Lending Standards Over the Credit Cycle*

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Abstract

We empirically identify the lending standards applied by banks to small and medium firms over the cycle. We exploit an institutional feature of the Italian credit market that generates a sharp discontinuity in the allocation of comparable firms into credit risk categories. Using loan-level data, we show that during the expansionary phase of the cycle, lax standards mean that substandard firms pay significantly higher interest rates. During the contractionary phase of the cycle, the abrupt tightening of lending standards leads to the exclusion of substandard firms from credit. These firms then report significantly lower production, investment, and employment. Finally, we find that the drying up of the European interbank market is an important factor determining the change in bank lending standards.

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1 Introduction

An important role that banks play in financial intermediation is to determine the creditworthiness of borrowers. To perform this task, banks set lending standards that potential borrowers must meet. The theoretical literature highlights the importance of lending standards in explaining the dynamics of aggregate fluctuations (e.g., Martin, 2008), and the consensus is that lax standards lead to downturns (e.g., Dell'Ariccia and Marquez, 2006). Yet, empirically identifying corporate lending standards and their implications for credit and real allocations is challenging for three reasons. First, credit policies are likely to simultaneously reflect a firm's demand for credit and the banks' lending policies. Second, lending standards can vary, often suddenly, over the cycle (Ruckes, 2004; Gorton, 2008). Finally, most of the available evidence relies on loan officer surveys (e.g., Maddaloni and Peydro, 2011; Bassett, Chosak, Driscoll and Zakrajšek, 2014) rather than on direct information from firm-bank credit contracts.

This paper addresses these challenges and provides a direct measure of a bank's corporate lending standards over the cycle. We exploit the institutional features of the Italian credit market for small- and medium-sized enterprises (SMEs) to conduct a quasi-natural experiment that resembles key aspects of the following ideal laboratory setting: A bank interacts with two ex-ante economically identical firms. Firm A is randomly allocated into the investment grade category of credit risk, and firm B is assigned the speculative category. In such an environment, demand-side characteristics are kept constant, and differences in financial contracts only reflect the bank's lending standards. Due to the time-varying nature of these standards, an ideal experiment would then repeat this across time.

Our quasi-natural experiment relies on two key institutional features. First, for historical reasons, the credit risk assessment of SMEs performed by Italian banks relies on a common credit rating that is purchased from an external agency (*Centrale dei Bilanci*, or *CEBI*). This rating, which is constructed following Altman's (1968) methodology, is not solicited by firms and is computed based on lagged balance sheet information. Second, within this rating methodology, firms are allocated into two main rating classes—performing and substandard—based on the value of a continuous variable. However, for regulatory, market-driven, and strategic reasons, banks use the categorical value of the rating to set credit conditions; thus, our framework features rating segmentation.[1]

In this rating system, only the categorical value of the rating provides an estimate of the expected probability of firm default (Altman, 2003). This explains why banks adopt it to assess counterparty risk, determine risk management strategies, and report credit

[1]See, among others, Kisgen (2006), Kisgen and Strahan (2010), Ellul, Jotikasthira, and Lundblad (2011), Chernenko and Sunderam (2012).

risk exposure to the regulator and investors.[2] Moreover, the literature on the use of credit rating mechanisms shows that segmentation arises for strategic reasons. Paravisini and Schoar (2012) provide evidence supporting Stein's (2002) conjecture that the adoption of standardized rating methods can mitigate loan officers' agency problems when lending decisions are influenced by soft information, as is the case of lending to SMEs.[3]

This institutional setting allows us to replicate the ideal experiment described above by exploiting the sharp discontinuity in the allocation of firms into risk classes. We measure differences in credit allocations between firms marginally classified into the performing class and those marginally classified into the substandard class based on the value of the rating's continuous variable.

To interpret how differences in credit conditions arising at the threshold inform us about a bank's lending standards, we employ a simple model of screening with adverse selection (Bolton and Dewatripont, 2006) in which, due to rating segmentation, the bank solves a distinct contracting problem within each class.

When determining the credit conditions it will offer a firm, the bank observes an imperfect signal of the applicant's risk profile, using a combination of the categorical and continuous values of the rating. The bank then has two options: It can offer a contract that pools the applicant firm with all the other firms in the same class, or it can engage in costly screening, which allows it to offer contracts targeting each distinct risk profile in a given class.[4] Consequently, although firms at the threshold between rating classes are economically comparable, their credit conditions can differ depending on whether an equilibrium featuring pooling or screening arises in each class. Consistent with the literature, we equate pooling to lax standards and screening to tight standards.

We show that when liquidity in the banking sector is plentiful, and the severity of the adverse selection problem is limited, the bank pools the firms at the threshold with the other firms in the class: All borrowers receive lending at a return that reflects the average degree of risk in a class. Thus, only differences in the price of lending emerge at the threshold. In comparison, when the adverse selection problem is exacerbated and banking sector liquidity becomes limited, the bank engages in screening at equilibrium. Screening leads to differences in the quantity of credit offered to the firms at the threshold, penalizing borrowers that fall in the substandard class.[5] That is, the firms marginally classified as

[2] In addition, the value of the continuous variable is industry specific and thus difficult to communicate externally. Consequently, in their annual reports, banks provide the distribution of loans across discrete risk categories.

[3] Berg, Puri, and Rocholl (2013) document the presence of agency problems on the loan officers' side within an institutional context in which, differently from ours, the rating's categorical value can be manipulated by the loan officer.

[4] In the model, the cost of screening is captured by the information rent that the bank needs to leave firms to separate between borrowers with a different risk profile.

[5] Consistent with the standard risk-return trade-offs, in the model we assume that the firms with a

performing receive more credit than the firms marginally classified as substandard.

To test these predictions, we use a unique loan-level dataset collected by the Italian central bank. We evaluate contractual differences in terms of the quantities of credit granted and the interest rates charged by financial intermediaries. Our sample is composed of about 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 during this time that reached its peak in 2006–2007 (Drehmann, Borio, and Tsatsaronis, 2012).

Our analysis produces three major results. First, we show that during the expansionary phase of the cycle, lending to firms at the threshold features price differences but little (if any) difference in credit granted. More specifically, a firm marginally classified into the performing class pays up to 10% (or 60 basis points) lower interest rates on new term loans than a firm marginally classified into the substandard class. Consistent with a further relaxation of banks' credit standards, this interest-rate premium disappears during the cycle's boom phase in 2007. This evidence is consistent with the emergence of a pooling equilibrium within each credit class during the boom.

Second, during the contractionary phase of the cycle, firms at the threshold report differences in the quantity of credit. Through 2008 and 2009, firms in the performing class obtain up to 60% more credit than comparable firms in the substandard class. The turmoil affecting interbank markets in late 2007 and the exacerbation of the adverse selection problem induce banks to tighten their lending standards. More specifically, we find that banks reduce the credit supplied to substandard firms; as a result, only differences in the amount of credit granted arise at the threshold.

Third, we trace the implications of lending standards for firms' real activity. Consistent with the theoretical insights above, we show that periods of lax standards imply that firms at the threshold do not differ in the value of production and input choices. When lending standards tighten, instead, production and investment of ex-ante economically comparable firms significantly diverge. A firm marginally above the threshold in the performing class produces 30% to 50% more between 2008 and 2010 than a firm below the threshold in the substandard class. This difference in production is caused by a significant reduction in firms' investments, intermediate purchases, and employment.

Our results confirm the importance of lending standards in explaining aggregate financial and real fluctuations. At an aggregate level our estimates imply that during the pre-crisis period substandard firms paid additional interest payments for 2 BE per year to banks compared to performing firms. The subsequent tightening of credit standards then

higher probability of default yield a bigger return. Therefore, when the screening equilibrium arises, the bank gives privileged access to funding to the high-yield, high-risk firms.

accounts for a fall in the supply of bank financing to substandard firms of approximately 208 BE, or 1.2 ME per firm. This contraction in the supply of credit resulted in a 10.6% lower value of production for these firms.

To corroborate the interpretation of our results we show that, consistent with Stein (2002), small banks are more inclined to rely on soft information than large banks when taking lending decisions. A decentralized decision-making structure gives the loan officer of a small bank the incentive to collect additional information regarding the risk profile of firms. This effort then results in a lower cost of screening. In line with this hypothesis, we find that the credit conditions offered by small banks to firms at the threshold are not significantly different across the cycle, with the exception of 2008.

We explore the relative merits of regulatory capital and liquidity in determining the tightness of lending standards (Diamond and Rajan, 2011; Kashyap and Stein, 2004; Repullo and Suarez, 2012). Using data from the banking supervisory authority, we split banks in our sample according to their pre-crisis capital ratios and exposure to the interbank market. We show that the reduction of credit supply to firms in the substandard class in 2008 and 2009 was mainly driven by banks that were highly exposed to the dry up of the European interbank market in August 2007. In contrast, we find no differential pattern in the contraction of credit supply when splitting the bank sample based on the value of bank capital ratios computed using banks' equity and tier 1 financing.

We also consider whether these results can be explained by the implementation of the Basel II agreements. A potential concern is that the quantity differences arising at the threshold in 2008 and 2009 are a consequence of the adoption by banks of internal rating based tools for credit-risk assessment purposes. We show below that between 2008 and 2011, the vast majority of banks continued employing standardized methods to fulfil their regulatory obligations.[6] Moreover, since the SMEs in our sample belong to the retail portfolio, the transition from Basel I to Basel II did not equate to a differential change in the risk weights applied to firms falling into different rating classes.[7]

To confirm the internal validity of our results, we present several robustness checks to our empirical design. Given the importance of the credit rating system for banks' credit decisions, a natural question to ask is whether firms are able to manipulate their assignment and self-select into a safer category. Manipulation of the rating is unlikely, not only because the rating is not solicited by firms and is computed based on firms' past balance sheets, but also because its exact algorithm is a business secret. Nonetheless, we test empirically for the presence of a systematic discontinuity in firm distribution at the threshold due either to the absence of observations near the threshold or to the presence of

[6] Importantly, data from the Bank of Italy confirm that the rating methodology we study was used by the majority of Italian banks to assess SMEs' credit merits between 2004 and 2006.

[7] For additional details on Basel II implementation, see Bank of Italy (2006:45).

clusters of observations on the side of the threshold assigning a firm to the safer category. We do not find any systematic or significant evidence of manipulation.

The second identifying assumption in our empirical setting is that close to the threshold firms are as if randomly sampled. If firms were nonrandomly sorted, we would expect firm characteristics to differ systematically at the threshold. We test this assumption of our empirical design by running balancing tests on a set of invariant and pre-treatment firm characteristics. The results suggest no statistically or economically significant difference in firms' characteristics. Furthermore, we directly test and reject the hypothesis that differences in credit at the threshold capture a discontinuity in the probability of a firm having a credit event.

The third and most important assumption in our research design relates to the relevance of the threshold that assigns firms to the performing and substandard classes. Finding a significant discontinuity in the lending conditions at the threshold indicates that there is rating segmentation. However, it does not necessarily establish a causal relationship between the threshold we consider and the design of financial contracts. For example, analogous results might arise when comparing financing conditions borne by firms whose value of the continuous assignment variable lies further away from the "true" threshold. To address this concern, we first show that our discontinuity estimates effectively capture variation close to the threshold. Second, we show that these estimates are not consistent with randomly placed thresholds along the support of the assignment variable. Finally, we provide evidence suggesting that other rating thresholds do not equate to significant differences in lending policies.

This paper contributes to the literature on the identification of corporate lending standards and their implications for credit conditions and economic allocations. The paper is also closely related to Keys, Mukherjee, Seru, and Vig (2010), who study the screening process of household mortgages in the United States.[8] They exploit a rule of thumb in the household rating system to obtain variation in the ease of securitization. We exploit rating segmentation generated by the Italian credit market institutional features, and we are able to exploit the repeated nature of the framework to identify credit standards over the credit cycle.

Consistent with our results, the macro-finance literature studying the dynamics of credit has shown 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.[9] Moreover, the literature

[8]Relatedly, Kara, Marques-Ibanez, and Ongena (2015) study the link between bank lending standards and securitization using a dataset of European banks.

[9]Relatedly, Gilchrist and Zakrajšek (2012) analyze the relationship between credit spreads and economic activity.

studying the role of banks in the economy has analyzed the disruptive impact of banks' adverse supply shocks on credit conditions and firm real activity (e.g., among others, Peek and Rosengren, 2000; Ashcraft, 2005; Chodorow-Reich, 2014). We expand on this work in two ways. First, by relying on contract-level information, we are able to provide novel evidence on the use by banks' of the price and quantity margin over the cycle. Second, our detailed firm-level dataset allows us to trace the consequences of the differences in credit conditions for firm production and input choice along the credit cycle.

2 Lending to Italian SMEs

In this section, we present the institutional features of the Italian credit market that we exploit in our empirical analysis. For historical reasons, Italian banks rely on a common credit rating produced by Centrale dei Bilanci (*CEBI*) when making decisions about lending to SMEs. This rating is unsolicited and cannot be manipulated by the loan officer. The construction of the rating is based on a sharp allocation mechanism of firms into discrete categories that is based on the value of a continuous variable. Below we argue that for strategic, market, and regulatory reasons, banks rely on the categorical variable when making lending decisions.

CEBI was 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 for the assessment of SMEs' credit risk. The largest Italian bank, Unicredit (2008:72), reports that the *Score* is the *prima-facie* criterion to assess credit risk in the corporate segment. Similarly, smaller banks such as Banca Popolare di Vicenza (2005:218) use the *Score* because *CEBI* constitutes "the leading provider of risk management tools to the quasi totality of Italian credit institutions." It is not surprising then that in 2004 the share of credit granted to SMEs by banks subscribing to the *Score* rating system amounted to 73%.

Manipulation of the *Score* is difficult. Unlike U.S. credit ratings, the *Score* is not solicited by firms and is available for all Italian corporations; that is, its availability is not the result of firms' strategic considerations. Moreover, the exact algorithm employed by *CEBI* is a business secret. Finally, because of accounting rules and data collection requirements, a firm's *Score* for any given year is computed by the Cerved group on the basis of lagged balance sheet information. These features give us confidence that firms cannot precisely determine their allocation into rating categories. In addition, we show empirically in Section 7 that there is no evidence that firms manipulate the *Score* to self-select into more favorable rating categories.

The value of a firm's *Score* is computed based on multiple discriminant analyses of financial ratios (Altman, 1968). The *Score* takes integer values ranging from 1, for those firms that are the least likely to default, to 9, for those that are the most likely to default. To construct the *Score*, *CEBI* employs a two-step algorithm that uses lagged firm balance sheet information to generate a continuous variable. Within Altman's rating methodology, the value of a firm's continuous variable is used to allocate firms into the nine *Score* risk categories according to predetermined thresholds. These categorical values correspond to the expected likelihood of a firm's default within one year. A firm's continuous *Score* value, instead, does not provide the bank with a direct estimate of the firm default probability (Altman, 2003), as it merely captures the position of the firm within a certain category.

Banks use the categorical value of the *Score* to assess counterparty risk.[10] Indeed, the expected loss associated with credit risk exposure depends, among other things, on the borrower's probability of default. To this end, the *Score* categorical value provides a particularly accurate estimate of a firm's average default probability. Figure 1 illustrates some of the key empirical features of the *Score*.

[Figure 1 Here]

The left panel of Figure 1 is taken from Panetta, Schivardi, and Shum (2009), who use the same annual report and bank data as we do but for the 1988–1998 period to plot the *Score* variable against an indicator of actual default incidence. Firms with a *Score* of up to 4 in a given year have less than a 1% probability of defaulting within the next two years. This probability rises to 10% for firms with a *Score* of 7. The right panel of Figure 1 plots the empirical distribution of our sample of 25,000 firms allocated into the *Score*'s nine categories.[11]

The use of the *Score*'s categorical value is also market driven. Because it can be interpreted as a probability of default, the *Score* constitutes a piece of information that can be meaningfully communicated outside the bank and through a bank's hierarchy. In contrast, the value of a firm's *Score* continuous variable is difficult to communicate internally and externally, not only because it does not provide a default probability, but also because its value is industry specific. As a consequence, in their annual reports to external investors, Italian banks display their corporate credit exposure by classifying firms based on the categorical value of the *Score* (e.g., Unicredit, 2008). Thus, the financing conditions set by outside investors will depend on the volume of banks' lending by risk category.

[10]In Section 3, we further discuss further the regulatory environment during our sample period.

[11]In Appendix B.4, Figure B1 plots the empirical distribution for any two consecutive years in our sample period. It shows that the distribution of firms into *Score* categories is stable across time. This evidence is consistent with the fact that the methodology used to compute the *Score* and the thresholds assigning firms into the discrete categories did not change during our sample period.

Finally, the use of the categorical value of the *Score* may also be a strategic decision. The literature shows that the implementation of standardized rating methods can mitigate loan officers' agency problems when, as it happens with SMEs, lending decisions are influenced by soft information (Stein, 2002).[12]

These institutional features introduce rating segmentation into the Italian market for SMEs.[13] Segmentation implies that the bank is solving a distinct contracting problem in each rating class when determinining credit conditions it will offer firms in that category. Thus, the difference in the lending policies applied to the firms at the threshold between rating categories informs us about the lending standards adopted by banks within each rating class.

Within the rating methodology used to compute the *Score*, firms are allocated into two broad classes (Altman, 2003). Firms with a *Score* between 1 and 6 fall into the "performing" class, and firms in categories 7 to 9 are in the "substandard" class. Our empirical framework exploits this classification. Although firms can be classified based on other narrower subclasses, our empirical analysis confirms that the distinction between performing and substandard firms is the most compelling one (see Section 7).

3 Data

We use confidential datasets from the Italian Central Bank that contain information on the *Score*, the financial contracts signed between banks and SMEs, and firm and bank balance sheets. 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 Appendix B.[14]

The aim of this section is twofold. First, we document the sources of cross-sectional heterogeneity in our dataset and the time-series variation in firm financial contracts. Second, we present key developments in the Italian banking environment that occurred during our sample period.

[12]The results in Paravisini and Schoar (2012) support this conjecture. Moreover, Berg, Puri, and Rocholl (2013) provide additional evidence on the presence of agency problems within a bank in a context where, differently from ours, the rating value can be manipulated by the loan officer.

[13]See, among others, Kisgen (2006), Kisgen and Strahan (2010), Ellul, Jotikasthira, and Lundblad (2011), Chernenko and Sunderam (2012).

[14]Data from the Italian Central Credit Register have been used by, e.g., among others, Sapienza (2002) and Rodano, Serrano-Velarde, and Tarantino (fothcoming).

3.1 Firm Financing Environment

Table I provides the cross-sectional characteristics of our sample. The descriptive statistics for the overall sample are presented in column (1), for the group of performing and substandard firms in columns (2) to (3), and for firms in rating categories 6 and 7 in columns (4) and (5), respectively. Figure 2 plots these sample characteristics across time.

Cross-sectional Descriptive Statistics Panel A of Table I shows that important differences arise in the characteristics of financial contracts granted to firms in different *Score* classes (performing and substandard) and categories (1–9). In the cross section, 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. Moreover, the interest rates for firms in category 6 are 50 points lower than those of firms in category 7. Finally, the average loan in the sample is approximately 816,000 Euro, and short-term loans account for around two-thirds of the total granted loans.

[Table I Here]

Panel B of Table I reports the aggregate financing characteristics of the firms in our sample. On average, total bank lending amounts to 8.5ME 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. Similarly, while an average of 55% of the total granted bank lending is actually drawn down by firms, this share is on average larger if a firm belongs to the substandard class.

Panel C of Table I provides an overview of the main balance sheet characteristics of Italian manufacturing firms based on unique firm-year observations. Firms in our sample have on average 92 employees, 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.

The picture that emerges from Table I is of significant heterogeneity across risk classes and rating categories, not just with respect to firm financial characteristics but also in terms of balance sheet characteristics. Consequently, a naïve comparison between the financing conditions of firms in different rating classes would likely yield misleading conclusions, because the resulting differences could simply reflect differences in firms' economic conditions.

Time Series Descriptive Statistics We next document the variation in financial contracts across time. In the upper panel of Figure 2, we plot the pattern of aggregate bank financing per firm. The middle panel focuses on firms' nominal average interest rates. In the bottom panel, we plot the ten-year Italian government bond interest rate together with the Euro overnight index average rate (EONIA). These two indicators capture the stance of monetary policy in the ECB/Eurosystem (Bernanke and Blinder, 1992; Christiano, Eichenbaum and Evans, 1996).

[**Figure 2 Here**]

The amount of bank financing to Italian SMEs across time is humped in shape, suggesting that, like other OECD economies (Drehmann, Borio, and Tsatsaronis, 2012), Italy was experiencing a credit cycle between 2004 and 2011. Indeed, from the first quarter of 2004 to the first quarter of 2008, 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 only 13%, but by 29% for substandard firms. This disparity suggests that credit standards were particularly lax in 2006 and 2007; however, firm heterogeneity prevents us from establishing whether lax standards were driven by demand- or supply-side considerations.

The middle panel of Figure 2 shows that nominal interest rates increased from 4.3% in 2004 to 6.11% in late 2008. ECB policy rates rapidly dropped between the end of 2008 and the beginning of 2009—illustrated by the pattern of the EONIA rate in the bottom panel—, which corresponded to a reduced average interest rate of 3.6%. Finally, rates rapidly increased up to 5.5% in 2011, primarily due to the sovereign crisis that hit Europe that Fall, demostrated by the value of the Italian government bond rate that year (bottom panel). Overall, the spread between interest rates applied to performing and substandard firms increases from 63 basis points at the beginning of 2004 to 90 basis points at the beginning of 2008. In the fourth quarter of 2011, the last in our sample period, the spread reached about 160 basis points.

3.2 Banking Environment

In Figure 3, we use bank balance sheet data from the banking system supervisory authority to document the main developments in the Italian banking environment between 2004 and 2011.

[**Figure 3 Here**]

The top panel of Figure 3 shows that Italian banks experienced a dramatic reversal in their access to the interbank market. Between 2005 and 2007, the amount of financing raised by banks on the interbank market represented up to 16% of their total assets. Dependence on the interbank market is also reflected in the pattern of Italian banks' funding gap. Indeed, the difference in the amount lent by banks and their deposits increased from 100BE in 2004 to more than 300BE in 2007. In August 2007, the Italian banking system was therefore largely exposed to the shock that dried up wholesale funding (Angelini, Nobili and Picillo, 2011). Not surprisingly, the share of bank assets funded through the interbank market plummeted to 6% in 2008 and 2009.

The middle panel of Figure 3 provides evidence regarding 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% toward the end of the sample period. This evidence shows that the crisis had an impact on Italian banks' balance sheets, which led them to try to improve their capitalization ratios.

The bottom panel of Figure 3 provides evidence on the implementation of the Basel II agreements. The figure shows that 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 fraction of capital allocations calculated using internal rating systems hovers around 20%. This result indicates that the vast majority of Italian banks relied on the standardized approach to comply with capital regulations during our sample period, and thus were bound to use the categorical value of a firm's *Score* when deciding on corporate lending conditions.

4 Framework and Methodology

In this section, we first describe our methodology and then present the theoretical framework that guides the interpretation of our empirical results.

4.1 Empirical Framework

We exploit the unique institutional framework behind Italian SME financing to study lending standards across time. We take advantage of firms' segmentation into rating categories. We compare the credit conditions applied to firms that lie close to the threshold that uniquely divides the performing rating class (1–6) from the substandard rating class (7–9).

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. In all of our analyses, 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:

$$Score_i = \begin{cases} 6 & \text{i.e. Performing} \quad \text{if} \quad 0 \leq s_i < 1.35 \\ \\ 7 & \text{i.e. Sub-Standard} \quad \text{if} \quad -.75 \leq s_i < 0 \end{cases}$$

We focus on the threshold between performing and substandard firms for two reasons. First, the default probability of firms in rating categories 1–5 is close to zero (Figure 1). Moreover, the threshold between categories 5 and 6 cannot be used because the *CEBI* system employs a different continuous variable to assign firms to categories 6–9 from the one used to allocate firms to categories 1 to 5.[15]

Let $\bar{s}$ denote the normalized threshold for allocating firms into rating categories 6 and 7. Then, for each quarter t between 2004 and 2011, we estimate the following sharp regression discontinuity model:

$$y_i = \alpha + \beta S_i + f(s_i - \bar{s}) + S_i \cdot g(s_i - \bar{s}) + u_i. \tag{1}$$

In our main specification, the dependent variable capturing the supply of bank financing is the (log) total value of bank financing granted to firm i. This measure accounts for the possibility that firms obtain credit from multiple banks. Thus, our empirical analysis of the bank lending channel (e.g., Kashyap and Stein, 2000) takes an aggregate perspective. The variable capturing the cost of bank financing is the (log) value of the interest rate applied to the loans granted to firm i. By estimating our specification at the quarterly level, we control for the stance of monetary policy affecting nominal rates. We also estimate alternative specifications in which we scale the supply of bank financing by assets and express interest rates in terms of basis point differences.

Because below $\bar{s}$ a firm is in the substandard class (i.e., its *Score* is 7 or larger) and above $\bar{s}$ it is in the performing class (i.e., its *Score* is 6 or lower), the indicator S_i takes value of 1 if $s_i \geq 0$ and 0 otherwise. 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

[15]To confirm the importance of the threshold between categories 6 and 7, we implement the discontinuity design on alternative thresholds and find no systematic evidence of differences in credit conditions at those thresholds (see Table XI in Section 7.3.3).

closely to the data as possible. Function $f(\cdot)$ is estimated from 0 to the left, whereas the $S_i \cdot g(\cdot)$ term is estimated from 0 to the right. To simplify the analysis, we restrict $f(\cdot)$ and $g(\cdot)$ to be of the same polynomial order. Finally, u_i is a mean-zero error term.[16]

As previously mentioned, the data are centered so that the original 0.15 threshold between *Score* categories 6 and 7 corresponds to 0. It follows 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 β as the magnitude of the discontinuity in credit conditions at the threshold. Importantly, this coefficient should be interpreted locally, in the immediate vicinity of the rating threshold. As we show in the theoretical framework below, a significant difference in lending conditions applied to firms at the cutoff, and captured by the value of β in (1), will reflect the banks' credit standards.

The empirical interpretation of the β coefficient relies on several identifying assumptions. First, we need to rule out the concern that firms are able to manipulate their continuous rating. To this end, we show in Table VII that, based on the test proposed by McCrary (2008), there is no evidence of a systematic discontinuity in firms' distribution at the threshold. The second identifying assumption is that close to the threshold firms are as if randomly sampled. In the presence of non-random sorting, one would expect firm characteristics to differ systematically around the threshold. We test this assumption of our empirical design by running balancing tests on a set of invariant and pre-treatment firm characteristics. The results of these tests are reported in Tables VIII and IX of Section 7.1.

The third and most important assumption in our research design relates to the relevance of the threshold that assigns firms to the performing and substandard classes. Finding a significant discontinuity in the lending conditions at the threshold indicates that there is rating segmentation. However, it does not necessarily establish a causal relationship between the threshold we consider and the design of financial contracts. For example, analogous results might arise comparing financing conditions borne by firms whose value of the continuous assignment variable lies further away from the "true" threshold. To address this concern we first show that our discontinuity estimates effectively capture variation close to the threshold. Second, we implement falsification tests in which we draw 100 randomly distributed "fake" thresholds along the support of *Score* categories 6

[16] Our results are not sensitive to the choice of the polynomial order, or of the estimation method. We estimated the model using also polynomial functions with degree of between 4 to 7. Moreover, in Table B2 (Appendix B.4) we estimate the discontinuity at the threshold through a local polynomial regression. The estimator we use is linear with a local-quadratic bias correction, and a triangular kernel. The bandwidth is chosen following Imbens and Kalyanaraman (2012), but is robust to the use of alternative measures based on cross validation. Consistent with Calonico, Cattaneo, and Titiunik (2014), we present conventional discontinuity estimates with a conventional variance estimator, bias-corrected estimates with a conventional variance estimator, and bias-corrected estimates with a robust variance estimator.

and 7, and show that the estimates we obtain are not consistent with our main results. Finally, we provide evidence suggesting that other *Score* rating thresholds do not imply significant differences in lending policies.

4.2 Interpretation of the Discontinuity Estimates

To interpret our empirical design, we follow the theoretical literature on lending standards (e.g., Dell'Ariccia and Marquez, 2006; Martin, 2008) and use a model of screening that features adverse selection in the bank-firm relationship (Bolton and Dewatripont, 2006). Moreover, in our theoretical framework the bank, due to rating segmentation, sets lending conditions by solving a different contracting problem in each credit class (performing and substandard).

When determining the credit conditions it will offer a firm, the bank observes an imperfect signal of the applicant's risk profile, using a combination of the categorical and continuous values of the rating. The bank then has two options: It can offer a contract that pools the applicant firm with all the other firms in the same class, or it can engage in costly screening, which allows it to offer contracts targeting each distinct risk profile in a given class.[17] In this setting, we equate pooling to lax credit standards and screening to tight standards.

In the model, each class contains two types of firms. Consistent with the standard risk-return trade-off, safer firms enjoy a higher probability of success but deliver a lower return than riskier firms.[18] Since we are interested in studying situations in which a firm's exclusion from credit is inefficient, all firms are engaged in projects with positive net present value. Moreover, firms at the threshold between two risk classes have identical projects, but their credit conditions can differ depending on the nature of the equilibrium (pooling versus screening).

One advantage of the model is that it allows us to establish a link between lending standards, the severity of the adverse selection problem faced by banks and the liquidity in the banking sector. We assume that the adverse selection problem is particularly relevant during the phases of downturn (Tirole, 2006). Moreover, reflecting the evidence on the Italian banks' funding gap (see Section 3.2), we say that there is excess supply of liquidity in the phases of boom. As we will show, the equilibrium with screening is more likely to arise when the adverse selection problem intensifies and the liquidity in the banking sector is scarce.

[17]In the model, the cost of screening is captured by the information rent that the bank needs to leave firms to separate between borrowers with a different risk profile.

[18]This assumption then gives rise to two types in each category: the low-risk-and-low-yield type, and the high-risk-and-high-yield type. In Appendix B, we provide the formal analysis yielding the predictions that follow.

We proceed by illustrating the features of the equilibrium contracts that target the firms at the threshold across the credit cycle. Consider first a scenario featuring excess demand for liquidity in the banking sector and a mild adverse selection problem. In these circumstances, the bank screens firms by setting a higher repayment value and offering privileged access to funding to the high-yield borrowers in each class, leading us to our first prediction:

Prediction 1 (Upturn and recovery)**.** *The contracts targeting the firms at the threshold grant privileged access to funding and a lower repayment to the performing-class firms marginally above the threshold relative to the substandard-class firms marginally below the threshold.*

During periods of economic upturn and recovery, excess demand for bank financing induces the bank to keep its lending standards tight (screening equilibrium). Thus, the contract offered to the substandard firms at the threshold has a higher value of the repayment and a lower amount of funding than those offered to performing firms. The intuition is that within their class, these firms represent the low-yield borrowers.[19]

During a boom phase, bank liquidity is abundant and the perception of the adverse selection problem is not particularly relevant; the bank then offers pooling contracts that finance all firms in each class.

Prediction 2 (Boom)**.** *The contracts for the firm marginally in the performing or substandard class are no different in terms of access to funding, but have a lower repayment value for performing-class firms marginally above the threshold.*

An excess supply of banks funding results in lax lending standards (pooling equilibrium). The bank grants equal access to funding to the firms across the threshold, at a return that reflects the average degree of risk in each class. Therefore, the value of the repayment is lower for the performing-class firms marginally above the threshold.

During downturns, there is again excess demand for bank funds, and the perception of the adverse selection problem intensifies. The bank then tightens its lending standards. Differently from the upturn and recovery phases, however, the intensification of the adverse selection problem implies that the screening contracts prevailing in the downturn phase exclude the substandard firms next to the threshold from credit.

Prediction 3 (Downturn)**.** *The contracts targeting the firms at the threshold give access to funding to the firms in the performing class and exclude from lending the firms in the substandard class.*

[19] Accordingly, the performing firms on the other side of the threshold pay a lower premium and are not excluded from funding because they represent the high-yield firms in their class.

Stein (2002) shows that in settings with adverse selection, small banks tend to rely on soft information more than large banks when making lending decisions. A decentralized decision-making structure gives the loan officer of a small bank the incentive to collect additional information regarding the risk profile of firms, thereby reducing the cost of screening. Accordingly, small banks are more likely to offer similar credit conditions to the firms at the threshold. In Section 6.1, we study the role of soft information within our institutional setting by testing this ancillary implication.

5 Results

In this section, we present the results on the differences in credit conditions, price, and quantity of bank financing for firms at the threshold dividing the performing and the substandard classes. We then explore whether differences in credit conditions give rise to differences in real outcomes in terms of production and input choices. Finally, we analyze the aggregate implications of these estimates for Italian firms.

5.1 Results on Credit Allocations

Table II reports the estimates of the specification in equation (1). For expositional convenience, in Figure 4 we plot the estimated value of β, i.e., the coefficient that captures differences in credit conditions at the threshold. Specifically, the top panel of Figure 4 reports the results related to the total amount of granted bank financing, and the bottom panel shows those related to loan interest rates.

[**Table II and Figure 4 Here**]

The top panel of Figure 4 shows that between 2004 and 2005, differences in the quantity of lending are positive but not significant. Instead, during the same period firms in the substandard class are charged up to 10% higher interest rates than similar firms in the performing class.[20] Analogous results arise through 2010 and 2011, although the spread between comparable firms in different rating classes rises to 20%, or 120 basis points. These results are consistent with our Prediction 1 for upturn and recovery phases. Excess demand for financing induces the bank to keep lending standards tight, causing a screening equilibrium to arise in each rating class. At this screening equilibrium, the firms at the threshold that fall in the performing class obtain more favourable credit conditions.

Between 2006 and 2007, both the quantity and the interest-rate differences are economically small and statistically not significant. As shown in Figure 2, in 2007 the credit

[20]To obtain the exact percentage changes associated with the value of $\hat{\beta}$, we compute $\left(exp^{\hat{\beta}} - 1\right)$.

cycle culminated in a boom phase. Prediction 2 suggests that during booms, the bank grants equal access to funding to the firms across the threshold and a lower interest rate to the firms in the performing class. These outcomes are consistent with the results in the theoretical literature that banks relax credit standards during booms (e.g., Dell'Ariccia and Marquez, 2006; Martin, 2008).

Finally, through 2008 and 2009 the difference in the quantity of credit obtained by similar firms across the threshold is statistically significant and ranges between 50% to 60%, or 9 percentage points in terms of the debt-to-assets ratio. At the same time, interest rate differences remain close to 0 for these firms. Consistent with Prediction 3, during an economic downturn, the excess demand for bank funds combined with an exacerbation of the adverse selection problem pushes the bank to tighten its lending standards. Therefore, the screening equilibrium contracts, which are more common during economic downturns, exclude from credit the firms that marginally fall in the substandard class.

Our regression discontinuity design allows us to identify how lending standards evolve over the credit cycle as a function of the liquidity available to banks for lending and the severity of the adverse selection problem faced by banks. Our results are consistent with the conclusions in the theoretical literature, and quantify lending standards consequences for financial contracting. We next empirically document the importance of the threshold in our framework.

Nonparametric Plots We first confirm the interpretation of our discontinuity estimates by showing that they effectively capture contract variation for firms marginally at the threshold. The top panels of Figures 5 and 6 provide a graphical analysis of the variation in credit conditions at the threshold. Figure 5 focuses on the second quarter of 2009, showing evidence of tight credit standards leading to quantity differences at the threshold. Figure 6 focuses on the second quarter of 2011, providing evidence of lax credit standards leading to interest rate differences.

[**Figure 5 and 6 Here**]

To show that our discontinuity estimates capture variation directly at the threshold between the substandard and performing classes, we provide nonparametric plots of the outcome variable as a function of the continuous assignment variable. We divide the domain of s into mutually exclusive bins of size 0.03.[21] 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 closely the sixth order polynomial approximates the variation of bank financing conditions at the threshold.

[21]The results of the empirical analysis remain identical when plotting bins of different size, like 0.02 or 0.01. For the ease of the exposition, we only report the results obtained using bins of 0.03.

The top right panel of Figure 5 shows that a clear discontinuity arises in the 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, indicating that the estimate of β captures variation directly at the threshold. The top left panel of Figure 5 repeats this exercise for interest rates. 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—the value of the average interest rate is not significantly different when comparing the value corresponding to the bins next to the threshold.

The top panels of Figure 6 present the same plots in a quarter featuring interest rate differences. The estimated polynomial indicates no significant difference in the average value of the credit granted to the firms across the threshold. Instead, the nonparametric plot of the conditional regression function for interest rates displays a significant discontinuity at the threshold. The polynomial estimate reflects the 20% variation in interest rates that is implied by the two bins immediately at the threshold.

5.2 Implications for Firms' Real Activity

Do differences in credit conditions result in real effects? We address this question by applying our regression discontinuity analysis to firm-level balance sheet variables that measure firms' expenditures in production inputs and value of production. The balance sheet information we use is reported in end-of-the-year statements; thus, it reflects a firm's lending conditions throughout the year. This analysis should identify the relationship between credit standards and firms' real decisions.

Table III reports the results of our baseline regression in (1) using as dependent variables the log of firms' sales and expenditure in investment, employment, and intermediates.

[**Table III Here**]

We first find that in periods of relatively lax lending standards the value of production reported by firms at the threshold is not significantly different. This is consistent with the fact that lending contracts feature similar amounts of bank financing and only interest rate differences. Although the marginally substandard firms pay a higher price to the bank than the marginally performing firms, this interest rate difference is unlikely to constrain production choices. Our second finding highlights the importance of shifts in lending standards across the cycle. We show that the production choices of firms at the threshold diverge, especially during the periods when access to credit is limited for the marginally substandard firms. Indeed, in a downturn phase, the marginally performing firms report up to a 50% larger value of production than the marginally substandard ones. The economic magnitude of these estimates suggests that differences in the amount of credit translate into a (close to) one-on-one difference in the value of production.

To further investigate the implications of lending standards for firm real activity, we also report the differences in input choices made by the firms at the threshold over time. More specifically, we estimate our discontinuity design using as dependent variables the value of firms' investment in capital, expenditures in intermediates, and employment. Again, we find no statistically or economically significant difference in the input choices of firms at the threshold between 2004 and 2007.

Between 2008 and 2010 input choices diverge significantly. During that period, the most economically significant differences arise in the purchase of intermediates reported by firms at the threshold.[22] This result is intuitive given that unless a firm is able to substitute bank financing with trade credit, the reduction in bank financing immediately transmits into a reduction of intermediates. The value of investment also reacts to the tightening of credit standards. In 2008, marginally performing firms invest nearly twice as much as marginally substandard firms. An analogous result arises when differences in employment are considered, although with a lag: In 2010, firms in the substandard class report 50% lower employment than comparable firms in the performing class. This lag can be explained by the rigidities of the Italian labor market during that time.

5.3 Aggregate Implications

We next discuss the aggregate implications of our estimates, using information on the rating, bank financing, and sales of all Italian limited liability firms between 2004 and 2011. The set of firms we look at is larger than the one used for our threshold analysis for two reasons. First, we extend the sample from the manufacturing sector to all sectors of activity. Second, we include firms rated by the agency using a methodology based on simplified balance sheets.

To compute the impact of lending standards on interest repayments, we consider the amount of bank financing granted to firms with a substandard rating. To determine the increased value of the repayments due by substandard firms versus performing firms in periods of lax standards, we take the interest rate spread estimated by our discontinuity design at the threshold. Between 2004 and 2006, we estimate a total transfer of roughly

[22] The results are statistically significant at the 5% level for 2008 and 2009, but slightly above the 10% significance level in 2009. However, the difference in 2009 is statistically significant for alternative polynomial specifications.

2 BE per year, or 15,000 Euros paid by each substandard firm to the bank. Because of the larger interest rate spreads in 2010–2011, these transfers from substandard firms to banks increased to 4.7 BE per year, or 27,000 Euros per firm.

We next quantify the aggregate impact of the differences in credit supply arising in 2008 and 2009. We determine the additional bank financing that would have been granted to substandard firms, with respect to performing firms, had lending standards not tightened. On average, we estimate a fall in the supply of bank financing of approximately 1,2 ME per firm. This suggests that, at the aggregate level, bank financing was 208 BE lower than that available for the performing category. This figure represents 14.3% of total bank financing in the Italian economy. Moreover, the contraction in credit provision led to a 700 KE per substandard firm drop in production, representing 231 BE, or 10.6% of the value of total production in the economy.

While these calculations highlight that lending standards are important in explaining aggregate financial and real fluctuations, they need to be interpreted with some caution. First, they are based on a partial equilibrium exercise that may overlook other important aggregate factors. However, it is outside the scope of this paper to address the general equilibrium effects of lending standards. Second, our aggregate calculations implicitly assume that the threshold estimates influence all substandard firms with the same intensity. However, it is reasonable to believe that firms lying further away from the threshold receive worse financing conditions than the firms at the threshold. Consequently, our aggregate calculations provide a lower bound estimate for the aggregate impact of credit standards.

6 Mechanism

6.1 The Role of Soft Information

In settings characterized by adverse selection, the use of soft information facilitates the screening of firms. Stein (2002) shows that small banks are more inclined to rely on soft information than large banks when making lending decisions. A decentralized decision-making structure gives the loan officer of a small bank the incentive to collect additional information regarding the risk profile of firms. This effort then results in a lower cost of screening, so small banks should be more likely to offer similar credit conditions to the firms at the threshold.

To test this prediction, we compare the contractual differences at the threshold after splitting our sample into large and small banks. Our measure of size is the value of total financing granted to SMEs at the beginning of the sample period.[23] We expect that small banks are more likely to offer the same contracts to firms at the threshold, because they rely more on soft information when setting lending conditions. Table IV presents our results.

[Table IV Here]

The table shows that the differences in the quantity and price of lending offered by large banks to the firms at the threshold mirror the qualitative patterns predicted by our theoretical setting (Section 4.2). The magnitude of these differences are comparable to those obtained using a sample of both small and large banks. The differences in the quantity and price of lending offered by small banks to the firms at the threshold are small, if not negligible, through our sample period, except in 2008. That is, small banks seem to offer the same contract to the firms at the threshold even in 2009, when costly screening caused large banks to exclude from credit the substandard firms.

6.2 Credit Supply and Differences in the Demand for Credit

We next analyze whether the lower amount of credit granted to the marginally substandard firms stemmed from a reduction in these firms' demand for credit. The Italian credit register records all monthly requests for information about new borrowers made by banks.[24] We use these data to construct two variables. The first variable, *Asked*, is a binary variable equal to one if a bank requests information on a new loan applicant. The second variable, *Rejected*, is a binary variable equal to one if a bank requested information on a new borrower, but did not grant credit to the applicant within the next two quarters. Table V reports the estimates of the baseline specification in equation (1), using *Asked* and *Rejected* as dependent variables.

[Table V Here]

The estimated coefficients in the first row, which refer to information requests, suggest that firms at the threshold do not display a different propensity to apply for loans to new banks. The second row lists the threshold estimates regarding loan rejections. Again, we find no evidence that marginally substandard firms were rejected more often by new banks. Taken together, these results suggest that the differences in the amount of credit granted to the firms at the threshold were not the outcome of firms' different demand

[23]Note that we verify that the balancing characteristics presented in Section 7 below hold in the subsamples.

[24]Recall that, on a monthly, banks receive the information related to the financial position of their current borrowers only.

for lending. Moreover, the result that banks reject new applicants on both sides of the threshold is consistent with the theoretical result in Dell'Ariccia and Marquez (2006) that in times of tight standards banks cut down on lending to unknown borrowers.

6.3 Bank Liquidity, Capital, and Regulation

The theoretical setting in Section 4.2 predicts that shortages in bank liquidity can lead to a switch from lax to tight lending standards. According to the literature (Diamond and Rajan, 2011; Kashyap and Stein, 2004; Repullo and Suarez, 2012), bank funding shortages can arise because of insufficient regulatory capital, a liquidity shock, or a combination of these two events. Below, we analyze how these factors shaped banks' tightening of credit to substandard firms in 2008 and 2009. We also discuss whether our results can be explained by the implementation of Basel II agreements.

We divide the banks in our sample between those that lie above and below the median of the distribution of pre-2008 bank capital and interbank exposure ratios. Accordingly, the dependent variable is the amount of lending a firm takes out from banks with high and low interbank market exposure and capital ratios. The results are reported in Table VI.

[Table VI Here]

The banks with low exposure to the interbank market funded approximately 3% of their asset base through loans from other banks, at the median. We find that only in 2008 these banks significantly cut the lending granted to substandard firms. In sharp contrast, banks that were highly exposed to the interbank market in 2008 funded, at the median, 14% of their asset base through this channel. After the European interbank market dried up in August 2007, these banks began allocating up to 60% more credit to the firms in the performing class, in both 2008 and 2009.

In the middle and bottom panels, we split our sample based on two measures of bank capitalization. These two variables feature an economically significant cross-sectional variation. The equity-to-asset ratio before 2008 is 6% for less capitalized banks, while it is 11% for highly capitalized banks, at the median. However, these cross-sectional differences do not seem to explain why firms at the threshold between the substandard class and the performing class were offered different levels of credit. We find that the banks in both groups restricted access to financing disproportionally more to the firms in the substandard category in 2008 only. In 2009, we see neither an economically nor a statistically significant difference in the amount of lending at the threshold. These results are confirmed when splitting the sample of banks based on the value of the Tier 1 capital ratio.

Finally, we note that our results cannot be explained by the implementation of the Basel II agreements. The Basel II accord gave banks the ability to use internal rating tools, which might have also implied a change in the risk weights applied to specific categories of borrowers. However, as we show in Section 3, a minority of banks switched to the internal rating-based methods for credit risk assessment. Moreover, the transition from Basel I to Basel II did not imply a differential change in the risk weights applied to the SMEs in our sample, as they belong to the retail portfolio (Bank of Italy, 2006:45).

7 Robustness of the Results

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 affirm that firms at the threshold are balanced in terms of their economic characteristics. Finally, we present placebo estimates showing that estimates of the discontinuity found at the true threshold are not due to coincidental variation that occurs along the support of the continuous variable.

7.1 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 into 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. Since our empirical analysis focuses on the threshold separating the performing from the substandard class, in Table VII and Figure 7 we test for the presence of a discontinuity of the density at that threshold.

[**Table VII and Figure 7 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 and Figure 7 show 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.

The lack of manipulation, as suggested by the absence of discontinuities at the threshold, can also be seen through the distribution of firms that enter rating categories 6 or 7 in any given year. For each year, *CEBI* computes the *Score* based on the latest available balance sheets, and the share of firms assigned to a new rating category each year ranges between 46% and 51% of the same year's sample. For instance, 47% of the 6,514 firms sampled into categories 6 and 7 in 2007 were not in those categories in 2006. Figure 8 plots the distribution of the new firms entering categories 6 and 7 along the support of the continuous variable.

[**Figure 8 Here**]

If firms were able to determine the value of their own continuous variable, then we should not observe firms entering the sample just below the threshold separating the two categories. Rather, we should observe a disproportionate number of firms clustering just above the threshold, in category 6. Figure 8 shows that a significant fraction of firms systematically enters right around the threshold. That is, a significant mass of firms enters the sample with a value of the continuous variable that lies just below the threshold, in category 7. This confirms that manipulation of the assignment variable is highly unlikely.

7.2 Balancing Tests

In Tables VIII and 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 VIII tests whether firms at the threshold differ in terms of their pre-sample characteristics. Table IX tests whether firms differ in terms of time-invariant characteristics. In each row, we report the coefficient for the difference in the intercepts at the threshold, estimated using equation (1). To compare our regression discontinuity estimates across time, we also provide the mean of each characteristic for the cohort of firms in categories 6 and 7 in each year.

[Tables VIII and IX Here]

In Table VIII, the dependent variable is a broad set of firm financing, investment, and profitability measures taken in 2003. In the first row, we show that firms at the threshold did not differ in terms of leverage choices in the pre-sample period. Moreover, we find no significant difference in firms' return on assets, cash holdings, or investments.

The last row in the table changes when the dependent variable's value is measured. There, we assign a credit event to a firm in a given year if any of its banks classified its credit as nonperforming. If there were a discontinuity in the probability of a firm's credit event at the threshold, then our results can be explained by the fact that banks correctly price this difference. None of these tests reveal statistically or economically significant differences at the threshold.

In Table IX, we focus on differences in time-invariant firm characteristics. In the first row, the dependent variable is the firms' activity sector proxied by its SIC code. The yearly estimates indicate no statistically or economically significant evidence of firms clustering into sectors such as the automobile or food industries. Next, we look at time-invariant characteristics related to firms' geographical locations. Geographic location 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 (Ichino and Maggi, 2000; Brollo, Nannicini, Perotti and Tabellini, 2013) and could thus be associated with opportunistic manipulation. None of the variables capturing location in the largest cities or the most entrepreneurial areas display a statistically significant discontinuity.

7.3 Relevance of the Threshold

We now provide further evidence on the relevance of the threshold between performing and substandard firms.

7.3.1 The Importance of Local Identification

The middle panels in Figures 5 and 6 provide further evidence on the variation captured by our discontinuity design estimates. We estimate a simple mean difference specification for increasingly larger bins around the threshold, which can be written as:

$$y_i = \delta + \gamma S_i + u_i \quad \text{for} \quad \bar{s} - h \leq s_i \leq \bar{s} + h, \tag{2}$$

in which S_i takes a value of 1 if $s_i \geq 0$, and 0 otherwise. We start with a very small bin around the threshold and examine how the value of the estimate of γ changes as we increase the size of the bin.[25] The objective of this exercise is twofold. The first is to to determine the source of variation behind our estimates (and their sensitivity with respect to the width of the support one considers). The second is to determine how our threshold analysis, which yields the estimates of coefficient β in (1), improves on a naïve specification that compares the average differences obtained using the value of all the observations in categories 6 and 7, and yields the estimates of γ in (2). In the figures, the value of γ is reported on the vertical axis, while the width of the bins around the threshold is reported on the horizontal axis. The solid line represents the estimated value of γ as a function of the distance from the threshold. The dashed lines are 90% confidence bands.

The left-middle panel of Figure 5 plots the estimated value of γ for the second quarter of 2009 for total bank financing; the right-middle panel repeats the exercise for firms' interest rates. The estimate obtained using our main regression (1) for the difference in bank financing at the threshold is 0.4. The estimated value of γ corresponds to this value of β in a range of values of h between 0.01 and 0.04. The results differ when looking at how the estimated interest rate differences change away from the threshold. For interest rates, the value of the discontinuity estimate resulting from (1) is statistically nonsignificant. The value of the coefficient γ estimated from (2) is the same as that of β when looking at bins with a support as wide as $[-0.08; +0.08]$. For larger intervals, a naïve comparison would produce a statistically significant difference in interest rates of approximately 11%.

The middle panels of Figure 6 plot the estimated value of γ in the second quarter of 2011, looking at firms' total bank financing (left panel) and interest rates (right panel). Our main specification in (1) showed that during this period firms across the threshold obtain the same amount of bank financing, although a 20% larger interest rate is applied to firms in the substandard class. The difference in the amount of bank financing estimated by (2) based only on observations immediately at the threshold confirms this finding. Yet, the value of the coefficient γ estimated using increasingly larger supports yields a difference in the quantity of bank financing of approximately 10%. The pattern of estimates of γ relative to interest rates documents again that the variation identifying our estimates of β in (1) comes from the observations immediately at the threshold. If, instead, we were to take larger bins around the threshold, we would underestimate the interest rate differences.

This exercise allows us to conclude that our main estimates capture variation directly around the threshold and that a naïve comparison of average differences obtained using the value of (nearly) all the observations in the support of *Score* categories 6 and 7 would

[25] Specifically, the procedure starts with a value of h equal to 0.01. So the starting bin has a support given by $[-0.01; +0.01]$. In each further step we increment h by 0.01 until we reach the $[-0.50; +0.50]$ interval.

give rise to misleading conclusions.

7.3.2 Placebo

A critical assumption in our empirical design concerns the relevance of the threshold that divides firms into the performing and substandard classes. Finding a significant discontinuity in lending conditions at the threshold, as shown in Figure 4 and Table II, 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*'s categories 6 and 7, and rerun the baseline specification in (1) for all the quarters in our sample.

We report the results in three ways. First, in the bottom panels of Figures 5 and 6 we plot the distribution of the placebo estimates for the second quarter of 2009 and 2011. Second, in Table X we report descriptive statistics about the mean, median, and statistical significance of the placebo tests across all quarters. Finally, Figure 9 plots the estimates obtained considering randomly selected placebo thresholds over the entire sample period.

[**Table X and Figure 9 Here**]

The bottom panels of Figures 5 and 6 illustrate 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. We find that the 100 placebo estimates for the differences in the quantity of bank financing are approximately normally distributed around 0. Only in 6% of the cases we do find placebo estimates that are actually equal to or larger than the true threshold estimate of 0.33. In other words, our discontinuity estimates stemming from the "true" threshold cannot be interpreted as resulting from coincidental variation in the amount of bank financing. Similarly, Figure 6 shows that in the second quarter of 2011 interest rate differences of 20% are well outside the normal variation arising from randomly placed thresholds.

Table X provides more systematic evidence on the distribution of placebo threshold estimates across the sample period. We report the mean and the median of the estimates obtained using the placebo thresholds in each quarter. The estimated values are about zero and are not significant in most of the quarters. This finding is reassuring, especially for the periods and variables for which we find economically and statistically significant differences using the true threshold. The table also reports the fraction of significant placebo estimates as well as the fraction of "false positives"—i.e., significant placebo estimates with signs opposite of what we find. Out of the approximately 3,100 placebo estimates for granted bank financing across the sample period, around 9% of them are statistically significant, but nearly 3/4 of them are "false positives." The same conclusion holds when analyzing the estimates of the interest rate differences obtained at the placebo thresholds.

Finally, Figure 9 illustrates that a randomly drawn placebo threshold is also unlikely to yield an economically sensible pattern of estimates across time. We plot the estimates associated with a placebo threshold situated close to the midpoints of the support within each category. Visual inspection of the figures suggests that a given placebo threshold is likely to yield significant estimates only in one or two quarters. However, in most of the cases the rest of the estimates are not significant.

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

7.3.3 Other Rating Thresholds

Finally, we provide evidence showing that the threshold between the substandard and the performing categories is important for formulating banks' risk management policies. We estimate our baseline specification at all seven thresholds associated with the categorical value of the rating system.[26] In Table XI, the reported dummy variable is equal to one for firms in the better, i.e., lower value, rating category, and 0 otherwise.

[Table XI Here]

Most of our estimates are not statistically significant. Moreover, across time, the sign of the coefficients is not consistent with the impact of lending standards predicted in Table II. These estimates suggest that the threshold between categories 6 and 7, i.e., the performing category and the substandard category, is particularly relevant for banks' risk management decisions.

[26] Recall that due to the construction of the *CEBI* rating, the threshold between categories 5 and 6 cannot be used.

8 Conclusions

We empirically identify the lending standards applied by banks to SMEs over the cycle. We exploit an institutional feature of the Italian credit market that generates a sharp discontinuity in the allocation of firms into credit risk categories. Using loan-level data, we then compare the credit conditions applied to firms marginally classified into the performing class with those marginally classified into the substandard class.

During the expansionary phase of the cycle, we find that lax lending standards imply that substandard firms pay significantly higher interest rates. However, there is no difference in the amount of credit granted to the firms next to the threshold. During the contractionary phase of the cycle, the abrupt tightening of lending standards leads to the exclusion of substandard firms' access to credit. Finally, we show that when lending standards tighten, firms in the substandard class report a significant drop in the value of production and input choices.

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A Tables and Figures

Table I: Descriptive Statistics

	All	Performing	Sub-Standard	Score 6	Score 7
	Panel A: Loan Information				
Term Loans: Interest Rate	4.57	4.32	5.3	4.79	5.29
	(1.62)	(1.56)	(1.6)	(1.58)	(1.59)
Term Loans: Amount	816	885	617	451	569
	(9850)	(5156)	(17300)	(1623)	(17700)
Term Loans: Maturity	.66	.66	.65	.73	.65
	(.47)	(.47)	(.48)	(.44)	(247)
N	253502	188026	65475	49265	60326
	Panel B: Aggregate Financing Information				
All Bank Financing Granted	8503	9237	6167	7542	6392
	(37200)	(40600)	(23100)	(24600)	(21100)
Share of Used to Granted Financing	.55	.50	.74	.66	.74
	(.27)	(.25)	(.22)	(.20)	(.21)
Share of Term Loans Granted	.35	.35	.36	.33	.35
	(.25)	(.25)	(.25)	(.21)	(.25)
Share of Write-downs	.01	.01	.03	.00	.01
	(.09)	(.04)	(.17)	(.05)	(.09)
N	543855	414041	129754	63722	104253
	Panel C: Balance Sheet Information				
Employment	92	95	76	73	72
	(294)	(295)	(290)	(170)	(207)
Investment to Assets	.05	.05	.04	.04	.04
	(.06)	(.06)	(.06)	(.06)	(.06)
Return to Assets	.05	.07	.00	.05	.03
	(.10)	(.08)	(.13)	(.07)	(.07)
Leverage	.67	.61	.86	.79	.85
	(.19)	(.18)	(.10)	(.10)	(.09)
N	143953	108353	35600	16432	27350

Notes: All panels use data for the period 2004.Q1–2011.Q4, and monetary values expressed in KE (1,000 Euro). Standard errors are reported in brackets. 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 the credit register data with observations at the firm-quarter level. *All Bank Financing Granted* is the firms' total amount of bank financing granted for all categories (loans, credit lines, backed loans). *Share of Used to Granted Financing* is the firms' total amount of bank financing granted for all categories, divided by the firms' total amount of bank financing drawn down for all categories. *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 the 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 defined as 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 defined as the firms' ratio of debt (both short- and long-term) over total assets. In all panels, *N* corresponds to the pooled number of firms in our sample.

Table II: Credit Allocation

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
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	5614	5621	5621	5599	5601	5608	5604	5605	5822	5822	5815	5829	6224	6230	6237	6234
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	1758	1922	2229	3522	3048	3177	3459	4002	3318	3922	4204	5123	4808	4680	4921	5853

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
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	5328	5323	5330	5316	5108	5106	5102	5093	4105	4104	4102	4098	3955	3952	3942	3943
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	3845	3633	3431	3466	2918	2884	2783	3407	2542	2762	2911	3299	3019	2957	3120	2699

Notes: The table reports estimates from regressions which use either *All Bank Financing Granted* (Quantity) or *Interest Rate* (Price) as a dependent variable for each quarter between 2004.Q1–2011.Q4. In order to estimate the discontinuity ($s_i \geq 0$) we use a flexible sixth-order polynomial on either side of the threshold between *Score* categories 6 and 7, allowing for a discontinuity at 0. The reported estimates refer to S_i, a binary variable that takes value of one if the continuous variable $s_i \geq 0$; i.e., if the firm is allocated to the performing category as opposed to the substandard category. See Table I for the definition of the 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 III: Real Effects

Period	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	5951	5875	6097	6512	5549	5358	4307	4109
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	5085	5116	5033	4104	4952	4491	3677	3614
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	5852	5786	6013	6398	5454	5275	4256	4061
Employment	-.01	-.14	.04	.14	.25	-.09	.4*	-.23
	(.22)	(.20)	(.19)	(.17)	(.22)	(.25)	(.23)	(.27)
R-squared	.01	.01	.01	.01	.01	.01	.00	.01
N	2911	2846	2980	3137	2623	2386	2148	1922

Notes: The table reports estimates from regressions which use either *Sales*, *Investment*, *Intermediates*, *Employment* in logs as a dependent variable for each year between 2004–2011. Standard errors are reported in brackets. In order to estimate the discontinuity ($s_i \geq 0$) we use a flexible sixth-order polynomial on either side of the threshold between *Score* categories 6 and 7, allowing for a discontinuity at 0. The reported estimates refer to S_i, a binary variable that takes value of one if the continuous variable $s \geq 0$, i.e., if the firm is allocated to the performing category as opposed to the substandard category. *Sales* corresponds to the total value of production.*Investment* is the value of the firm's the investment in material assets. Finally, we analyze the value of the *Intermediates* factors of production. 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: Credit Allocation and Bank Size

Period	2004	2005	2006	2007	2008	2009	2010	2011
				Large Banks				
Quantity	.14	.29	-.04	-.05	.51**	.41**	.17	.15
	(.22)	(.21)	(.16)	(.18)	(.21)	(.2)	(.22)	(.24)
N	5494	5491	5700	6102	5189	4938	4018	3837
Price	-.07	-.07	-.07**	.05	-.01	.07	-.19**	-.11*
	(.05)	(.05)	(.04)	(.03)	(.03)	(.06)	(.09)	(.07)
N	8119	12053	14628	17931	12449	10323	9968	10127
				Small Banks				
Quantity	.13	.09	.07	-.16	.38*	.1	-.02	-.18
	(.2)	(.24)	(.21)	(.19)	(.21)	(.21)	(.25)	(.23)
N	3860	3872	4093	4423	3817	3653	3016	2936
Price	-.1	-.02	-.05	.11**	-.02	.09	-.39**	-.48**
	(.1)	(.1)	(.06)	(.05)	(.04)	(.13)	(.18)	(.22)
N	1310	1633	1939	2331	1926	1667	1455	1447

Notes: The table reports estimates from split regressions according to bank size. We report standard errors in brackets. Banks' size is defined on the basis of total bank financing granted to SMEs in 2004.Q1, with *Large Banks* belonging to the top decile of the distribution. Accordingly the dependent variables *All Bank Financing Granted* (Quantity) and *Interest Rate* (Price) refer to financing from each category of banks between 2004–2011. In order to estimate the discontinuity ($s_i \geq 0$) we use a flexible sixth-order polynomial on either side of the normalized threshold between each continguous *Score* category, allowing for a discontinuity at 0. The reported estimates refer to S_i, a binary variable that takes 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 I for the definition of the 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 V: Demand for Credit and Information Request

Period	2004	2005	2006	2007	2008	2009	2010	2011
Asked	.02	0	-.02	-.07	-.03	.04	.03	-.07
	(.04)	(.05)	(.04)	(.05)	(.04)	(.04)	(.05)	(.05)
N	5687	5677	5889	6306	5370	5264	4217	4030
Rejected	.02	-.01	.02	-.03	.02	-.1	-.02	.11
	(.05)	(.06)	(.05)	(.05)	(.06)	(.06)	(.09)	(.1)
N	3947	4028	4419	4673	3817	3503	3078	2670

Notes: The table reports estimates from regressions which use either *Asked* or *Rejected* as a dependent variable for each year between 2004–2011. We report the standard errors in brackets. *Asked* is a binary variable equal to one if any non-current bank requested information on the firm during the year. *Rejected* is a binary variable equal to one if any non-current bank requested information on the firm, but did not grant credit to the applicant within the next two quarters. In order to estimate the discontinuity ($s_i \geq 0$) we use a flexible sixth-order polynomial on either side of the normalized threshold between each continguous *Score* category, allowing for a discontinuity at 0. The reported estimates refer to S_i, a binary variable that takes 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. 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: Credit Allocation Based, Bank Liquidity and Bank Capitalization

Period	2004	2005	2006	2007	2008	2009	2010	2011
				Exposure to Interbank Market				
Low Exposure	.03	-.23	.01	-.2	.75***	.02	.28	-.1
	(.2)	(.22)	(.18)	(.2)	(.22)	(.24)	(.23)	(.26)
N	3605	3656	3988	4362	3491	3329	2733	2713
High Exposure	.08	.15	.05	.03	.49**	.46**	.32	.1
	(.23)	(.19)	(.16)	(.18)	(.2)	(.2)	(.23)	(.24)
N	5369	5359	5601	5981	5081	4828	3776	3499
				Equity Ratio				
Low Ratio	.04	.07	-.02	.03	.49***	.17	.2	.1
	(.25)	(.22)	(.15)	(.19)	(.18)	(.21)	(.22)	(.25)
N	5411	5413	5625	5947	5119	4845	3751	3577
High Ratio	0	.07	-.07	-.05	.8***	.2	.15	.17
	(.23)	(.24)	(.18)	(.21)	(.21)	(.19)	(.22	(.27)
N	3291	3293	3518	4578	3334	3292	2789	2379
				Tier 1 Ratio				
Low Ratio	.17	.13	-.01	.05	.49**	.31	.18	.07
	(.25)	(.18)	(.16)	(.18)	(.2)	(.21)	(.19)	(.28)
N	5447	5436	5679	6066	5165	4909	3835	3603
High Ratio	-.07	-.17	.26	.2	.52**	.03	-.04	-.11
	(.24)	(.27)	(.2)	(.21)	(.23)	(.23)	(.27)	(.29)
N	2430	2536	2766	3320	2579	2564	2187	2224

Notes: The table reports estimates from regressions that split the sample according to the credit conditions granted to a firm by a bank with higher (respectively, lower) exposure to the interbank market or capital ratio. *Exposure to Interbank Market* is measured as the ratio of interbank financing divided by total assets. Bank capitalization is measured either as *Equity Ratio*, the ratio of book equity to total assets, or as *Tier 1 Ratio*, the ratio of tier 1 capital to total assets. Accordingly, the dependent variable *All Bank Financing Granted* (Quantity) refers to financing from each category of banks between 2004–2011. In order to estimate the discontinuity ($s_i \geq 0$) we use a flexible sixth-order polynomial on either side of the normalized threshold between each continguous *Score* category, allowing for a discontinuity at 0. The reported estimates refer to S_i, a binary variable that takes 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. 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 Ratings 6 and 7

Period	2004	2005	2006	2007	2008	2009	2010	2011
Mc Crary Density Estimate	.10	.13	.02	.08	.3***	-.00	.08	.17
	(.06)	(.07)	(.07)	(.06)	(.07)	(.08)	(.10)	(.10)
N	5951	5876	6098	6514	5551	5360	4307	4110

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: Model Diagnostics - 2003 Balancing Checks

Period	2004	2005	2006	2007	2008	2009	2010	2011
Leverage	0	.01	-.04	-.03	.05	-.01	-.04	.01
	(.03)	(.04)	(.03)	(.03)	(.04)	(.04)	(.05)	(.06)
Pooled Mean	.79	.78	.77	.76	.76	.74	.74	.73
N	3967	3636	3595	3678	2888	2705	2168	2024
Return to Assets	0	0	0	-.01	-.02	0	0	0
	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.02)	(.02)
Pooled Mean	.05	.05	.05	.05	.06	.06	.06	.06
N	5306	4844	4750	4836	3776	3504	2721	2508
Cash Holdings	.02	0	.01	.01	-.01	-.04	-.02	0
	(.01)	(.01)	(.01)	(.02)	(.02)	(.02)	(.03)	(.03)
Pooled Mean	.04	.05	.05	.05	.06	.06	.06	.06
N	4750	4380	4317	4364	3422	3147	2487	2297
Investment to Assets	.02	.02	.01	.02	.02	-.02	-.03	-.02
	(.01)	(.02)	(.01)	(.02)	(.02)	(.02)	(.03)	(.02)
Pooled Mean	.06	.06	.06	.06	.06	.06	.06	.06
N	4501	4136	4083	4174	3353	3100	2414	2237
Non Performing		.01	0	.01	0	-.01	0	-.03
		(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.03)
Pooled Mean		.01	.01	.01	.01	.01	.01	.01
N		5736	5944	6358	5411	5276	5276	4235

Notes: The table estimates differences in pre-sample firm characteristics at the threshold. We report the standard errors in brackets. In all rows, except for the last, the dependent variable is measured in 2003. The discontinuity is estimated using a flexible sixth-order polynomial on either side of the threshold between *Score* categories 6 and 7. The reported estimates refer to S_i, a binary variable that takes value of one if the continuous variable $s_i \geq 0$; i.e., if the firm is allocated to the performing category as opposed to the substandard category. The last row in the table changes the timing in which the dependent variable's value is measured. There, *Non Performing* is a binary variable equal to one if any of a given firm's banks classified the firm's credit as non-performing. *Cash Holdings* are defined as cash over total assets. See Table I 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. *Pooled Mean* reports the average of each variable for firms in *Score* categories 6 and 7.

Table IX: Model Diagnostics - Balancing Checks and Self Selection

Period	2004	2005	2006	2007	2008	2009	2010	2011
Activity: Automobile Industry	.01	.02	.00	.00	-.03	.00	.01	-.02
	(.02)	(.02)	(.01)	(.00)	(.03)	(.02)	(.02)	(.02)
Pooled Mean	.02	.02	.02	.02	.02	.02	.02	.02
Activity: Food Industry	.03	-.04	.03	-.01	.05	.04	.06	-.06
	(.04)	(.05)	(.04)	(.04)	(.04)	(.04)	(.06)	(.06)
Pooled Mean	.10	.10	.10	.11	.11	.10	.12	.11
Location: Top 5 Cities	.06	.03	.05	-.06	.02	-.01	.07	.05
	(.06)	(.06)	(.06)	(.06)	(.06)	(.06)	(.08)	(.07)
Pooled Mean	.27	.27	.27	.28	.26	.26	.27	.28
Location: Top 10 Cities	.05	.01	.02	-.04	.02	-.02	.11	.07
	(.07)	(.07)	(.07)	(.07)	(.07)	(.07)	(.09)	(.08)
Pooled Mean	.39	.39	.40	.40	.39	.38	.39	.41
Location: Firm Clusters	.07	.06	.09	.03	.01	.06	.05	.01
	(.07)	(.07)	(.07)	(.06)	(.07)	(.07)	(.08)	(.08)
Pooled Mean	.40	.40	.40	.40	.37	.38	.39	.38
N	5951	5876	6098	6514	5551	5360	4307	4110

Notes: The table estimates differences in firm characteristics unaffected by the threshold using a flexible sixth-order polynomial on either side of the threshold between *Score* categories 6 and 7, allowing for a discontinuity at 0. Standard errors are in brackets. The reported estimates refer to S_i, a binary variable that takes value of one if the continuous variable $s_i \geq 0$; i.e., if the firm is allocated to the performing category as opposed to the substandard category. The dependent variables are sector of activity and geographic location. *Automobile Industry* and *Food Industry* are binary variables indicating whether the firms' SIC code belongs to the automobile or to the food industry, respectively. *Top 5 Cities* and *Top 10 Cities* is a binary variable indicating whether the firms' headquarter zip code is in one of the largest 5/10 cities. *Firm Clusters* is a binary variable indicating whether the firms' headquarter 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. *Pooled Mean* reports the average of each variable for firms in *Score* categories 6 and 7.

Table X: 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

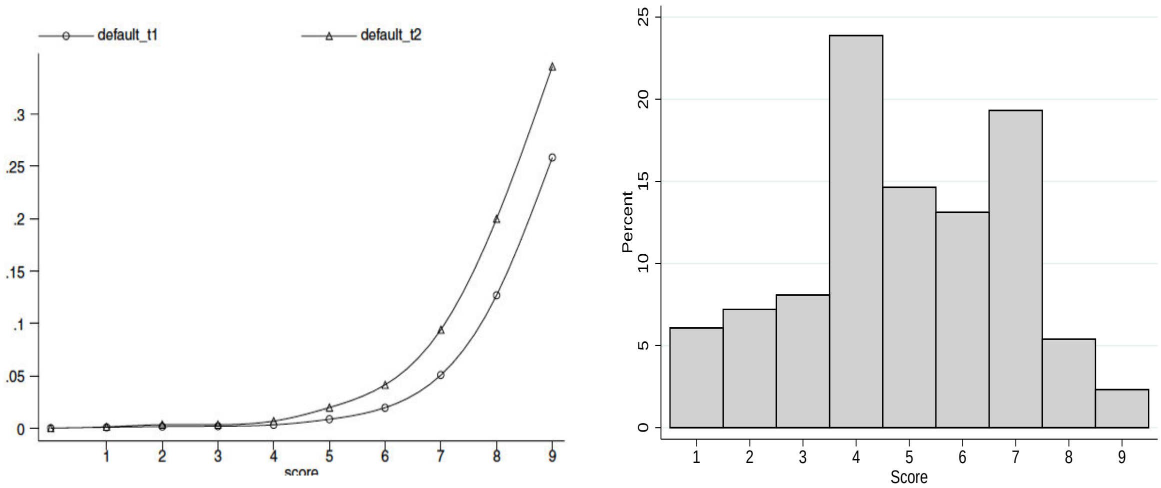
Notes: The table reports placebo estimates from regressions which use either *All Bank Financing Granted* (Quantity) or *Interest Rate* (Price) as a dependent variable for each quarter between 2004.Q1–2011.Q4. The placebo threshold $\left(\bar{s}^{Placebo}\right)$ is randomly drawn from the support of the continuous variable in *Score* categories 6 and 7. In order to estimate the placebo discontinuity $\left(s_i \geq \bar{s}^{Placebo}\right)$ we use a flexible sixth-order polynomial on either side of the threshold $\left(\bar{s}^{Placebo}\right)$, allowing for a discontinuity at $\left(\bar{s}^{Placebo}\right)$. The reported estimates refer to the placebo variable $S_i^{Placebo}$, a binary variable that takes value of one if the continuous variable $s_i \geq \bar{s}^{Placebo}$. See Table I for the definition of the 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 XI: Yearly RDD Estimates - Other Thresholds

Period	2004	2005	2006	2007	2008	2009	2010	2011
				Threshold Between Categories 1 and 2				
Quantity	-.3	-.15	.07	.17	-.28	-.19	-.3	-.32
	(.24)	(.26)	(.26)	(.31)	(.27)	(.25)	(.23)	(.21)
N	2555	2693	2648	2684	2886	2975	2677	2773
Price	.04	.13	.08	.03	-.12	-.23	-.04	-.22
	(.11)	(.12)	(.11)	(.08)	(.08)	(.2)	(.18)	(.22)
N	583	716	782	815	715	712	832	775
				Threshold Between Categories 2 and 3				
Quantity	-.12	-.19	-.45	-.3	-.25	-.2	-.45	-.51
	(.39)	(.4)	(.39)	(.35)	(.41)	(.34)	(.36)	(.35)
N	2311	2508	2480	2383	2265	2243	2243	2375
Price	0	.16	-.1	.01	-.02	-.1	-.23	.7***
	(.13)	(.12)	(.11)	(.08)	(.14)	(.27)	(.22)	(.22)
N	1099	1427	1595	1702	1475	1260	1406	1825
				Threshold Between Categories 3 and 4				
Quantity	-.24	-.03	-.14	.29	.11	-.29	-.15	.29
	(.31)	(.3)	(.35)	(.29)	(.33)	(.32)	(.29)	(.3)
N	6087	6361	6371	6526	6040	5968	5840	6128
Price	-.03	.03	.09	-.03	-.08	-.01	-.12	-.03
	(.08)	(.09)	(.08)	(.04)	(.06)	(.13)	(.15)	(.12)
N	7197	9359	10255	10547	9033	8625	11153	13158
				Threshold Between Categories 4 and 5				
Quantity	-.33	.22	-.44*	-.18	-.2	-.06	-.26	-.41*
	(.24)	(.24)	(.24)	(.21)	(.24)	(.24)	(.24)	(.23)
N	7019	7359	7437	7616	6960	6878	6711	7058
Price	0	-.05	.03	-.01	0	-.02	-.23***	.07
	(.05)	(.06)	(.04)	(.03)	(.03)	(.1)	(.08)	(.07)
N	11072	14972	16561	17056	14662	13505	17687	19743
				Threshold Between Categories 7 and 8				
Quantity	-.25	-.28	-.29	-.06	-.36	-.63	1.44*	1.01
	(.48)	(.51)	(.55)	(.55)	(.63)	(.66)	(.73)	(.88)
N	4160	4136	4256	4602	3752	3472	2875	2688
Price	0	-.2	.1	-.22**	-.08	.35*	-.56	-.12
	(.19)	(.17)	(.11)	(.09)	(.1)	(.2)	(.56)	(.27)
N	6058	8394	10412	13192	8280	6047	5883	5791
				Threshold Between Categories 8 and 9				
Quantity	-.9	.18	.51	-1.31	-1.26	-.42	-.97	-1.68
	(1.4)	(1.16)	(1.12)	(1.36)	(1.09)	(1.24)	(.95)	(1.2)
N	596	649	598	646	595	668	517	616
Price	-1.29	-.01	.21	.09	-.02	.07	.4	-.31
	(54.98)	(.53)	(.26)	(.27)	(.13)	(.5)	(.47)	(.4)
N	380	494	655	761	518	701	471	489

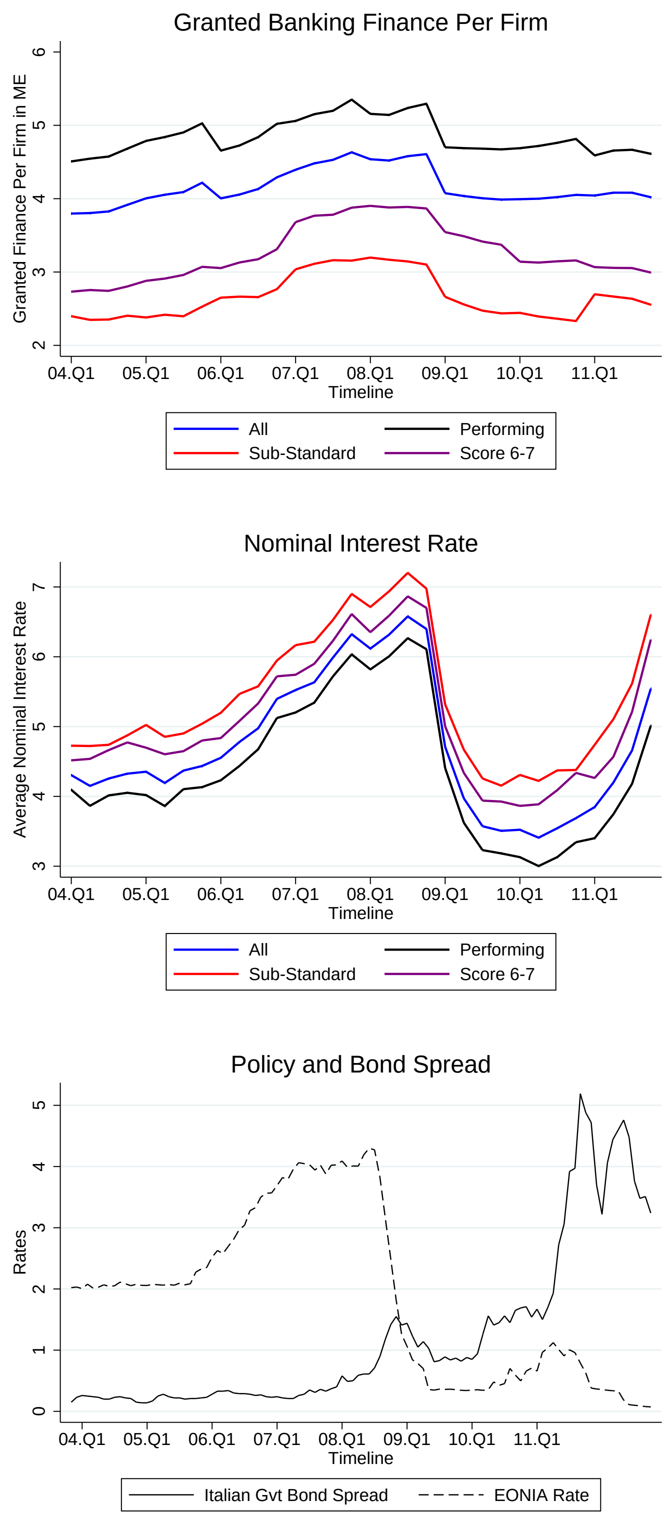
Notes: The table reports estimates from our baseline specification at all the seven thresholds associated to the categorical value of the rating system. We report standard errors in brackets. The dependent variable we use is either *All Bank Financing Granted* (Quantity) or *Interest Rate* (Price) as a dependent variable 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 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 I for the definition of the 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.

Figure 1: Characteristics of the Score Assignment Variable



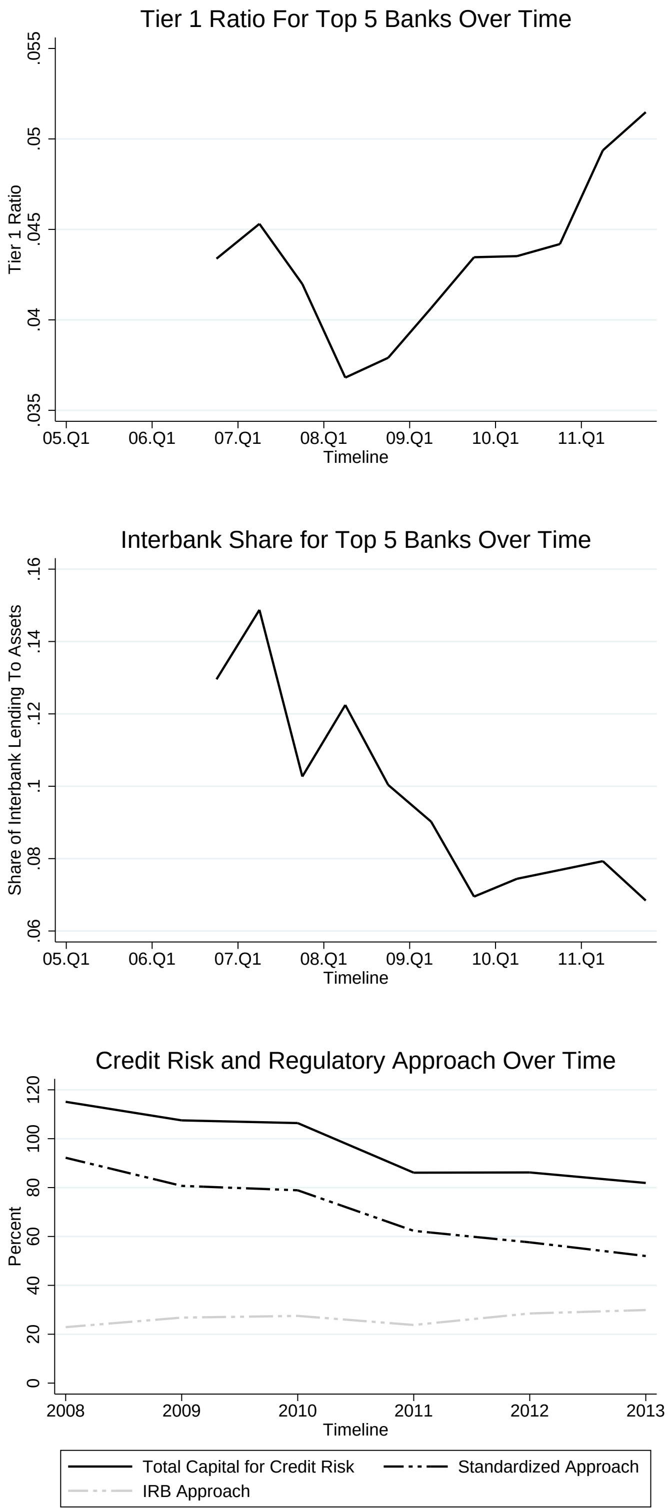
The left panel is taken from Panetta et al. (2007) who, using the same balance sheet and bank data for the period between 1988 to 1998, plot the *Score* variable against an indicator of default within the next one (circle) and two years (triangle). The right panel plots the share of firms within each *Score* category between 2004 and 2011.

Figure 2: Descriptive Statistics Across Time



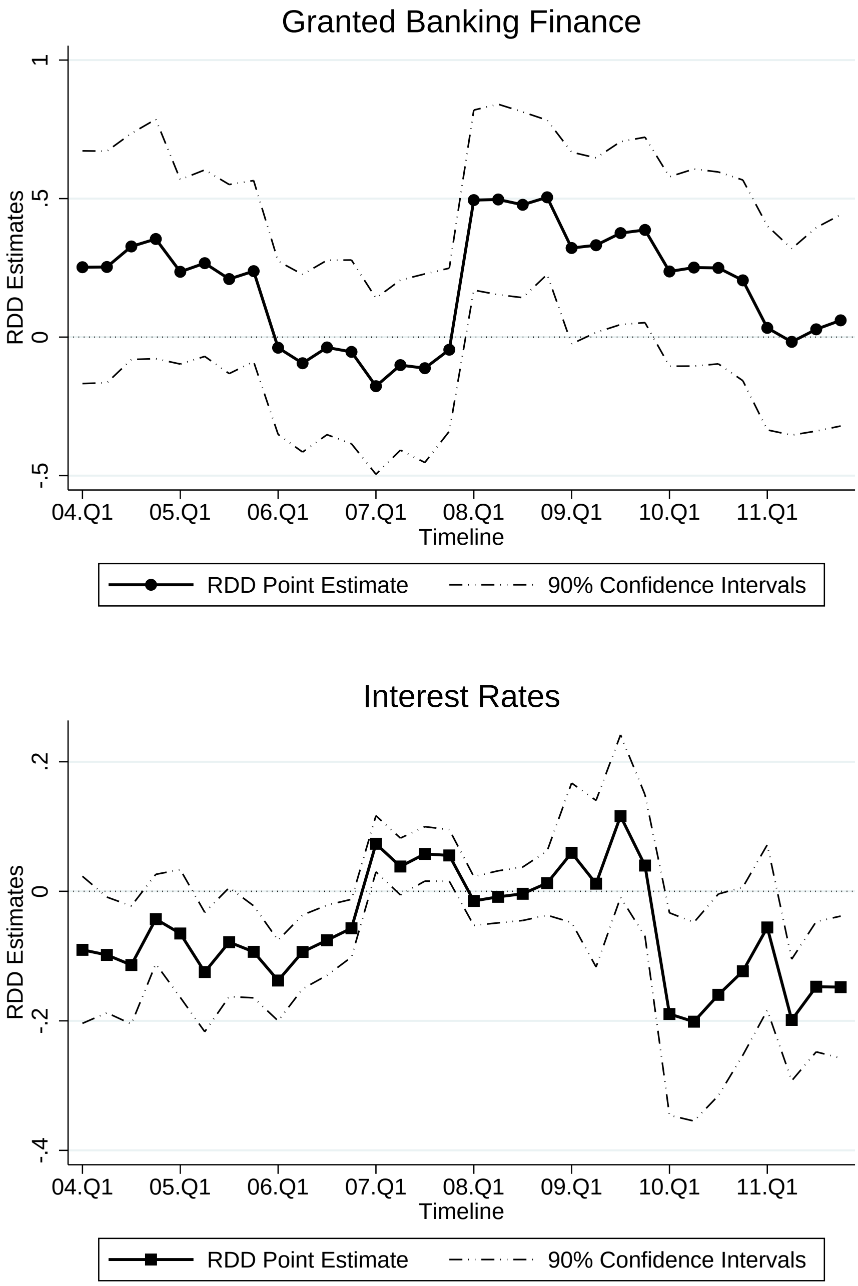
In the upper panel we plot the per-firm aggregate value of bank financing for different rating categories across time. In the middle panel we plot nominal average interest rates applied to firms in different rating categories across time. In the bottom right panel we plot the ten-year Italian government bond interest rate together with the Euro overnight index average rate.

Figure 3: Bank Capital and Credit Risk



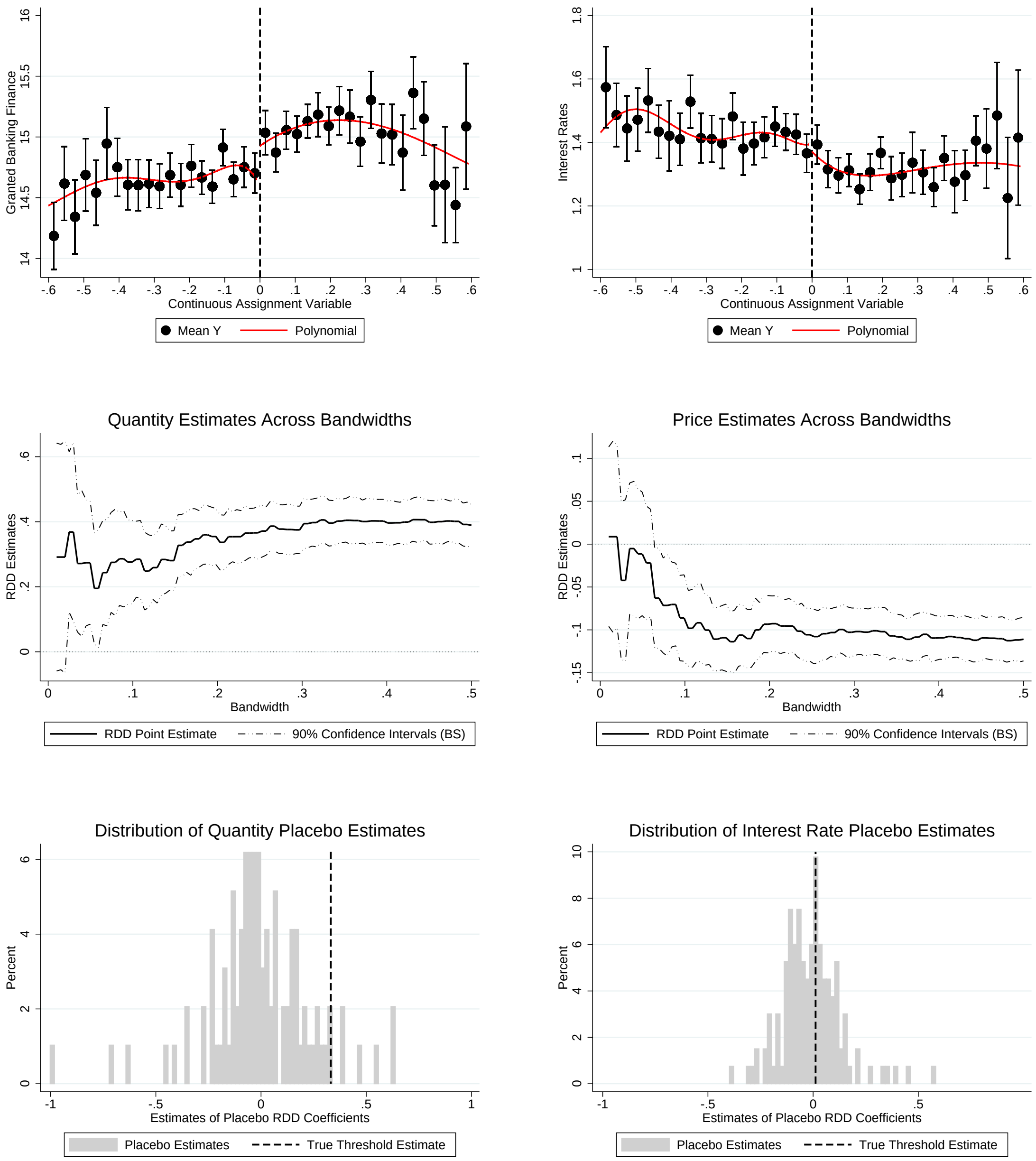
In the top panel we plot the amount of financing raised by Italian banks on the interbank market as a fraction of their total assets. In the middle panel we plot the tier 1 capital ratio for the 5 largest banks in our dataset across time. In the bottom panel we use data from the ECB statistical data 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 line).

Figure 4: RDD Quantity and Price Treatment Effects



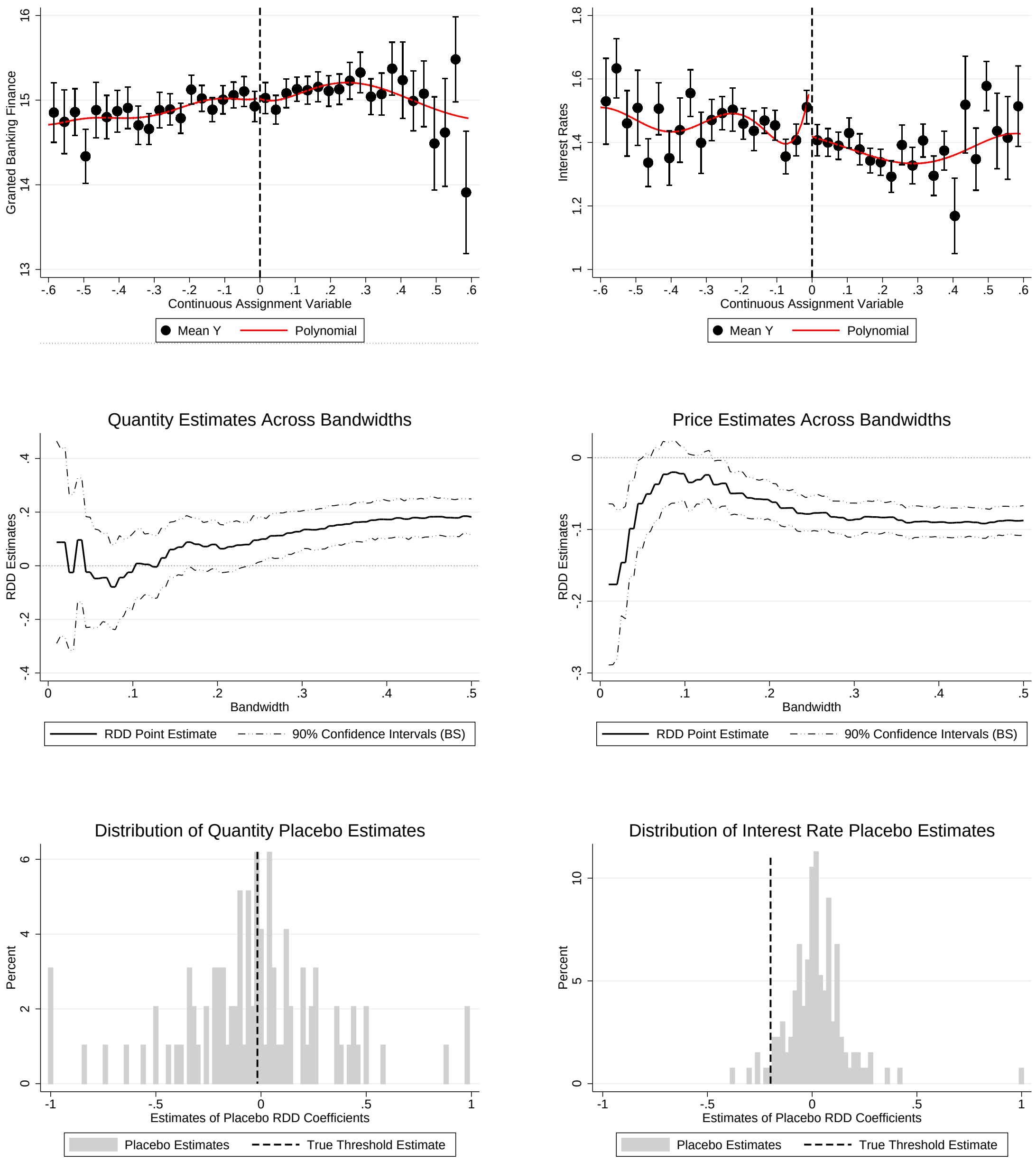
The figure plots the quarterly discontinuity estimates and 90% confidence intervals of specification (1) using either *All Banking Financing Granted* (top panel) or *Interest Rate* (bottom panel) as a dependent variable between 2004.Q1–2011.Q4. The plotted estimates refer to S_i, a binary variable that takes value of one if the continuous variable $s_i \geq 0$; i.e., if the firm is allocated to the performing category as opposed to the substandard category.

Figure 5: 2nd Quarter of 2009



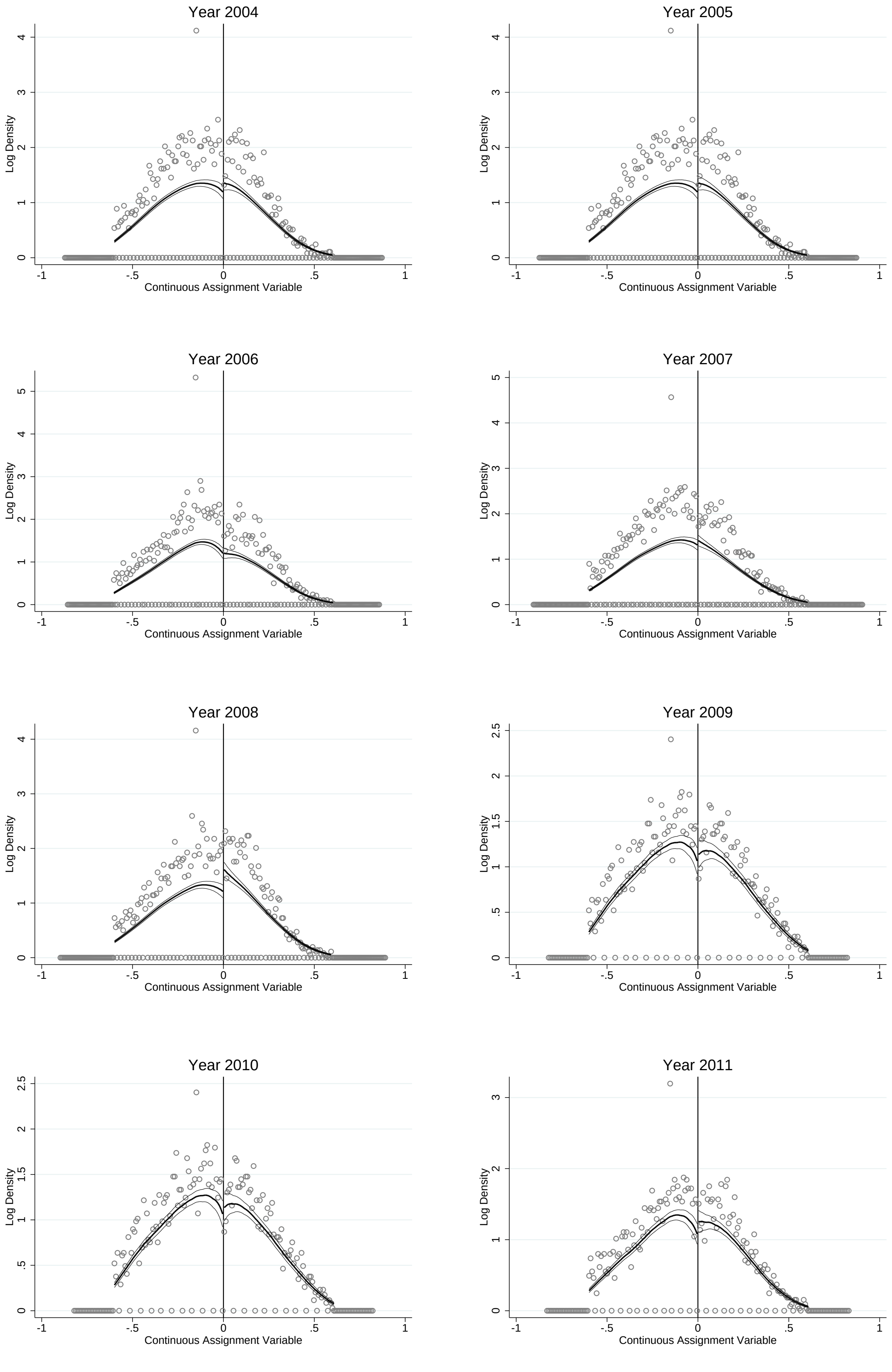
The figure focuses on the second quarter of 2009. The top panel divides the domain of s_i into mutually exclusive bins with size of 0.03. For each bin, we compute the average and the 90% confidence interval of the outcome variable, and plot these values at the bin's mid-point. The fitted red line shows how closely the sixth order polynomial approximates the variation of bank financing conditions at the threshold. The middle panels estimate a simple mean difference specification for increasingly larger bins ($\pm h$) around the threshold. The value of γ is reported on the vertical axis, while the width of the bins around the threshold is reported on the horizontal axis. The solid line represents the estimated value of γ as function of the distance from the threshold. The dashed lines are 10% confidence bands calculated using clustered standard errors. The bottom panels plot the empirical distribution of estimates based on approximately 100 randomly drawn placebo thresholds. The vertical dotted line represents the estimate obtained from the true threshold.

Figure 6: 2nd Quarter of 2011



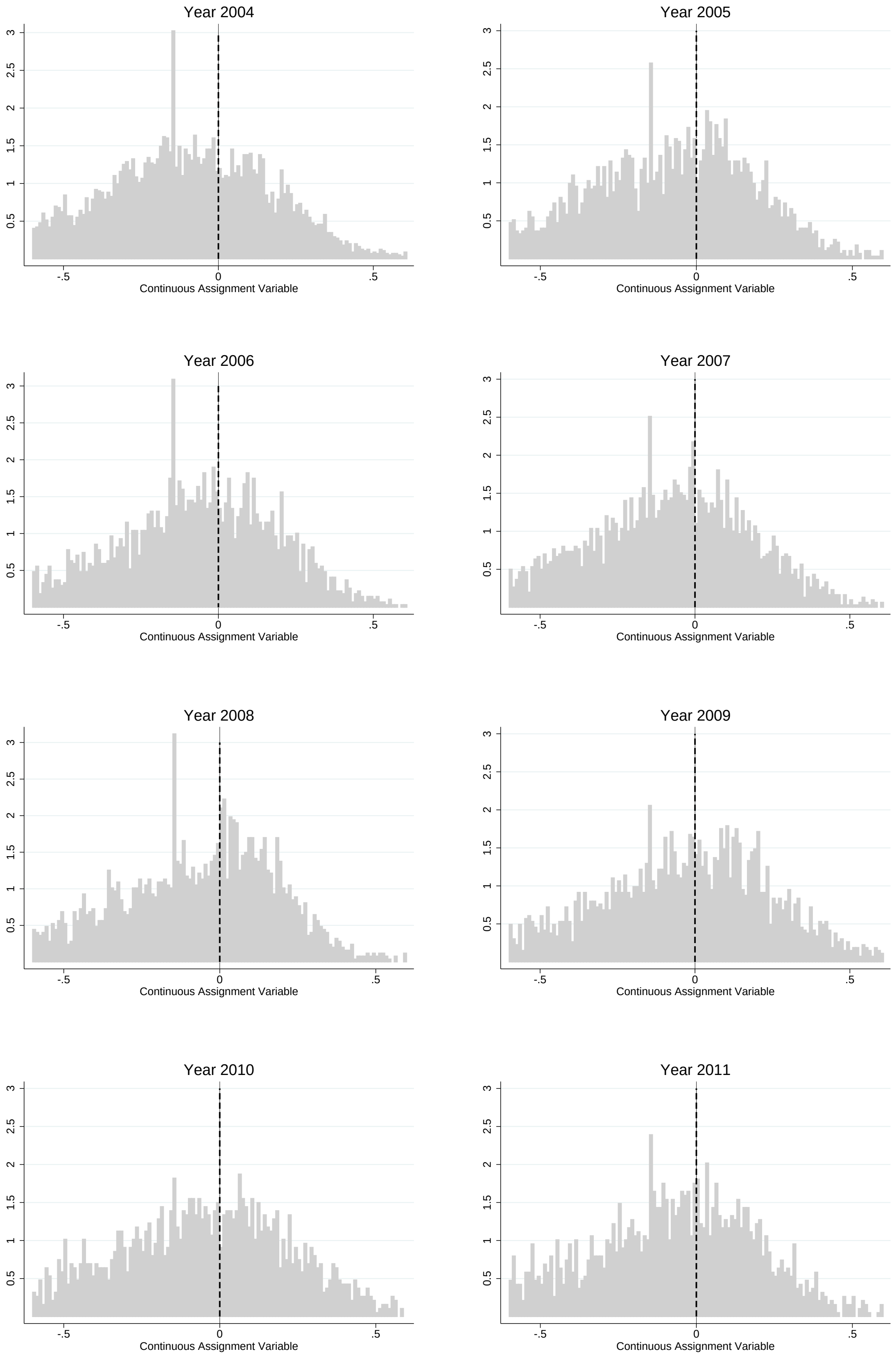
The figure focuses on the second quarter of 2011. The top panel divides the domain of s_i into mutually exclusive bins with size of 0.03. For each bin, we compute the average and the standard deviation of the outcome variable, and plot these values at the bin's mid-point. The fitted red line shows how closely the sixth order polynomial approximates the variation of bank financing conditions at the threshold. The middle panels estimate a simple mean difference specification for increasingly larger bins ($\pm h$) around the threshold. The value of γ is reported on the vertical axis, while the width of the bins around the threshold is reported on the horizontal axis. The solid line represents the estimated value of γ as function of the distance from the threshold. The dashed lines are 10% confidence bands calculated using clustered standard errors. The bottom panels plot the empirical distribution of estimates based on approximately 100 randomly drawn placebo thresholds. The vertical dotted line represents the estimate obtained from the true threshold.

Figure 7: McCrary Self-Selection Test



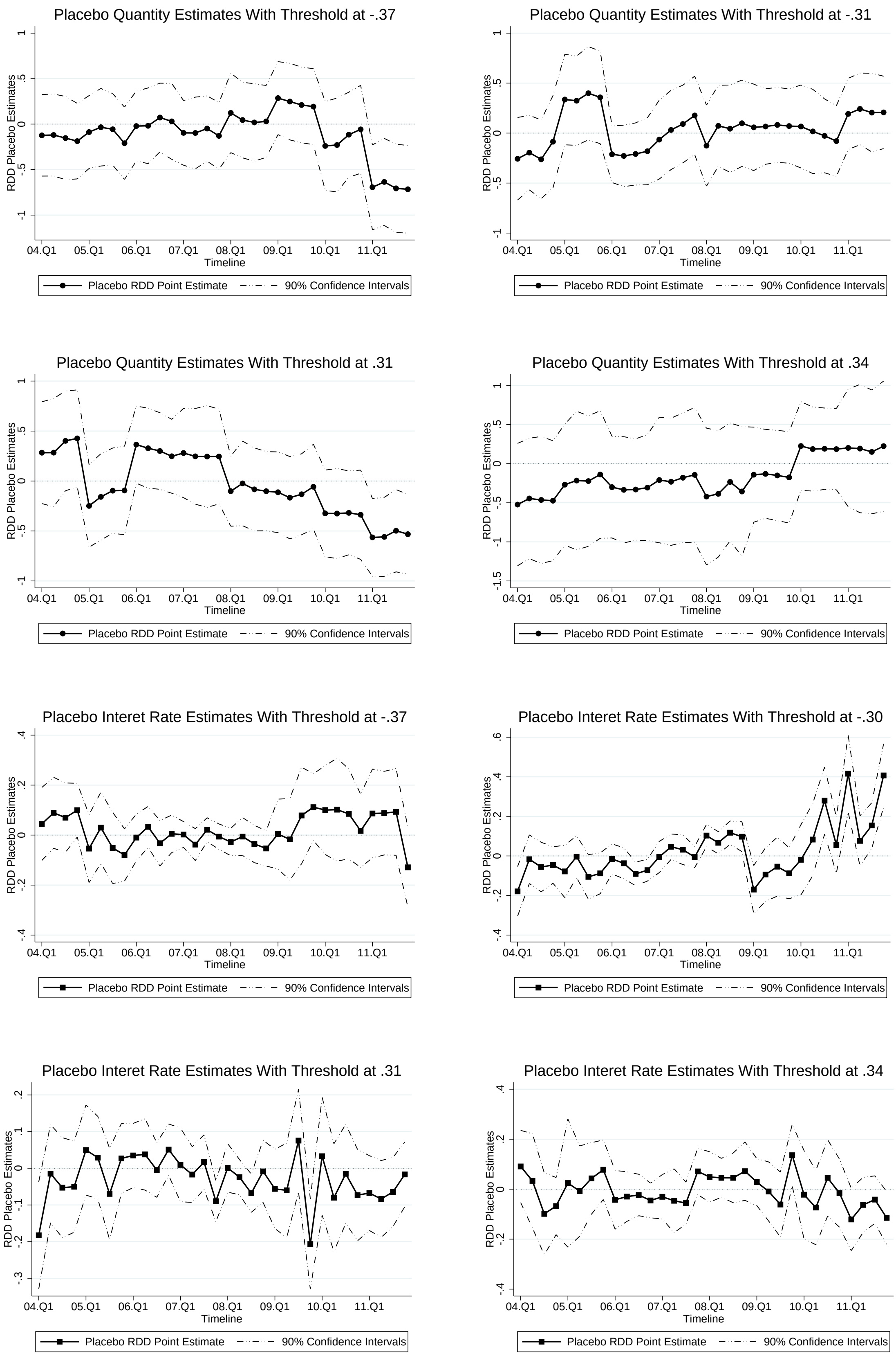
In the figure, we plot the distribution of firms along the support of the continuous variable (s_i) between *Score* rating categories 6 and 7. The solid line is a fitted kernel local linear regression of the log of the density on both sides of the threshold separating firms in category 7 from firms in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

Figure 8: 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 9: Sequence of RDD Estimates for Placebo Thresholds



The panels plot the sequence of discontinuity estimates obtained running specification (1), and the associated 90% confidence intervals, on a fixed and randomly drawn placebo threshold.

B Online Appendix

In this appendix, we discuss data organization, present the theoretical framework delivering the predictions in Section 4.2 and provide additional results corroborating the interpretation of our results.

B.1 Data Organization

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

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.[27] 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, 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 non-price characteristics, such as loan maturity and the presence or the absence of real and personal guarantees.

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 us with 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. Yet, the qualitative nature of our results remains the same when we include the firms that change risk categories in two consecutive years in the sample used to run our empirical analysis.

[27] During the sample period, the threshold for the aggregate financial exposure above which banks had to report the 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.

B.2 Definition of Variables

We use information from the Taxia dataset to compute variables describing each bank financing contract. *Loan Interest Rate* computes 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 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. *Share of Used to Granted Financing* is the firm's total used bank financing, divided by the total granted bank financing to the firm. *Share of Term Loans Granted* is the firm's total term loans, divided by the total amount of bank financing granted to the firm. *Share of Write-downs* is the firm's total bank financing that has been written down by banks, divided by the total amount of bank financing granted to the firm.

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.3 Theoretical Framework

We first introduce and solve the model of screening that the bank solves in each class (Section B.3.1). This setting draws on the screening model in Bolton and Dewatripont (2006) adapting it to the institutional framework we are analyzing. We will first show that the nature of the equilibrium (pooling v. screening) depends on the amount of liquidity in the banking sector and the adverse selection problem's perception.

We then illustrate in Section B.3.2 the implications of the results obtained within the model in Section B.3.1 for the credit contracts offered to the firms in the substandard and performing classes.

B.3.1 A Model of Bank Screening

A monopoly bank faces a population of risk neutral firms (or borrowers) who each own a project requiring a fixed initial outlay of $\tilde{I} = 1$ and yielding a random return $\tilde{X}$, where $\tilde{X} = \{\tilde{R}, 0\}$ and $\tilde{p} = Prob\{\tilde{X} = \tilde{R}\}$.[28] Firms are cashless and must obtain investment funds from outside sources. The bank can offer to finance the initial outlay in exchange for a future repayment. It knows that firms can be either risky (r) or safe (s), but does not know each firm's type.[29] Thus, the characteristics of a firm's project are given by $\{p_j, R_j\}$, with $j = s, r$, depending on the type. Projects' characteristics are such that:

$$1 > p_s > p_r > 0, \tag{3}$$

$$R_r > R_s > 1, \tag{4}$$

$$p_s R_s = p_r R_r > 1. \tag{5}$$

Reflecting the standard risk-return trade-off, the firms of a safer type succeed with higher probability and their return is lower than the firms of a riskier type.

The bank knows that the proportion of safe firms is equal to $\beta \in (0, 1)$, and that of risky firms is $1 - \beta$. Moreover, the bank has funds for a proportion $\alpha \leq 1$ of firms, with $\alpha > \max\{\beta, 1 - \beta\}$. In periods of excess demand, we say that the bank funds are $\alpha = \alpha^l < 1$. If $\alpha = \alpha^h = 1$, instead, the bank has enough funds for all firms. We will see how distinguishing between these two cases affects the equilibrium outcomes.

The bank offers debt contracts. Specifically, we denote by $\tilde{C} \equiv (\tilde{x}, \tilde{D})$ the contract that offers financing with a probability $\tilde{x}$ and at a repayment of $\tilde{D}$. Since $\tilde{I} = 1$, we can interpret $\tilde{x}$ as the fraction of the firm's project that receives funding. The timing of the game is such that in $t = 1$ the bank posts the contracts to the firms. In case of acceptance, investment takes place and payoffs realize in $t = 2$. A firm remains inactive in the case of rejection. Finally, the entrepreneur is protected by limited liability.

As it is standard, we will show that the bank faces two options. It can offer a contract that pools the applicant firm with all the other firms in the same class. Or, it can offer screening contracts that target each distinct risk profile in a given class.[30] When taking this choice, the bank trades off the rents extracted from risky borrowers with the ability to lend all its funds. Consistent with the literature, we say that a situation featuring pooling corresponds to lax standards, and a situation featuring screening to tight standards.

[28] We find analogous results in a model of competitive screening.

[29] This approach is consistent with our institutional setting because, as we argue in Section 2, the bank observes an imperfect signal of the firm's risk profile, as represented by the combination of the categorical and continuous values of the rating.

[30] Note that screening is costly because the bank needs to leave an information rent to firms to separate borrowers with a different risk profile.

Excess demand for banking funds ($\alpha = \alpha^l < 1$) We start by solving the bank's contracting problem under the assumption of excess demand for liquidity. We show that, at the unique equilibrium, the bank offers screening credit contracts.

Proposition 1. *In periods of excess demand ($\alpha = \alpha^l < 1$), at the unique equilibrium in pure strategies the bank posts the following screening contracts:*

$$(x_s, D_s) = (x_s^*, R_s)\,, \tag{6}$$

$$(x_r, D_r) = (1, R_r - x_s^*(R_r - R_s)), \tag{7}$$

with $x_s^* = 0$ if $\beta < \beta^*$ and $x_s^* = \frac{(\alpha^l - (1-\beta))}{\beta} < 1$ if $\beta \geq \beta^*$, with β^* determined by

$$\beta(p_s R_s - 1) - (1-\beta)p_r(R_r - R_s) = 0. \tag{8}$$

Proof. The proof follows the same steps as in Bolton and Dewatripont (2006:57ff). The bank sets (x_r, D_r) and (x_s, D_s) to maximize the following expression:

$$\beta x_s(p_s D_s - 1) + (1-\beta)x_r(p_r D_r - 1), \tag{9}$$

subject to the participation and incentive compatibility constraints

$$D_s \leq R_s, \tag{10}$$

$$D_r \leq R_r, \tag{11}$$

$$x_s p_s(R_s - D_s) \geq x_r p_s(R_s - D_r), \tag{12}$$

$$x_r p_r(R_r - D_r) \geq x_s p_r(R_r - D_s), \tag{13}$$

and the following feasibility and resource constraints:

$$0 \leq x_s, x_r \leq 1, \tag{14}$$

$$\beta x_s + (1-\beta)x_r \leq \alpha^l. \tag{15}$$

Due to our parametric assumptions, the binding participation constraint is (10) and the binding incentive compatibility constraint is (13), so that

$$D_s = R_s, \tag{16}$$

$$x_r(R_r - D_r) = x_s(R_r - D_s). \tag{17}$$

Solving for D_r, we find

$$D_r = R_r - \frac{x_s}{x_r}(R_r - R_s). \tag{18}$$

Plugging the value of D_s and D_r into the bank's objective function, we obtain the new maximization problem:

$$\max_{x_s, x_r} \; \beta x_s(p_s R_s - 1) + (1-\beta)[x_r(p_r R_r - 1) - x_s p_r(R_r - R_s)], \tag{19}$$

subject to

$$0 \leq x_s \leq x_r \leq 1, \tag{20}$$

$$\beta x_s + (1-\beta)x_r \leq \alpha^l. \tag{21}$$

Since $p_r R_r = p_s R_s = m > 1$, the first-order condition with respect to x_r yields $x_r = 1$. Instead, the probability of getting access to funding for the safe ones is equal to zero ($x_s = 0$) whenever

$$\beta(p_s R_s - 1) - (1-\beta)p_r(R_r - R_s) < 0. \tag{22}$$

Instead, if the value of (22) is positive, then the resource constraint commands to raise x_s up to $(\alpha^l - (1-\beta))/\beta < 1$ for all $\alpha^l, \beta < 1$. Therefore, the candidate equilibrium contracts feature

$$(x_s, D_s) = (x_s^*, R_s)\,, \tag{23}$$

$$(x_r, D_r) = (1, R_r - x_s^*(R_r - R_s)), \tag{24}$$

with $x_s^* = 0$ if $\beta < \beta^*$ and $x_s^* = \frac{(\alpha^l - (1-\beta))}{\beta} < 1$ if $\beta \geq \beta^*$, and β^* determined by

$$\beta^*(p_s R_s - 1) - (1-\beta^*)p_r(R_r - R_s) = 0. \tag{25}$$

At this candidate equilibrium, the safe types are indifferent between receiving credit and staying inactive. Moreover, the bank's profits are given by

$$(1-\beta)(p_r R_r - 1) \tag{26}$$

if $\beta < \beta^*$ (and $x_s^* = 0$) and

$$(\alpha^l - (1-\beta))(p_s R_s - 1) + (1-\beta)(p_r R_r - 1) - (1-\beta)\frac{(\alpha - (1-\beta)}{\beta}p_r(R_r - R_s) \tag{27}$$

otherwise.

We proceed by analyzing the bank's incentives to deviate by offering a pooling contract such that $(x^p, D^p) \equiv (\alpha, R_s)$. Under this pooling equilibrium the bank raises

$$\pi^p \equiv \alpha^l(\beta(p_s R_s - 1) + (1-\beta)(p_r R_s - 1)), \tag{28}$$

which is clearly increasing in α^l. First, we find that the value of (28) evaluated at $\alpha^l \to 1$ falls below (26) for all $\beta < \beta^*$. Second, we find that the value of (27) is smaller than (28) for all $R_r > R_s$ and $\alpha^l < 1$. This establishes that at the unique equilibrium in pure strategies the bank offers the screening contracts in (23) and (24). □

The proposition shows that, at equilibrium, if funds are limited ($\alpha = \alpha^l < 1$) the bank is better off screening types rather than offering a contract that pools all firms. Moreover, if the adverse selection problem is not particularly relevant (i.e., β is large), the bank does not exclude safe firms from credit (i.e., $1 > x_s^* > 0$). Thus, the repayment set in the contract is such that safe borrowers are indifferent between investing and remaining inactive ($D_s = R_s$) and risky borrowers earn rents ($D_r < R_r$). Instead, if β is low the bank excludes safe borrowers from lending (i.e., $x_s^* = 0$) and extracts all the rents of the risky borrowers ($D_r = R_r$).

Abundance of banking funds ($\alpha = \alpha^h = 1$) We now assume that there is abundance of liquidity in the banking system. We will show that the nature of the equilibrium depends on the proportion of safe types (β).

Proposition 2. *In periods featuring abundant liquidity in the banking system ($\alpha = \alpha^h = 1$), at the unique equilibrium in pure strategies the bank posts the following screening contracts*

$$(x_s, D_s) = (0, R_s)\,, \tag{29}$$

$$(x_r, D_r) = (1, R_r), \tag{30}$$

if $\beta < \beta^*$, with β^* determined by (22). *Instead, if $\beta \geq \beta^*$ the bank offers a pooling contract featuring ($x^p = 1, D^p = R_s$).*

Proof. We build on the proof of Proposition 1. If $\beta < \beta^*$, we show in the proof of Proposition 1 that the profits under the screening equilibrium contracts are larger than the profits under the pooling equilibrium deal ($x^p = 1, D^p = R_s$) for all $R_r > R_s$. This establishes the first part of the claim.

For the second part, note that the screening contracts in Proposition 1 coincide with the pooling contract ($x^p = 1, D^p = R_s$) for all $\alpha^l \to 1$. Thus, when banking funds are

Table B1: OVERVIEW OF EQUILIBRIUM RESULTS

	Small proportion of safe types: $\beta < \beta^*$	Large proportion of safe types: $\beta \geq \beta^*$
Excess demand for liquidity: $\alpha = \alpha^l < 1$	**Screening Equilibrium** $(x_s, D_s) = (0, R_s)$ $(x_r, D_r) = (1, R_r)$	**Screening Equilibrium** $(x_s, D_s) = (x_s^*, R_s)$ $(x_r, D_r) = (1, R_r - x_s^*(R_r - R_s))$ with $x_s^* = (\alpha - (1 - \beta))/\beta$.
Abundance of liquidity: $\alpha = \alpha^h = 1$	**Screening Equilibrium** $(x_s, D_s) = (0, R_s)$ $(x_r, D_r) = (1, R_r)$	**Pooling Equilibrium** $(x^p, D^p) = (1, R_s)$

aplenty, the bank gives access to all borrowers in the category ($x^p = 1$) at a repayment equal to the rents of the safe types ($D^p = R_s$). □

In periods with abundant liquidity in the banking sector, the nature of the equilibrium depends on the share of safe types. More specifically, if the value of β is low (i.e., $\beta < \beta^*$) then the bank sets a screening contract that excludes safe types from lending and extracts the rents of the risky borrowers. Otherwise, the bank sets a pooling contract at which it lends all its funds ($x^p = 1$) at a repayment equal to the rents of the safe borrowers ($D^p = R_s$).

Summary of the results and credit cycle's phases We summarize our results in Table B1. We expect a situation with pooling equilibrium contracts and lax standards to arise when the perception of the adverse selection problem is limited and the liquidity is abundant in the banking sector. Otherwise, the bank tightens its standards by offering screening contracts that differ in the extent they limit the safe types' access to lending.

We then distinguish between three main phases. First the phase of upturn, in which the liquidity is limited ($\alpha = \alpha^l < 1$) but the adverse selection problem is not relevant ($\beta \geq \beta^*$). Then the phase of boom, in which liquidity is abundant ($\alpha = \alpha^h = 1$) and the proportion of safe types is large ($\beta \geq \beta^*$). Finally, the phase of downturn, in which the adverse selection problem is relevant (i.e., $\beta < \beta^*$) and the amount of liquidity is scarce ($\alpha = \alpha^l < 1$).

B.3.2 Bank Screening with Rating Segmentation

With rating segmentation, the monopolistic bank solves the model in Section B.3.1 within each rating class. More specifically, we assume that firms fall either into the substandard class (σ) or into the performing class (π). In each class firms can be of two types, which implies that there are four different combinations of classes and types:

- High-risk-and-high-yield firms in category σ, with project's characteristics given by p_σ and R_σ.
- Low-risk-and-low-yield firms in category σ, with project's characteristics given by p and R.
- High-risk-and-high-yield firms in category π, with project's characteristics given by p and R.
- Low-risk-and-low-yield firms in category π, with project's characteristics given by p_π and R_π.

Consistent with our institutional setting, we assume that the projects of the high-risk-and-high-yield firms in π and the low-risk-and-low-yield firms in σ feature the same characteristics. Moreover,

$$1 > p_\pi > p > p_\sigma > 0, \tag{31}$$

$$R_\sigma > R > R_\pi > 1, \tag{32}$$

$$p_\pi R_\pi = pR = p_\sigma R_\sigma = m > 1. \tag{33}$$

In the model, when deciding on the credit conditions to a firm, the bank observes the class the firm falls in (σ or π) and the distribution of types in each class. In particular, the bank knows that, in each class, there is a proportion $\beta \in (0, 1)$ of low-risk-and-low-yield firms.[31]

As in the main model the bank can invest at most α in each class.[32] Moreover, it can either offer a contract that pools the applicant firm with all the other firms in the same class. Or, it can engage in costly screening. Therefore, although firms at the threshold between rating classes are economically comparable, their credit conditions can differ depending on the nature of the equilibrium (pooling and screening) arising in each class.

Before proceeding, we define the threshold values of β that imply whether the low-risk-and-low-yield firms are fully excluded from credit (β^* in Propositions 1 and 2 of the model in Section B.3.1). More specifically, we denote by β^π the value of β such that

$$\beta^\pi(m-1) - (1-\beta^\pi)p(R - R_\pi) = 0 \tag{34}$$

in class π. Instead, we use β^σ to denote the threshold value of β in class σ:

$$\beta^\sigma(m-1) - (1-\beta^\sigma)p_\sigma(R_\sigma - R) = 0. \tag{35}$$

[31] We obtain the same conclusions provided the difference between the share of low-risk-and-low-yield types in class π and the share of low-risk-and-low-yield firms in class σ is sufficiently small.

[32] Our results would be stronger if we assume that $\alpha^\pi \geq \alpha^\sigma$.

Credit conditions over the cycle In the corollaries that follow, we apply the results derived in Propositions 1 and 2 to a setting featuring rating segmentation. In class σ, we denote by $(\underline{x}, \underline{D})$ the contracts that target the low-risk-and-low-yield borrowers and by (x_σ, D_σ) those that target the high-risk-and-high-yield borrowers. Moreover, we denote by (x_π, D_π) and $(\overline{x}, \overline{D})$ the contracts that target the low-risk-and-low-yield borrowers and the high-risk-and-high-yield borrowers in class π, respectively. For our empirical predictions, we compare the contracts to the high-risk-and-high-yield firms in class π $(\overline{x}, \overline{D})$ with the contracts to the low-risk-and-low-yield firms in class σ $(\underline{x}, \underline{D})$.

Let us start with a situation of upturn (or recovery), featuring a relatively large value of β and a relatively small value of α.

Corollary 1. *If $\beta \geq \beta^\pi, \beta^\sigma$ and $\alpha = \alpha^l < 1$, the bank posts:*

$$(x_\pi, D_\pi) = (x_\pi^*, R_\pi), \tag{36}$$

$$(\overline{x}, \overline{D}) = (1, R - x_\pi^*(R - R_\pi)), \tag{37}$$

$$(\underline{x}, \underline{D}) = (\underline{x}^*, R)\,, \tag{38}$$

$$(x_\sigma, D_\sigma) = (1, R_\sigma - \underline{x}^*(R_\sigma - R)), \tag{39}$$

with $x_\pi^* = \underline{x}^* = (\alpha^l - (1 - \beta))/\beta < 1$.

Corollary 1 corresponds to a scenario with excess demand and relative abundance of low-risk-and-low-yield firms in each category. In these circumstances, a screening equilibrium arises in each class. At this equilibrium, the contracts that target the firms at the threshold feature a difference in terms of both the firms' cost and access to funding ($\overline{x} - \underline{x} > 0$ and $\overline{D} - \underline{D} < 0$). That is, Corollary 1 gives rise to Prediction 1.

We proceed with the corollary that illustrates the equilibrium contracts in a phase of boom.

Corollary 2. *If $\beta \geq \beta^\pi, \beta^\sigma$ and $\alpha = \alpha^h = 1$, the bank posts:*

$$(x_\pi, D_\pi) = (1, R_\pi), \tag{40}$$

$$(\overline{x}, \overline{D}) = (1, R_\pi), \tag{41}$$

$$(\underline{x}, \underline{D}) = (1, R)\,. \tag{42}$$

$$(x_\sigma, D_\sigma) = (1, R). \tag{43}$$

With excess supply and abundance of safe types, the bank offers a pooling contract that finances all firms at a repayment equal to the return of the low-risk-and-low-yield firms in each class (R and R_π), so that $\overline{D} - \underline{D} < 0$. Moreover, the contracts that target the firms at the threshold exhibit no differences in terms of firms' access to funding (i.e., $\overline{x} - \underline{x} = 0$). These results give rise to Prediction 2.

We proceed with the corollary that gives the equilibrium contracts in the downturn phase.

Corollary 3. *If $\beta^\pi, \beta^\sigma > \beta$, the bank posts:*

$$(x_\pi, D_\pi) = (0, R_\pi), \tag{44}$$
$$(\overline{x}, \overline{D}) = (1, R), \tag{45}$$
$$(\underline{x}, \underline{D}) = (0, R), \tag{46}$$
$$(x_\sigma, D_\sigma) = (1, R_\sigma). \tag{47}$$

In the phase of downturn, the adverse selection problem becomes relevant (that is, the fraction of low-risk-and-low-yield firms is particularly small). In these circumstance, at equilibrium the high-risky-and-high-yield firms obtain full access to funding. Instead, the low-risk-and-low-yield firms are fully excluded from credit ($\underline{x}^* = \underline{x}_\pi^* = 0$). This gives rise to the positive difference between the quantity of lending granted to the firms across the threshold in Prediction 3 ($\overline{x} - \underline{x} > 0$).[33]

B.4 Additional Robustness Checks

[33]The corollary allows us to rationalize the difference in the amount of credit granted at the threshold, however it gives rise to a situation in which the price of the firms in the substandard category is not defined (as they are fully excluded from lending). To reconcile our theoretical results with the empirical evidence, one needs to assume that

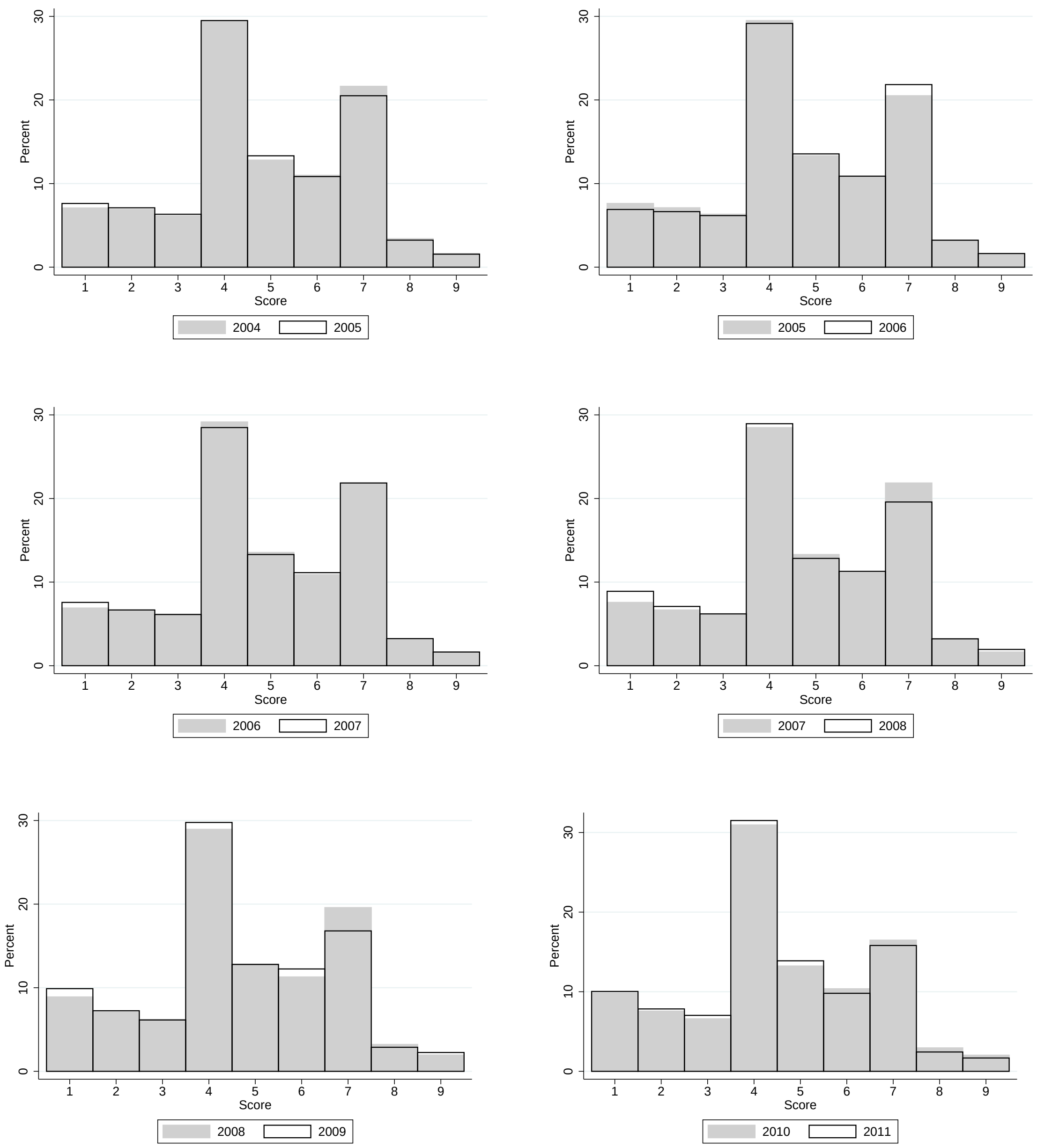
$$p(R - R_\pi) > p_\sigma(R_\sigma - R) \iff p_\sigma R > pR_\pi, \tag{48}$$

which holds true provided R is sufficiently large. This assumption implies that $\beta^\pi > \beta^\sigma$; that is, the condition determining the probability of getting access to funding of the low-risk-and-low-yield firms is more binding in class π than in class σ (i.e., (34) is more binding than (35)). Under (48) and $\beta^\pi > \beta \geq \beta^\sigma$, one finds that the equilibrium contracts in the phase of downturn are given by:

$$(x_\pi, D_\pi) = (0, R_\pi), \tag{49}$$
$$(\overline{x}, \overline{D}) = (1, R), \tag{50}$$
$$(\underline{x}, \underline{D}) = (\underline{x}^*, R), \tag{51}$$
$$(x_\sigma, D_\sigma) = (1, R_\sigma - \underline{x}^*(R_\sigma - R)), \tag{52}$$

with $\underline{x}^* = (\alpha^l - (1 - \beta))/\beta < 1$. So that contracts at the threshold feature a difference in terms of quantity of lending, but no difference in terms of price of lending.

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



In the figure, we plot of the share of firms within each *Score* category in two consecutive years for the period between 2004 and 2011.

Table B2: Local Polynomial Regression

Period	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	5657	5652	5870	6274	5356	5136	4126	3969
Price	-.03**	-.03***	-.05***	-.01	.01	-.02	-.07***	-.02**
	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.02)	(.01)
N	9431	13686	16567	20262	14375	11992	11478	11795
				Bias-Corrected				
Quantity	.32***	.12	-.09	-.2**	.19***	.22***	.09	-.06
	(.08)	(.08)	(.06)	(.07)	(.07)	(.07)	(.07)	(.09)
N	5657	5652	5870	6274	5356	5136	4126	3969
Price	-.03***	-.03***	-.06***	0	.01*	-.01	-.11***	0
	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.02)	(.01)
N	9431	13686	16567	20262	14375	11992	11478	11795
				Bias-Corrected and Robust Standard Errors				
Quantity	.32***	.12	-.09	-.2**	.19*	.22**	.09	-.06
	(.11)	(.1)	(.12)	(.09)	(.1)	(.11)	(.11)	(.11)
N	5657	5652	5870	6274	5356	5136	4126	3969
Price	-.03**	-.03***	-.06***	0	.01	-.01	-.11***	0
	(.02)	(.01)	(.01)	(.01)	(.01)	(.02)	(.02)	(.02)
N	9431	13686	16567	20262	14375	11992	11478	11795

Notes: The table reports estimates from regressions which use either *All Bank Financing Granted* (Quantity) or *Interest Rate* (Price) as a dependent variable for each year between 2004–2011. In order to estimate the discontinuity ($s_i \geq 0$) we use 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 refer to S_i, a binary variable that takes 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 I for the definition of the 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.