Which Banks Recover from a Banking Crisis?*

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Preliminary Conference Version, not for citation or circulation

April 4, 2008

Abstract

We analyze the fate of 120 Italian banks that experienced abrupt drops in profitability. About 1/3 of these banks subsequently attain comparable levels of profitability. 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. 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 that have a large share of high risk customers are aggressive trimming loans.

*We thank Raghuram Rajan for helpful comments and suggestions. We thank Roberto Felici for outstanding research assistance. Kashyap thanks the Stigler Center and the Initiative on Global Markets at the University of Chicago Graduate School of Business for research support. The views expressed here are those of the authors only and not necessarily of the institutions with which they are affiliated. All errors are our own. In order to maintain confidentiality of the microeconomic data, the analysis and estimation was done at the Bank of Italy.

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 19070s 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.

The Japanese banking crisis of the late 1990s offers a classic example of the differences of opinion over what should be done in a crisis. The Japanese government used across the board capital infusions to the largest banks and was quick to declare that the problem was resolved.[2] Subsequently the government gave capital to insolvent banks and permitted mergers between large banks that did little to reduce capacity in the industry. Critics such as Hoshi and Kashyap (2005) argued that the additional funding was needed early in the crisis, that the capital injections should have been targeted to only healthiest banks, and the some exit was desirable. But even in this debate little was said about the specific adjustments to the operating strategies of individual banks. More generally the doctrine of "prompt corrective action" presumes that limiting asset growth and raising capital is the key to reviving distressed institutions; as opposed to (say) making adjustments in the loan portfolio of a troubled bank.

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 opaqueness, this

[1] They also document 51 borderline and nonsystemic episodes in 45 countries during the same period.

[2] For instance, on February 2, 1999 on the eve of what would turn out to be the first capital infusion the Vice Minister of Finance, Eisuke Sakikabara, declared that the banking crisis would be over within 2 weeks. By the end of the month the U.S. Deputy Treasury Secretary Lawrence Summers gave a speech asserting that even with the capital infusion anticipated by Sakakibara, the Japanese banks remained significantly undercapitalized.

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 credit crisis of 2007, at any given time many large borrowers have lines of commitment from large banks. The liquidity provision hypothesis holds that the removal of these credit lines is potentially costly, even if the borrowers are themselves large.[3]

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 pointing 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?

[3] 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 heath 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). In contrast, Ongena, Smith and Michalsen (2000) do not find any fallout for the customers of Norwegian banks during their banking crisis.

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 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. 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.

Based on loan level data it does not appear that recovering banks make any across the board differences in their post-shock lending decisions. Indeed, overall they seem more likely to continue lending or to give additional credit to their customers. But in cases where the share of high risk customers is substantial, the recovering banks show more of a propensity to tighten credit.

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 1986 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 risk such as a sector or a region. 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.[4]

The table highlights the consolidation that occurred as branching restrictions were progressively eliminated (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 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

[4] 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.

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. Table 1 shows they also tend to higher default rates (defined as newly bad loans relative to the stock of previously performing loans). 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

Turning to the time series patterns, there are several waves of distress when many banks got into trouble at the same time. The first such period is between 1992 and 1994, while the second is between 2001 and 2003. Table 2 reports basic data on economy-wide conditions. It is clear from Table 2 that both of waves of distress occur during periods of slow growth.

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. 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[6], 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 9.42 percent in 1996. Table 2 also reports aggregate data on the default rate for all Italian banks that is analogous to sample statistics in Table 1. The default rate was elevated

[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 (20 percent), 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.

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, this crisis is relatively modest. For instance, the World Bank's Caprio and Klingebiel dataset on "Episodes of Systemic and Borderline Financial Crises" notes that the peak share of insolvent bank assets to banking total system assets was 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, with an increase in the ratio of credit to GDP by 15 percentage points. Default rates and the bad loan 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 2001-3 a second wave of distress followed. So even the crudest reading of the evidence suggests 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, we can also see that there is interesting heterogeneity in the causes of the distress. One dimension of the heterogeneity is the propensity of some banks to underperform 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 represented in 1992 around 5 percent of production (versus 18 percent in the Center-North), the fall in domestic demand swamped the exchange rate depreciation. During this period the central government also reduced

subsidies that had been granted to support infrastructure investment. This policy switch led to a drop in construction and since the subsidies had been disproportionately granted to Southern firms this also exacerbated the downturn in the South. Thus, the regions of the country performed very differently during this downturn, 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 large and small banks (defined as having assets of above or below 1.05 billion 1995 euros) in the North, Center and South of Italy.[7] As hinted out above, more than 30 percent of the banks in the South (whether large or small) got into trouble at some point during our sample. In contrast, large and small banks had very different experiences in the central part of the country: with many more large banks in the central region becoming 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.

Section 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 of the same size and 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 small bank headquartered in the northern region that got into trouble in 1998, we compare each of the indicators to the average value of those indicators for other small banks in the northern 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

[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 only to other banks in their region and the important patterns in Table 4 are present with that adjustment too.

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 ignore the exiting banks and base our contrasts at different points in time on the sample of banks that were currently operating.

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 t=0 the banks on average had slightly higher profits rates than others (of the same size and region). At time t=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 is important so 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, a bank is considered to have recovered if any of the following conditions holds:

1) At t = 1 its ROA is greater than 25th percentile and at t=2 ROA is greater or equal to ROA the year before the shock <u>or</u> the ROA percentile is greater or equal to the percentile observed 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, <u>or</u> the ROA percentile is greater or equal to the percentile observed in 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, <u>or</u> 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, a total of 42 of the 120 banks with complete data recover. The information in Table 4 compares recovering (R) and non-recovering (NR) banks to each other and 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 t=0. While both the R and NR banks have relatively high profitability prior to the shock, the NR banks are doing especially well, having significantly higher profitability than the R banks in both years t=-1 and t=-3. This pattern flips starting in year t=0, and the NR banks significantly underperform compared to the R banks for the following 3 years. More specifically, in years t=1, t=2, and t=3, the recovering banks ROA is between 90 and 110 basis points higher then the non-recovering banks. From Table 1 we know that from 1989 to 2002, average ROA fluctuated between 120 and 55 basis, so the R/NR gap is substantial.

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 was 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,

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

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 t-1 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 significantly higher values than other banks between time t=-3 to t=-1, but then the differences disappear.

Comparing the distressed banks, there are no significant differences between the R and NR banks before year t=0. While after the shock the non-recovering banks show substantially lower net interest income (with the differences being significant in years t=1, t=2 and t=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 are consistently higher than other banks. Comparing the R and NR banks, however, shows no significant differences. 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. Based on this finding we conclude that while cost containment might be a significant drag on the overall profitability of these banks, changes in costs have little to do with the onset or recovery from distress.

The data on extraordinary items also show no meaningful differences between R and NR banks. Relative to all banks, the pattern of provisions and write-downs fluctuates between being above and below average. Given the discretion that the banks have in choosing when to recognize losses, we are not inclined to put too much weight on the

exact timing of when these entries appear on the financial statements. If we further disaggregate, to separate the provisions and write-downs associated with loans from other provisions and write-downs, we do find that the differences that are present are coming from lending activities. So this reinforces our impression that lending policies seem to be important.

The last panel in Table 4 looks further at three aspects of lending behavior. The first entry shows the patterns in the default rates. We draw three conclusions from the default statistics. First, both the R and NR banks have substantially higher default rates than other banks in at least two years before ROA deteriorates. While the NR banks have consistently higher default rates, the differences between the two are insignificant up until time t=0. This suggests that both seem to be lending to riskier clients. Second, the gap in default rates between R and NR banks becomes significantly different starting in year t=0. The rates are higher for the NR banks are also significantly higher in year t=2. Third, the absolute level of the default rate for the recovering banks drops noticeably after the drop in ROA. In each of the three years after the shock the recovering banks' default is no different than the full sample default rate. This suggests to us that the adjustment in the loan portfolio and in particular the ability to find good lending opportunities could be important.

The interest margins on performing loans is mostly higher for the distressed banks relative the full sample – which is again consistent with the high risk interpretation. The recovering banks consistently have higher margins, but differences between the R and NR banks are mostly insignificant. Instead, that there are substantial and significant differences in the bad loan percentages between the R and NR banks. The non-recovering banks start to show a higher bad loan percentage in year t=-1 and this difference persists for the rest of the years.

Overall, the data from Table 4 are consistent with the following simple story. The distressed banks tend to be lending to relatively high risk customers. Prior to year t=0, their interest margins for both R and NR banks are high and default rates are also high. But up until year t=0, the differences between the two are not terribly pronounced; ironically all the way up until t=0, the banks that will subsequently not recover have higher profits rates (significantly so in some of the years). At time t=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, or in provisioning, or write-downs, 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 t=0 onward.

Section 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. Distinguishing between these types is very difficult.

In part of the analysis we seek to explain recovery using information on the choices made by the banks. This creates a second complication for the exiting banks because for these institutions we only have data on them up to the point where they drop out of the sample. For variables where we would seek average values over years 1 to 3, we compute the averages over the years where data are available. This means for the 15 banks that disappear in the same year as the profit shock we cannot compute these variables.

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 105 banks where data exist. As a benchmark in what follows note that 35 percent of the full set of banks recover. Also, the Table shows the 15 banks that exit as of time 0 are essentially randomly scattered across the region-size bins; this follows from the fact that the mean values of the indicator variables for bank size and region are almost identical

for the sample of 120 and 105 banks. We start by investigating the effects of variables that are outside of the control of the banks, and then look at bank-specific determinants.

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 North 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.

The coefficients of all three of the control variables in the first specification are border-line statistically significant (between 8 and 15 percent), and economically quite important. For instance, the marginal difference in the probability of recovery (evaluated at average regional GDP growth rate) is 25 percentage points higher for northern 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 8 percentage points.

The next column of the table reports the results from further disaggregating the regional dummy variables to separate small and large banks in the the north, center and south. In this specification, the benchmark group is the set of small banks in the center of the country. Relative to this group the small southern banks are 38 percentage points less likely to recover. The Southern banks are also less likely to recover, with the small ones faring worse than the larger ones. The GDP coefficient is roughly the same as in the first specification.

The third specification includes an 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. Because of the time variation in the average level of profitability, we measure ROA relative to the average value of ROA for banks of the same size, in the same region. Column 5 shows the results of adding this variable to specification with the 5 region/size dummies and the regional GDP control. The level of ROA at the time of the shock has a positive, statistically significant coefficient, indicating that banks that had a relatively better performance at the time of the shock are more likely to recover. The magnitude of the effect is large. A bank that underperformed its benchmark by 109 basis points (which is the 25th percentile of the distribution) compared to one that underperformed by 46 basis points (the 75th percentile), would be 7 percentage points less likely to recover. Including the initial profit decline also reduces the significance of the GDP variable.

The evidence from Table 4 suggested that recovering banks tended to have lower default rates during the years after the initial distress. In the last specification in the table we add the average value of the default rate from the three years after the onset of distress.[9] The default rates are normalized relative to the rate that prevails at banks of the same size in the same region. The coefficient on this variable is negative and statistically significant at the 1 percent level. The magnitude is effect is sizable. A bank that keeps default rates 1.15 percentage points below benchmark is at the 25th percentile of the distribution, while a bank with an average default rate 1.60 percentage points above the

[9] For banks that disappear prior to year 3 we take the average of the default rate for the years where the bank has data.

benchmark is at the 75th percentile of the distribution. The bank with the lower default rate would be 6.9 percentage points more likely to recover.

The inclusion of the default rate raises the magnitude of the coefficients on GDP and leaves the coefficient on the initial drop in profits roughly the same. The estimated GDP coefficient suggests that moving from the 25th percentile to the 75th percentile in growth raises the probability of recovery by 11.3 percentage points. Thus, with the full set of controls, growth, the initial profit drop, and subsequent portfolio management each appear to be important determinants of which banks recover.

Section 5: Evidence from specific bank loans

To better understand the Table 6 results we next turn to data on individual loans. The data set is 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.

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.[10] 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.

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 the creditworthiness of the applicants, 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 have either loan commitments or loans in place which exceed a specified

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

threshold.[11] 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. We then 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 t=0. The relationships between the banks and these borrowers are tracked back to t=-3 and forward up to t=3.

The matching between CADS borrowers and the banks at the year of the shock yields around 90,000 observations. For a large share of these the z score or other control variables are missing. The final data set includes 62,626 observations of credit relationships between our sample of crisis banks and their clients.

5.1 Quality of the corporate portfolio: z scores

An important advantage of the z score computed by CADS is that it provides an ex ante measure of credit risk. The observed default rate of a portfolio of loans is an ex post measure of credit risk and as noted earlier the timing of the exact default on any given loan involves a certain amount of discretion. So we focus here on an ex ante measure of portfolio quality given by a credit risk score.

The z score measures the probability of default and groups firms into 9 categories, with z's of 1 representing the lowest credit risk and 9 indicating the highest credit risk.

[11] 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 honor the commitment nor includes anything like a material adverse change clause.

CADS maps the score into four levels of risk: i) safe (score equal to 1 or 2), solvent (3, 4), vulnerable (5, 6), risky (7, 8, 9).

The relationship between the z score in one year and the probability of default in the next year based on the CADS firms between 1986 and 2006 is reported in Box A below.

BOX A: Default probability by z-score class for CADS firms, 1986-2006

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

Note: Default occurs when the firm is legally bankrupt or recorded as a nonperforming borrower. Source: CADS.

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 to 1.94 percent, 5.22 percent and 15.69 percent respectively 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.

The data on the characteristics of the loans that we can analyze are shown in Table 7. The two primary measures of credit risk that we analyze are the level of the z-score (the variable labeled ZSCORE) and the share of all credit in a given bank's portfolio that is tied up in loans to high risk borrowers (SHHIGHZ). While not shown in the table, the average values of the zscore are 5.15 and 5.25 for the R and NR banks respectively at time 0. Given the huge number of loans in the sample the difference in the means is statistically significant. 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.

The variable ZPOST gives the average value of the scores for the banks in years 0, 1 and 2. We form this variable so that we can study how the banks' customers' risks evolved. The average value of ZPOST for the R and NR banks is about the same as for the year zero differences.

If the small difference in the average ZSCORE (or ZPOST) was coming because the NR banks had more high risk borrowers, then the small difference might be very relevant for the default patterns documented in Tables 4 and 6. The share of high risk loans (at time 0) is 20.5% and 21.5% for the R and NR banks. Put differently, for every 100 euros of loans made, the NR banks are lending one more euro to the high risk borrowers. This strikes us as a small difference.

Moreover, a regression analysis that compares these shares after controlling years and regions uncovers no significant differences. Recall also from Table 4 that the difference in the year 0, year 1 and year 2 default rates were (after regional and size adjustments) roughly 2 to 2.5 percentage points. Thus, the ex-post outcomes seem more disparate than would be expected given that the underlying share of high risk borrowers was only 1 percentage point different. This circumstantial evidence suggests to us that pure differences in the credit-worthiness of the borrowers do not seem to be a likely driver of the differences between R and NR banks.

5.2 Borrower-Level Regressions

To assess how the banks are managing their portfolios we compute various measure of how bank lending changed in the wake of the initial profit decline. We calculated whether the bank completely stops lending, as well as whether they reduced the level of credit (to zero or any other amount). The variable LOANSDOWN is an indicator that equals 1 if loans as of year 3 are lower than year 0; if the relationship is terminated for reasons other than default, the variable takes the value of 0.[12] We also considered other variants of this type of measure of bank lending behavior. For instance, looking only at loan commitments, whether drawn or undrawn, or checking whether a bank totally cuts off a borrower, we get similar results to those shown below. So in the interest of brevity we show only results pertaining to LOANSDOWN.

We then specify a regression model to estimate whether the R and NR banks differ in the probability that a borrower that had a relationship with the bank at the time of the

shock experiences a reduction in credit. These regressions can tell us whether the recovering and non-recovering treated similar borrowers similarly.

Of course, 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. However, even with these caveats 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[13] and are mainly in the form of mortgages, a component of lending that is less flexible than others. 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.[14]

The first logit regression estimated is of the form:

$$\text{Prob(LOANSDOWN=1)} = f(\text{RECOVER, ZSCORE, FIRMSIZE, RELWEIGHT, RELLENGTH, region dummies, year dummies}) \quad (1)$$

The probability of observing a reduction in credit is a function of whether the bank recovers or not, firm risk (ZSCORE), and several firm and relationship characteristics. These addition controls include, FIRMSIZE which is the natural log of total assets at t=0, RELWEIGHT which is the proportion of credit that the firm gets from the bank, and an estimate of the length of the relationship (RELLENGTH), computed as the number of

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[12] It is considered missing if the firm defaults because in this case credit can grow because unpaid interest cumulates or other reasons that do not necessarily capture the willingness of the bank to grant more loans.

[13] See Annual Report on 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.

[14] 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.

years before t=0 for which the relationship is observed.[15] We also account for the region where the bank is located and a set of dummy variables for the year of the shock.

Recovering and non recovering banks are likely to apply different strategies to different types of borrowers and their strategies should depend on the size of the shock they face. We allow for a non-linear relation between credit decisions and the z score by adding a quadratic term (½$ZSCORE^2$), and we add an interaction term between RECOVER and ZSCORE and one between RECOVER and the square of the z score.

The results are reported in the first column of Table 8. On average recovering banks are 14.4 percent more likely to continue extending credit to their clients than the non-recovering banks.[16] Both R and NR banks discriminate between high and lower risk borrowers, as evidenced by the opposite signs on the ZSCORE and its square. For low risk borrowers credit reductions are less likely, but as the z-score moves above 3, the banks become more likely to cut credit. Comparing firms with z scores of 3 and 9, the estimates imply that the banks about 40 percent more likely to reduce credit to the high z borrower than the medium risk borrower.

Interestingly, the R and NR banks show no significant differences in how they treat borrowers with the same z-scores. Thus, there does not appear to be a simple rule related to the z-scores that explains the lower default rates for the recovering banks.

Not surprisingly, firms that have longer borrowing relationships are more likely to see their credit sustained. We have no obvious explanation for why the borrowers that are getting large amounts of credit from the distressed banks are more likely to see their credit decline. This is something we will explore further in subsequent drafts of this paper.

In the second regression we explore whether the NR and R banks make different credit decisions when their own portfolio has high shares of risky borrowers. We do this by adding the variable SHHIGHZ and its interaction with RECOVER to the prior specification; we remove the interactions between RECOVER and ZSCORE and ½$ZSCORE^2$.

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[15] 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.

[16] This calculation, and the next one in this paragraph, ignores the interaction coefficients that are not significantly different from zero.

The results, reported in the second column of Table 8. Most of the estimates from the first specification are very similar. But the coefficient on RECOVER jumps substantially, suggesting that the recovering banks are much more likely to continue granting credit to their clients once we recognize that the banks with many high risk borrowers behave differently than other banks. For the NR banks, when their portfolio is filled with high risk borrowers, they are more prone to keep extending credit. Conversely, the recovering banks become more likely to trim lending when their portfolios are filled with high risk borrowers.

The difference between how the NR and R banks behave in this case is substantial. For example, a two standard deviation change in the share of credit going to high risk borrowers moves SHHIGHZ by 0.15. A change of this size implies that the NR banks would be 9 percentage points less likely to reduce credit to the typical customer. In contrast, the recovering banks would 9 percentage points more likely to reduce credit.

The third specification allows the recovering banks to have separate effects with respect to both zscores and the share of high risk borrowers. In this case, the high z firms are again less likely to receive credit than the lower risk borrowers. The magnitudes are virtually the same as in the first specification. The recovering banks are slightly less aggressive about cutting off the worst risks: for a borrower with a ZSCORE of 9, the NR banks are 15.4 percentage points are less likely to extend credit, while R banks are 12.5 percentage points less likely to extend credit. The results regarding credit decisions when the share of high z borrowers is large is virtually identical to those in the second specification.

We view these regressions as a first start toward exploring the distressed banks' portfolio adjustments. In subsequent drafts of the paper, we plan to investigate additional specifications. One particularly important direction is to look at how bank dependent borrowers are treated.

Section 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. Some of this appears to occur because recovering banks that have a large share of high risk customers are more aggressive in trimming loans, while non-recovering banks become less likely to cut credit when their portfolio is filled with many high risk borrowers.

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.

	Banks in Sample*						Newly distressed banks						
year	Number of banks	Median Assets (deflated)	Median ROA	Median Bad Loan ratio	Default rate	Operating cost/Assets	N.	Total Assets (% of Sample)	Median Assets (deflated)	Median ROA	Median Bad Loan ratio	Default rate	Operating Cost/Assets
1986	337	605.07	1.35	6.46		3.16	-	-	-	-			
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 Industry 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. Sources: Istat for GDP, Bank of Italy. Note: based on individual banking data. The totals may differ from published statistics due to incomplete data and partial estimation of data for the special credit institutions (etc.). [We might want to get the published stats where available].

Year	Real GDP growth	3-month interbank)	Real lending growth	ROA	Bad loan 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 and size

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. Small banks are those with total assets below 1 million euros (1995=100; 1.034 billion euros is the sample median).

	North		Center		South	
	Small	Large	Small	Large	Small	Large
Total banks operating in all years	116	108	57	53	89	34
Number of banks experiencing a crisis	18	22	11	21	36	12
Number of banks recovering	8	12	8	4	6	4
Total banks operating 1992-1994	53	79	33	34	51	22
Number of banks experiencing a crisis 1992- 1994	5	12	3	9	12	6
Number of 1992-1994 crisis banks that recovered	1	9	2	2	2	1

Table 4: Event time statistics, deviations from industry means

Deviations of individual banks with respect to region and size mean. The variables are in percentage points. The default rate is defined as New Bad loans over the existing stock of performing loans at t-1.

	ROA					Interest margin/Total Assets					Other Revenues/Total Assets				
t	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	0.507	0.214	**	0.397	***	0.547	0.468		0.519	***	0.006	0.179	**	0.062	
-2	0.469	0.259		0.387	***	0.624	0.550		0.599	***	-0.012	0.167		0.054	
-1	0.433	0.092	***	0.317	***	0.429	0.400		0.419	***	0.264	0.195		0.237	**
0	-1.014	-0.688	***	-0.909	***	-0.016	0.162		0.046		-0.041	0.018		-0.022	
1	-0.776	-0.386	**	-0.627	***	-0.150	0.342	***	0.035		0.203	0.078		0.151	
2	-0.834	0.083	***	-0.433	***	-0.061	0.396	***	0.137		-0.024	0.077		0.022	
3	-0.859	0.159	***	-0.397	***	-0.278	0.400	***	0.025		-0.044	0.058		0.001	

	Operating Costs/Total Assets					Loan Write-Offs, Losses and Provisions/Total Assets					Write-Offs, Losses and Provisions on Other Assets/Total Assets				
T	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	0.159	0.532	*	0.290	***	-0.054	-0.021		-0.043	*	-0.047	-0.038		-0.044	
-2	0.237	0.551		0.345	***	-0.041	0.003		-0.029		-0.035	-0.074		-0.048	
-1	0.414	0.542		0.458	***	0.032	0.055		0.040		-0.192	-0.099		-0.160	
0	0.506	0.530		0.514	***	0.545	0.254		0.444	***	-0.081	0.086		-0.022	
1	0.505	0.531		0.515	***	0.582	0.192		0.436	***	-0.254	0.079	**	-0.129	
2	0.492	0.501		0.496	***	0.296	-0.009	**	0.164	**	-0.051	-0.107		-0.075	
3	0.301	0.411		0.350	**	0.253	-0.024	*	0.129	*	-0.038	-0.101		-0.066	

Table 4, continued

	Default Rate					Bad Loans/Total Loans					Interest Margin/Performing Loans				
t	NR	R	H:NR=R	All	H: A=0	NR	R		All		NR	R		All	
-3	0.804	-0.072		0.492		-0.353	-1.168		-0.639		1.284	1.375		1.316	***
-2	1.216	0.385		0.930	**	0.445	-0.511		0.115		1.236	2.053		1.517	***
-1	2.007	0.725		1.565	***	1.546	-0.217	*	0.938		1.160	1.456		1.262	***
0	2.857	0.894	**	2.175	***	2.983	0.239	**	2.031	***	0.417	0.837		0.562	
1	2.713	0.277	*	1.796	**	3.837	0.171	***	2.458	***	0.196	1.315	*	0.617	*
2	1.769	-0.077	***	0.970	**	3.665	0.312	**	2.213	***	0.202	1.328	*	0.689	**
3	1.211	0.084		0.707	*	4.286	0.370	**	2.536	***	0.136	1.147		0.588	

Table 5: Variables employed in the regressions and stats

	120 banks			105 banks that exist after year 0		
Variable	**25th percentile**	**Mean**	**75th percentile**	**25th percentile**	**Mean**	**75th percentile**
Recovery	0	0.35	1	0	0.39	1
Dummy North Region	0	0.33	1	0	0.34	1
Dummy South Region	0	0.39	1	0	0.35	1
Dummy North X Large	0	0.18	0	0	0.2	0
Dummy North X Small	0	0.15	0	0	0.14	0
Dummy South X Large	0	0.10	0	0	0.10	0
Dummy South X Small	0	0.29	1	0	0.26	1
Dummy Center X Large	0	0.18	0	0	0.19	0
Dummy 1992 to 1994						
Ave Regional GDP Growth t=1 to t= 3	0.97	1.45	1.86	1.06	1.45	1.85
Return on Asset Deviation at t=0	-1.09	-1.00	-0.46	-1.03	-0.95	-0.47
Ave Default rate deviation t=1 to t=3	NA	NA	NA	-1.15	0.64	1.60

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 (std error)	dy/dx (std error)	dy/dx (std error)	dy/dx (std error)	dy/dx (std error)
Dummy Northern Region	0.122 (0.081)				
Dummy Southern Region	-0.139 (0.084)				
Dummy North X Large		-0.124 (0.098)	-0.121 (0.096)	-0.105 (0.109)	-0.067 (0.121)
Dummy North X Small		-0.168 (0.126)	-0.168 (0.125)	-0.156 (0.126)	-0.072 (0.146)
Dummy Center X Large		-0.338 (0.052)	-0.336 (0.050)	-0.334 (0.058)	-0.345 (0.068)
Dummy South X Large		-0.208 (0.109)	-0.206 (0.108)	-0.221 (0.107)	-0.182 (0.153)
Dummy South X Small		-0.387 (0.055)	-0.386 (0.055)	-0.377 (0.060)	-0.385 (0.065)
Dummy 1992 to 1994			-0.011 (0.059)		
Average Regional GDP Growth t=1 to t= 3	0.094 (0.052)	0.100 (0.062)	0.102 (0.064)	0.061 (0.077)	0.143 (0.092)
Return on Asset Deviation from benchmark at time t=0				0.116 (0.055)	0.095 (0.046)
Average Default rate deviation from benchmark from time t=1 to t=3					-0.025 (0.012)
Number of observations	120	120	120	120	105
Pseudo R-Squared	0.067	0.128	0.128	0.150	0.188

Table 7: Variables employed in the regressions with lending relationships and descriptive statistics

		Mean	Std. Dev.	Min	Max
	Dependent Variables				
LOANSDOWN	Equal to 1 if credit granted decreases between t=0 and t=3, and 0 otherwise	0.618	0.486	0	1
	Explanatory Variables				
RECOVER	Equal to 1 if the bank recovers, and 0 otherwise	0.365	0.481	0	1
ZSCORE	Credit risk score, from 1 to 9 (9 is highest risk)	5.221	1.775	1	9
SHHIGHZ	Share of credit used by firms with credit score equal or greater than 7	0.211	0.073	0.022	0.706
ZPOST	Average firm credit score in years t=0 to t=2	5.117	1.723	1	9
FIRMSIZE	Log of firm's total assets at t=0	9.078	1.329	1.098	17.783
RELWEIGHT	Credit of firm j from bank i divided by total credit of firm j	15.733	22.235	0	100
RELLENGTH	Length of the relationship in years. Equal to 4 if greater than 4				
d89	Dummy for the year of the shock to the bank	0.010	0.101	0	1
d90	Dummy for the year of the shock to the bank	0.025	0.157	0	1
d91	Dummy for the year of the shock to the bank	0.019	0.138	0	1
d92	Dummy for the year of the shock to the bank	0.175	0.380	0	1
d93	Dummy for the year of the shock to the bank	0.049	0.215	0	1
d94	Dummy for the year of the shock to the bank	0.089	0.285	0	1
d95	Dummy for the year of the shock to the bank	0.061	0.239	0	1
d96	Dummy for the year of the shock to the bank	0.189	0.392	0	1
d97	Dummy for the year of the shock to the bank	0.029	0.168	0	1
d98	Dummy for the year of the shock to the bank	0.026	0.158	0	1
d99	Dummy for the year of the shock to the bank	0.022	0.145	0	1
d00	Dummy for the year of the shock to the bank	0.069	0.253	0	1
d01	Dummy for the year of the shock to the bank	0.237	0.425	0	1
ne	Dummy for bank located in the North East	0.070	0.255	0	1
no	Dummy for bank located in the North West	0.431	0.495	0	1
su	Dummy for bank located in the South	0.125	0.331	0	1
Number of observations		62626			

Table 8: Logit model on lending relationships data

The observations are bank-firm relationships. The coefficients estimates are reported as marginal effects after logit transformation Standard errors below coefficients are clustered at the bank level.

Dependent Variable: LOANSDOWN						
RECOVER	-0.144	**	-0.390	***	-0.443	***
	(0.057)		(0.119)		(0.118)	
ZSCORE	-0.097	***	-0.087	***	-0.099	***
	(0.011)		(0.012)		(0.011)	
1/2ZSCORE2	0.027	***	0.026	***	0.028	***
	(0.002)		(0.002)		(0.002)	
RECOVER*ZSCORE	0.026		-		0.029	*
	(0.017)		-		(0.017)	
RECOVER*1/2ZSCORE2	-0.005		-		-0.006	*
	(0.004)		-		(0.003)	
SHHIGHZ	-		-0.600	**	-0.606	**
	-		(0.281)		(0.280)	
RECOV*SHHIGHZ	-		1.219	***	1.231	***
	-		(0.456)		(0.454)	
FIRMSIZE	-0.004		-0.004		-0.004	
	(0.009)		(0.009)		(0.009)	
RELWEIGHT	0.002	***	0.002	***	0.002	***
	(0.0002)		(0.0002)		(0.0002)	
RELLENGTH	-0.046	***	-0.046	***	-0.046	***
	(0.008)		(0.008)		(0.009)	
REGION DUMMIES INCLUDED (NOT SHOWN)						
YEAR DUMMIES INCLUDED (NOT SHOWN)						
Pr(LOANSDOWN)	0.637		0.638		0.638	
Pseudo R squared	0.083		0.086		0.086	
Number of observations = 61312						

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