

Which Banks Recover from a Banking Crisis?*

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Abstract

We analyze the fate of 120 Italian banks that experienced abrupt drops in profitability. About 1/3 of these banks subsequently recover in the sense of attaining profits, adjusted for industry conditions, comparable to their prior levels of profitability. In the years before the performance decline, it appears that the banks that get into trouble were lending to riskier clients than the average in the overall economy. One important factor governing recovery is the size of the initial profit drop that occurs at the onset of distress. General business climate after the shock also matters. But so does the adjustments made by the bank in the wake of the shock. Thus, recovery depends both on factors that banks can and cannot 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. Some of this appears to occur because recovering banks are aggressive in managing their riskiest clients.

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Introduction

This paper provides an empirical assessment of why some banks do and do not recover from sudden declines in profitability. This question is of considerable practical relevance because collapses in bank health have become common place: Caprio and Klingbiel (2003) document 117 systemic banking crises around the world between the late 1970s and 2002.¹ Yet, despite the prevalence of these events there seems to be disagreements about the best way for regulators to proceed during a crisis.

With the wave of bank failures and nationalizations that have occurred during the current global crisis this question has taken on a new urgency. The standard prescription prior to the crisis has been the doctrine of “prompt corrective action.” This view holds that limiting asset growth and raising capital is the key to reviving distressed banks; as opposed (say) to focusing on making adjustments to the loan portfolio of the troubled institution. Given the massive amount of assets now under state control, deciding between these views is of considerable practical importance.

Beyond the policy interest in this issue, there is also theoretical interest since various theories of financial intermediation make different predictions about the best response to a large shock. For instance, monitoring based theories (such as Diamond (1984)) suggest that portfolio adjustments will play a critical role. In particular, these theories highlight the special role of banks in providing credit to opaque borrowers, implying that the efficiency costs of the banks failure are governed by the changes in credit to these borrowers. If borrower size were used as a proxy for opacity, this reasoning would imply that tracking changes in credit to small customers would be important.

In contrast, theories that emphasize the importance of liquidity provision suggest that the fallout from a crisis depends on the ability of banks to keep financing their commitments. As has been evident in the current credit crisis, at any given time many large borrowers have lines of commitment from large banks. The liquidity provision

¹ They also document 51 borderline and nonsystemic episodes in 45 countries during the same period. See Demirgüç-Kunt and Detragiache (2005) for a survey of the effects of systemic crises on the economy.

hypothesis holds that the removal of these credit lines is potentially costly, even if the borrowers are themselves large.²

Our contribution is to analyze bank-level data to determine the factors that govern recovery from distress. In addition to bank level data we employ micro data on bank-firm relationships to study how lending policies change after the shock and how such changes differ between banks that recover and do not recover.

Importantly, we begin tracking banks only after they register a sharp deterioration in performance. By design our analysis cannot address certain important questions such as how do banks avoid trouble in the first place; we acknowledge we do not have a fully identified structural model of bank performance that permits us to identify the exact shocks hitting our banks. Nonetheless, given the paucity of existing evidence on what does and does not matter, we believe our reduced form analysis can serve as a useful starting point for further investigation.

We organize our investigation around three specific questions. First, what are the key differences in the characteristics of the banks that do and do not recover? Second, how much of the recovery depends on macro or regional conditions that are out of the hands of the individual banks? Third, to the extent that bank choices do matter, which ones are most important and why?

We find that there are several critical factors that distinguish the banks that survive a crisis from those that do not recover. In the years prior to the performance decline, it appears that the banks that get into trouble were lending to riskier clients than the average in the overall economy. One important factor governing recovery is the size of the initial profit drop that occurs at the onset of distress. General business climate after the shock also matters, although we find no evidence that recovery patterns were

² There is a large literature looking at the effect of bank distress on borrowers. For example Gibson (1995, 1997) finds that in Japan firms' investment is highly sensitive to the financial health of their main banks. Slovin, Sushka and Polonchek (1993) find that the share price of firms borrowing from Continental Illinois bank suffered when negative news about Continental bank public. Kang and Stultz (2000) find that firms listed on the Tokyo Stock Exchange with a high share of bank debt experienced an above average drop in stock prices and a decline in their investment levels at the beginnings of the Japanese banking crisis. Similar results from the 1997-98 Korean banking crises are in Bae, Kang and Lim (2001). Ivashina and Scharfstein (2008) find that banks which had large amounts of loan commitments outstanding (relative to their deposit base) were more inclined to reduce lending in the fall of 2008. In contrast, Ongena, Smith and Michalsen (2003) do not find any fallout for the continuing customers of Norwegian banks during their banking crisis.

different during 1992, 1993 and 1994 when roughly 11% of the Italian banking system's assets were in impaired banks. Recovery also depends on the adjustments made by the bank in the wake of the shock.

Among the choices made by the banks the decision to continue lending to their riskiest clients stands out as being particularly important. Banks that ultimately recover are more prone to limit lending to customers which are current on their loans but have defaulted with other banks on other loans. Likewise, the recovering banks are much less prone to extend credit to the customers with the highest (ex-ante) probabilities of default. Thus, recovery depends both on factors that the banks can and cannot control.

The remainder of the paper is organized into five 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. Section 6 concludes.

2. Background on the Italian banking industry and our sample

Table 1 provides some basic information on the Italian banking industry between 1987 and 2004. The set of banks that we consider is all banks operating in Italy excluding the cooperative banks and the foreign bank branches. The sample we focus upon excludes banks 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 a 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 very volatile profitability.³

³ 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 view the exclusion of potentially chronically distressed institutions as a problem.

The table highlights the consolidation that occurred as branching restrictions were progressively eliminated (Bonaccorsi di Patti and Gobbi (2001) and Girardone et al (2004)). 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)).

2.1. Distressed Banks

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 do not want to include chronically poor performing banks. The second condition compares the ROA decline relative to 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. 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 right hand panel of Table 1. In total 151 banks are identified as being distressed between 1987 and 2004, these banks represent 50 percent of the industry assets. To allow for sufficient leads and lags to study the behavior before and after the dip in profits, we analyze cases where the crisis 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 1 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.

2.2. 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.⁴ 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.⁵ In the summer of 1992 there was a monetary tightening, and exchange rate tensions that led Italy to withdraw from ERM.⁶ 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. Table 2 also reports aggregate data on the default rate for all Italian banks that is analogous to the default measure shown in Table 1. 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. Looking back to Table 1, we can see that there was a spike on the number of newly distressed starting in 1992.

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

⁴ 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.

⁵ 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.

⁶ The monetary tightening was not based on administrative credit controls even if between October 1992 and 1993 there was surveillance on credit growth for single banks, essentially based on moral suasion.

Financial Crises” calculates the peak share of insolvent bank assets to banking total system assets as 11 percent. In the Swedish and Finnish banking crises, which occurred around the same time, the percentages were 22 and 33 percent respectively.

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. Overall, we read Tables 1 and 2 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 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 had been granted to 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 3 provides some basic data on the heterogeneity by comparing the incidence of distress across the North West, North East, Center and South of Italy.⁷ 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

Table 4 provides data on our sample of distressed banks for the mean values of several indicators. In recognition of the systematic differences in Table 3, we normalize the various indicators by comparing them to other banks in the same region.⁸ The data are also tabulated 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 headquartered in the north-western region that got into trouble in 1998, we compare each of the indicators to the average value of those indicators for other banks in the north-western region in 1998 and those deviations are the year 0 statistics for that bank.

One issue throughout the analysis is how to handle banks that disappear through merger, acquisition or failure. Because we do not analyze the details surrounding each exit, it is not clear whether one would expect these banks 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. Hence in the comparisons in this section we base our contrasts at different points in time on the sample of banks that were currently operating.

⁷ 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.

⁸ We also compared the distressed banks to other banks in their region of the same size and the important patterns in Table 4 are present with that adjustment too.

Ideally we would account for these selection issues in the analysis. Standard approaches to this problem require us to have some restrictions regarding factors that would 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. For instance a multinomial regression of the three possible outcomes - exit, surviving but not recovering, recovering - suggests that exiting banks are not like either recovering or not recovering banks.⁹ So based on observable characteristics dropping these banks would not bias other regressions. But all of what follows should be considered in light of this caveat.

The premise of our analysis is that these troubled banks are not chronic underperformers, but instead suffered from a shock that abruptly impaired their profitability. The data in Table 4 on ROA supports this interpretation. In particular, for the full sample, prior to time 0 the banks on average had slightly higher profits rates than others (of the same region). At time 0, this pattern flips and the mean ROA falls below average.

The next step is to understand what determines the fate of the banks after the initial drop in profitability. We define recovery from the distressed 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. Empirically this is challenging because the mean level of industry profitability is time-varying, so using a single cut off level of profitability to identify healthy banks would make little sense. Accordingly, we gauge recovery by looking at both the absolute level of profits and the level 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 25th percentile and in year 2 ROA is greater or equal to ROA the year before the shock or the ROA percentile is greater or equal to the percentile observed the year before the shock; or

⁹ These results are available upon request.

2) In year 2 its ROA is greater than the 25th percentile and in year 3 ROA is greater or equal to ROA the year before the shock, or 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 ROA is greater or equal to ROA the year before the shock, or 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 will have restored its profitability.

As indicated in Table 3, 42 of the 120 distressed banks ultimately recover. The information in Table 4 compares recovering (R) and non-recovering (NR) banks to each other and then the combination of all distressed banks to the entire sample. 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 1, 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.

To explore this further it is helpful to recognize that net income (the numerator of ROA) can be decomposed into sources of income, costs, and extraordinary items (consisting of write downs and provisions). Specifically,

$$\begin{aligned} \text{Net income} = & \text{Interest margin} + \text{Other revenues} - \text{Operating costs} + \\ & \text{Net loan write-downs and provisions} + \text{Other write-downs and provisions} \end{aligned}$$

Table 4 also 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 1 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. Perhaps these results are not surprising since we have defined distress based on sharp changes in performance, but whatever the reason, changes in costs have little to do with the onset or recovery from distress as we have defined it.

The data on writeoffs, 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 4 looks further at 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 default rates that are if anything lower than the non-distressed banks, while the NR banks default rates remain elevated. The difference between the R and NR banks is significant only in year 2, but it looks like there may have been a change in behavior after the onset of trouble by the recovering banks.

Comparisons involving the stock of non-performing loans are consistent with these hunches. The stock of non-performing loans is consistently higher for the distressed banks than for the other banks starting in year 0. This difference is due to the NR banks, whose stock of bad loans is consistently higher starting in year 0.

Overall, the data from Table 4 fit with the following simple story. The distressed banks tend to be lending to relatively high risk customers. Prior to year 0, their interest margins for both R and NR banks are high and default rates are also high. But 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 profit 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.

4. Logit regressions on bank data

To better understand the patterns in Table 4, we next explore the determinants of recovery. In what follows, 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. The presence of the exits complicates the analysis since mergers and liquidations in principle are very different. In practice, few banks actually fail and are liquidated; in our sample only 1 bank is liquidated. Instead, some mergers are purely market transactions and others are consummated with the encouragement of supervisors. We have no way of separating the two and 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 year 3.

Ideally, the econometric analysis would account for exits, but to do so in a convincing way would require information that would be relevant for the merger but did not affect profitability/recovery. We cannot think of any plausible variable that fits this description. We did estimate a multinomial logit model that compared the exiting firms to the ones remaining in the sample, drawing on the main controls described below. This analysis implied that it was impossible to distinguish the exiting banks from the recovering and non-recovering banks.¹⁰ So we believe it is unlikely that the way we are handling the exiting banks explains the main findings stressed in what follows.

Given the descriptive nature of this exercise, 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. For the exiting banks we only have data on them up to the point where they drop out of the sample, and so for variables where we would seek average values over years 1 to 3, we compute the averages over the years where data are

¹⁰ The test is a Wald test 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). 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.

available. This also means for the 10 banks that disappear in the same year as the profit shock we cannot compute these variables. As a robustness check (that is not reported) we confined the analysis to only the 93 banks for which we have complete information and we find virtually identical regression results as shown in the Table 6.

Table 5 shows the summary statistics for the variables that will be used in the regressions. We report the statistics both for the full sample of 120 banks and the sample of 110 banks for which data after year 0 exist. As a benchmark in what follows note that 35 percent of the full set of banks recover. Also, the Table shows the 10 banks that exit as of time 0 are essentially randomly scattered across the regions; this follows from the fact that the mean values of the indicator variables for bank region are almost identical for the samples of 120 and 110 banks.

The types of variables that we consider can be thought of as proxies for three different factors affecting recovery probabilities. The first set of these relate to factors outside of the control of the individual banks. As suggested by the simple statistics in Table 3, recovery rates differ across regions. Hence we construct indicator variables for region where the banks are based: Northwest, Northeast, and South (so that the central region is the excluded category). We also construct an index of macro conditions in the regions which we approximate by the average growth rate of value added in the region over the three years after the bank gets in trouble. The last of these indicators is another indicator variable that identifies the crisis years of 1992 to 1994. Roughly 38% of the cases in our sample correspond to banks that fell into distress during this crisis episode. This dummy variable will allow us to see whether this period stands out in terms of recovery.

A 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. The proxy we use, ROADEV, is the difference between the return on assets for the afflicted bank and the average rate of return on assets for all banks; transforming the profits to be relative to the industry average is appropriate given the trend in profit rates

The test does reject that recover and not recover can be combined. Loosely, speaking the test suggests that the coefficients associated the exit predictions are so noisy that they are totally uninformative.

and our definition of distress, which also measured ROA relative to the industry average. We measure this variable as of year 0.

Finally, motivated by the comparisons in Table 4, we attempt to measure adjustments in the loan portfolio after the bank becomes distressed. The simplest measure we consider, DEFAULTDEV, is the difference between the bank's default rate and the national average. We average this variable over years 1 to 3.

The national average default rate is defined as 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; hence, it is the default rate of the national loan portfolio. Using this observation we can break down DEFAULTDEV into components that determine the portion of the difference that is due to different loan shares (for certain customer types) and the portion due to different default rates for each customer type. There are many potential decompositions of this sort, but in keeping with the earlier evidence on potential regional differences, we start with the following identity.

$$\begin{aligned} & \textit{Bank Specific Default Rate} - \textit{National Default Rate} \equiv \\ & \quad \textit{Bank Specific Default Rate} - \textit{Predicted Bank Specific Rate} \\ & + (\textit{Predicted Bank Specific Rate} - \textit{Predicted Regional Default Rate}) \\ & + (\textit{Predicted Regional Default Rate} - \textit{National Default Rate}) \end{aligned}$$

where 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 as is typical for each type of customer in that region. In these calculations we allow for six types of borrowers, separating 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. 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 the risk of concentrating loans in different regions will vary (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 separating out the importance of the three terms can shed light on why controlling for the default rate could be important. 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.

4.1. Macroeconomic conditions

The first hypothesis tested is that recovery is basically pre-determined and depends solely on external conditions (the macro-economy and the region). In our simplest specification, the explanatory variables are regional dummies for Northwest, Northeast, and South (Center is the excluded category) and a measure of regional GDP growth in the post crisis years. The results are shown in the second column of Table 6; throughout the table we report coefficients after transforming them to represent the impact on the marginal probability of recovery from a one-unit change in each variable.

As suggested by Table 3, the Southern banks are much 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 35 percentage points higher for Northeastern banks relative to southern banks. Likewise, an increase in regional growth from 0.97 percent (the 25th percentile) to 1.86 (the 75th percentile), raises the marginal probability of recovery by just over 7 percentage points.

The next column of the table adds the indicator for banks that became distressed during the 1992 to 1994 banking crisis. This specification is designed to test the

hypothesis that recoveries during an economy-wide banking crisis differ from other recoveries. The coefficient on the indicator is small and insignificantly different from zero. 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. Thus, it appears that recovery is no more or less likely for banks that fell into trouble during the downturn. Given the highly variable recovery rates shown in Table 3 this is not surprising. Perhaps the magnitude of the 1992-1994 crisis was not large enough to be deemed a systemic problem, but it appears that there was nothing special about recovery patterns during this episode compared to others.

4.2. Bank-Specific Factors

A third hypothesis is that recovery is determined mainly by the size of the initial profit decline. Column 4 shows the results of adding this variable to the initial specification that accounted for average regional differences and near-term regional growth prospects. 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, but the magnitude of this effect is modest (in 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 4.7 percentage points less likely to recover.

The evidence from Table 4 suggested that recovering banks tended to have lower default rates during the years after the initial distress. 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 raises the magnitude of

the coefficients on GDP (although the precision of the estimate rises too) and reduces the coefficient on the initial drop in profits roughly the same. Thus, with the full set of controls, growth and subsequent portfolio management appear to be the quantitatively important determinants of which banks recover.

To further explore the importance of the default rate we decompose it into idiosyncratic, customer mix and regional risk components defined above. The results, reported in the last column of Table 6, show that all three variables have a negative effect on the probability of recovery. However, only the proxy for the idiosyncratic risk is statistically significant in the regression at the 95 percent level; the regional risk proxy is close to significant and becomes so if the regional dummies are removed. 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 42.8 to 29.9 percent.

To understand why the idiosyncratic risk is so important we need to find out more about the specific lending choices that the banks are making. So in the remainder of our analysis we turn to loan-level data.

5. Evidence on lending outcomes for specific borrowers

The data employed in the remainder of our 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.¹¹

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.¹² 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 5.1 below.

¹¹ 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 Foglia et al. (1998), Sapienza (2002), and Panetta, Schivardi and Schum (forthcoming)

¹² CADS firms represent around 49 percent of total sales of nonfinancial firms in the national accounts.

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.¹³ 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 currently contains data on more than 900,000 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.

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. This reduces the number of observations to 64,200 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 approximately 46,600 observations of credit

¹³ Until December of 1995 this cutoff value was 80 million Lire, about 40,000 euros, since then the cutoff has been 150 million Lire (75,000 euros). A loan commitment in Italy is typically used for over-draft protection. At the outset of one these over-draft agreements the bank evaluates the borrower and determines the appropriate credit limit. Typically the borrower does not immediately tap the credit. If the borrower subsequently asks for the credit, then the bank will typically grant it. Usually the contract neither requires that the bank honour the commitment nor includes anything like a material adverse change clause.

relationships between 97 of our crisis banks and their clients. Descriptive statistics are reported in Table 7.

One limitation of the analysis is that we do not observe the entire portfolio of the banks. Likewise, 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 less flexible than others.¹⁴ 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.¹⁵

Our primary 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 the shorter spell.¹⁶ Average credit growth is about 9 percent per year, but the range across borrowers is huge. We also show results that describe lending policy by simply sorting borrowers based on whether credit growth was positive or negative. About 40 percent of borrowers in the sample had their credit increase.

¹⁴ 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.

¹⁵ 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.

¹⁶ 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.

In some of the analysis we try to account for some borrower characteristics. 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.

Lastly we consider the length of the relationship (RELLENGTH), computed as the log of the number of year 0 for which the relationship is observed.¹⁷ This factor could be important if the banks view the distress as temporary and in adjusting credit give priority to their long standing customers.

5.1. Proxies for high risk borrowers

Given the importance of controlling defaults suggested by the aggregate findings we concentrate on the banks' lending practices for high risk borrowers (which drive the default statistics). 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 are more likely to be driven by the lender's preference.

Because there is no single way to identify these customers we consider three different candidates. The first focuses on the profitability of the borrowers. We flag any

¹⁷ 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.

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 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, while they rise sharply for z's between 7 and 9. Hence in what follows we isolate the borrowers with z's above 6 and call those borrowers the high risk borrowers.

While not shown in table 7, 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.

5.2. Matched Lender-Borrower Regressions

We compare credit growth at NR and R banks using a regression of the form:

$$CREDITGROW = f(\text{Risk Proxy}, \text{Risk Proxy} * \text{Recover}, \text{Borrower Controls}, \text{Bank Fixed Effects}) \quad (1)$$

The presence of the bank fixed-effects in the regressions means that we make no attempt to directly estimate the direct effect of recovery on credit growth. But the advantage of estimating the model in this way is that we have controlled for other bank-level sources

of variation such as capital levels or lending standards that would arguably belong in the regression. Instead we focus on the interaction of the RECOVER dummy and the three variables measuring borrowers' quality. The initial specifications shown in columns 2 to 4 of Table 8 present the results when there are no other borrower controls (other than the bank fixed effects) in the regression.

Firms with average negative operating profits in the years following the shock will experience 11 percent lower credit growth (per year) at the NR banks; the interaction term coefficient is not statistically significant although it is small and negative, suggesting that recovering banks perhaps slightly reduce their lending relative to the NR banks.

In column 3 we find that credit growth of firms that will default is 16.6 percent lower (per year) than other firms; recovering banks will reduce credit growth more by about 3 percentage points although that estimate is noisy. In some sense, this pattern is not very surprising. Once a borrower defaults the supervisors would seriously question any bank that does not aggressively trim lending and so continuing lending is a dangerous way for a bank to forbear or gamble.

The more interesting finding pertains to the firms that default at another bank. These borrowers tend to increase their borrowing by about 3.5 percent per year at a non-recovering bank where they are still considered as performing. In contrast, credit growth is zero at the recovering banks. 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 lack of a negative coefficient for the R is perhaps understandable. We see no good reason (other than gambling for redemption) that the NR banks would be increasing lending to these customers.

The results using the z scores as the risk proxy also show signs of gambling on the part of 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. The recovering banks are consistently more cautious in lending to borrowers that are not safe than the NR banks. On an absolute level the credit growth for the R banks is flat for the z's of the 3 and 4, and then turns negative for borrowers that are 5 and above. The NR banks are expanding credit to borrowers with ratings of 3 and 4

and are much less prone to reduce credit for the most risky clients. For the worst risks, the z's of 9, the differences are quite large: the R banks are shrinking credit by 14 percentage points per year more than the NR banks.

The remaining columns of the table show the estimates when we control for some borrower characteristics. Generally, firms that borrow more in the initial year tend to experience slower credit growth subsequently. Not surprisingly, firms that have longer borrowing relationships are more likely to see their credit sustained. The share of credit by the distressed bank appears to make little difference: the estimated effect is tiny.

The controls mostly sharpen the estimates of how the R and NR banks handle their riskiest clients. In particular, the contrast between how the banks handle customers that are in default at other banks becomes much more precisely estimated. The NR banks expand credit to these troubled clients by about 7 percentage points per year, while the R banks keep the amount fixed. Likewise, the comparison of how the high z firms are handled also becomes slightly clearer. The recovering banks cut credit to the z=9 customers by twice as much as the non-recovering banks.

To assess the robustness of these findings we considered a number of alternatives. We report two in Table 9. The first three columns change the dependent variable to be a zero/one indicator of whether credit to the borrower in question rises. We transform the logistic regression coefficients so that they correspond to the marginal effects of a one unit change in each regressor. The results are similar to what we found in Table 8 – although the information that is lost by eliminating the magnitudes of the changes in credit makes the standard errors of most of the coefficients much larger. In particular, the risk measure based on the profitability of the borrowers is not different for the R and NR banks. But, customers that default at other banks and customers with very high z scores are much more likely to have growing credit at NR banks.

The last 3 columns show the estimates when we exclude the largest banks in our sample. About 56% of the borrowers in the sample have credit from the three biggest banks in the sample. To make sure that we were not just learning about the lending policy of these banks, we also analyzed the sample excluding these banks. These estimates are also very similar to the findings in Table 8. Unprofitable firms receive about 8.9 percent per year less credit than healthy firms, but the R and NR banks are not

different in how they lend to these customers. For customers in default to another bank, the recovering banks keep credit fixed, while the NR banks expand credit by about 9 percentage points per year. The borrowers with z-scores of 8 or 9 receive 6 and 16 percentage points less credit per year from the R banks relative to the NR banks.

Overall Tables 8 and 9 complete the picture that had emerged in the earlier analysis pointing to the relevance of the default rate in influencing recovery. The earlier findings seem to be coming from the way the banks handle their riskiest clients. The recovering banks are simply much tougher about extending credit to these customers. Whether the NR banks are actively gambling or simply misjudge the risks associated with these borrowers is impossible to tell. But regardless of the explanation, it suggests that supervisory policies that ignore the lending decisions made by an impaired bank could be improved.

6. Conclusions

Little is known about what governs recovery from banking crises. 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 both 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. Loan level 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.

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. To the extent they are not doing so, the regulators could push in this direction. For countries that have credit registers and credit ratings that are readily available this would be easy to implement. Likewise, where regulatory assessments concentrate on a CAMELS (capital, assets, management, earnings, liquidity and sensitivity to market risk) rating system, the supervisors might want to pay particular attention to the riskiest assets and customers.

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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 income before taxes divided by gross total assets. 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). 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. 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 variable CREDITUP is computed with the following algorithm. It is equal to 1 if: i) credit in year 3 is greater than credit in year 0; ii) credit in year 3 is missing and credit in year 2 is greater than credit in year 0; iii) credit in years 3 and 2 is missing and credit in year 1 is greater than credit in year 0; iv) the variable is missing if the firm is already defaulted in year 0 or if credit is 0 both in year 0 and year 3. In all cases if a firm defaults, the CR data record 0 credit and a positive value for bad loans. 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.

Table 1: 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.

Year	Banks in Sample*							Newly distressed banks					
	Number of banks	Median Assets	Median ROA	Median NPL ratio	Default rate	Operating Cost/Assets	N.	Total Assets (% of Sample)	Median Assets	Median ROA	Median NPL ratio	Default rate	Operating Cost/Assets
1987	326	649.84	1.20	7.03	2.09	3.24	11	8.83	376.65	0.52	8.00	2.69	3.51
1988	326	725.99	1.15	6.14	1.50	3.20	6	0.80	354.91	0.27	7.72	3.63	4.02
1989	312	835.65	1.20	5.44	1.46	3.08	11	0.49	354.49	0.41	7.79	1.30	3.01
1990	309	868.22	1.23	5.11	1.59	3.23	6	2.77	819.90	-0.16	7.79	3.37	3.04
1991	296	963.91	1.15	5.02	2.15	3.21	8	0.97	455.62	0.24	7.44	7.09	3.39
1992	278	1046.29	1.01	4.85	2.34	3.22	20	6.51	1937.53	0.31	6.67	3.19	2.98
1993	276	1085.27	1.17	6.10	3.93	3.16	10	2.06	1414.58	0.33	7.71	6.57	3.33
1994	259	1090.21	0.55	7.45	2.70	3.10	17	2.56	892.76	0.04	9.84	3.97	3.96
1995	237	1135.52	0.98	7.95	2.50	3.12	10	2.24	1084.44	0.08	14.32	7.78	3.05
1996	240	1150.40	0.91	7.33	2.31	3.05	3	5.48	650.20	0.10	9.71	4.97	2.83
1997	229	1200.15	0.77	6.69	1.81	2.94	7	0.60	478.87	0.12	14.75	2.81	3.66
1998	222	1211.24	0.94	6.25	1.42	2.80	7	1.10	987.66	-0.83	24.38	7.29	3.54
1999	218	1271.28	0.82	4.82	1.05	2.65	7	0.49	658.76	0.18	15.84	2.94	3.70
2000	210	1276.98	0.98	3.45	0.94	2.62	7	2.89	790.39	0.23	2.83	0.87	2.70
2001	209	1409.30	0.93	3.08	0.94	2.57	8	7.76	1619.89	-0.85	2.40	0.59	2.60
2002	202	1336.00	0.78	2.57	0.83	2.46	6	0.56	164.18	0.05	4.59	1.78	2.89
2003	195	1570.46	0.79	2.67	0.95	2.38	4	3.66	1591.01	-0.04	4.64	3.40	2.71
2004	197	1612.55	0.86	2.69	0.79	2.33	3	0.41	1429.01	0.15	5.63	1.48	1.88

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: 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.

	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	9	11	12	10
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	6	4	4	3

Table 4: Event time statistics, deviations from industry means

Deviations of individual banks with respect to the mean of banks in the region. 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. See the data appendix for the other definitions.

Year	ROA					Interest margin/Total Assets					Other Revenues/Total Assets				
	NR	R	H:NR= R	All	H: A=0	NR	R	H:NR= R	All	H: A=0	NR	R	H:NR= R	All	H: A=0
-3	0.224	0.067		0.169	***	-0.110	0.012		-0.067		-0.057	0.128	**		0.009
-2	0.240	0.103		0.193	***	0.058	0.096		0.071		-0.077	0.119	*		-0.009
-1	0.238	-0.029	***	0.267	***	-0.138	-0.053		-0.108		0.196	0.142		0.177	**
0	-1.165	-0.768	***	-1.026	***	-0.527	-0.246		-0.429	***	-0.097	-0.020		-0.070	
1	-0.712	-0.487		-0.626	***	-0.516	-0.040	***	-0.335	***	0.140	0.036		0.100	
2	-0.949	0.017	***	-0.531	***	-0.499	0.034	***	-0.268	***	-0.084	0.037		-0.032	
3	-0.915	0.113	***	-0.456	***	-0.665	0.074	***	-0.334	**	-0.111	0.003		-0.060	

Year	Operating Costs/Total Assets					Loan Write-Offs, Losses and Provisions/Total Assets					Write-Offs, Losses and Provisions on Other Assets/Total Assets				
	NR	R	H:NR= R	All	H: A=0	NR	R	H:NR= R	All	H: A=0	NR	R	H:NR= R	All	H: A=0
-3	-0.254	0.171	**	-0.103		-0.114	-0.054		-0.093	***	-0.011	-0.014		-0.012	
-2	-0.142	0.194	*	-0.025		-0.116	-0.033		-0.089	**	0.019	-0.040		-0.002	
-1	0.001	0.171		0.060		-0.032	0.022		-0.013		-0.146	-0.081		-0.123	**
0	0.133	0.182		0.150		0.452	0.211		0.368	***	-0.044	0.105		0.008	
1	0.164	0.209		0.181		0.319	0.174		0.264	**	-0.147	0.098	*	-0.054	
2	0.122	0.175		0.145		0.244	-0.034	**	0.124	*	-0.009	-0.087		-0.043	
3	-0.057	0.095		0.011		0.193	-0.048	**	0.085		-0.004	-0.094		-0.044	

Table 4, continued

Year	Default Rate				NPL Ratio			
	NR	R	H:NR= R	All	H: A=0	NR	R	All
-3	0.148	-0.383		-0.041		-0.757	-1.427	-0.994 **
-2	0.418	0.082		0.301		-0.173	-0.825	-0.399
-1	1.298	0.345		0.967 ***		0.955	-0.594	0.417
0	1.842	0.549		1.389 ***		2.374	-0.234	** 1.461 ***
1	1.240	-0.028		0.759 *		2.626	-0.254	** 1.533 ***
2	1.270	-0.426 **		0.536		3.121	-0.273	** 1.651 ***
3	0.867	-0.139		0.418		3.507	-0.269	** 1.820 ***

Table 5: Variables employed in the regressions and descriptive statistics

Name	Description	120 banks			110 banks that exist after year 0		
		25 th percentile	Mean	75 th percentile	25 th percentile	Mean	75 th percentile
RECOV	Recovery	0	0.350	1	0	0.382	1
NORTHWEST	Dummy North Western Region	0	0.183	1	0	0.191	1
NORTHEAST	Dummy North Eastern Region	0	0.150	1	0	0.136	1
SOUTH	Dummy Southern Region	0	0.392	1	0	0.373	1
D9294	Dummy 1992 to 1994	0	0.392	1	0	0.382	1
GDPGROWTH	Average Regional GDP Growth from years 1 to 3	0.971	1.453	1.861	1.066	1.450	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
DEFAULTDEV	Average Default rate deviation from industry portfolio years 1 to 3	NA	NA	NA	-0.450	1.863	2.870
IDRISK	Idiosyncratic Risk	NA	NA	NA	-1.072	0.621	1.736
CUSTRISK	Customer Mix Risk	NA	NA	NA	-0.067	0.180	0.537
REGRISK	Regional Risk	NA	NA	NA	-0.485	1.083	1.690

Table 6: Logit model of probability of 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.

Dependent Variable:	Probability of Recovery				
	dy/dx	dy/dx	dy/dx	dy/dx	dy/dx
NORTHWEST	0.059 (0.123)	0.060 (0.121)	0.071 (0.134)	0.057 (0.146)	0.033 (0.158)
NORTHEAST	0.213 (0.172)	0.213 (0.170)	0.193 (0.172)	0.287 * (0.155)	0.289 * (0.165)
SOUTH	-0.142 * (0.082)	-0.142 * (0.082)	-0.139 * (0.082)	-0.045 (0.098)	0.054 (0.187)
GDPGROWTH	0.081 * (0.047)	0.082 * (0.048)	0.054 (0.056)	0.110 (0.071)	0.087 (0.080)
D9294	- -	-0.001 (0.065)	- -	- -	- -
ROADEV	- -	- -	0.105 * (0.057)	0.079 (0.059)	0.085 (0.060)
DEFAULTDEV	- -	- -	- -	-0.045 *** (0.011)	- -
IDRISK	- -	- -	- -	- -	-0.045 *** (0.017)
CUSTRISK	- -	- -	- -	- -	-0.030 (0.059)
REGRISK	- -	- -	- -	- -	-0.074 (0.047)
Pred. Prob.	0.337	0.337	0.328	0.351	0.347
Pseudo. R squared	0.072	0.072	0.093	0.157	0.160
Number of observations	120	120	120	110	110

Table 7: 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	0.088	0.625	-0.999	2.5
CREDITUP	Dummy equal to 1 if credit in year 3 is greater than credit in year 0; if the relationship is not observed or the firm has defaulted in year 3, credit is measured the in the last year the relationship is observed prior to year 3.	0.398	0.490	0	1
RECOV	Equal to 1 if the bank recovers, and 0 otherwise	0.383	0.486	0	1
EBITNEG	Equal to 1 if the firm has negative average Earnings Before Interest and Taxes in years 1 to 3	0.109	0.311	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

Number of observations: total 64,200, of which 46,636 are for borrowers with z-scores

**Table 8: 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.

Dependent Variable: CREDITGROW							
EBITNEG	-0.113 ***	-	-	-0.110 ***	-	-	-
	(0.009)	-	-	(0.008)	-	-	-
EBITNEG*RECOV	-0.023	-	-	-0.024	-	-	-
	(0.018)	-	-	(0.015)	-	-	-
DEFAULTOTH	-	0.035 **	-	-	0.067 ***	-	-
	-	(0.017)	-	-	(0.015)	-	-
DEFAULTOTH*RECOV	-	-0.048	-	-	-0.063 **	-	-
	-	(0.029)	-	-	(0.027)	-	-
DEFAULT	-	-0.166 ***	-	-	-0.155 ***	-	-
	-	(0.022)	-	-	(0.023)	-	-
DEFAULT*RECOV	-	-0.029	-	-	-0.026	-	-
	-	(0.027)	-	-	(0.027)	-	-
DZSCORE3	-	-	0.052 **	-	-	0.052 ***	-
	-	-	(0.023)	-	-	(0.019)	-
DZSCORE3*RECOV	-	-	-0.060	-	-	-0.065 *	-
	-	-	(0.038)	-	-	(0.036)	-
DZSCORE4	-	-	0.048 *	-	-	0.056 ***	-
	-	-	(0.025)	-	-	(0.019)	-
DZSCORE4*RECOV	-	-	-0.059 *	-	-	-0.064 **	-
	-	-	(0.031)	-	-	(0.027)	-
DZSCORE5	-	-	0.031	-	-	0.043 ***	-
	-	-	(0.021)	-	-	(0.015)	-
DZSCORE5*RECOV	-	-	-0.068 **	-	-	-0.072 ***	-
	-	-	(0.027)	-	-	(0.024)	-
DZSCORE6	-	-	-0.001	-	-	0.013	-
	-	-	(0.024)	-	-	(0.019)	-
DZSCORE6*RECOV	-	-	-0.065 **	-	-	-0.066	-
	-	-	(0.031)	-	-	(0.029) **	-
DZSCORE7	-	-	-0.038	-	-	-0.019	-
	-	-	(0.024)	-	-	(0.019)	-
DZSCORE7*RECOV	-	-	-0.049	-	-	-0.053 *	-
	-	-	(0.030)	-	-	(0.029)	-
DZSCORE8	-	-	-0.129 ***	-	-	-0.100 ***	-
	-	-	(0.023)	-	-	(0.024)	-
DZSCORE8*RECOV	-	-	-0.068 *	-	-	-0.067 *	-
	-	-	(0.036)	-	-	(0.036)	-
DZSCORE9	-	-	-0.225 ***	-	-	-0.177 ***	-
	-	-	(0.034)	-	-	(0.034)	-
DZSCORE9*RECOV	-	-	-0.139 ***	-	-	-0.160 ***	-
	-	-	(0.047)	-	-	(0.049)	-
LOGCREDIT_0	-	-	-	-0.088 ***	0.072 ***	-0.083 ***	-

	-	-	-	(0.008)	(0.007)	(0.008)
RELLENGTH	-	-	-	0.028 **	0.019	0.028 **
	-	-	-	(0.013)	(0.012)	(0.012)
BANKSHARE	-	-	-	-0.008 ***	-0.008 ***	-0.008 ***
	-	-	-	(0.001)	(0.001)	(0.001)
1/2BANKSHARE ²	-	-	-	0.0001 ***	0.0001 ***	0.0001 ***
	-	-	-	(0.000)	(0.000)	(0.000)
CONSTANT	0.103 ***	0.103 ***	0.103	1.259 ***	1.041 ***	1.177 ***
	(0.001)	(0.001)	(0.014)	(0.108)	(0.085)	(0.108)

BANK FIXED EFFECTS INCLUDED (NOT SHOWN)

Adj. R squared	0.039	0.035	0.042	0.107	0.092	0.104
Number of observations	43,647	64,200	46,636	43,647	64,200	46,636

Table 9: Robustness Tests - Lending relationships data

The observations are bank-firm relationships. Standard errors below coefficients are clustered at the bank level. In the first three regressions the model is specified as a logit and the dependent variable is equal to 1 if credit in the last year the relationship is observed is higher than credit in the initial year; marginal effects are reported instead of coefficients. In columns 4-6 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.

Dependent Variable: Sample:	CREDITUP			CREDITGROW		
	Full sample			Sample without 3 largest banks		
EBITNEG	-0.110 *** (0.016)	-	-	-0.089 *** (0.006)	-	-
EBITNEG*RECOV	-0.017 (0.020)	-	-	-0.033 (0.029)	-	-
DEFAULTOTH	-	0.142 *** (0.030)	-	-	0.092 *** (0.020)	-
DEFAULTOTH*RECOV	-	-0.077 * (0.042)	-	-	-0.076 * (0.043)	-
DEFAULT	-	-0.137 *** (0.029)	-	-	-0.097 *** (0.020)	-
DEFAULT*RECOV	-	-0.022 (0.042)	-	-	-0.075 ** (0.035)	-
DZSCORE3	-	-	0.047 *** (0.018)	-	-	0.052 *** (0.019)
DZSCORE3*RECOV	-	-	-0.065 ** (0.027)	-	-	-0.065 * (0.036)
DZSCORE4	-	-	0.055 *** (0.014)	-	-	0.056 *** (0.019)
DZSCORE4*RECOV	-	-	-0.032 (0.030)	-	-	-0.064 ** (0.027)
DZSCORE5	-	-	0.058 *** (0.018)	-	-	0.043 *** (0.015)
DZSCORE5*RECOV	-	-	-0.042 (0.039)	-	-	-0.072 *** (0.024)
DZSCORE6	-	-	0.033 (0.020)	-	-	0.013 (0.019)
DZSCORE6*RECOV	-	-	-0.016 (0.043)	-	-	-0.066 ** (0.029)
DZSCORE7	-	-	0.014 (0.018)	-	-	-0.019 (0.019)
DZSCORE7*RECOV	-	-	-0.027 (0.044)	-	-	-0.053 * (0.029)
DZSCORE8	-	-	-0.067 ** (0.027)	-	-	-0.100 *** (0.024)
DZSCORE8*RECOV	-	-	-0.044 (0.044)	-	-	-0.067 * (0.036)
DZSCORE9	-	-	-0.165 *** (0.042)	-	-	-0.177 *** (0.034)
DZSCORE9*RECOV	-	-	-0.110 * (0.042)	-	-	-0.160 *** (0.034)

	-		-	(0.058)	-	-	(0.049)
LOGCREDIT_0	-0.041 ***	-0.036 ***	-0.039 ***	-0.065 ***	-0.056 ***	-0.083 ***	
	(0.006)	(0.005)	(0.006)	(0.013)	(0.011)	(0.008)	
RELENGTH	0.030 **	0.031 **	0.032 **	0.016	0.007	0.028 **	
	(0.012)	(0.013)	(0.013)	(0.017)	(0.015)	(0.012)	
BANKSHARE	-0.005 ***	-0.004 ***	-0.005 ***	-0.004 ***	-0.004 ***	-0.008 ***	
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	
1/2BANKSHARE ²	0.0007 ***	0.0006 ***	0.0008 ***	0.0008 ***	0.0001 ***	0.0001 ***	
	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.000)	(0.000)	
CONSTANT	-	-	-	0.886 ***	0.772 ***	1.177 ***	
	-	-	-	(0.171)	(0.137)	(0.108)	

BANK FIXED EFFECTS INCLUDED (NOT SHOWN)

Adj. R squared	0.067	0.059	0.064	0.089	0.082	0.085
Number of observations	43,644	64,195	46,633	18,910	29,545	20,779