Do Mergers Improve Information? Evidence from the Loan Market*

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Abstract

We examine the informational effects of M&As investigating how bank mergers affect the pricing of business loan contracts. Our test is based on the principle that in loan markets, informational benefits should improve banks' abilities to screen their borrowers, leading to a closer correspondence between the default risk of each borrower (which is imperfectly observed by lenders) and the interest rate on its loan. We find evidence of these informational effects: after a merger, risky borrowers experience an increase in the interest rate, while non-risky borrowers enjoy lower interest rates. Further results suggest that that these information benefits derive from improvements in information processing resulting from the merger, rather than from explicit information sharing on individual customers among the merging parties. Our results imply that mergers might affect different categories of customers in different ways, so that average price changes might not be sufficient to gauge their welfare effects.

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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 (1993) , Sapienza (2002), Focarelli & Panetta (2003)).

However, market power and efficiency are hardly the only important channels through which M&As can affect the pricing policy of the merging company. In many industries, mergers allow companies to enlarge their information set and improve their knowledge of important characteristics of the markets in which they operate. This is likely to be particularly relevant in markets characterized by informational frictions, such as credit, insurance and used goods markets. In these markets, 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 valuable information on the health status of its customers, which could help it price its automobile insurance policies better. Even in the case of a purely horizontal merger among identical parties, 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.

How important are these informational benefits from mergers? In this paper, we consider a market in which information effects 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] To address this question, we employ a unique matched panel dataset

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

from Italy containing information on individual business loan contracts for a nearly complete sample of firms from 1988 to 1998. For each loan contract, we observe the interest rate 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 informational effects for several reasons. 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; hence, 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 which 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 which is more "sensitive" to this risk. Consider a bank with no screening ability: to such a bank, 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 borrowers with higher perceived risks and vice versa. 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, unlike the standard market power and efficiency effects, which has been the focus of the existing empirical literature cited above, the price impact of these informational benefits might have important distributional effects which differ across customers.

One difficulty in implementing this 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 which, due to accounting rules and data collection requirements, is only made available to banks after a two year lag.

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. This finding, which proves to be very robust, is consistent with the hypothesis that consolidation improves banks' informational abilities in discriminating among low- and high-quality borrowers. Additional results support this interpretation versus a number of alternative ones, such as that merged banks exert more price discrimination due to their increased market power.

We also investigate the channels whereby 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 for the companies that before the deal were borrowing from only one of the merging parties and for those that were borrowing from both merging parties. This finding suggests that the potential gains from explicit *pooling* or sharing of firm-specific information - that can only emerge when both of the merging banks were lending to the company before the consolidation - is not the relevant channel of informational gains. Instead, our result are consistent with the view that the informational efficiencies arise from an improvement in banks' ability (or an increase in their incentives) to process a given information set, arguably due to increasing returns to scale to information processing (i.e., larger databases, higher fixed costs expenditure in information and communications technology (ICT), etc.). 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 acquired banks improve mostly in acquiring new information (thus suggesting the importance of managerial improvements in these banks), acquiring banks become more adept at both using existing information as well as gaining new information.

Our results carry important implications for the controversy on the welfare redistributions associated with consolidations. 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 also in other markets, implies new challenges for the antitrust authorities, because it excludes the possibility of using Paretian criteria to assess the welfare effects of mergers.

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 as to the presence and magnitudes of informational effects deriving from a mergers. We consider (and rule out) various alternative explanations for these informational effects in Section 5, and investigate the sources of informational benefits in Section 6. Section 7 contains concluding remarks.

2 Mergers, Prices, and Information

The effect of consolidation on market prices is *a priori* ambiguous. On the one hand, mergers can increase efficiency (through economies of scale and scope or an improvement in managerial x-efficiency), potentially decreasing 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 1993). Recent studies, 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) or the timing at which the price effects are considered (Focarelli & Panetta 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 merged companies. In this paper, we focus on one such factor: information. The starting point of our empirical analysis is a plot using the raw data, contained in Figure 1. 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).[2] The two lines in each graph correspond to merged and unmerged banks. Clearly, the lines for the merged banks exhibit a steeper slope; furthermore, lending rates charged by the merged banks are lower for the less risky firms (those with a low SCORE measure), but actually higher for riskier firms (those with a high SCORE measure). In this paper, we will interpret such a 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. We explain the theoretical underpinnings of such an interpretation here.

[2]Both the SCORE variable and the definition of interest rates will be discussed in detail below. We net our year effects by including year dummies before plotting the interest rate data.

Consider bank i, which is risk-neutral (an assumption that follows from the fact that it owns a well diversified portfolio of loans). One of its borrowers, firm j, has an individual probability of default p_j, unknown to the bank (i.e., from the perspective of bank i, firm j's default probability is unknown and a random variable). 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 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 $r_{ij} \approx E\{p_j|\Omega_i\}$.[3]

Assume furthermore that, across firms, the default probabilities p_j are random draws from a beta distribution with parameters (a, b), so that the average probability of failure in the population is $\bar{p} = \frac{a}{a+b}$. In addition, the information set Ω_i consists of n_i binary signals $s \in \{\text{repay,default}\}$, with $\Pr\{s = \text{default}\} = p_j$, i.e. to the true probability of default. Hence, n_i measures the screening ability of the bank, with larger values of n_i indicating that bank i is better informed. Using Baye's rule, the posterior mean (and hence the interest rate) after n_i signals and y defaults is

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

Given a level of informedness n_i and conditional on p_j, the expected number of defaults out of n_i signals is $E\{y|n_i, p_j\} = n_i p_j$ so that, on average, a bank with screening ability n_i charges to a p_j firm the following interest rate:

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

where $\alpha(n) \equiv \frac{n}{a+b+n}$. Expression (2) formalizes the fact that, as more information becomes available, the posterior shifts away from the prior mean $\bar{p}$ towards the true default probability p_j. In fact, $\alpha(0) = 0, \lim_{n\to\infty} \alpha(n) = 1$, and $\frac{\partial \alpha}{\partial n} = \frac{a+b}{(a+b+n)^2} > 0$. This equation offers an empirical strategy to detect informational improvements in banks' screening abilities, provided that we have a measure of the true probability of default p_j and of banks' screening ability n_i. As the screening capability increases, the interest-rate/risk relationship shifts down and tilts upward:

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

[3] In our data, the probability of non-repayment of a loan from one year to the next has a mean value of 1.3% and a median one of 0.05%, small enough for the linear approximation to be valid.

If mergers indeed lead to informational improvements, then a merger event would proxy for increases in screening ability n_i, which would lead to graphs which resemble those in Figure 1. This is the strategy we will follow in our empirical specification, where we will run regressions of the form

$$r_{ij} = \beta_0 + \beta_1 * MERGE_i + p_j \left(\beta_2 + \beta_3 * MERGE_i\right) + \epsilon_{ij} \tag{3}$$

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. The hypothesis that mergers improve information (i.e. an increase in n_i) would imply that $\beta_1 < 0$ and $\beta_3 > 0$, in line with the graphs in Figure 1.[4]

Needless to say, there could be alternative interpretations, besides the information one, for the increased steepness of the interest-rate/risk relationship documented in Figure 1.[5] Hence, 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.[6]

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 information come from the Banking Supervision Register at the Bank

[4]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 true 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 true probability of default p_j in the regression (3) 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 $\beta_2 < \beta_2 + \beta_3$, as a result of the usual attenuation bias due to the "mismeasured" variable p_j.

[5]Indeed, a recent paper by Hauswald & Marquez (2003) contains a model in which improvements in information 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 more details on winner's curse effects).

[6]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.

of Italy. (4) Data on the mergers and acquisitions are drawn from the Census of Banks (SIOTEC). By combining these data, we obtain a matched panel dataset of borrowers and lenders extending over a 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, to the CR, data at the individual borrower level on the amount granted and effectively utilized for all loans exceeding a given threshold,[7] 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 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 encompasses 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 nonfinancial 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 nonfinancial sector.[8] Table 2 reports descriptive statistics for the firms 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 a 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.

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

[8] According to a recent analysis (see Centrale dei Bilanci, 1999) based on a subset of 5,249 firms included in the database, the CB sample represented 49.4 per cent of the total sales reported in the national accounting data for the Italian non-financial, non-agricultural sector.

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 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" firms (SCORE=1,2), (ii) "solvent" firms (SCORE=3,4), (iii) "vulnerable" firms (SCORE=5,6), and (iv) "risky" firms (SCORE=7,8,9). Table 4 report firms characteristics for different SCORE classes. As expected, higher SCORE firms are smaller and more leveraged; they also pay a higher loan rate.

Two characteristics of the SCORE are key for 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 "true" quality of the firm in each year. In Figure 2, we plot the SCORE variable against indicators of actual default incidence. 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 around 10%. An even more pronounced trend is true when considering the event of defaulting 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 with a delay of approximately 15 months: for example, the information on the balance sheets for 1995 were 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 $SCORE$ that was computed in 1990): thus, it represents information that is not yet available to banks when they set interest rates in year t.

The amount of innovation in $SCORE_t$ with respect to $SCORE_{t-2}$ is non-negligible: Table 5 (Panel A) shows that, even 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%. The change in SCORE between year $t-2$ and t appears therefore to represent a potentially important source of uncertainty from the banks' point of view. 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.[9] A comparison of the first two columns indicates that using $SCORE_t$ instead of $SCORE_{t-2}$ almost doubles the fit of the regression, as measured by the pseudo-R^2, indicating that the former has more predictive power.

To examine this issue more closely, we also run 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), in order to quantify how important the information which banks do not have, namely $resid_t$, is in predicting firm defaults. 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 0.01 (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 $SCORE_{t-2}$.

This two characteristics, namely that the most current measure of $SCORE$ is not observed by banks at the time they extend their loans, and that it is a better predictor of actual default incidence than than observed by banks, make it an ideal proxy for the true default probability p_j in the model above.

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

4 Empirical Results

The raw data presented in Figure 1 above are consistent with the hypothesis that mergers improved information, by making banks more adept at screening borrowers according to their default risk (as measured by $SCORE$). However, the interest rate curves shown in the graph could merely reflect differences between merged and non-merged banks, or differences in the pool of borrowers. Therefore, we now turn to the regression analysis, to check whether the relation persists once we control for the characteristics of the borrowers and those of the lenders.

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

$$\begin{aligned} r_{ijt} &= \beta_0 + \beta_1 * MERGE_{it} + \beta_2 * SCORE_{jt} + \beta_3 * (SCORE_{jt} * MERGE_{it}) \\ &\quad + \beta_4 * FIRM_{j,t-1} + \beta_5 * BANK_{i,t} + \beta_6 * CONC_t + u_j + d_t + e_{ijt}. \end{aligned} \tag{4}$$

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.[10] 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 which were borrowing from bank i in the year prior to the merger.[11] $SCORE_{jt}$ is the default risk measure for firm j in year t. $FIRM_{j,t-1}$ 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}.

[10] 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 by both shortening this lag period to 3 years, as well as extending it to 11 years (our sample length), with no noticeable effects on the results.

[11] Thus, new borrowers which initiate their lending relationship with a bank shortly after a merger are not included among the treatment observations. For work on the related question of portfolio reallocations where a merged bank drops some of its pre-merger borrowers, see Sapienza (2002). In this paper, both dropped pre-merger borrowers and new post-merger borrowers are included in the control group. However, to ensure the robustness of our results to banks' portfolio allocation decisions, we also performed unreported regressions where both of these groups of borrowers were excluded from the sample, with virtually no change in the results.

Within the framework of Eq. (2), 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 the 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 (see Focarelli & Panetta (2003)). 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.

The hypothesis that mergers improve banks' informational efficiency translates into a testable prediction on the value of β_3, which represents the effect of the merger on the steepness of the interest rate profile. A positive value for β_3 would be consistent with the hypothesis that a merger leads to informational efficiencies, in the form of a steeper interest rate profile.[12]

Our specification of the interest rate equation is similar to Pagano, Panetta & Zingales (1998) and Sapienza (2002). In particular, 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 equation (2), reported in Panel A of Table 6, confirm that, after a merger, banks' sensitivity to the SCORE rises by 8.7 basis points (the coefficient is significant at the 1 percent level). This finding squares with the 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, so that post-merger banks price loans more efficiently. The point estimate of β_3 implies non-trivial costs for the borrowing firms. These costs, to put them in perspective, come to approximately 78 basis points for the worst companies (SCORE=9). However, this calculation does not consider the average price effect of the

[12]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 view 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.

merger, i.e. the effect on the intercept of the interest rate profile. 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.[13] 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 high loan interest rates as a result of the consolidation.

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, while they are lower for larger companies, while profitability (measured by return on sales) has no effect. The loan rate are 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.

We re-estimate our model including firm- *and* bank-specific fixed-effects, in order to account for bank-level unobserved heterogeneity. 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 (see Panel B of Table 6). The other coefficients remain significant and of the expected sign, apart from the banks' variables, that are not significant anymore.[14] 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.

While bank-level fixed effects account for any 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 postpone discussion of this possibility until below, where we explicitly test the hypothesis that positive shocks to screening ability drive mergers.

[13] 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); Focarelli & Panetta (2003) find that mergers lead to a change in the deposit rate of 3.3 percent.

[14] We estimate our model also including only bank-specific fixed effects (unreported). The results do not change. Moreover, our sample comprises both private and public banks. Sapienza (2003) shows that state-owned banks differ in their lending policies from private banks. We have therefore also run the regresssions excluding public banks. Results were virtually unchanged.

Robustness checks One potential concern is that our results might suffer from a lack of generality, as they could depend on our specific definition of the firms' default risk (i.e. the SCORE). A simple and direct way to address this issue is to use a variable measuring *actual* defaults, i.e. to see whether merged banks charge higher rates to firms that default some time in the future. This is clearly a crude check, because defaulting is a rare event, even for many risky firms, but it allows us to compare the pricing policy of merged and unmerged banks using an ex-post measure of credit worthiness. To perform this check, we replaced $SCORE$ in Eq. (4) with a measure of actual default incidence (namely, an indicator for whether a firm defaulted two years into the future).[15] Results, not reported for brevity, indicate that firms that will default in the next two years are charged 20 basis points more than non-defaulting firms by unmerged banks, while for merged banks the difference more than doubles ($\beta_3 = .23$ with a t-stat of 5.86).[16] This is clearly evidence in favor of the idea that merged banks have a higher capacity to identify risky borrowers.

This finding also allows us to make a further point. The post-merger increase in the slope of the interest rate curve may also be consistent with an alternative interpretation, one which implies more adverse welfare implications: in pricing loan contracts, smaller non-merged banks may rely more on "soft" information (i.e., uncodifiable information collected for example through direct interaction with the firms' managers) rather than on the hard information (objective and codified measures of firm performance) summarized by the SCORE, so that the increased post-merger interest rate sensitivity could merely reflect the fact that mergers destroy soft information.[17] The destruction of soft information would however imply a lower ability to detect troubled firms, an implication that goes against the finding that firms that ex-post defaulted were charged higher rates by merged banks.

Next, we investigate the possibility that the results could also 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 which do not merge within our sample period, and cannot be interpreted as causal effects of the merger. To check for this possibility, we have rerun the regressions excluding all the observations relating to banks that

[15] The default indicator corresponds to the *default_t2* variable graphed in Figure 2.

[16] As an additional check, we also constructed our own measure of default probability by estimating a probit model of the probability to default, and used this alternative proxy in the place of SCORE in the regression. Again, the main results are similar to the previous ones.

[17] Evidence that smaller banks (which are more likely to be the target banks in a merger) tend to rely to a larger extent on soft information is presented in Cole, Goldberg & White (2000) using US data.

never merged. In this case, the control group is composed solely of the the pre-merger (and post-merger+ six years) observations for the merging banks. Results, not reported for brevity, turn out to be stronger than the previous ones, with β_3 estimated to be 0.136 in the basic specification with firm fixed effects. This indicates that our results are not driven by a selection hypothesis whereby banks which merge are better than average in their information-screening abilities: the increased steepness appears predicated by the merger itself.

Another possible problem is that, given the increase in the number of mergers over time (see Table 3), the interaction term $SCORE * MERG$ could capture a trend in banks' informational efficiency that is unrelated to the mergers. For example, the improvements in informational efficiency could merely reflect the positive effects of an expansion in banks' ICT spending on their informational efficiency. Therefore, as a final robustness check, we re-estimate our model interacting the $SCORE$ with a set of year dummies, which capture any trend effects in banks' informational improvement common across all banks. This specification – which represents an extreme test of the robustness of our model – yielded results (unreported) which are qualitatively similar to the previous ones. Namely, the coefficient on the SCORE*MERGE interaction remains statistically significant, albeit reduced in magnitude.[18]

Hence, all these results suggest that the steepness in the interest rate curve predicated by a bank merger appears to be a very robust empirical result.

5 Is it really information? Results 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 considering several alternative interpretations of the empirical finding. We examine 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 the change in

[18] In another set of unreported results, we addressed the potential endogeneity of the SCORE variable (arising perhaps from firm-year unobservables which might also influence the interest rate that a firm is granted) by fixing SCORE at its pre-merger average, across all firms. This removes all time variation in SCORE, so that we are not able to estimate the level effect of SCORE (ie., the coefficient β_2 in Eq. (2)) 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.

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. long 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 lender from bank i. Because banks develop information over time, through repeated interactions with their customers, longer relationships are likely to be associated with better knowledge of the borrower (Rajan (1992), Petersen & Rajan (1994)). Therefore, the merger-related gain in information should be larger for firms with a short relationship with the bank than for firms with long relationships, for which there is less uncertainty to confront. Accordingly, we expect the post-merger increase in the slope of the interest rate curve to be larger for short relationships than for long ones.

We split our sample into two subgroups: "long 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 4 years or less (we have experimented with alternative splitting points, obtaining similar results).We re-estimate equation (2) separately for these two groups. The results, reported in Table 7, 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 to only 2 basis points for the firms with long 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 firms and the best firms (SCORE=1 or 9, respectively) increases by 48 basis points. In contrast, for the firms with long 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.

This result also reinforces the point made above that our findings are not driven by a stronger reliance of merged banks on hard information. While soft information is difficult to define or measure precisely, it is reasonable to assume that the amount of it which a bank possesses about a borrower increases in the length of the lending relationship. The shift from soft to hard information should therefore be more pronounced for long relationships, which would in turn imply a larger increase in the SCORE coefficient. Our findings yield exactly the opposite result, suggesting little support for the hypothesis of lower reliance on

soft information.

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 more 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 i provided by bank j, and split our bank-firm observations into two subsamples. The first sub-sample includes all observations for which w_{ijt} is below the median (15 percent)[19]; the second, those with w_{ijt} above the median. Results, reported in Table 8, are consistent with our hypothesis: the increase in the sensitivity of the loan rate to the SCORE is higher for firm-bank relations with a low share of credit, 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 the fact that both the firm and the bank headquarters are in the same region, on the presumption that geographical proximity improves the bank's information about the firm, so that less should be gained from the merger. Results, not reported for brevity sake, again indicate that the increase in the sensitivity is higher 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.

5.3 Is it a market power effect?

If the merging banks have significant local market overlap, the merger could lead to an increase in market power. Therefore, we consider the alternative explanation that the effects we have documented in Section 4 may be attributed to market power: specifically, a merged

[19] Our data set contains the amount of credit utilized at the end of each year. Therefore, for the banks that have lent to the firm only during the year the value of w_{ijt} is equal to zero. To avoid the bias induced by this feature of our data, we compute the median of w_{ijt} by excluding the bank-firm observations with end-of-year credit utilized equal to zero.

bank, with enhanced monopoly power, may be able to exercise more 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 raising interest rates to these borrowers.

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.[20] On the other hand, if the merger had both market power and cost-reduction effects, then our observed results could still be consistent with the explanation 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 observed in the data. 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 observations where $MERGE_{ijt} = 1$, we classify that observation as an in-market observation 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 were active in firm j's province before the merger, we classify it as an out-of-market observation.[21]

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; in contrast, for the out-of-market sub-sample the sensitivity of the loan rate to the SCORE should not be affected by the merger. We re-estimate the basic regression for the two sub-samples separately. The results from this regression, reported in Table 9, indicate that the regression results are similar for the in-market and out-of-market subsamples. Indeed, not only does the interest rate curve becomes 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 coefficient is equal to 11.9 and 6.6 basis points, respectively) – exactly the opposite result that one would expect under the market power interpretation of our result.

[20] 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 (2002), section 2 and Holmes (1989). Also see Borenstein (1989) and Busse & Rysman (2001) for empirical work on the effects of competition on price discrimination.

[21] Italy is divided into 103 provinces that by and large correspond to U.S. counties. In previous research, local markets have been identified with the provinces by Sapienza (2002) and Focarelli & Panetta (2003).

6 Characterizing the mechanisms of informational benefits from mergers

Since we found little evidence in the previous section to support several alternative non-informational explanations for our empirical result that the interest rate curve steepens following a merger, we turn next to characterizing the channels whereby the informational benefits of a merger operate. In doing this, we exploit several unique features of our dataset. 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 from the acquired ("target") bank, and also on the set of firms which borrowed from *both* the bidder and target banks. Second, we observe the SCORE variable two years before the banks in our data do, and we exploit this timing feature in order 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 information which it has at its disposal at the time of the merger, versus the bank's production of new information. By exploiting these features of the data, we hope to pin down the mechanisms whereby informational improvements affect banks' pricing behavior after a merger.

6.1 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 before the merger was borrowing only from the acquiring bank. Analogously, the dummy $TARGET_{ijt}$ refers to firms which, before the consolidation, were borrowing only from the acquired bank. Finally, $BIDTAR_{ijt}$ is 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 observation for each of these categories. Given that the large banks in our dataset are more likely to be the acquiring partner in a consolidation, a majority of 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:

$$\begin{aligned} r_{ijt} &= a_0 + a_1 * BIDDER_{ijt} + a_2 * TARGET_{ijt} + a_3 * BIDTAR_{ijt} + a_4 * SCORE_{jt} + \\ & a_5 * (SCORE_{jt} * BIDDER_{ijt}) + a_6 * (SCORE_{jt} * TARGET_{ijt}) + \\ & a_7 * (SCORE_{jt} * BIDTAR_{ijt}) + a_8 * FIRM_{j,t-1} + a_9 * BANK_{i,t} + \\ & a_{10} * CONC_t + u_j + d_t + e_{ijt}. \end{aligned} \quad (5)$$

By comparing the sizes and magnitudes of a_5, a_6,and a_7, we can distinguish between several hypotheses of interest. First, the merger may improve banks' abilities 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 cost 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 which were not feasible for the merging parties before the deal. The hypothesis that informational gains arise from a general improvement in the merged banks' ability (or an increase in their incentives) to process information 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 in line with the true default risk of firms only for the loans of the target bank, which were priced badly 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 the company's performance abroad, while the other bank could manage the company's checking account and thus obtain privileged information on its sales in the domestic market. This means that the consolidated bank, by pooling

these different sources of information, could improve its knowledge of the company relative to each of the merger parties individually.[22] These information-pooling effects would only apply to $BIDTAR$ observations, the firms which borrowed from both the 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 10. We find that for companies borrowing from only one of the merger parties - 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 equation 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, regarding the potentially endogenous timing of mergers: that the MERGE variable could be correlated with bank- and year-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: it is equal to 3.9 basis points with firm fixed-effects to 5.5 basis points with both firm and bank fixed effects.[23] This result therefore goes against the notion that

[22] 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.

[23] In addition to the small number of observations that might result in imprecise estimates, a possible

informational effects accrue from pooling information on single customers. Moreover, one potential disadvantage of multiple banking is that it might curtail the incentives of each bank to gather information on firms, due to a free-riding mechanism.[24] 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 reduce the extent of the free riding problem. Hence, these results also indicate that the free riding problem connected with multiple banking does not seriously compromise information gathering.[25]

6.2 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: $E_{t-2}[SCORE_t]$, which denotes the fitted value from a linear regression of $SCORE_t$ on $SCORE_{t-2}$, and $resid_t$, the residual from this equation. Hence, the predicted value $E_{t-2}[SCORE_t]$ proxies for the existing information about firm i that banks possess at the same time that they decide on the interest rate, while $resid_t$ proxies for the "new" information about firm i that appears between year $t-2$ and t.[26] Given that the residual is, by

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, that 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 than 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.

[24]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.

[25]In these regressions, the implicit control group also includes all observations at banks which never merge throughout the sample period. To control for the possibility that banks which never merge are systematically different from banks which 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 10.

[26]That is, we first run the regression $SCORE_{it} = \beta_0 + \beta_1 * SCORE_{it-2} + \delta_i + \epsilon_{it}$, including a full set of firm dummies δ_i. Results are reported in Panel B of Table 5. Then we set $E_{t-2}[SCORE_{it}] = \hat{\beta}_0 + \hat{\beta}_1 SCORE_{it-2} + \hat{\delta}_i$ and $resid_{it} = SCORE_{it} - E_{t-2}[SCORE_{it}]$, where the hat's ($\hat{}$) denote estimated

construction, orthogonal to $SCORE_{t-2}$ and, hence, 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 $SCORE_{t-2}$. Therefore, we amend the basic regression (Eq. (2)) by using $E_{t-2}[SCORE_t]$ instead of $SCORE_t$, and by including the year t residual $resid_{it}$. We also interact both variables with the merger dummies.

The regression results are reported in Table 11. In the first column of results, the coefficients on both of the interactions $MERGE * E_{t-2}[SCORE_t]$ and $MERGE * resid_t$ are positive and significant (with point estimates of 0.113 and 0.011, respectively), indicating that a merger not only leads to increased acquisition of new information, but also leads to better use of existing information.

In the second set of results reported in Table 11 we break down the merger effects into those which occur to the $BIDDER$ firms, the $TARGET$ firms, and 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 (increased acquisition of new information and better use of existing information). Moreover, in the $E_{t-2}[SCORE_t]$ interactions, the BIDDER effect exceeds the TARGET effect (0.115 vs 0.047), while the reverse is true 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 the new information acquisition effect is predominant for customers of the acquired banks. In contrast, for the $BIDTAR$ firms, neither interaction is significantly different from zero, in line with the results of the previous subsection.

7 Concluding remarks

In this paper, we have documented evidence in favor of the hypothesis that an important effect of bank mergers is to improve banks' abilities to screen lenders. Consistently with the information hypothesis, we find that merged banks exhibit a closer correspondence between the price of loans and the 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

values.

increase interest rates after the merger. We attribute these effects to improvements in information processing rather than explicit information pooling between the merging parties. Additional results suggest an asymmetry in the information improvements between the acquiring and acquired banks: while acquired banks improve by making better use of existing information, acquiring banks become more adept at both using existing information as well as gaining new information.

Our results carry important implications for the controversy on the welfare redistributions associated with consolidations. The 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 may affect different categories of customers in different ways and increase the variance of market prices: even if some customers benefit from the consolidation, others could be harmed by the merger. Moreover, if consolidation leads to a 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 also in other markets, implies new challenges for the antitrust authorities, because it excludes the possibility of using Paretian criteria to assess the welfare effects of mergers.

A Sample construction: details

We restrict our attention to short term credit lines, which have features which are ideal for our analysis. First, the bank can change the interest rate on the loan at any point in time; the borrower, in turn, 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 pricing 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 Central Credit Register are homogeneous products, 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.

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 by another bank. Note that a bank could actually be both a bidder and a target, if it acquired another bank before being acquired itself during the sample period. The bidder banks are larger than average (the median size is 9,049 million euros and the number of employees is 2,789). 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, except that they are smaller (the 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 these effects into those arising from explicit information pooling among the merging banks, and those which arise 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, the leverage is higher 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 utilized credit exceeds credit granted) increases from 4 percent for safe firms to 31 percent for risky firms. A consistent pattern emerges for the interest rates, that range from 13.2 percent for companies with low credit risk to 14.7 percent for the firms in 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 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 of the observations refer to companies borrowing from the target banks, and 0.7 percent to companies borrowing from both merger parties (the bidder *and* the target banks). Hence, just more than half of the observations refer to firms which do not borrow from a bank which merges during our sample period.

B Results from auxiliary regressions

In this section, we consider results from auxiliary regressions to verify the interpretational assumption maintained in this paper 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 *a priori* classify as having better information or information processing ability, and those banks which have worse information. If our assumption is valid, banks which are better informed should have a steeper interest rate curve.

We consider two proxies of a bank's informedness. One is the length 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 long-term 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.[27] We estimate Eq. (2), 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 coefficients of the SCORE is also positive and significant, as expected.[28]

Our second proxy is the amount of expenditure in computer software per employee, a standard indicator of a bank's information processing capabilities. As in the previous case, we estimate equation (2) 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 which also affect the loan rates. But as we do not seek causal effects here, rather just a descriptive measure of how the 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.

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

[28] 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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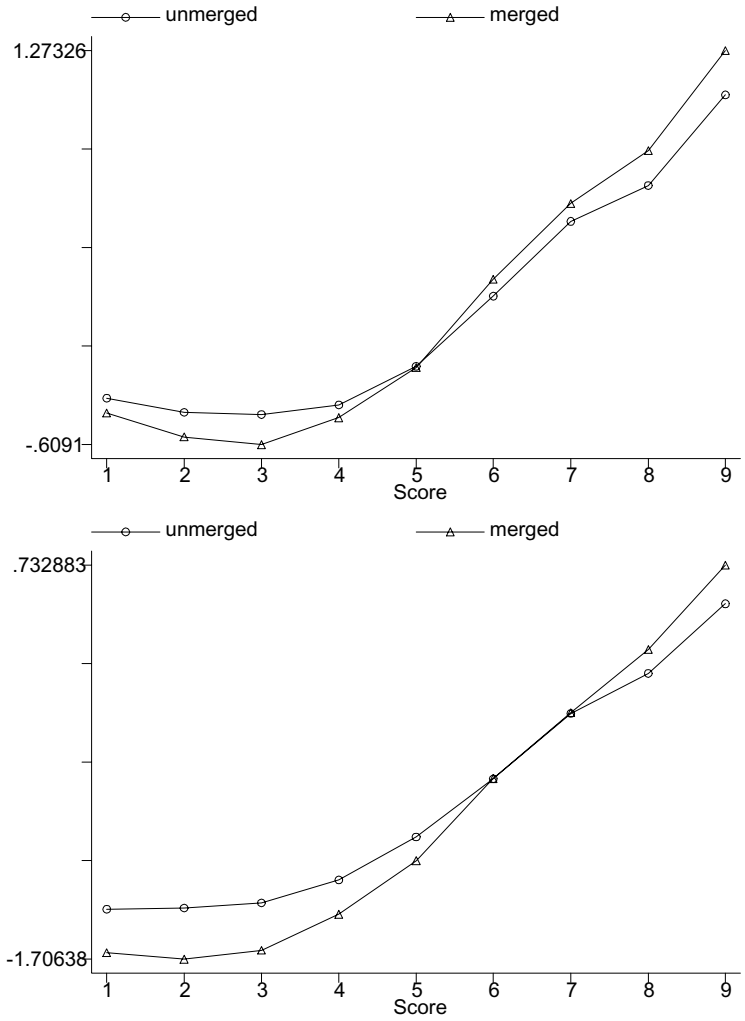
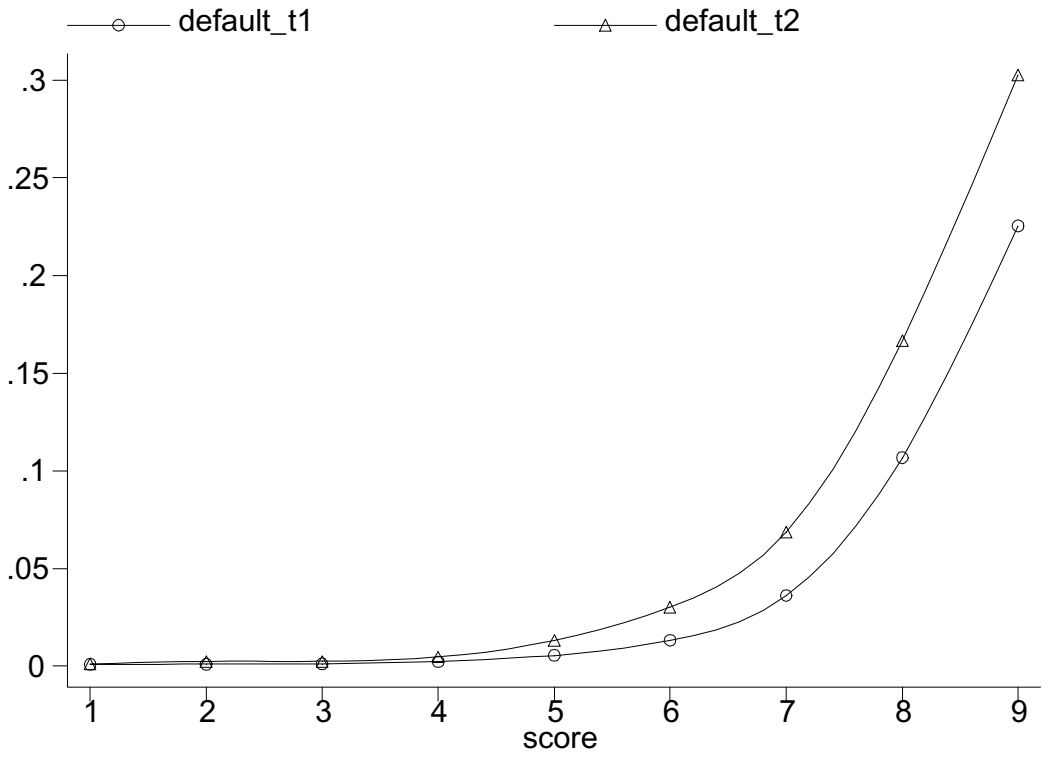
Figure 1: The relationship between interest rates and default risks: merged vs. unmerged banks



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

Figure 2: Does SCORE predict actual default accurately?



Each observation corresponds to a given firm j in year t. Each bar gives the percentage of (firm-year) observations with a given SCORE for which the firm defaulted during or after year t. For a given value of $SCORE_{jt}$, *default_t1* denotes the event of defaulting within years t or $t+1$, and *default_t2* denotes the event of defaulting within years t, $t+1$, and $t+2$.

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.	5^{th} pctile	Median	95^{th} 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.	5^{th}pctile	Median	95^{th}pctile
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). Percentage of loan market is the ratio between the loans of the reporting banks and total banking industry loans. 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.	5thpctile	Median	95thpctile
			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
			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
			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
			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)	.0123	***				
	(.0001)					
SCORE(t-2)			.0113	***	.0086	***
			(.0001)		*(.0001)*	
RESID(t)					.0097	***
					(.0002)	
No. of Observations	342,231		288,350		287,636	
Pseudo R-Square	15.10		8.59		16.62	

Table 6

Effect of M&As on Banks' Information

In Panel A we report the results of estimating equation (2) of the paper. In Panel B we report the results of estimating equation (2) of the paper using firm- and bank-specific fixed effects. 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 Mergers on Information: Long vs. Short Bank-Firm Relations

In Panel A we report the results of estimating equation (2) 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. 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)*	
Firm Controls:			
Size (log value)	-0.013 ***	-0.007	0.450
	(0.004)	*(0.007)*	
Return on Sales	0.077	-0.189 ***	0.002 ***
	(0.051)	*(0.072)*	
Leverage	0.171 ***	0.228 ***	0.160
	(0.024)	*(0.034)*	
Bank Controls:			
Size (log value)	-.0710 ***	0.069 ***	0.000 ***
	(0.014)	*(0.018)*	
Cost-Income ratio	3.155 ***	2.543 ***	0.000 ***
	(0.067)	*(0.092)*	
Market Concentration	2.302 ***	2.417 ***	0.826
	(0.381)	*(0.398)*	
No. of Observations	669,877	391,908	
R-Square	59.3	63.8	

Effect of Mergers on Information: Important vs. Fringe Banks

In Panel A we report the results of estimating equation (2) 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%. 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)*	
Firm Controls:			
Size (log value)	-.019 ***	-.038 ***	0.045 **
	(.005)	*(.010)*	
Return on Sales	.023	-.106 **	0.097 *
	(.065)	*(.053)*	
Leverage	.263 ***	.123 ***	0.000 ***
	(.030)	*(.026)*	
Bank Controls:			
Size (log value)	-.117 ***	-.140 ***	0.315
	(.015)	*(.017)*	
Cost-Income ratio	2.509 ***	2.648 ***	0.211
	(.071)	*(.086)*	
Market concentration	1.552 ***	1.890 ***	0.488
	(.395)	*(.351)*	
No. of Observations	607,285	385,615	
R-Square	58.4	70.9	

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

In Panel A we report the results of estimating equation (2) 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 (2) 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 (2) 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). 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)*
Firm Controls:		
Size (log value)	-.016 ***	-.020 ***
	(.004)	*(.004)*
Return on Sales	-.036	.070
	(.045)	*(.048)*
Leverage	.188 ***	.212 ***
	(.021)	*(.023)*
Bank Controls:		
Size (log value)	.036 ***	.211 ***
	(.012)	*(.014)*
Cost-Income ratio	3.008 ***	2.355 ***
	(.056)	*(.059)*
Market Concentration	2.071 ***	*2.615* ***
	(.288)	*(.368)*
No. of Observations	891,449	815,865
R-Square	59.3	58.1

Table 10

Whence Informational Improvements: Information Pooling

In Panel A we report the results of estimating equation (3) of the paper. In Panel B we report the results of estimating equation (3) of the paper using using firm- and bank-specific fixed effects. 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)*
Firm Controls:		
Size (log value)	-.018 ***	-.019 ***
	(.004)	*(.004)*
Return on Sales	-.002	-.006
	(.043)	*(.042)*
Leverage	.192 ***	.187 ***
	(.020)	*(.020)*
Bank Controls:		
Size (log value)	-.032 **	.003
	(.010)	*(.048)*
Cost-Income ratio	2.970 ***	.013
	(.053)	*(.088)*
Market Concentration	1.938 ***	1.747 ***
	(.271)	*(.270)*
No. of Observations	1,061,785	1,061,785
R-Square	58.4	60.0

Table 11

Distinguishing between Existing and New Information

In Panel A we report the results of estimating eq. (2) 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. (3) by using the same variables as regressors. 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)	
Firm Controls:				
Size (log value)	-0.019	***	-0.019	***
	(0.005)		*(0.005)*	
Return on Sales	-0. 029		-0.026	
	(0.047)		*(0.047)*	
Leverage	0.094	***	0.095	***
	(0.022)		*(0.022)*	
Bank Controls:				
Size (log value)	-0.020	*	-0.008	
	(0.011)		*(0.011)*	
Cost-Income ratio	2.984	***	2.962	***
	(0.055)		*(0.055)*	
Market Concentration	1.803	***	1.793	***
	(0.288)		*(0.288)*	
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 (1) 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)
Firm Controls:		
Size (log value)	-.005	-.010 ***
	(.004)	*(.004)*
Return on Sales	-.073	-.060
	(.048)	*(.044)*
Leverage	.170 ***	.183 ***
	(.021)	*(.020)*
Bank Controls:		
Size (log value)	.034 ***	.036 ***
	(.012)	*(.011)*
Cost-Income ratio	2.459 ***	2.653 ***
	(.065)	*(.058)*
Market concentration	2.549 ***	2.575 ***
	(.284)	*(.274)*
No. of Observations	811,945	965,696
R-Square	61.5	60.6