An Unexpected Crisis? Looking at Pricing Effectiveness of Heterogeneous Banks

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Credit quality of loans to Italian firms dramatically worsened during the cyclical downturn of 2008–09, compared with the previous period of growth (2006–07). This paper shows that, if credit quality transition matrices (i.e. the change in the actual firms' riskiness, gauged ex post) are mapped to interest rates (i.e. the conditions applied ex ante to the credit), banks appear to have been able at calibrating required risk premiums to actual firms' idiosyncratic risk, both during expansion and recession. However, the uncertainty generated by the crisis emphasized the unexpected component of credit worsening, thus making evident flaws in pricing effectiveness. Moreover, banks' organizational features did matter in driving the pricing effectiveness: the main finding is that larger banking groups were more affected than smaller ones by the sudden deterioration of credit quality, which was poorly reflected in their risk pricing on the eve of the crisis. The bank-size effect can be tackled through an efficient use of hard or soft information: both the banks using quantitative credit rating models and highly decentralized banks showed an above-average ability in calibrating rates to upcoming risk, suggesting that a clear-cut adoption of a consistent lending technique outperforms more ambiguous strategies; banks with a strong relationship with borrowers smoothed the risk–price curve in normal times.

(J.E.L.: G01, G21, E43, E32).

1. Introduction[1]

This paper addresses the question of which banks were more affected by the sudden deterioration of credit quality at the peak of a financial crisis (2008–09), as reflected in their ability to correctly price risk.

In order to answer this question, I compute the matrix of transitions across credit quality status for bank loans to Italian firms with reference to two distinct periods, before the crisis (2006–07) and a 'crisis' period (2008–09), and therefore use the inception of the crisis in 2008–09 as a natural experiment to gauge pricing effectiveness.

The focus of the paper is on the correspondence between the actual transitions in credit quality and the rates charged by banks to firms: risk pricing models state that interest rates should incorporate a risk premium, or spread, based upon the transition matrix estimated *ex ante* by the price setter. A weak correspondence signals that the actual riskiness of debtors has been assessed *ex ante* with poor accuracy. We can, therefore, detect for which banks credit deterioration had a larger unexpected component by looking at modifications in the link between interest rates and transitions in a untroubled period and in a period where, just after the price-setting, an unprecedented crisis occurred.

Two strands of literature are relevant to the present analysis. First, the effects of a crisis on rating migration patterns matter, as obligors' transitions between ratings are a key building block of credit risk models. A transition matrix characterizes the frequency or probability with which debtors within a portfolio shift across different credit qualities over a time horizon. It has been shown that the current regime of the economy or cross-section factors, such as the size, industry or location of the obligors, can affect these probabilities (Altman, 1998; Nickell *et al.* 2000; Bangia *et al.* 2002; Lando and Skodeberg, 2002). In particular, the impact of the business cycle suggests hypothesizing time nonhomogeneity, therefore, distinguishing between 'expansion matrices' and 'recession matrices'. The correct estimation of these conditional matrices can modify the assessment of the amount of capital that financial institutions should post against their credit risk (Jafry and Schuermann, 2004). Allowing for conditional migration frequencies leads to a measure of the increase in uncertainty driven by an upsurge in unexpected losses for banks during a recession (Bangia *et al.* 2002). Estimates of the Value at Risk (VaR) of a credit portfolio can change in a nontrivial way (25 to 30 per cent) if the matrix is computed under time nonhomogeneity. Kashyap and Stein (2004) show that capital requirements relating to a portfolio of credits can change following the cycle, and the size of this change depends on the method used to assess credit risk. Some credit risk assessment models explicitly assume that both transition probabilities and their correlations evolve over time (Nickell *et al.* 2000).

The importance of a correct estimation of credit migration matrices also stems from the fact that banks' interest rates should be consistent with the estimated transitions of debtors, according to risk pricing models (Jarrow *et al.* 1997). This leads us to the second strand of the literature, dealing with a specific microeconomic research topic which is at the core of this paper. It addresses the characteristics of the banks for which the link between *ex ante* rates and actual *ex post* debtors' riskiness has blurred to a greater extent owing

to the crisis. This issue will be investigated having regard to two dimensions: bank size and the use of different types of information (hard and soft).

As far as size is concerned, the diversification advantage of large portfolios vanishes when correlations between defaults rise to a significant degree (Amato and Remolona, 2005). Risk management systems tend to under-rate the increase in correlations. At times of a severe regime change, credit pricing in outsized portfolios might result *ex post* more inefficient, as it relies on lower-than-realised default correlations. Hence, the surprise effect (measured through rates) would be larger for larger banks. Furthermore, larger banks that in recent years extended their business might have suffered the winner's curse of entrants into new markets, which lowers their pricing effectiveness (Shaffer, 1997; Bofondi and Gobbi, 2004; Gobbi and Lotti, 2004; Hauswald and Marquez, 2006).

A look into the 'black box' of bank size is needed to disentangle the specific contribution of other factors to price effectiveness. First, the effects of the adoption of rating systems on the cost of credit are ambiguous (Berger *et al*. 2002). The use of quantitative methods could allow banks to extend credit availability to risky businesses (marginal borrowers). The overall portfolio riskiness would not necessarily rise, however, if the idiosyncratic risk of single debtors is identified with greater accuracy. Nor is a clear-cut hypothesis possible with respect to average rates. Rates could become unable to account for *ex post* losses, e.g. if the bank uses ratings mainly for granting credit rather than for pricing it. In general, strong reliance on hard information, which is typically lagged (e.g. for balance-sheet data), and low reliance on soft information might jeopardize timely identification of credit cycle changes (Berger *et al*. 2005).

Against this background, organizational arrangements could provide incentives to the bank structure to collect relevant information. In particular, broader delegation to loan officers would make them more willing to gather and process nontransmittable soft information, which in turn might influence the effectiveness of credit pricing (Stein, 2002).

Finally, the intensity of bank-borrower relationships also matters in that it allows information accumulation and hence more accurate pricing. At the same time, stronger relationships also allow room for strategic pricing on the part of the bank: a bank relying on a strong and long-lasting relationship might find it convenient to smooth interest rates with respect to the (change in the) borrower's riskiness (Petersen and Rajan, 1995; Machauer and Weber, 1998). This could lead the main bank of a firm to display a relatively weak correspondence between rates and riskiness, especially during turmoil.

2. Transition Matrices of Bank Loans to Firms and Loan Pricing

The crisis which erupted after the Lehman collapse in 2008 resulted in a deterioration of credit quality for Italian banks which was not homogeneous across banking groups of different dimensions (Table 1).

Table 1: Italian Banking Groups: Credit Quality (1) (Shares of Total Credit to Customers; Per Cent; 2005–2009)

	2005	2006	2007	2008	2009
Total banking groups (2)					
Fully regular (a)	93.8	94.9	95.4	93.5	90.9
Impaired (b)	6.2	5.1	4.6	6.5	9.1
Past-due and overdraft	*0.7*	*0.4*	*0.4*	*0.5*	*0.8*
Restructured	*0.2*	*0.3*	*0.1*	*0.2*	*0.6*
Sub-standard	*1.9*	*1.1*	*1.1*	*2.0*	*3.0*
Nonperforming	*3.4*	*3.2*	*3.0*	*3.8*	*4.7*
Total credit to customers (a + b)	100	100	100	100	100
Of which: major banking groups (3)					
Fully regular (a)	93.5	94.9	95.2	93.2	90.1
Impaired (b)	6.5	5.1	4.8	6.8	9.9
Past-due and overdraft	*0.7*	*0.4*	*0.3*	*0.5*	*0.7*
Restructured	*0.1*	*0.4*	*0.2*	*0.2*	*0.7*
Sub-standard	*2.2*	*1.1*	*1.1*	*2.1*	*3.3*
Nonperforming	*3.5*	*3.3*	*3.2*	*4.1*	*5.2*
Total credit to customers (a + b)	100	100	100	100	100

Source: Bank of Italy, Annual report, various years.
(1) Data retrieved from supervisory statistical reports. They are not perfectly comparable with Credit Register (CR) data reported in other tables. The rows in italics are breakdowns of the previous row.
(2) Includes Italian groups which are subsidiaries of foreign banks.
(3) Top five groups for total assets at the end of the reference year.

Firm-level data in the Italian Credit Register database (*Centrale dei Rischi*, CR) can be used to fill a matrix of the frequencies at which bank loans shift through different states of impairment. The sample covers all the bank-firm relationships in the database, about three million observations. The frequencies are based on conditional transition matrices, i.e. referring to two biennial periods, 2006–07 and 2008–09 (Bangia *et al.* 2002). The method adopted implements a cohort approach, which is common in matrix computation (see Appendix A)[2].

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[2]Lando and Skodeberg (2002). The cohort approach takes into account the situation of debtors at the start and the end of the period, disregarding transitions to other states during the period; moreover, statistical issues such as (right) censoring and (left) truncation are overlooked. This leads to a misalignment in transition estimates compared with sounder statistical methods, based on survival analysis. However, misalignment between different methods does not seem to be systematic, since within the same portfolio over- and under-estimations can be found simultaneously for different classes. Matrix frequencies should in principle be monotonically decreasing moving away from the diagonal. Violations of monotonicity are often found, however, and might depend on the effect of infra-period transitions within the relevant horizon, i.e. over a shorter period than the reference horizon for the estimation of the final transition (Bangia *et al*. 2002).

Table 2: Transition Matrix Between Situations of Impairment for Loans to Italian Firms (1) (Period 31 December 2007–09 and 2005–07; Percentage Frequencies)

State of the loan at the initial date of the reference period	State of the loan at the final date of the reference period							
	Fully regular	Overdraft	Past-due <180 days	Past-due >180 days	Sub-standard	Nonperforming	Loss	N. loans (000)
Panel a: 'Recession' matrix (31 December 2007–31 December 2009)								
Fully regular	79.5	14.2	1.4	1.2	2.1	1.4	0.2	962.4
Overdraft	43.1	35.3	3.4	3.3	8.0	6.0	0.9	267.4
Past-due <180 days	32.7	25.0	5.8	6.8	16.0	12.4	1.4	20.5
Past-due >180 days	30.1	19.7	4.2	10.9	19.5	14.2	1.3	19.6
Sub-standard	7.4	6.5	1.2	1.6	41.3	37.5	4.4	24.6
Nonperforming	0.1				0.1	94.7	5.1	256.0
Loss						10.4	89.6	82.1
Panel b: 'Expansion' matrix (31 December 2005–31 December 2007)								
Fully regular	81.1	15.1	1.1	1.0	0.8	0.8	0.1	847.4
Overdraft	47.0	38.5	2.9	2.9	3.8	4.0	0.8	249.6
Past-due <180 days	35.5	31.5	5.6	7.7	8.7	9.3	1.6	20.8
Past-due >180 days	30.6	25.2	4.7	12.3	12.4	12.6	2.2	24.9
Sub-standard	8.1	7.9	1.2	1.7	31.6	41.0	8.4	22.6
Nonperforming						88.1	11.8	271.9
Loss						1.0	99.0	74.7

Source: Central Credit Register. See Appendix A.

(1) Entries in the matrix represent the percentage frequencies at which bank–firm relationships, recorded in the state shown in the first column at the start of the reference period, moved towards the situation shown in the subsequent columns at the end of the following 24 months. Frequencies are reported as a percentage of the number of the bank–firm relationships in the sample belonging to the relevant initial state; they sum up to 1 by row. Values below 0.1 are not reported. Entries in bold for the 2007–09 matrix are statistically different from the corresponding entry in the 2005–07 matrix (at the 1 per cent confidence level). To perform these tests, I calculate *t*-statistics equal to the difference between corresponding entries in the first sample (2007–09) and the second sample (2005–07) transition probabilities divided by standard errors for the first sample estimate. The calculation is therefore conditional on the first sample probabilities. Standard errors are calculated under the simplifying assumption that rating transitions are temporally and cross-sectionally independent (Nickell *et al.* 2000). The last column (in italics) is a memo item showing the number of loans to which each row refers, in € thousands.

Table 2 presents transition matrices for bank loans to Italian firms. The distinction between expansion and recession matrices surfaces unambiguously. The bold figures in the 2008–09 matrix highlight entries which are statistically different from corresponding entries in the 2006–07 matrix (at the 1 per cent level). While frequencies in these matrices refer to the number of bank–firm relationships, matrices referring to the amount of bank credit exhibit very similar patterns (Table B.1 in the statistical Appendix)[3].

Matrices can be compared through summary indicators (see Appendix A). A mobility index documents the speed of changes in credit quality, while a net deterioration index shows how much of this mobility is due to credit worsening. Figure 1, panel a, shows that credit quality mobility increased by about 12 percentage points between 2006–07 and 2008–09; this figure provides a quantitative estimate of the increase in uncertainty facing the banking business following the onset of the crisis. At the same time, the net deterioration index worsened from −6.0 to −7.4 per cent.

It is possible to quantify changes in matrices through distance metrics. Figure 1, panel b, displays distance metrics between recession and expansion matrices, ranging from 2.5 to 6, depending on the specific segments of obligors. Transitions are more affected by business cycles for small firms, which therefore, according to this evidence, seem to have been hit harder by the downturn (Hancock and Wilcox, 1998). The matrices are also quite different across country areas, with major changes for companies in the Centre and South and for banks featuring different characteristics (Figure B.1)[4].

According to credit risk models, credit pricing should mirror the expected transition matrix. Banks should calibrate risk premiums charged to customers according to the *ex ante* likelihood that the relationship move to a different impairment situation[5]. As a consequence, the transition matrix makes it possible to gauge how consistently Italian banks have applied this risk management principle. If riskiness has been correctly estimated, interest rates to customers belonging to different entries in transition matrices (*ex post*) should display a monotonic upward slope on each row (*ex ante*). The steeper this curve, the stronger will appear the discriminatory capacity of banks to set rates: in fact, a positively sloped interest rate curve

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[3]A main departure of credit amount-based matrices from headcount-based matrices relates to transitions from/to overdraft. This is due to the relative diffusion of minor overdraft situations and to the stricter definition of overdraft loans used in amount-based matrices. See Appendix A.

[4]In Figure B.1, Italian banks are also classified according to organizational features. The Bank of Italy conducted a survey on a very large sample of Italian banks, asking questions about organizational features such as use of credit rating/scoring systems, and importance of qualitative information or collateral in extending credit, etc. The survey was carried out in two waves, in 2007 and 2010. For details, see Albareto *et al*. (2008).

[5]Crouhy *et al*. (2000). According to Jarrow *et al*. (1997) risk premia should be proportional to the probability that corporate credit evolves towards the worst state (the 'absorption' state), starting from the situation at the reference date.
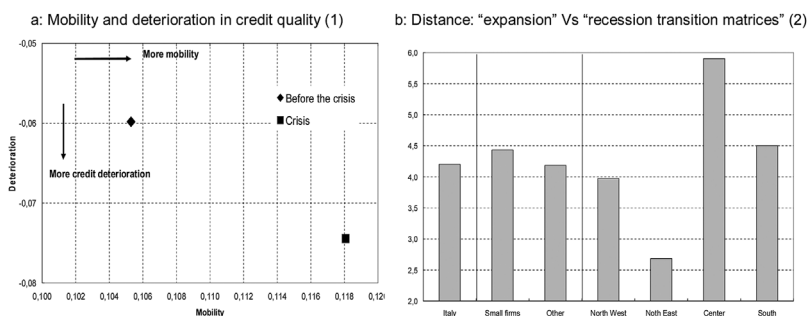
Figure 1: Mobility, Deterioration and the Distance Between Expansion and Recession Matrices (Indicator Values)

Source: Central Credit Register. See Appendix A. (1) The x-axis is a mobility index. The y-axis is a credit quality net deterioration/net improvement index, which ranges from -1 (maximum net deterioration) to $+1$ (maximum net improvement). See Appendix A. (2) The Euclidean distance L^2 between two matrices P_a and P_b is the square of the sum of the quadratic differences between each entry in matrix P_a and the corresponding entry in P_b, divided by N^2 (Jafry and Schuermann, 2004).

on the *ex post* matrix suggests, with hindsight, that the probabilities of credit worsening estimated *ex ante* and incorporated in rates closely mirrored the actual transitions.

The Bank of Italy's survey on interest rates covers a large sample of credits included in the CR database (see Appendix A), whose behaviour in terms of estimated transitions are very close to those displayed in Table 2. These data on interest rates can be used to look at the correspondence between credit transitions and pricing. Table 3 presents average rates charged at the initial reference dates (December 2007 and December 2005, respectively) on customers belonging to the entries of the transition matrices. In other words, Table 3 fills *ex ante* rates into the *ex post* matrices.

First, the rates distribution complies—to a large extent—with the implications of the risk models on correct credit pricing. In particular, the first row of the matrix, comprising loans which were fully regular at the starting date, displays a clear upward slope in connection with the situation of the credit relationship after 2 years. For instance, in December 2007 fully regular loans to firms which would have stayed regular in the subsequent 24 months paid an average of 7.11 per cent. At the same time, fully regular loans set to deteriorate to sub-standard paid 8.37 per cent, those heading towards nonperforming paid 9.01 per cent, and future losses paid 9.11 per cent (with a spread of 126, 190 and 200bp, in the order). The same pattern can be observed for end-2005 rates (panel b).

For loans which had already deteriorated before the start of the reference period, the curve does not always display a clear positive slope. This confirms that where probabilities of default and correlations are

Table 3: Interest Rates to Firms According to Firms' Transition Between Situations of (Non-) Impairment (1) (Period 31 December 2007–09 and 31 December 2005–07; Percentage Rates)

State of the loan at the initial date of the reference period	State of the loan at the final date of the reference period						
	Fully regular	Overdraft	Past-due <180 days	Past-due >180 days	Sub-standard	Nonperforming	Loss
Panel a: Interest rates relating to the 'Recession' matrix (December 2007 to December 2009)							
Fully regular	7.11	7.69	7.52	7.76	8.37	9.01	9.11
Overdraft	7.81	8.03	8.48	8.55	9.12	9.89	10.25
Past-due <180 days	8.19	8.44	8.66	8.38	9.45	9.98	10.82
Past-due >180 days	7.73	8.53	8.49	7.54	9.20	9.64	11.08
Sub-standard	9.27	10.47	10.25	9.86	9.20	10.20	10.17
Nonperforming					5.97	12.17	12.70
Loss						13.65	13.65
Panel b: Interest rates relating to the 'Expansion' matrix (December 2005 to December 2007)							
Fully regular	5.95	6.59	6.42	6.59	7.92	8.08	8.61
Overdraft	6.91	7.19	7.43	7.52	7.73	9.41	9.33
Past-due <180 days	6.66	8.24	7.74	7.38	8.61	10.23	10.21
Past-due >180 days	7.14	7.36	6.91	7.30	8.54	10.25	9.90
Sub-standard	7.49	8.43	6.09	8.49	8.54	9.64	9.68
Nonperforming	8.80	16.20			12.88	12.95	11.06
Loss					5.99	5.37	

Source: Central Credit Register and Bank of Italy's survey on interest rates. See Appendix A.
(1) Entries in the matrix represent the average interest rates on short-term credit charged by banks at the start of the relevant reference period to Italian firms which, from the state shown in the first column at the beginning of the reference period, would have moved towards the situation shown in the subsequent columns at the end of the following 24 months.
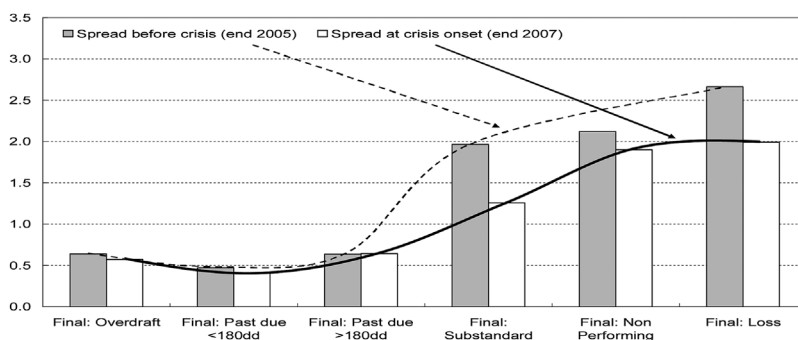
Figure 2: Discriminatory Capacity of Interest Rates before and after Crisis (1) (Per Cent)

Source: Central Credit Register. See Appendix A. (1) Spread between (a) average interest rates charged at the end of reference year to firms which would shift from a 'fully regular' situation to the state shown on the x-axis within the subsequent 24 months, and (b) average interest rate to firms which would stay in the 'fully regular' situation over the same period. The curves are simple graphic interpolations of the bars.

higher, estimating parameters for an appropriate assessment of credit risk is subject to greater uncertainty (Tarashev, 2009).

Table 3 shows the ability of banks to discriminate between obligors with different prospective riskiness in spite of a similar initial situation and confirms the banks' forward-looking approach. However, the main interest here is to understand how far this capacity was modified by the economic downturn. Figure 2 compares the end-2005 with the end-2007 curve of spreads and suggests that banks were actually surprised by the rapid deterioration in the financial situation of firms. A flatter risk-adjusted interest rate curve for end-2007 rates epitomizes the surprise effect triggered by a crisis whose progress was largely unforeseen, both in intensity and speed[6].

3. Econometric Analysis

Against the background of a widespread 'surprise effect' of the crisis discernible in interest rates (the vertical distance between the curves in

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[6]The actual unexpected component could be deemed to be even larger, taking into account the higher general level of rates at the end of 2007 compared with the end of 2005. Moreover, the unanticipated component caused by recorded deteriorations or unexpected losses on credits could be under-estimated in the light of the tendency to under-report losses in phases of banking system fragility. Another explanation for the correspondence between interest rates and transition might be self-fulfilling prophecies (i.e. the credit deterioration is driven by the high rates applied). However, the reduced correspondence rates/transitions after the crisis lends weak support to this interpretation, unless one assumes that after the crisis high rates were *less* able to push customer firms into credit default.

Figure 2), the econometric analysis will try to disentangle bank categories for which risk spreads were more affected by the ensuing crisis as regards their ability to account for the actual riskiness of loans, i.e. their possible transition to different impairment states. The baseline equation is as follows:

$$(1) \qquad s_{i,b,t} = f(Tr_{i,b,t}, X_b, Z_i, Crisis, [Tr_{i,b,t}*X_b*Crisis], [Tr_{i,b,t}*Z_i*Crisis])$$

In Equation (1), the dependent variable, $s_{i,b,t}$ is the rate applied by bank b to firm i at time t (t assumes two values, the crisis' eve and the untroubled period before the crisis). The rate is expressed as a spread with respect to the average rate applied to nonimpaired debtors that maintain the situation at the end of the period. Deducting the average rate applied to nonimpaired debtors clears the rate spread from the economy-wide impact of the crisis: the credit spread, in fact, can be decomposed into a systemic risk and an idiosyncratic risk component. The latter, which is partly driven by the impact of the crisis as well, allows us to gauge the 'surprise' effect to heterogeneous banks at the level of single borrowers.

Among the explanatory variables, $Tr_{i,b,t}$ are dummies for each possible transition between states of impairment for debtor i towards bank b in period t to $t + 24$ months (again, the benchmark case regards debtors that are regular at both the start and the end of the relevant period). In fact, the interest rate spread at t results from the combined effect of (a) the initial credit quality status of the loan and (b) the variation in loan quality in the subsequent (24 months) period. By controlling for the component (a), it is possible to disentangle the relationship between interest rate (spread) and the future loan performance (which is unknown to the bank at time t). The relationship does not suffer from endogeneity, since we control for the initial credit quality status of the loan (the spread at t should already account for the loan performance until t, i.e. for the credit quality of the loan at the beginning of the reference period), thus making the loan history prior to t irrelevant. X_b and Z_i are controls for bank and firm features, in the order. Some of these features are interacted with both the transition and the crisis dummies, between square brackets in Equation (1). These interactions are a major focus of the analysis in order to detect crisis-related changes in the relationship between *ex post* transitions and *ex ante* rates, i.e. to detect a possible weakening in the correct risk-price association. The bank features which are controlled for are size and proxies for the aptitude of banks to gather and employ hard or soft information. The firm features are size, industrial and institutional sector, incorporation technique (e.g. limited company), regional location, length of the firm's credit history, availability of some form of collateral and initial situation of the credit line (see

Appendix A). Tables B.2–B.5 report the results for different specifications of the general form of Equation (1)[7].

A few qualifications are needed before turning to the results. First, the interest rates we use for the econometric exercise are short-term rates on overdraft facilities, which are widely acknowledged to be the most suitable kind of rates in order to run comparisons across borrowers (see Berger and Udell, 1995, and Appendix A for details). Second, the lender's reaction to economic distress might well involve quantity tightening in addition to re-pricing. However, possibly reduced amounts of credit should in principle still be priced according to the estimated riskiness of the borrower; moreover, reducing credit lines *after* the crisis materializes is not a reason for mispricing risky loans *before* the crisis materializes: this leaves unaffected the research question of the econometric exercise, i.e. the banks' pricing effectiveness. Finally, the way the Italian banks price this type if credit lines (i.e. with frequent revisions of the applied rates) ensures that the observed rate takes into account (i) the general level of rates, driven by the general economic conditions; (ii) the past performance of the loan and (iii) the foreseeable credit quality performance. The model specification allows us to control for all these rate-drivers, in order to enuclate the unexpected component of the credit deterioration.

4. Results

4.1. Pricing Effectiveness and the Crisis

In Table B.2, the basic relationship is first estimated separately for the periods just before the crisis and the preceding untroubled biennium. The parameters of the regressions show that banks (i) do comply with the pricing rules suggested by the credit risk models (most transition dummies have statistically significant coefficients) and (ii) are able to foresee the future evolution of the quality of debtors. The coefficients of the transition dummies follow an upward slope across the matrix rows, often with nonoverlapping confidence intervals (Figure 3).

Credits which are already in a nonregular situation at the moment of pricing also command a premium, regardless of their final destination. This is the effect of the greater uncertainty surrounding unstable situations, which is also reflected in less significant coefficients in lower rows of the matrices (Tarashev, 2009). Finally, spreads are decreasing with firm size and if the credit line is assisted by collateral.

The previous remarks hold both before and during the crisis, confirming that banks largely maintained their pricing ability during the turmoil. However,

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[7]In principle, the econometric analysis could ask to what extent *ex ante* interest rates—as an independent variable—are able to predict future transitions via an ordered probit model, much in the vein of Nickell *et al.* (2000). However, such a setting would yield several effect estimates on every possible transition, whose interpretation would be complex for our purposes.
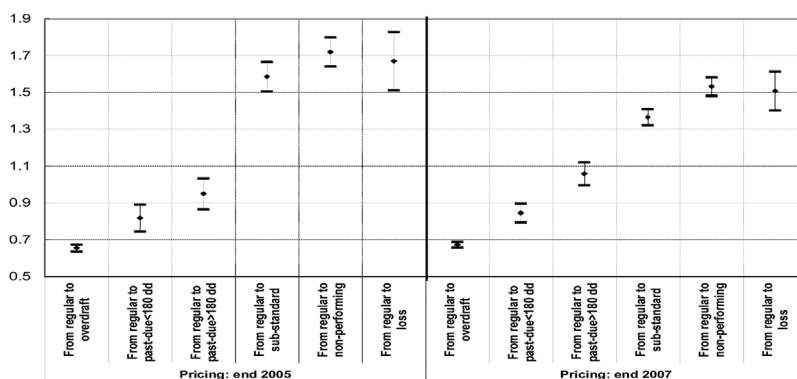
Figure 3: Estimated Risk-Related Interest Rate Spread before and after the Crisis (1)
(Percentage Points)

Source: Central Credit Register. See Appendix A. (1) Estimated coefficients for transition of credits from regular to impaired situations. Each coefficient gauges the spread of regular credits shifted to impaired situations with respect to the average rate applied to credit lines which were regular at both the beginning and the end of the relevant period. Estimation periods are end-2005 to end-2007 (before the crisis), end-2007 to -2009 (crisis). Vertical lines denote 5 per cent confidence intervals for estimated parameters.

some differences are noteworthy. First, during the crisis the fit of the estimation decreases, pointing to a weaker explanatory power of the credit transitions with respect to the applied interest rate. Second, the slope of the coefficient for worse transitions is milder during the crisis, again suggesting that banks were less sharp at calibrating rates to debtors' actual riskiness.

4.2. Major Banks Versus Other Banks

The regression in Table B.3 estimates Equation (1), the pivotal specification of this exercise, based on the whole sample. A dummy variable singles out banks belonging to the top five banking groups and is interacted with the crisis indicator. In 2007, the *ex ante* pricing accuracy of banks was reduced across the board by the ensuing crisis, with an average risk spread reduction of 13 basis points. However, the accuracy of larger banking groups was lessened by far more: the interaction between the dummy for the top five banking groups and the crisis has a coefficient of about −66 basis points, suggesting that bigger banks experienced a large *additional* decrease in pricing accuracy. Noticeably, the risk-related spread charged by major groups is apparently higher across the whole period (the top five groups' coefficient, not interacted with the crisis, is positive). Major banks experienced troubles in foretelling the future downturn, although their prices were more selective in the untroubled biennium.

   In order to shed light on the determinants of the larger unexpected component of credit deterioration for some banks, beyond bank group size, I will now try to disentangle the effect of the aptitude of banks to gather and employ information, either hard (i.e. codified) or soft (i.e. qualitative). To do so, additional regressions consider credit transitions interacted with a set of variables proxying bank features which could affect the ability to price risk, namely (i) the use of rating models (systematically exploiting hard information); (ii) the scope of delegation to loan officers (gathering soft information on-site) and (iii) the intensity of the bank–firm relationship (gathering soft information through interaction). The following sub-sections comment on the results of these specifications (Table B.4).

4.3. Gathering and Using Information (1): The Adoption of Rating Models by Banks

   In the first column of Table B.4 a dummy identifies banks which had already implemented quantitative rating models in 2007, i.e. before the crisis. The information is retrieved from the Bank of Italy survey on a large sample of banks (see Appendix A). Rating-users do not show a superior ability to price-discriminate for risk in normal times. However, on the eve of the crisis, banks using rating models show a smaller decrease in the slope of their risk-adjusted interest rate curve (the coefficient of the interaction for use of ratings and the ensuing crisis is positive).

   Albareto *et al.* (2008) find that some banks do not use rating models for pricing, but mainly for screening or monitoring borrowers. Table B.4, column 2, looks at banks which state that their rating models are 'important' or 'fundamental' in credit pricing. These banks do not display superior pricing effectiveness in normal times, but they are less affected by the surprise crisis than other banks. These findings suggest that the crisis magnified the informational improvements stemming from more intense use of hard information (see Panetta *et al.* 2009).

4.4. Gathering and Using Information (2): Delegation to Loan Officers

   Organizational diseconomies of scale can be tackled by banks through a larger autonomy granted to managers directly involved in the relationship with customers (Benvenuti *et al.* 2010). The Bank of Italy survey gauges the extent of this delegation, by means of an indicator of managers' relative autonomy, i.e. the ratio between (a) the maximum amount of credit a loan officer can grant and (b) the maximum amount the bank's CEO can grant. In column 3 of Table B.4, a dummy variable is equal to 1 if the scope of these delegated powers at the lending bank is above the median value of the sample.

The scope of delegation in normal times does not improve effective pricing of credit. However, when a crisis looms, highly decentralized banks seem to be less surprised by upcoming deterioration of their loans as their risk-adjusted interest rate curve stays more upward-sloping. The finding strengthens the soft information argument, as more empowered loan officers should be, in principle, more prone to gather noncodified information.

4.5. Gathering and Using Information (3): The Intensity of the Bank–Borrower Relationship

The last column in Table B.4 takes into account the strength of the bank–borrower relationship through the prominent role of the bank among lenders. The main bank dummy takes the value 1 if the bank extends the largest or only loan to the borrower. The main bank benefits from a stronger relationship with the firm and in principle is in a better position to acquire (soft) information about the intrinsic value of the business project. This would enhance its ability to calibrate rates to actual riskiness, even during turmoil. However, a stronger relationship often means a longer one, which could lead to interest rate smoothing along the life of the relationship, thus softening the reaction of rates to a changing credit situation of the borrower.

The results of the estimations shed light on these contrasting views. The dummy for the main bank is negative, which supports the idea that main lenders tend to smooth interest rates across the debtor's riskiness (Machauer and Weber, 1998). Consistently, when faced with a sudden turmoil, the decrease in the risk-related slope for main lenders is smaller, implying that the unexpected component of the credit deterioration is mitigated by the superior information provided by a stronger role of the bank among the firm's lenders.

Table 4 summarizes the main findings of the econometric analysis above.

Table 4: Main Results of the Econometric Analysis

	Slope of the risk-adjusted interest rate curve (1)	
	In untroubled period	On the eve of crisis
Larger banking groups	Steeper	Milder
Beyond bank size:		
Use of rating models	. . .	Steeper
Use of ratings for pricing	. . .	Steeper
High delegation (decentralization)	. . .	Steeper
Main bank	Milder	Steeper

Source: Econometric analysis. See figures in Appendix B.
(1) Slope of the risk-adjusted interest rate curve for the relevant category of bank, with respect to the average bank, according to econometric estimates reported in figures in Appendix B. Only statistically significant coefficients are reported.

4.6. Robustness Checks

In order to check for the robustness of the main findings, some alternative econometric exercises are run on the baseline specification (Table B.5).

First, an alternative explanation of the spread reduction during the crisis is investigated. A milder curve on the crisis' eve could stem not only from credit quality surprises, but also from other sources: during the crisis, some banks could have adopted heavier under-reporting of credit impairment than other banks. In order to check the under-reporting hypothesis, each bank–firm relationship has been assigned to the worst recorded status system-wide, regardless of which classification was reported by the specific lending bank.

Second, an endogeneity issue could arise: banks having some organizational features (e.g. small size or highly decentralized decisions) might select *ex ante* loans which are easier to price, e.g. because they pertain to segments of borrowers for which information is more crucial, such as smaller borrowers. In order to check for the endogeneity issue, model [1] has been run separately for larger and smaller firms.

Third, certain industries tend to react more to systemic shocks than others, which in turns affect both the level and the variation in their credit risk. As a consequence, variation across banks' pricing may be partly driven by differences in their portfolio composition across different types of industries, rather than by heterogeneity in their ability to price risk. To this end, we have interacted the industry sector of each firm with the crisis period, in order to allow for different impacts of the crisis on the firm's specific business area.

Moreover, the baseline regression was run using as dependent variable interest rates instead of spreads (in fact, according to model [1], the dependent variable in the baseline specification is spreads towards the average rate for the benchmark situation, i.e. the average rate charged to loans that are fully regular at both the start and the end of the period). The estimation was also run excluding fixed effects for banks and allowing for clustering of standard errors by firm, wherever a given firm accounts for multiple observations due to multiple-lending. Spreads outside the 5th and the 95th percentile were excluded, instead of only those beyond the 1st and 99th percentile. Further, some controls were omitted, which might overlap with other factors, such as guaranteed credits or banks' institutional category. Finally, base-line definitions were somewhat refined: impairment status was identified with regard to the credit amount in each impairment status, which entails a stricter definition of overdrafts (see Appendix A), and alternative reference periods were used, i.e. two 30-month periods, June 2008 to December 2010 (crisis) versus December 2005 to June 2008 (untroubled).

All these extensions, apart from an expected decrease in the overall fitting of the estimation, basically yield the same results for relevant parameters (see Table B.5).

5. Conclusions

This paper addresses the question of which banks were more affected by the sudden deterioration in credit quality during the crisis as was reflected by the ability of their (*ex ante*) rates to correctly price (*ex post*) risk. In order to answer this question, I begin by computing the credit quality transition matrices of bank loans to Italian firms, for the first time to my knowledge.

Matrices changed significantly between expansion and recession. Mobility and distance metrics provide a concrete yardstick of the increase in uncertainty faced by banks in their traditional business owing to the cyclical downturn. Second, banks have been remarkably able to calibrate interest rate spreads to the effective quality of credit as measured by the transition matrix. The discriminatory power of spreads remains unquestionable after the crisis surfaces, in spite of greater uncertainty.

The key result is that the crisis made the risk-related curve of rates applied to firms noticeably flatter, as the credit quality worsening often contradicted banks' *ex ante* credit risk assessments. The *unexpected* component of the credit worsening is sizeable and depends on the type of bank extending the credit. The unexpected downturn was more serious for the top five Italian groups, suggesting that the pricing effectiveness of banks is affected by the complexity of their governance. Interestingly, larger banks are more able, in general, to tailor *ex ante* spreads to the actual riskiness of their debtors. In other words, the blurring of their spread structure was the specific outcome of the surprise effect stemming from a rapid unfavourable development.

Looking beyond bank size, the more efficient use of hard information (quantitative rating models) improved pricing performance on the eve of downturn. The geographical or functional distance between decision hubs and local customers might have weakened the ability of some banks to spot the upcoming credit worsening just before the turmoil, and in fact decentralized banks suffered less of a surprise. These findings apparently suggest that the natural experiment provided by the crisis did not drive a wedge between hard information users and decentralized banks: instead, it can be inferred that either a systematic reliance on hard information or a full-fledged relationship lending strategy are both effective, whereas the lack of adoption of a well-defined lending technique leads to poorer pricing performances. Finally, the role of the bank–borrower relationship is two-sided: a stronger relationship with borrowers led reference banks (the main banks) to smooth the interest rates-risk relationship in normal times, which also stayed more stable as the downturn approached.

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Appendix A: Data and Methodology

A.1. Data

A.1.1. Computing the Matrices from the Italian Credit Register (CR) Data

Against the background of a conventional 12-month horizon for transition matrices, a 24-month period captures the specific dynamics of loan worsening in two stages, which can be labelled precrisis (or expansion) and crisis (or recession) situation.

In the matrix, single, nonnegative entries sum to 1 by row (right stochastic matrix). The diagonal represents the frequency of keeping the initial state; off-diagonal entries represent the frequency of transition from one state to another, with worsening on the right of the diagonal. The basic assumption behind the cohort approach is that, for a given sample, the probability of a transition from rating i to j is a constant parameter, p_{ij}: for a given initial state, transitions to different possible future states follow a constant parameter, temporally independent process. Estimation can then be performed by taking the fraction of occasions in the sample on which an obligor starts the year in state i and ends it in j (Nickell *et al*. 2000).

At the initial date of each reference period (i.e. end-2005 and -2007) a static pool of loans is defined, which are tracked until the end of the relevant

period. Transition matrices are computed from the cash credit lines from banks to firms recorded in the CR. Loans larger than 75,000€ are recorded (30,000€ from 1 January 2009). All the bank–firm relationships are included with actual credit usage above zero at both (i) the start of the reference period (end-2005, end-2007) and (ii) the end of the reference period (end-2007, end-2009). The state of the loan is observed at the start/end of the period, disregarding the state of the loan at intermediate dates. This entails the loss of a certain number of bank–firm relationships between the start and the end of each period, which therefore do not enter the matrix computation. A bank–firm relationship might be cancelled within a 24-month period due to (i) repayment; (ii) amount reduction below the CR threshold; and (iii) transition to loss and subsequent write-off. With regards to the credit quantities involved, the weight of the nonrecorded loans can be estimated at about 18.0 per cent of total initial credit in the two 24-month periods. Cancellations due to write-off (i.e. situation (iii) above) could cause under-estimation of the actual credit worsening. However, this portion should be minor because before write-off a credit is usually recorded in the nonperforming category, where the average stay is 54 months. In the reported matrices, loans classified in categories such as 'securitized', 'debt restructuring', 'other', etc, have been overlooked, because in these cases it is unclear how to rank the degree of impairment with respect to other states.

A.1.2. Matrices on the Number of Positions (Bank–Firm Relationships)

Frequencies are such that $f_{ij} = n_{ij}/n_i$, i.e. the frequency in each cell describing the transition from state i to state j is equal to the number of observations which displayed this migration at the end of the period, divided by the number of observations in the state i at the start of the period. When a credit line is simultaneously classified in different states of impairment, the worst impairment state has been deemed relevant. This approach could affect in particular the 'overdraft' classification, which refers to specific credit lines rather than to the overall bank-firm relationship: a given bank–firm relationship is classified as overdraft even if only a minor share of credit belongs to this state of impairment. In order to check for these possible distortions, estimations on credit amount-based matrices use a finer definition of overdraft credit (see Appendix A.1.3. below).

A.1.3. Matrices on the Amount of Granted and Used Credit

Frequencies have also been calculated having regard to loan amounts, attaching a size-weighted importance to each position. The total credit used within the bank–firm relationship at the reference date is assigned to the

worst reported state of impairment, provided that the amount of credit recorded in the relevant state of impairment is at least 10 per cent of the total used credit (30 per cent for overdraft). Frequencies in the table refer to the used credit amount at the initial reference date of each period.

A.1.4. Matrices on the Number of Positions Versus Credit Amounts

The base-line analysis in the paper refers to matrices calculated on the number of positions. Mobility and improvement/deterioration patterns are similar for matrices based on *numbers* of bank–firm relationships and on *quantities* of credit, suggesting that no major differences would emerge from using the latter in the descriptive or econometric analysis. Table A.1 reports the mobility index and the improvement/deterioration indices from the two estimation methods of the transition matrices.

Table A.1: Comparison Between Mobility and Deterioration Indices, Matrices Based on Number of Bank–Firm Relationships Versus Matrices Based on Quantity of Credit (1)

	Matrices based on numbers		Matrices based on quantities	
	2006–07	2008–09	2006–07	2008–09
Mobility index	10.5	11.8	9.1	13.0
Deterioration/improvement	−0.57	−0.63	−0.41	−0.75

(1) Indices are calculated collapsing fully regular loans with overdraft loans. See Appendix A for the method used to calculate the indices.

A.1.5. Definition of Absorbing States

Absorbing states are credit situations in which an improvement is probably not feasible. In a typical transition matrix, this is the *default* situation. In the CR classification, the absorbing state should be in principle the *loss* state. Please note that the *nonperforming* state also entails virtually no reversion as it is defined as credit '. . . towards debtors in a state of insolvency (although not judicially certified) or in substantially comparable situations' in the Bank of Italy's Annual Report. In fact, the CR database records some reversions from the loss state, i.e. bank-firm relationships which are recorded as loss at t and in a nonloss situation at $t + 1$. Such cases could occur as a result of (i) erroneous classifications of the firm situation (at t or $t + 1$); (ii) mergers between banks (e.g. bank a, recording debtor i as a loss at t, is merged into bank b at $t + 1$ and bank b might not record debtor i as a loss at $t + 1$ owing to previous relationships with the same debtor: since at each reference date the worst situation is accounted for, debtor i would

mark an 'improvement from loss' after the merger). The improvements from loss are purely erroneous or fictitious and hence there is no signal from their change between periods. The impact of these unusual transitions is negligible for the purpose of the paper: (i) they account for about 0.3 per cent of the recorded bank–firm relationships in both the periods; and (ii) none of these 'reverted' situations is used in the econometric estimation.

A.1.6. Survey Statistics on Interest Rates

Interest rates are retrieved from banks' survey reports to the Bank of Italy, which cover over 200 banks and a large share of loans to firms. Table A.2 displays the coverage of the interest rate survey with respect to the CR database: interest rates are calculated as the weighted average of simple rates, disregarding fees and commissions. Outlier rates are excluded (below the 1st and 99th percentile). In order to compute averages for end-2005 (end-2007) rates, debtors are classified according to their transition from end-2005 to -2007 (from end-2007 to -2009). Small businesses, or SMEs, are defined as firms with less than 20 employed units.

Table A.2: Average Coverage of Interest Rate Data on CR-Recorded Loans (1) (Per Cent)

	Period December 2005 to December 2007	Period December 2007 to December 2009
Overall	43.6	43.8
Of which: top 5 banking groups	*48.2*	*49.7*
SMEs	*37.5*	*37.8*
Other firms	*49.1*	*49.2*

Average coverage of interest rate data on CR-recorded loans (1)
(1) Percentage of bank–firm relationships for which interest rates on short-term bank credit are recorded in the interest rate survey at the initial date of the reference period (December 2005, December 2007) with respect to the corresponding number of bank–firm relationships recorded in the CR database and used to compute the transition matrix. The rows in italics are breakdowns of the first row.

The rates we use are applied to overdraft facilities (i.e. credit lines), as this form of short-term credit is apt to run comparisons across debtors. The economic conditions of the loan are regularly revised, thus ensuring that reported rates fully reflect the current credit quality of the loan and the general market conditions (i.e., the overdraft interest rate can be equated to a floating rate). The credit lines feature standard agreements and usually do not encompass special covenants, again increasing their comparability. Although the credit lines to which interest rates refer can belong to different vintages, the comparison among rates of different bank–firm couples does

not suffer from a vintage bias. In fact, we can assume that rates applied at a given date (end 2005, end 2007) fully reflect both past loan performance and the foreseeable credit quality transition. This allows comparison across bank-firm couples as if the loans had been *originated* at the same date.

A.1.7. *Survey on Organizational Features*

Organizational and lending technology variables are retrieved from the Bank of Italy survey carried out in early 2007 and early 2010 (Albareto *et al*. 2008).

A.2. *Mobility, Deterioration and Distance Indices for Matrices*

With respect to the tables in Section 2, mobility indices include some transitions which are not displayed ('restructured loans') because their ranking in terms of degree of deterioration is not univocally defined. Furthermore, slight deteriorations (overdraft) are collapsed with fully regular loans into an 'almost regular loans' category as small overdrafts are rather common in Italian bank–firm relationships.

The deterioration/improvement index ranges from 1 (maximum improvement) to -1 (maximum deterioration) and is calculated as follows:

$$(\text{Improvement} - \text{Deterioration})/(\text{Improvement} + \text{Deterioration} + \text{Stability})$$

where $\text{Improvement} = \Sigma_{i>j} (n_{ij})$, $\text{Deterioration} = \Sigma_{i<j} (n_{ij})$ and $\text{Stability} = \Sigma_{i=j} (n_{ij})$.

A distance metric between two matrices, PA and PB, is labelled L2 (Jafry and Schuermann, 2004): it averages root-mean-square differences between corresponding elements of the matrices:

$$(\text{A.1}) \qquad L^2(P_A, P_B) = \sqrt{\left(\Sigma\Sigma \left(P_{A,i,j} - P_{B,i,j} \right)^2 \right)}/N^2$$

A.3. *Econometric Analysis. Variables Description*

Dependent variable: spread. $-$ This is the difference between the short-term interest rate applied to any given bank–firm relationship in the sample and the average interest rate applied at the same date to fully regular loans which remained fully regular after 24 months within the same region as the relevant firm.

Transitions. $-$ Dummy variables, $= 1$ if the bank–firm relationship has recorded a shift between different credit impairments in the 24 months following the date the interest rate is recorded. Each dummy corresponds to

a given cell of the transition matrix (49 dummies, e.g. 'From fully regular to fully regular', 'From fully regular to overdraft', etc.).

Credit initial situation. − Dummy variables, = 1 if the bank–firm relationship starts the reference period in a given state of impairment (7 dummies, 'Fully regular', 'Overdraft', 'Past-due <180 days', 'Past-due >180 days', 'Sub-standard', 'Non-performing', 'Loss').

Crisis. Dummy variable, = 1 for period 2007–09 (interest rates recorded at end-2007, transitions recorded from end-2007 to -2009).

Top Five banking groups. − Dummy variable, = 1 if the bank belongs to the five largest Italian banking groups.

Firm size. − Logarithm, or square, of the size of bank credit recorded in the dataset of the interest rate survey, proxied by the computational numbers for interest rates charged by all banks to the relevant firm at the relevant date.

SMEs. − Dummy variable, = 1 for firms with a workforce <20 units.

Collateral. − Dummy variables, = 1 if the bank–firm relationship is assisted by collateral at the start or at the end of the relevant period (two dummies).

Firm's credit history length. − Dummy variables, = 1 if the firm has been recorded for the first time into the Italian Credit Register in the relevant year (13 dummies, <1995, 1996–2007).

Firm's institutional sector. − Dummy variables, = 1 if the firm belongs to the relevant institutional sector (16 dummies, e.g.: 'operational firms', 'holdings', 'pool of firms', etc.).

Firm's industry. − Dummy variables, = 1 if the firm operates in the relevant sector (192 dummies).

Firm's region. − Dummy variables, = 1 if the firm is located in the relevant Italian region (20 dummies).

Firm's incorporation technique. − Dummy variables, = 1 if the firm is incorporated according to the relevant scheme (5 dummies, e.g. 'limited company with equity capital', 'limited company', etc.).

Bank's category. − Dummy variables, = 1 if the bank belongs to the relevant institutional-dimensional group (3 dummies, 'Big, major and medium-sized banks', 'Small banks, not mutual (i.e. not Bcc)', 'Small, mutual banks (Bcc)').

Banks using rating models, using rating model for pricing, with high delegation. − Dummy variables, = 1 if, according to the Bank of Italy's survey (Albareto *et al.* 2008), banks used rating models for firms in 2007, or used rating models for pricing, or had an above-the-median relative delegation to the loan officer (amount of credit that the loan officer could grant to firms compared with the amount of credit that the CEO could grant).

Main bank. − Dummy variable, = 1 if the bank extended the largest amount of credit to the relevant firm at the initial date of the relevant period.

Appendix B: Tables and Figures

Table B.1: Transition Matrix (Credit Amounts) (1) (Period 31 December 2007–09 and 2005–07; Percentage Frequencies)

State of the loan at the initial date of the reference period	State of the loan at the final date of the reference period							Amount of loans (€ mn)
	Fully regular	Overdraft	Past-due <180 days	Past-due >180 days	Sub-standard	Nonperforming	Loss	
Panel a. 'Recession' matrix (December 2007 to December 2009)								
Fully regular	89.3	1.1	1.6	1.8	3.9	2.0	0.4	610,629.6
Overdraft	78.6	4.0	1.9	2.1	6.5	4.1	2.8	6,027.6
Past-due <180 days	57.8	1.1	5.4	5.8	16.7	12.4	0.7	7,342.3
Past-due >180 days	55.8	0.6	2.7	9.1	19.4	11.8	0.6	7,702.3
Sub-standard	14.1	0.3	0.8	1.2	40.7	39.2	3.7	9,571.5
Nonperforming	0.2	0.0	0.0	0.0	0.1	93.8	5.8	17,935.2
Loss	0.3	0.0	0.0	0.0	1.4	3.6	94.7	4,248.1
Panel b. 'Expansion' matrix (December 2005 to December 2007)								
Fully regular	93.7	1.3	1.2	1.3	1.4	1.0	0.2	492,580.3
Overdraft	83.2	7.3	1.3	2.0	2.7	2.9	0.5	5,953.6
Past-due <180 days	70.7	1.1	5.3	7.3	7.9	6.9	0.8	7,396.7
Past-due >180 days	61.3	1.0	3.8	12.3	12.5	8.7	0.5	10,036.6

Table B.1: Continued

State of the loan at the initial date of the reference period	State of the loan at the final date of the reference period							Amount of loans (€ mn)
	Fully regular	Overdraft	Past-due <180 days	Past-due >180 days	Sub-standard	Nonperforming	Loss	
Sub-standard	16.4	0.3	1.0	1.6	40.0	36.0	4.7	9,319.1
Nonperforming	0.3	0.1	0.0	0.0	0.2	92.1	7.2	19,161.7
Loss	0.4	0.0	0.0	0.0	0.0	8.6	90.9	8,222.2

Source: Central Credit Register. See Appendix A.
(1) Entries in the matrix represent the percentage frequencies at which the credit amounts relating to each bank–firm relationship recorded in the state shown in the first column at the start of the reference period moved towards the situation shown in the subsequent columns at the end of the following 24 months. Frequencies are reported as percentage of the number of bank–firm relationships in the sample belonging to the relevant initial state; they sum to 1 by row. Values below 0.1 are not reported.

Table B.2: Impact of the Crisis on Credit Risk Pricing (1) Dependent Variable: Interest Rate Spread towards Regular Loans at Start and End of the Relevant Period

Panel [1] Before the crisis (2005–07)

	1.	2.	3.	4.	5.	6.	7.
Transitions: (2)							
1. From regular loans		**0.66**	**0.82**	**0.95**	**1.59**	**1.72**	**1.67**
2. From overdraft	0.35	0.88	1.01	1.16	1.68	1.85	1.93
3. From past-due <180 days	**−0.71**	−0.12		−0.02	**0.64**	**0.79**	**0.84**
4. From past-due >180 days	**−0.57**	0.01		0.07	**0.84**	**1.07**	**1.34**
5. From sub-standard	**−0.39**	−0.03	−0.08		−0.18	0.19	0.24
6. From nonperforming							0.66
Initial credit situation:							
2. Overdraft	0.591						
3. Past-due <180 days	1.883***						
4. Past-due >180 days	1.850***						
5. Sub-standard	2.523***						
6. Nonperforming	1.954***						
Top five banking groups	0.411						
Firm size (log)	−0.192***						
Firm size (squared)	−0.002***						
Non-SMEs	0.084						
Collateral							
Start period	−0.047***						
End period	−0.063***						
Firm credit history length	Yes						
Firm institutional sector	Yes						
Firm industry	Yes						
Firm region	Yes						
Firm incorporation technique	Yes						
Bank category	Yes						
Bank fixed effects	Yes						
Constant	6.533***						
N. observations	596,717						
Adj. R-squared	0.29						

Panel [2] During the crisis (2007–09)

	1.	2.	3.	4.	5.	6.	7.
Transitions: (2)							
1. From regular loans		**0.67**	**0.85**	**1.06**	**1.37**	**1.53**	**1.51**
2. From overdraft	**−1.53**	**−0.99**	**−0.82**	**−0.70**	**−0.38**	**−0.17**	
3. From past-due <180 days	**−1.57**	**−1.10**	**−1.06**	**−0.93**	**−0.48**	−0.28	
4. From past-due >180 days	**−0.73**	**−0.24**		−0.09	**0.46**	**0.68**	**0.95**
5. From sub-standard	**−0.39**	−0.09		0.04	−0.15	0.21	0.32
6. From nonperforming						**5.73**	
Initial credit situation:							
2. Overdraft	2.482***						
3. Past-due <180 days	2.820***						
4. Past-due >180 days	1.961***						
5. Sub-standard	2.408***						
6. Nonperforming							

Table B.2: Continued

Top five banking groups	−1.353***
Firm size (log)	−0.055***
Firm size (squared)	−0.008***
Non-SMEs	0.103
Collateral	
Start period	−0.020
End period	−0.043***
Firm credit history length	Yes
Firm institutional sector	Yes
Firm industry	Yes
Firm region	Yes
Firm incorporation technique	Yes
Bank category	Yes
Bank fixed effects	Yes
Constant	4.499***
N. observations	682,246
Adj. *R*-squared	0.27

Source: estimation of regressions based on Equation (1) in Section 3.

(1) * = significant at 10 per cent; ** = significant at 5 per cent; *** = significant at 1 per cent. Missing values mean that the estimation is not possible for the relevant parameter. Interest rates outside the 1st or 99th percentile are dropped.

(2) The reported coefficients refer to the spread of loans shifting from the situation in the first column to the situations in the subsequent columns, labelled as follows: 1. regular 2. overdraft, 3. past-due <180 days, 4. past-due >180 days, 5. sub-standard, 6. nonperforming, 7. loss. Figures in bold denote parameters statistically significant at least at the 1 or 5 per cent level.

Table B.3: Impact of the Crisis on Credit Risk Pricing: Top Five Groups (1) Dependent Variable: Interest Rate Spread Towards Regular Loans at Start and End of the Period

	1.	2.	3.	4.	5.	6.	7.
Transitions, basis spread: (2)							
1. From regular loans		**0.67**	**0.82**	**0.99**	**1.43**	**1.56**	**1.44**
2. From overdraft	**−1.47**	**−0.94**	**−0.79**	**−0.66**	**−0.23**	−0.05	
3. From past-due <180 days	**−0.58**	−0.06		0.05	**0.61**	**0.81**	**0.88**
4. From past-due >180 days	0.73	1.28	1.33	1.32	2.01	2.21	2.53
5. From sub-standard	1.40	1.81	1.85	1.92	1.70	2.01	2.00
6. From nonperforming							0.23
Unexpected worsening for top five groups: (2) (3)							
1. From regular loans		0.04	0.07	**0.19**	−0.03	0.08	**0.40**
2. From overdraft	**−0.04**	**0.06**	0.08	**0.22**	**−0.10**	−0.04	0.30
3. From past-due <180 days	−0.09	0.00	0.24	0.21	−0.03	−0.05	0.47
4. From past-due >180 days	−0.05	−0.06	0.22	**0.41**	−0.06	0.03	0.06
5. From sub-standard	−0.01	**−0.33**	−0.45	−0.54	**−0.32**	**−0.17**	**0.29**
6. From nonperforming						**3.49**	
Initial credit situation:							
2. Overdraft	2.42***						
3. Past-due <180 days	1.79***						

Table B.3: Continued

	1.	2.	3.	4.	5.	6.	7.
4. Past-due >180 days	0.54						
5. Sub-standard	0.67						
6. Nonperforming	2.20***						
Top five banking groups	0.396***						
Crisis	−0.133***						
Top5 banking groups*Crisis	−0.658***						
Firm size (log)	−0.127***						
Firm size (squared)	−0.005***						
Non-SMEs	0.162***						
Non-SMEs*Crisis	−0.052***						
Collateral							
Start period	−0.039***						
End period	−0.038***						
Firm credit history length	Yes						
Firm institutional sector	Yes						
Firm industry	Yes						
Firm region	Yes						
Firm incorporation technique	Yes						
Bank category	YES						
Bank fixed effects	Yes						
Constant	5.598***						
N. observations	1,278,963						
Adj. R-squared	0.27						

Source: Estimation of regressions based on Equation (1) in Section 3.

(1) * = significant at 10 per cent; ** = significant at 5 per cent; *** = significant at 1 per cent. Missing values mean that the estimation is not possible for the relevant parameter. Interest rates outside the 1st or 99th percentile are dropped.

(2) The reported coefficients refer to the spread of loans shifting from the situation in the first column to the situations in the subsequent columns, labelled as follows: 1. regular 2. overdraft, 3. past-due <180 days, 4. past-due >180 days, 5. sub-standard, 6. nonperforming, 7. loss. Figures in bold denote parameters statistically significant at least at the 1 or 5 per cent level.

(3) The coefficients estimate the interaction of the transition dummies * top five groups * Crisis, and gauge the differential unexpected component of the credit worsening, as reflected in credit risk pricing efficiency, for the top five groups.

Table B.4: Impact of the Crisis on Credit Risk Pricing: Beyond the Size Effect (1) Dependent Variable: Interest Rate Spread towards Regular Loans at Start and End of the Relevant Period

	[1] Use of rating	[2] Use of rating for pricing	[3] Delegation to loan officer	[4] Main bank
Credit transitions	Yes	Yes	Yes	Yes
Transitions*bank feature*crisis	Yes	Yes	Yes	Yes
Initial credit situation:				
2. Overdraft	2.490***	2.515***	1.845***	2.476***
3. Past-due <180 days	1.894***	1.834***	2.800***	1.882***
4. Past-due >180 days	0.523	0.519	3.086***	0.532
5. Sub-standard	0.894	0.858	2.495***	0.891
6. Nonperforming	2.212***	2.190***	4.001***	3.949***
Top five banking groups	0.406***	0.368***	0.394***	0.389***
Crisis	−0.221***	−0.151***	−0.067***	−0.203***
Top 5 banking groups*Crisis	−0.667***	−0.647***	−0.733***	−0.637***
Use of rating models	0.015			
Use of rating models * Crisis	0.111***			
Use of ratings for pricing		0.002		
Use of ratings for pricing*Crisis		0.188***		
High delegation to loan officer			−0.351	
High delegation to L.O.*Crisis			0.058***	
Main bank				−0.491***
Main bank*Crisis				0.079***
Firm size (log)	−0.127***	−0.127***	−0.110***	−0.071***
Firm size (squared)	−0.005***	−0.005***	−0.006***	−0.008***
Non-SMEs	0.162**	0.162**	0.117*	0.129**
Non-SMEs*Crisis	−0.051***	−0.056***	−0.054***	−0.022***
Collateral				
Start period	−0.039***	−0.040***	−0.034**	−0.028**
End period	−0.038***	−0.037***	−0.049***	−0.032**

Table B.4: Continued

	[1] Use of rating	[2] Use of rating for pricing	[3] Delegation to loan officer	[4] Main bank
Firm credit history length	Yes	Yes	Yes	Yes
Firm institutional sector	Yes	Yes	Yes	Yes
Firm industry	Yes	Yes	Yes	Yes
Firm region	Yes	Yes	Yes	Yes
Firm incorporation technique	Yes	Yes	Yes	Yes
Bank category	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	Yes
Constant	5.579***	5.607***	4.755	5.738***
N. observations	1,278,963	1,278,963	1,111,357	1,278,963
Adj. R-squared	0.27	0.27	0.27	0.27

Source: estimation of regressions based on Equation (1) in Section 3.
* = significant at 10 per cent; ** = significant at 5 per cent; *** = significant at 1 per cent. Missing values mean that the estimation is not possible for the relevant parameter. Interest rates outside the 1st or 99th percentile are dropped.

Table B.5: Impact of the Crisis on Credit Risk Pricing: Robustness Checks (1) Dependent Variable: Interest Rate or Spread towards Regular Loans at Start and End of the Relevant Period

	Robustness check (a)	Robustness check (b)	Robustness check (c)	Robustness check (d)
Credit transitions	Yes	Yes	Yes	Yes
Credit transitions*Topfive*Crisis	Yes	Yes	Yes	
Initial credit situation:				
2. Overdraft	2.417***	2.543***	2.418***	2.424***
3. Past-due <180 days	1.790***	1.874***	1.790***	1.807***
4. Past-due >180 days	0.539	0.489***	0.576	0.621
5. Sub-standard	0.706***	0.766***	.0780***	0.763***
6. Nonperforming	2.204***	1.178***	2.186***	2.191***
Top five banking groups	0.407***	0.752***	0.393***	0.403***
Crisis	−0.125***	−0.293***	0.025	1.043***
Top five banking groups*Crisis	−0.667***	−0.194***	−0.659	
Firm size (log)	−0.127***	−0.128***	−0.127	−0.129***
Firm size (squared)	−0.005***	−0.005***	−0.005	−0.005***
Non-SMEs	0.162***	0.265***	0.157	0.176***
Non-SMEs*Crisis	−0.052***	−0.100***	−0.043	−0.074***
Collateral				
Start period	−0.039***	−0.043***	−0.039	−0.042***
End period	−0.038***	−0.047***	−0.039	−0.037***
Firm credit history length	Yes	Yes	Yes	Yes
Firm institutional sector	Yes	Yes	Yes	Yes
Firm industry	Yes	Yes		Yes
Firm industry*Crisis			Yes	
Firm region	Yes	Yes	Yes	Yes
Firm incorporation technique	Yes	No	Yes	Yes
Bank category	No	No	Yes	Yes
Bank fixed effects	Yes		Yes	Yes
Constant	5.589	4.595***	5.780	11.713***
N. observations	1,278,963	1,278,963	1,278,963	1,278,963
				continued

Table B.5: Continued

	Robustness check (a)	Robustness check (b)	Robustness check (c)	Robustness check (d)
Adj. R-squared	0.27	0.21	0.27	0.24

Source: Estimation of regressions based on Equation (1) in Section 3. (1) $*$ = significant at 10%; $**$ = significant at 5%; $***$ = significant at 1%. Missing values mean that the estimation is not possible for the relevant parameter. Each column refers to a different modification of the baseline specification in Equation (1): Column (a): bank category excluded and nonfixed effect for banks; (b): bank category excluded; (c): industry-time-varying effects added; (d): dependent variable = interest rates not spread towards the benchmark case (i.e. the average rate to firms whose loans were in a regular situation both at the start and at the end of the relevant period).

	Robustness check (e)	Robustness check (f)	Robustness check (g)
Credit transitions	Yes	Yes	Yes
Credit transitions*Topfive*Crisis	Yes	Yes	Yes
Initial credit situation:			
2. Overdraft	0.771***	1.405***	0.484***
3. Past-due <180 days	2.415***	−0.331	0.456***
4. Past-due >180 days	1.678***	1.156***	0.597***
5. Sub-standard	2.316***	1.994***	0.192***
6. Nonperforming	1.839***	1.241	−0.121***
Top five banking groups	0.098***	−0.599***	0.421***
Crisis	−0.499***	−0.017**	−0.217***
Top five banking groups*Crisis	−0.338***	−0.337***	−0.655***
Firm size (log)	−0.120***	0.299***	−0.027***
Firm size (squared)	−0.004***	−0.013***	−0.010***
Non-SMEs	0.179***	0.046	0.124*
Non-SMEs*Crisis	−0.125***	0.005	−0.026***

Table B.5: Continued

Collateral			
Start period	−0.027**	−0.065***	−0.032***
End period	−0.052***	No	−0.038***
Firm credit history length	Yes	Yes	Yes
Firm institutional sector	Yes	Yes	Yes
Firm industry	Yes	Yes	Yes
Firm region	Yes	Yes	Yes
Firm incorporation technique	Yes	Yes	Yes
Bank category	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes
Constant	5.571***	0.342	5.184***
N. observations	1,186,593	1,161,899	1,278,963
Adj. R-squared	0.26	0.16	0.28

Source: Estimation of regressions based on Equation (1) in Section 3. (1) * = significant at 10%; ** = significant at 5%; *** = significant at 1%. Missing values mean that the estimation is not possible for the relevant parameter. Each column refers to a different modification of the baseline specification in Equation (1): Column (e): excluded outlier observations with spreads beyond the 5th and 95th percentile. Estimates for coefficient of the transition matrices and the same coefficients interacted with the crisis variable are omitted. (f): Impairment situations for each bank–firm relationship are defined according to the quantities of credit in each situation at the reference date (see Appendix A, Data and Methodology). The reference periods are December 2005–June 2008 (noncrisis), June 2008–December 2010 (crisis). (g): The impairment situation is defined having regard to the worst recorded classification of the debtor in the CR database at the reference date, regardless of which bank had provided the worst classification.

	[1] Small and medium enterprises (SMEs)	[2] Nonsmall and medium enterprises
Credit transitions	Yes	Yes
Credit transitions*Topfive*Crisis	Yes	Yes

Table B.5: Continued

Initial credit situation:		
2. Overdraft	2.275***	0.854
3. Past-due <180 days	2.794***	2.646***
4. Past-due >180 days	3.310***	2.953***
5. Sub-standard	2.666***	2.829***
6. Nonperforming		
Top five banking groups	0.349***	0.414***
Crisis	−0.157***	−0.169***
Top five banking groups*Crisis	−0.589***	−0.693***
Firm size (log)	−0.077***	0.001
Firm size (squared)	−0.009***	−0.009***
Collateral		
start period	−0.009	−0.066
end period	−0.052***	−0.017***
Firm credit history length	Yes	Yes
Firm institutional sector	Yes	Yes
Firm industry	Yes	YES
Firm region	Yes	Yes
Firm incorporation technique	Yes	Yes
Bank category	Yes	Yes
Bank fixed effects	Yes	Yes
Constant	5.273***	3.232***
N. observations	495,523	783,440
Adj. R-squared	0.30	0.25

Source: Estimation of regressions based on Equation (1) in the text.
(1) * =significant at 10%; ** = significant at 5%; *** = significant at 1%. Missing values mean that the estimation is not possible for the relevant parameter. Interest rates outside the 1st or 99th percentile are dropped. Small firms are firms with up to 20 employees.
(2) The reported coefficients refer to the spread of loans shifting from the situation in the first column to the situations in the subsequent columns, labelled as follows: 1. regular 2. overdraft, 3. past-due <180 days, 4. past-due >180 days, 5. sub-standard, 6. nonperforming, 7. loss. Figures in bold denote parameters statistically significant at least at the 1% or 5% level.
(3) The coefficients estimate the interaction of the transition dummies*banks within the top five groups*Crisis, and gauge the differential unexpected component of the credit worsening, as reflected in credit risk pricing efficiency, for banks in the top five groups.
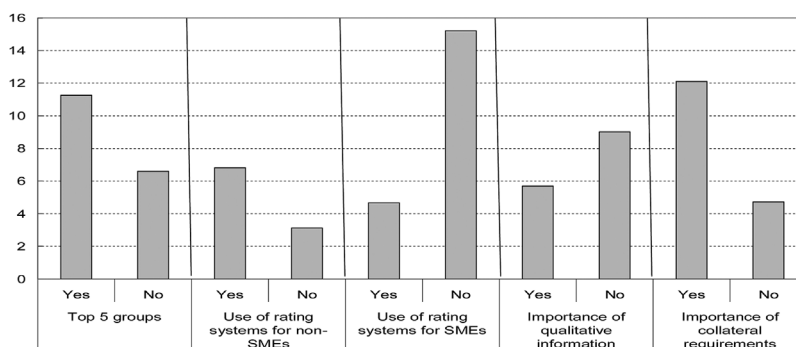
Figure B.1: Distance Between Expansion and Recession Matrices by Type of Bank (1)
(Indicator Values)

Sources: Central Credit Register, banks' supervisory reports, Bank of Italy organizational survey of banks. See Appendix A. (1) Euclidean distance L^2 between two matrices P_a and P_b is the square of the sum of the quadratic differences between each entry in matrix P_a and the corresponding entry in P_b, divided by N^2 (Jafry and Schuermann, 2004). Apart from bank size, banks are classified according to a survey run by the Bank of Italy in 2007 and 2010.

Non-technical Summary

This paper analyses to what extent the 2008–09 crisis has affected the ability of banks to assess the credit risk of borrowing firms and to account for it in the applied price conditions. Moreover, it investigates whether this effect of the crisis has been heterogeneous for banks with different size or organizational features.

Transition matrices of the credit quality of loans to Italian firms are calculated for the first time, based on micro-data from the central credit register. Transition matrices, a widely spread tool of credit risk analysis, display the frequency at which a credit portfolio changes its credit quality within a given time horizon. The transition matrices for Italian firms for the pre-crisis period (2006–07) are found to differ significantly from those of the crisis period (2008–09). In particular, credit quality mobility increases, due to more frequent credit deteriorations. This first finding provides a hint of the rise in uncertainty faced by banks, as a result of the crisis, in their lending activity.

The transition matrices are subsequently matched to applied interest rates. According to this analysis, Italian banks have, overall, been able to account for the actual riskiness of the borrower in pricing the loans. However, the ability of banks to calibrate interest rates to the different risk profiles of the borrower has apparently waned during the crisis years, presumably due to a surge in the *unexpected* credit deterioration. The

increased weakness of the link between credit quality and pricing has apparently affected to a larger extent the banks belonging to the top five Italian groups.

This effect of the size of banking group has been mitigated when the use of quantitative information to assess creditworthiness is framed within a rating or a scoring model: the reduction in credit pricing ability has been lower for banks that assign a key role to quantitative information-based ratings, especially during the credit-pricing phase. The impact of the crisis on pricing effectiveness has also been lower for banks that delegate more power to their branch officers and for those that are the main lender of the firm; both these features (decentralized lending power and a strong lender–borrower relationship) foster the accumulation and usage of soft information about the customers.