Do Mergers Improve Information? Evidence from the Loan Market*

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Abstract

We examine the informational effects of M&As by investigating whether bank mergers improve banks' ability to screen borrowers. By exploiting a dataset in which we observe a measure of a borrower's default risk that the lenders observe only imperfectly, we find evidence of these informational improvements. Mergers lead to a closer correspondence between interest rates and individual default risk: after a merger, risky borrowers experience an increase in the interest rate, while non-risky borrowers enjoy lower interest rates. These informational benefits appear to derive from improvements in information processing resulting from the merger, rather than from explicit information sharing on individual customers among the merging parties. Our evidence suggests that part of these informational improvements stem from the consolidated banks using "hard" information more intensively.

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1 Introduction

The unprecedented merger wave observed in the last decade is reshaping the corporate landscape in most countries, in mature and innovative sectors alike. According to Thomson Financial, between 1990 and 2001 there were 54,143 M&As in the major industrial countries, with total value equal to $9,526 billion. A large body of empirical work has investigated the pricing effects of mergers, considering mainly changes in market power and efficiency and the ensuing net variations in average prices induced by the merger (see, for example, Barton & Sherman (1984), Kim & Singal (1993), Prager & Hannan (1998), Sapienza (2002), Focarelli & Panetta (2003)).

However, market power and efficiency are not the only important channels through which M&As can affect the pricing policy of the merging company. In many industries, mergers might change both companies' information sets as well as how they process information. This is likely to be particularly relevant in markets characterized by informational frictions, such as credit and insurance markets, where mergers could modify the ability of, and the incentives for, the merging parties to reduce the informational problems. For example, by acquiring a health insurer, an automobile insurance company might gain information on the health status of its customers, which could be useful in pricing its automobile insurance policies. Even for purely horizontal mergers, the increased volume induced by the merger might justify the adoption of costly improvements in information technology, which enable the consolidated firm to maintain better databases on its customers. On the other hand, mergers could also destroy some knowledge capital of the merging parties, due to corporate cultural differences among the parties, a need to harmonize the way information is processed, and changes in the incentives of the workers to produce and gather information in the wake of the organizational changes arising from the merger.

In this paper we analyze the importance of these informational effects of mergers. We consider a market in which they are likely to be particularly relevant: bank loans, in which borrowers' default risks are an important source of asymmetric information between lenders and borrowers. We identify the informational benefits of mergers by investigating whether mergers improve banks' abilities to screen and assess the unknown default risk of their borrowers.[1] We employ a unique bank-firm matched panel dataset from Italy of individual

[1] See, for instance, Stiglitz & Weiss (1981) for an equilibrium analysis of loan markets in which the default risks of borrowers is unobservable. A number of papers has emphasized the unique role of banks in managing the problems resulting from imperfect information on borrowers (see for example the seminal papers of Leland & Pyle (1977) and Diamond (1984) and the review in Gorton & Winton (2003)). Empirical contributions

business loan contracts for a nearly complete sample of firms from 1988 to 1998. For each loan contract, we observe the interest rate, the amount borrowed, and the characteristics of the bank and the firm involved, making it possible to analyze rate changes for different types of borrowers (e.g., according the their default risk) and lenders (e.g., large vs. small banks).

The Italian loan market constitutes a natural laboratory for studying the informational effects of consolidation. First, in the last decade, technological innovation and substantial deregulation prompted an unprecedented merger wave that reduced the number of Italian banks by nearly 25 percent. Second, the Italian economy is mainly composed of small and unlisted firms, for which the problems posed by asymmetric information are likely to be important, so if mergers did indeed result in informational efficiencies, we are most likely to detect them in this market. Third, Italian companies secure almost all their external financing through credit lines, which are highly homogeneous products and can be meaningfully compared over time and across different banks.

The intuition that underlies our empirical approach is simple: banks with superior screening abilities should have a more precise estimate of a firm's default risk, so that they should charge an interest rate that is more "sensitive" to this risk. Consider a bank with no screening ability: to it, all potential borrowers are identical, and should be charged identical interest rates. As the bank improves its screening capacity, it should discriminate among borrowers according to their default risk, charging higher interest rates to riskier borrowers and lower rates to high-quality borrowers. Hence, if mergers lead to informational benefits, one ought to observe a stricter correspondence between the interest rates and default risks of a bank's borrowers after a merger. Therefore, the price impact of these informational benefits might differ considerably across customers. These potential distributional effects of mergers have been overlooked by the empirical literature cited above, which has only analyzed the effect of mergers on average market prices.

One difficulty in implementing our empirical approach is that it requires a measure of a firm's default risk, which is unobserved by banks at the time they extend their loans: however, a crucial feature of our dataset is the availability of such a variable, in the form of an independent measure of a firm's default risk (the Z-score of Altman (1968)) which, due to accounting rules and data collection requirements, is only made available to banks with a two-year lag.

have confirmed the specific role of banks in producing information on borrowers (see, for example, James (1987)).

We find that after a merger the interest rate curve – the relation between the default probability of each firm and its loan rate – becomes steeper. Thus, while for the low-risk borrowers the loan rates decline, for the riskier borrowers – which before the merger benefited from underpriced loans, due to the informational inefficiencies of their lenders – they actually rise.

We provide evidence that this "increasing slope" finding is larger for lending relationships for which, *a priori*, the degree of asymmetric information should be higher and, therefore, the scope for merger-related informational gains larger (such as shorter bank-firm relationships, or relationships where the bank supplies a smaller percentage of the borrowing firm's total credit). These findings support our interpretation that M&As improve banks' abilities to screen borrowers. Moreover, we find some support for the hypothesis articulated in Stein (2002) that the "increasing slope" also reflects the fact that consolidated banks price their loans based more on hard information, de-emphasizing soft information in the process. We also confirm that the increase in the slope of the interest rate profile does not simply reflect the fact that merged banks are able to better price discriminate due to their increased market power.

Finally, we seek to identify the channels through which the informational benefits from a merger operate. In order to do this, we exploit the fact that Italian firms often borrow from multiple lenders (Detragiache, Garella & Guiso 2000). We find that the increase in the slope of the interest rate curve is broadly similar both for the companies that before the deal were borrowing from only one of the merging parties and for those that were borrowing from both. This finding suggests that the potential gains from explicit *pooling* or sharing of firm-specific information - which emerges only when both of the merging banks were lending to the same company before consolidation - is not the relevant channel of informational gains.[2]

We also find little support for the idea that the information benefits arise via a transfer of screening abilities from a more informationally efficient acquiring bank to a less efficient acquired bank. Nevertheless, we uncover an asymmetry in the information improvements between the acquiring and acquired banks: while acquiring banks improve mostly in processing existing information (thus suggesting the importance of managerial improvements in these banks), those taken over become more adept both at using existing information and at gaining new information.

[2]See also Chen, Hong, Huang & Kubik (2003) for empirical evidence on the effects of scale on mutual fund performance.

Our results carry important implications for the controversy on the welfare redistributions associated with consolidations. First, we show that mergers may affect different categories of customers in different ways and increase the variance of market prices. This implication, which is likely to hold in other markets as well, implies new challenges for the antitrust authorities, because it excludes the possibility of using Paretian criteria to assess the welfare effects of mergers. Second, the simple consideration of average price effects might underestimate the welfare effects of mergers, because information improvements should imply a better allocation of resources. While it is hard to quantify such allocative effects, they are likely to be nontrivial.[3]

The rest of the paper is organized in the following way. In the next section we analyze the related literature and discuss our empirical approach. In Section 3 we introduce the data. In Section 4 we present and discuss our main empirical findings on the presence and magnitude of informational effects deriving from mergers. In Sections 5 and 6 we consider and test various explanations for these informational effects. We investigate the sources of informational benefits in Section 7. Section 8 concludes.

2 Mergers, Prices, and Information

A priori the effect of consolidation on market prices is ambiguous. On the one hand, mergers can increase efficiency (through economies of scale and scope or an improvement in managerial x-efficiency), which tends to decrease prices. On the other, if the merging companies have significant market overlap, their market power might increase, leading to adverse price changes for consumers. Several early papers found that mergers increase market power, harming consumers (Kim & Singal 1993, Prager & Hannan 1998). Recent studies relative to the banking sector, however, have found that after taking into consideration important features of the transaction, such as multi-product firms (Kahn, Pennacchi & Sopranzetti 1999), the degree of increase in market power (Sapienza 2002), the length of the post-merger period at which the price effects are measured (Focarelli & Panetta 2003) or conceptual problems in measuring service output (Wang 2003), then mergers might actually decrease prices for consumers.

One limitation of these studies is that they only consider the market power and efficiency effects of consolidation, ignoring other factors that might affect the pricing policy of the

[3]For example, in a recent paper, Caballero, Hoshi & Kashyap (2003) argue that an important factor behind the Japanese economic stagnation is that banks lend too much to inefficient firms.

merged companies. In this paper, we focus on one such factor: information. We consider the market for bank loans. Figure 1, containing plots of the raw data, motivates our empirical analysis. In the upper (lower) graph, we plot average (median) interest rates charged by banks to firms against SCORE, a measure of firms' default risk (with larger values of SCORE corresponding to a higher risk).[4] The two lines in each graph correspond to merged and unmerged banks. Clearly, the lines for the merged banks exhibit a steeper slope; furthermore, the lending rates of the merged banks are lower for the less risky firms (those with a low SCORE measure), but actually higher for riskier firms.

In this paper, we interpret this steeper tilt of the interest-rate/risk relationship after mergers as evidence of informational improvements (improved ability to screen borrowers according to their unknown default risk) stemming from the merger. To see this, consider a lending relationship between bank i and firm j. Firm j's default probability, p_j, is unknown to the bank and represents a source of asymmetric information between firm j and bank i. Assuming zero expected profits, the interest rate that bank i charges to firm j, r_{ij}, satisfies $(1 - E\{p_j|\Omega_i\}) * (1 + r_{ij}) = 1$, where Ω_i denotes bank i's information about firm j. For default probabilities p_j close to zero, this relationship between interest rates r_{ij} and expected default probabilities $E\{p_j|\Omega_i\}$ is approximately $r_{ij} \approx E\{p_j|\Omega_i\}$.[5]

Across firms, the default probabilities p_j are randomly drawn from a beta distribution with parameters (a, b), so that the average probability of failure in the population is $\bar{p} = \frac{a}{a+b}$. The information set Ω_i consists of n_i binary signals $s \in \{h, l\}$, with $\Pr\{s = l\} = p_j$. Here, n_i measures the screening ability of the bank, with larger values of n_i indicating that bank i is better informed. Using Bayes rule, the posterior mean (and hence the interest rate) after n_i signals and y "l" signals is

$$r_{ij} \approx E\{p|n_i, y\} = \frac{a + y}{a + b + n_i}. \tag{1}$$

For a given level of informedness n_i, the expected number of "l" signals out of n_i signals is $E\{y|n_i, p_j\} = n_i p_j$ so that, on average, bank i charges firm j an interest rate of

$$E\{r_{ij}|n_i, p_j\} = \frac{a + p_j n_i}{a + b + n_i} = [1 - \alpha(n_i)]\,\bar{p} + \alpha(n_i) p_j \tag{2}$$

[4] Both the SCORE variable and the definition of interest rates are discussed in detail below. We net out year effects by regressing the raw interest rates on year dummies. The interest rates used in the subsequent analysis are the residuals from this regression.

[5] In our data, the incidence of non-repayment of a loan from one year to the next is 1.3%, small enough for the linear approximation to be valid.

where $\alpha(n) \equiv \frac{n}{a+b+n}$. Expression (2) illustrates how, as more information becomes available, the posterior mean shifts away from the prior mean $\bar{p}$ towards the actual default probability p_j. In fact, $\alpha(0) = 0, \lim_{n\to\infty} \alpha(n) = 1$, and $\frac{\partial\alpha}{\partial n} = \frac{a+b}{(a+b+n)^2} > 0$. As the screening capability increases, the interest-rate/risk curve shifts down and steepens in slope:

$$\frac{\partial E\{r_{ij}|n_i, p_j\}}{\partial n_i} = -\frac{\partial\alpha(n_i)}{\partial n_i}\bar{p} + \frac{\partial\alpha(n_i)}{\partial n_i}p_j. \tag{3}$$

This equation offers an empirical strategy to detect informational improvements in banks' screening abilities, provided that we have a measure of the actual default probability p_j and of banks' screening ability n_i. If mergers indeed lead to informational improvements, then a merger event would proxy for increases in screening ability n_i, so that Eq. (3) would imply relationships between merger activity, average interest rates, and default probability resembling the graphs in Fig. 1. This is the strategy we will follow in our empirical specification, where we will run regressions of the form

$$r_{ij} = \beta_0 + \beta_1 * MERGE_i + p_j\left(\beta_2 + \beta_3 * MERGE_i\right) + \epsilon_{ij} \tag{4}$$

where $MERGE_i$ is a dummy variable set equal to one if bank i has recently merged and $\epsilon_{ij} \equiv E\{r_{ij}\} - r_{ij}$ is an orthogonal error. Within the context of this model, the hypothesis that mergers improve information can be modeled by assuming that a merged bank obtains more signals, i.e. has a higher n_i.[6] Hence, in this case, we expect $\beta_1 < 0$ and $\beta_3 > 0$ in Eq. (4), in line with the graphs in Figure 1: merged banks should put less weight on the common prior and price more in accordance with the firm's true probability of default.[7]

Needless to say, there could be alternatives to the information-based interpretation of the increased steepness of the interest-rate/risk relationship documented in Figure 1.[8] Hence,

[6]The zero profit condition ensures that changes in the bank's assessment of the default probability immediately leads to changes in the interest rate. However, a countervailing effect is that banks may wish to lower interest rates to good firms, in order to supply more of this firm's ccredit needs. Indeed, this second effect is likely to be important in Italy, where firms typically borrow from a large number of lenders.

[7]The result that the steepness of the profile increases with screening ability also has a very natural interpretation in terms of measurement error in a regression framework. Assume that each bank forms its own assessment of the probability of default, which is equal to the actual one plus some random noise: $p_{ij} = p_j + \varepsilon_{ij}$, with ε_{ij} distributed *i.i.d.* with zero mean and bank-specific variance σ_i inversely related to screening abilities. Then, the use of the actual default probability p_j in the regression (4) can be seen as a variable measured with error, where the "true" variable is the bank's assessment. If mergers improve screening abilities, resulting in a smaller σ_i, we should expect $\beta_3 > 0$, as a result of the usual attenuation bias due to the "mismeasured" variable p_j.

[8]Indeed, a recent paper by Hauswald & Marquez (2003) contains a model in which improvements in infor-

it is an empirical question to distinguish our informational interpretation from alternative non-informational explanations, and a substantial portion of this paper focuses on these issues.[9]

3 Data

We use four main sources of data. (1) Interest rate data and data on outstanding loans come from the Italian *Centrale dei Rischi*, or Central Credit Register. (2) The firm-level balance sheet data come from the *Centrale dei Bilanci* database. (3) Banks' balance-sheet and income-statement data come from the Banking Supervision Register at the Bank of Italy. (4) Data on the mergers and acquisitions are drawn from the Census of Banks. By combining these data, we obtain a matched panel dataset of borrowers and lenders extending over an eleven-year period. We begin with a brief descriptions of the data sources. Specific details regarding the construction of the sample and further descriptive analysis are contained in the appendix.

The Central Credit Register (hereafter CR) is a database that contains detailed information on all individual bank loans extended by Italian banks. Banks must report data at the individual borrower level on the amount granted and effectively utilized for all loans exceeding a given threshold,[10] with a breakdown by type of the loan (credit lines, financial and commercial paper, collateralized loans, medium and long-term loans and personal guarantees). In addition, a subgroup of around 90 banks (accounting for more than 80 percent of total bank lending) have agreed to file detailed information on the interest rates they charge to individual borrowers on each type of loan. Summary statistics for these banks are reported in Table 1.

We restrict our attention to short-term credit lines, which have ideal features for our analysis. First, the bank can change the interest rate at any time, while the borrower can close the credit line without notice. This means that (i) a change in the merging banks' ability to process firm-specific information can have almost immediate repercussions on the pric-

mation technology among lenders leads to a decreased interest rate sensitivity to firms' risk characteristics, arising from "winner's-curse" effects which occur in models of lender competition (see Broecker (1990) for additional modeling of winner's curse effects in a banking context).

[9] Moreover, we focus on informational effects as reflected in loan prices (interest rates), not on other loan parameters such as credit availability, or loan size. However, Bonaccorsi di Patti & Gobbi (2003) present evidence, using the same dataset, that mergers have rather small effects on borrowers' credit availability.

[10] The threshold was 41,000 euros (U.S. $42,000) until December 1995 and 75,000 euros thereafter.

ing of the loans; and (ii) differences between the interest rates on loans are not influenced by differences in the maturity of the loan. Second, the loan contracts included in the CR are homogeneous products (for example, they are not collateralized), so that they can be meaningfully compared across banks and firms. Third, short term bank loans are the main source of borrowing of Italian firms. For example, in 1994 they represented 53 percent of the total debts according to the Flow of Funds data. We define the interest rate as the ratio of the payment made in each year by the firm to the bank to the average amount of the loan. The interest payment includes the fixed expenses charged by the bank to the firm (e.g. which encompass the cost of opening the credit line or the cost of mailing the loan statement).

The *Centrale dei Bilanci* (hereafter CB) collects yearly data on the balance sheets and income statements of a sample of about 35,000 Italian non-financial and non-agricultural firms. This information is collected and standardized by a consortium of banks interested in pooling information about their customers. A firm is included in the CB sample if it borrows from at least one of the banks in the consortium. The database is fairly representative of the Italian non-financial sector.[11] Table 2 reports descriptive statistics for the sample.

The unique feature of the CB data set is that, unlike other widely used data sets on individual companies (such as the Compustat database of US companies), it has wide coverage of small and medium companies; moreover, almost all the companies in the CB sample are unlisted. The coverage of these small firms makes the data set particularly well suited for our analysis, because informational asymmetries are potentially strongest for these firms so that, if mergers did indeed result in informational efficiencies, we are most likely to detect them in this sample.

Table 3 (Panel A) details the M&A activity of reporting banks. Given that reporting banks tend to be larger banks, they are more likely to be the acquiring party in a merger. The final sample includes 1,300,000 bank-firm-year observations.

3.1 Measure of firm default risk: SCORE

In addition to collecting the data, the CB computes an indicator of the risk profile of each firm (which we refer to in the remainder of this paper as the SCORE). The SCORE

[11] The firms in the CB sample represent about 49.4% of the total sales reported in the national accounting data for the Italian non-financial, non-agricultural sector.

represents our measure of a firm's default risk, and plays a crucial role in the analysis. Therefore, before turning to the econometric tests and discussing the empirical evidence, we describe in detail the computation, timing of the release and the characteristics of the SCORE.

The SCORE, which takes values from 1 to 9, is computed annually using discriminant analysis based on a series of balance sheet indicators (assets, rate of return, debts etc.) according to the methodology described in Altman (1968) and Altman, Marco & Varetto (1994). The CB classifies firms into four credit-worthiness categories on the basis of the SCORE variable: (i) "safe" (SCORE=1,2), (ii) "solvent" (SCORE=3,4), (iii) "vulnerable" (SCORE=5,6), and (iv) "risky" (SCORE=7,8,9). Table 4 reports firm characteristics for different SCORE classes. As expected, higher SCORE firms are smaller and more leveraged; they also pay a higher interest rate.

Two characteristics of the SCORE are crucial to our analysis. First, the SCORE is computed by the *Centrale dei Bilanci* ex post, using actual balance-sheet data, so that it represents a good proxy of the actual default probability of the firm in each year. In Figure 2, we plot the SCORE variable against indicators of actual default incidence.[12] We see that the SCORE is an accurate predictor of actual default incidence among the firms in our dataset: for instance, firms with a SCORE of 3 in a given year have a probability of defaulting within the next two years (i.e. during years t or $t+1$) of less than 1%, but this probability rises for firms with a SCORE of 8 to 10%. An even more pronounced trend appears when considering the event of default within the next three years (i.e. years t, $t+1$, $t+2$).

Second, the SCORE for firm j in year t (along with all the other data collected by the CB) only becomes available to banks after approximately 15 months: for example, the information on the balance sheets for 1995 was made available to banks only at the end of March 1997. Hence, because the data used in this paper are measured at the end of each year, the $SCORE_t$ only becomes available to banks in year $t+2$ (that is, the $SCORE$ that a bank observed in December 1992 was the $SCORE$ for 1990): thus, the innovation $(SCORE_t - SCORE_{t-2})$ represents information that is not available to banks when they set interest rates in year t, and a potential source of asymmetric information between firms and banks in year t.

It is possible that, on its credit application, a firm may be required to report up-to-date

[12] The definition of default in the dataset includes firms in liquidation or other bankruptcy proceedings, and those which have not paid repayment installments on loans for at least six months.

balance-sheet information, which is more current than the balance-sheet data reflected in the $SCORE$ measure which the bank possesses about the firm. However, it is unlikely that this information is as accurate as that reflected in $SCORE$. First, almost all firms in our sample are unlisted, so have no infra-annual reporting duties. Any information supplied in addition to the official balance sheet would therefore not be subject to the controls and requirements that the law imposes on balance sheets. Moreover, even if it had the most current information for one particular firm, the bank would still be unable to compute $SCORE_t$, because it is also a function of the up-to-date balance-sheet data of all other firms, which the bank does not possess.

The amount of innovation in $SCORE_t$ with respect to $SCORE_{t-2}$ is non-negligible: Table 5 (Panel A) shows that, after including firm fixed effects, the slope coefficient in a regression of $SCORE_t$ on $SCORE_{t-2}$ is only 0.30, and the R-squared is only 64%. Moreover, the additional information contained in $SCORE_t$ greatly helps in predicting actual firm defaults: in Panel B of Table 5, we display results from probit regressions of actual default incidence (as measured by whether a given firm defaulted within years t, $t+1$, or $t+2$) on the different $SCORE$ measures.[13] A comparison of the first two columns indicates that using $SCORE_t$ instead of $SCORE_{t-2}$ improves the fit of the regression almost twofold, as measured by the pseudo-R^2, indicating that the former has more predictive power.

In order to quantify the importance of the information that banks do not have in predicting firm defaults, we also ran probit regressions of the default incidence on both $SCORE_{t-2}$ and the residual (denoted $resid_t$) from the linear projection of $SCORE_t$ on $SCORE_{t-2}$. By construction, $resid_t$ is orthogonal to $SCORE_{t-2}$ and thus represents an innovation with respect to the information available to the bank at time t. The third column shows that even after controlling for $SCORE_{t-2}$, the marginal effect of the new information $resid_t$ on the probability of actual default is statistically significant and equal to 0.016 (this is not a small magnitude considering that the mean default incidence is only 0.04); furthermore, the pseudo-R^2 doubles with respect to the regression with only $SCORE_{t-2}$.

Hence, the change in SCORE between year $t-2$ and t appears to represent a potentially important and useful source of uncertainty from the bank's point of view. This makes SCORE an appropriate proxy for the default probability p_j in the model given in Section 2 above. However, in our analysis below, we also check that our results are robust to using alternative measures of a firm's default risk.

[13] The default indicator used in these regressions corresponds to the *default_t2* graphed in Figure 2.

4 Empirical Results

Most of our empirical work is based on the following basic regression for bank i, firm j, and year t:

$$\begin{aligned} r_{ijt} &= \beta_0 + \beta_1 * MERGE_{it} + \beta_2 * SCORE_{jt} + \beta_3 * (SCORE_{jt} * MERGE_{it}) \\ &\quad + \beta_4 * FIRM_{j,t-1} + \beta_5 * BANK_{i,t} + \beta_6 * CONC_t + u_j + d_t + e_{ijt}. \end{aligned} \tag{5}$$

In the above equation, r_{ijt} is the interest rate on credit lines charged by bank i to firm j in year t, measured by the difference between the bank's loan rate and the 3-month interbank interest rate. $MERGE_{it}$ is a dummy variable that equals 1 if bank i was involved in a merger in the five years prior to year t.[14] To abstract away from any pricing effects due to the compositional changes of portfolio reallocations after a merger, we restrict $MERGE_{it}$ to be equal to one only for *continuing borrowers*, defined as firms that were borrowing from bank i in the year prior to the merger. (Thus, new borrowers that initiate their lending relationship with a bank shortly after a merger are not included among the treatment observations.) Moreover, in all the results presented in this paper, both dropped pre-merger borrowers and new post-merger borrowers are included in the control group.[15]

$SCORE_{jt}$ is the default risk measure for firm j in year t, as described in the previous section. $FIRM_{j,t-1}$ and $BANK_{i,t}$ are, respectively, a set of time-varying firm- and bank-specific control variables. To control for changes in market concentration that are unrelated to consolidation, we include the Herfindahl-Hirschman Index (HHI) of the local market (defined at the provincial level, following the antitrust authority definition) for bank loans ($CONC_t$); u_j is a firm-specific fixed effect and d_t is a time dummy. Finally, we include a zero-mean random error e_{ijt}.

Within the framework of Eq. (5), β_1 captures the price effect of the merger. A positive value would imply that the market power effect prevails over the efficiency effect, harming borrowers, while a negative value would indicate that the efficiency gains outweigh the increase in market power, leading to a reduction in the loan rate. The value of β_2 represents the slope of the interest rate profile, i.e. the risk-return relationship prevailing in the market for bank loans. We expect a positive value for this parameter. A positive value for β_3 would

[14] Focarelli & Panetta (2003) point out that the effects of mergers are long-lived, and that it can take up to five years for some effects to occur. We have also experimented both by shortening this lag period to 3 years and by extending it to 11 years (our sample length), with no noticeable effects on the results.

[15] Results are robust with respect to different selection rules.

be consistent with the hypothesis that a merger leads to informational efficiencies, in the form of a steeper interest rate profile.[16]

By employing firm-level fixed effects, we use a firm before the merger as a control for itself after the merger. Moreover, by including a calendar-year fixed effect we control for cyclical patterns common across all firms and banks. The firm covariates capture the relation between the loan rates and firms' characteristics that are not captured by the *SCORE* (to avoid simultaneity, all variables are lagged one year). We include size (the log of total assets), leverage (the ratio of debt to the sum of debt plus capital) and profitability (the return on sales). We also control for bank-specific variables that might influence the loan rates. We include size (proxied with total assets) and the cost-income ratio (a standard proxy for efficiency).

The estimates of Eq. (5), reported in Panel A of Table 6, confirm that, after a merger, banks' sensitivity to the SCORE rises by 8.7 basis points (significant at the 1 percent level).[17] The negative estimate of β_1 indicates that M&As reduce the intercept of the *r-SCORE* curve by 29.7 basis points, or 2.5 percent of the median loan rate.[18] The change in shape of the *r-SCORE* relationship implies that only the good firms (i.e. those with SCORE below 4) benefit from the merger: the lower-quality firms (with SCORE exceeding 4), in contrast, experience higher loan interest rates. Specifically, the results imply that the interest rate differential between otherwise identical firms with SCORE's of 3 and 7 increases from 14.4 basis points pre-merger to 19.5 basis points post-merger, over a 30% increase. This squares with the graphical evidence from Figure 1 and is consistent with the hypothesis that M&As lead to higher sensitivity of the loan rates to the risk profile of the borrower.

The other coefficients are all significant and have the expected signs. The loan rates are higher for riskier companies (higher SCORE) and for companies with higher leverage, and lower for larger companies; profitability (measured by return on sales) has no effect. The

[16] Because the interpretation of our results depends critically on the idea that high-quality information implies a higher sensitivity of the loan rate to the risk characteristics of the firm (i.e., a steeper interest rate curve), we have run auxiliary regressions to confirm that the data support the thesis that a bank's responsiveness to the SCORE is correlated to its informational ability. Details of and results from these regressions, which strongly support this view, are contained in the appendix.

[17] In our baseline results, we cluster by each firm-year combination in computing the standard errors, to accommodate the feature that SCORE and the other firm-level covariates vary only across firms and years, while our dependent variable varies across firms, banks, and years.

[18] This result is consistent with the findings of previous research on the Italian banking industry: Sapienza (2002) finds that the typical merger leads to a rate reduction of about 40 basis points (considering a market share of the target bank of 2.9 percent; see Table III in her paper).

loan rate is also higher for small banks (measured by total assets) and inefficient ones (high ratio of costs to gross income) and, as expected, for more concentrated markets.

In Panel B of Table 6, we re-estimate our model including both firm- and bank- fixed effects, in order to account for bank-level unobserved heterogeneity.[19] The results obtained using this alternative specification are similar to those previously reported: the estimate of β_3 is equal to 8.8 basis points and remains strongly significant.[20] Throughout the paper, in order to retain the comparability of our results with those of the previous studies, we will continue to use the results obtained using firm-specific fixed effects as our preferred specification.

While bank-level fixed effects account for time-invariant unobserved heterogeneity, they do not control for time-varying unobserved heterogeneity at the bank-year level, which could drive the timing of mergers. For example, some banks may experience unobservable improvements in screening ability, which cause them to acquire less informationally efficient banks, furnishing a reverse-causality explanation for our empirical finding that $\beta_3 > 0$. We discuss this possibility below, explicitly testing the hypothesis that mergers are driven by positive shocks to screening ability.

4.1 Robustness checks

We undertake a number of analyses to assess the robustness of results to the inclusion of other control variables and the use of alternative estimation methods. Our results prove to be remarkably robust.

Unobserved heterogeneity

In the specifications presented so far, the inclusion of time dummies and firm and bank characteristics controls for heterogeneity which may be affecting the level of the interest rate. But given our focus on how mergers affect the interest rate-SCORE relationship, we want to confirm that our results are robust to potential heterogeneity in the sensitivity of the

[19] For banks which merge during the sample period, the post-merger fixed effect is set equal to the fixed-effect of the acquiring (bidder) bank before the merger.

[20] We estimate our model also including only bank-specific fixed effects (unreported), and the results remain unchanged. While fixed effects account for time-invariant unobserved heterogeneity, they do not control for time-varying unobserved heterogeneity which could drive the timing of mergers. For example, some banks may experience unobservable improvements in screening ability, which cause them to acquire less informationally efficient banks, furnishing a reverse-causality explanation for our empirical finding that $\beta_3 > 0$. In Section 7 below, we consider this possibility by explicitly testing the hypothesis that mergers are driven by positive shocks to screening ability.

interest rate to SCORE, both across time, firms and banks. Therefore, we run regressions in which we interact additional variables with SCORE, as reported in Table 7.

First, we interact SCORE with a full set of year dummies. Because there was an increasing trend in merger activity during the sample period (see Table 3), we wish to ensure that the SCORE*MERGE interaction is not simply picking up across-time improvements in screening activity (due, for example, to improvements in computing technology over the sample period). The results, reported in Panel A of Table 7, indicate that the post-merger increasing slope result persists and is statistically significant, albeit with a smaller magnitude (0.024).[21] The point estimates of this specification imply that the interest rate differential between otherwise identical firms with a SCORE of 3 and 7 increases from 12.8 basis points pre-merger to 26.6 basis points post-merger, over a 100% increase.

Ideally, one would also wish to interact SCORE with a full set of firm fixed effects, but given the large number of firms in the dataset (exceeding 30,000), this was not feasible. Instead, in Panel B of Table 7, we report results from a specification in which SCORE is interacted not only with year dummies, but also with firm characteristics (leverage, return on sales, and size). While these additional interactions (unreported) are significant, indicating the importance of firm-level heterogeneity in the sensitivity of interest rates to SCORE, the coefficient on the SCORE*MERGE interaction is basically the same as that obtained with SCORE*year interactions only.

Finally, in Panel C of Table 7, we present results from a specification which included interactions between SCORE and a full set of bank dummies (for a total of almost 100 additional regressors), to control for any bank-specific sensitivity to SCORE which are unrelated to mergers. Uninteracted bank dummies were also included, to allow for both the level and the steepness of the interest rate curve to differ across banks. With this arguably very complete set of controls, the magnitude of the β_3 parameter increases slightly to 0.30 and is highly statistically significant. Hence, these results suggest that the increasing slope finding remains statistically and economically significant even after carefully controlling for heterogeneity in the interest-rate/SCORE relationship.

Clustering

As pointed out by Bertrand, Duflo & Mullainathan (2004), our estimates of the standard errors could be downward biased due to the serial correlation in both the dependent variable

[21] The unreported year*SCORE interactions show an increasing trend over time in the sensitivity of the interest rate to SCORE, in line with the idea that the banks' screening abilities have improved over time.

and in the SCORE*MERGE interaction. We address this issues in several ways. First, to account for the correlation in the MERGE variable, we allow for different clustering criteria. in the most extreme case, we cluster by banks, giving a unique identifier to the bidder, the target and the resulting bank after the merger, obtaining 74 distinct clusters. As expected, standard errors increase significantly: in particular, the one on the SCORE*MERGE interaction becomes .024 from .004 in the basic specification. Still, we can reject the null hypothesis of no difference in sensitivity at 0.1%.[22]

Sample selection

Another potential concern is that the results could be driven by a form of sample selection: specifically, if informationally superior banks are more likely to merge, then the β_3 parameter could simply be capturing systematic differences between the information-screening ability of merging banks relative to banks that do not merge, and thus should not be read as causal effects of the merger.

Ideally, the best way to control for selection would be an instrumental variable procedure. Unfortunately, finding valid instruments is far from obvious, as it is difficult to find a variable correlated with the merging decision but unrelated to screening ability. Therefore, we pursue an alternative approach where we run our regressions on subsamples that are less likely to be affected by any selection issue and, check if the results change in any way.

As a first check, we reran the regressions after excluding all the observations for banks which never merged. This selection rule ensures that our results are not driven by the possibility that never merging banks simply have lower screening abilities, and that mergers are coincident with an increase in ability. Results, reported in Appendix Table A2, Panel A, show that the improvement in sensitivity increases slightly when compared to the basic specification, suggesting that our results are not driven by selection.

The first check was based on the assumption that banks' screening ability are fixed over time. Another possibility is that banks' screening abilities change over time, and that banks merge after experiencing positive shocks to their screening ability.[23] Bank mergers are

[22] We have also clustered using separate bank identifiers for bidder and targets, bank-year interaction, and firm. Given that the resulting clusters are smaller, standard errors are lower than those of the exercise discussed in the main text. We also follow Bertrand et al. (2004) (pg. 267) to accommodate potential serial correlation in the dependent variable by re-running the regressions using time averages. The resulting point estimates of β_3 are very similar to the ones reported in Table 6, and we still reject the null of no difference in sensitivity at 0.1%.

[23] We thank one referee for suggesting this possibility.

complex events, both technically and also from a regulatory point of view. It is therefore natural to expect that a certain amount of time elapses between the decision to merge, and the actual merger. Because of this merger lag, then, a bank which decides to merge because of a positive shock to its screening ability should have experienced the positive shock a substantial period of time before the merger actually takes place; therefore, if this selection story is true, the increasing slope result should be smaller (or even disappear) when comparing a firm immediately after and immediately before a merger. To check this, in Panels B and C of Table A2, we present results from the regression where we further restrict the control sample to include observations for merging banks only in either the two years before the merger (Panel B), or one year before the merger (Panel C). By comparing these results to the baseline results in Table 6, we see that the estimates of β_3 remains very stable when performing these regressions.[24] These checks suggest that our results are not driven by a selection story whereby banks that merge are (or have become) better than average in their information-screening abilities: our results are consistent with the interpretation that the increased steepness is driven by the merger itself.[25]

Another type of selection problem arises if, after mergers, banks just drop riskier firms. In Figure 3 we present a histogram showing the percentage of loan observations associated with firms of a given SCORE, broken down according to whether the lending bank did or did not merge in the sample period (denoted *nevermerge*). For banks that merged, we further break down the loan observations into whether they occurred before (denoted *premerge*) or after (denoted *postmerge*) the merger. As the graph shows, the loan portfolio of merging banks is virtually unchanged before and after the merger; furthermore, the loan portfolios of merging banks are identical to those of non-merging banks. The data thus appear inconsistent with the notion that merging banks drop their riskiest borrowers.[26]

[24] We have performed many robustness checks, such as including banks' fixed effects, changing the inclusion period, keeping in the control groups only bidder or target banks. In all cases, the results where similar to those reported in the table.

[25] In another set of unreported results, we addressed the potential endogeneity of the $SCORE_t$ variable to the lending decision at time t (arising perhaps because debt at time t is a factor in computing the SCORE at time t). We reran the baseline regressions, fixing a firm's SCORE at its pre-merger average. This definition of SCORE alleviates potential correlation between SCORE and time-varying firm unobservables which might influence the firm's interest rate. However, this removes all time variation in SCORE, so that the level effect of SCORE (ie., the coefficient β_2 in Eq. (2)) is no longer identifiable in the presence of firm dummies. However, we can still estimate the important interaction of MERGE and SCORE, and we find that it remains positive and significant.

[26] Moreover, we estimate non-linear specifications of our model (to check whether the increasing slope finding could simply reflect a movement along a non-linear interest rate profile). The (unreported) results

We check that our results are not influenced by the inclusion in our sample of both private and state-owned banks (Sapienza (forthcoming) shows that state-owned banks differ in their lending policies from private banks). To address this issue, we have also run the regressions excluding state-owned banks. Results were virtually unchanged.[27]

Alternative measures of credit worthiness

We also assessed the robustness of our results to alternative measures of a firm's default risk. First, we used the actual default indicator *default_t2* (graphed in Figure 2) in the place of SCORE in the regressions. Second, we created our own measure of a firm's default probability by regressing default_t2 on firm characteristics. The results from both of these alternative specifications (not reported) suggest that our findings are robust when alternative measures of firm riskiness are used.

Bundling of bank services

A potential concern with our analysis is that loans are just one of the products banks offer to their customers. This means that the interest rates used in our regressions could be affected by strategies for marketing other products to firms - for example, a bank may offer a low loan rate but charge a higher fee on bond issues or IPOs. However, this problem is likely to be negligible for our analysis. In fact, credit lines are by far the most important financial product purchased by Italian firms from their bank, while only a tiny fraction of companies purchase other important financial products. For example, only 80 Italian companies went public during our sample period (1988-98) and only 28 issued bonds on public markets. These corporate events - which could influence the pricing of loans and generate confounding effects - are uncommon in the Italian financial system generally and virtually non-existent for small, closely-held companies, which represent by far the largest component of our sample.

5 Is it really information? Evidence from sub-samples

Up to now, we have ascribed the increase in the slope of the interest rate curve to the informational gains from mergers. In this section, we reinforce this interpretation by examining the effect of mergers on sub-samples of firms for which, *a priori*, the informational gains from consolidation should differ in a predictable way. If we found that our estimates of

remained unchanged.

[27] Sixteen of the banks in our full sample were public banks, which were excluded in this robustness check.

the change in the slope of the interest rate curve across these sub-samples confirmed our priors, we would take this as evidence in favor of the hypothesis that this change is indeed determined by informational gains and not by other factors.

5.1 Short vs. lasting bank-firm relationships

First, we consider the duration of bank-firm relationships, i.e. the number of years for which firm j has been a borrower of bank i. Because banks develop information over time, through repeated interactions with their customers, lasting relationships are likely to be associated with less asymmetric information (Rajan (1992), Petersen & Rajan (1994)). Therefore, for firms with a short relationship with the bank, there should be more scope for merger-related informational gains than for firms with long lasting relationships. Accordingly, we expect the post-merger increase in the slope of the interest rate curve to be larger for short than for lasting relationships.

We split our sample into two subgroups: "long lasting relationships", i.e. the bank-firm pairs that have a relationship of 5 years or more; and "short relationships", i.e. those with duration of less than 5 (we have experimented with alternative splitting points, obtaining similar results). We re-estimate Eq. (5) separately for these two groups. The results, reported in Table 8, are consistent with our hypothesis: the increase in the slope of the interest rate curve (the coefficient of the interaction term MERGE*SCORE) is equal to 6.7 basis points for the short duration sub-sample, but only 2 basis points for the firms with lasting relationships (the difference between the two coefficients is highly significant). Economically this result implies that for firms with short relationships, the difference between the lending rate of the worst and the best firms (SCORE=1 or 9, respectively) increases by 48 basis points. In contrast, for the firms with lasting relationships the spread between low- and high-quality firms increases by 16 basis points. The estimates of the other coefficients are generally similar to those reported in Table 6.

5.2 Main vs. fringe lenders

For the same reasoning that we used for the length of the relation, one should expect that banks should be better informed about firms for which they supply a large share of credit. Therefore, according to our hypothesis the merger-related informational gains (and the increase in the slope in the interest rate profile) should be larger for banks that represent a

small proportion of a firm's total borrowing.

To test this hypothesis, we compute w_{ijt}, the proportion of total lending to firm j provided by bank i, and split our bank-firm observations into two subsamples. The first "fringe lender" sub-sample includes all observations for which w_{ijt} is below the median (15 percent), and the second "main lender" subsample contains observations with w_{ijt} above the median. The results, reported in Table 9, are consistent with our hypothesis: the increase in the sensitivity of the loan rate to the SCORE is higher for loan relationships in which the bank is a "fringe bank", where we expect informational gains to be stronger (the difference is statistically significant). Again, we find this result to be robust to alternative splitting points.

As a further check, we have also used a measure of firm-bank distance, splitting according to whether firm and bank headquarters are in the same region, on the assumption that geographical proximity improves the bank's information about the firm, so that less should be gained from the merger. The results, not reported for brevity sake, again indicate that the increase in the sensitivity is greater when the firm and the bank are located in different regions, suggesting larger informational gains.

All in all, we find this evidence remarkably supportive of the hypothesis that mergers increase the banks' screening ability.

6 The "increasing slope": Explanations

In this section we analyze potential explanations of the increase in the slope of the interest rate curve.

6.1 Do mergers increase emphasis on hard information?

We begin by considering the alternative explanation that merging banks might rely increasingly on hard information (objective and codified measures of firm performance, such as that contained in the default risk measure SCORE) in pricing loans, so that lending relationships based on soft information (i.e., uncodifiable information collected, for example, through direct interaction with the firms' managers) may be disproportionately de-emphasized. This intuition is formalized by Stein (2002), who shows that larger, more hierarchical banks — such as those which may result from a merger — could provide less incentives for loan

officers to collect soft information about borrowers. Under this interpretation, the higher slope we find might reflect a shift from soft to hard information, as proxied by SCORE, rather than an overall increase in screening ability.[28]

We explore this issue by considering mergers involving small target banks, for which the impact of the organizational changes, and the ensuing modifications in banks' lending policies, resulting from the merger are likely to be larger.[29] Accordingly, we check whether the magnitude of the increasing slope effect for the borrowers of small target banks differs from the other the borrowers of merging banks. If our results only reflect an increase in banks' reliance on hard information after the merger at the expense of soft information, then we should expect the increasing slope effect to be concentrated in the sub-sample of previous borrowers of small target banks, which are likely to experience a shift from soft to hard information.

In Table 10 we report the results obtained by including an additional variable obtained by adding interactions of MERGE, SCORE, and MERGE*SCORE with a dummy variable SMALLTAR, which equals 1 (both before and after the merger) if the firm was borrowing from a small target bank. A small target bank is defined as one for which the average number of pre-merger customers was smaller than the median number of customers in the CR sample for all target banks, equal to 650.

The results obtained in Panel A of Table 10 offers support for Stein's (2002) hypothesis: particularly, the significantly positive coefficient on the interaction between MERGE, SMALLTAR and SCORE (0.053) indicates that the incremental change in the slope of the interest rate curve for firms borrowing from small target banks is significantly larger than the corresponding change for all other firms. Furthermore, the coefficient on SCORE*SMALLTAR (-0.072) is significantly negative, suggesting that smaller target banks were less sensitive to SCORE before they merged. These findings are consistent with the idea that smaller target banks rely more on soft information (ie., information other than SCORE), so that the merger led to a shift toward hard information in interest rate determination. Indeed,

[28] Our distinction between soft vs. hard information follows the existing literature. With this definition, information on credit risk contained in SCORE, whether publicly available or not, is hard information, whereas soft information would include things like loan officers' private and subjective assessments of managers' abilities, qualities of firms' projects, etc.

[29] Using US data, Berger, Miller, Petersen, Rajan & Stein (2002) and Cole, Goldberg & White (2000) find that small banks (which are more likely to be the target banks in a merger) tend to use soft information more extensively in dealing with their customers. Sapienza (2002) provides evidence consistent with this hypothesis for the Italian credit market.

the results indicate that the interest rate spread between firms with a SCORE of 4 and 7 rose by 41.7 basis points if the firms borrowed from a small target bank before the merger, and only 25.8 basis points otherwise. Moreover, in Panel B of Table 10, we show that the results are robust even after a full set of year dummies interacted with SCORE are included. These results echo findings in Berger et al. (2002), which were obtained using US data.

However, the increasing slope finding is not wholly attributable to a shift towards hard information: in the specifications reported in Table 10, the coefficient on MERGE*SCORE (0.086) remains positive and significant, implying that the increasing slope effect remains significant for firms borrowing from large target banks and bidder banks, for which we do not expect an increase in the use of hard information in the loan-granting process.[30]

6.2 Is the "increasing slope" due to market power?

If the merging banks have significant local market overlap, the merger could lead to an increase in market power. Therefore, we consider a non-information explanation for the increasing slope effect: specifically, a merged bank, with enhanced monopoly power, may be able to exercise greater price discrimination among its customers. If firms with high SCORE have a less elastic demand curve for loans, due to difficulties in obtaining funding from alternative sources, then a monopolist may exploit this situation by charging higher rates.

While the market power hypothesis is consistent with the steeper interest rate profile and increased post-merger interest rate dispersion, it has difficulty explaining the decrease in rates for the less risky firms.[31] On the other hand, if the merger had both market power and cost-reduction effects, then our observed results could be consistent with the explanation

[30] Some of the regression results presented earlier also offers additional evidence that the increasing slope effect is not solely due to a shift from soft to hard information. The increasing slope effect persists when actual default incidence – which should depend on the use of soft or hard information – is used in the regression as a measure of credit-worthiness. Additionally, as shown in Table 8, the increasing slope effect is more prominent for short lending relationships, which are likely to be characterized by a lower content of soft information. Finally, the results in Section 7.1 show that the slope of the interest rate-SLOPE curve increases also for customers of bidder banks only. This corroborates the hypothesis that the increasing slope finding is not solely attributable to shifts of merging banks from soft to hard information.

[31] For instance, the literature on competition and third-degree price discrimination shows that a monopoly tends to raise prices to *all* consumers, relative to the duopoly case. See Stole (forthcoming), section 2 and Holmes (1989). See also Borenstein (1989) and Busse & Rysman (forthcoming) for empirical work on the effects of competition on price discrimination.

that the market power effect dominated for the risky firms, resulting in higher interest rates, but the cost-reduction effects dominated for the less risky firms, leading to the lower interest rates that we observe. In order to test this hypothesis, we decompose the merger observations in our sample into *in-market* and *out-of-market* observations. Specifically, for every observation where $MERGE_{ijt} = 1$, we classify that observation as "in-market" if both parties to the merger in which bank i participated were active lenders in firm j's province in the year before the merger; if only one of the merging banks was active in firm j's province before the merger, we classify it as "out-of-market".[32]

Since an increase in local market concentration only occurs for the in-market sample, if the market power interpretation of our results is correct, then the slope of the interest rate profile should increase only for the in-market observations; by contrast, for the out-of-market sub-sample the sensitivity of the loan rate to the SCORE should not be affected. We re-estimate the basic regression for the two sub-samples separately. The results from this regression, reported in Table 11, are similar for the in-market and out-of-market sub-samples. Indeed, not only does the interest rate curve become steeper in both sub-samples, but the increase in the slope is also larger for out-of-market mergers than for in-market mergers (the SCORE*MERGE interaction coefficients are equal to 11.9 and 6.6 basis points, respectively) – exactly the opposite to what one would expect under the market power interpretation.

7 Characterizing the channels of the informational improvements

Next, we exploit several unique features of our dataset to investigate potential channels through which the informational benefits of a merger may work. First, due to the matched nature of our dataset, we can distinguish between a given merger's effects on the borrowers of the acquiring ("bidder") bank, the borrowers of the acquired ("target") bank, and also on the set of firms which borrowed from *both* bidder and target banks. Second, we observe the SCORE variable two years before the banks, which we exploit to distinguish between the types of informational improvements effected by a merger: namely, we distinguish between the merger's effects on a bank's use of the information that is at its disposal at the time of the merger, and on its production of new information. We hope to pinpoint the mechanisms

[32] Italy is divided into 103 provinces, corresponding roughly in dimension to U.S. counties.

whereby informational improvements affect banks' pricing behavior after a merger.

7.1 Differential effects on customers of bidder vs. target banks

In the first set of regressions, we split the $MERGE_{ijt}$ dummy into three mutually exclusive and exhaustive dummies $BIDDER_{ijt}$, $TARGET_{ijt}$, and $BIDTAR_{ijt}$. The first dummy is equal to 1 if the observation refers to a firm that was a pre-merger borrower only of the bidder bank. Analogously, the dummy $TARGET_{ijt}$ refers to firms that were borrowing only from the target bank. Finally, $BIDTAR_{ijt}$ is set equal to one if, before the deal, the firm was borrowing from both the bidder and target banks in a given merger. Table 3 (panel B) reports the number of observations for each of these categories. Since the large banks in our dataset are more likely to be the bidder than the target, most commonly the observations have $BIDDER_{ijt} = 1$ (43%), while 2.8% of the observations have $TARGET_{ijt} = 1$ and only 0.7% have $BIDTAR_{ijt} = 1$. We estimate the following regression:

$$\begin{aligned} r_{ijt} \quad = \quad & a_0 + a_1 * BIDDER_{ijt} + a_2 * TARGET_{ijt} + a_3 * BIDTAR_{ijt} + a_4 * SCORE_{jt} + \\ & a_5 * (SCORE_{jt} * BIDDER_{ijt}) + a_6 * (SCORE_{jt} * TARGET_{ijt}) + \\ & a_7 * (SCORE_{jt} * BIDTAR_{ijt}) + a_8 * FIRM_{j,t-1} + a_9 * BANK_{i,t} + \\ & a_{10} * CONC_t + u_j + d_t + e_{ijt}. \end{aligned} \tag{6}$$

By comparing the sizes and magnitudes of a_5, a_6,and a_7, we can distinguish between several hypotheses. First, the merger may improve banks' ability to process information, simply because information processing is likely to be characterized by increasing returns to scale: for example, the implementation of internal rating systems or the construction of detailed customer databases may require large fixed outlays that need to be allocated over a large volume of output; moreover, the accuracy of the predictions of the rating procedures will increase with the number of customers in the database. As a consequence, the larger banks that result from consolidation may invest more heavily in such activities and install costly technologies that were not feasible for either partner before the deal. The hypothesis that informational gains arise from a general improvement in the merged banks' ability to process information (or an increase in their incentives) implies that all firms borrowing from a bank involved in an M&A should be affected: $a_5 > 0, a_6 > 0, a_7 > 0$; moreover, if this is the only source of informational gain, we should find that the increase in the steepness does not depend on the identity of the lender(s) before the merger: $a_5 = a_6 = a_7$.

On the other hand, a finding that $a_6 > a_5$ is consistent with the interpretation that the informational gains arise when a more efficient bidder bank transfers its superior information processing capabilities or managerial skills to a less efficient target bank. In this case, the reassessment of the loan portfolio of the acquired bank would bring interest rates more closely into line with the actual default risk of firms only for the loans of the target bank, which were mis-priced prior to the merger.

Finally, the informational gains may result from pooling information that, before the deal, was only available separately to each of the merging parties. Even when both merger parties have a business relationship with the firm, they might have access to different sources of information. For example, by assisting the firm in its international activity, one of the banks might have good information on its performance abroad, while the other might manage the company's checking account and thus obtain privileged information on its sales in the domestic market. This means that the consolidated bank, pooling these different sources of information, could have better knowledge of the company than either individually.[33] These information-pooling effects would only apply to $BIDTAR$ observations, the firms that borrowed from both bidder and target banks before the merger, and should therefore generate a larger increase in the steepness for these subset of observations: $a_7 > a_{5,} a_7 > a_6$.

The results from this regression are presented in Table 12. We find that for companies borrowing from only one of the merged banks - the bidder *or* the target - the interest rate curve becomes steeper. For the loans that refer to the bidder banks, the estimate of the coefficient of the interaction term (a_5 in Eq. 3) is equal to about 9 basis points using both firm-specific fixed effects (see Panel A of the Table) and bank- and firm-specific effects (see Panel B). In economic terms, this implies that the spread between the worst and best firms (with SCORE equal to 9 and 1) increases by approximately 70 basis points. The estimate of a_6 (i.e. the increase in the slope of the interest rate curve for target banks) ranges from 7.6 to 8.6 basis points (using firm-specific and firm and bank-specific dummies, respectively). The fact that the gains are similar for the bidder and target banks (an F-test indicates that the difference between a_5 and a_6 is not statistically significant) suggests that the merger does not result in a transfer of managerial skills from one party to the other, but instead improves the operations of both banks in equal magnitude.

This result also addresses the issue, which we raised earlier, of the potentially endogenous timing of mergers: that the MERGE variable could be correlated with bank- and year-

[33] See Broecker (1990) and Vives (1999) (chap. 10)) for theoretical discussions of information sharing in oligopoly, and Genesove & Mullin (1999) for empirical evidence from the sugar industry.

specific unobservables related to a bank's screening ability, which also affect interest rates. However, the finding that mergers improve the screening abilities of both merging banks roughly equally implies that differences in screening abilities between the merging partners should not be driving mergers and, hence, that the timing of mergers is not related to unobserved changes in banks' screening abilities. Indeed, this corroborates previous research on bank M&As in Italy: Focarelli, Panetta & Salleo (2002) show that the decision to merge is not related to credit management, but rather to strategies aimed at increasing the bank's revenue from services (e.g., sales of mutual funds).

The estimate of a_7 (the coefficient of the $SCORE * BIDTAR$ term) is slightly smaller than a_5 and a_6: 3.9 basis points with firm fixed-effects and 5.5 basis points with both firm and bank fixed effects. This tells against the notion that informational effects accrue from pooling information on single customers.[34]

This result also allows us to assess one potential informational disadvantage of multiple banking, which is that it might curtail the incentives of each bank to gather information on firms, due to free-riding.[35] If this were the case, we would expect that the effects of mergers on information are stronger for firms borrowing from both banks, because centralizing two previously separated relations should attenuate the free riding problem. Hence, these results also indicate that the free riding problem connected with multiple banking does not seriously compromise information gathering.[36]

[34] Apart from the small number of observations, which might result in imprecise estimates, a possible explanation for the slightly lower coefficient on $SCORE*BIDTAR$ is firm selection. Indeed, the probability of having a loan from both a bidder and target bank is higher for large companies, which have more bank relationships than small companies. This conjecture is supported by the data: the $BIDTAR$ firms are twice as large in terms of total assets as the others, and have a larger number of bank relations. These factors imply that, due to the sample design, $BIDTAR$ firms may be informationally more transparent that $BIDDER$ or $TARGET$ firms, so that the informational gains from the merger are likely to be small.

[35] For example, the "arm's length investors" in Rajan (1992) are assumed to have no incentive to monitor the firm, due to free-riding problems.

[36] In these regressions, the implicit control group also includes all observations at banks that do not merge throughout the sample period. To control for the possibility that they are systematically different from the banks that do merge, we re-ran these regressions omitting never-merging banks from the sample, with no noticeable changes in the results. Furthermore, we also ran the regressions on the BIDDER, TARGET, and BIDTAR subsamples separately, using as a control group in each case only the same firms before the merger. The results did not yield appreciable differences: in particular, the rankings of the magnitudes of a_5, a_6 and a_7 remained the same as in the results reported in Table 12.

7.2 Distinguishing between existing and new information

Next, we exploit another dimension of our data — specifically, the peculiar timing features of the SCORE variable — to distinguish between two types of improvements in information processing. We observe the risk indicator SCORE two years before the banks in our dataset do. As such, we decompose the SCORE variable in year t as the sum of two parts: $E_{t-2}[SCORE_{jt}]$, which denotes the fitted value from a linear regression of $SCORE_{jt}$ on $SCORE_{jt-2}$, and $resid_{jt}$, the residual from this equation. Hence, the predicted value $E_{t-2}[SCORE_{jt}]$ proxies for the existing information about firm j that banks possess at the same time that they decide on the interest rate, while $resid_{jt}$ proxies for the "new" information about firm j that appears between year $t-2$ and t.[37] Given that the residual is, by construction, orthogonal to $SCORE_{jt-2}$ and, thus represents an innovation with respect to the balance sheet information available to the bank at time t, the sensitivity of the interest rate to it measures the ability of a bank to gather further information on the default risk beyond that contained in $SCORE_{jt-2}$. Therefore, we amend the basic regression (Eq. 5) by using $E_{t-2}[SCORE_{jt}]$ instead of $SCORE_{jt}$, and by including the year t residual $resid_{jt}$. We also interact both variables with the merger dummies.[38]

The regression results are reported in Table 13. In the first column, the coefficients on both $MERGE * E_{t-2}[SCORE_t]$ and $MERGE * resid_t$ are positive and significant (with point estimates of 0.113 and 0.011, respectively), indicating that a merger leads not only to increased acquisition of new information but also to better use of existing information.

In the second set of results reported in Table 13 we break down the merger effects into those on the $BIDDER$ firms, on the $TARGET$ firms, and on the $BIDTAR$ firms. The coefficients of the interaction with $E_{t-2}[SCORE_t]$ and $resid_t$ are positive and significant for both the $BIDDER$ and $TARGET$ firms, suggesting that after the merger these firms are affected by both types of informational changes. Moreover, in the $E_{t-2}[SCORE_t]$ interactions, the BIDDER effect exceeds the TARGET effect (0.115 vs 0.047), while the

[37] That is, we first run the regression $SCORE_{jt} = \beta_0 + \beta_1 * SCORE_{jt-2} + \delta_j + \epsilon_{jt}$, including a full set of firm dummies δ_j. Results are reported in Panel A of Table 5. Then we set $E_{t-2}[SCORE_{jt}] = \hat{\beta}_0 + \hat{\beta}_1 SCORE_{jt-2} + \hat{\delta}_j$ and $resid_{jt} = SCORE_{jt} - E_{t-2}[SCORE_{jt}]$, where the hats (^) denote estimated values.

[38] Note that the older information $E_{t-2}[SCORE_{jt}]$ still contains valuable information about a firm's creditworthiness, which is not superseded by that contained in the innovation $resid_{jt}$. As such, both of these components should be used by the bank in setting the firm's interest rate. An analogous example from the pricing of auto insurance is that both a driver's driving record up to last year, as well as any accidents she has caused this year, are valuable for pricing her car insurance policy.

reverse holds for the $resid_t$ interactions (0.011 vs. 0.034). This suggests that the acquiring banks improve primarily in the processing of existing information, while vis-a-vis borrowers from the acquired banks the new information acquisition effect dominates. In contrast, for the $BIDTAR$ firms, neither interaction is significantly different from zero.

8 Concluding remarks

In this paper, we have presented evidence in favor of the hypothesis that an important effect of bank mergers is to improve banks' abilities to screen borrowers. We find that merged banks exhibit a closer correspondence between the price of loans and the default risk of each firm than unmerged banks, resulting in a steeper interest rate profile. Our results indicate that the pricing effects of mergers differ across firms: specifically, high-quality firms benefit from the merger, while riskier firms experience increased interest rates. We attribute these effects to improvements in information processing rather than explicit information pooling between the merging parties.

Our results also raise additional questions, which we plan to address in future work. First, it will be important to investigate further the causes of the informational improvements. Could a more general sort of information pooling be at work, whereby the merging banks combine their pre-merger expertise in lending to particular industrial sectors or geographical locations? The second question regards the effect of the changes in loan rates on banks' lending to different categories of firms. A number of papers have found that merged banks reduce the small-business share of their portfolio (see, for example, Berger, Saunders, Scalise & Udell (1998)). It would be interesting to explore whether this effect is solely the consequence of the rate changes induced by the merger, or whether it also reflects modifications in the production technology or management objectives of merged banks. Finally, this paper has only focused on informational effects of mergers, as reflected in prices. One might expect that a bank's superior informational advantage would also translate into changes along other margins, such as the provision of credit. In future work, we also plan to explore a merger's informational effects on these non-price margins.

More broadly, our findings carry important implications for the controversy on the welfare redistributions associated with consolidations. Previous empirical studies have examined only the effect of M&As on the average level of market prices, ignoring potentially important consequences for higher moments of the price distribution. We show that mergers can affect different categories of customers differently: while some customers benefit from the

consolidation, others could be harmed. Moreover, if consolidation leads to better pricing of risk, the welfare effects might be stronger than those obtained by considering average price changes only. This implication, which is likely to hold in other markets as well, implies new challenges for antitrust authorities, because it excludes the possibility of using Paretian criteria to assess the welfare effects of mergers.

A Sample construction: details

Summary statistics for the banks that report interest rates are shown in Table 1. In Panel A we report data for all banks in our sample. Over the entire period the median bank size (as proxied by total assets) is about 3,700 million euros and 1,137 employees. The ratio of operating costs to gross revenues (a standard indicator of efficiency) is 33.1 percent, while the ratio of bad loans to total lending (a proxy for riskiness) is 4.9 percent. Software expenses per employee are equal to about 1,100 euros.

In Panels B and C we distinguish banks on the basis of their participation in a merger during the period 1988-98. In particular, we classify a bank as a "bidder" if it acquired another bank during our sample period, and a "target" if it was acquired (a bank could be both bidder and target, if it acquired another bank before itself being taken over). The bidder banks are larger than average (median of 9,049 million euros and 2,789 employees). The cost-income ratio, the ratio of bad loans to total loans and the software expenses per employee are similar to the rest of the sample. The target banks are similar to the bidders in these parameters, but smaller in size (median size is 4,999 million euros).

Summary statistics on the firms included in the Centrale dei Bilanci are shown in Table 2. The median firm in the sample has total assets equal to 0.78 million euros, 31 employees, a return on sales of 8 percent, and leverage of 60 percent. Short-term debt represents the largest component of total debt (81 percent).

As for bank-firm relationships, the median firm borrows from 4 banks. As we noted before, this feature of the Italian loan market makes it appropriate not only to examine the informational consequences of bank mergers, but also to disentangle them into those arising from explicit information pooling among the merging banks, and those arising when the consolidated bank is able to exploit economies of scale in information processing. Finally, for the median firm the ratio between credit utilized and credit granted is 38.2 percent.

In table 3 we group firms according to their SCORE. As expected, leverage is greater for riskier firms, ranging from 15 percent for safe firms (SCORE=1,2) to 81 percent for risky firms (SCORE=7,8 and 9). Another interesting difference emerges in the pattern of bank-firm relationships. In particular, the credit lines are more likely to be exhausted for riskier firms: the proportion of companies recording an overdraft (i.e. a credit line for which credit utilized exceeds that granted) increases from 4 percent for safe to 31 percent for risky firms. A consistent pattern emerges for the interest rates, which range from 13.2 percent for

companies with low credit risk to 14.7 percent for those in the worst shape (SCORE=7,8,9).

The banks reporting detailed interest rate data range from 68 in 1997 to 88 in 1989. In total, we have 863 bank-year observations (see Panel A of Table 4). These reporting banks are larger than average, and they account for more than two thirds of total Italian banking industry loans. The number of bank-year observations affected by a merger ranges from 6 in 1990 to 26 in 1995. Our sample includes 1,300,000 bank-firm-year observations (see Panel B). Of these observations, 43 percent of the observations refer to companies borrowing from bidder banks, 2.8 percent to companies borrowing pre-merger from target banks, and 0.7 percent to companies borrowing from both. Hence, just over half of the observations refer to firms that do not borrow from a bank that merges during our sample period.

B Results from auxiliary regressions

In this section, we consider results from auxiliary regressions to verify the hypothesis that a bank's responsiveness to the SCORE variable (namely, a steeper interest rate curve) is correlated to its informational ability. To this end, we examine how the slope of the interest rate curve differs between banks which we classify *a priori* as having better information or information processing ability, and those banks that have worse information. If our assumption is valid, banks that are better informed should have a steeper interest rate curve.

We consider two proxies of a bank's informedness. One is the duration of the bank-firm relation, measured by the number of consecutive years that a bank has had a lending relationship with a given firm. The potential informational benefits of lasting bank-firm relationships are analyzed by Rajan (1992). The empirical evidence has shown that the length of the relationship affects the availability and the cost of credit.[39] We re-estimate Eq. (5), replacing the dummy $MERGE$ with this proxy. The coefficient of the interaction between the SCORE and our indicator represents the increase in the slope of the interest rate curve resulting from an increase in the duration of the relationship, so that we expect a positive value. The results, reported in Panel A of Table A1, are consistent with our view. In particular, the coefficient of the interaction term is positive (equal to 0.0191) and statistically significant. The coefficient of the SCORE is also positive and significant, as

[39] See Petersen & Rajan (1994) and Berger & Udell (1995) for the U.S. and Angelini, di Salvo & Ferri (1998) for Italy.

expected.[40]

Our second proxy is the amount of expenditure in computer software per employee, a standard indicator of a bank's information processing capability. As above, we estimate Eq. (5) replacing the dummy $MERGE$ with our proxy (see Panel B of Table A1). Again, the results are consistent with the hypothesis that more informed banks exhibit a steeper interest rate curve: the coefficient of the interaction between the SCORE and software expenditure is positive (equal to 0.0246) and statistically significant (the coefficient of the SCORE is also positive and statistically significant).

We note that our two proxies may be endogenous, correlated with unobservables that also affect the loan rates. But as we are not seeking causal effects here, but just a descriptive measure of how interest rate sensitivity differs across banks depending on their information characteristics, this does not matter to us. By and large, these findings validate our interpretational assumption that the sensitivity of the loan rates to the SCORE variable is related to the informational sophistication of the banks.

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[40] We perform a further check on the relation between the loan rates and the SCORE by dropping from the right-hand side of the regression our proxy of banks' informedness (the length of bank-firm relationships) and the interaction term. The results (unreported) confirm the existence of a positive and significant relation between loan rates and the SCORE.

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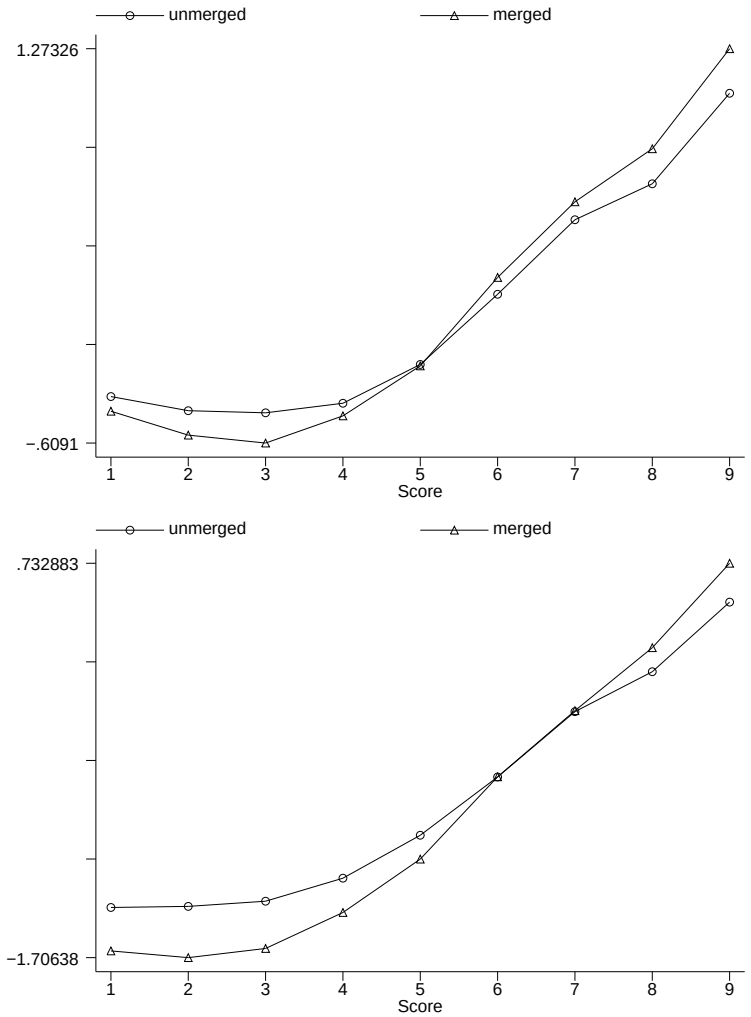
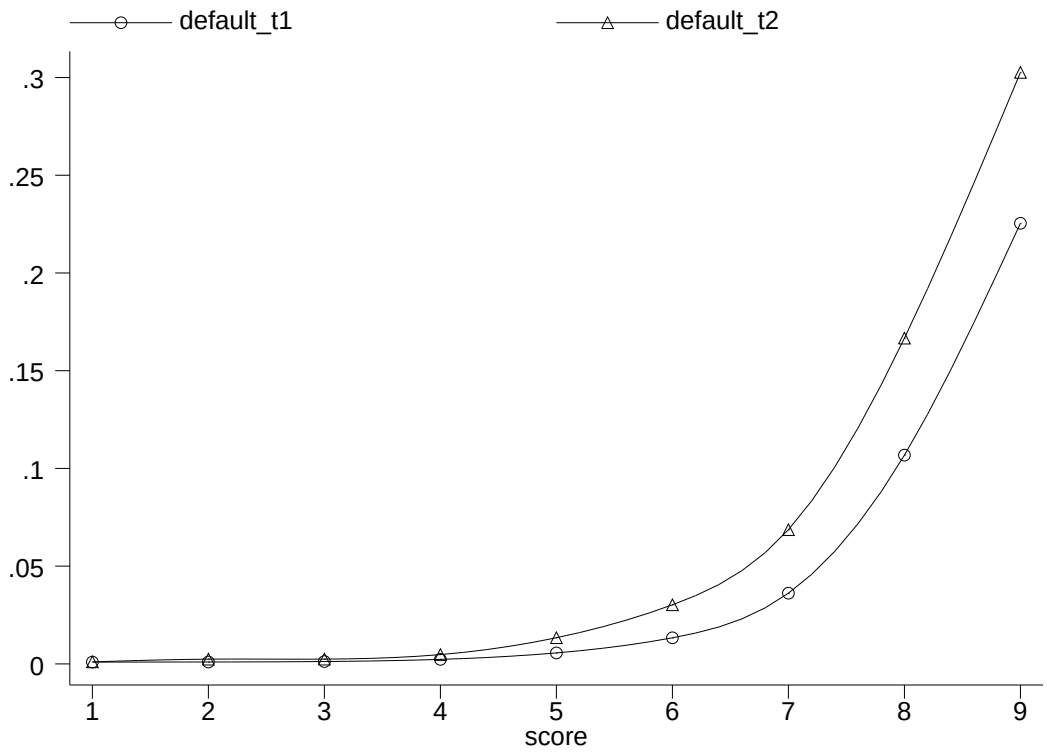
Figure 1: The relationship between interest rates and default risks: merged vs. unmerged banks



y-axis: Interest rate; x-axis: firm default risk measure $SCORE$ (see Section 3.1 for details)

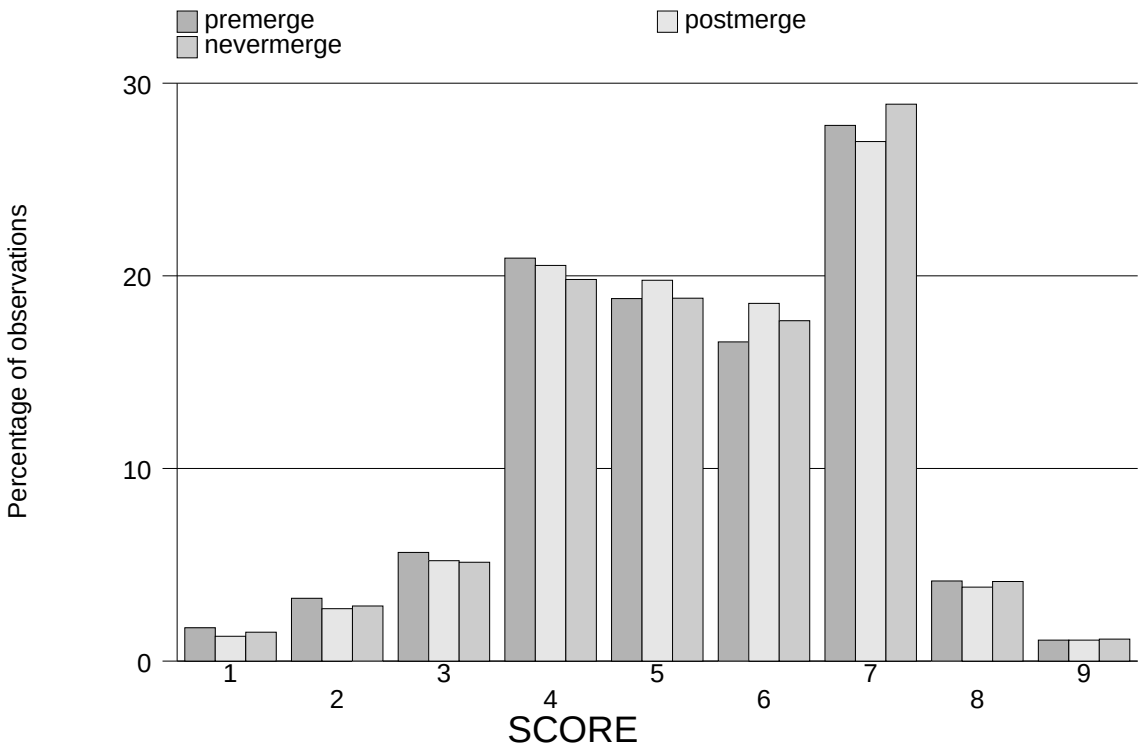
Note: The upper panel refers to average and the lower to median interest rate. The average and median interest rate may be negative because we netted out year effects by regressing the raw interest rates on year dummies. The interest rates plotted here are the residuals from this regression.

Figure 2: Does SCORE predict actual default accurately?



Each point gives the percentage of (firm-year) observations with a given SCORE for which the firm defaulted during or after year t. The *default_t1* line graphs the percentage of observations in which the firm defaults within years t or $t+1$, for different values of SCORE, and the *default_t2* line graphs the percentage of observations in which the firm default within years t, $t+1$, and $t+2$.

Figure 3: Do banks reallocate portfolio towards less risky borrowers after a merger?



Each bar shows the percentage of borrowers with a given SCORE value, for different subsamples of banks. The *nevermerge* subsample are observations at banks which never merge in the sample period; the *premerge* subsample are the pre-merger observations for banks which merge during the sample period; the *postmerge* subsample contains the post-merger observations for banks which merge during the sample period.

Table 1

Summary Statistics: the Bank Sample

The summary statistics of Panel A refer to all banks that report the interest rates charged on credit lines. Panel B to the banks that were bidders in a merger. Panel C to the banks that were target in a merger. The number of observations is the number of bank-years. Size is the bank's total assets in millions of euros. Employees is the number of employees at the end of the year. Bad loans is a percentage of total loans. Cost-income ratio is the ratio of overhead to gross income (in %). Software per employee is the ratio of expenses in software to the number of employees, expressed in thousands euros.

Variables	Obs.	Mean	Stand. Dev.	5th pctile	Median	95th pctile
			Panel A: All Banks			
Size	900	10,726.8	16,965.6	481.3	3,709	54,354.1
Employees	896	3,179.9	4,582.5	206	1,137	14,038
Bad loans	893	6.2	6.3	1.9	4.9	15.8
Costs-income ratio	893	34.5	6.1	25.4	33.1	43.2
Software per employee	792	1.3	1.1	0.1	1.1	3.2
			Panel B: Bidder Banks in Mergers			
Size	107	19,386	23,902	1,193	9,049	75,096
Employees	106	5,325	5,733	365	2,789	18,987
Bad loans	107	6.2	4.7	2.0	5.6	15.1
Cost-income ratio	106	33.6	6.8	25.2	33.2	44.3
Software per employee	91	1.4	1.3	0.4	1.1	3.9
			Panel C: Target Banks in Mergers			
Size	28	7,254	7,804	144	4,999	26,952
Employees	28	2,270	2,769	67	1,551	10,014
Bad loans	28	9.3	13.4	1.2	4.2	50.0
Cost-income ratio	24	34.0	8.9	23.6	31.9	51.6
Software per employee	23	1.1	0.8	0.1	1.1	3.1

Table 2

Summary Statistics: the Firms Sample

The summary statistics in the table refer to the company sample. Total assets are expressed in million euros. Employees is the number of employees at year-end**.** Short term debt is expressed as a proportion of total debt. The SCORE is the indicator of the risk of the company computed each year by the *Centrale dei Bilanci* (higher values indicate riskier companies). Number of lenders is the number of banks from which the company borrows. Utilized credit is expressed as a proportion of credit granted.

Variable	Obs.	Mean	Stand. Dev.	5thpctile	Median	95thpctile
Total Assets	329,622	3.6	119.9	0.04	0.78	8.4
Employees	293,281	73.7	637.9	3	31	224
Leverage	329,611	55.3	30.1	0.1	60.3	96.0
Return on Sales	328,650	9.1	9.9	4.3	8.6	20.4
Short term debt	304,440	70.2	31.9	0.2	81.0	100.0
SCORE	318,645	5.1	1.8	2	5	8
No. of lenders	329,623	4.4	3.3	1	4	11
Utilized credit	319,792	50.2	54.3	0	38.2	138.4

Table 3

Merger Activity: Overall Sample

Panel A: Bank-year Observations

Number of banks is the number of bank-year observations in the sample of banks that report detailed information on the loan rates to individual borrowers (the reporting banks). Number of bidders (targets) is the number of reporting banks that in each year was involved in a merger as a bidder (target).

Year	No. Of Banks	No. of bidders	No. Of targets
1988	87	7	0
1989	88	13	0
1990	87	5	1
1991	84	12	4
1992	81	11	4
1993	79	5	2
1994	75	8	0
1995	73	22	4
1996	71	8	3
1997	68	7	2
1998	70	8	1
Total	863	106	21

Panel B: the bank-firm-year observations

A firm is classified as a borrower of a bidder, a target or both for the 5 years following the merger if the firm was borrowing from the merging bank in the year before the merger. Number of observations is the number of bank-firm-year observation in our sample.

Year	No. Of observations	% of firms that borrow from a bidder	% of firms that borrow from a target	% of firms that borrow from a bidder & target
1988	96,353	10.1	0,0	0,0
1989	95,648	25.4	0,0	0,0
1990	105,073	27.7	0.1	0.1
1991	112,088	33.0	1.8	0.9
1992	116,942	39.3	6.0	0.5
1993	122,606	40.1	4.5	0.4
1994	134,037	48.9	3.6	0.3
1995	128,549	69.7	4.2	0.5
1996	116,307	61.9	4.0	1.4
1997	143,844	50.3	3.2	1.3
1998	126,075	53.9	2.0	1.6
Total	1,297,522	43.3	2.8	0.7

Table 4

Firm Characteristics by Risk Class

The summary statistics refer to the company sample. Companies have been grouped on the basis of the risk indicator computed each year by the *Centrale dei Bilanci* (the SCORE: higher values indicate riskier firms). Panel A refers to safe firms (SCORE=1,2). Panel B refers to solvent firms (SCORE=3,4). Panel C refers to vulnerable firms (SCORE=5,6). Panel D refers to risky firms (SCORE=7,8,9). Employees is the number of employees at year-end. Average loan rate is the average interest rate paid by the company on credit lines. Number of lenders is the number of banks from which the company borrows. Percentage of overdrafts is the proportion of firms with at least one credit line with credit utilized exceeding credit granted.

Variable	Obs.	Mean	Stand. Dev.	5th pctile	Median	95th pctile
		Panel A: Safe firms (SCORE=1,2)				
Employees	26,954	80.7	292	5	34	261
Leverage	29,317	19.2	16.8	0.5	15.2	50.7
Average loan rate	23,906	14.3	4.0	10.2	13.2	22.2
No. of lenders	29,317	2.8	2.3	1	2	7
Percentage of overdrafts	29,317	4.2	14.1	0	0	29.8
		Panel B: Solvent firms (SCORE=3,4)				
Employees	88,841	85.5	539.5	6	35	254
Leverage	98,047	40.2	21.7	0.3	42.1	73.6
Average loan rate	91,022	14.2	3.4	10.4	13.5	20.4
No. of lenders	98,047	4.1	3	1	3	10
Percentage of overdrafts	98,047	8.3	18.9	0	0	50.2
		Panel C: Vulnerable firms (SCORE=5,6)				
Employees	90,115	70.1	650.1	4	31	212
Leverage	101,195	63.3	24.1	0.4	68.8	92.3
Average loan rate	98,595	14.5	3	10.8	14.0	20.0
No. of lenders	101,198	5	3.5	1	4	12
Percentage of overdrafts	101,198	15.7	25.9	0	0	75.2
		Panel D: Risky firms (SCORE=7,8,9)				
Employees	78,135	57.0	487.8	2	24	177
Leverage	90,076	74.3	26.7	0.6	81.4	103.8
Average loan rate	88,627	15.1	3	11.1	14.7	20.4
No. of lenders	90,083	4.8	3.4	1	4	11
Percentage of overdrafts	90,083	31.0	33.5	0	20.2	100

Table 5

Score Predictability

Panel A: Regression of SCORE(t) on SCORE(t-2)

In Column A we report the results of regressing $SCORE_t$ on $SCORE_{t-2}$ including firm fixed effect, while in Culumn B without fixed effects. Standard errors are reported in parentheses. The symbol *** indicates a significance level of 1 per cent or less; ** between 1 and 5 per cent; * between 5 and 10 per cent.

	Panel A:		Panel B:	
Variables	Firm fixed effects		No fixed effets	
$SCORE_{t-2}$	.296	***	.752	***
	(.002)		*(.001)*	
Constant	3.12	***	.918	***
	(.009)		*(.006)*	
No. of Observations	538,714		538,714	
R-Square	63.5		42.1	

Panel B: Predicting the default probability

Results of the probit regressions where the dependent variable is a dummy that takes the vaule 1 if the firm defaults within the next three years and the independent variable are SCORE(t), SCORE(t-2) and RESID(t), i.e. the residual from the pooled (across banks, firms and years) regression of SCORE on SCORE(t-2). RESID(T) summarizes the new information contained in SCORE(t) with respect to SCORE(t-2). Coefficients are the marginal estimates.

SCORE(t)	.0215	***				
	(.0001)					
SCORE(t-2)			.0183	***	.0147	***
			(.0002)		*(.0002)*	
RESID(t)					.0166	***
					(.0002)	
No. of Observations	208,932		178,859		178,254	
Pseudo R-Square	15.80		8.80		17.57	

Table 6

Effect of M&As on Banks' Information

In Panel A we report the results of estimating equation (5) of the paper with firm fixed effects. In Panel B we add bank fixed effects. All regressions include bank and firm characteristics and year dummies. Standard errors adjusted for clustering over firm-year are reported in parentheses. The symbol *** indicates a significance level of 1 per cent or less; ** between 1 and 5 per cent; * between 5 and 10 per cent.

	Panel A:		Panel B:	
Variables	Firm fixed effects		Bank *and* firm fixed effects	
SCORE	.036	***	.032	***
	(.004)		*(.004)*	
MERGE*SCORE	.087	***	.088	***
	(.004)		*(.004)*	
MERGE	-.297	***	-.347	***
	(.021)		*(.021)*	
Firm Controls:				
Size (log value)	-.019	***	-.019	***
	(.004)		*(.004)*	
Return on Sales	-.003		-.007	
	(.043)		*(.042)*	
Leverage	.191	***	.186	***
	(.020)		*(.020)*	
Bank Controls:				
Size (log value)	-.033	***	-.012	
	(.011)		*(.048)*	
Cost-Income ratio	2.962	***	.017	
	(.053)		*(.089)*	
Market Concentration	1.937	***	1.737	***
	(.271)		*(.271)*	
No. of Observations	1,061,785		1,061,785	
R-Square	58.4		60.2	

Table 7

Effect of M&As on Banks' Information: Score-year and Score-firm characteristics interactions

In Panel A we report the results of estimating equation (5) of the paper, allowing for the score coefficient to differ for each year. In Panel B we also include score-firm characteristics interactions. In panel C we also include score-bank interactions, as well as bank dummies. The score coefficient is not estimated because perfectly collinear with the score-year and the score-bank interactions. All regressions include bank and firm characteristics and year dummies. Standard errors adjusted for clustering over firm-year are reported in parentheses. The symbol *** indicates a significance level of 1 per cent or less; ** between 1 and 5 per cent; * between 5 and 10 per cent.

	Panel A:		Panel B:		Panel C:	
Variables						
MERGE*SCORE	.024	***	.023	***	.030	***
	(.004)		*(.004)*		*(.004)*	
MERGE	.040	*	.044	*	-.023	
	(.022)		*(.022)*		*(.022)*	
Score-year interactions	YES		YES		YES	
Score-firm char. interactions	NO		YES		YES	
Score-banks interactions	NO		NO		YES	
No. Of Observations	1,061,785		1,061,785		1,061,785	
R-Square	58.5		58.5		60.2	

Table 8

Effect of Mergers on Information: Long vs. Short Bank-Firm Relations

In Panel A we report the results of estimating equation (5) of the paper for firm-bank relations with a length less than 5 year, while in Panel B for relations of 5 years or more. All regressions include bank and firm characteristics and year dummies. Difference Test is the value of an F-test on the difference between the coefficients for the short and long relations. Standard errors adjusted for clustering over firm-year are reported in parentheses. The symbol *** indicates a significance level of 1 per cent or less; ** between 1 and 5 per cent; * between 5 and 10 per cent.

Variables	Panel A: Short bank-firm relations	Panel B: Long bank-firm relations	Panel C: Difference test (long vs. short relations)
SCORE	0.035 ***	0.060 ***	0.003 ***
	(0.004)	*(0.007)*	
MERGE*SCORE	0.067 ***	0.020 ***	0.001 ***
	(0.005)	*(0.006)*	
MERGE	-0.179 ***	-0.0294	0.001 ***
	(0.029)	*(0.035)*	
No. of Observations	669,877	391,908	
R-Square	59.3	63.8	

Table 9

Effect of Mergers on Information: Important vs. Fringe Banks

In Panel A we report the results of estimating equation (5) of the paper for firm-bank relations where the bank account for less that 15% of the total loan of the firm, while in Panel B for more than 15%. All regressions include bank and firm characteristics and year dummies. Difference Test is the p-value of an F-test on the difference between the coefficients for the short and long relations. Standard errors adjusted for clustering over firm-year are reported in parentheses. The symbol *** indicates a significance level of 1 per cent or less; ** between 1 and 5 per cent; * between 5 and 10 per cent.

	Panel A:	Panel B:	Panel C:
Variables	Less than 15% of total loans	More than 15% of total loans	P-value for the null: less = more
SCORE	.052 ***	.050 ***	0.26
	(.005)	*(.005)*	
MERGE*SCORE	.101 ***	.079 ***	0.003 ***
	(.005)	*(.006)*	
MERGE	-.314 ***	-.255 ***	0.176
	(.030)	*(.033)*	
No. of Observations	607,285	385,615	
R-Square	58.4	70.9	

Table 10

Effect of M&As on Banks' Information: Small Targets

Small targets are defined as the acquired banks that before the merger had a number of customers (as reported in the sample) below the median number of customers for all target banks (650). We report the results of estimating equation (5) of the paper allowing for a different score coefficient for customers of small targets both before (the SMALLTAR*SCORE variable) and after (the MERGE*SMALLTAR*SCORE variable) the merger. All regressions include bank and firm characteristics and year dummies. Standard errors adjusted for clustering over firm-year are reported in parentheses. The symbol *** indicates a significance level of 1 per cent or less; ** between 1 and 5 per cent; * between 5 and 10 per cent.

	Panel A			
Variables				
SCORE	.037	***	.034	***
	(.004)		*(.004)*	
SMALLTAR*SCORE	-.072	***	-.094	***
	(.004)		*(.012)*	
MERGE*SCORE	.086	***	.087	***
	(.004)		*(.004)*	
MERGE*SMALLTAR*SCORE	.053	**	.082	***
	(.022)		*(.024)*	
MERGE	-.290	***	-.334	***
	(.022)		*(.021)*	
MERGE*SMALLTAR	-.211	*	-.111	
	(.124)		*(.122)*	
No. of Observations	1,061,785		1,061,785	
R-Square	58.4		60.0	

Table 11

Effect of Mergers on Information: In-Market vs. Out-of-Market Mergers

In Panel A we report the results of estimating equation (5) of the paper for in-market mergers, i.e. mergers where both the acquiring and acquired parties to a period t merger were already active lenders in a given province during period t-1. In Panel B we report the results of estimating equation (5) of the paper for out-of-market mergers, i.e. mergers where only one of the merging parties (the acquiring *or* the acquired bank) to a period t merger was already active lender in a given province during period t-1. In Panel C report the results of estimating equation (5) of the paper for the pooled sample, letting the coefficient of the MERGE*SCORE variable to differ for in and out of market mergers (the INMKT coefficient represents the deviation from the out of market one). All regressions include bank and firm characteristics and year dummies. Standard errors adjusted for clustering over firm-year are reported in parentheses. The symbol *** indicates a significance level of 1 per cent or less; ** between 1 and 5 per cent; * between 5 and 10 per cent.

	Panel A: In market mergers	**Panel B: Out of market mergers**
Variables		
SCORE	.044 ***	.046 ***
	(.004)	*(.004)*
MERGE*SCORE	.065 ***	.119 ***
	(.004)	*(.005)*
MERGE	-.364 ***	-.241 ***
	(.025)	*(.030)*
No. of Observations	891,449	815,865
R-Square	59.3	58.1

Table 12

Whence Informational Improvements: Information Pooling

In Panel A we report the results of estimating equation (5) of the paper. In Panel B we report the results of estimating equation (5) of the paper using using firm- and bank-specific fixed effects. All regressions include bank and firm characteristics and year dummies. Standard errors adjusted for clustering over firm-year are reported in parentheses. The symbol *** indicates a significance level of 1 per cent or less; ** between 1 and 5 per cent; * between 5 and 10 per cent.

	Panel A:	Panel B:
Variables	Firm fixed effects	Bank *and* firm Fixed effects
SCORE	.035 ***	.032 ***
	(.004)	*(.004)*
BIDDER*SCORE	.091 ***	.090 ***
	(.004)	*(.004)*
TARGET*SCORE	.073 ***	.086 ***
	(.010)	*(.010)*
BIDTAR*SCORE	.039 *	.055 ***
	(.020)	*(.020)*
BIDDER	-.294 ***	-.343 ***
	(.022)	*(.020)*
TARGET	-.445 ***	-.445 ***
	(.059)	*(.060)*
BIDTAR	-.306 ***	*-.416* ***
	(.116)	*(.114)*
No. of Observations	1,061,785	1,061,785
R-Square	58.4	60.0

Table 13

Distinguishing between Existing and New Information

In Panel A we report the results of estimating eq. (5) of the paper by using E_{t-2}SCORE(t), i.e. the predicted value of SCORE from a pooled (across banks, firms and years) regression of SCORE on SCORE(t-2) and including RESID(t), i.e. the residual from the same regression. In Panel B we report the results of estimating eq. (5) by using the same variables as regressors. All regressions include bank and firm characteristics and year dummies. Standard errors adjusted for clustering over firm-year are reported in parentheses. The symbol *** indicates a significance level of 1 per cent or less; ** between 1 and 5 per cent; * between 5 and 10 per cent.

	Panel A:		Panel B:	
Variables	No distinction between bidder and target banks		Distinguishing bidders from targets	
E_{t-2}SCORE(t)	0.312	***	0.123	***
	(0.013)		*(0.005*	
RESID(t)	0.054	***	0.054	***
	(0.004)		*(0.004)*	
MERGE* E_{t-2}SCORE(t)	0.113	***	—	
	(0.005)			
BIDDER* E_{t-2}SCORE(t)	—		0.115	***
			(0.005)	
TARGET* E_{t-2}SCORE(t)	—		0.047	***
			(0.012)	
BIDTAR* E_{t-2}SCORE(t)	—		0.001	
			(0.024)	
MERGE*RESID(t)	0.011	*	—	
	(0.006)			
BIDDER*RESID(t)	—		0.011	*
			(0.006)	
TARGET*RESID(t)	—		0.034	**
			(0.016)	
BIDTAR*RESID(t)	—		-0.035	
			(0.032)	
MERGE	-0.401	***	—	
	(0.024)			
BIDDER	—		-0.412	***
			(0.025)	
TARGET	—		-0.380	***
			(0.067)	
BIDTAR	—		-0.185	
			(0.131)	
No. of Observations	973,237		973,237	
R-Square	58.9		58.9	

Table A1

The Effect of Information on the Slope of the Interest Rate Curve

In this table we report the results of estimating equation (5) of the paper replacing the *MERG* dummy with two proxies of the quality of the information that banks produce on their borrowers. The first proxy is the length of the bank-firm relationship (Panel A). The second is the bank's computer software expenditures per employee (see Panel B). The dependent variable is the bank-firm-specific interest rate on credit lines. The equations includes firm-specific fixed effects and time dummies. Standard errors adjusted for clustering over firm-year are reported in parentheses. The symbol *** indicates a significance level of 1 per cent or less; ** between 1 and 5 per cent; * between 5 and 10 per cent..

Variables	**Proxy of the degree of banks' informedness:**	
	Panel A	Panel B
	Length of bank-firm relationship	Software expenses
SCORE	.010 *	.047 ***
	(.006)	*(.004)*
Length of relationship	-.019 **	—
	(.007)	
SCORE*Length of relationship	.019 ***	—
	(.001)	
Software expenses	—	-.077 ***
		(.010)
SCORE*software expenses	—	.024 ***
		(.002)
No. of Observations	811,945	965,696
R-Square	61.5	60.6

Table A2

Selection effects: Alternative Control Groups

In Panel A we report the results of estimating equation (5) of the paper restricting the control group (i.e. observations for which the MERGE dummy is 0) to observations relating to merging banks in the pre-merge years. In Panel A we report the results of estimating equation (5) of the paper further restricting the control groups to observations relating to merging banks 1 and 2 years before the merge, and in Panel C to observations in merging banks in the year before the merge. All regressions include bank and firm characteristics and year dummies. Standard errors adjusted for clustering over firm-year are reported in parentheses. The symbol *** indicates a significance level of 1 per cent or less; ** between 1 and 5 per cent; * between 5 and 10 per cent.

	Panel A:	Panel B:	Panel C:
Variables	Control group: Merging banks before the merger	Control group: Merging banks 1 or 2 years before the merger	Control group: Merging banks 1 year before the merger
SCORE	.026 ***	-.001	-.007
	(.004)	*(.004)*	*(.007)*
MERGE*SCORE	.096 ***	.100 ***	.096 ***
	(.004)	*(.005)*	*(.006)*
MERGE	-.396	-.510	-.459
	(.003)	*(.003)*	*(.004)*
No. Of Observations	950,813	556,343	495,756
R-Square	58.7	58.5	62.5