Lending Standards Over the Credit Cycle*

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Abstract

We analyze how firms' segmentation into credit classes affects the lending standards applied by banks to small and medium enterprises over the cycle. We exploit an institutional feature of the Italian credit market that generates a discontinuity in the allocation of comparable firms into the performing and substandard classes of credit risk. In boom, segmentation results in a positive interest rate spread between substandard and performing firms. In bust, the increase in the banks' cost of wholesale funds implies that substandard firms are excluded from credit. These firms then report lower values of production and capital investments.

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1 Introduction

A growing empirical literature shows that segmentation between investment- and speculative-grade firms can have important implications for their access to capital markets. Most of this evidence relates to the financing conditions borne by large publicly traded US firms in the corporate bond markets (e.g., Kisgen and Strahan, 2010; Lemmon and Roberts, 2010; Chernenko and Sunderam, 2013). An important question is therefore whether the effects of such segmentation extend to the relationship between small- and medium-sized enterprises (SME) and banks. This question is relevant not only because SME account for up to 70% of jobs in most OECD countries, but also because they nearly exclusively rely on bank financing (OECD, 1997). In this paper, then, we study whether segmentation influences the bank lending standards applied to SME, and, relatedly, how the consequences of firm segmentation vary over the credit cycle.

The empirical identification of the link between SME segmentation and bank lending standards is a challenging one. A major reason is that to understand the mechanism through which banks adjust lending policies requires detailed contract-level information on the price and quantity at which firms borrow from banks. Indeed, neoclassical theories suggest that banks tighten credit by raising the credit spread, so that quantity drops along the credit demand. An alternative is that, for given price, lenders tighten standards by rationing risky firms' quantity of credit—as in models with informational frictions. A possibility would be to carry out this analysis by focusing on the US syndicated loan market: such a study would have the advantage of using a long time series of data within a well-known environment. However, borrowers in this market tend to be significantly larger than a typical SME.[1]

To address this challenge, our analysis relies on a unique loan-level dataset collected

[1] Sufi (2007) and Ivashina (2009) document that the average syndicated loan to a US nonfinancial firm involves a borrower with turnover between 1.8$ billion and 2.8$ billion, and its amount ranges between 270$ million and 364$ million (as compared to 0.5 million Euro for the average loan in our data). Another important issue relates to the availability, and use, of credit ratings in the syndicated loan market. The literature documents that the set of borrowers or loans with a rating is a selected subset of the market participants.

by the Italian central bank. This dataset allows us to evaluate contractual differences in terms of the total quantity of credit granted and the per-loan interest rate charged by financial intermediaries to SME. Our sample is composed of 144,000 firm-year observations in the manufacturing sector and 253,000 funding contracts covering the period between 2004 and 2011. Like other OECD economies, Italy was experiencing a credit cycle that reached its peak between 2006–2007 (Drehmann, Borio, and Tsatsaronis, 2012) and then culminated with the great recession. To study the consequences of segmentation for firms' real decisions, we also use a comprehensive dataset containing information on firms' balance sheet statements. Our full datasets then give us an untapped opportunity to study how firm segmentation shapes the relationship between banks and SME.

An additional empirical challenge to our analysis is how to isolate changes in banks' lending supply from changes in firms' desire to borrow. To do so, we exploit the institutional features of the Italian credit market for SME. First, for historical reasons, the credit risk assessment of SME performed by Italian banks uses a common credit rating (the *Score*) that banks purchase from an external agency (*Centrale dei Bilanci*, or *CEBI*). Unlike US corporate credit ratings, the *Score* is unsolicited, available for all SME, and computed based only on firms' past balance sheets. Second, within this rating methodology, firms are allocated into two main rating classes—performing and substandard—based on the value of a continuous variable. Importantly, the bank has access to information on both the risk class and the continuous value of the firm's rating when taking its decisions, but, when reporting its loan portfolio to financial markets, it classifies firms only based on their rating classes.

The structure of the rating, and its construction, give us the opportunity to follow an intuitive empirical strategy to identify the effects of segmentation on financial contracts. Specifically, we exploit the sharp discontinuity in the allocation of firms into the performing and substandard classes of credit risk. As our measure of lending standards, then, we take the differences in the credit conditions between a firm marginally classified as performing and one that is marginally classified as substandard based on the value of the rating's continuous variable. These threshold differences inform us about how banks' supply of credit is affected by segmentation, while holding constant the demand for credit.

The classification between substandard and performing risks is important for bank lending choices because it affects the banks' cost of financing. The national banking regulator adopts a conservative definition of Non-Performing Loans (NPL), which also includes loans of substandard credit quality (World Bank, 2002; Bank of Italy, 2013; Barisitz, 2013; Jassaud and Kang, 2015; Bholat, Lastra, Markose, Miglionico, and Sen, 2016).[2] Banks then allocate loans in the category of non-performing loans based, amongst others, on the risk status provided by their credit scoring (e.g., Intesa, 2015). This has implications for bank capital regulation and investor assessment of bank balance sheets. Indeed, NPL absorb valuable bank capital (Jassaud and Kang, 2015), and their volume is often referenced as the major indicator of banks' asset quality by rating agencies (Moody's, 2015; Fitch, 2016). We empirically confirm the importance of the distinction between performing and substandard credit quality by relating the cost of funding borne by Italian banks to the composition of their loan portfolio.

We present the following results on how segmentation affects lending policies to SME. In boom, segmentation results in a positive interest rate spread between substandard and performing firms. Indeed, we find an interest rate spread on new loans of about 2% (or 10 basis points), and a positive but not statistically significant difference in the total amount of granted credit. The financial crisis that hit the Italian banking sector caused an exacerbation of the effects of segmentation on lending policies. Importantly, tighter lending standards essentially translate into differences in the quantity of credit: in bust, the performing firms obtain 31% more financing than comparable substandard firms, while the interest rate spread remains similar to the one prevailing in boom. For the final years in our sample (2010–2011), the results are in line with an incomplete recovery of total bank lending that is accompanied by an increase in the interest rate spread. These

[2] Specifically, the definition of NPL also includes bad loans, past due, loans to insolvent firms other than substandard credits. The latter are defined as exposures to counterparty facing temporary difficulties defined on the basis of objective factors.

results are therefore consistent with those arising from a model of financial contracting in the presence of informational frictions and market segmentation.

To quantify the importance of segmentation for bank lending, we compare the estimates of our threshold analysis to those arising from a naïve specification that analyzes differences in the lending conditions between *all* performing and substandard firms. We find that, in bust, segmentation can account for nearly 70% of the observed differential in the amount of credit. Another key insight arising from our discontinuity strategy relates to the patterns of the interest rate spread. While the naïve interest rate differences are increasing throughout the cycle, we show that, during the crisis, the threshold spread is close to zero—reflecting the implementation of lending standards' adjustment primarily via a restriction of substandard firms' access to credit.

We then trace the implications of lending standards for firms' real activity. The production choices of the firms at the threshold significantly diverge during the crisis, to the point that the marginally performing firms report up to 40% larger values of production than the marginally substandard ones. After decomposing production values into firms' investment in inputs, we find that an increase in the interest rate spread induces firms to adjust their expenditures in variable inputs (i.e., intermediates and employment). Instead, in bust, when banks act on the quantity margin to adjust lending standards, firms respond by cutting capital investments, which typically have a long-run nature.

The richness of our contract-level data allows us to document the economic mechanism driving the sensitivity of bank lending to segmentation. Specifically, we jointly test for the relative importance of bank capitalization and bank investor composition in explaining the relationship between segmentation and lending choices. In line with, among others, Ivashina and Scharfstein (2009) and Iyer, Puri, and Ryan (2016), we show that the degree of exposure to funding from short-term investors represents a quantitatively more important channel than bank capitalization to explain our threshold differences. We then look into the role of bank organizational design, and find that intermediaries putting more weight on soft information are more reluctant (in relative terms) to cut lending and raise the interest rate spread applied to substandard borrowers. Finally, we compare the lending conditions applied to two comparable firms, one of which is downgraded to the substandard class as a result of a small change in the value of its continuous rating (which is observed only by the bank).

We confirm the internal validity of our results by presenting the following robustness checks to our empirical design. First, we find no systematic evidence of manipulation of the rating, which confirms the fact that, as we argue in the description of our institutional setting, it is very difficult for firms to manipulate the *Score*. Second, we show that, close to the threshold, firms feature comparable economic characteristics, and are thus "as if" randomly sampled. Third, we confirm the relevance of the threshold that assigns firms to the performing and substandard classes. In particular, we run our threshold analysis at all the other six thresholds associated with the categorical value of the rating, and find that most of the estimates are not statistically significant. This suggests that our results capture a form of market segmentation, not a simple rating effect.

In addition to the literature on the consequences of market segmentation for financial contracts, our paper also contributes to the macro-finance literature studying the dynamics of credit over the cycle.[3] Specifically, Greenwood and Hanson (2013) show that the deterioration of credit quality during booms forecasts low excess returns to bondholders. Similarly, in their historical account of credit cycles, Lopez-Salido, Stein, and Zakrajšek (2015) find that elevated credit sentiment is associated with a more aggressive pricing of risk and a subsequent contraction in economic activity. Consistent with these studies, we provide evidence of how the 2004–2011 cycle affected the transmission of market segmentation into bank lending policies. Our paper is also related to the body of work on empirical banking (e.g., Jiménez, Ongena, Peydró, and Saurina, 2012 and 2014; Chodorow-Reich, 2014). We extend this literature by showing that, to understand the dynamics of bank lending standards, one needs to jointly analyze the price and quantity of lending.[4]

[3]This literature finds that the flow of credit (e.g., Covas and Den Haan, 2011; Jermann and Quadrini, 2012; Becker and Ivashina, 2014) and the value of credit spreads (Gilchrist, Yankov, and Zakrajšek, 2012) are both highly procyclical.

[4]Our results also inform the (growing) theoretical literature on lending standards over the cycle (e.g.,

2 Documenting Segmentation in the Credit Market

The goal of this section is to establish the presence of segmentation in the Italian credit market for SME. We will first present the institutional features of this market that generate segmentation, and then document the relationship between segmentation and the banks' cost of wholesale funds.

2.1 The *Score* Rating System

For historical reasons, Italian banks use a common credit rating produced by *Centrale dei Bilanci* (*CEBI*) when making decisions about lending to SME. *CEBI* is a credit agency founded in 1983 as a joint initiative of the Italian Central Bank and the Italian Banking Association to record and process firms' financial statements. According to Standard & Poor's (2004), "banks are the main users of the outputs of *CEBI*," referring to the *Score* rating produced by *CEBI* as the major tool used to assess SME credit risk. In 2004, the share of credit granted to SME by banks subscribing to the *Score* rating system was 73%. Evidence from the 2006 Bank of Italy survey of Italian banks indicates that 90% of the banks using a firm's rating find it important when deciding on whether to process a loan application, 76% of them use the rating to set the amount of lending, and 62% use it to formulate an interest-rate offer.

The following features of the *Score* are of particular interest to our research design:

1. The *Score* is unsolicited by firms, is computed based on firms' past balance sheets, and its exact algorithm is a business secret of *CEBI*. Information provided to the regulator by the agency that produces the *Score* shows that the construction of the rating is based on multiple discriminant analyses of past firm balance sheet information (Altman, 1968).[5] These features make the manipulation of the rating

Dell'Ariccia and Marquez, 2006; Martin, 2008; Kovbasyuk and Spagnolo, 2016; Gete, 2017).

[5]While the formula in the original Altman's model is publicly known, the agency uses its own version. Specifically, to our knowledge, *CEBI*'s version of the model uses approximately 15 factors taken from firms' balance sheets, however the exact composition and weights in the formula are a business secret. That is, they are not shared with the regulator or the banks.

very unlikely.

2. The system generates two continuous variables that determine the assignment to discrete rating categories. Based on predetermined thresholds, the first continuous variable is used to allocate the firms between one of the first five rating categories (1–5), the second to allocate firms into categories 6 to 9. The *Score* therefore ranges from 1, for firms that are the least likely to default, to 9, for those most likely to default.[6]

We obtained from *CEBI* direct access to the information on the values of the continuous and discrete variables for the manufacturing firms rated by the agency. We also have access to the exact thresholds that determine the allocation of firms into the different rating categories. This means that we can reconstruct the exact firm allocation mechanism implemented within the *Score* rating system.

Figure 1 illustrates some of the key empirical features of the *Score*.

[**Figure 1 Here**]

The left panel of Figure 1 plots the *Score* variable of firms in year t against the share of delinquent firms in year $t+1$. To construct this figure, we combine information from Italian bankruptcy courts and the credit register of the Italian central bank for the period 2004–2011. We define a firm as delinquent if it entered a formal bankruptcy process, or if its loan was flagged as late/defaulted in the credit register. Finally, we decompose the informativeness of the rating variable across three periods: boom (2004–2007), bust (2008-2009), and recovery (2010-2011). The panel suggests a monotonic relationship between the rating variable and future credit events. Indeed, the share of delinquent firms with a *Score* of up to 4 in a given year hovers around 4%. This share rises to about 10% for firms with a *Score* of 7. At the same time, the decomposition of default rates across subperiods indicates that the informativeness of the rating variable is relatively stable over the cycle.

[6]The continuous variables are difficult to interpret because their value is industry specific. Moreover, differently from the discrete value of the rating, by construction, they do not provide the bank with a direct estimate of the firm default probability (Altman, 2003).

More specifically, the increase in delinquency rates between the boom and the bust period for a *Score* of 7 is less than one percentage point.

The right panel of Figure 1 plots the rating variable against the interest rate on loans for the first quarter of 2005. A strong positive relationship exists between the rating variable and interest rates on loans. The best (lowest) *Score*, in terms of creditworthiness, is on average associated with a loan interest rate of 4%, and the worst (highest) category pays an average loan interest rate of around 5%.[7]

Figure 1 therefore suggests that the *Score* rating provides a useful estimate of the expected likelihood of a firm's delinquency, which is then taken into account by the banks for their lending decisions.

2.2 Segmentation of SME in the Italian Credit Market

Within the *Score* rating methodology, the distinction between the performing and substandard classes of credit risk stands out as particularly relevant for banks and their stakeholders. The performing class consists of the firms with a *Score* category between 1 and 6, and the substandard class comprises firms with a *Score* between 7 and 9.[8]

The importance of this classification stems from its implications for bank disclosure and reporting of their loan portfolio. National regulators decide on the loan categories that enter the class of NPL: this is relevant for our purposes because the Bank of Italy adopts a conservative definition of Non-Performing Loans (NPL), which also includes loans of substandard credit quality (World Bank, 2002; Bank of Italy, 2013; Barisitz, 2013; Jassaud and Kang, 2015; Bholat, Lastra, Markose, Miglionico, and Sen, 2016).[9] NPL absorb valuable bank capital: the capital charge for NPL amounts on average to 12% of banks' risk weighted assets, and are estimated to tie up more than 6% of bank capital

[7]Descriptive statistics on firms' distribution in the rating categories can be found in Online Appendix B (Figure B1).

[8]To understand the consequences for firms of this classification in terms of S&P's ratings, note that a *Score* of 6 corresponds to class B, and a *Score* of 7 to class CCC.

[9]Specifically, the definition of NPL also includes bad loans, past due, loans to insolvent firms other than substandard credits. The latter are defined as exposures to counterparty facing temporary difficulties defined on the basis of objective factors.

(Jassaud and Kang, 2015).[10] Moreover, a bank's exposure to NPL is often referenced as the major indicator of asset quality by the bank's rating agencies.[11]

Banks then allocate loans in the category of non-performing loans based, amongst others, on the risk status provided by their credit scoring (e.g., Intesa, 2015). Moreover, in their annual reports, they clearly distinguish between their exposure to the firms classified as substandard and performing by the rating (e.g., Unicredit, 2008). As a consequence, investors monitor the volume of substandard lending in order to assess a bank's risk profile. The presence of such segmentation gives rise to clear testable implications. First, one expects outside investors to charge a higher cost of funding to those banks that carry a higher volume of substandard loans in their loan book. Second, one should find that the continuous variables should not contain any useful information to explain the bank cost of funding on wholesale funding markets.

2.3 Segmentation and Bank Cost of Financing

We now provide evidence consistent with the presence of segmentation in the Italian credit market. We use three confidential datasets from the Bank of Italy. The first provides us with information on the amount and interest rate at which Italian banks raise financing from repo markets, households, and firms at a monthly frequency between 2004 and 2011. The second dataset contains yearly bank balance sheets between 2006 and 2011, and provides us with information about a bank's size, capitalization, and liquidity. Finally, we use information from the credit register to determine the composition of each bank's SME portfolio based on the categorical and continuous variables of the rating system.

To estimate the relationship between a bank's cost of financing and its lending port-

[10]Additionally, NPL weigh in the banks' balance sheets for two main reasons. The first is that there are very limited fiscal and accounting incentives for banks to write off and sell NPL. The second is related to the lengthy Italian bankruptcy system (Rodano, Serrano-Valarde, and Tarantino, 2016), and the small number of asset management companies willing to buy these assets.

[11]For example, in their banks' rating guidelines, Moody's (2015:33) reports that "[asset] risks are captured, to a considerable degree, by a single financial ratio, problem loans/gross loans (which we term the problem loan ratio)" and Fitch (2016) specifies that the "core metric" to measure asset quality is the problem loan ratio.

folio, we use the following Ordinary Least Squares (OLS) specification:

$$
\begin{aligned}
r_{b,t} \quad = \alpha_0 \quad & + \alpha_1 \text{Substandard to Total Credit}_{b,t-1} + \alpha_2 \text{Continuous Score } 1_{b,t-1} \\
& + \alpha_3 \text{Continuous Score } 2_{b,t-1} + X_{b,t-1}\Psi + I_{b,t}\Phi + \pi_t + \epsilon_{b,t}. \qquad (1)
\end{aligned}
$$

In (1), the dependent variable, $r_{b,t}$, is the (volume) weighted average interest rate paid by banks across all investors. Substandard to Total Credit$_{b,t-1}$ is the share of a bank's volume of lending to SME in the substandard rating class relative to total lending. Continous Variable $1_{b,t-1}$ and Continous Variable $2_{b,t-1}$ characterize the SME portfolio of the bank in terms of the average continuous ratings. $X_{b,t-1}$ denotes a vector of bank characteristics, and $I_{b,t}$ denotes issuance characteristics such as amounts, maturity, and investor composition, and π_t are month-year fixed effects. All explanatory variables, except for issuance characteristics, are measured before the issuance. Standard errors are clustered at the bank level.

[Table I Here]

In columns (1) and (2) of Table I we show that external investors monitor banks by pricing lending portfolios based on banks' exposure to the substandard and performing classes. The estimate in column (1) implies that a 25% higher share of substandard lending in the bank portfolio is associated with an increase in the bank's interest rate of approximately 28%, or 31 basis points. Column (2) extends the baseline specification in (1) by including the continuous values produced by the rating system. The coefficient on the share of substandard loans remains significant and economically identical to the first specification. Instead, the coefficients on the values of the continous variables are neither statistically nor economically significant. Our evidence is therefore consistent with the presence of market driven segmentation in the Italian credit market for SME. Investors observe the distribution of loans into rating classes, and set a higher interest-rate premium to compensate for a larger exposure to substandard loans.

In columns (3) and (4), we focus on the cost of financing on the repurchase market, the primary source of funds for the securitized banking system. This market is of particular interest, because Gorton and Metrick (2012) describe the crisis as a "run on repo" that was triggered by concerns about bank solvency. We therefore re-estimate our pricing equation in (1) separately for the period before and after 2008, and augment our specification with bank fixed effects. In the boom phase of the credit cycle, the correlation between interest rates on the repurchase market and the composition of banks' lending portfolio is low and statistically nonsignificant. In bust, the correlation is positive and economically significant, implying an increase in the interest rate premium required by investors from banks that are relatively more exposed to substandard credit risk.

3 Theoretical Framework

To motivate our empirical analysis, we propose a model of credit with market segmentation and moral hazard. Specifically, we extend the basic framework in Tirole (2006), Chapter 3, to accommodate the institutional features of the Italian credit market for SME. We show that a bank's ability to tame a firm's moral hazard problem can be impaired when funding conditions on the wholesale market heat up. This can push the bank to reduce lending at the expense of the substandard firms.[12]

The model features three classes of agents: the bank, its investors and two firms. The two firms are allocated by the rating system used by the bank into two different rating classes, performing and substandard. We consider the case in which the two firms fall exactly at the threshold between the two classes of credit risk. The bank knows this, and understands that they are economically identical. The cost of funds to the bank is set by external investors who, consistent with our empirical evidence, only observe the firms' rating class. The existence of market segmentation has then two main implications for bank lending.[13] First, the bank's cost of funding to a firm will reflect the composition of

[12]In this section, we present the main insights arising from the model. The full derivation can be found in Online Appendix D.

[13]Note that, in the absence of segmentation, the two firms would always obtain the same contract with the bank at equilibrium.

demand in the credit class. Second, the cost of financing paid by the bank will vary over the cycle according to the conditions on the wholesale funding market.

In boom, the low cost at which the bank raises financing in the wholesale market implies that both firms can obtain access to unmonitored credit. More specifically, both firms receive the same amount of lending, but the substandard firm pays a higher interest rate—mirroring the higher risk in their class.

In bust, worse conditions on the market for wholesale funds erode firms' net worth, and imply that lending is not viable for the bank. Then, firms have two options: the first is to use the bank's monitoring technology, which comes at a cost, but also alleviates the moral hazard problem. Alternatively, they are (partially) rationed from credit. Assume that monitoring works with the performing firm, so that the bank can break even on this firm project. Instead, the monitoring technology does not work for the substandard firm: that is, the rise in the cost of wholesale funding for the bank, combined with the cost of monitoring, imply that the net present value of its project is negative. Then, the substandard firm is credit rationed at equilibrium. To sum up: in bust, quantity differences arise in the credit contracts offered to the two firms at the threshold.

As we will further discuss below, these results will guide the interpretation of the credit differences arising in our empirical analysis.

4 Data Preview and Economic Environment

To test the link between segmentation of firms and bank lending standards, we use confidential datasets from the Bank of Italy that contain information on bank balance sheets and the financial contracts signed between banks and SME. We instead obtain firm balance sheets and rating information from *CEBI*. Our final sample is composed of about 144,000 firm-year observations in the manufacturing sector and 253,000 funding contracts signed between the first quarter of 2004 and the last quarter of 2011. Further details on the dataset and its organization can be found in Online Appendix A.

This section first documents the presence of substantial heterogeneity across rating classes. This heterogeneity suggests that a naïve comparison between the credit conditions of firms in different rating classes is likely to yield misleading conclusions on the pattern of lending standards, because the resulting credit differences could simply reflect differences in firms' demand for credit. Then, we show the patterns of firms' financial contracts over time, which document how the phases of the credit cycle that Italy experienced between 2004 and 2011 affect financial allocations. Finally, we present key developments in the Italian banking environment that occurred during our sample period, illustrating the significant effects of the financial crisis on the wholesale funding and capitalization of Italian banks.

4.1 Firm Financing Environment

We begin by presenting the sources of cross-sectional heterogeneity in our dataset and the time-series variation in firm financial contracts.

Cross-sectional Descriptive Statistics Table II provides the cross-sectional characteristics of the full sample in column (1). Columns (2) and (3) show corresponding results for the group of performing and substandard firms, and columns (4) and (5) show the same for categories 6 and 7. Finally, column (6) reports the mean difference between the values of the variables in categories 6 and 7.

[Table II Here]

The table shows that there is significant heterogeneity among firms across different risk profiles, not only with respect to financial characteristics, but also in terms of balance sheet characteristics.

More specifically, Panel A of Table II shows that in the full sample, the average nominal interest rate charged for a loan is 4.57%. However, the interest rates applied to performing and substandard firms are 4.32% and 5.3%, respectively. Although the average loan in the sample is approximately 816,000 Euro, it is about 617,000 Euro for a firm in the substandard class. Moreover, the maturity structure of the loans in our sample is biased towards short-term credit, as short-term loans account for around two-thirds of the total value of granted loans.

Panel B reports the aggregate financing characteristics of the firms in our sample. On average, total bank lending amounts to 8.5 million Euro (ME) per firm, 35% of which is in the form of loans. While firms in the performing class receive bank financing that adds up to about 9.2ME, firms in the substandard class receive an average of 6ME.

Panel C provides an overview of the main balance sheet characteristics of Italian manufacturing firms based on unique firm-year observations. Firms in our sample are relatively small. On average, they employ 92 workers, with firms in the performing class being relatively larger than those in the substandard class. While the investment-to-asset ratio is stable across classes, the values of leverage and return to assets are not. The leverage ratio increases from 0.61 for firms in the performing class to 0.86 for those in the substandard class. Moreover, return on assets decreases from 0.07 to zero for firms in these two classes.

Finally, column (6) of Panel C shows that the heterogeneity in firm characteristics extends to rating categories 6 and 7. The cost and availability of bank financing suggests significantly tighter conditions for firms in category 7 as opposed to category 6. For instance, interest rates for firms in category 6 are 50 points lower than those of firms in category 7. At the same time, these firms are again significantly different in terms of characteristics related to the demand for credit, such as the value of investment and profitability.

Taken together, the descriptive statistics show the importance of obtaining a measure of lending standards that is not biased by demand heterogeneity.

Time Series Descriptive Statistics In Figure 2, we document the variation in financial contracts across time.

[**Figure 2 Here**]

The upper panel illustrates that, like other OECD economies (Drehmann, Borio, and Tsatsaronis, 2012), between 2004 and 2011 Italy was experiencing a credit cycle that reached its peak in 2007. The middle panel focuses on firms' nominal average interest rates, showing that nominal rates mirrored the pattern of the indicators for the monetary policy of the ECB.

More specifically, the top panel shows that the time series of the amount of bank financing to Italian SME features a humped shape. From the first quarter of 2004 to the fourth quarter of 2007, bank financing increased by 18%, on average. It then decreased by 11% through the end of the sample period. Although this pattern is qualitatively similar across risk classes, the variation in bank financing is larger for substandard firms: between 2004 and 2008 bank financing to performing firms increased by 13%, while it rose by 29% for substandard firms. This evidence is consistent with the historical account of credit booms by Greenwood and Hanson (2013), who show that the quality of credit deteriorates as aggregate credit increases. Finally, the bottom panel of Figure 2 shows that nominal interest rates increased from 4.3% in 2004 to 6.11% in late 2008. Similar to the patterns in the top panel, the levels of the interest rate spreads are consistent with the risk categories in our rating system.

4.2 Banking Environment

In Figure 3, we illustrate the key developments in the Italian banking environment that occurred during our sample period. We use bank balance sheet data between 2006 and 2011 from Bank of Italy.

[**Figure 3 Here**]

The top panel of Figure 3 plots the share of repo financing of banks relative to their total assets for the five largest banks in our sample. In the expansionary phase of the cycle, the dependence of banks on repo financing grew from 5% in 2005 to nearly 12% at the beginning of 2008. During the financial crisis, this source of financing plummeted to 2.5% and remained at low levels until the end of our sample period.

The middle panel of Figure 3 illustrates the capitalization of Italian banks: we compute the tier 1 capital ratio for the five largest banks in our sample by dividing banks' tier 1 capital by their total assets. The figure shows that the average value of banks' capital ratio at the beginning of the financial crisis period was approximately 4.5%. In 2008 the ratio fell to around 3.6%, before rising above 5% towards the end of the sample period. The patterns in these two panels are shared by the banking systems of other European countries during the same time interval.

The bottom panel of Figure 3 provides evidence on the implementation of the Basel II agreements. Credit risk capital allocations account for more than 100% of total capital requirements through 2008 and 2010, implying that credit risk management was critical for Italian banks during our sample period. Moreover, the transition from Basel I to Basel II is unlikely to drive the evolution of lending standards in our sample. Indeed, the total fraction of capital allocations calculated using internal rating systems oscillates around 20%.

5 The Empirical Model

5.1 Identification Strategy

Empirically identifying how segmentation influences bank lending standards is challenging for two reasons. First, it requires a setup where the econometrician observes the exact information held by the bank about the firm credit risk profile. Then, to isolate demand from supply considerations, the econometrician would like to compare firms that are identical from the perspective of the loan officer, but classified into different classes of credit risk.

To address these challenges, we exploit the institutional features of the Italian credit market for SME introduced in Section 2. The structure of the rating, and its construction, give us the opportunity to follow an intuitive empirical strategy to identify the effects of segmentation on financial contracts. Specifically, we exploit the sharp discontinuity in the allocation of firms into the performing and substandard classes of credit risk. As our measure of lending standards, then, we take the differences in the credit conditions between a firm marginally classified as performing and one that is marginally classified as substandard based on the value of the rating's continuous variable. These threshold differences inform us about how banks' supply of credit is affected by segmentation, while holding constant the demand for credit.

The support of the continuous variable for categories 6 and 7 ranges between -0.6 and 1.5, and the threshold is 0.15. Below this threshold, a firm's *Score* is 7 and thus the firm falls into the substandard class. Above the threshold, a firm's *Score* is 6 and it is in the performing class. Throughout the analysis, we normalize the threshold to 0 and only use the support of the continuous variable that spans between categories 6 and 7. Thus, if s_i is the value of firm i's continuous variable, the allocation of this firm into a rating class takes place according to the following sharp mechanism:

$$Score_{i,t} = \begin{cases} 6 \text{ (Performing)} & \text{If } 0 \leq s_{i,t} < 1.35 \\ \\ 7 \text{ (Substandard)} & \text{If } -0.75 \leq s_{i,t} < 0 \end{cases} . \tag{2}$$

5.2 Main Specification

Let $\bar{s}$ denote the normalized threshold that allocates firms into rating categories 6 and 7. Our main specification follows:

$$\begin{aligned} y_{i,t} = \beta_0 \quad & +\beta_1 \text{Performing}_{i,t} + \beta_2(\text{Performing}_{i,t} \times \text{Crisis}_t) \\ & +\beta_3(\text{Performing}_{i,t} \times \text{Recovery}_t) + f(s_{i,t} - \bar{s}) \\ & +\text{Performing}_{i,t} \times g(s_{i,t} - \bar{s}) + \pi_t + u_{i,t}. \end{aligned} \tag{3}$$

The dependent variable capturing the supply of bank financing is the (log) total value of bank lending granted to firm i in quarter t. This measure accounts for the possibility that firms obtain credit from multiple banks. The variable capturing the cost of bank financing is the (log) value of the interest rate applied to a new loan granted to firm i in quarter t. The indicator $\text{Performing}_{i,t}$ takes a value of 1 if a firm is in the performing class (i.e., $s_{i,t} \geq 0$ implying a *Score* of 6), and 0 otherwise. It is interacted with two indicator variables associated with the phases of the credit cycle. Crisis_t takes a value of one from the first quarter of 2008 onwards, while Recovery_t takes a value of one from the first quarter of 2010 onwards. Functions $f(\cdot)$ and $g(\cdot)$ correspond to flexible sixth-order polynomials whose goal is to fit the smoothed curves on either side of the cutoff as closely to the data as possible. Function $f(\cdot)$ is estimated from 0 to the left, whereas the $\text{Performing}_{i,t} \times g(\cdot)$ term is estimated from 0 to the right. Moreover, π_t are quarter-year fixed effects, and $u_{i,t}$ is a mean-zero error term clustered at the firm level.[14] Finally, we also control for the past value of the rating.

The interpretation of equation (1) is the following. First, note that at the cutoff the $f(\cdot)$ and $g(\cdot)$ polynomials are evaluated at 0 and drop out of the calculation. This allows us to interpret the parameters $(\beta_1, \beta_2, \beta_3)$ as capturing the magnitude of the discontinuity in credit conditions at the threshold $\bar{s}$. The null hypothesis of our framework is that if a bank uses all its information on the borrowing firm there should be no discontinuity in lending contracts at the threshold. In other words, under our null hypothesis segmentation should not matter for lending decisions. Second, the estimated discontinuity parameters $(\beta_1, \beta_2, \beta_3)$ have a cumulative interpretation. The estimate of β_1 captures the baseline difference between marginally performing firms and substandard firms in the period between 2004 and 2007. The estimates of β_2 and β_3 then capture how this baseline difference changes across the cycle. Suppose we estimate the specification us-

[14]We estimate alternative specifications in which we scale the supply of bank financing by assets or express interest rates in terms of basis point differences, and we obtain the same results. To simplify the analysis, we restrict $f(\cdot)$ and $g(\cdot)$ to be of the same polynomial order. However, our results are not sensitive to this choice. Finally, we also use local-linear functions to estimate differences in credit conditions at the threshold. Our results remain robust to these additional checks.

ing as a dependent variable the (log) quantity of credit, and we obtain as estimates ($\hat{\beta}_1 = 0.1, \hat{\beta}_2 = 0.1, \hat{\beta}_3 = -0.2$). This would mean that the log difference between performing and substandard firms was 0.1 in the boom phase, it grew to 0.2 during the crisis, before becoming 0 during the recovery period.

In the main specification, we restrict our attention to the sample of firms that remain in the same rating category for at least two consecutive years. This condition limits two potential concerns. The first is that the bank reports a firm as performing on the basis of its rating in $t-1$, even though it is already downgraded in t. The second is related to the possibility that large variations in the value of the continuous rating that then lead to downgrades might themselves be correlated to the firms' demand for credit. To address these two issues, we separately study the implications of a firm downgrade for financial contracting, and provide evidence based on downgrades caused by small changes in the value of the continuous rating.

We extend our main specification in two directions. First, we study whether, via its impact on lending standards, segmentation is relevant for firms' real choices. Specifically, we estimate equation (3) using as dependent variables firms' expenditures in production inputs and the value of production. The balance sheet information we use for this analysis is reported in end-of-the-year statements; thus, it reflects a firm's lending conditions throughout the year. Second, we look at the differences between the lending conditions at the threshold within each phase of the credit cycle. To this end, we estimate equation (4) separately for each quarter-year cross-section of firms at the threshold in our sample period:

$$y_{i,\cdot} = \beta_0 + \beta_1 \text{Performing}_{i,\cdot} + f(s_{i,\cdot} - \bar{s}) + \text{Performing}_{i,\cdot} \times g(s_{i,\cdot} - \bar{s}) + u_{i,\cdot} \tag{4}$$

In (4), the dot indicates that we fix the time period. This exercise also gives us more flexibility in estimating the impact of the continuous rating across time.

5.3 Mechanism for the Transmission of Market Segmentation

We exploit the heterogeneity of the banks in our dataset to study which banks are more sensitive to market segmentation. First, we consider heterogeneity in banks' financial structure, and then turn our attention to differences in banks' organizational design. Finally, we study the implications of segmentation for marginally downgraded firms over the cycle.

Banks' financial structure We consider two channels through which financial structure can affect banks' sensitivity to market segmentation: capital requirements and investor composition. Intuitively, low levels of regulatory capital can help explain a bank's greater sensitivity to market segmentation. Similarly, investor composition can account for the sensitivity of banks to market segmentation: certain investor categories are more responsive than others to bank solvency risk, and update their assessment of bank loan quality over the cycle (Ivashina and Scharfstein, 2009; Iyer, Puri, and Ryan, 2016).

In order to explore the relative merits of these two channels in determining bank sensitivity to segmentation, we compute the following measures of bank heterogeneity. To study the role played by capital requirements we compute, for the pre-crisis period, each bank's Tier 1 capital ratio. To study heterogeneity in investor composition, we focus on the importance of repo markets for a bank funding structure. As we show in Table I above, during the crisis investors in repo markets updated their interest rate conditions based on banks' exposure to substandard firms. We therefore measure each banks' pre-crisis share of financing from repo markets. We augment our main specification with interactions between the Performing_{it} indicator and these bank specific characteristics:

$$
\begin{aligned}
y_{i,b,t} = \beta_0 \quad & +\beta_1 \text{Performing}_{i,t} + \beta_2(\text{Performing}_{i,t} \times \text{Crisis}_t) \\
& +\beta_3(\text{Performing}_{i,t} \times \text{Recovery}_t) \\
& +\gamma_1(\text{Performing}_{i,t} \times \text{Tier1}_b) + \gamma_2(\text{Performing}_{i,t} \times \text{Tier1}_b \times \text{Crisis}_t) \\
& +\gamma_3(\text{Performing}_{i,t} \times \text{Tier1}_b * \text{Recovery}_t) \\
& +\delta_1(\text{Performing}_{i,t} \times \text{Repo}_b) + \delta_2(\text{Performing}_{i,t} \times \text{Repo}_b \times \text{Crisis}_t) \\
& +\delta_3(\text{Performing}_{i,t} \times \text{Repo}_b \times \text{Recovery}_t) \\
& +f(s_{i,t} - \bar{s}) + \text{Performing}_{i,t} \times g(s_{i,t} - \bar{s}) + X_{i,b,t}\Psi + \pi_t + u_{i,t}. \qquad (5)
\end{aligned}
$$

In (5), Tier1_b is defined as a bank b's core equity capital divided by its total assets, and Repo_b is defined as the share of the bank's total financing from repo markets. $X_{i,b,t}$ is a vector that includes the levels and interactions of all the variables in the set of triple interactions. Standard errors are clustered at the firm-bank level. As an additional robustness check, we augment equation (5) by including (firm×year) fixed effects.

Banks' organizational design We next analyze the role played by organizational structures. Using a 2006 bank survey run by the Bank of Italy, we have information on the importance of soft information in banks' lending decisions. The indicator variable Organization_b is equal to 1 if banks report a high reliance on soft information in their lending process. The estimated specification is the same as equation (5), but we replace the bank financing variables with the indicator Organization_b constructed for each bank b in our sample. Building on Stein (2002), we expect that some categories of banks are more inclined to rely on soft information when taking lending decisions.[15]

[15] One caveat is that organizational structures might be endogenous to the financing structure, and banks' investor composition. For instance, confirming Stein (2002) intuition, the banks in our dataset featuring a higher reliance on soft information tend to be small and less dependent on short-term wholesale funding.

Exploiting downgraded firms Finally, we study how market segmentation affects the lending policies set on firms that are marginally downgraded over the cycle. This allows us to derive results on the dynamic consequences of segmentation for a firm: What is the implication of a downgrade to substandard quality for credit conditions over the cycle? Does the bank exploit its superior information on the company's downgrade?

We compare two firms that fall in the performing class until year $t-1$, but differ in their rating class in year t.[16] The specification follows:

$$\begin{aligned} y_{i,b,t} = \beta_0 \quad & + \beta_1 \text{Down}_{i,t} + \beta_2(\text{Down}_{i,t} \times \text{Crisis}_t) + \beta_3(\text{Down}_{i,t} \times \text{Recovery}_t) \\ & + f(s_{i,t} - s_{i,t-1}) + \text{Down}_{i,t} \times g(s_{i,t} - s_{i,t-1}) + \pi_t + u_{i,t}. \end{aligned} \tag{6}$$

$\text{Down}_{i,t}$ is a binary variable equal to 1 if the firm is downgraded from category 6 to category 7 in year t, and is 0 otherwise. In (5), the polynomials in $f(\cdot)$ and $g(\cdot)$ are a function of the change in the continuous variable between $t-1$ and t. By evaluating these polynomials close to 0, our analysis considers those firms that were downgraded as a consequence of a similar and small change in the value of the continuous rating.

6 Results

In this section, we present the results on the differences in credit conditions—specifically, differences in the interest rates and in the total amount of bank financing—for firms at the threshold between the performing and the substandard classes. We then explore whether differences in credit conditions give rise to differences in firms' production and input choices. Finally, we further our analysis of lending standards' evolution across the credit cycle by focusing on the cross-section of firms at the threshold within each phase.

[16] Clearly, one limitation of this analysis is that the reason for the downgrade might itself be correlated to the demand for credit of the firm.

6.1 Results on Credit Allocations

Table III reports the estimates of the main specification in equation (3). The dependent variable in columns (1) and (2) is the log amount of bank financing granted to the firm, while in columns (3) and (4) the dependent variable is the log interest rate on new bank loans.

[**Table III Here**]

The estimates related to the period between 2004 and 2007 suggest that segmentation mainly results in a positive interest rate spread between substandard and performing firms at the threshold. The difference in the total amount of lending granted to the firms are positive but economically small, around 8%, and not statistically significant. At the same time, firms in the substandard class are charged up to 2%, or 10 basis points, higher interest rates on new bank loans than similar firms in the performing class. These results are consistent with our theoretical prediction on bank lending in boom (see Section 3): low costs of funding paid by banks on wholesale markets imply that firms at the threshold receive the same amount of funding, but substandard firms pay a smaller interest rate premium than substandard firms.

Through 2008 and 2009, the financial crisis that hit the Italian banking sector led to an exacerbation of the consequences of segmentation for lending policies. Importantly, we find that tighter lending standards essentially translate into differences in the quantity of lending for the firms at the threshold. Indeed, marginally performing firms obtain 31% more bank financing than similar firms across the threshold.[17] Instead, interest rate differences remain stable and close to zero (in economic and statistical terms). These results are again consistent with the prediction of our theoretical framework. A rise in the interest rates paid by banks to outside investors, together with the increase in the opportunity cost of lending to substandard firms, translate into an equilibrium in which banks monitor the performing firms and (partly) exclude substandard firms from lending.

[17] To obtain the exact percentage changes in the crisis period, we compute $\left[\left(\exp\left\{\hat{\beta}_1 + \hat{\beta}_2\right\} - 1\right) \times 100\right]$.

Between 2010 and 2011, our estimates are in line with an incomplete recovery of bank lending. During this period, segmentation means a reduction in the differences in the quantity of credit from 31% to 20%. However, the reduction in the amount of granted bank financing is accompanied by an increase in the interest rate spread of approximately 6%, or 30 basis points.

To understand the relevance of the impact of segmentation on bank lending, we compare, in columns (3) and (6), the results obtained with our threshold analysis to those arising from a naïve specification that compares lending conditions to *all* performing and substandard firms during the sample period. First, the naïve estimates show that the implications of segmentation for the amount of bank lending is time varying. Recall that, in boom, the threshold estimate for quantities is economically small and non significant from a statistical point of view. This suggests that the 41% differential in the amount of bank credit arising from the naïve specification cannot be explained by segmentation. In 2008-2009, the overall differential between the quantity of lending across rating classes remains stable, while it increases to 28% for the firms at the threshold. In bust, then, segmentation can account for nearly 70% of the observed differential in the amount of credit. Second, the analysis of the interest rate spreads arising from a naïve comparison would lead to misleading conclusions, not only quantitatively but also qualitatively. The results of the naïve regression suggest that the interest rate difference is persistently large in economic terms, and increasing throughout the cycle. Instead, we show that, within our discontinuity design, the interest rate spread is small and narrows with the crisis. This reflects the fact that, in bust, bank lending standards' adjustments are implemented primarily by changing the quantity of credit.

6.2 Implications for Firms' Real Activity

Table IV reports the results of our baseline regression in (3) using as dependent variables the log of firms' sales and expenditures in investment, employment, and intermediates. The balance sheet reports only contain partial information about employment choices;

thus, to fill this data gap, we obtain employment figures from firms' mandatory contributions to the Italian pension system, and merge this information based on the firms' fiscal identifier.

[Table IV Here]

Columns (1) and (2) yield three main findings. First, in periods of lax lending standards, relatively small differences in the amount of lending can still have implications for production. Between 2004 and 2007, marginally performing firms on average produce 20% more than marginally substandard firms.[18] Our second finding is that production choices of firms at the threshold increasingly diverge during the period in which access to credit is limited for the marginally substandard firms: in 2008 and 2009, the marginally performing firms report up to 40% larger values of production than the marginally substandard ones. Finally, consistent with the partial recovery of lending taking place between 2010 and 2011, we find that, in this period, production differences decrease to pre-crisis levels.

To further investigate the implications of shifts in lending standards for firm real activity, we also report the differences in input choices made by the firms at the threshold. We estimate our discontinuity design using as dependent variables the value of firms' investment in capital, expenditures in intermediates, and employment. The main finding is that the divergence in production outcomes during the crisis is mainly driven by investment choices. During the most acute phase of the financial crisis, on average, performing firms invest up to 50% more than substandard firms. In boom and recovery, instead, lower values of production are essentially driven by reduced expenditures in intermediate and labor inputs.

These findings suggest the following mechanism: in boom and recovery, a mere increase in the cost of lending induces firms to adjust their expenditures in short-term inputs. In bust, when banks operate on the quantity margin to change their lending standards, firms instead act on their capital investments, which typically have a long-run nature.

[18]A yearly decomposition of these estimates suggests that production differences arise mainly in the early years of the boom. These differences then vanish as the credit cycle reaches its peak.

6.3 Within-Cycle Dynamics

Our main specification estimates the average effects of lending standards across the different phases of the credit cycle. We now extend it to study in greater detail how market segmentation affects bank lending within each phase of the cycle. We estimate equation (4) separately at the quarterly level using as dependent variables the total quantity of lending and the interest rate on new bank loans. For expositional convenience, we plot in Figure 4 the time series of the estimated coefficients.[19]

[**Figure 4 Here**]

In Figure 4, the estimates related to the amount of granted bank financing are in the top panel, and those for the interest rates in the bottom panel. The boom phase (2004–2007) is characterized by a gradual expansion of lending supply. In 2004 and 2005, differences in the total amount of lending granted to the firms at the threshold are positive and large, but statistically nonsignificant. These differences vanish in 2006 and 2007, when the credit cycle reaches its peak. Interest rate spreads follow a similar pattern. Early in the boom phase, firms in the substandard class are charged up to 10%, or 60 basis points, higher interest rates on new bank loans than similar firms in the performing class. At the peak of the credit cycle, these differences vanish. Our findings are then in line with Greenwood and Hanson (2013): as in their analysis of historical cycles, we find that, in boom, the deterioration of credit quality documented in Figure 2 is accompanied by narrowing interest rate spreads.

Inspection of our estimates for the 2008-2009 period provides additional insights onto the effects of the tightening of bank lending policies for firms' access to credit. The difference in the amount of total credit supplied to similar firms across the threshold is statistically significant. However, in the same period, interest rate differences remain close to zero. These results suggest that banks rationed the credit supplied to substandard firms at the threshold. Recall that our empirical strategy allows us to hold demand constant at

[19]Table C1 in Online Appendix C reports the details of the regression results. Table C2 provides estimates of equation (4) at the yearly level for real outcomes.

the threshold. Since marginally performing and marginally substandard firms are charged the same interest rate, a revealed preference argument implies that they should also be supplied with the same volume of lending. Thus, the result that substandard firms receive a substantially lower amount of credit hints that they are inefficiently rationed.

Finally our disaggregated estimates confirm that, in line with Table III, the recovery in bank lending was gradual. Differences in the quantity of credit are still economically large in 2010, and disappear only in 2011. During this period, lending standards translate into a 20%, or 120 basis points, interest rate spread between comparable firms in different rating classes.

7 The Economic Mechanism

In this section, we investigate the economic mechanism driving the transmission of segmentation onto bank lending standards.

7.1 Bank Heterogeneity

Table V investigates the possible channels through which bank heterogeneity can explain how segmentation affects credit supply. In columns (1) and (2), we jointly test for the relative importance of bank capitalization and investor composition in determining the sensitivity of bank lending to segmentation. Recall that, to capture bank capitalization, we measure banks' Tier 1 capital ratio. Instead, as a measure of investor composition, we take the banks' dependence on fundings from repo markets. Both measures are taken as a pre-2008 average at the bank level.

[Table V Here]

We begin by interpreting our results in column (1). First, notice that the baseline effects remain qualitatively very similar to the results obtained with the main specification. Second, in the pre-crisis period, bank heterogeneity does not seem to affect how banks establish their lending standards. This is intuitive: in boom, banks expect favorable financing conditions on wholesale markets. This means that they can lend "as if" unconstrained by segmentation, and make full use of their information on the firms' risk profile. This changes dramatically during the crisis. The negative sign on the interaction (Performing$\times$Tier1) indicates that highly capitalized banks are less likely to offer different amounts of credit to borrowers at the threshold. Similarly, those banks that are less dependent on short-term investors are also less likely to cut on lending as a consequence of market segmentation. Interestingly, the sensitivity of bank lending to these factors remains high even in the recovery period. Column (2) augments the discontinuity design by including firm-year fixed effects. This means that we exploit heterogeneity in the amount of lending to the same firm and in the same year from different banks. The estimates remain very similar despite the increase in the number of estimated parameters.

Columns (4) and (5) repeat the analysis by looking at the differences in interest rates. Our estimates suggest that bank heterogeneity is not particularly helpful to explain banks' price setting. For instance, there is no evidence of significant differences in the spreads set by highly and lowly capitalized banks. Although, in principle, investor composition could account for the interest rates spreads, the evidence arising from the estimated parameters in Table V is rather mixed and, thus, inconclusive.

To analyze the quantitative importance of bank capitalization and investor composition, we relate the results in the table to the drop in capitalization and repo financing that happened between 2007 and 2009. During that period, Italian banks' Tier 1 capitalization fell by almost 1 percentage point. If we take the implied cumulative effect of segmentation and multiply it by the drop in capitalization we obtain a differential tightening at the threshold of only 0.5% (or $(\exp\{0.21 - 0.90\} - 1) \times 0.01$). Instead, the share of repo financing by banks went from 10% in 2007, to approximately 2% at the end of 2009. This suggests that the investor composition channel can account for a differential quantity tightening of approximately 4.2% (or $(\exp\{-0.01 + 0.43\} - 1) \times 0.08$). This represents 30% of the observed threshold difference during the crisis, and indicates that investor composition is quantitatively a more important channel than bank capitalization to explain the consequences of segmentation on lending policies.

Columns (3) and (6) of Table V investigate the link between bank organizational design and the transmission of market segmentation into lending policies. Consistent with our previous findings, the pre-crisis period features little differences in the amount of lending set by banks with different organizational structures. Instead, during the crisis, intermediaries putting more weight on soft information when setting credit policies raised significantly less the spreads applied to substandard borrowers. Again, one needs to be careful when interpreting these results, as bank organizational structure is likely to be correlated with differences in size and investor composition.[20]

7.2 Evidence from Downgrades

In Table VI, we report estimates of lending conditions to marginally downgraded firms obtained based on equation (5). In the table, the columns labeled (1) estimate the specification without the polynomial term in the continuous variables, while those labeled (2) include this term.

[Table VI Here]

The first two columns suggest that the financing conditions applied to downgraded firms change significantly over the cycle. In boom, a downgraded firm obtains 25% more bank financing than a firm that experienced a similar change in the value of the continuous variable, but was not downgraded. This is in line with the stylized fact that, in boom, the growth rate of credit to high credit risk is significantly larger than that of low credit risk (see Figure 2). These findings also suggest that banks exploit their superior information on the dynamics of the continuous rating's value to allocate their exposure to substandard firms. In crisis and recovery, however, banks revise their credit allocations

[20] In fact, a joint estimation of the distinct impact of these three factors in a single specification yields nonsignificant estimates on the importance of the use of soft information within banks.

to marginally downgraded firms. Specifically, the preferred access granted to downgraded firms is significantly reduced in bust, and vanishes altogether in recovery (2010 and 2011).

We then study whether the banks extract informational rents when raising credit to the marginally downgraded firms. To this end, in columns (3) and (4), we analyze the pattern of interest rate spreads. Column (3) suggests that banks charge very similar interest rates to marginally downgraded and non-downgraded firms in boom and bust. Only in the recovery phase we observe 2% higher interest rates charged to downgraded firms. These results show that banks exploit their finer information by affecting credit allocation within classes, and giving preferential access to the marginally downgraded firms.

Finally, columns (6) and (7) focus on the production choices of downgraded firms. Our estimates show that the preferential access to credit granted to downgraded firms also translates into larger volumes of production. Intuitively, these production differences are reversed during the subsequent phases of the cycle.

8 Empirical Tests

In this section, we test the three identifying assumptions underlying our empirical setting. First, we show that firms do not seem to manipulate their ratings to self-select into more favorable categories. Second, we show that firms at the threshold are balanced in terms of their economic characteristics. Finally, we present placebo tests to provide further evidence on the relevance of the threshold between the substandard and performing classes of credit risk. Given that the *Score* is computed on a yearly basis, we perform these tests on the yearly cross-section of firms, unless otherwise stated.

8.1 Manipulation of the Score and Self-Selection

Given the importance of the *Score* in bank credit decisions, a natural question to ask is whether firms are able to manipulate their credit rating and self-select into a better category. Manipulation of the rating is very unlikely, not only because the *Score* is unsolicited by firms and is computed based on firms' past balance sheets, but also because its exact algorithm is a business secret. Nevertheless, manipulation can be detected empirically: it would result in a systematic discontinuity of firms' distribution at the threshold, due either to the absence of observations near the threshold or to the presence of clusters of observations on the side of the threshold assigning a firm to the safer category. In Table VII, we test for the presence of a discontinuity in firm density at that threshold.

[**Table VII Here**]

Following McCrary (2008), for each year we run a kernel local linear regression of the log of the density on both sides of the threshold separating substandard firms in category 7 from performing firms in category 6. Table VII shows that, with the exception of 2008, there is no evidence of significant discontinuities in the distribution of firms at the threshold. The discontinuity in 2008 is most likely coincidental for two reasons. First, if firms had discovered the exact formula of the *Score* and how to manipulate their assignment, a discontinuity should emerge systematically in every year following 2008. Second, had strategic manipulation occurred, it would mean that firms had anticipated by at least one year the financial crisis and the associated benefits of being classified as marginally performing entities.[21]

8.1.1 Policy Experiment

We also exploit a policy experiment to address the potential concern that the discontinuity arising in the McCrary tests for 2008 reflects firms' strategic manipulation of the *Score*. In November 2008, Law 185 (*decreto legislativo n. 185*) granted firms the possibility to

[21] Figure C2 in Online Appendix C provides the year-by-year plots associated with these tests. We also plot the distribution of firms that enter rating categories 6 or 7 in any given year. If firms were able to determine the value of their own continuous variable, then we should observe a disproportionate number of new firms clustering just above the threshold, in category 6. Confirming the lack of manipulation, Figure C3 of Online Appendix C shows that a significant mass of firms enters the sample with a value of the continuous variable that lies just below the threshold, in category 7. Finally we also jointly test for manipulation across the entire cycle and find no evidence of bunching.

revaluate the fixed assets. Crucially, differently from previous laws with the same goal, Law 185 does not require the firm to pay taxes on the higher values of the assets in its balance sheet.

We exploit this policy experiment in the following way: we run our main specification in (3) using as dependent variable the (log) value of revalued assets. If the *Score* was manipulated, then we should observe that those firms that marginally fall in the performing class during the crisis, were also those that revaluated assets disproportionally more than the marginally substandard firms.

[**Table VIII Here**]

Table VIII shows that there is no significant difference in the outcome variable across the three phases of the credit cycle. This evidence further confirms that manipulation of the assignment variable is highly unlikely.

8.2 Balancing Tests

In Table IX, we analyze whether firms close to the threshold are as if randomly sampled, a critical identification assumption within regression discontinuity models. If firms are nonrandomly sorted into specific rating classes, we would expect firm characteristics to differ systematically across the threshold. Following the regression discontinuity literature, the firm characteristics we test are those logically unaffected by the threshold but plausibly related to firm financing.

[**Table IX Here**]

In Panel A of Table IX, the dependent variables are a broad set of firm financing, investment, and profitability measures taken in 2003. In the first row, we show that firms at the threshold do not differ in terms of leverage choices in the pre-sample period. Moreover, we find no significant difference in firms' return on assets or investments.

Panel B tests for differences in bank-firm relationships at the threshold. The first row in the table focuses on the banks' probability of reporting a delinquent loan. If there were a discontinuity in the probability of a firm's credit event at the threshold, then our results could be explained by the fact that banks correctly price this difference. However, we find no statistically or economically significant differences at the threshold. In the second row, the variable *Asked* is a binary indicator equal to one if a bank requests information on a new loan applicant. The estimates suggest that firms at the threshold do not display a different propensity to apply for loans to new banks. The last row of the panel tests for the presence of assortative matching between banks and firms at the threshold (Paravisini, Rappoport, Schnabl, and Wolfenzon, 2014). For each firm, we compute its bank's average size. Again, we find no evidence of a systematic difference at the threshold.

Panel C focuses on differences in time-invariant firm characteristics. In the first row, the dependent variable is the firm's activity sector proxied by its SIC code. The yearly estimates indicate no statistically or economically significant evidence of firms clustering into sectors such as food industries. Next, we look at time-invariant characteristics related to firms' geographic locations. This is a particularly interesting dimension to study within this setting because Italian geography is correlated with heterogeneity in economic development, crime rates, and political accountability (Brollo, Nannicini, Perotti, and Tabellini, 2013) and could thus be associated with opportunistic manipulation. The variable capturing location in the largest cities or the most entrepreneurial areas does not display a statistically significant discontinuity.[22]

8.3 Empirical Relevance of the Threshold

We now provide further evidence on the relevance of the threshold between performing and substandard firms. First, we confirm the local interpretation of our estimates by providing nonparametric plots of the outcome variable as a function of the continuous assignment variable. Second, we implement placebo tests in which we randomly re-label the value of the threshold. Finally, we investigate whether banks use alternative ratings' cutoffs to formulate lending standards.

[22]Table C4 of Online Appendix C shows the results of additional balancing tests.

8.3.1 Nonparametric Plots

In the top panel of Figure 5, we focus on data from the second quarter of 2009, when our results at the threshold feature quantity differences and no interest rate differences. We divide the domain of s into mutually exclusive bins of size 0.03.[23] For each bin, we compute the average and the 90% confidence interval of the outcome variable, and plot these values at the bin's midpoint. The fitted red line shows how close the sixth-order polynomial approximates the variation in bank financing conditions at the threshold.

[Figure 5 and 6 Here]

The left panel of Figure 5 shows that a clear discontinuity arises in the total amount of bank financing close to the threshold. The magnitude of this discontinuity can be quantified by comparing the mean value of the variable of interest in the two bins next to the threshold. Immediately to the left of the threshold, the average value of (log) granted credit is approximately 14.6, whereas immediately to the right this value is 15, implying that the estimated value of β captures the variation arising directly at the threshold. The right panel of Figure 5 repeats this exercise for the interest rates on new bank loans. It shows that when there is no discontinuity in the value of the conditional regression function at the threshold, the polynomial fit does not display any significant discontinuity.

Figure 6 confirms this analysis by focusing on the second quarter of 2011, when our results at the threshold feature significant interest rate differences and no quantity differences.[24]

[23] Our results remain the same when plotting bins of different size, like 0.02 or 0.01.

[24] Note that, around the threshold, the relationship between credit outcomes and the continuous value of the rating is not necessarily monotonic. Two comments are in order here. First, deriving the identification of the estimates from the units closest to the threshold is precisely the focus of the applied literature on discontinuity designs. Second, on average, the relationship between the value of the rating and the interest rates of the loans is monotonic. To address potential concerns on the sensitivity of our results with respect to bandwidth choices we re-estimate our specification using lower polynomial orders, and local linear methods. Our results are robust to these changes, and can be found in Table C5 of Online Appendix C.

8.3.2 Placebo Tests

Finding a significant discontinuity in lending conditions at the threshold, as shown in Figure 4, might not necessarily establish a causal relationship between the threshold and the design of financial contracts. For example, analogous results might arise when comparing financing conditions borne by firms whose *Score* lies further away from the true threshold. We thus implement the following falsification tests: we draw approximately 100 randomly distributed placebo thresholds along the support of *Score* categories 6 and 7, and rerun our specification on the cross-section of firms at the threshold in all the quarters in our sample.

We plot in Figure 7 the distribution of the placebo estimates for the second quarters of 2009 and 2011.

[**Figure 7 Here**]

Figure 7 illustrates that the contractual differences identified by the true threshold estimates (vertical dotted line) are not due to a coincidental discontinuity. If this were the case, then we should observe similar estimates arising when considering randomly placed thresholds. In the top panel, we find that the 100 placebo estimates for the differences in the quantity of bank financing are approximately normally distributed around 0. Similarly, the bottom panel shows that in the second quarter of 2011 the interest rate differences of 20% that we find in the main analysis are well outside the normal variation arising from randomly placed thresholds.[25]

This evidence demonstrates the relevance of the categorical value of the *Score* for Italian banks' lending decisions. If banks were not using the categorical rating when taking their credit choices, then the threshold should not yield financial outcomes that are significantly and systematically different from those obtained using a randomly set

[25] In Online Appendix C, Table C3 reports the descriptive statistics about the mean, median, and statistical significance of these placebo tests across all quarters. The estimated values are about zero and are not significant in most of the quarters. Finally, Figure C4 illustrates that a randomly drawn placebo threshold is also unlikely to yield an economically sensible pattern of estimates across time.

threshold along the support of the continuous variable. Our evidence rejects this claim on the basis of the distribution of placebo estimates within and across the sample period.

8.3.3 Other Rating Thresholds

Finally, as in Agarwal, Chomsisengphet, Mahoney, and Stroebel (2015), we investigate whether banks use alternative ratings' cutoffs to formulate lending standards. We estimate our specification on the cross-section of firms at all the other six thresholds associated with the categorical value of the rating system.[26] In Table X, the reported dummy variable is equal to one for firms in the better, i.e., lower value, rating category, and zero otherwise.

[Table X Here]

Table X shows that most of our estimates on the other thresholds of the *Score* are not statistically significant. This confirms that our results capture a form of market segmentation, not a simple rating effect, as the only rating values that matter are those moving firms between the performing and substandard classes of credit.

9 Conclusions

In this paper, we ask whether the effects of firm segmentation into performing and substandard rating classes can affect the lending policies of banks. We take advantage of the institutional features of the Italian credit market for SME in order to obtain a quasi-random assignment of firms into these classes of credit risk. The resulting patterns of lending differences give us a new, contract-level measure for the bank lending standards across the credit cycle. In this setting, bank lending standards are driven by market segmentation, and reflect banks' sensitivity to the markets for banks capital.

We find that, in boom, banks relax lending standards by narrowing the interest rate spreads between comparable firms falling at the threshold between the substandard and

[26] Due to the construction of the *CEBI* rating, the threshold between categories 5 and 6 cannot be used (see Section 2).

performing classes. Moreover, in this phase there is no difference in the total amount of credit granted to these firms. In bust, the abrupt tightening of lending standards leads to substandard firms losing access to credit. Finally, when lending standards tighten substandard firms report lower values of production and capital investments.

While our analysis focuses on the single credit cycle that interested the Italian economy between 2004 and 2011, there are two considerations that support both the external validity and the interest of our results. First, the aggregate financing patterns of the Italian economy during this period were similar to those of other OECD economies. Second, the credit cycle in our data culminates with the great recession. This renders the analysis particularly interesting, as it allows us to provide implications for the qualitative and quantitative features of lending standards before and during those years, and the consequences for real allocations.

References

[1] Agarwal, S., Chomsisengphet, S., Mahoney, N., Stroebel, J., 2015, Do Banks Pass Through Credit Expansions? The Marginal Profitability of Consumer Lending During the Great Recession, Unpublished Manuscript.

[2] Altman, E. I., 1968, Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy, *Journal of Finance*, 23(4), 589–609.

[3] Altman, E. I., 2003, Managing Credit Risk: The Challenge for the New Millennium (Presentation Slides Available at http://people.stern.nyu.edu/ealtman/2-%20CopManagingCreditRisk.pdf.

[4] Ashcraft, A., 2005, Are Banks Really Special? New Evidence from the FDIC-Induced Failure of Healthy Banks, *American Economic Review*, 95(5), 1712–1730.

[5] Bank of Italy, 2013, The Recent Asset Quality Review on Non-performing Loans Conducted by the Bank of Italy: Main features and results.

[6] Barisitz, S., 2013, Nonperforming Loans in Western Europe—A Selective Comparison of Countries and National Definitions, in Oesterreichische Nationalbank (Austrian Central Bank),*Focus on European Economic Integration*, Q1/13, 28–47.

[7] Becker, B., Ivashina, V., 2014, Cyclicality of Credit Supply: Firm Level Evidence, *Journal of Monetary Economics*, 62, 76–93.

[8] Bholat, D., Lastra, R., Markose, S., Miglionico, A., Sen, K., 2016, Non-performing Loans: Regulatory and Accounting Treatments of Assets, Bank of England Staff Working Paper No. 594.

[9] Brollo, F., Nannicini, T., Perotti, R., Tabellini, G., 2013, The Political Resource Curse, *American Economic Review*, 103(5), 1759–1796.

[10] Chernenko, S., Sunderam, A., 2012, The Real Consequences of Market Segmentation, *Review of Financial Studies*, 25(7), 2041–2069.

[11] Chodorow-Reich, G., 2014, The Employment Effects of Credit Market Disruptions: Firm-level Evidence from the 2008-2009 Financial Crisis, *Quarterly Journal of Economics*, 129(1), 1–59.

[12] Calonico, S., Cattaneo, M. D., Titiunik, R., 2014, Robust Nonparametric Confidence Intervals for Regression Discontinuity Designs, *Econometrica*, 82(6), 2295–2326.

[13] Covas, F., Den Haan, W. J., 2011, The Cyclical Behavior of Debt and Equity Finance, *American Economic Review*, 101(2), 877–899.

[14] Dell'Ariccia, G., Marquez, R., 2006, Lending Booms and Lending Standards, *Journal of Finance*, 61(5), 2511-2546.

[15] Drehmann, M., Borio, C. E., Tsatsaronis, K., 2012, Characterising the Financial Cycle: Don't Lose Sight of the Medium Term!, Unpublished Manuscript.

[16] Fitch, 2016, Global Bank Rating Criteria.

[17] Gete, P., 2017, Banking Crises, Lending Standards and Misallocation, Unpublished manuscript.

[18] Gilchrist, S., Yankov, V., Zakrajšek, E., 2009, Credit Market Shocks and Economic Fluctuations: Evidence from Corporate Bond and Stock Markets, *Journal of Monetary Economics* 56, 471–493.

[19] Gorton, G. B., Metrick, A., 2012, Securitized Banking and the Run on Repo, *Journal of Financial Economics*, 104(3), 425–451.

[20] Greenwood, R., Hanson, S. G., 2013, Issuer Quality and Corporate Bond Returns, *Review of Financial Studies*, 26(6), 1483–1525.

[21] Imbens, G., Kalyanaraman, K., 2014, Optimal Bandwidth Choice for the Regression Discontinuity Estimator, *Review of Economic Studies*, 79(3), 933–959.

[22] Intesa, 2015, Intesa Sanpaolo Group, Consolidated Financial Statements (Part E).

[23] Ivashina, V., 2009, Asymmetric Information Effects on Loan Spreads, *Journal of Financial Economics*, 92(2), 300–319.

[24] Ivashina, V., Scharfstein, D., 2009, Bank Lending During the Financial Crisis of 2008, *Journal of Financial Economics*, 97(3), 319—338.

[25] Iyer, R., Peydró, J.L., da-Rocha-Lopes, S., Schoar, A., 2014, Interbank Liquidity Crunch and the Firm Credit Crunch: Evidence from the 2007-2009 Crisis, *Review of Financial Studies*, 27(1), 347–372.

[26] Iyer, R., Puri, M., Ryan, N., ..., A Tale of Two Runs: Depositor Responses to Bank Solvency Risk, *Journal of Finance*, 71(6), 2687–2726.

[27] Jassaud, N., Kang, K., 2015, A Strategy for Developing a Market for Nonperforming Loans in Italy, IMF Working Paper No. 15/24.

[28] Jermann, U., Quadrini, V., 2012, Macroeconomic Effects of Financial Shocks, *American Economic Review*, 102(1), 238–271.

[29] Jiménez, G., Ongena, S., Peydró, J.L., Saurina, J., 2012, Credit Supply and Monetary Policy: Identifying the Bank Balance-Sheet Channel with Loan Applications, *American Economic Review*, 102(5), 2301–2326.

[30] Jiménez, G., Ongena, S., Peydró, J.L., Saurina, J., 2014, Hazardous Times for Monetary Policy: What Do 23 Million Loans Say About the Impact of Monetary Policy on Credit Risk-Taking?, *Econometrica*, 82(2), 463–505.

[31] Kisgen, D. J., Strahan, P. E., 2010, Do Regulations Based on Credit Ratings Affect a Firm's Cost of Capital, *Review of Financial Studies*, 23(12), 4324–4347.

[32] Khwaja, A. I., Mian, A., 2008, Tracing the Impact of Bank Liquidity Shocks: Evidence from an Emerging Market, *American Economic Review*, 98(4), 1413–1442.

[33] Kovbasyuk, S., Spagnolo, G., 2016, Memory and Markets, Unpublished Manuscript.

[34] Lopez-Salido, D., Stein, J., Zakrajšek, E., 2015, Credit-Market Sentiment and the Business Cycle, Unpublished Manuscript.

[35] Maddaloni, A., Peydro, J. L., 2011, Bank Risk-taking, Securitization, Supervision, and Low Interest Rates: Evidence from the Euro-area and the US Lending Standards, *Review of Financial Studies*, 24(6), 2121–2165.

[36] McCrary, J., 2008, Manipulation of the Running Variable in the Regression Discontinuity Design: A Density Test, *Journal of Econometrics*, 142(2), 698–714.

[37] Moody's, 2015, Rating Methodology: Banks.

[38] OECD, 1997, Small Businesses, Job Creation and Growth: Facts, Obstacles and Best Practices.

[39] Martin, A., 2008, Endogenous Credit Cycles, Unpublished Manuscript.

[40] Rodano, G., Serrano-Velarde, N., Tarantino, E., 2016, Bankruptcy Law and Bank Financing, *Journal of Financial Economics*, 120(2), 363–382.

[41] Stein, J. C., 2002, Information Production and Capital Allocation: Decentralized versus Hierarchical Firms, *Journal of Finance*, 57(5), 1891–1921.

[42] Sufi, A., 2007, Information Asymmetry and Financing Arrangements: Evidence from Syndicated Loans, *Journal of Finance*, 62(2), 629–668.

[43] Standard & Poor's, 2004, Credit Risk Tracker Italy, Standard & Poor's Risk Solutions.

[44] Tirole, J., 2006, *The Theory of Corporate Finance*, Princeton University Press: Princeton and Oxford.

[45] Unicredit Bank, 2008, Unicredit S.p.A. 2008 Annual Report.

[46] World Bank, 2002, Bank Loan Classification and Provisioning Practices in Selected Developed and Emerging Countries (A Survey of Current Practices in Countries Represented on the Basel Core Principles Liaison Group).

A Tables and Figures

Table I: Banks' Cost of Financing and Rating Segmentation

	(1)	(2)	Pre 2008 (3)	Post 2008 (4)
Substandard to Total Credit	1.26***	1.24*	-0.37	1.34**
	(0.46)	(0.66)	(0.29)	(0.68)
Continuous Variable 1		-0.2		
		(0.15)		
Continuous Variable 2		0.09		
		(0.31)		
Bank Characteristics	Yes	Yes	Yes	Yes
Bank Fixed Effects	No	No	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
R-squared	0.76	0.76	0.85	0.54
N	4,788	4,728	2,233	2,212

Notes: The table reports the estimates of the specification in equation (1), using as a dependent variable the interest rate at which Italian banks raise financing. In columns (1) and (2), the dependent variable is the (volume) weighted average interest rate at which banks raised financing across different types of investors (repo markets, households, firms) between 2004 and 2011. In columns (3) and (4), we re-estimate our pricing equation for the period before and after 2008, respectively. Accordingly, the dependent variable is the interest rate at which banks raised financing on repurchase markets before 2008 in column (3) and after 2008 in column (4). *Substandard to Total Credit* is the share of a bank's volume of lending to SME in the "substandard" rating class relative to total lending. *Continous Variable 1* denotes the mean of the continuous variable of firms in rating categories 1 to 5. *Continous Variable 2* denotes the mean of the continuous variable of firms in rating categories 6 to 9. The specification includes a vector of bank and issuance characteristics. Issuance characteristics include amounts raised, maturity, and investor composition. Bank characteristics include size (in terms of total assets), the value of the Tier 1 capitalization ratio, and the bank's liquidity ratio. The specification includes monthly fixed effects, with standard errors clustered at the bank level. One star denotes significance at the 10% level, two stars denote significance at the 5% level, and three stars denote significance at the 1% level.

Table II: Descriptive Statistics

	All	Performing	Substandard	Score 6	Score 7	6-7 Comparison
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: Loan Information			
Term Loans: Interest Rate	4.57	4.32	5.3	4.79	5.29	-0.48***
	(1.62)	(1.56)	(1.6)	(1.58)	(1.59)	
Term Loans: Amount	816	885	617	451	569	-118
	(9850)	(5156)	(17300)	(1623)	(17700)	
Term Loans: Maturity	0.66	0.66	0.65	0.77	0.72	0.05***
	(0.47)	(0.47)	(0.48)	(0.44)	(247)	
N	253,502	188,026	65,475	49,265	60,326	109,591
			Panel B: Aggregate Financing Information			
All Bank Financing Granted	8,503	9,237	6,167	7,542	6,392	1,150***
	(37,200)	(40,600)	(23,100)	(24,600)	(21,100)	
Share of Term Loans Granted	0.35	0.35	0.36	0.33	0.35	-0.02***
	(0.25)	(0.25)	(0.25)	(0.21)	(0.25)	
Share of Write-downs	0.01	0.01	0.03	0.00	0.01	-0.01***
	(0.09)	(0.04)	(0.17)	(0.05)	(0.09)	
N	543,855	414,041	129,754	63,722	104,253	167,975
			Panel C: Balance Sheet Information			
Employment	92	95	76	73	72	1
	(294)	(295)	(290)	(170)	(207)	
Investment to Assets	0.05	0.05	0.04	0.04	0.039	0.001**
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	
Return to Assets	0.05	0.07	0.00	0.05	0.03	0.02***
	(0.10)	(0.08)	(0.13)	(0.07)	(0.07)	
Leverage	0.67	0.61	0.86	0.79	0.85	-0.06***
	(0.19)	(0.18)	(0.10)	(0.10)	(0.09)	
N	143,953	108,353	35,600	16,432	27,350	43,782

Notes: All panels use data for the period 2004.Q1–2011.Q4, and monetary values expressed in KE (1,000 Euro). Standard deviations are reported in brackets. The last column reports the difference in means of each variable between categories 6 and 7. One star denotes significance at the 10% level, two stars denote significance at the 5% level, and three stars denote significance at the 1% level. Panel A uses pooled loan-level data with observations at the loan-quarter level. *Interest Rate* is the gross annual interest rate inclusive of participation fees, loan origination fees, and monthly service charges. *Amount* is the granted amount of the issued term loan. *Maturity* is a binary variable indicating whether the maturity of the newly issued loans is up to one year, or longer. Panel B uses credit register data with observations at the firm-quarter level. *All Bank Financing Granted* is the firms' total amount of bank financing granted summing across all categories (loans, credit lines, backed loans). *Share of Term Loans Granted* is the firms' total amount of term loans granted, divided by the total amount of bank financing granted for all categories. *Share of Write-downs* is a binary variable indicating whether the firms' total amount of bank financing granted for all categories has experienced write-downs by banks. Panel C uses balance sheet and cash flow statements at the firm-year level. *Employment* is defined as the firms' average employment over the year. *Investment to Assets* is the firms' investment in material fixed assets over total fixed assets. *Returns to Assets* is defined as the firms' earnings before interest and taxes over total assets. *Leverage* is the firms' ratio of debt (both short- and long-term) over total assets. In all panels, *N* corresponds to the pooled number of observations in our sample.

Table III: Credit Effects

Dependent Variable	Quantity			Price		
	(1)	(2)	(3)	(1)	(2)	(3)
Performing	0.08	0.07	0.35***	-0.02	-0.02*	-0.15***
	(0.07)	(0.07)	(0.01)	(0.01)	(0.01)	(0.01)
Crisis×Performing	0.19***	0.18***	-0.03**	0.00	0.00	-0.00
	(0.03)	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)
Recovery×Performing	-0.09**	-0.08**	-0.02	-0.04***	-0.04**	-0.11***
	(0.04)	(0.04)	(0.01)	(0.01)	(0.01)	(0.01)
Lagged Rating		-0.01***	0.00***		0.00***	0.00***
		(0.00)	(0.00)		(0.00)	(0.00)
Polynomial	Yes	Yes	No	Yes	Yes	No
Quarter × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.05	0.05	0.01	0.37	0.37	0.43
N	166,993	157,775	518,047	109,586	105,865	246,240

Notes: In the columns denoted (1) and (2), the table reports OLS estimates of the threshold specification in equation 3. Instead, the columns denoted by (3) estimate a simple mean difference specification using data for all firms in the rating system. The dependent variable in the first three columns is the (log) total value of bank lending granted to firm i in quarter t. The dependent variable in the last three columns is the (log) value of the interest rate applied to a new loan granted to firm i in quarter t. The indicator $Performing_{i,t}$ takes a value of 1 if a firm is in the performing class (i.e., $s_{i,t} \geq 0$ implying a *Score* of 6), and 0 otherwise. It is interacted with two indicator variables associated with the phases of the credit cycle. $Crisis_t$ takes a value of one from the first quarter of 2008 onwards, while $Recovery_t$ takes a value of one from the first quarter of 2010 onwards. Functions $f(\cdot)$ and $g(\cdot)$ correspond to flexible sixth-order polynomials. Function $f(\cdot)$ is estimated from 0 to the left, whereas the $Performing_{i,t} \times g(\cdot)$ term is estimated from 0 to the right. Finally, *Lagged Rating* controls for the past value of the rating. Standard errors, clustered at the firm level, are reported in brackets. One star denotes significance at the 10% level, two stars denote significance at the 5% level, and three stars denote significance at the 1% level.

Table IV: Real Effects

Dependent Variable	Production (1)	Production (2)	Investment (1)	Investment (2)	Intermediates (1)	Intermediates (2)	Employment (1)	Employment (2)
Performing	0.18**	0.21***	0.07	0.13	0.11*	0.14**	0.18**	0.18**
	(0.07)	(0.07)	(0.11)	(0.11)	(0.07)	(0.07)	(0.06)	(0.06)
Crisis×Performing	0.17***	0.17***	0.32***	0.31***	0.19***	0.18***	0.16***	0.15***
	(0.03)	(0.03)	(0.05)	(0.06)	(0.03)	(0.03)	(0.03)	(0.03)
Recovery×Performing	-0.16**	-0.15**	-0.29***	-0.29**	-0.12***	-0.11**	-0.16***	-0.13***
	(0.04)	(0.04)	(0.06)	(0.06)	(0.04)	(0.04)	(0.03)	(0.03)
Lagged Rating		-0.01***		-0.00*		-0.00*		-0.01***
		(0.00)		(0.00)		(0.00)		(0.00)
Polynomial	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.08	0.08	0.07	0.07	0.09	0.09	0.02	0.02
N	43,758	41,157	36,072	33,889	43,095	40,585	41,441	39,041

Notes: The table reports the estimates of the threshold specification in model (3) using as dependent variables the (log) sales, investment, employment, and intermediates of firm i in year t. The indicator $Performing_{i,t}$ takes a value of 1 if a firm is in the performing class (i.e., $s_{i,t} \geq 0$ implying a *Score* of 6), and 0 otherwise. It is interacted with two indicator variables associated with the phases of the credit cycle. $Crisis_t$ takes a value of one from the first quarter of 2008 onwards, while $Recovery_t$ takes a value of one from the first quarter of 2010 onwards. Functions $f(\cdot)$ and $g(\cdot)$ correspond to flexible sixth-order polynomials. Function $f(\cdot)$ is estimated from 0 to the left, whereas the $Performing_{i,t} \times g(\cdot)$ term is estimated from 0 to the right. Finally, *Lagged Rating* controls for the past value of the rating. Standard errors, clustered at the firm level, are reported in brackets. One star denotes significance at the 10% level, two stars denote significance at the 5% level, and three stars denote significance at the 1% level.

Table V: Bank Heterogeneity

Dependent Variable	Quantity			Price		
	(1)	(2)	(3)	(1)	(2)	(3)
Performing	0.06			-0.03		
	(0.05)			(0.02)		
Crisis×Performing	0.14**			-0.03		
	(0.06)			(0.03)		
Recovery×Performing	-0.09			-0.04***		
	(0.08)			(0.06)		
Performing×Tier1	0.21	-0.07		0.04	0.23	
	(0.31)	(0.23)		(0.16)	(0.11)	
Crisis×Performing×Tier1	-0.90**	-0.75**		0.01	0.17	
	(0.03)	(0.36)		(0.27)	(0.25)	
Recovery×Performing×Tier1	0.01	-0.14		0.24	0.04	
	(0.53)	(0.45)		(.40)	(.38)	
Performing×Repo	-0.01	-0.02		-0.21**	0.11	
	(0.15)	(0.11)		(0.08)	(0.11)	
Crisis×Performing×Repo	0.43*	0.33*		0.49**	0.10	
	(0.26)	(0.2)		(0.15)	(0.14)	
Recovery×Performing×Repo	0.16	-0.05		-0.33	-0.11	
	(0.38)	(0.30)		(0.27)	(0.27)	
Performing×Organization			-0.01			-0.02**
			(0.01)			(0.01)
Crisis×Performing×Organization			-0.04**			-0.00
			(0.02)			(0.01)
Recovery×Performing×Organization			0.01			0.02
			(0.02)			(0.02)
Lagged Rating	-0.00***			0.00***		
	(0.00)			(0.00)		
Polynomial	Yes	Yes	Yes	No	Yes	Yes
Quarter × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	No
Firm × Year Fixed Effects	No	No	No	Yes	No	Yes
R-squared	0.02	0.55	0.61	0.36	0.77	0.76
N	787,634	787,634	814,864	89,140	89,140	99,471

Notes: The table reports OLS estimates of the threshold specification in equation (5). The dependent variable in the first three columns is the (log) total value of bank lending granted by bank b to firm i in quarter t. The dependent variable in the last three columns is the (log) value of the interest rate applied to a new loan granted by bank b to firm i in quarter t. The indicator $Performing_{i,t}$ takes a value of 1 if a firm is in the performing class (i.e., $s_{i,t} \geq 0$ implying a *Score* of 6), and 0 otherwise. It is interacted with two indicator variables associated with the phases of the credit cycle. $Crisis_t$ takes a value of one from the first quarter of 2008 onwards, while $Recovery_t$ takes a value of one from the first quarter of 2010 onwards. $Tier1_b$ is defined as a bank b's core equity capital divided by its total assets, and $Repo_b$ is defined as the share of the bank's total financing from repo markets. The indicator variable $Organization_b$ is equal to 1 if banks report a high reliance on soft information in their lending process. All of the bank specific variables are measured pre-crisis. Functions $f(\cdot)$ and $g(\cdot)$ correspond to flexible sixth-order polynomials. Function $f(\cdot)$ is estimated from 0 to the left, whereas the $Performing_{i,t} \times g(\cdot)$ term is estimated from 0 to the right. *Lagged Rating* controls for the past value of the rating. Standard errors, clustered at the firm-bank level, are reported in brackets. One star denotes significance at the 10% level, two stars denote significance at the 5% level, and three stars denote significance at the 1% level.

Table VI: Downgrades from Performing to Substandard

Dependent Variable	Quantity		Price		Production	
	(1)	(2)	(1)	(2)	(1)	(2)
Down	0.10***	0.25**	0.03***	0.01	0.08***	0.21*
	(0.03)	(0.11)	(0.00)	(0.02)	(0.03)	(0.11)
Crisis×Down	-0.08*	-0.09**	-0.02**	-0.01**	-0.08*	-0.11**
	(0.05)	(0.05)	(0.01)	(0.01)	(0.05)	(0.05)
Recovery×Down	-0.15***	-0.13**	0.02*	0.02*	-0.01	0.01
	(0.05)	(0.05)	(0.01)	(0.01)	(0.05)	(0.05)
Polynomial	No	Yes	No	Yes	No	Yes
Quarter × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.01	0.02	0.39	0.39	0.02	0.04
N	88,830	88,830	70,848	70,848	22,978	22,978

Notes: The table reports OLS estimates of the threshold specification in equation (6) using the sample of firms downgraded from *Score* 6 to 7. The dependent variable in the first two columns is the (log) total value of bank lending granted to firm i in quarter t. The dependent variable in the third and fourth columns is the (log) value of the interest rate applied to a new loan granted to firm i in quarter t. The dependent variable in the fifth and sixth columns is the (log) value of sales of firm i in year t. The indicator $Down_{i,t}$ is a binary variable equal to 1 if the firm is downgraded from category 6 to category 7 in year t, and is 0 otherwise. It is interacted with two indicator variables associated with the phases of the credit cycle. $Crisis_t$ takes a value of one from the first quarter of 2008 onwards, while $Recovery_t$ takes a value of one from the first quarter of 2010 onwards. Functions $f(\cdot)$ and $g(\cdot)$ correspond to flexible sixth-order polynomials. The polynomials in $f(\cdot)$ and $g(\cdot)$ are now a function of the change in the continuous variable between $t-1$ and t. Standard errors, clustered at the firm level, are reported in brackets. One star denotes significance at the 10% level, two stars denote significance at the 5% level, and three stars denote significance at the 1% level.

Table VII: Self-Selection Into Rating Categories 6 and 7

Year	2004	2005	2006	2007	2008	2009	2010	2011
McCrary Density Estimate	0.10	0.13	0.02	0.08	0.3***	-0.00	0.08	0.17
	(0.06)	(0.07)	(0.07)	(0.06)	(0.07)	(0.08)	(0.10)	(0.10)
N	5,951	5,876	6,098	6,514	5,551	5,360	4,307	4,110

Notes: The table reports, at a yearly level, the McCrary density estimates of the continuous variable's distribution. For each year, we run a kernel local linear regression of the log of the density on both sides of the threshold separating substandard firms in category 7 from performing firms in category 6. One star denotes significance at the 10% level, two stars denote significance at the 5% level, and three stars denote significance at the 1% level.

Table VIII: Manipulation - Revaluations

Dependent Variable	Log Revaluations	
	(1)	(2)
Boom×Performing	-0.04	-0.05
	(.05)	(.06)
Crisis×Performing	0.03	0.02
	(0.03)	(0.03)
Recovery×Performing	0.01	0.01
	(0.03)	(0.04)
Polynomial	Yes	Yes
Quarter × Year Fixed Effects	Yes	Yes
Control Variables	No	Yes
R-squared	0.12	0.21
N	77,079	57,243

Notes: the table reports OLS estimates of the threshold specification in model 3. The dependent variable is the (log) value of revalued assets of firm i in year t. The indicator $Performing_{i,t}$ takes a value of 1 if a firm is in the performing class (i.e., $s_{i,t} \geq 0$ implying a *Score* of 6), and 0 otherwise. It is interacted with two indicator variables associated with the phases of the credit cycle. $Crisis_t$ takes a value of one from the first quarter of 2008 onwards, while $Recovery_t$ takes a value of one from the first quarter of 2010 onwards. Functions $f(\cdot)$ and $g(\cdot)$ correspond to flexible sixth-order polynomials. Function $f(\cdot)$ is estimated from 0 to the left, whereas the $Performing_{i,t} \times g(\cdot)$ term is estimated from 0 to the right. Standard errors, clustered at the firm level, are reported in brackets. One star denotes significance at the 10% level, two stars denote significance at the 5% level, and three stars denote significance at the 1% level.

Table IX: Model Diagnostics - Balancing Checks

Year	2004	2005	2006	2007	2008	2009	2010	2011
				Panel A: Presample Characteristics				
Leverage	0.00	0.01	-0.04	-0.03	0.05	-0.01	-0.04	0.01
	(.03)	(.04)	(.03)	(.03)	(.04)	(.04)	(.05)	(.06)
N	3,967	3,636	3,595	3,678	2,888	2,705	2,168	2,024
Return to Assets	0.00	0.00	0.00	-0.01	-0.02	0.00	0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
N	5,306	4,844	4,750	4,836	3,776	3,504	2,721	2,508
Investment to Assets	0.02	0.02	0.01	0.02	0.02	-0.02	-0.03	-0.02
	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)
N	4,501	4,136	4,083	4,174	3,353	3,100	2,414	2,237
				Panel B: Bank Balancing Characteristics				
Credit Event		0.01	0.00	0.01	0.00	-0.01	0.00	-0.03
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)
N		5,736	5,944	6,358	5,411	5,276	4,235	4,045
Asked	0.02	0.00	-0.02	-0.07	-0.03	0.04	0.03	-0.07
	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.04)	(0.05)	(0.05)
N	5,687	5,677	5,889	6,306	5,370	5,264	4,217	4,030
Bank Size	-0.12	-0.05	-0.02	0.23**	0.1	0.09	0.04	0.23
	(0.14)	(0.14)	(0.11)	(0.12)	(0.14)	(0.17)	(0.19)	(0.18)
N	5,652	5,641	5,855	6,287	5,356	5,108	4,105	3,937
				Panel C: Time Invariant Characteristics				
Activity: Food Industry	0.03	-0.04	0.03	-0.01	0.05	0.04	0.06	-0.06
	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.06)	(0.06)
N	5,951	5,876	6,098	6,514	5,551	5,360	4,307	4,110
Location: Top 5 Cities	0.06	0.03	0.05	-0.06	0.02	-0.01	0.07	0.05
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.08)	(0.07)
N	5,951	5,876	6,098	6,514	5,551	5,360	4,307	4,110

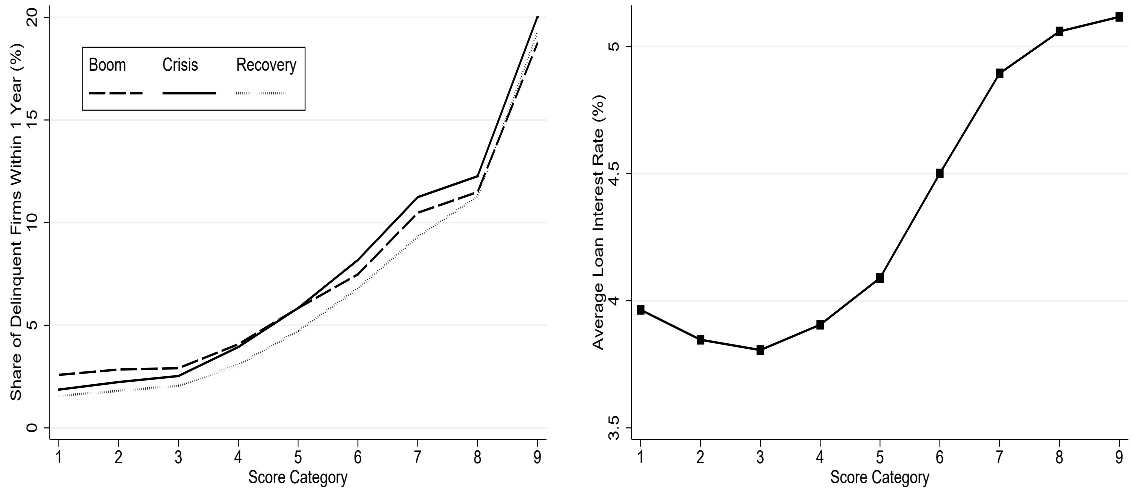
Notes: The table estimates differences in presample firm characteristics at the threshold. In all rows, the dependent variable is measured in 2003. The estimates refer to the indicator variable $Performing_{i,t}$ takes a value of 1 if a firm is in the performing class (i.e., $s_{i,t} \geq 0$ implying a *Score* of 6), and 0 otherwise. *Credit Event* is a binary variable equal to one if any of a given firm's banks classified the firm's credit as nonperforming. *Asked* is a binary variable equal to one if any non-current bank requested information on the firm during the year. *Food Industry* is a binary variable indicating whether the firms' SIC code belongs to the food industry. *Top 5 Cities* is a binary variable indicating whether the firms' headquarters zip code is in one of the largest five cities. See Tables II for the definition of the other variables. One star denotes significance at the 10% level, two stars denote significance at the 5% level, and three stars denote significance at the 1% level.

Table X: Yearly RDD Estimates - Other Thresholds

Year	2004	2005	2006	2007	2008	2009	2010	2011
				Threshold Between Categories 1 and 2				
Quantity	-0.3	-0.15	0.07	0.17	-0.28	-0.19	-0.3	-0.32
	(0.24)	(0.26)	(0.26)	(0.31)	(0.27)	(0.25)	(0.23)	(0.21)
N	2,555	2,693	2,648	2,684	2,886	2,975	2,677	2,773
Price	0.04	0.13	0.08	0.03	-0.12	-0.23	-0.04	-0.22
	(0.11)	(0.12)	(0.11)	(0.08)	(0.08)	(0.2)	(0.18)	(0.22)
N	583	716	782	815	715	712	832	775
				Threshold Between Categories 2 and 3				
Quantity	-0.12	-0.19	-0.45	-0.3	-0.25	-0.2	-0.45	-0.51
	(0.39)	(0.4)	(0.39)	(0.35)	(0.41)	(0.34)	(0.36)	(0.35)
N	2,311	2,508	2,480	2,383	2,265	2,243	2,243	2,375
Price	0.00	0.16	-0.1	0.01	-0.02	-0.1	-0.23	0.7***
	(0.13)	(0.12)	(0.11)	(0.08)	(0.14)	(0.27)	(0.22)	(0.22)
N	1,099	1,427	1,595	1,702	1,475	1,260	1,406	1,825
				Threshold Between Categories 3 and 4				
Quantity	-0.24	-0.03	-0.14	0.29	0.11	-0.29	-0.15	0.29
	(0.31)	(0.3)	(0.35)	(0.29)	(0.33)	(0.32)	(0.29)	(0.3)
N	6,087	6,361	6,371	6,526	6,040	5,968	5,840	6,128
Price	-0.03	0.03	0.09	-0.03	-0.08	-0.01	-0.12	-0.03
	(0.08)	(0.09)	(0.08)	(0.04)	(0.06)	(0.13)	(0.15)	(0.12)
N	7,197	9,359	10,255	10,547	9,033	8,625	11,153	13,158
				Threshold Between Categories 4 and 5				
Quantity	-0.33	0.22	-0.44*	-0.18	-0.2	-0.06	-0.26	-0.41*
	(0.24)	(0.24)	(0.24)	(0.21)	(0.24)	(0.24)	(0.24)	(0.23)
N	7,019	7,359	7,437	7,616	6,960	6,878	6,711	7,058
Price	0.00	-0.05	0.03	-0.01	0.00	-0.02	-0.23***	0.07
	(0.05)	(0.06)	(0.04)	(0.03)	(0.03)	(0.1)	(0.08)	(0.07)
N	11,072	14,972	16,561	17,056	14,662	13,505	17,687	19,743
				Threshold Between Categories 7 and 8				
Quantity	-0.25	-0.28	-0.29	-0.06	-0.36	-0.63	1.44*	1.01
	(0.48)	(0.51)	(0.55)	(0.55)	(0.63)	(0.66)	(0.73)	(0.88)
N	4,160	4,136	4,256	4,602	3,752	3,472	2,875	2,688
Price	.00	-0.2	0.1	-0.22**	-0.08	0.35*	-0.56	-0.12
	(0.19)	(0.17)	(0.11)	(0.09)	(0.1)	(0.2)	(0.56)	(0.27)
N	6,058	8,394	10,412	13,192	8,280	6,047	5,883	5,791
				Threshold Between Categories 8 and 9				
Quantity	-0.9	0.18	0.51	-1.31	-1.26	-0.42	-0.97	-1.68
	(1.4)	(1.16)	(1.12)	(1.36)	(1.09)	(1.24)	(0.95)	(1.2)
N	596	649	598	646	595	668	517	616
Price	-1.29	-0.01	0.21	0.09	-0.02	0.07	0.4	-0.31
	(54.98)	(0.53)	(0.26)	(0.27)	(0.13)	(0.5)	(0.47)	(0.4)
N	380	494	655	761	518	701	471	489

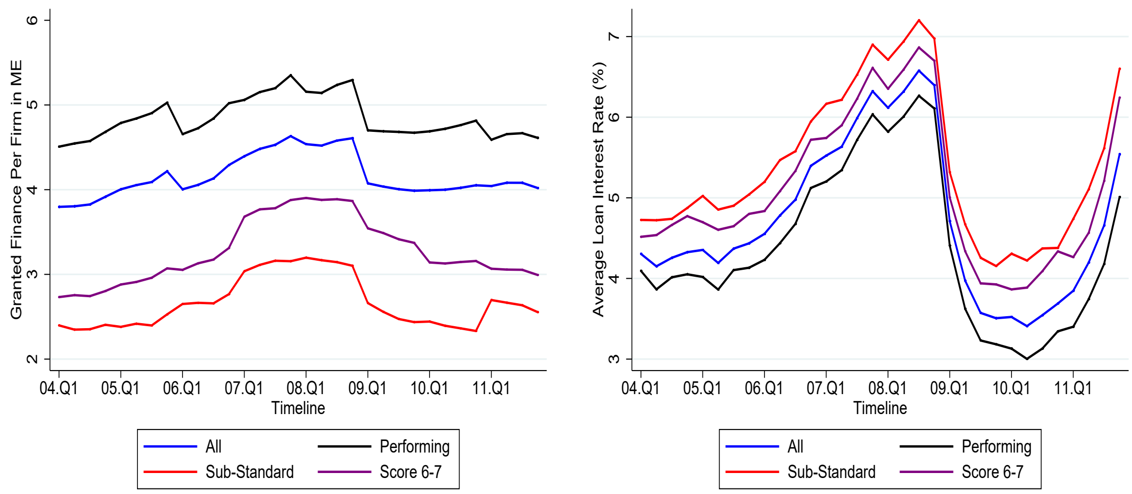
Notes: The table reports estimates from our baseline specification at all the seven thresholds associated with the categorical value of the rating system. We report standard errors in brackets. The dependent variable is either *All Bank Financing Granted* or *Interest Rate* for each year between 2004.Q1–2011.Q4. We estimate the discontinuity ($s_i \geq 0$) using a flexible sixth-order polynomial on either side of each normalized threshold between each contiguous *Score* category, allowing for a discontinuity at 0. The reported estimates refer to S_i, a binary variable that takes a value of one if the continuous variable $s_i \geq 0$, i.e., if the firm is allocated to the lower credit risk category as opposed to the higher credit risk category. See Table II for other variable definitions. One star denotes significance at the 10% level, two stars denote significance at the 5% level, and three stars denote significance at the 1% level.

Figure 1: Characteristics of the *Score* Assignment Variable



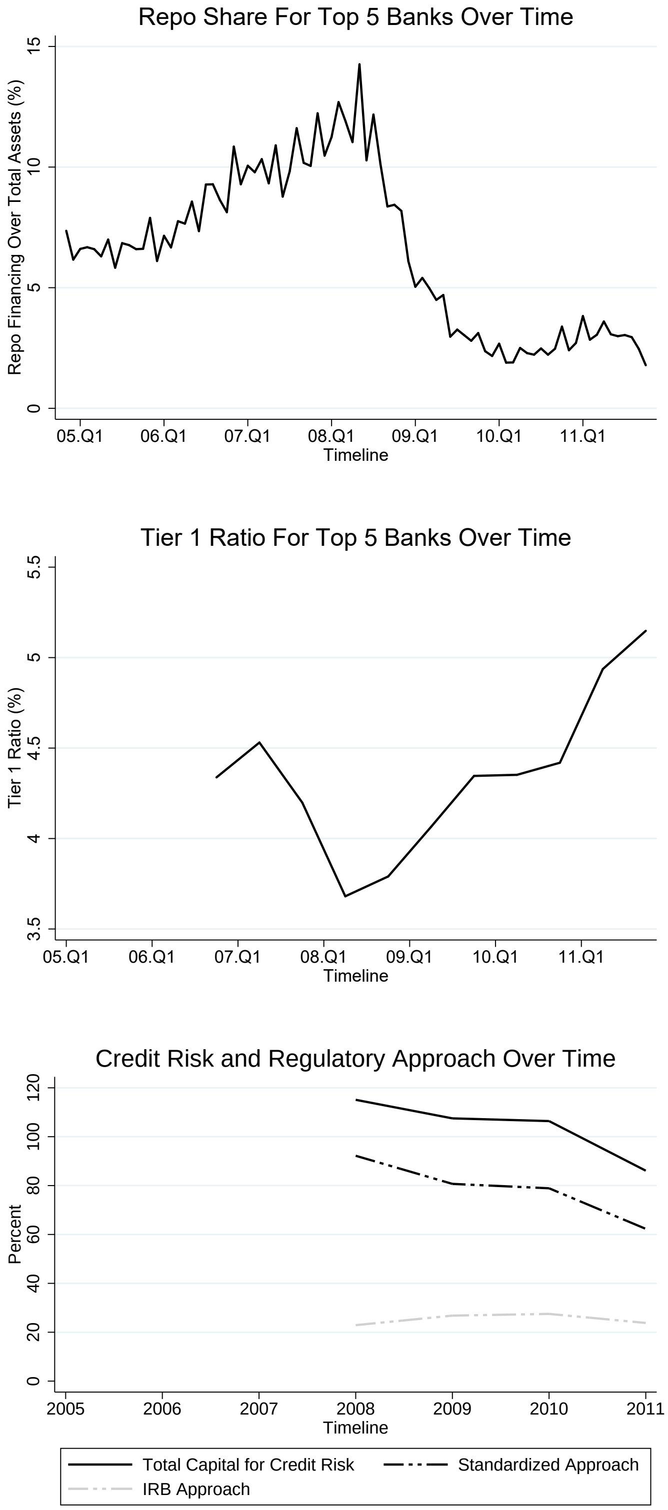
The left panel plots the *Score* variable against the share of defaults within the next year in boom (dashed), crisis (solid) and recovery (dotted). The right panel plots the average loan rate by *Score* category for the first quarter of 2005.

Figure 2: Descriptive Statistics Across Time



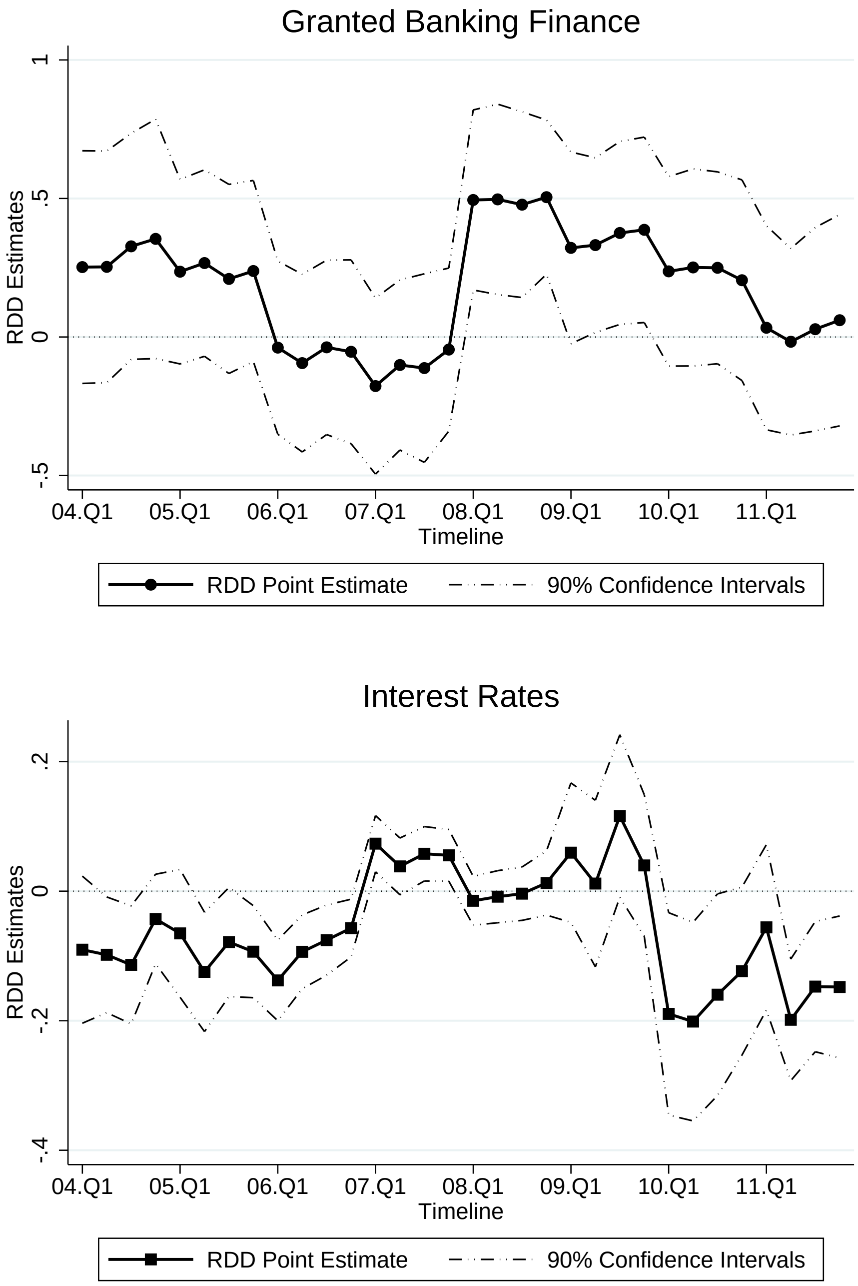
In the left panel, we plot the per-firm aggregate value of bank financing for different rating categories across time. In the right panel, we plot the nominal average interest rates applied to firms in different rating categories across time.

Figure 3: Bank Capital and Credit Risk



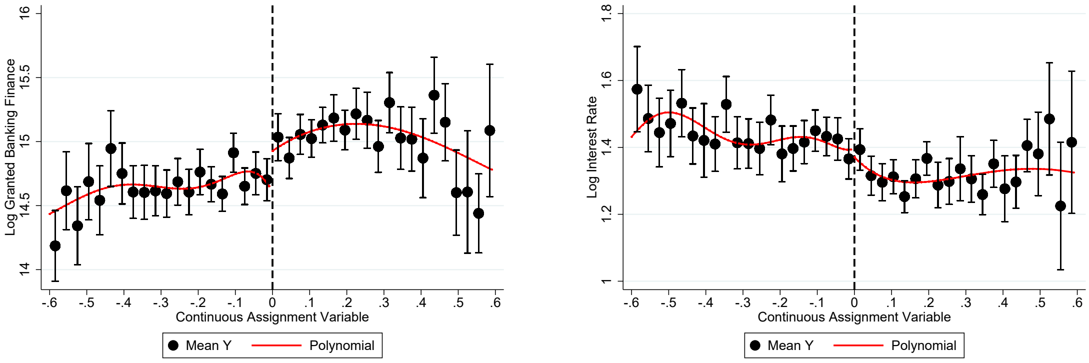
In the top panel, we plot the cost of funding paid by the five largest banks in our dataset on the repo markets. In the middle panel, we plot the Tier 1 capital ratio for the five largest banks in our dataset across time. In the bottom panel, we use data from the European Central Bank statistical data warehouse to plot the credit risk capital allocations over total capital requirements (black line), the fraction of capital allocations computed using the standardised approach (grey line), and the fraction computed using the internal rating-based approach (dashed black line).

Figure 4: Discontinuity Quantity and Price Treatment Effects



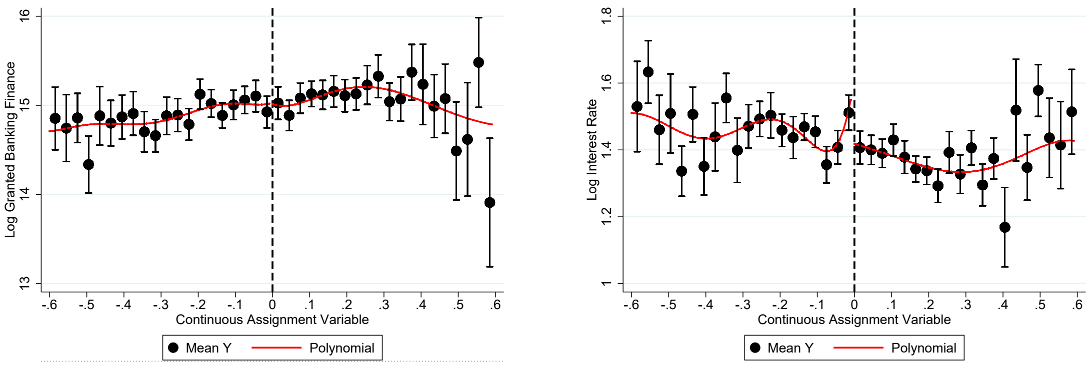
The figure plots the estimates and 90% confidence intervals of the threshold specification in equation (4), run on each distinct quarter in our sample period (2004.Q1–2011.Q4). The dependent variable in the top panel is the (log) total value of bank lending granted to firm i in quarter t (top panel). The dependent variable in the bottom panel is the (log) value of the interest rate applied to a new loan granted to firm i in quarter t (bottom panel). The plotted discontinuity estimates refer to $Performing_{i,t}$, an indicator variable that takes a value of 1 if a firm is in the performing class (i.e., $s_{i,t} \geq 0$ implying a *Score* of 6), and 0 otherwise.

Figure 5: 2nd Quarter of 2009



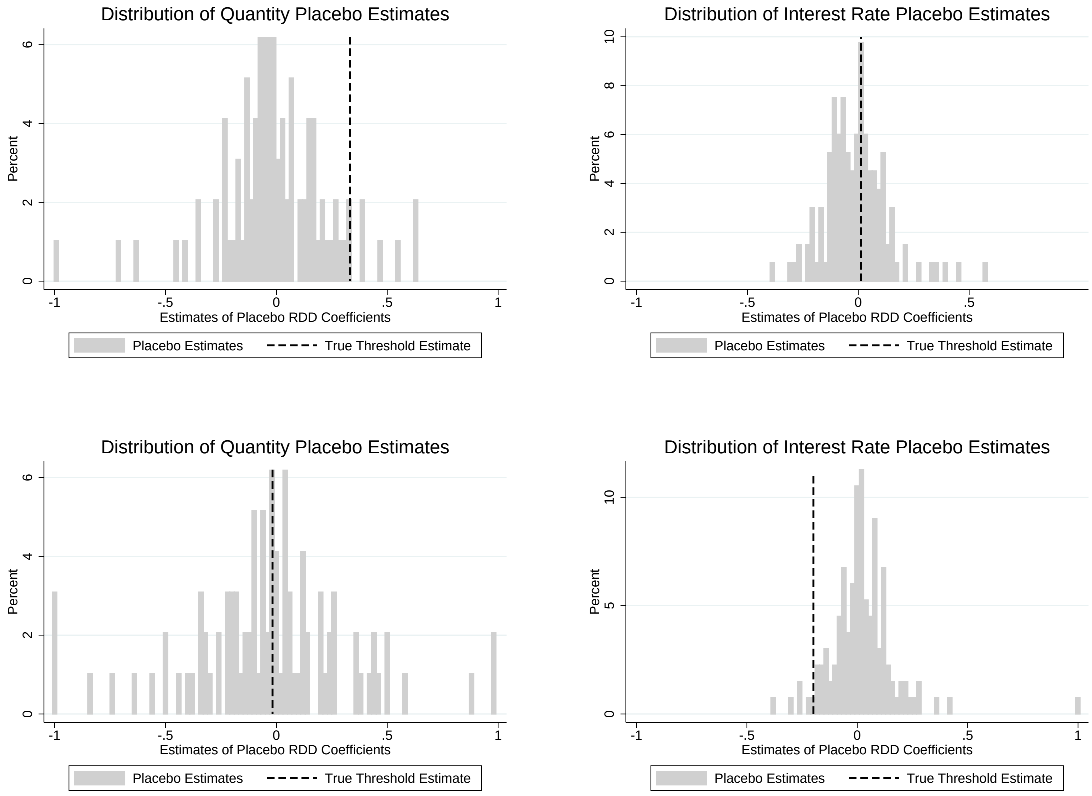
The figure focuses on the second quarter of 2009. We divide the domain of s_i into mutually exclusive bins with a size of 0.03. For each bin, we compute the average and the 90% confidence interval of the outcome variable, and plot these values at the bin's mid-point. The fitted red line shows how closely the sixth-order polynomial approximates the variation in bank financing conditions at the threshold.

Figure 6: 2nd Quarter of 2011



The figure focuses on the second quarter of 2011. We divide the domain of s_i into mutually exclusive bins with a size of 0.03. For each bin, we compute the average and the standard deviation of the outcome variable, and plot these values at the bin's mid-point. The fitted red line shows how closely the sixth-order polynomial approximates the variation in bank financing conditions at the threshold.

Figure 7: Placebo Estimates—2nd Quarters of 2009 (top panel) and 2011 (bottom panel)



The figure plots the empirical distribution of discontinuity estimates based on approximately 100 randomly drawn placebo thresholds. The vertical dotted line represents the estimate obtained from the true threshold. The top panel figures focus on the second quarter of 2009, while the bottom panel focuses on the second quarter of 2011.

Online Appendix

for

Lending Standards over the Credit Cycle

February 24, 2017

This internet appendix contains supplemental material for the paper "Lending Standards over the Credit Cycle." We present the results in the order they are mentioned in the main text.

A Online Appendix: Data Organization

We first describe the characteristics of the datasets used in the empirical analysis and then define the variables that we construct from these sources.

A.1 The Central Credit Register

Each month, all financial intermediaries operating in Italy (banks, special purpose vehicles, other financial intermediaries providing credit) report financial information to the Bank of Italy for each borrower whose aggregate exposure exceeds 75,000 Euro.[1] Thus, we can use the central credit register to compute the aggregate financial characteristics of firms. For each borrower-bank relationship, we have information on financing levels, both granted and utilized, for three categories of financial instruments: term loans, revolving credit lines, and loans backed by account receivables (advances on trade credit). The information on term loans is supplemented by other nonprice characteristics, such as loan maturity and the presence or absence of real and personal guarantees.

A.2 Taxia

Taxia is a subset of the Central Credit Register that covers information on more than 80% of total bank lending in Italy. More specifically, this dataset provides detailed quarterly information on the interest rates that banks charge to individual borrowers on each newly issued term loan. In addition, the dataset provides information on the maturity and presence of real collateral for each newly issued term loan.

Our analysis focuses on limited liability firms in the manufacturing sector in the 32 quarters between the beginning of 2004 and the end of 2011. We drop all new loans with an amount smaller than 10,000 Euro and the extreme percentiles of the term loan interest-rate distribution. Finally, we focus on those firms that fall in the same rating category for two consecutive years. This ensures that our results do not simply capture the effect of a firm's upgrade or downgrade over time. Note that the qualitative nature of our results remains the same when we include the firms that change risk categories in two consecutive years in our empirical sample.

A.3 Definition of Variables

We use information from the Taxia dataset to compute variables describing each bank financing contract. *Loan Interest Rate* is the gross annual interest rate for each newly issued term loan, inclusive of participation fees, loan origination fees, and monthly service charges. This rate is calculated so that the present value of loan installments equals the present value of payments at loan origination. We also have information on the following term loan characteristics: *Amount* is the granted amount of the issued term loan, and *Maturity* is a set of binary variables indicating whether the maturity of the

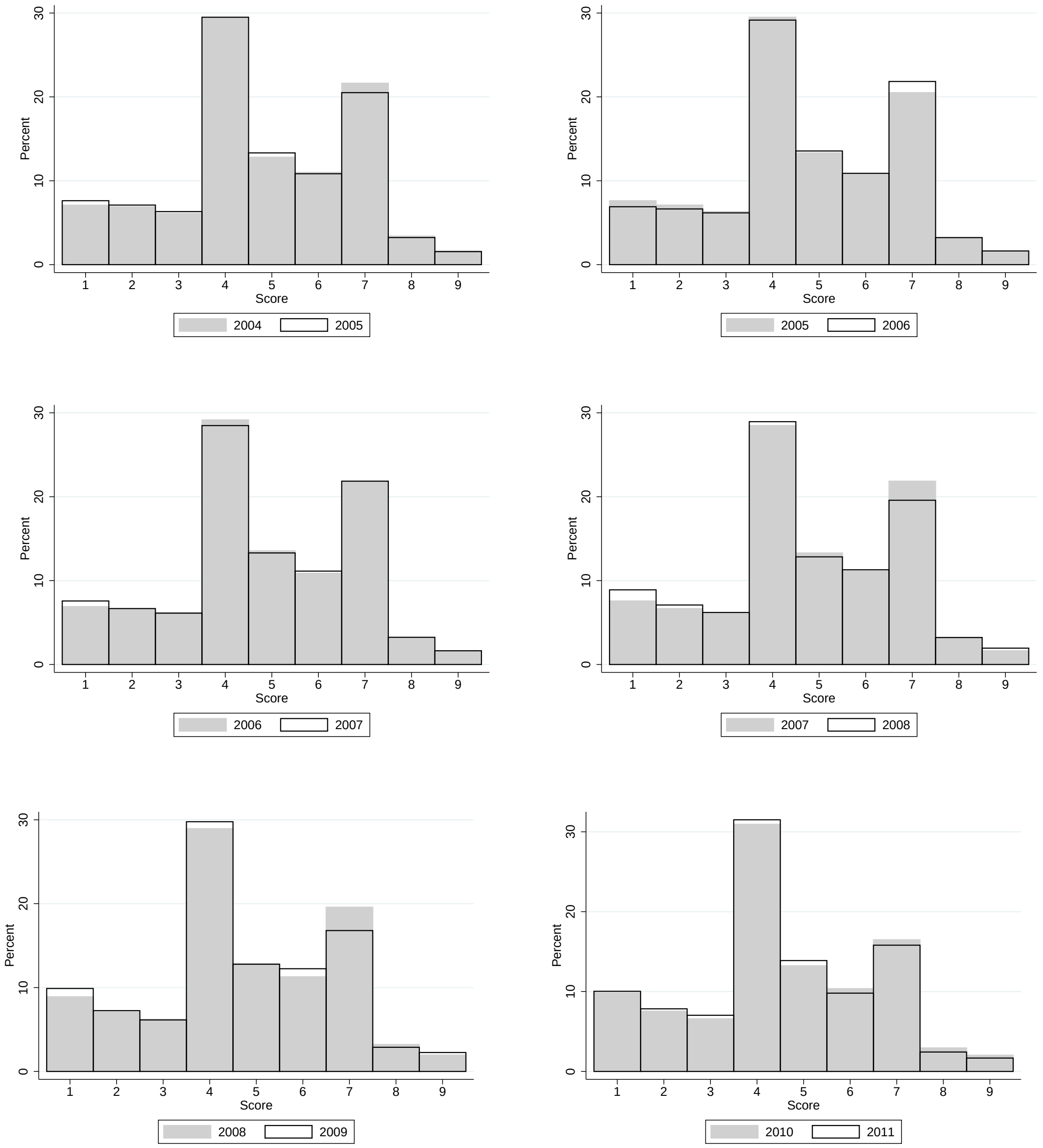
[1] During the sample period, the threshold for the aggregate financial exposure above which banks had to report borrower information to the Bank of Italy changed for administrative reasons. To keep the scope of the sample constant across time, we focus on firms whose aggregate exposure exceeded 75,000 Euro across our sample period.

newly issued loan is up to one year, between one and five years, or more than five years. We use information from the Credit Register to compute aggregate variables describing the financial structure of firms. *All Bank Financing Granted* is the firm's total bank financing granted, including term loans, credit lines, and advances on trade credit.

We use information in the *CEBI* database to compute firm's balance sheet characteristics. *Employment* is the firm's number of employees at the beginning of the year. *Investment to Assets* is the firm's investment in material fixed assets divided by material fixed assets. *Return to Assets* is the firm's earnings before interest and depreciation divided by total assets. *Leverage* is defined as the ratio of debt (both short and long term) to total assets.

B Online Appendix: Score Ratings

Figure B1: Distribution of Firms in *Score* Rating Categories Over Time



This figure plots the share of firms within each *Score* category in two consecutive years for the period between 2004 and 2011.

C Online Appendix: Additional Results

Table C1: Credit Allocation

Year	04.Q1	04.Q2	04.Q3	04.Q4	05.Q1	05.Q2	05.Q3	05.Q4	06.Q1	06.Q2	06.Q3	06.Q4	07.Q1	07.Q2	07.Q3	07.Q4
Quantity	.25	.25	.33	.35	.24	.27	.21	.24	-.04	-.09	-.04	-.05	-.18	-.10	-.11	-.04
	(.24)	(.25)	(.25)	(.26)	(.20)	(.21)	(.19)	(.19)	(.20)	(.18)	(.21)	(.20)	(.20)	(.18)	(.19)	(.19)
R-squared	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.03	.03	.02	.02	.02	.02
N	5,614	5,621	5,621	5,599	5,601	5,608	5,604	5,605	5,822	5,822	5,815	5,829	6,224	6,230	6,237	6,234
Price	-.09	-.10**	-.11**	-.04	-.07	-.13***	-.08*	-.09**	-.14***	-.09***	-.07***	-.06**	.07**	.04	.06**	.05**
	(.07)	(.05)	(.06)	(.05)	(.06)	(.05)	(.05)	(.04)	(.04)	(.04)	(.03)	(.03)	(.03)	(.03)	(.03)	(.02)
R-squared	.17	.18	.18	.16	.15	.17	.17	.19	.17	.15	.14	.15	.14	.14	.13	.12
N	1,758	1,922	2,229	3,522	3,048	3,177	3,459	4,002	3,318	3,922	4,204	5,123	4,808	4,680	4,921	5,853

Year	08.Q1	08.Q2	08.Q3	08.Q4	09.Q1	09.Q2	09.Q3	09.Q4	10.Q1	10.Q2	10.Q3	10.Q4	11.Q1	11.Q2	11.Q3	11.Q4
Quantity	.49**	.50***	.48***	.51***	.32	.33*	.37*	.39**	.23	.25	.25	.21	.03	-.02	.03	.06
	(.19)	(.18)	(.18)	(.19)	(.21)	(.20)	(.20)	(.20)	(.21)	(.22)	(.22)	(.20)	(.25)	(.22)	(.23)	(.23)
R-squared	.02	.02	.02	.02	.02	.03	.03	.03	.02	.02	.02	.02	.01	.01	.01	.01
N	5,328	5,323	5,330	5,316	5,108	5,106	5,102	5,093	4,105	4,104	4,102	4,098	3,955	3,952	3,942	3,943
Price	-.02	-.01	-.00	.01	.06	.01	.11	.04	-.19*	-.20**	-.16*	-.12	-.06	-.20***	-.15***	-.15**
	(.02)	(.02)	(.02)	(.03)	(.06)	(.07)	(.08)	(.07)	(.10)	(.10)	(.09)	(.08)	(.08)	(.06)	(.06)	(.08)
R-squared	.13	.10	.13	.12	.09	.07	.08	.09	.08	.11	.10	.13	.14	.15	.13	.10
N	3,845	3,633	3,431	3,466	2,918	2,884	2,783	3,407	2,542	2,762	2,911	3,299	3,019	2,957	3,120	2,699

Notes: the table reports quarterly estimates of the threshold specification in model (4). The dependent variable *Quantity* is defined as the (log) total value of bank lending granted to firm i in quarter t. The dependent variable *Price* is defined as the (log) value of the interest rate applied to a new loan granted to firm i in quarter t. The reported estimates relate to the indicator variable $\text{Performing}_{i,t}$, that takes a value of 1 if a firm is in the performing class (i.e., $s_{i,t} \geq 0$ implying a *Score* of 6), and 0 otherwise. Functions $f(\cdot)$ and $g(\cdot)$ correspond to flexible sixth-order polynomials. Function $f(\cdot)$ is estimated from 0 to the left, whereas the $\text{Performing}_{i,\cdot} \times g(\cdot)$ term is estimated from 0 to the right. Standard errors, clustered at the firm level, are reported in brackets. One star denotes significance at the 10% level, two stars denote significance at the 5% level, and three stars denote significance at the 1% level.

Table C2: Real Effects

Year	2004	2005	2006	2007	2008	2009	2010	2011
Sales	.21	.22	.23	.07	.51***	.42**	.40**	.13
	(.21)	(.18)	(.17)	(.17)	(.18)	(.18)	(.20)	(.21)
R-squared	.04	.04	.04	.03	.04	.04	.02	.01
N	5,951	5,875	6,097	6,512	5,549	5,358	4,307	4,109
Investment	.31	.19	-.28	.43	.71**	.19	-.01	.2
	(.30)	(.30)	(.28)	(.31)	(.32)	(.32)	(.32)	(.35)
R-squared	.01	.01	.01	.01	.01	.00	.00	.00
N	5,085	5,116	5,033	4,104	4,952	4,491	3,677	3,614
Intermediates	.15	.23	.15	.00	.54***	.29	.38*	.06
	(.22)	(.19)	(.18)	(.18)	(.19)	(.19)	(.21)	(.22)
R-squared	.04	.03	.03	.03	.04	.03	.02	.01
N	5,852	5,786	6,013	6,398	5,454	5,275	4,256	4,061
Employment	.22	.30	.09	.17	.45***	.36**	.37**	.14
	(.17)	(.17)	(.15)	(.14)	(.16)	(.15)	(.18)	(.20)
R-squared	.02	.02	.03	.02	.03	.05	.03	.01
N	5,606	5,589	5,802	6,181	5,247	5,061	4,063	3,892

Notes: the table reports yearly estimates of the threshold specification in model (4) using as dependent variables the (log) sales, investment, employment, and intermediates of firm i in year t. The reported estimates relate to the indicator variable Performing$_{i,t}$, that takes a value of 1 if a firm is in the performing class (i.e., $s_{i,t} \geq 0$ implying a *Score* of 6), and 0 otherwise. Functions $f(\cdot)$ and $g(\cdot)$ correspond to flexible sixth-order polynomials. Function $f(\cdot)$ is estimated from 0 to the left, whereas the Performing$_{i,t} \times g(\cdot)$ term is estimated from 0 to the right. Standard errors, clustered at the firm level, are reported in brackets. One star denotes significance at the 10% level, two stars denote significance at the 5% level, and three stars denote significance at the 1% level.

Table C3: Model Diagnostics - Placebo Threshold Estimates

Period	04.Q1	04.Q2	04.Q3	04.Q4	05.Q1	05.Q2	05.Q3	05.Q4	06.Q1	06.Q2	06.Q3	06.Q4	07.Q1	07.Q2	07.Q3	07.Q4
True Threshold: Quantity Estimates	.25	.25	.33	.35	.24	.27	.21	.24	-.04	-.09	-.04	-.05	-.18	-.10	-.11	-.04
Mean of Placebo Estimates	.08	.11	.10	.11	-.09	-.09	-.09	-.03	.011	.03	.01	.03	-.09	-.09	-.09	-.08
Median of Placebo Estimates	.07	.09	.09	.06	-.06	-.02	-.06	-.03	.00	.03	.04	.08	-.03	-.02	-.01	.00
Fraction of Significant Placebo Estimates	.10	.10	.12	.11	.12	.15	.14	.11	.04	.08	.06	.08	.04	.06	.07	.07
Fraction of Placebo Estimates with Opposite Sign	.04	.03	.03	.03	.08	.08	.08	.06	.01	.02	.01	.02	.01	.02	.03	.03
Number of Placebos	97	97	97	97	97	97	97	97	97	97	97	97	97	97	97	97
True Threshold: Price Estimates	-.09	-.10**	-.11**	-.04	-.07	-.13***	-.08*	-.09**	-.14***	-.09***	-.07***	-.06**	.07**	.04	.06**	.05**
Mean of Placebo Estimates	-.03	.00	-.01	-.01	-.01	.02	-.20	.07	-.01	-.13	1.03	-.01	-.00	.02	-.00	.02
Median of Placebo Estimates	-.00	.02	-.01	-.00	.00	.01	.00	.01	.00	.00	.00	.00	-.00	.01	.00	.00
Fraction of Significant Placebo Estimates	.13	.14	.11	.16	.25	.15	.20	.15	.24	.21	.26	.22	.23	.23	.15	.20
Fraction of Placebo Estimates with Opposite Sign	.05	.00	.00	.08	.15	.00	.11	.00	.00	.00	.00	.00	.12	.10	.07	.10
Number of Placebos	133	133	133	133	133	133	133	133	133	133	133	133	133	133	133	133

Period	08.Q1	08.Q2	08.Q3	08.Q4	09.Q1	09.Q2	09.Q3	09.Q4	10.Q1	10.Q2	10.Q3	10.Q4	11.Q1	11.Q2	11.Q3	11.Q4
True Threshold: Quantity Estimates	.49**	.50***	.48***	.51***	.32	.33*	.37*	.39**	.23	.25	.25	.21	.03	-.02	.03	.06
Mean of Placebo Estimates	.06	.07	.07	.10	-.00	-.00	.00	.01	.05	.04	.02	.03	-.04	-.04	-.07	-.07
Median of Placebo Estimates	.04	.03	.03	.03	-.02	-.02	.00	-.01	.03	.03	.03	.01	-.04	-.03	-.02	-.02
Fraction of Significant Placebo Estimates	.11	.12	.10	.08	.06	.07	.06	.10	.09	.08	.06	.08	.12	.08	.06	.09
Fraction of Placebo Estimates with Opposite Sign	.02	.02	.01	.00	.04	.05	.04	.05	.04	.03	.02	.03	.05	.04	.03	.04
Number of Placebos	97	97	97	97	97	97	97	97	97	97	97	97	97	97	97	97
True Threshold: Price Estimates	-.02	-.01	-.00	.01	.06	.01	.11	.04	-.19*	-.20**	-.16*	-.12	-.06	-.20***	-.15***	-.15**
Mean of Placebo Estimates	.05	.01	-.02	.07	-.02	-.01	.00	-.02	-.02	-.13	-.05	.01	-.00	.02	-.05	-.04
Median of Placebo Estimates	.00	.00	.00	.00	-.01	-.01	-.01	-.01	-.02	-.02	-.01	.01	-.00	.01	.00	-.00
Fraction of Significant Placebo Estimates	.20	.17	.20	.21	.21	.20	.23	.16	.23	.26	.23	.20	.24	.17	.11	.21
Fraction of Placebo Estimates with Opposite Sign	.09	.04	.11	.09	.14	.10	.11	.09	.00	.00	.00	.11	.11	.00	.00	.00
Number of Placebos	133	133	133	133	133	133	133	133	133	133	133	133	133	133	133	133

Notes: the table reports the distribution of quarterly placebo estimates of the threshold specification in model (4). The dependent variable *Quantity* is defined as the (log) total value of bank lending granted to firm i in quarter t. The dependent variable *Price* is defined as the (log) value of the interest rate applied to a new loan granted to firm i in quarter t. The procedure is as follows. For each quarter we first randomly draw a new value for the threshold. We then re-define $\text{Performing}_{i,t}$, to take a value of 1 if a firm above the placebo threshold, and 0 otherwise. Finally the functions $f(\cdot)$ and $g(\cdot)$ correspond to flexible sixth-order polynomials defined along the placebo threshold. Function $f(\cdot)$ is estimated from 0 to the left of the placebo threshold, whereas the $\text{Performing}_{i,\cdot} \times g(\cdot)$ term is estimated from 0 to the right of the placebo threshold. Standard errors, clustered at the firm level, are reported in brackets. One star denotes significance at the 10% level, two stars denote significance at the 5% level, and three stars denote significance at the 1% level.

Table C4: Model Diagnostics - Additional Balancing Checks

Year	2004	2005	2006	2007	2008	2009	2010	2011
Cash Holdings	.02	0	.01	.01	-.01	-.04	-.02	0
	(.01)	(.01)	(.01)	(.02)	(.02)	(.02)	(.03)	(.03)
N	4,750	4,380	4,317	4,364	3,422	3,147	2,487	2,297
Automobile Industry	.01	.02	.00	.00	-.03	.00	.01	-.02
	(.02)	(.02)	(.01)	(.00)	(.03)	(.02)	(.02)	(.02)
N	5,951	5,876	6,098	6,514	5,551	5,360	4,307	4,110
Top 10 Cities	.05	.01	.02	-.04	.02	-.02	.11	.07
	(.07)	(.07)	(.07)	(.07)	(.07)	(.07)	(.09)	(.08)
N	5,951	5,876	6,098	6,514	5,551	5,360	4,307	4,110
Firm Clusters	.07	.06	.09	.03	.01	.06	.05	.01
	(.07)	(.07)	(.07)	(.06)	(.07)	(.07)	(.08)	(.08)
N	5,951	5,876	6,098	6,514	5,551	5,360	4,307	4,110

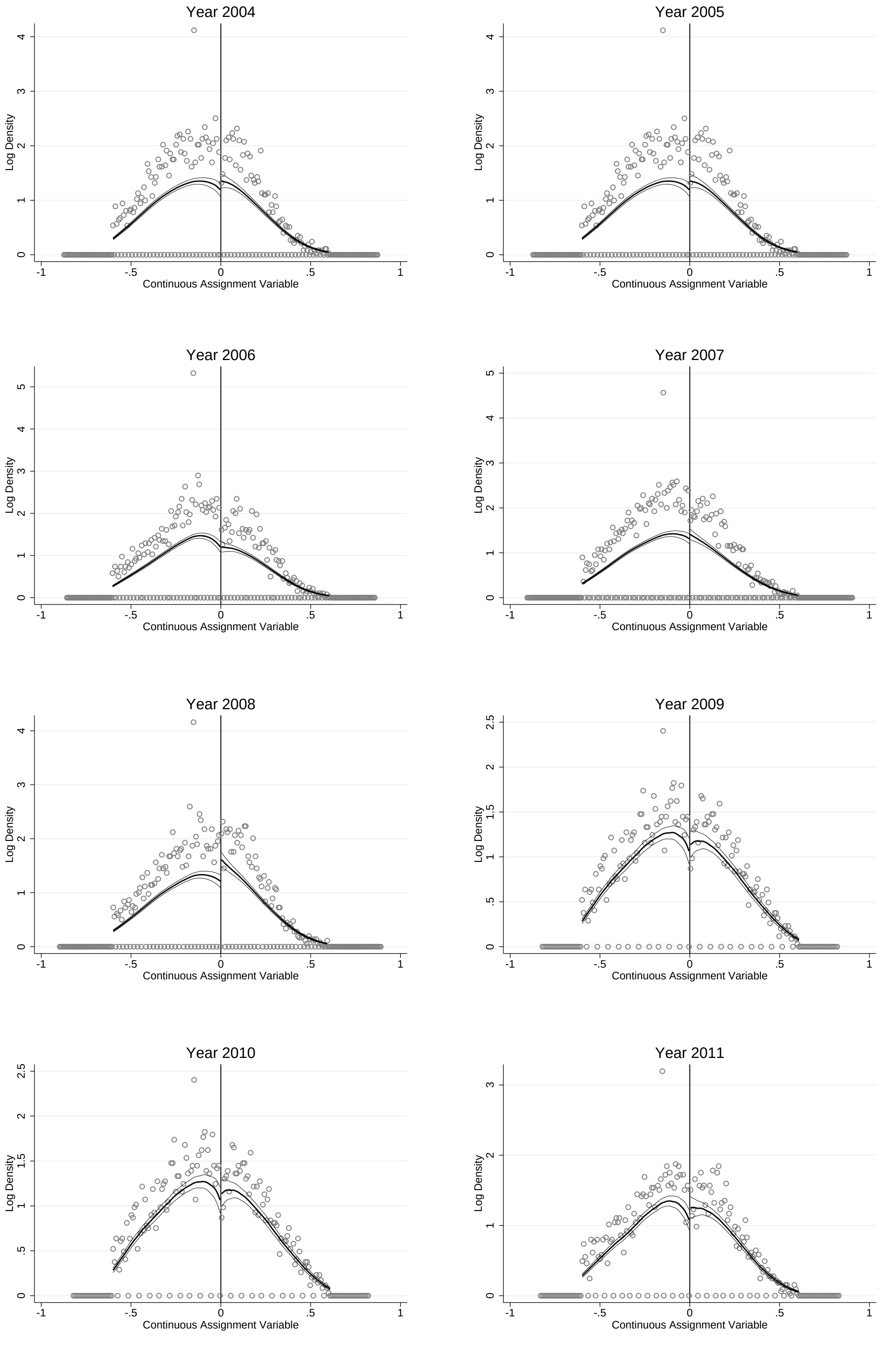
Notes: The table estimates differences in presample firm characteristics at the threshold. In all rows, the dependent variable is measured in 2003. The estimates refer to the the indicator variable $\text{Performing}_{i,t}$ takes a value of 1 if a firm is in the performing class (i.e., $s_{i,t} \geq 0$ implying a *Score* of 6), and 0 otherwise. *Cash Holdings* are defined as cash over total assets. *Automobile Industry* is a binary variable indicating whether the firms' SIC code belongs to the automobile industry. *Top 10 Cities* is a binary variable indicating whether the firms' headquarters zip code is in one of the largest ten cities. *Firm Clusters* is a binary variable indicating whether the firms' headquarters is in a zip code containing more than 100 other industrial firms. One star denotes significance at the 10% level, two stars denote significance at the 5% level, and three stars denote significance at the 1% level.

Table C5: Local Polynomial Regression

Year	2004	2005	2006	2007	2008	2009	2010	2011
				Conventional				
Quantity	.29***	.15**	.07	-.13*	.22***	.27***	-.01	-.06
	(.08)	(.08)	(.06)	(.07)	(.07)	(.07)	(.07)	(.09)
N	5,657	5,652	5,870	6,274	5,356	5,136	4,126	3,969
Price	-.03**	-.03***	-.05***	-.01	.01	-.02	-.07***	-.02**
	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.02)	(.01)
N	9,431	13,686	16,567	20,262	14,375	11,992	11,478	11,795
				Bias-Corrected				
Quantity	.32***	.12	-.09	-.2**	.19***	.22***	.09	-.06
	(.08)	(.08)	(.06)	(.07)	(.07)	(.07)	(.07)	(.09)
N	5,657	5,652	5,870	6,274	5,356	5,136	4,126	3,969
Price	-.03***	-.03***	-.06***	0	.01*	-.01	-.11***	0
	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.02)	(.01)
N	9,431	13,686	16,567	20,262	14,375	11,992	11,478	11,795
				Bias-Corrected and Robust Standard Errors				
Quantity	.32***	.12	-.09	-.2**	.19*	.22**	.09	-.06
	(.11)	(.1)	(.12)	(.09)	(.1)	(.11)	(.11)	(.11)
N	5,657	5,652	5,870	6,274	5,356	5,136	4,126	3,969
Price	-.03**	-.03***	-.06***	0	.01	-.01	-.11***	0
	(.02)	(.01)	(.01)	(.01)	(.01)	(.02)	(.02)	(.02)
N	9,431	13,686	16,567	20,262	14,375	11,992	11,478	11,795

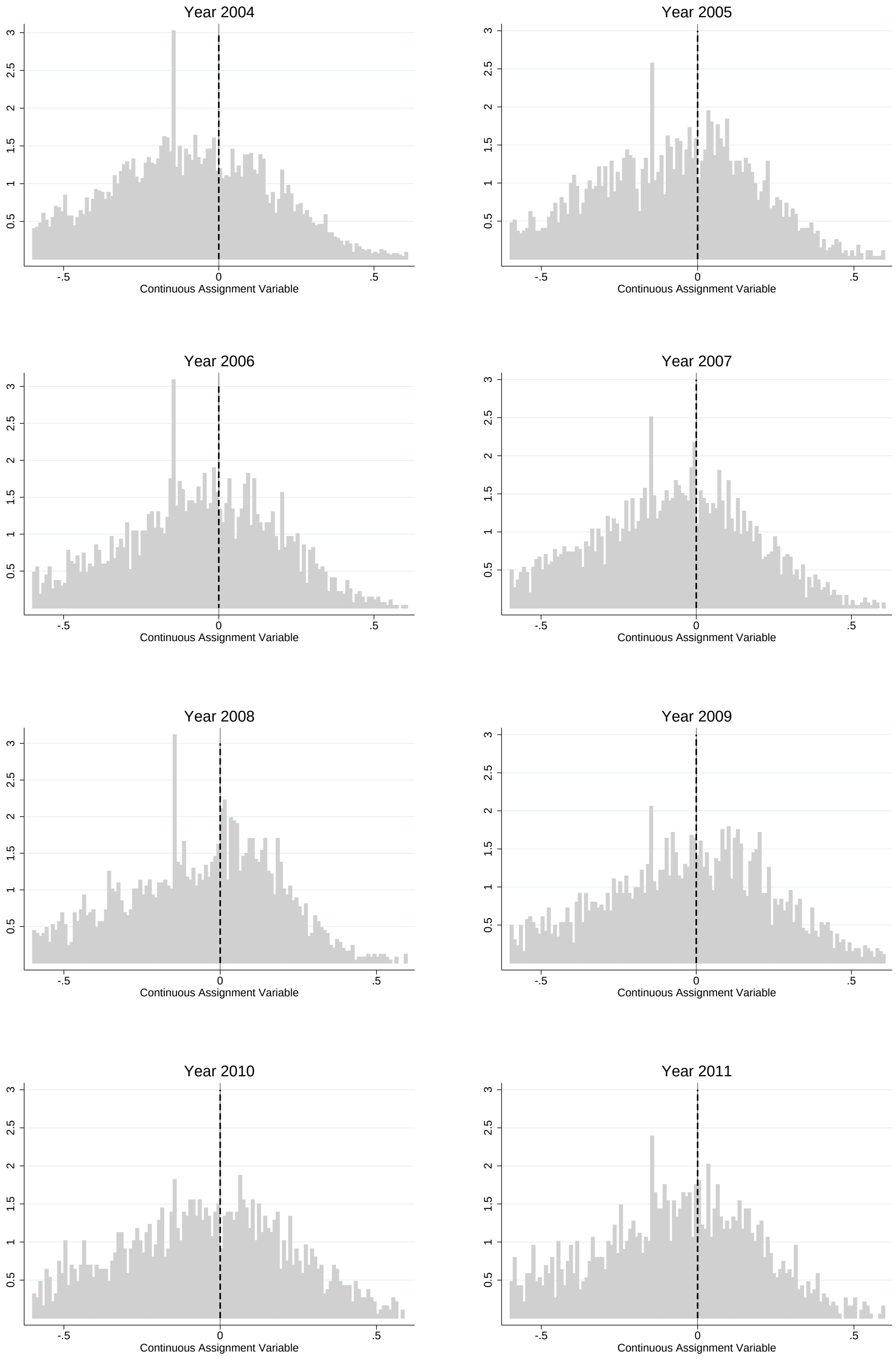
Notes: the table reports quarterly estimates of the threshold specification in model (4). The dependent variable *Quantity* is defined as the (log) total value of bank lending granted to firm i in quarter t. The dependent variable *Price* is defined as the (log) value of the interest rate applied to a new loan granted to firm i in quarter t. The specification is estimated using a local polynomial regression. The estimator is linear with a local-quadratic bias correction and a triangular kernel. The bandwidth is chosen following Imbens and Kalyanaraman (2012). Consistent with Calonico, Cattaneo, and Titiunik (2014), we present conventional discontinuity estimates with a conventional variance estimator, the bias-corrected estimates with a conventional variance estimator, and the bias-corrected estimates with a robust variance estimator. The reported estimates relate to the indicator variable $\text{Performing}_{i,t}$, that takes a value of 1 if a firm is in the performing class (i.e., $s_{i,t} \geq 0$ implying a *Score* of 6), and 0 otherwise. One star denotes significance at the 10% level, two stars denote significance at the 5% level, and three stars denote significance at the 1% level.

Figure C2: McCrary Self-Selection Test



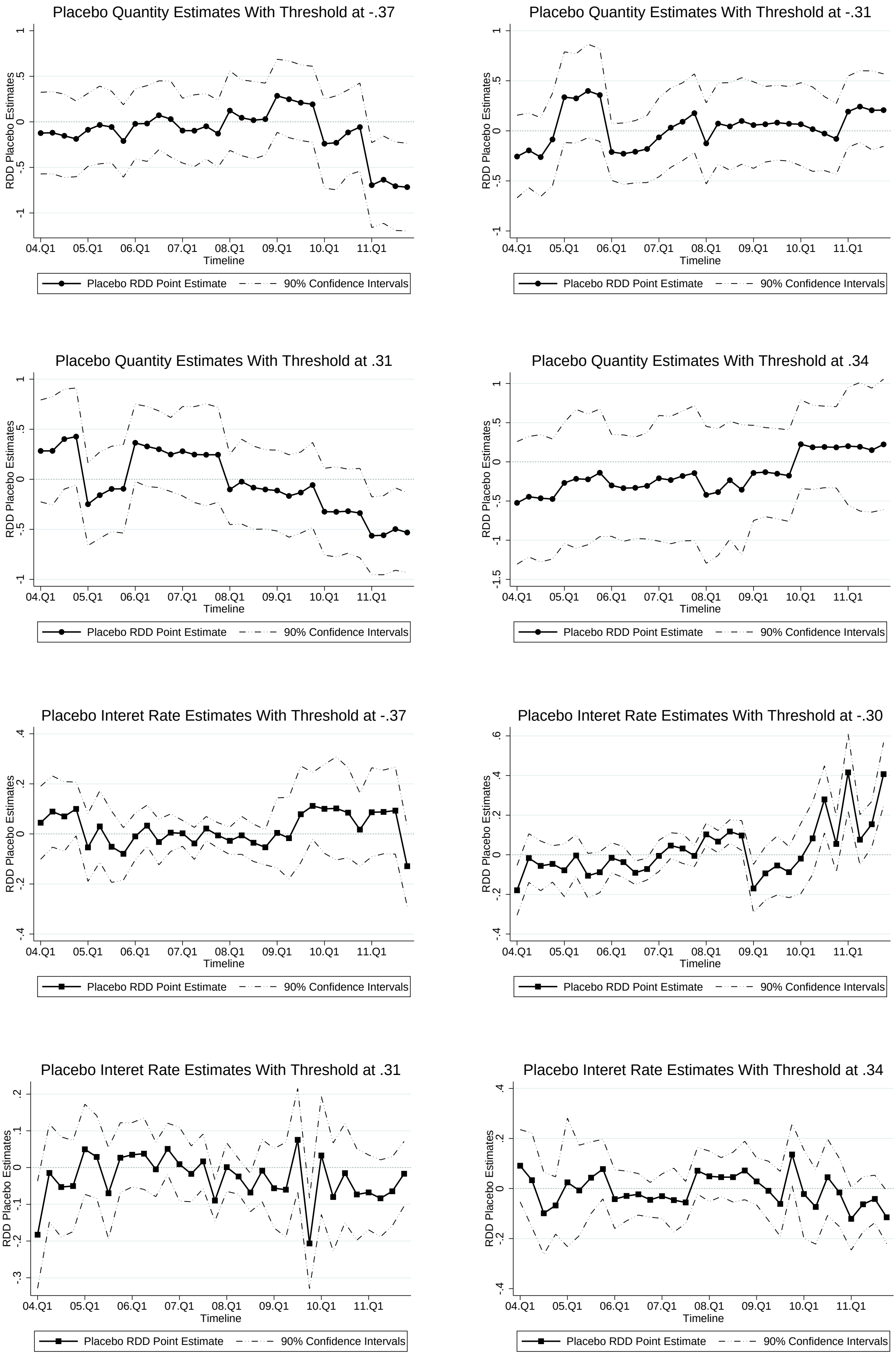
In the figure, we plot the distribution of firms along the support of the continuous variable (s_i) between *Score* rating categories 6 and 7. The solid line is a fitted kernel local linear regression of the log of the density on both sides of the threshold separating firms in category 7 from firms in category 6.

Figure C3: Firms' Inflow Into Score Categories 6 and 7



In the figure, we plot the yearly distribution of firms entering each year into categories 6 and 7 along the support of the continuous variable s_i.

Figure C4: Sequence of RDD Estimates for Placebo Thresholds



The panels plot the sequence of discontinuity estimates obtained running specification (4), along with the associated 90% confidence intervals, on a fixed and randomly drawn placebo threshold.

D Model Presentation

To guide our empirical analysis, we propose a model of credit with market segmentation and moral hazard. The theoretical framework is designed to account for the institutional features of the Italian credit market for SMEs. First, it illustrates how market segmentation influences financial contracting and the allocation of credit. Specifically, we take two firms that the bank observes as economically identical, but fall into different rating classes (which is what bank outside investors know about the firms). Second, it allows for the consequences of market segmentation for SME financing to vary over time. We find that the banks' ability to tame the firms' moral hazard problem can be impaired when funding conditions on the wholesale market heat up. This can push the bank to cut on lending at the expense of the substandard firms.

D.1 Model Structure

- Agents: banks, banks' investors, two firms.
- Assume that financial markets are competitive and all agents are risk neutral. Firms have bargaining power vis-à-vis the bank.
- Banks receive funding from investors. Instead, firms can only be funded by the banks.
- Firms fall between either one of two rating classes: Performing (π) and substandard (σ).
- A bank's investors only observe whether a firm to whom a bank lends belongs to the performing or substandard class, not where the firm falls within these classes.
- The bank's opportunity cost of funding to a firm in each class is $1+r$ for a performing firm and $1+\tilde{r}$ for a substandard firm, with $\tilde{r}-r=\Delta>0$; thus, Δ captures the marginal increase in cost of funding associated to substandard class. This is a direct implication of the assumption that investors set cost of funding to the bank based on their observation of the categorical rating borne by the firms in the bank's loan portfolio.
- The bank instead observes whether two firms fall at the threshold between the two classes. Moreover, these firms are observationally identical, and have the following economic characteristics:[2]

  $$\{p, R, A, I, B\},$$

  where $p \in (0,1)$ is the probability of project's success if a firm's entrepreneur puts in effort (it is zero with shirking), R is the firms' project return conditional on success (it is 0 with failure), A is the amount of firms' cash on hand and I is the value of the (fixed) initial investment. B are the private benefits with shirking.

[2]Note: Each firm holds only one project, with same probability of success p, same return R and initial investment I.

- Contract structure: If funding occurs, the entrepreneur offers the following triple:

$$\{x, K, R_l\},$$

which means that, after obtaining A, the bank funds the project with probability $x \in [0,1]$. Consequently, net of the value of assets on hands, the initial transfer corresponds to $K = xI - A$. The sharing rule in case of success is such that $R = R_l + R_b$.

We also allow the bank and the firm to negotiate on the use of the bank's monitoring technology: It costs $c > 0$, but reduces to $b < B$ the entrepreneur's private benefits.

D.2 Model Solution

In what follows, we solve the model under two distinct scenarios: First, the setting without monitored credit, then the one with monitored credit.

D.2.1 Setting without Monitoring

- Assume that

$$pR - I(1+\tilde{r}) > 0 \tag{1}$$
$$pR - I(1+\tilde{r}) < B < I(1+r). \tag{2}$$

Both conditions are standard within this family of models (see Tirole, 2006). Specifically, condition (1) implies that the project of the substandard firm (and thus the one of the performing firm for all $r < \tilde{r}$) has positive NPV if the entrepreneur puts effort. Instead, condition (2) has two consequences: Its left-hand side implies that the project of both firms has negative NPV only if the entrepreneur exerts effort. Finally, its right-hand side implies that the threshold value of A above which lending occurs is strictly positive for both firms.

- As standard, the (IC) ensuring that the entrepreneur exerts effort is

$$pR_b \geq B \iff R_b \geq B/p.$$

- For the bank (PC), we distinguish between two cases.

1. If A is large,

$$pR_l = (pR - B) \geq (1+r)(I - A) \iff A \geq \overline{A}(r) \equiv I - \frac{(pR - B)}{1+r}.$$

Note: $\overline{A}(r) < \overline{A}(\tilde{r})$ for all $\Delta > 0$. That is, the threshold value of A above which lending occurs is larger for the substandard firm.

– From a binding (PC),

$$pR_l = (1+r)(I - A) \iff R_l = \frac{(1+r)(I-A)}{p} \equiv R_l(r).$$

Note: $R_l(r) < R_l(\tilde{r})$ for all $\Delta > 0$. This means that the contractual repayment is larger for a substandard firm.

– By standard computations, firm's resulting utility is

$$U_b(r) = pR - I(1+r),$$

which is positive by (1).

– Thus, in this case the equilibrium contract without monitoring features

$$\mathcal{C}(r) \equiv \{1, I - A, R_l(r)\}$$

and the entrepreneur puts effort in the project.

2. If A is small,

$$x(pR - B) \geq (1+r)(xI - A) \iff A \geq x\left[I - \frac{(pR-B)}{1+r}\right],$$
$$\iff x \leq \frac{A}{\overline{A}(r)} \equiv x^\star(r).$$

– From a binding (PC):

$$pxR_l = (1+r)(xI - A) \iff R_l = \frac{(1+r)(xI-A)}{xp} \equiv R_l(r,x).$$

Note: $R_l(r,x) \leq R_l(r)$ for all $x \leq 1$. Thus, for given value of r, the contractual repayment paid by a firm that receives funding with probability $x \leq 1$ is lower than the one paid by a firm that receives funding with certainty.

– In this case, the firm's ensuing utility is

$$U_b(r,x) = x[pR - I(1+r)] \leq U_b(r) \text{ for all } x \leq 1.$$

This means that the entrepreneur's utility at equilibrium is larger for a firm that receives lending with certainty ($x = 1$).

– Thus, in this case the equilibrium contract without monitoring features

$$\mathcal{C}(r,x) \equiv \{x^\star(r), x^\star(r)I - A, R_l(r, x^\star(r))\}$$

and the entrepreneur puts effort in the project.

D.2.2 Setting with Monitoring

- Assume that monitoring costs $c > 0$, but allows for a reduction of private benefits from B to b, with $B - b > (1+r)c$. Moreover, let

$$pR - (I+c)(1+r) < b < (I+c)(1+r) \tag{3}$$
$$pR - (I+c)(1+\tilde{r}) < 0 < pR - (I+c)(1+r). \tag{4}$$

In analogy to (2), condition (3) implies that firms' NPV is negative if the entrepreneur shirks (left-hand side) and that the threshold value of A below which lending happens is strictly larger than zero (right-hand side). Moreover, (4) implies that a substandard firm will not take bank's monitoring, as its project's NPV is negative given the cost of monitoring. Thus, we solve the model with monitoring only for the performing firm.

- Let $A < \overline{A}(r)$, if a performing firm takes the monitoring technology, then the (IC) implies that

$$pR_b \geq b \iff R_b \geq b/p.$$

- From the (PC),

$$pR_l \geq (1+r)(I - A + c),$$

which accounts for the fact that the bank does not only provide funds, but also the monitoring service. Then,

$$(pR - b) \geq (1+r)(I - A + c) \iff A \geq \overline{A}(r, c) \equiv I + c - \frac{(pR - b)}{1+r}.$$

From a binding (PC), we compute the contractual repayment

$$pR_l = (1+r)(I - A + c) \iff R_l = \frac{(1+r)(I - A + c)}{p} \equiv R_l(r, c).$$

- By standard computations, the firm's utility in this case is

$$U_b(r, c) = pR - (I + c)(1+r),$$

which is again positive given our working assumptions.

- Thus, the equilibrium contract with monitoring features

$$\mathcal{C}(r, c) \equiv \{1, I - A, R_l(r, c)\}$$

and the entrepreneur puts effort in the project.

D.3 Equilibrium Characterization

The following propositions summarize the equilibrium contract choices of performing and substandard firms.

Proposition 1 (Performing firm). *At equilibrium, the choice of a performing firm features:*

1. *Contract* $\mathcal{C}(r)$ *if* $A \geq \overline{A}(r)$.
2. *If* $A < \overline{A}(r)$, *then*

(a) *Contract* $\mathcal{C}(r,c)$ *if* $A \geq \overline{A}(r,c)$ *and* $U_b(r,c) \geq U_b(r,x^\star(r))$.

(b) *Contract* $\mathcal{C}(r,x^\star(r))$ *if otherwise.*

The first proposition characterizes the equilibrium choices of the performing firm: If its assets are large enough, then the firm chooses the contract with certain funding (i.e., $x = 1$) and without monitoring. If assets instead are lower than threshold $\overline{A}(r)$, then the firm has two options: It takes on monitored credit if *(i)* its assets are larger than the threshold that implies lending with monitoring ($\overline{A}(r,c)$), and *(ii)* its ensuing utility is larger than the one without monitoring but with random funding by the bank ($x \leq 1$). Otherwise, it accepts the contract with random funding by the bank.

Proposition 2 (Substandard firm)**.** *At equilibrium, the choice of a substandard firm features contract* $\mathcal{C}(\tilde{r})$ *if* $A \geq \overline{A}(\tilde{r})$, *and contract* $\mathcal{C}(\tilde{r},x^\star(\tilde{r}))$ *otherwise.*

For a substandard firm, the assumption that the NPV of the project is negative with monitoring implies that the firm has only two possibilities: It gets the contract with full funding if $A \geq \overline{A}(\tilde{r})$, it accepts the contract with random credit otherwise.

In the next section, we discuss the empirical predictions arising from this model. Then, we give a parametric example showing the conditions under which the predictions we characterize can arise at equilibrium.

D.4 Predictions

- The predictions compare the amount of lending K and the interest rate R_l/K of the performing and substandard firms at the threshold across the credit cycle. To capture the phases of the cycle, we let the cost of funding borne by the bank vary (higher in bust, lower in boom).

- For the first prediction, let $A \geq \overline{A}(\tilde{r})$: Both firms obtain a quantity of $I - A$, but the performing promises to repay $R_l(r)$ while the substandard promises to repay $R_l(\tilde{r}) > R_l(r)$.

  Prediction 1 (Lending in Boom)**.** *The contracts at the threshold feature no quantity difference and a larger interest rate for the substandard.*

- When the economy is in boom, the cost of funding paid by the bank features small values of r and Δ. At these values of r and Δ, the firms hold positive-NPV projects if the entrepreneur puts effort. Then, if the value of A is large enough that lending takes place, both firms will receive $K = I - A$. However, each pays an interest rate that reflects the bank's different opportunity cost of lending to a firm in a specific category. Indeed, the performing firm pays $R_l/K = (1+r)/p$ while the substandard firm pays $R_l/K = (1+r+\Delta)/p \geq (1+r)/p$. Thus, as we write in the claim of the prediction, we expect that only interest rate differences arise at the threshold when the economy is in a phase of boom.

- For the second prediction, assume that after an increase in r and Δ to $r' > r$ and $\Delta' > \Delta$ (so that $\tilde{r}' = r' + \Delta'$), $\overline{A}(r',c) \leq A < \overline{A}(r')$ and $U_b(r',c) \geq U_b(r',x^\star(r'))$: The performing obtains a quantity of $I - A$ but prefers to take monitored credit to random lending. Thus, it pays the monitoring cost (so that its interest rate is $R_l(r',c)/(I-A)$). Monitoring is not viable for the substandard; thus, it gets $x^\star(\tilde{r}')I-A$ and pays an interest rate of $R_l(\tilde{r}', x^\star(\tilde{r}'))/(x^\star(\tilde{r}')I-A)$.

Prediction 2 (Crisis times). *The contracts at the threshold feature a larger quantity for the substandard firm. Interest-rate differences are zero for all* $\Delta' = c(1+r')/(I-A)$.

- When the economy is in bust, the values of r and Δ rise, while all the other parameters of the model remain the same. Given the new conditions on the market for banks' wholesale funding, lending cannot occur even if the entrepreneur puts effort. Then, two things can happen: Either the entrepreneur asks for the use of the bank monitoring technology, which reduces private benefits to $b < B$ at the cost of $c > 0$ (with $B - b > c$). Alternatively, it agrees to reduce the probability of lending to $x < 1$ in the funding contract.

- Assume that monitoring works only with the performing firms: The reduction in the private benefits from B to b allows for lending to take place in equilibrium. Accordingly, performing firms obtain $I - A$ at an interest rate of $R_l/K = (1+r')(I-A+c)/p(1-A)$. However, the monitoring technology might not work for the substandard firms: If the rise in the cost of funding for the bank, combined with the cost of monitoring, imply that the NPV of these firms is negative, then the only option for these companies is to accecpt $x = x(r, \Delta') < 1$. Consequently, these firms receive $x(r', \Delta')I-A$ and pay an interest rate of $R_l/K = (1+r'+\Delta')/p(x(r',\Delta')I-A)$. Clearly, while the value of lending granted to the two firms is easy to compare, the ranking of the interest rates depends on the relative value of monitoring cost c and the opportunity cost of lending to the substandard firms (as measured by r' and Δ').

- To see that $R_l(\tilde{r}', x^\star(\tilde{r}'))/(x^\star(\tilde{r}')I-A) \leq R_l(r',c)/(I-A)$ for $\Delta' \leq c(1+r')/(I-A)$, note that:

$$\frac{R_l(\tilde{r}', x^\star(\tilde{r}'))}{x^\star(\tilde{r}')I-A} \leq \frac{R_l(r',c)}{I-A} \iff \frac{1+\tilde{r}'}{p} \leq \frac{(1+r')}{p} + \frac{c(1+r')}{(I-A)p}$$
$$\iff \Delta' \leq \frac{c(1+r')}{(I-A)}.$$

- Finally, note that both of our predictions arise under the following parameter constellation (among others): $p = 0.5$, $R = 4$, $I = 1$, $B = 0.9$, $b = 0.3$, $c = 0.2$, $A = 0.1$, $\Delta = 0.07$.
  - If, in boom, $r = 0.15$ and $\Delta = 0.07$, then all the relevant assumptions are satisfied, $U_b(r) = 1 > U_b(\tilde{r}) = 0.75$ and $\overline{A}(r) = 0.04 < \overline{A}(\tilde{r}) = 0.098 < A$. Moreover, $R_l(r) = 2.3 < R_l(\tilde{r}) = 2.44$. Thus, we obtain the results in the first prediction.
  - Instead, if, in bust, $r' = 0.5$, we get that all our parametric assumptions are satisfied, $U_b(c, r') \geq x^\star(r')$, $\overline{A}(r', c) \leq A < \overline{A}(r')$ and $\Delta' \leq (c(1+r'))/(I-A)$

for all $0.17 < \Delta' \leq 0.33$. Specifically,

$$\Delta' = \frac{c(1 + r')}{(I - A)} \iff \Delta' = 0.33.$$

This again confirms the claim in the second prediction.