	376.65	0.52	8.00	2.69	3.51
1988	6	0.80	354.91	0.27	7.72	3.63	4.02
1989	11	0.49	354.49	0.41	7.79	1.30	3.01
1990	6	2.77	819.90	-0.16	7.79	3.37	3.04
1991	8	0.97	455.62	0.24	7.44	7.09	3.39
1992	20	6.51	1937.53	0.31	6.67	3.19	2.98
1993	10	2.06	1414.58	0.33	7.71	6.57	3.33
1994	17	2.56	892.76	0.04	9.84	3.97	3.96
1995	10	2.24	1084.44	0.08	14.32	7.78	3.05
1996	3	5.48	650.20	0.10	9.71	4.97	2.83
1997	7	0.60	478.87	0.12	14.75	2.81	3.66
1998	7	1.10	987.66	-0.83	24.38	7.29	3.54
1999	7	0.49	658.76	0.18	15.84	2.94	3.70
2000	7	2.89	790.39	0.23	2.83	0.87	2.70
2001	8	7.76	1619.89	-0.85	2.40	0.59	2.60
2002	6	0.56	164.18	0.05	4.59	1.78	2.89
2003	4	3.66	1591.01	-0.04	4.64	3.40	2.71
2004	3	0.41	1429.01	0.15	5.63	1.48	1.88

Table 4: Count of newly distressed banks by region

The number of banks refers the total number of banks in existence in any of the years between 1987 and 2004, excluding foreign bank branches, cooperative banks, banks with total assets below 100 billion ITL (51 million euros) and banks that are less than 4 years old. A bank is considered distressed in year t if the following two conditions are met: i) its return on assets (ROA), measured by profits before tax divided by total assets, drops by at least half and ii) the drop in ROA is such that the bank moves from above to below the 25th percentile of the distribution. Recovery is measured in relative terms as described in the text.

	North West	**North East**	**Center**	**South**
Total banks operating in all years	99	96	89	103
Number of banks experiencing a crisis	22	18	33	47
Number of banks recovering (relative definition)	9	11	12	9
Total banks operating 1992-1994	67	62	65	72
Number of banks experiencing a crisis 1992- 1994	10	7	12	18
Number of 1992-1994 crisis banks that recovered according to the relative recovery definition.	6	4	4	3

Table 5: Event time statistics, deviations from industry means (41 recovering banks)

Deviations of individual banks with respect to the mean of banks in the industry. The variables are in percentage points. The default rate is defined as new bad loans in t over the existing stock of performing loans at t-1. Non-Performing loan ratio is the ratio of non-performing loans relative to the stock of performing and non-performing loans. Recovery is calculated using the relative recovery definition given in the text. See the data appendix for the other definitions. Three asterisks indicated significance at the 1% level of confidence, two asterisks indicate significance at the 5% level of confidence and a single asterisk indicates significance at the 10% level of confidence.

	ROA					Interest margin/Total Assets					Other Revenues/Total Assets				
	NR	R	H:NR=R	All	H: All=0	NR	R	H:NR=R	All	H: All=0	NR	R	H:NR=R	All	H: All=0
-3	0.208	0.040		0.150	***	0.112	0.001		0.074		-0.126	0.130	**	-0.035	
-2	0.225	0.078		0.175	***	0.258	0.087		0.199		-0.130	0.099	*	-0.052	
-1	0.181	-0.081	***	0.092	***	0.070	-0.059		0.026		0.145	0.119		0.136	
0	-1.219	-0.834	***	-1.088	***	-0.317	-0.255		-0.296	**	-0.145	-0.062		-0.117	*
1	-0.808	-0.466		-0.681	***	-0.355	-0.053		-0.243	***	0.062	0.018		0.046	
2	-1.042	0.017	***	-0.594	***	-0.344	0.031	**	-0.268	***	-0.152	0.044		-0.069	
3	-1.019	0.140	***	-0.513	***	-0.485	0.076	***	-0.240	**	-0.157	-0.008		-0.092	

	Operating Costs/Total Assets					Loan Write-Offs, Losses and Provisions/Total Assets					Write-Offs, Losses and Provisions on Other Assets/Total Assets				
Year	NR	R	H:NR=R	All	H: All=0	NR	R	H:NR=R	All	H: All=0	NR	R	H:NR=R	All	H: All=0
-3	-0.131	0.152		-0.033		-0.029	-0.035		-0.031	***	-0.048	-0.002		-0.032	
-2	-0.033	0.180		0.039		-0.014	-0.023		-0.017	**	-0.033	-0.037		-0.034	
-1	0.133	0.170		0.145		0.095	0.060		0.083		-0.192	-0.096		-0.159	**
0	0.268	0.187		0.240		0.572	0.215		0.450	***	-0.082	0.109	*	0.017	
1	0.268	0.177		0.234		0.441	0.146		0.332	**	-0.195	0.106	***	-0.054	
2	0.223	0.192		0.210		0.373	-0.061	***	0.190	*	-0.063	-0.078		-0.069	
3	0.101	0.105		0.103		0.337	-0.084	**	0.153		-0.067	-0.097		-0.080	

Table 5, continued

	Default Rate					NPL Ratio					Equity Capital/Total Assets				
Year	NR	R	H:NR=R	All	H: All=0	NR	R		All		NR	R	H:NR=R	All	H: All=0
-3	0.972	-0.521	**	0.456		0.650	-1.323	***	-0.994	**	-0.611	-0.055		-0.419	
-2	1.422	-0.236	***	0.860		1.469	-0.749	**	-0.399		-0.749	-0.049		-0.512	
-1	2.216	0.392	**	1.597	***	2.908	-0.463	***	1.765	**	-0.626	-0.195		-0.480	
0	2.742	0.471	**	1.967	***	4.413	-0.167	***	2.848	***	-0.696	-0.145		-0.508	
1	2.130	-0.156	**	1.283	**	5.018	-0.372	***	3.021	***	-0.479	-0.037		-0.315	
2	2.286	-0.587	***	1.072	**	5.896	-0.269	***	3.290	***	-1.058	-0.202		-0.696	
3	1.814	-0.303	***	0.891	**	6.668	-0.409	***	3.580	***	-1.086	-0.157		-0.929	

Table 6: Contrast between Recovering and Non-Recovering banks in the nature of their credit risk

R and NR banks are defined using the relative recovery definition given in the text. The columns report a decomposition of each bank's default rate relative to the national default rate in a given year into three components. IDRISK is the Bank Specific Default Rate – Predicted Bank Specific Rate, where the predicted rate is the imputed rate for that bank based on using the national default rates for 24 different customer types that vary by sector and region. REGRISK is the Predicted Regional Default Rate – National Default Rate, where the predicted regional default rate is imputed for the bank by assuming that each of the bank's 24 different types of customer default at the regional average default rate for that customer type. CUSTRISK is the Predicted Bank Specific Rate - Predicted Regional Default Rate. Three asterisks indicated significance at the 1% level of confidence, two asterisks indicate significance at the 5% level of confidence and a single asterisk indicates significance at the 10% level of confidence.

	IDRISK			**REGRISK**			**CUSTRISK**		
Year	NR	R	H:NR=R	NR	R	H:NR=R	NR	R	H:NR=R
-3	0.93	0.00	**	1.09	0.43	*	0.09	0.18	
-2	1.07	0.11	***	1.16	0.55	*	0.16	0.17	
-1	1.39	0.14	**	1.25	0.50	**	0.16	0.69	
0	2.02	0.60	**	1.31	0.51	**	0.30	0.29	
1	1.15	-0,01	**	1.50	0.46	**	0.10	0.30	
2	1.35	-0,33	***	1.43	0.36	***	0.12	0.21	
3	0.97	-0,04	***	1.45	0.25	***	0.06	0.11	

Table 7: Variables employed in the regressions and descriptive statistics

		120 banks			110 banks that exist after year 0			93 banks that exist through t+3		
Name	Description	25^{th} p.	Mean	75^{th} p.	25^{th} p.	Mean	75^{th} p.	25^{th} p.	Mean	75^{th} p.
RECOV_R	Relative Recovery	0	0.342	1	0	0.373	1	0	0.441	1
RECOV_A	Absolute Recovery	0	0.250	1	0	0.273	1	0	0.322	1
NORTHWEST	Dummy North Western Region	0	0.183	1	0	0.191	1	0	0.183	1
NORTHEAST	Dummy North Eastern Region	0	0.150	1	0	0.136	1	0	0.140	1
SOUTH	Dummy Southern Region	0	0.392	1	0	0.373	1	0	0.365	1
D9294	Dummy 1992 to 1994	0	0.392	1	0	0.382	1	0	0.376	1
GDPGROWTH	Average Regional GDP Growth from years 1 to 3	0.971	1.453	1.861	1.066	1.450	1.854	1.226	1.484	1.854
ROADEV	Return on Asset Deviation from industry mean in year 0	-1.019	-1.088	-0.572	-0.973	-1.016	-0.561	-0.984	-1.018	-0.561
DEFAULTDEV	Average Default rate deviation from industry portfolio years 1 to 3	NA	NA	NA	-0.450	1.863	2.870	-0.463	1.683	2.648
IDRISK	Idiosyncratic Risk	NA	NA	NA	-1.072	0.621	1.736	-1.072	0.557	1.196
CUSTRISK	Customer Mix Risk	NA	NA	NA	-0.067	0.180	0.537	-0.079	0.110	0.509
REGRISK	Regional Risk	NA	NA	NA	-0.485	1.083	1.690	-0.485	1.015	1.652
REGCONC	Sum of squares of shares of loan portfolio in each region	0.569	0.755	0.942	0.592	0.757	0.939	0.608	0.762	0.942
SAMEREG	Share of loan portfolio in the same region as the charter of the bank	0.105	0.566	0.956	0.109	0.566	0.956	0.114	0.578	0.955
PUBLIC	State-owned bank dummy	0	0.117	0	0	0.127	0	0	0.139	0
S&L	Saving & Loans bank dummy	0	0.208	0	0	0.218	0	0	0.236	0
MUTUAL	Cooperative bank dummy	0	0.325	1	0	0.318	1	0	0.333	1

Table 8A: Logit model of probability of relative recovery

Bank-level observations. The coefficients estimates reported as marginal effects after logit transformation. The standard errors are below coefficients. Robust Huber-White standard errors. Three asterisks indicated significance at the 1% level of confidence, two asterisks indicate significance at the 5% level of confidence and a single asterisk indicates significance at the 10% level of confidence.

Dependent Variable:	Probability of Relative Recovery				
	(1)	(2)	(3)	(4)	(5)
	dy/dx	dy/dx	dy/dx	dy/dx	dy/dx
NORTHWEST	0.087	0.080	0.086	0.039	0.009
	(0.144)	(0.139)	(0.145)	(0.133)	(0.143)
NORTHEAST	0.364**	0.379**	0.360**	0.304*	0.320*
	(0.159)	(0.166)	(0.167)	(0.167)	(0.181)
SOUTH	-0.140	-0.141	-0.147	-0.086	0.054
	(0.095)	(0.101)	(0.101)	(0.111)	(0.232)
GDPGROWTH	0.108	0.103	0.085	0.082	0.050
	(0.076)	(0.076)	(0.076)	(0.083)	(0.091)
D9294	-	0.077	0.061	0.102	0.144
	-	(0.102)	(0.092)	(0.079)	(0.114)
ROADEV	-	-	0.083	0.065	0.069
	-	-	(0.052)	(0.048)	(0.048)
DEFAULTDEV	-	-	-	-0.044***	-
	-	-	-	(0.011)	-
IDRISK	-	-	-		-0.049***
	-	-	-	-	(0.018)
CUSTRISK	-	-	-	-	-0.010
	-	-	-	-	(0.062)
REGRISK	-	-	-	-	-0.082
	-	-	-	-	(0.058)
Pred. Prob.	0.361	0.362	0.358	0.344	0.341
Pseudo. R squared	0.103	0.107	0.118	0.161	0.167
Number of observations	110	110	110	110	110

Table 8B: Logit model of probability of relative recovery (small sample)

Bank-level observations, referring to banks that survive until t+3. The coefficients estimates reported as marginal effects after logit transformation. The standard errors are below coefficients. Robust Huber-White standard errors. Three asterisks indicated significance at the 1% level of confidence, two asterisks indicate significance at the 5% level of confidence and a single asterisk indicates significance at the 10% level of confidence.

Dependent Variable:	Probability of Relative Recovery				
	(1)	(2)	(3)	(4)	(5)
	dy/dx	dy/dx	dy/dx	dy/dx	dy/dx
NORTHWEST	0.108	0.101	0.100	0.039	-0.003
	(0.146)	(0.141)	(0.146)	(0.143)	(0.183)
NORTHEAST	0.367**	0.376**	0.358**	0.303	0.326
	(0.176)	(0.179)	(0.181)	(0.188)	(0.211)
SOUTH	-0.145	-0.148	-0.157	-0.094	0.145
	(0.103)	(0.109)	(0.109)	(0.122)	(0.244)
GDPGROWTH	0.089	0.087	0.067	0.064	0.019
	(0.091)	(0.092)	(0.097)	(0.102)	(0.117)
D9294	-	0.073	0.056	0.125	0.197
	-	(0.092)	(0.082)	(0.076)	(0.125)
ROADEV	-	-	0.109*	0.081	0.094*
	-	-	(0.058)	(0.059)	(0.056)
DEFAULTDEV	-	-	-	-0.051***	-
	-	-	-	(0.009)	-
IDRISK	-	-	-		-0.060***
	-	-	-	-	(0.015)
CUSTRISK	-	-	-	-	0.026
	-	-	-	-	(0.081)
REGRISK	-	-	-	-	-0.112
	-	-	-	-	(0.069)
Pred. Prob.	0.428	0.429	0.424	0.409	0.404
Pseudo. R squared	0.101	0.104	0.121	0.171	0.191
Number of observations	93	93	93	93	93

Table 8C: Logit model of probability of absolute recovery

Bank-level observations. The coefficients estimates reported as marginal effects after logit transformation. The standard errors are below coefficients. Robust Huber-White standard errors. Three asterisks indicated significance at the 1% level of confidence, two asterisks indicate significance at the 5% level of confidence and a single asterisk indicates significance at the 10% level of confidence.

Dependent Variable:	**Probability of Absolute Recovery**				
	(1)	(2)	(3)	(4)	(5)
	dy/dx	dy/dx	dy/dx	dy/dx	dy/dx
NORTHWEST	-0.022	-0.012	-0.008	-0.036	-0.052
	(0.147)	(0.146)	(0.146)	(0.136)	(0.137)
NORTHEAST	0.167	0.156	0.144	0.080	0.090
	(0.158)	(0.154)	(0.151)	(0.131)	(0.135)
SOUTH	-0.067	-0.067	-0.068	0.022	0.098
	(0.090)	(0.079)	(0.088)	(0.093)	(0.186)
GDPGROWTH	0.067	0.091	0.067	0.078	0.060
	(0.063)	(0.047)	(0.063)	(0.052)	(0.059)
D9294	-	-0.081	-0.089	-0.088	-0.065
	-	(0.089)	(0.078)	(0.063)	(0.083)
ROADEV	-	-	0.047	0.045	0.047
	-	-	(0.048)	(0.050)	(0.047)
DEFAULTDEV	-	-	-	-0.036***	-
	-	-	-	(0.011)	-
IDRISK	-	-	-		-0.038**
	-	-	-	-	(0.017)
CUSTRISK	-	-	-	-	-0.014
	-	-	-	-	(0.043)
REGRISK	-	-	-	-	-0.057
	-	-	-	-	(0.040)
Pred. Prob.	0.254	0.251	0.249	0.237	0.235
Pseudo. R squared	0.021	0.045	0.053	0.098	0.100
Number of observations	110	110	110	110	110

Table 8D: Logit model of probability of absolute recovery (small sample)

Bank-level observations. The coefficients estimates reported as marginal effects after logit transformation. The standard errors are below coefficients. Robust Huber-White standard errors. Three asterisks indicated significance at the 1% level of confidence, two asterisks indicate significance at the 5% level of confidence and a single asterisk indicates significance at the 10% level of confidence.

Dependent Variable:	Probability of Absolute Recovery				
	(1)	(2)	(3)	(4)	(5)
	dy/dx	dy/dx	dy/dx	dy/dx	dy/dx
NORTHWEST	-0.049	-0.034	-0.035	-0.071	-0.073
	(0.152)	(0.154)	(0.151)	(0.139)	(0.158)
NORTHEAST	0.163	0.154	0.141	0.082	0.108
	(0.180)	(0.178)	(0.176)	(0.160)	(0.172)
SOUTH	-0.066	-0.062	-0.063	-0.006	0.101
	(0.101)	(0.103)	(0.099)	(0.109)	(0.218)
GDPGROWTH	0.053	0.063	0.054	0.044	0.026
	(0.076)	(0.078)	(0.078)	(0.075)	(0.084)
D9294	-	-0.114	-0.121	-0.091	-0.065
	-	(0.089)	(0.080)	(0.080)	(0.097)
ROADEV	-	-	0.059	0.045	0.050
	-	-	(0.053)	(0.049)	(0.042)
DEFAULTDEV	-	-	-	-0.036***	-
	-	-	-	(0.011)	-
IDRISK	-	-	-		-0.042***
	-	-	-	-	(0.014)
CUSTRISK	-	-	-	-	0.032
	-	-	-	-	(0.054)
REGRISK	-	-	-	-	-0.057
	-	-	-	-	(0.049)
Pred. Prob.	0.294	0.289	0.287	0.271	0.264
Pseudo. R squared	0.034	0.046	0.053	0.088	0.100
Number of observations	93	93	93	93	93

Table 8E: Logit model of probability of relative recovery, robustness

Bank-level observations. The coefficients estimates reported as marginal effects after logit transformation. The standard errors are below coefficients. Robust Huber-White standard errors. Three asterisks indicated significance at the 1% level of confidence, two asterisks indicate significance at the 5% level of confidence and a single asterisk indicates significance at the 10% level of confidence.

Dependent Variable:	Probability of Relative Recovery							
	(1)		(2)		(3)		(4)	
	dy/dx		dy/dx		dy/dx		dy/dx	
NORTHWEST	-0.055		0.594	**	0.072		0.025	
	(0.150)		(0.254)		(0.172)		(0.180)	
NORTHEAST	0.187		0.721	***	0.334	**	0.224	
	(0.212)		(0.142)		(0.147)		(0.180)	
SOUTH	-0.019		-0.007		0.092		0.079	
	(0.190)		(0.207)		(0.212)		(0.216)	
GDPGROWTH	0.075		0.049		0.045		0.017	
	(0.077)		(0.080)		(0.092)		(0.091)	
D9294	0.159		0.144		0.151		0.144	*
	(0.108)		(0.114)		(0.108)		(0.086)	
ROADEV	0.044		0.086	*	0.049		0.061	
	(0.048)		(0.049)		(0.050)		(0.061)	
IDRISK	-0.043	***	-0.042	***	-0.057	***	-0.057	***
	(0.012)		(0.014)		(0.016)		(0.015)	
CUSTRISK	-0.074		-0.057		0.004		0.001	
	(0.069)		(0.067)		(0.074)		(0.068)	
REGRISK	-0.099	*	-0.094	*	-0.065		-0.085	
	(0.058)		(0.057)		(0.057)		(0.054)	
REGCONC	0.874	***	-		-		-	
	(0.266)		-		-		-	
SAMEREG	-		0.849	**	-		-	
	-		(0.355)		-		-	
PUBLIC	-		-		-0.049		0.009	
	-		-		(0.117)		(0.113)	
S&L	-		-		0.346	**	0.438	***
	-		-		(0.157)		(0.154)	
MUTUAL	-		-		-		0.299	**
	-		-		-		(0.137)	
Pred. Prob.	0.324		0.324		0.339		0.327	
Pseudo. R squared	0.242		0.210		0.212		0.246	
Number of observations	110		110		110		110	

Table 9: Variables employed in the regressions with lending relationships

		Mean	Std. Dev.	Min	Max
CREDITGROW	Average credit growth between years 1 and 3 for firm i at bank j. The average is computed over the years in which the relationship is observed.	-0.051	0.652	-1	2.5
COMMITGROW	Average credit commitments growth between years 1 and 3 for firm i at bank j. The average is computed over the years in which the relationship is observed.	-0.043	0.640	-1	2.5
RECOV_R	Equal to 1 if the bank recovers, and 0 otherwise. Recovery is defined as 1 if ROA reverts to above the 25th percentile in either t1, t2 or t3 and then to the t-1 percentile in t2, t3 or t4 respectively (41 banks).	0.380	0.485	0	1
RECOV_A	Equal to 1 if the bank recovers, and 0 otherwise Recovery is defined as 1 if ROA reverts to above the 25th percentile in either t1, t2 or t3 and then to the t-1 level of ROA in t2, t3 or t4 respectively (30 banks).	0.275	0.447	0	1
PRUDENT	Equal to 1 if the bank's default rate on its loans in year 0 is below the median value and its capital ratio is above the median value for the sample, 0 otherwise.	0.422	0.494	0	1
GAMBLE	Equal to 1 if in year 0 the bank is below the sample median of the capital ratio and above the median for the default rate, 0 otherwise.	0.118	0.323	0	1
EBITNEG	Equal to 1 if the firm has negative average Earnings Before Interest and Taxes in years 1 to 3.	0.109	0.312	0	1
DEFAULTOTH	The firm defaults between 1 and 3 on a loan at a bank other than bank j	0.022	0.146	0	1
DEFAULT	The firm defaults between 1 and 3 on a loan at bank i	0.053	0.223	0	1
DZSCORE3	Dummy equal to 1 if the zscore of the firm in year 0 is equal to 3, 0 otherwise.	0.051	0.219	0	1
DZSCORE4	Dummy equal to 1 if the zscore of the firm in year 0 is equal to 4, 0 otherwise.	0.192	0.394	0	1
DZSCORE5	Dummy equal to 1 if the zscore of the firm in year 0 is equal to 5, 0 otherwise.	0.188	0.390	0	1
DZSCORE6	Dummy equal to 1 if the zscore of the firm in year 0 is equal to 6, 0 otherwise.	0.180	0.384	0	1
DZSCORE7	Dummy equal to 1 if the zscore of the firm in year 0 is equal to 7, 0 otherwise.	0.282	0.450	0	1
DZSCORE8	Dummy equal to 1 if the zscore of the firm in year 0 is equal to 8, 0 otherwise.	0.054	0.226	0	1
DZSCORE9	Dummy equal to 1 if the zscore of the firm in year 0 is equal to 9, 0 otherwise.	0.014	0.116	0	1
LOGCREDIT_0	Log of total credit to firm i from bank j in year 0	12.479	1.418	9.243	22.081
BANKSHARE	Credit of firm i from bank j divided by total credit of firm j.	22.971	26.123	0.001	100
RELLENGTH	Log of the length of the relationship in years; the number of years is equal to 4 if greater than 4.	1.143	0.426	0	1.386
FSIZE	Log of firm total assets.	9.046	1.316	1.098	17.783

Number of observations: total 46,823, of which 46,636 are for borrowers with z-scores. The number of observations with all firm controls is slightly lower.

Table 10: Bank fixed effects model on lending relationships data
Average Growth Rate in years 1 to 3

The observations are bank-firm relationships. Standard errors below coefficients are clustered at the bank level. The dependent variable is the average annual growth rate of total credit used by firm i at bank j where the average is computed for the years the relationship is observed. Definitions of variables are in Table 7. The RECOV variable differs as shown in the headers at the top of the table. Three asterisks indicated significance at the 1% level of confidence, two asterisks indicate significance at the 5% level of confidence and a single asterisk indicates significance at the 10% level of confidence.

Dependent Variable: CREDITGROW

	Relative Recovery (RECOV_R)			Absolute Recovery (RECOV_A)		
	(1)	(2)	(3)	(4)	(5)	(6)
EBITNEG	-0.148 ***	-	-	-0.148 ***	-	-
	(0.012)	-	-	(0.011)	-	-
EBITNEG*RECOV	-0.056 ***	-	-	-0.074 ***	-	-
	(0.019)	-	-	(0.017)	-	-
DEFAULTOTH	-	0.048 *	-	-	0.045 **	-
	-	(0.025)	-	-	(0.022)	-
DEFAULTOTH*RECOV	-	-0.060	-	-	-0.077 **	-
	-	(0.036)	-	-	(0.034)	-
DEFAULT	-	0.057 **	-	-	0.055 **	-
	-	(0.026)	-	-	(0.022)	-
DEFAULT*RECOV	-	-0.002	-	-	0.009	-
	-	(0.035)	-	-	(0.034)	-
DZSCORE3_4	-	-	0.108 ***	-	-	0.093 ***
	-	-	(0.026)	-	-	(0.030)
DZSCORE3_4*RECOV	-	-	-0.065 *	-	-	-0.041
	-	-	(0.037)	-	-	(0.034)
DZSCORE5_6_7	-	-	0.101 ***	-	-	0.080 **
	-	-	(0.028)	-	-	(0.034)
DZSCORE5_6_7*RECOV	-	-	-0.068	-	-	-0.028
	-	-	(0.047)	-	-	(0.042)
DZSCORE8_9	-	-	-0.042 *	-	-	-0.059 **
	-	-	(0.023)	-	-	(0.026)
DZSCORE8_9*RECOV	-	-	-0.095 **	-	-	-0.083 *
	-	-	(0.045)	-	-	(0.046)
LOGCREDIT_0	-0.079 ***	-0.075 ***	-0.072 ***	-0.079 ***	-0.075 ***	-0.072 ***
	(0.015)	(0.014)	(0.016)	(0.015)	(0.014)	(0.016)
RELLENGTH	0.092 ***	0.108 ***	0.103 ***	0.091 ***	0.108 ***	0.102 ***
	(0.021)	(0.024)	(0.023)	(0.022)	(0.024)	(0.023)
BANKSHARE	-0.191	-0.154	-0.177	-0.189	-0.153	-0.178
	(0.146)	(0.144)	(0.135)	(0.146)	(0.144)	(0.135)
$1/2BANKSHARE^2$	0.346	0.269	0.325	0.342	0.269	0.328
	(0.224)	(0.216)	(0.200)	(0.225)	(0.216)	(0.199)
FIRMSIZE	0.046 ***	0.043 ***	0.040 ***	0.046 ***	0.043 ***	0.040 ***
	(0.012)	(0.012)	(0.013)	(0.012)	(0.012)	(0.013)
CONSTANT	0.454 ***	0.359 ***	0.308 ***	0.455 ***	0.359 ***	0.304 ***
	(0.126)	(0.126)	(0.124)	(0.126)	(0.126)	(0.124)
BANK FIXED EFFECTS	YES	YES	YES	YES	YES	YES
INDUSTRYxYEAR FE	YES	YES	YES	YES	YES	YES
PROVINCE FE	YES	YES	YES	YES	YES	YES
Adj. R squared	0.09	0.08	0.08	0.09	0.072	0.08
Number of observations	43,630	46,823	46,621	43,630	46,823	46,621

Table 11: Robustness Tests – Excluding the three largest banks

The observations are bank-firm relationships. Standard errors below coefficients are clustered at the bank level. The dependent variable is the average growth rate of total credit used by firm i at bank j where the average is computed for the years the relationship is observed; the sample excludes loans issued by the three largest banks in the sample. The definition of RECOV variable differs according to the description at the heading of the table. Three asterisks indicated significance at the 1% level of confidence, two asterisks indicate significance at the 5% level of confidence and a single asterisk indicates significance at the 10% level of confidence.

	Relative Recovery (RECOV_R)			Absolute Recovery (RECOV_A)		
Dependent Variable:	**CREDITGROW**			**CREDITGROW**		
Sample:	**Sample without 3 largest banks**			**Sample without 3 largest banks**		
	(1)	(2)	(3)	(4)	(5)	(6)
EBITNEG	-0.109 ***	-	-	-0.117 ***	-	-
	(0.014)	-	-	(0.014)	-	-
EBITNEG*RECOV	-0.079 **	-	-	-0.117 ***	-	-
	(0.032)	-	-	(0.038)	-	-
DEFAULTOTH	-	0.099 ***	-	-	0.082 ***	-
	-	(0.029)	-	-	(0.026)	-
DEFAULTOTH*RECOV	-	-0.116 **	-	-	-0.168 **	-
	-	(0.053)	-	-	(0.075)	-
DEFAULT	-	0.130 ***	-	-	0.103 ***	-
	-	(0.035)	-	-	(0.028)	-
DEFAULT*RECOV	-	-0.104 **	-	-	-0.099	-
	-	(0.048)	-	-	(0.063)	-
DZSCORE3_4	-	-	0.049 *	-	-	0.040
	-	-	(0.027)	-	-	(0.031)
DZSCORE3_4*RECOV	-	-	-0.010	-	-	0.020
	-	-	(0.054)	-	-	(0.073)
DZSCORE5_6_7	-	-	0.053	-	-	0.032
	-	-	(0.036)	-	-	(0.038)
DZSCORE5_6_7*RECOV	-	-	-0.065	-	-	-0.038
	-	-	(0.064)	-	-	(0.080)
DZSCORE8_9	-	-	-0.021	-	-	-0.060
	-	-	(0.042)	-	-	(0.039)
DZSCORE8_9*RECOV	-	-	-0.160 **	-	-	-0.164 *
	-	-	(0.069)	-	-	(0.088)
LOGCREDIT_0	-0.032	-0.029	-0.023	-0.032	-0.029	-0.023
	(0.021)	(0.020)	(0.021)	(0.021)	(0.020)	(0.021)
RELLENGTH	0.047 ***	0.057 ***	0.055 **	0.046 ***	0.057 ***	0.054 ***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
BANKSHARE	0.037	0.052	-0.007	0.044	0.055	0.0003
	(0.126)	(0.112)	(0.099)	(0.126)	(0.111)	(0.098)
$1/2BANKSHARE^2$	-0.007	-0.030	0.059	-0.020	-0.035	0.048
	(0.229)	(0.207)	(0.198)	(0.229)	(0.207)	(0.197)
FIRMSIZE	0.031 **	0.031 **	0.026 **	0.032 **	0.031 **	0.026 **
	(0.013)	(0.013)	(0.013)	(0.014)	(0.013)	(0.013)
CONSTANT	-0.028	-0.125	-0.150	-0.026	-0.126	-0.147
	(0.181)	(0.163)	(0.151)	(0.181)	(0.144)	(0.153)
BANK FIXED EFFECTS	YES	YES	YES	YES	YES	YES
INDUSTRYxYEAR FE	YES	YES	YES	YES	YES	YES
PROVINCE FE	YES	YES	YES	YES	YES	YES
Adj. R squared	0.11	0.10	0.09	0.10	0.09	0.09
Number of observations	18,900	20,874	20,770	18,900	20,874	20,770

Table 12: Lending relationships data – prudent and gambling banks

The observations are bank-firm relationships. Standard errors below coefficients are clustered at the bank level. The dependent variable is the average growth rate of total credit used by firm i at bank j where the average is computed for the years the relationship is observed. In columns 1-3 the BANKTYPE is given by the variable PRUDENT, equal to 1 if the bank default rate is below the median of the troubled banks and the capital ratio is above the median, 0 otherwise; in columns 4-6 BANKTYPE is given by GAMBLING, equal to 1 if the bank has a capital ratio below the median and a default rate above the median, 0 otherwise. Three asterisks indicated significance at the 1% level of confidence, two asterisks indicate significance at the 5% level of confidence and a single asterisk indicates significance at the 10% level of confidence.

Dependent Variable:	CREDITGROW			CREDITGROW		
BANKTYPE	**PRUDENT**			**GAMBLING**		
	(1)	(2)	(3)	(4)	(5)	(6)
EBITNEG	-0.148 ***	-	-	-0.175 ***	-	-
	(0.013)	-	-	(0.013)	-	-
EBITNEG*BANKTYPE	-0.050 ***	-	-	0.070 ***	-	-
	(0.019)	-	-	(0.024)	-	-
DEFAULTOTH	-	0.066 ***	-	-	0.004	-
	-	(0.026)	-	-	(0.018)	-
DEFAULTOTH*BANK TYPE	-	-0.114 ***	-	-	0.138 ***	-
	-	(0.035)	-	-	(0.044)	-
DEFAULT	-	0.054 **	-	-	0.056 ***	-
	-	(0.023)	-	-	(0.020)	-
DEFAULT*BANKTYPE	-	-0.010	-	-	0.022	-
	-	(0.040)	-	-	(0.058)	-
DZSCORE3_4	-	-	0.112 ***	-	-	0.083 ***
	-	-	(0.025)	-	-	(0.028)
DZSCORE3_4*BANK TYPE	-	-	-0.074 **	-	-	-0.011
	-	-	(0.037)	-	-	(0.043)
DZSCORE5_6_7	-	-	0.102 ***	-	-	0.072 ***
	-	-	(0.029)	-	-	(0.029)
DZSCORE5_6_7*BANK TYPE	-	-	-0.069	-	-	0.016
	-	-	(0.046)	-	-	(0.064)
DZSCORE8_9	-	-	-0.025	-	-	-0.100 ***
	-	-	(0.026)	-	-	(0.022)
DZSCORE8_9*BANK TYPE	-	-	-0.134 ***	-	-	0.127
	-	-	(0.043)	-	-	(0.086)
BANK FIXED EFFECTS	YES	YES	YES	YES	YES	YES
INDUSTRYxYEAR FE	YES	YES	YES	YES	YES	YES
PROVINCE FE	YES	YES	YES	YES	YES	YES
FIRM & REL CONTROLS	YES	YES	YES	YES	YES	YES
Adj. R squared	0.084	0.073	0.076	0.084	0.073	0.076
Number of observations	43,630	46,823	46,621	43,630	46,823	46,621

Data Appendix

Data on national GDP growth and regional GDP growth are from ISTAT (Italian Statistical Institute, National Accounts) and Bank of Italy archives.

The bank-level data are obtained from the Supervisory Statistics (Matrice dei Conti) and the Central Credit Register (Centrale dei Rischi). All the stock variables are based on end-of-year data. We consider only commercial banks chartered in Italy, meaning that we drop cooperative banks (Banche di Credito Cooperativo) and the foreign bank branches. Before the 1993 reforms, Italian banks were separated based on the maturity of their lending with the "Istituti di Credito Speciale" (ICS) providing long term credit and other banks short term loans. We define commercial banks prior to 1993 to include national banks, the "banche popolari", small private banks and the ICS. Many short-term commercial banks had special credit sections, formally separated from the parent bank, providing long-term loans. In 1994, after the removal of regulatory barriers based on maturity, these sections were absorbed into their controlling banks. To avoid a discontinuity from this change we use pro forma data for the sections and their controlling banks for the years prior 1995.

This sample of banks is employed to compute the distribution of profitability and identify the banks that have profitability shocks. As mentioned in the text, we omit from consideration banks whose charter was less than 4 years old because new banks have very erratic data (high rates of growth of loans) and volatile profitability. We also drop the very small banks defined as those with real total assets below 100 billion ITL. For this purpose, assets are deflated by the GDP deflator with 1995=100. We excluded ISVEIMER (a specialized credit institution for development of Southern regions) that was being liquidated slowly starting in 1996 and its controlling shareholder, the Banco di Napoli, a state-controlled bank that was bailed out with public funds in 1996 and subsequently privatized. We also dropped other special banks that were created to hold all the non-performing loans of a banking group. Likewise, we drop banks that have a ratio of loans to total assets of less than 15 percent. If a bank experiences more than one profit collapse we consider the first time the bank gets into trouble.

The variables described in Section 3 reflect the standard definitions employed in the Banca d'Italia Annual Reports (see the Chapter on Credit Institutions and the methodological appendices in the Italian version for years 2005, p. 259, and 2007, p. 243). Broadly speaking, return on assets is defined as the ratio of net income before taxes divided by gross total assets. Net income is given by the intermediation margin (interest margin plus other revenues) minus operating costs and net write-downs, write-offs and provisions on loans and other assets. Operating costs are the sum of staff costs and other administrative and operating costs including depreciation. Write-offs, losses and provisions on loans include net write-offs and write-downs, and specific and general provisions on loans. Write-offs, losses and provisions on other assets include the items just described with reference to assets other than loans.

The non-performing loan ratio is the stock of non-performing loans divided by the sum of performing and non-performing loans. According to the Italian Supervisory Statistics, a loan is non-performing if the bank considers the borrower to be insolvent, regardless of the existence of a legal bankruptcy procedure. Loosely speaking default is defined as the change of status from performing to non-performing, i.e. the repayment of the loan is considered no longer certain by the lender because the borrower is financially insolvent.

The default rate is the ratio of newly defaulting loans in a given year divided by the end-of-previous year stock of performing loans. The definition is consistent with the one adopted in the Bank of Italy Annual Report (see the Chapter on Credit Institutions in the Annual Report on 2005) in the sample period. The numerator is obtained from the Credit Register data on the flow of “new adjusted non-performing loans” (“sofferenze rettificate”); the denominator is obtained from the data on loans in the Supervisory Statistics. During our sample period, in the Credit Register an “adjusted non-performing loan” (“sofferenza rettificata”) is defined as all outstanding credit to a given borrower if either of the following holds:

i) the borrower has defaulted and has a single lender;
ii) the borrower has defaulted at one lender and has drawn more than its commitments at the only other lender it has
iii) the borrower has defaulted at one lender for an amount that is at least 70 percent of its total outstanding credit in the CR or there are overdrafts for at least 10 percent.
iv) the borrower has defaulted at two lenders for amounts that are at least 10 per cent of total outstanding credit.

In Section 4, the default rate of each bank is decomposed into industry-level default rates and portfolio shares referring to households, manufacturing, agriculture, construction, services, other sectors (government and financial firms) and four macro-regions (North West, North East, Center, South). For the ICS, the portfolio composition is computed from Credit Register data whereas for all other banks from the Supervisory Statistics. Data below the CR threshold for the ICS are entirely attributed to households in computing portfolio shares.

In Section 5 the sources of the individual bank-firm relationship data are the CR for loan information and CADS (Centrale dei Bilanci) for balance sheet data and z scores. In the estimation we impose that the bank be in existence through year 3.

In the matched bank-firm relationships the variable definitions are based on the corresponding balance sheet and income statement items published by CADS. EBIT is earnings before interest and taxes. The dummy DEFAULT is based on the definition of non-performing credit with reference to the single bank-firm relationship. The definition is meant to capture the insolvency of a borrower with respect to the borrower’s ability to repay the loan from one bank, regardless the current default status at each of its lenders, some of which might still consider the borrower to be in good standing.