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Information Asymmetry, External Certification, and the Cost of Bank Debt

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Abstract
This paper examines how the cost of bank debt reflects public information about borrower quality, and whether such information complements or substitutes the private information of banks. Using a sample of small business loans, and the award of a competitive public subsidy as an observable positive signal of external certification, we find that a certification is associated with a lower cost of debt for the recipients if the amount of private information of the lender is low. As the bank accumulates more information over the course of the lending relationship with a borrower, public information loses importance and no longer has a significant effect. Our results highlight a potential positive effect of external certification, and suggest that public and private information can be substitutes in the pricing of bank debt.

JEL classification: D83, D21, G21, G30, L11.

Keywords: Information, Financial Contracting, Interest rate, SMEs Financing.

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1. Introduction

Small and medium-sized enterprises (SMEs) heavily depend on banks for external finance, and information asymmetry is a key driver of the cost of their bank debt. During their interactions with banks, firms reveal information about their financial and business conditions on a continuous basis. This happens initially, when firms apply for a loan, and subsequently over the course of the lending relationship through provision of financial statements, accounting data, and disclosure of business prospects, profitability, future investments, etc. (Petersen and Rajan, 1994; Berger and Udell, 1995; Bharat et al., 2008; Cassar et al., 2015; Vander Bauwedhe et al., 2015). Most of the information is generated internally to the bank-firm relationship and remans private with the bank. Over the course of the lending relationship, however, borrowers often become subject to evaluation and screening by non-bank entities as well.[1] For example, firms apply for government subsidies and grants, participate in public programs or partnerships for funding of research and development (R&D) projects and innovation, or receive certification of their products and operations. Outcomes of such evaluations, to the extent that they become publicly observable, can be relevant external information signals that certify borrower quality for both the lending bank and its competitors.

While vast empirical research explores the effects of private information of banks on credit availability and loan terms, insights into the role of public signals obtained by banks and external certification of borrower quality, and especially how they interact with banks' private information to shape loan contracts and determine cost of debt, are limited. Hence, in this paper, we investigate how banks incorporate in their loan pricing information from public signals about borrowing firms obtained during the lending relationship, and whether such information complements or substitutes the private information accumulated by banks.

To be specific, we empirically examine whether the interest rates in a sample of loans made to SMEs by a large Italian regional bank (hereafter, the bank) respond to a *favorable* publicly observable signal about some of the borrowers. To capture such a signal, we use the outcomes of applications for a competitive public subsidy program (hereafter, the program) that took place in 2005 in the Marche region of Italy.[2] The objective of the program was to facilitate funding of R&D

[1] Firms could apply for loans from other banks that also conduct screening and evaluation. Positive outcomes can be observed through public credit registries or private credit bureaus. The pure information effect, however, cannot easily be captured because lending by multiple banks generates additional competitive and incentive effects for both banks and firms (Jappelli and Pagano, 2002).

[2] The program had two independent rounds. The first round was in 2005 and the second in 2007. Due to data limitation of the loan contacts sample, we consider only the 2005 round. We describe the program in a subsequent section.

and innovation by offering subsidies in the form of monetary grants. The grants were awarded on a competitive basis after comprehensive evaluation of the application by the regional public agency and a committee of independent experts, and the list of successful applicants was made publicly available on the agency's website. Hence, subsidy award could serve as a favorable public signal of external certification of the quality of the recipient.

Using this setting, we investigate whether the interest rates charged by the bank respond to the public signal of borrower certification. The signal is *positive by construction* and should be associated with lower interest rates if the bank incorporates the incremental public information in its pricing decisions. We then explore if public and private information could act as substitutes or complements in the loan pricing process by examining the interaction between the public signal and the amount of private information about a borrower accumulated by the bank. We capture the amount through the length of the lending relationship.

We find that the public signal from the subsidy award does not have a significant effect on the cost of bank debt of recipient firms, compared to non-recipient firms, on average. However, when we examine the interaction between the public signal and the private information available to the bank, we find that the receipt of subsidy is associated with lower interest rates for borrowers without an established lending relationship with the bank. Thus, our analysis suggests that the two sources of information can function as substitutes.

A major concern about the estimated effect of public certification – lower cost of debt when the bank has limited private information about a firm – is internal validity. Subsidy recipients are not randomly drawn and might be systematically different from non-recipients. For instance, lower interest rates might reflect factors associated with a higher likelihood of success in the competition for the public subsidy. It might be that only the most productive firms apply and ultimately receive a subsidy. In addition, there might also be systematic unobservable differences between recipients and non-recipients that can be associated with the interest rate charged by the bank.

While our main results are based on difference-in-differences (DD) and triple-differences (DDD) estimations that account for unobservable heterogeneity between groups of recipient and non-recipient borrowers, and for a number of observable covariates, we conduct several tests to address the selection concerns. First, we implement a combined propensity score (PS) matching and DD estimator to adjust for differences in observable borrower characteristics such as industry, size, and organizational form, that could affect the likelihood of receiving a subsidy, i.e., being selected into treatment, and demonstrate that our findings continue to hold. However, inferences based on matching methods are not robust to presence of unobservable factors that simultaneously affect outcome and assignment into treatment (DiPrete and Gangl, 2004; Becker and Caliendo, 2007). Therefore, we conduct a sensitivity analysis based on the bounding approach of Rosenbaum (2002) to quantify the magnitude of possible unobservable factors needed to invalidate our finding that the public signal has a favorable effect on interest rates when bank information is low. The analysis suggests that the estimated effect is robust to presence of possible hidden bias that more than doubles the odds of subsidy receipt. Second, to strengthen validity of our empirical strategy, we perform a placebo analysis to explore the presence of trends prior to subsidy receipt, as this would jeopardize our DD strategy. With the limited timeframe we have, we conduct the test by estimating our main model in the cross-section using data for the year preceding the subsidy award, i.e., when the signal has not yet been realized. As expected, we find no effect in this case.

We also conduct some additional tests to assess the reliability of our results. First, we verify the robustness of our insights to an alternative proxy for bank information to ensure that our findings are not driven by the specific measure used in the main analysis. Second, we introduce a measure of credit risk: the internal credit rating assigned to the borrowers by the bank. Our key result of a favorable effect of the public signal when bank information is low continues to hold.

The certification effect produced by the subsidy award may be due to two possible, and not mutually exclusive, mechanisms related to the role of asymmetric information in credit markets. On the one hand, in absence of private information, the lending bank might simply be incorporating the public signal about borrower quality. Once the bank accumulates more information over the course of the lending relationship, the bank starts to weigh its own information more heavily and the public signal loses importance. On the other hand, however, since the subsidy award is public information, and observable by other banks in the local credit market, it leads to increased market contestability. The increased competitive pressure on the lending bank can affect the interest rates it charges recipient firms, especially those with unestablished lending relationships as they are also less likely to suffer from hold-up problems and could switch banks more easily. In this vein, Saidi and Žaldokas (2020) document that greater innovation disclosure created from changes in the US patent legislation makes credit markets more contestable, which ultimately increases opportunities for innovative firms to switch lenders more easily, and lowers their cost of debt.

We try to examine the relevance of these two mechanisms – incremental information vis-à-vis incremental market contestability – by exploring the structure of the local credit markets. The underlying idea is that if the incremental market contestability mechanism is at work, reduction in interest rates after subsidy receipt should be significant and more pronounced for firms in credit markets with a low competition. In such markets, the public signal about quality of a borrower can boost, the otherwise weak, pressure from bank's competitors to poach this borrower away and thus leads the lender to lower the interest rate. By contrast, if the markets already have a large presence of banks, the competitive pressure is strong and the information rent of the lending bank is already minimized. In this case, the incremental market contestability effect of the public signal should be limited.

Our finding that the subsidy receipt is associated with a lower cost of debt can also reflect a loan demand effect rather than certification. To the extent that the subsidy covers only part (35% in this case) of the funds required for the proposal, it is possible that subsidized firms will increase demand for credit. As a result, the lending bank might be willing to lower the interest rate to entice these borrowers. Thus, it is possible that the information content of the public signal is more about demand for credit. To explore the argument, we replace in our model the bank information measure with a measure of credit increase from our bank, and find that it does not have a significant effect. This result indicates a limited role of the credit demand channel and suggests that the information content of the public signal is unlikely to be about credit demand.

Our paper contributes to several streams of research in corporate finance, accounting, and banking. First, our work is related to studies that examine cost of debt implications of changes in the information environment of firms resulting from shocks such as adoption of external audits, loss of analyst coverage, litigation, or modification in disclosure regulations (e.g., Kim et al., 2011; Minnis, 2011; Derrien et al., 2016; Ni and Yin, 2018). In particular, our findings are consistent with Cassar et al. (2015) and Saidi and Žaldokas (2020). The former study shows that adoption of accrual accounting reduces information asymmetry between firms and banks, which leads to lower interest rates on approved loans. Importantly, consistent with the substitution result we document, the effect is more pronounced for borrowers with low credit score and recent lending relationship with the lender.[3] Our finding that the two sources of information can be substitutes is also consistent with the results generated by Saidi and Žaldokas (2020), albeit in a different setting. Specifically, they exploit changes in innovation disclosure requirements generated by the American Inventor's Protection Act (AIPA) to show that increased public information via patent disclosure allows firms to switch lenders and ultimately leads to lower cost of debt in the market for syndicated loans. We complement their findings by offering evidence from the small business credit market, where the information frictions can have a larger effect, observable signal of public information provided by an external party, as well as international context and different institutional setting.

Second, we add to existing literature that explores interactions between public funding and private sources of capital, and the implications for financing and capital structure of firms. Extant research shows that receiving an R&D subsidy or government support is deemed a positive signal with certification effect and improves access to venture capital (Lerner, 1999; Feldman and Kelley, 2006; Howell, 2017; Islam et al., 2018), equity (Söderblom et al., 2015; Wei and Zuo, 2018), and debt (Meuleman and De Maeseneire, 2012; Hottenrott and Demeulemeester, 2017; Li et al., 2019; Bellucci et al., 2019; Moro et al., 2020). While these studies utilize firm-level survey and balance sheet data, our analysis allows for directs test using loan-level data on cost of debt. Along this line, the work closest to ours is by Bonfim et al. (2021), who analyze a government program in Portugal that provides SMEs with a certification and show that certified firms pay lower rates. Depending on the specification, they estimate a certification effect of about 1.8% and up to 2.1%, on average. Our results indicate that for an unestablished borrower in our sample, the public signal is associated with a rate that is about 3% lower, while a borrower with lending relationship of 1 year pays about 1.2% less. This points to the external validity of our estimates and inferences.

Third, we contribute to research that examines how the information available to banks can affect loan contract terms, especially in the context of small business lending. Extant studies focus on various sources of bank information such as length and exclusivity of the lending relationship

[3] In a similar vein, Acconcia et al. (2022) find that firms that obtain the certification of the "Legality Rating" provided by the Italian government increase their investments more in provinces where the risk of firms' insolvency is greater, and it is more difficult for banks to assess their quality.

(Petersen and Rajan, 1994; Berger and Udell, 1995; Elsas and Krahnen, 1998), geographical proximity to borrowers (Degryse and Ongena, 2005; Bellucci et al., 2013; Hollander and Verriest, 2016; Bellucci et al., 2019), hierarchical distance within the bank organization (Alessandrini et al., 2009; Gambacorta and Mistrulli, 2014; Calcagnini et al., 2018), and adoption of credit scoring or other information technology (Berger et al., 2005; Liberti and Mian, 2009; Filomeni et al., 2021). Most studies rely on proxies for stock of information available to the bank or adopt measures that reflect the flow of all types of information generated by loan officers, but do not draw a distinction between private and public signals. We add to the stream of literature by identifying a public signal of incremental favorable information generated by an external, non-financial party, and observed by the bank during the lending relationship, and tracing its effect on interest rates. In addition, we investigate whether public and private information could be substitutes or complements over the course of the lending relationship between bank and borrower.

The rest of the paper is organized as follows. In the next section we describe the program we use for identification, discuss data, provide background information, and outline our empirical strategy. In section 3 we present the main results of the analysis and offer some robustness and specification tests. We explore underlying mechanisms and alternative explanations in section 4. We conclude in section 5.

2. Data and empirical strategy

For our empirical analysis we combine information from two data sources. The first source is a proprietary dataset of credit lines granted to a sample of SMEs by a large Italian regional bank as of September 2004 and September 2006. The dataset covers the bank's entire portfolio of credit line contracts made by its branches in two provinces of the Marche region in Italy to borrowers located in the provinces. Our main analysis is based on triple-differences estimations and we focus on borrowers present in the dataset at both points in time.

The two provinces covered by our sample are fairly representative of the Italian economic structure. They are characterized by the presence of industrial districts and a large number of SMEs (Dei Ottati, 1994, 2018; Randelli and Boschma, 2012). During the sample period, our bank has branches in 16 provinces but more than 25% of its branches are located in the two provinces. Also, the bank is headquartered in one of the provinces. The bank identifies as key sources of competitive advantage its close proximity to borrowers and focus on the local communities and credit markets where it operates. Consistently, the bank has implemented over time a strategy of acquisitions of small community banks in order to grow but maintain its local presence.[4]

Table 1 provides some characteristics for the local credit markets where the bank operates as of the first year in our dataset. We define a local credit market as a municipality where the bank has at least one branch. Thus, we identify 31 markets across the two provinces. On average, our bank has 1.6 branches per market, with a minimum of 1 and a maximum of 6. We also note that some of these markets can be very competitive. On average, our bank competes with 14 banks, operating about 31 branches per market.

INSERT TABLE 1 HERE

The second data source is public information releases by the regional agency for innovation in the Marche region of Italy (Marche Innovazione) about public subsidy programs administered by the agency. The primary goal of the agency is to promote collaboration between firms on R&D projects and innovation activity, facilitate access to technological expertise, and improve scientific knowledge in the region. At the time, information on recipient firms of public subsidy programs organized by the agency was hosted by the Department of Information Engineering at Marche Polytechnic University in Ancona, Italy.[5] We manually identify firms that borrow from our bank and also receive public subsidy through a competitive program (described next) administered by the agency. We use the receipt of a subsidy through the program as a public signal of positive information and a possible source of external certification of firm quality.

2.1. The program

The public subsidy program we use for the signal of favorable information about borrowers – Program 1.1.1.4.1, *Promotion of Industrial Research and Experimental Development in SMEs* (hereafter, PIREDS) – is designed and implemented by the regional government of the Marche region. The aim of the PIREDS initiative is to promote R&D and innovation by SMEs by providing financial support in the form of a subsidy for development of industrial research. To be eligible,

[4] Stated in the notes to the 2006 financial statements of the bank.

[5] We are grateful to Donato Iacobucci at the Department of Information Engineering for graciously providing the data on public subsidy recipients.

an applicant firm has to meet the SME definition of the European Commission.[6] Applicants must be located within the Marche region and operate in an industry related to food technology, clothing, information and communication technology, nanotechnology, development of new materials and building automation.[7] The funded projects can last up to 18 months and the cost should be between €100,000 and €2,000,000. The subsidy is in the form of a capital contribution of 35% of eligible expenses.[8]

Funding requests are evaluated by a committee of independent innovation experts who are registered with the Ministry of Education, University, and Research, as well as financial experts, to determine the merit of the research project and its financial feasibility. Each project receives a score between 0 and 100 and grants are awarded based on this score.[9] If an application is approved and the project is funded, the awardee firm cannot receive funding from any other public program – regional, national, or international – for the same project. For our purposes, this ensures that the signal is not confounded by the role of other public programs.

The PIREDS program had two independent calls for applications. The first was in 2005 and the second was in 2007. We consider only the 2005 call due to the time period covered by our loan-level dataset (bank data are available only for 2004 and 2006). The 2005 call received 193 applications of which 103 were accepted and 90 rejected. A total of about €21 million of public subsidies were granted with an average of €201,685 per project. At the end of the selection process, a list of recipient firms was made publicly available by the regional government on its website. Firms not selected for the subsidy were not announced.

2.2. Sample construction and key variables

To construct the sample used in the analysis, and to identify the borrowers for which the bank receives a public certification signal generated by the subsidy award, we manually match the two data sources – the portfolio of borrowers provided by the bank and the list of firms receiving

[6] Fewer than 250 employees and turnover below €50 million or total assets below €43 million. The definition is based on the European Commission Recommendation C(2003) 1422 of 6 May 2003.
[7] One of the advantages of the program is that its regional scope reduces unobserved heterogeneity in economic and institutional environment that could characterize programs at the national or international level.
[8] Eligible expenses include personnel (researchers and technicians), machinery, equipment, raw materials, consulting, and non-material goods such as patents, licenses, and software. The contributions are provided to firms in two tranches, the first within 3 months of acceptance of the application and the second after completion of the project. Firms could, however, ask for up to 50% of the capital contribution in advance.
[9] Information on the scores of applications is not publicly available.

a subsidy through the PIREDS program – using firm name and location. Out of all recipient firms, 18 are not borrowing from the bank and are excluded from the sample. Since the outcome variable is interest rate, we exclude borrowers that overdraw and exceed the credit line limit set by the bank. Overdrawing involves penalty fees added to the interest rate and this could affect our inferences. Moreover, access to additional financial resources through the subsidy can make subsidized firms less likely to overdraw. In this case, a lower rate for subsidized firms might reflect a resource effect rather than a certification effect of the public signal. Hence, we focus on non-overdrawing firms. We also exclude borrowers with missing data for the control variables or outcome of interest. Thus, the final sample used in our analysis includes 4,459 firms with a credit line in both 2004 and 2006, out of which 82 obtain funds through the 2005 PIREDS program.

Our objective is to investigate how the cost of bank debt reflects public information and its interaction with the private information of the bank. To capture cost of bank debt, we use *Interest Rate,* which is the percentage rate of interest paid on the credit line by the borrower as reported in the loan contract provided by the bank. We construct a variable *Public Signal* that takes value of 1 if a borrower receives a subsidy through the 2005 PIREDS program, and 0 otherwise. We note that we do not know the exact subsidy amount. To capture amount of private information available to the bank, we rely on established theoretical and empirical research that banks produce and accumulate private information over the course of the lending relationship with a borrower. Hence, we construct a variable *Relationship Length* as the natural logarithm of 1 plus the number of days since the firm first borrowed from our bank.[10] We also construct an indicator *Post* that takes value of 1 for the period after the PIREDS program, i.e., year 2006, and 0 otherwise.

In Table 2 we present summary statistics for the variables for each group of firms: subsidy recipients (*Public Signal* = 1) and non-recipients (*Public Signal* = 0). Firms that receive the subsidy pay an interest rate of about 6.69% on average in the year before the subsidy, while firms that do not receive a subsidy pay slightly lower rate of 6.47%, but the difference is not significant. In the year after the PIREDS program, recipient firms pay on average 7.11%, while non-recipients pay 7.20%. Thus, even though non-recipients experience a more pronounced increase in interest rates, it seems that on average the public signal does not have a material effect on the cost of bank debt.

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[10] As a robustness check, we explore the idea that banks acquire information about their borrowers via the provision of other services, such as checking account, brokerage account, etc. To this end, we construct an indicator *Other Services* that takes value of 1 if a borrower obtains other services from the bank branch (besides line of credit), and 0 otherwise. We use this measure only in the robustness tests (Section 4) because of its limited variation.

However, we also note that subsidy recipients tend to have longer relationships with the bank. As of year 2004, the average length is 4,559 days for recipients and 3,380 days for non-recipients. The difference is significant at 1% level.[11]

INSERT TABLE 2 HERE

2.3. Control variables

Various firm characteristics related to the likelihood of receiving a subsidy can affect cost of bank debt. Lender characteristics also impact interest rates. Hence, we introduce several control variables. The summary statistics are computed as of the first year in our dataset (2004). We start with borrower size measured using firm sales. The bank provides sales categories rather than actual sales figures. Hence, we construct an indicator *D(Sales i)* for each category $i = 1,\ldots 6$, where 1 (6) denotes the smallest (largest) borrowers. Table 2 shows that, based on the distribution of these categories, firms that receive a subsidy tend to be larger. Another factor we consider is the legal form or structure of a borrower (Sikochi, 2020). We construct an indicator *Corporation* that takes value of 1 if a borrower is a corporation, and 0 otherwise. Subsidy recipients are more likely to be incorporated relative to non-recipients: 91% vs. 35%, respectively.

The PIREDS program, with its focus on promoting collaboration for innovation and R&D, could attract firms operating in industrial clusters or areas of concentrated innovation activity. To account for this possibility, we construct an indicator *Cluster* that takes value of 1 if a borrower is located in an industrial cluster, and 0 otherwise.[12] The percentage of firms in such clusters is higher among borrowers with a signal than among other borrowers (79% vs. 60%, respectively).

We also consider possible variations in the decision-making process of the bank across its market segments. We introduce an indicator *Portfolio*, which identifies the operating segment of the bank where a borrower falls. The variable takes value of 1 if the bank considers a line of credit as part of its *corporate market*, and 0 if it is part of the *small business market*. In our sample, 57% of the firms receiving a subsidy are part of the corporate segment, compared to only 10% of the

[11] Despite variation between groups, the average lending relationship length is comparable to findings for Italy and other countries (Cole, 1998; Degryse and Van Cayseele, 2000; and Gambini and Zazzaro, 2012).

[12] The Marche region has several industrial cluster districts focused on furniture (Pesaro), footwear (Ascoli and Fermo), machinery (Jesi and Fabriano), and musical instruments (Recanati-Osimo-Castelfidardo), among others. We identify districts using Marche Region Law no. 20/2003 (Testo unico delle norme in materia industriale artigiana e dei servizi).

non-recipients. We control for bank-borrower proximity because distance between the contracting parties can also affect interest rates (e.g., Degryse and Ongena, 2005; Bellucci et al, 2013). We construct *Distance* as natural logarithm of 1 + the metric distance between borrower and lending branch. Table 2 shows that firms with a signal are located farther away from the branch.

In the empirical specifications, we control for unobservable heterogeneity at the provincial level through province fixed effects as local conditions are important determinants of cost of bank debt (Hasan et al., 2021). We account for sectorial differences in cost of bank debt through industry fixed effects based on 2-digit ISTAT level, which roughly corresponds to 2-digit SIC level in the U.S. Last, we allow interest rates to reflect unobservable branch-specific factors by adding branch fixed effects. Construction of the variables used in the estimations is described in the Appendix.

2.4. Empirical models

To examine how the bank incorporates public information into the pricing process and cost of bank debt for borrowing firms, and to explore whether the two information sources can operate as complements or substitutes, we adopt DD and DDD strategies. First, we estimate the following model:

$$Interest\ Rate_{it} = \beta_0 Public\ Signal_i + \beta_1 Post_t + \beta_2 Public\ Signal_i \times Post_t + \delta Controls_{it} + \varepsilon_{it} \tag{1}$$

where *Interest Rate* is the percentage rate of interest paid by borrower *i* at time *t*. *Public Signal* is the indicator for firms that obtain a public signal via subsidy award (i.e., treatment group). *Post* is the indicator for post-award (i.e., post-treatment) period. *Controls* is a vector of other determinants of interest rate including borrower characteristics as well as province, industry, and branch fixed effects. To account for a possible lack of independence for credit lines granted to borrowers from the same industry, we cluster the error term ε_{it} at the industry level. Our inferences are robust to alternative clustering conventions such as at the branch or branch-industry level.

In model (1), the coefficient of interest is β_2 and captures average treatment effect on the treated: The change over time (from before to after subsidy) in the difference between the average interest rate paid by borrowers in the treatment group (firms receiving subsidy) and average interest rate paid in the control group formed by non-subsidized borrowers. If the bank incorporates the favorable information from the public signal in loan pricing, the estimate of β_2 should be negative.

We then proceed to implement a DDD strategy by augmenting model (1) with the triple interaction term *Public Signal* × *Relationship Length* × *Post*. This allows us to condition the effect of the public signal on the amount of bank information accumulated over the course of the lending relationship. Specifically, we estimate the following model:

$$\begin{aligned} Interest\ Rate_{it} = {} & \beta_0 Public\ Signal_i + \beta_1 Post_t + \beta_2 Relationship\ Length_{it} + \beta_3 Public\ Signal_i \times Post_t + \\ & \beta_4 Public\ Signal_i \times Relationship\ Length_{it} + \beta_5 Relationship\ Length_{it} \times Post_t + \\ & \beta_6 Public\ Signal_i \times Relationship\ Length_{it} \times Post_t + \delta Controls_{it} + \varepsilon_{it} \end{aligned} \tag{2}$$

where *Relationship Length*$_{it}$ reflects the amount of private information accumulated by the bank about borrower *i* at time *t*. In equation (2), β_3 is the effect of the public signal when the relationship length is 0, that is when the bank has not accumulated any information. The coefficient β_6 indicates whether the effect of public information on interest rate depends on the stock of private information of the bank and the sign of the coefficient points to the nature of the relationship between the two sources of information. Assuming that in the absence of private information the public signal does not adversely affect the interest rate ($\widehat{\beta_3} \leq 0$), we can observe three outcomes:[13]

a) The coefficient $\widehat{\beta_6}$ is negative: The effect of the public signal is magnified by the private information of the bank and the two operate as *complements*.

b) The coefficient $\widehat{\beta_6}$ is positive: The effect of the public signal is attenuated by the private information of the bank and the two operate as *substitutes*.

c) The coefficient $\widehat{\beta_6}$ is statistically indistinguishable from zero: The effect of the public signal is independent of the private information of the bank.

3. Results

3.1. Baseline estimates

Our analysis exploits the longitudinal structure of the dataset. We observe the borrowers at two points in time, in 2004 and 2006, while the public subsidy program takes place in 2005. This allows us to examine interest rates paid by borrowers with and without a signal before and after its realization. Thus, we conduct DD and DDD analyses of the effect of the public signal on the cost

[13] The insights about a) and b) would be reversed if the estimate of β_3 is positive.

of debt by estimating the models shown in equations (1) and (2). The approach also allows us to account for unobservable time-invariant heterogeneity across groups of recipient and non-recipient borrowers. The estimation results are presented in Table 3.

INSERT TABLE 3 HERE

In column (1) we estimate the average effect of the signal without conditioning on amount of information accumulated by the bank. The effect is captured by the coefficient of the interaction *Public Signal* × *Post*. The estimate of the coefficient is negative, which indicates that the signal is associated with lowering the interest rate, as expected, but it is not significant. Thus, on average, the public signal does not have an effect. To establish an effect conditional on the amount of bank information about a borrower, in column (2) we estimate the triple-difference model outlined in equation (2). The estimation results show that once we condition the effect of the public signal on amount of bank information, and allow public information to interact with private information, the coefficient on the interaction *Public Signal* × *Post* becomes negative and statistically significant at 1% level. That is, for newly established borrowers, the public signal is interpreted by the lender as a source of additional information and leads to significantly lower interest rates. The impact of the signal for such hypothetical borrowers is also economically important, resulting in a reduction in the interest rate of about 303 basis points (bps).

The estimate of the coefficient β_6 on the triple interaction term in column (2) is positive and statistically significant at 5% level. This falls within case b) above and suggests that the two sources of information can operate as substitutes. In other words, the stock of private information attenuates the effect of the public signal, and as the bank accumulates information over the course of the lending relationship, the effect of the public signal diminishes. To illustrate, a subsidy receipt allows a firm with a line of credit with the bank for 1 year to pay interest rate that is 121 bps lower than the rate it would have paid without a subsidy. For firms with lending relationships of 5 years, the certification effect of the subsidy leads to a reduction in the interest rate of about 71 bps. The positive coefficient on the triple interaction term also implies that there exists a threshold value for the duration of the lending relationship, beyond which the signal is associated with higher rates. We compute that the threshold value corresponds to a lending relationship of about 50 years.[14]

[14] The threshold value falls outside our sample because the longest lending relationship in our dataset is 31 years.

Hence, we conclude that the effect of the public signal on the cost of bank debt remains negative for all firms in our sample that receive a subsidy.

In column (3), following the canonical DDD design (Wooldridge, 2010; Olden and Møen, 2022), we replace the continuous variable *Relationship Length* with an indicator *D(Short)*, which takes value of 1 if a borrower has a lending relationship with the bank in the bottom tercile of the sample distribution of *Relationship Length* of 7.65. In this model, the coefficient on the interaction term *Public Signal* × *Post* shows the treatment effect for borrowers with long lending relationships, while the coefficient on the triple interaction *Public Signal* × *D(Short)* × *Post* shows the effect for borrowers with short lending relationships. The coefficient on the triple interaction term is negative and significant at 5% level. The signal is associated with an interest rate that is about 78 bps lower for borrowers with short lending relationships. As expected, the public signal loses importance once the bank accumulates information. Hence, the insignificant coefficient on the interaction term *Public Signal* × *Post*.

To facilitate interpretation, and to offer an alternative that avoids triple interaction terms, we partition the sample into subsamples characterized by varying amounts of bank information. Specifically, we categorize borrowers into low and high information cases. In columns (4) and (5), low (high) information borrowers are those with short (long) lending relationships. Again, short lending relationship is one that falls in the bottom tercile of the sample distribution of *Relationship Length*, while long lending relationship is one that falls in the top tercile of the sample distribution. The DD estimate of the effect of the public signal is statistically significant at 5% level in the low information subsample in column (4). By contrast, the estimated effect is insignificant in the high information subsample in column (5).

With respect to the control variables, we find that larger firms tend to pay lower interest rates, as shown by the coefficients of the sales indicators, *D(Sales i)*. Borrowers located farther away from the bank pay higher rates because the coefficient on *Distance* is positive and significant. Organizational form (*Corporate*) and market segment (*Portfolio*) associated with the borrower can also affect interest rates. By contrast, firms located in industrial clusters of economic activity are not charged different rates. We note that our estimations control for industry and branch, as well as province, fixed effects.

3.2. Validity tests

A key premise of the DD approach is parallel trends assumption, according to which, the evolution of interest rates would have been the same between subsidized and non-subsidized firms in the absence of a subsidy, and the resulting public signal. In addition, with the triple-difference approach, the trend of the relative interest rate paid by subsidized and non-subsidized firms should be the same regardless of lending relationship length (Olden and Møen, 2022).

To offer some insights into the validity of our empirical strategy and these assumptions, we perform a placebo test. Specifically, we focus on year 2004, before the PIREDS program takes place, and estimate a cross-sectional version of equation (2) using only data for this year. As this is prior to the program, and actual award of the subsidy, the test is intended to examine the power of our strategy. The results of this placebo test are in column (1) of Table 4. Consistent with the assumption of parallel trends, in this falsification exercise neither *Public Signal* nor the interaction *Public Signal* × *Relationship Length* has a significant coefficient.

INSERT TABLE 4 HERE

In column (2) we estimate the same cross-sectional model but using only 2006 data, after the public signal is realized. The coefficient of *Public Signal* is negative and significant at 5% level and the coefficient of the interaction term *Public Signal* × *Relationship Length* is positive and significant at 1% level. Thus, we confirm our insights generated from the DD analysis about the relationship between the information sources. We again note that the effect of the public signal is economically important also in this cross-sectional analysis. An unestablished borrower with a lending relationship of 1 year would pay about 114 bps less in interest if certified externally via subsidy receipt, compared to a borrower without a signal, while for firms that have opened a line of credit with the bank for 5 years, the certification effect of the subsidy is about 20 bps. This again confirms the positive effect of the public signal when the private information of the bank is low.

3.3. Propensity score matching

To identify the effect of the public signal on interest rates, we should ideally compare the rates paid by firms with and without a signal that are otherwise identical. To complement our DD analysis, we employ an alternative approach based on matching recipient firms to observationally similar non-recipients. Thus, we use a combined PS matching and DD approach previously applied to analyses of the effects of R&D subsidies on innovation (e.g., Almus and Czarnitzki, 2003; Gorg and Strobl, 2007; Bellucci et al., 2019).

The key assumption of the approach is un-confoundedness or conditional independence: conditional on observable covariates, treatment assignment is as good as random and independent of potential outcomes (Rosenbaum and Rubin, 1983; Rubin, 2008). The idea is to find in the large group of non-recipient firms those that are as similar as possible (along all relevant pre-treatment characteristics) to those in the small group of recipients. To reduce dimensionality, characteristics are aggregated in a PS that reflects the probability of assignment into treatment. In our context, we model the probability of receiving a subsidy and create a control group for the recipient borrowers using non-recipients with the closest PS. To predict the probability that a firm receives a subsidy, and to compute its PS, we use data for year 2004 (prior to the program) and estimate a logistic regression model for *Public Signal* with the following covariates: *Portfolio*, *Corporate*, *D(Sales i)*, *Cluster,* as well as fixed effects for province and macro sectors of industrial activity.[15]

In Table 5 we provide the results of the PS estimation. Most of the variables are significant determinants of subsidy receipt. Using the estimates, we compute a PS for each firm and match all recipient firms to "similar" (with the closest PS) non-recipients. The resultant PS-matched sample consists of 377 firms: 82 with *Public Signal* = 1 and 295 with *Public Signal* = 0.

INSERT TABLE 5 HERE

In Table 6 we use the PS-matched sample to repeat the analysis conducted so far. In column (1) we show results of the estimation of equation (2), the triple-difference specification, using the PS-matched sample. In column (2) we perform the placebo exercise using data for year 2004 only, while in column (3) we use data for year 2006 only. Our results continue to hold. If the stock of bank information is relatively low, the public signal is associated with lower interest rates. As the bank accumulates information over the course of the lending relationship, the effect of the public signal diminishes. Importantly, once we match recipient firms to a control group of observationally similar non-recipients, the estimated effect of the public signal for cases when the bank does not

[15] We have more than 20 industry indicators in the full sample and the number prevents us from estimating the logistic regression. To address the estimation issues, we aggregate industries into 4 macro sectors (agriculture, manufacturing, construction, and services). We keep industry fixed effects in subsequent estimations that rely on the matched sample.

have private information becomes stronger. The analysis also corroborates the insight that the two sources of information can function as substitutes.

INSERT TABLE 6 HERE

3.4. Endogenous assignment into treatment

Rosenbaum (2002) points out that matching estimators are not consistent if assignment into treatment is endogenous. If there are unobserved variables that simultaneously affect assignment into treatment (*Public Signal*) and outcome (*Interest Rate*), inferences from matching estimators are biased and unreliable. To explore the extent to which "selection on unobservables" might bias the estimated effect of *Public Signal* on *Interest rate*, we follow Bharath et al. (2011) and perform sensitivity analysis based on the bounding approach of Rosenbaum (2002). The idea is to examine how strong the influence of an unmeasured variable on the selection process has to be in order to undermine the matching estimator. In other words, the approach allows us to determine "bounds" for the reliability of the insights derived from the matching analysis.[16]

Following standard notation, let γ denote the effect of a potentially unmeasured variable on the probability of assignment into treatment, i.e., subsidy receipt. If γ is 0, the estimate of the average treatment effect on the treated (ATT) is unbiased as the assignment is fully determined by observables. In this case, the odds ratio of two borrowers receiving a subsidy is 1 as long as they are matched on observable characteristics. Rosenbaum (2002) shows that the odds ratio is bounded between $1/\exp(\gamma)$ and $\exp(\gamma)$. If $\exp(\gamma)$ is 1, two matched borrowers have the same probability of assignment into treatment because the odds ratio is bounded by 1 from below and above. If $\exp(\gamma)$ is 1.25, for instance, the borrowers could differ in their probability of assignment with a factor of up to .25 because the odds ratio is bounded by .8 from below and 1.25 from above, and this can create "hidden bias". Hence, for values of $\exp(\gamma)$ greater than 1, the "hidden bias" due to a possibly unmeasured characteristic affects the probability of assignment into treatment. The approach of Rosenbaum (2002) allows us to compute for different levels of $\exp(\gamma)$ the probabilities (*p-critical*), at the upper and lower bounds, that the estimated treatment effect reflects potential nonrandom

[16] We note that the approach does not test the unconfoundedness assumption per se but tries to capture to what degree any significant results hinge on this (untestable) assumption (DiPrete and Gangl, 2004; Becker and Caliendo, 2007).

assignment rather than a treatment effect. These p-values are based on a Wilcoxon signed rank test at each bound of the odds ratio.

INSERT TABLE 7 HERE

Table 7 reports the p-values at different levels of exp(γ) from the test of no actual treatment effect of *Public Signal* on *Interest Rate*. We limit the analysis to the subsample of borrowers with low information (*Relationship Length* in the bottom tercile), given that our estimate of the public signal effect is significant when the bank has not accumulated information about the borrower. We report the critical values for both upper and lower bounds, but we focus on the lower bound given that the estimated effect has a negative sign. In other words, the main concern is that possible non-random assignment might reduce (and ultimately turn negative) the estimated treatment effect.

We perform the analysis using *rbounds* command in Stata (DiPrete and Gangl, 2004) and nearest neighbor (n=10) matching for year 2006, including as covariates the characteristics used in the PS matching analysis. We vary exp(γ) between 1 and 3 with an increment of .1 for this test. At each level, we calculate the hypothetical significance level "p-critical" for both the lower and upper bounds on the odds ratio. By examining the bounds at different levels of exp(γ), we are able to assess the strength an unmeasured variable needs to achieve before it invalidates our result. This would mean that the estimated treatment effect from the PS matching analysis is due to nonrandom assignment. The results in Table 7 shows that to overturn our insights about the effect of the public signal, the unmeasured variable affecting assignment into treatment has to increase the odds of assignment by a factor of more than 100%. To interpret, the unmeasured characteristic needs to more than double the odds of subsidy receipt. While we cannot completely rule out this possibility, we can conclude that the estimated effect of the public signal is fairly robust.

4. Underlying mechanisms and additional tests

4.1. Incremental information vs. incremental contestability

The favorable effect of the public signal on the interest rates paid by borrowers without an established lending relationship with the bank is consistent with a certification effect generated by the subsidy. However, two channels that are not mutually exclusive might be driving this effect.

First, the public signal can offer incremental information for the lending bank. In this case, in the absence of much private information, the lending bank merely incorporates in the contract the content of the signal about the borrower. Once more information is accumulated over the course of a lending relationship, the bank starts to weigh its own information more heavily and the public signal loses importance.

Second, the public signal from the subsidy award might decrease the information advantage of the lending bank. As the subsidy award is public information, it is observable by other banks in the local credit market. This increases competitive pressure by other banks for recipient borrowers, especially those without an established relationship with the lending bank, who are more likely to be approached by competitors, less likely to be subject to hold-up problems, and where information rent of the lender is lower. Thus, as the signal increases market contestability, it forces the bank to lower the interest rate.

We explore the incremental market contestability argument by conditioning the effect of the public signal on the structure of the local credit market. The underlying idea is that if a large number of banks operate in a market, competitive pressure is strong, switching banks is easier, and the information rent of the lending bank is already minimized. In this case, the incremental market contestability effect stemming from the public signal generated by the award of the subsidy is low. By contrast, when there are only very few banks present in the local credit market, the incremental contestability channel is more relevant, just as the information rent of the lending bank is likely higher. In this case, the bank would have the incentive to respond to increased competitive pressure by lowering the interest rate for firms receiving the subsidy. To investigate this effect, we construct a variable *Number of Banks* as the total number of banks in the local credit market, and introduce a triple interaction *Number of Banks* × *Public Signal* × *Post*.

We first examine the relevance of the incremental contestability argument and estimate a model that focuses exclusively on this point. Therefore, in this model we drop all interaction terms that involve *Relationship Length*. The results are presented in Table 8. In column (1) we see that the interaction *Public Signal* × *Post* is negative and significant at 5% level. This suggests that in highly monopolistic markets, where *Number of Banks* is 0, the signal is associated with a reduction in the interest rate. In such markets, the information rent of the lending bank is higher and the bank has more incentives to preserve it and to respond to the pressure created by the public signal. The triple interaction *Number of Banks* × *Public Signal* × *Post* is positive and significant. This suggests that where markets are more competitive, the signal loses importance. Thus, the result from column (1) is consistent with the incremental market contestability role of the public signal.

INSERT TABLE 8 HERE

We next examine if the incremental market contestability channel rules out the incremental information role of the public signal. To this end, we augment the model in column (1) of Table 8 with all interaction terms that involve *Relationship Length*. While the contestability channel is still present – the coefficient on the interaction *Number of Banks* × *Public Signal* × *Post* in column (2) remains positive and significant – the coefficient on the interaction *Public Signal* × *Relationship Length* × *Post* is positive and significant and the coefficient on *Public Signal* × *Post* is negative and significant at 1% level, as previously established. Thus, we infer that the effect of the subsidy award on the cost of debt of recipient firms stems from both the incremental information available to the lending bank about borrower quality and the increased competition produced by the public signal that reduces the information advantage of the lending bank and forces it to lower the interest rate charged to firms that receive the subsidy.

4.2. Certification versus loan demand

An alternative explanation for our finding that the subsidy leads to lower cost of bank debt for recipient firms can be based on increased demand for credit rather than certification of borrower quality. Recall that the subsidy covers only a fraction of the expenses faced by the recipient. Hence, subsidy recipients might need additional capital. Consequently, it is possible that the information content of the signal is more about such demand for additional credit and less about the quality of a borrower, and the lender reduces the interest rates to entice borrowers that need additional funds in the present and likely in the future. This implies that the favorable effect of the signal should be more pronounced for subsidized firms that eventually ask the bank for additional funds. While we do not observe credit requests, we make an attempt to test this argument.

To implement the test, we construct a variable *D(Credit Increase)* that takes value of 1 for borrowers that increase their loan amount between year 2004 and 2006, and 0 otherwise. We then estimate equation (2) but replace *Relationship Length* with *D(Credit Increase)* in all interactions. The results in column (3) of Table 8 suggest that the information content of the signal is less likely to be about credit demand, and yield additional support for the certification argument. Specifically, we note that both interaction terms *Public Signal* × *Post* and *D(Credit Increase)* × *Public Signal* × *Post* are insignificant. Thus, we infer that it is the lack of bank information about a borrower that drives the effect of the subsidy award, and not its potential impact on demand for credit.

4.3. Additional tests

We next perform two additional tests to examine the robustness of our insights. Due to data limitations (e.g., for some variables we have data for only a subset of borrowers and one year), we consider insights offered by the tests as suggestive. First, default risk is an important determinant of loan interest rates and could also affect the probability of winning the subsidy. To examine this point, we incorporate into our analysis a measure of borrower risk using the internal rating assigned by the bank to borrowers. The rating is an integer numeric score that ranges from 1 to 9, with lower scores indicating lower risk. Our dataset, however, contains internal ratings only for year 2006 and for a small subset of borrowers (we have rating for about 18% of the borrowers). To overcome the issue, we estimate the model cross-sectionally using a modified zero order regression procedure as proposed by Greene (2003) and used in the banking literature by Hollander and Verriest (2016) and Bellucci et al. (2019). First, we create an indicator *D*(*Rated*), which takes value of 1 for rated borrowers, and 0 otherwise. Second, we create indicator *D*(*Rating i*) for each rating score *i*, where *i* ranges from 1 to 9. Only a tiny number of firms fall into the lowest two and the highest two categories of our rating variable and therefore we merge scores 1 and 2 and scores 8 and 9 into two separate categories. Last, we augment equation (2) with a set of interaction terms *D(Rated)* × *D(Rating i)*. The results, presented in column (4) of Table 8, show that our insights about the effect of the public signal and its interplay with private information of the bank continue to hold.

Our main analysis assumes that the amount of information accumulated by the bank and the extent of information asymmetry about a borrower are captured by the length of the lending relationship. However, extant research identifies other measures that can reflect the information about borrowers available to the lender. In particular, several papers argue that banks gather more information when they provide multiple services to a borrower (Berger and Udell, 1995; Cole and Wolken, 1995; Boot, 2000; Degryse and Van Cayseele 2004; Neuhann and Saidi, 2018). As an alternative measure of bank information, we use the scope of the lending relationship. Specifically, we construct the indicator *Other Services* that takes value of 1 if a borrower uses additional services provided by the bank, such as a checking account or brokerage account, and 0 otherwise. We then replace *Relationship Length* with *Other Services* and again estimate the model cross-sectionally due to data limitation. The results, shown in column (5) of Table 8, are consistent with certification effect of the public signal and its substitutability with private information. This suggests that our insights are not driven by the specific measure of information we use in the main analysis.

5. Conclusion

Motivated by theory, existing research examines the relationship between the amount of private information banks accumulate about their borrowers and the availability and cost of credit. By contrast, less is known about how sources of public and private information interact to shape the outcome of the lending process in terms of cost of debt. In this paper, we use a competitive public subsidy program in Italy as a source of external certification of some borrowers and examine how this favorable public signal is reflected in the cost of bank loans and whether it acts as a substitute or complement to the private information accumulated by the bank over the course of the lending relationship.

Using a sample of small business loans, we find that the public signal, which is positive by construction, does not affect the cost of bank debt on average. However, the signal is associated with significantly lower interest rates for borrowers without an established lending relationship with the bank when the bank's stock of private information is low. This suggests that in the absence of private information, the bank relies on the public signal about borrower quality and the two sources of information can operate as substitutes. Once the bank accumulates information about the borrower over the course of the lending relationship, the public signal loses importance.

Table 1 Local credit markets

	Mean	*Min*	*Max*
Number of branches of the bank	1.6	1	6
Number of competitor banks	13.8	1	38
Number of branches of competitor banks	30.7	1	108

The table shows characteristics of the local credit markets included in our dataset. The markets are defined with respect to the operations of the bank as the municipalities in which the bank has at least one branch.

Table 2 Summary statistics

	Public Signal = 1 82 Firms		*Public Signal* = 0 4377 Firms		Means differences
	Mean	*St. dev.*	*Mean*	*St. dev.*	p-values
Dependent variable					
Interest Rate (pre-subsidy)	6.69	2.55	6.47	2.36	0.399
Interest Rate (post-subsidy)	7.11	2.03	7.20	2.11	0.709
Interest Rate (average)	6.90	2.07	6.83	2.04	0.768
Information variable					
Relationship Length (days)	4559	2981	3380	2718	0.000
Control variables					
D(Sales 1)	0.02	0.02	0.51	0.01	0.000
D(Sales 2)	0.04	0.19	0.10	0.30	0.063
D(Sales 3)	0.11	0.31	0.16	0.37	0.224
D(Sales 4)	0.26	0.44	0.12	0.33	0.000
D(Sales 5)	0.41	0.50	0.09	0.29	0.000
D(Sales 6)	0.16	0.37	0.02	0.15	0.000
Corporate	0.91	0.28	0.35	0.48	0.000
Cluster	0.79	0.41	0.60	0.49	0.000
Portfolio	0.57	0.50	0.10	0.30	0.000
Distance	8.22	1.25	7.67	1.37	0.000

The table provides descriptive statistics for the variables used in the analysis for two groups of borrowing firms. Firms that receive external certification under the PIREDS program in the form of a competitive subsidy (*Public Signal* = 1) and firms that do not (*Public Signal* = 0). *Interest Rate* is the interest rate on the credit line, expressed in percentage terms. *Relationship Length (days)* is the number of days since the borrower started lending relationship with the bank. In the multivariate analysis we use *Relationship Length* defined as natural logarithm of 1 + *Relationship Length (days)*. *D(Sales i)* is an indicator that takes value of 1 if the sales of a borrower fall in the *i*-th category (where *i* ranges from 1 through 6), and 0 otherwise. Category 1 (6) indicates the smallest (largest) firms. *Corporate* is an indicator that takes value of 1 if the legal status of a borrower takes the form of corporation, and 0 otherwise. *Cluster* is an indicator that takes value of 1 if a borrower is located within an industrial district area, and 0 otherwise. *Portfolio* is an indicator that takes value of 1 if the bank considers a borrower as part of its corporate market, and 0 if it is part of its small business market. *Distance* measures bank-borrower distance constructed as natural logarithm of 1 + the metric distance between the location of a borrower and the lending branch. The summary statistics for the control variables are computed as of the first year in our dataset. All variables are defined in the text and the Appendix. The table reports mean and standard deviation of each variable for each group of firms and the *p-value* of a test of equality of means across the two groups (in the last column).

Table 3 Public certification and private information

	(1)	(2)	(3)	(4)	(5)
		Full Sample		Low Information	High Information
Public Signal	0.562**	-1.838	0.763**	0.180	0.468
	(0.258)	(1.592)	(0.281)	(0.388)	(0.421)
Post	0.758***	1.276***	0.764***	0.711***	0.681***
	(0.034)	(0.348)	(0.034)	(0.105)	(0.036)
Public Signal × Post	-0.318	-3.031***	-0.364	-1.130**	0.086
	(0.208)	(0.877)	(0.229)	(0.409)	(0.388)
Relationship Length × Post		-0.064			
		(0.041)			
Public Signal × Relationship Length		0.296			
		(0.200)			
Public Signal × Relationship Length × Post		0.309**			
		(0.110)			
D(Short) × Post			-0.044		
			(0.088)		
Public Signal × D(Short)			-0.645**		
			(0.309)		
Public Signal × D(Short) × Post			-0.779**		
			(0.374)		
Relationship Length	-0.049	-0.042		0.025	0.177
	(0.038)	(0.036)		(0.071)	(0.173)
D(Short)			0.107**		
			(0.046)		
Distance	0.038**	0.038**	0.039**	0.027	0.037
	(0.017)	(0.017)	(0.017)	(0.029)	(0.035)
Cluster	0.098	0.096	0.094	0.150	0.162
	(0.086)	(0.085)	(0.085)	(0.148)	(0.125)
Corporate	0.276***	0.273***	0.278***	0.192**	0.271
	(0.074)	(0.074)	(0.077)	(0.084)	(0.193)
Portfolio	-0.481**	-0.492**	-0.493**	-0.229	-0.545*
	(0.199)	(0.202)	(0.202)	(0.228)	(0.296)
D(Sale 2)	-0.328***	-0.326***	-0.329***	-0.129	-0.507***
	(0.103)	(0.103)	(0.104)	(0.174)	(0.103)
D(Sale 3)	-0.288***	-0.282***	-0.288***	-0.104	-0.245***
	(0.075)	(0.073)	(0.075)	(0.126)	(0.068)
D(Sale 4)	-0.149	-0.140	-0.148	-0.005	-0.089
	(0.096)	(0.095)	(0.097)	(0.195)	(0.126)
D(Sale 5)	-0.417*	-0.407*	-0.410*	-0.479	-0.102
	(0.212)	(0.215)	(0.215)	(0.279)	(0.272)
D(Sale 6)	-0.693***	-0.697***	-0.695***	-0.826***	-0.728**
	(0.198)	(0.201)	(0.203)	(0.219)	(0.295)
Constant	6.310***	6.260***	5.888***	6.005***	4.327**
	(0.307)	(0.286)	(0.223)	(0.496)	(1.737)
Province FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Branch FE	Yes	Yes	Yes	Yes	Yes
Observations	8,918	8,918	8,918	2,947	3,019
R-squared	0.071	0.071	0.071	0.084	0.106

The table reports regression results of DD analysis using data for both years 2004 and 2006. Column (1) uses the full sample and presents results of a baseline specification that estimates the average effect of *Public Signal*, while columns (2) and (3) present comprehensive models that condition the effect of the public signal on the amount of information accumulated by the bank (*Relationship Length*) using continuous or indicator variables, respectively. Columns (4) and (5) use subsamples of borrowers with low information (bottom tercile of *Relationship Length*) and high information (top tercile of *Relationship Length*). The dependent variable is *Interest Rate*, the rate charged by the bank, expressed as a percentage. *Public Signal* is an indicator that takes value of 1 if a borrower receives certification under the PIREDS program in the form of a competitive subsidy, and 0 otherwise. *Post* is an indicator that takes value of 1 in post-subsidy period (i.e., year 2006), and 0 otherwise. *Relationship Length* is natural logarithm of 1 + the number of days since a borrower first started lending relationship with the bank. *D(Short)* is an indicator that takes value of 1 if *Relationship Length* is in the bottom tercile of the sample distribution, and 0 otherwise. All variables are defined in the text and the Appendix. The table reports coefficient estimates followed by robust standard errors, clustered at industry level, in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Table 4 Cross-sectional analysis: Placebo test

	(1) Cross-section 2004	(2) Cross-section 2006
Public Signal	-2.019	-4.584**
	(1.689)	(1.658)
Relationship Length	-0.048	-0.092
	(0.036)	(0.069)
Public Signal × Relationship Length	0.305	0.584***
	(0.213)	(0.195)
Distance	0.028	0.047**
	(0.017)	(0.020)
Cluster	0.133	0.058
	(0.119)	(0.064)
Corporate	0.368***	0.180**
	(0.092)	(0.070)
Portfolio	-0.464*	-0.521***
	(0.259)	(0.177)
D(Sale 2)	-0.275**	-0.376***
	(0.111)	(0.130)
D(Sale 3)	-0.174**	-0.390***
	(0.070)	(0.098)
D(Sale 4)	-0.063	-0.217***
	(0.154)	(0.074)
D(Sale 5)	-0.331	-0.485**
	(0.233)	(0.213)
D(Sale 6)	-0.730***	-0.664**
	(0.206)	(0.238)
Constant	6.112***	7.619***
	(0.302)	(0.587)
Province FE	Yes	Yes
Industry FE	Yes	Yes
Branch FE	Yes	Yes
Observations	4,459	4,459
R-squared	0.054	0.055

The table reports results of the estimation of cross-sectional regressions using one year of the dataset at a time. Column (1) shows results of a placebo test that uses only data for year 2004 (i.e., before receipt of subsidy), while column (2) shows results using only data for year 2006 (i.e., after receipt of subsidy). The dependent variable is *Interest Rate*, the rate charged by the bank, expressed as a percentage. *Public Signal* is an indicator that takes value of 1 if a borrower receives certification under the PIREDS program in the form of a competitive subsidy, and 0 otherwise. *Relationship Length* is natural logarithm of 1 + the number of days since a borrower first started lending relationship with the bank. All variables are defined in the text and the Appendix. The table reports coefficient estimates followed by robust standard errors, clustered at industry level, in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Table 5 Propensity score matching

	Coefficient	Standard Error	p-value
Portfolio	0.338	0.182	0.063
Corporate	0.644	0.167	0.000
D(Sales 2)	0.491	0.323	0.129
D(Sales 3)	0.572	0.269	0.034
D(Sales 4)	0.862	0.263	0.001
D(Sales 5)	0.970	0.295	0.001
D(Sales 6)	1.111	0.339	0.001
Cluster	0.330	0.135	0.001
Constant	-3.668	0.266	0.000
Province FE	Yes		
Industry Sector FE	Yes		
Observations	4,459		
Pseudo R-squared	0.323		

The table presents results from a logistic regression model of the probability of *Public Signal* used in the PS matching process. *Public Signal* is an indicator that takes value of 1 if a borrower receives certification under the PIREDS program in the form of a competitive subsidy, and 0 otherwise. The PS matching is performed using psmatch2 Stata command (Leuven and Sianesi, 2003). We use the option of nearest neighbor (within caliper, without replacement) and impose a common support. The estimation is performed using data for year 2004, i.e., prior to subsidy receipt. All variables are defined in the text and the Appendix.

Table 6 PS-matched sample analysis

	(1) Full Sample	(2) Cross-section 2004	(3) Cross-section 2006
Public Signal	-1.058	-0.903	-7.984**
	(2.488)	(2.646)	(3.785)
Post	4.915***		
	(1.463)		
Public Signal × Post	-6.495***		
	(1.711)		
Relationship Length × Post	-0.525***		
	(0.176)		
Public Signal × Relationship Length	0.196	0.171	1.002**
	(0.308)	(0.329)	(0.446)
Public Signal × Relationship Length × Post	0.751***		
	(0.204)		
Relationship Length	0.052	0.055	-0.488
	(0.145)	(0.172)	(0.303)
Distance	-0.027	0.004	-0.057
	(0.078)	(0.123)	(0.075)
Cluster	0.539	0.458	0.620
	(0.439)	(0.584)	(0.376)
Corporate	0.163	0.195	0.130
	(0.234)	(0.305)	(0.244)
Portfolio	-0.077	-0.082	-0.073
	(0.308)	(0.387)	(0.319)
D(Sales 2)	-0.540	-0.722	-0.359
	(0.621)	(0.917)	(0.503)
D(Sales 3)	-0.113	-0.083	-0.143
	(0.393)	(0.524)	(0.440)
D(Sales 4)	0.121	0.114	0.129
	(0.458)	(0.560)	(0.641)
D(Sales 5)	-0.999**	-0.942	-1.056**
	(0.447)	(0.731)	(0.415)
D(Sales 6)	-1.322***	-1.612**	-1.037**
	(0.379)	(0.671)	(0.442)
Constant	6.850***	7.374***	11.319***
	(1.474)	(1.982)	(2.432)
Province FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Branch FE	Yes	Yes	Yes
Observations	754	377	377
R-squared	0.201	0.251	0.220

The table reports results of cross-sectional regressions using one year of the dataset at a time and the triple-difference model based on equation (2) on a PS-matched sample. Column (1) presents results of the main model using the full sample, column (2) shows results using only data for year 2004, i.e., before receipt of subsidy, and column (3) shows results using only data for year 2006, i.e., after receipt of subsidy. The dependent variable is *Interest Rate*, the rate charged by the bank, expressed as a percentage. *Public Signal* is an indicator that takes value of 1 if a borrower receives certification under the PIREDS program in the form of a competitive subsidy, and 0 otherwise. *Relationship Length* is natural logarithm of 1 + the number of days since a borrower first started lending relationship with the bank. All variables are defined in the text and the Appendix. The table reports coefficient estimates followed by robust standard errors, clustered at industry level, in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Table 7 Rosenbaum bounds: Effect of hidden bias on interest rate

	p-critical	
Exp(γ)	Upper bound	Lower bound
1.0	.002	.002
1.1	.001	.004
1.2	.001	.006
1.3	.001	.009
1.4	.000	.012
1.5	.000	.016
1.6	.000	.021
1.7	.000	.026
1.8	.000	.032
1.9	.000	.038
2.0	.000	.044
2.1	.000	.051
2.2	.000	.058
2.3	.000	.065
2.4	.000	.073
2.5	.000	.081
2.6	.000	.089
2.7	.000	.097
2.8	.000	.106
2.9	.000	.114
3.0	.000	.123

The table reports p-values of Wilcoxon signed rank tests for the significance of the effect of *Public Signal* on *Interest Rate* for different levels of exp(γ), where γ denotes the effect of a potentially unmeasured variable on the probability of assignment into treatment, i.e., subsidy receipt. The analysis is for the subsample of borrowers with low information (bottom tercile of *Relationship Length*). Following Bharath et al. (2011), we compute a hypothetical significance level at each exp(γ) for both the upper and lower bound of the odds ratio for treatment assignment (Rosenbaum, 2002). The estimation is based on nearest neighbor (n=10) matching and includes as covariates the variables used for the matching analysis in Table 5.

Table 8 Underlying mechanisms and additional tests

	(1)	(2)	(3)	(4)	(5)
		Full Sample		Cross-section 2006	
Public Signal	0.988**	-1.227	0.778**	-4.869**	-2.328***
	(0.460)	(2.034)	(0.351)	(1.743)	(0.205)
Post	0.818***	1.301***	0.694***		
	(0.053)	(0.362)	(0.047)		
Public Signal × Post	-1.273**	-4.939***	-0.378		
	(0.487)	(1.376)	(0.435)		
Number of Banks × Post	-0.014***	-0.014***			
	(0.003)	(0.003)			
Number of Banks	0.063**	0.062**			
	(0.023)	(0.023)			
Number of Banks × Public Signal	-0.031	-0.026			
	(0.029)	(0.030)			
Number of Banks × Public Signal × Post	0.062***	0.063***			
	(0.021)	(0.022)			
Relationship Length × Post		-0.059			
		(0.041)			
Public Signal × Relationship Length		0.265		0.617***	
		(0.226)		(0.206)	
Public Signal × Relationship Length × Post		0.419**			
		(0.156)			
D(Credit Increase)			-0.242***		
			(0.069)		
D(Credit Increase) × Post			0.120**		
			(0.052)		
D(Credit Increase) × Public Signal			-0.493		
			(0.455)		
D(Credit Increase) × Public Signal × Post			0.159		
			(0.759)		
Relationship Length	-0.050	-0.043	-0.044	-0.093	
	(0.038)	(0.036)	(0.039)	(0.069)	
D(Rated) × D(Rating 1 or 2)				-0.344	
				(0.346)	
D(Rated) × D(Rating 3)				-0.175	
				(0.160)	
D(Rated) × D(Rating 4)				-0.065	
				(0.141)	
D(Rated) × D(Rating 5)				-0.306***	
				(0.088)	
D(Rated) × D(Rating 6)				-0.220*	
				(0.124)	
D(Rated) × D(Rating 7)				-0.228	
				(0.211)	
D(Rated) × D(Rating 8 or 9)				0.126	
				(0.204)	
Public Signal × Other Services					2.719***
					(0.262)
Other Services					-0.396**
					(0.151)
Constant	4.258***	4.237***	6.425***	7.621***	7.181***
	(0.923)	(0.914)	(0.322)	(0.583)	(0.300)
Controls	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes

Branch FE	Yes	Yes	Yes	Yes	Yes
Observations	8,918	8,918	8,918	4,459	4,459
R-squared	0.071	0.072	0.073	0.056	0.056

The table reports results of analyses of underlying mechanisms as well as additional tests. Columns (1) to (3) use the full sample, while columns (4) and (5) use only data for year 2006, i.e., after receipt of subsidy. The dependent variable is *Interest Rate*, the rate charged by the bank, expressed as a percentage. *Public Signal* is an indicator that takes value of 1 if a borrower receives certification under the PIREDS program in the form of a competitive subsidy, and 0 otherwise. *Number of Banks* is the total number of different banks present in the local credit market. *D(Rated)* is an indicator that takes value of 1 for rated borrowers, and 0 otherwise. *D(Rating i)* is an indicator that takes value of 1 for an internal rating score of *i*, and 0 otherwise. *Other Services* is an indicator that takes value of 1 if the bank branch provides other (besides credit line) services to the borrower, and 0 otherwise. *D(Credit Increase)* is an indicator that takes value of 1 if a borrower increases the loan amount between year 2004 and 2006, and 0 otherwise. The set of *Controls* includes *Distance*, *Cluster*, *Corporate*, *Portfolio* and sales indicators. All variables are defined in the text and the Appendix. The table reports coefficient estimates followed by robust standard errors, clustered at industry level, in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Appendix

List of variables

Variable	*Definition*
Public Signal	An indicator that takes value of 1 if a borrower is awarded the competitive subsidy and thus receives certification under the PIREDS program, and 0 otherwise.
Interest Rate	The interest rate charged by the bank, expressed as a percentage.
D(Sales i)	An indicator that takes value of 1 if the sales of a borrower fall in the *i*-th category (1 through 6), and 0 otherwise. The categories are: 1 for sales less than €250,000; 2 for sales between €250,000 and €500,000; 3 for sales between €500,000 and €1,500,000; 4 for sales between €1,500,000 and €5,000,000, 5 for sales between €5,000,000 and €25,000,000; 6 for sales between €25,000,000 and €50,000,000.
Other Services	An indicator that takes value of 1 if the bank branch provides other (besides credit line) services to the borrower, and 0 otherwise.
Relationship Length	A continuous variable constructed as natural logarithm of 1 + the length of the bank-borrower relationship expressed in days.
D(Short)	An indicator that takes value of 1 if *Relationship Length* is in the bottom tercile of the sample distribution, and 0 otherwise.
Portfolio	An indicator that takes value of 1 if the bank considers a borrower as part of its *corporate market*, and 0 if it is part of the *small business market*.
Post	An indicator that takes value of 1 in the post-subsidy period, i.e., year 2006, and 0 otherwise.
Cluster	An indicator that takes value of 1 if a borrower is located within an industrial district area, and 0 otherwise.
Corporate	An indicator that takes value of 1 if the legal status of a borrower takes the form of corporation, and 0 otherwise.
Distance	A continuous variable that measures bank-borrower distance constructed as natural logarithm of 1 + the metric distance between the location of a borrower and the lending branch.
Number of Banks	A continuous variable the measures total number of different banks present in the local credit market. The markets are defined as the municipalities in which the bank has at least one branch.
D(Credit Increase)	An indicator that takes value of 1 if a borrower increases loan amount between year 2004 and 2006, and 0 otherwise
D(Rated)	An indicator that takes value of 1 for rated borrowers, and 0 otherwise.
D(Rating i)	An indicator that takes value of 1 for an internal rating score of *i*, and 0 otherwise. The score is an integer that ranges from 1 to 9, with a lower score indicating lower risk.

References

Acconcia, A., Alfano, M., Baraldi, L., Cantabene, C., (2022). Public certification, information asymmetry, and investments. *Working Paper*.

Almus, M., Czarnitzki, D., (2003). The effects of public R&D subsidies on firms' innovation activities: The case of Eastern Germany. *Journal of Business & Economic Statistics* 21, 226-236.

Alessandrini, P., Presbitero, A., Zazzaro, A., (2009). Banks, distances and firms' financing constraints. *Review of Finance* 13, 261-307.

Bellucci, A., Pennacchio, L., Zazzaro, A., (2019). Public R&D subsidies: Collaborative versus individual place-based programs for SMEs. *Small Business Economics* 52, 213-240.

Bellucci, A., Borisov, A., Zazzaro, A., (2013). Do banks price discriminate spatially? Evidence from small business lending in local credit markets. *Journal of Banking and Finance* 37, 4183-4197.

Bellucci, A., Borisov, A., Giombini, G., Zazzaro, A. (2019). Collateralization and distance. *Journal of Banking and Finance* 100, 205-217.

Berger, A., Udell, G., (1995). Relationship lending and lines of credit in small firms finance. *Journal of Business* 68, 351-381.

Berger, A., Miller, N., Petersen, M., Rajan, R., Stein, J., (2005). Does function follow organizational form? Evidence from the lending practices of large and small banks. *Journal of Financial Economics* 76, 237-269.

Bharath, S., Sunder, J., Sunder, S., (2008). Accounting quality and debt contracting. *The Accounting Review* 83, 1-28.

Bharath, S., Dahiya, S., Saunders, A., Srinivasan, A., (2011). Lending relationships and loan contract terms. *Review of Financial Studies* 24, 1141-1203.

Bonfim, D., Custodio, C., Raposo, C. (2021). The sensitivity of SME's investment and employment to the cost of debt financing. Banco do Portugal, Working Papers, 15.

Boot, A., (2000). Relationship banking: What do we know? *Journal of Financial Intermediation* 9, 7-25.

Calcagnini, G., Cole, R., Giombini, G., Grandicelli, G. (2018). Hierarchy of bank loan approval and loan performance. *Economia Politica* 35, 935-954.

Cassar, G. Ittner, C., Cavalluzzo, K. (2015). Alternative information sources and information asymmetry reduction: Evidence from small business debt. *Journal of Accounting and Economics* 59, 242-263.

Cole, R. (1998). The importance of relationships to the availability of credit. *Journal of Banking and Finance* 22, 227–251.

Cole, R., Wolken, J., (1995). Financial services used by small businesses: Evidence from the 1993 National Survey of Small Business Finances. Federal Reserve Bulletin 7, Board of Governors of the Federal Reserve System (U.S.), 629-667.

Degryse, H., Ongena, S., (2005). Distance, lending relationships, and competition. *Journal of Finance* 60, 231-266.

Degryse, H., Van Cayseele, P., (2000). Relationship lending within a bank-based system: Evidence from European small business data. *Journal of Financial Intermediation* 9, 90-109.

Dei Ottati, G. (1994). Trust, interlinking and credit in the industrial district. *Cambridge Journal of Economics* 18, 529-546.

Dei Ottati, G. (2018). Marshallian industrial districts in Italy: The end of a model or adaptation to the global economy. *Cambridge Journal of Economics* 42, 259-284.

Derrien, F., Kecskés, A., Mansi, S. A. (2016). Information asymmetry, the cost of debt, and credit events: Evidence from quasi-random analyst disappearances. *Journal of Corporate Finance* 9, 295-311.

DiPrete, T., Gangl, M. (2004). Assessing bias in the estimation of causal effects: Rosenbaum bounds on matching estimators and instrumental variables estimation with imperfect instruments. *Sociological Methodology* 34, 271-310.

Elsas, R., Krahnen, J. P. (1998). Is relationship lending special? Evidence from credit-file data in Germany. *Journal of Banking and Finance* 22, 1283-1316.

Feldman, M., Kelley, M. (2006). The ex-ante assessment of knowledge spillovers: government R&D policy, economic incentives and private firm behavior. *Research Policy* 35, 1509-1521.

Filomeni, S., Udell, G., Zazzaro, A., (2021). Hardening soft information: does organizational distance matter?, *European Journal of Finance*, DOI: 10.1080/1351847X.2020.1857812

Gambacorta, L., Mistrulli, P., (2014). Bank heterogeneity and interest rate setting: what lessons have we learned since Lehman Brothers?, *Journal of Money, Credit and Banking* 46, 753-778.

Gambini, A., Zazzaro, A., (2013). Long-lasting bank relationships and growth of firms. *Small Business Economics* 40, 977-1007.

Görg, H., Strobl, E., (2007). The effect of R&D subsidies on private R&D. *Economica* 74, 215-234.

Hasan, I., Shen, Y., Yuan, X., (2021). Local product market competition and bank loans. *Journal of Corporate Finance* 70, 102054.

Hollander, S., Verriest, A., (2016). Bridging the gap: the design of bank loan contracts and distance. *Journal of Financial Economics* 119, 399-419.

Hottenrott, H., Demeulemeester, S., (2017). R&D subsidies and firms' cost of debt. Beiträge zur Jahrestagung des Vereins für Socialpolitik 2017: Alternative Geld- und Finanzarchitekturen - Session: Innovation and R&D, No. D13-V3.

Howell, S., (2017). Financing innovation: Evidence from R&D grants. *American Economic Review* 107, 1136-1164.

Islam, M., Fremeth, A., Marcus, A., (2018). Signaling by early stage startups: US government research grants and venture capital funding. *Journal of Business Venturing* 33, 35-51.

Kim, J.-B., Simunic, D., Stein, M., Yi, C., (2011). Voluntary audits and the cost of debt capital for privately held firms: Korean evidence. *Contemporary Accounting Research* 28, 585-615.

Lerner, J., (1999). The government as venture capitalist: the long-run impact of the SBIR program. *Journal of Business* 72, 285-318.

Leuven, E., Sianesi, B., (2003). psmatch2: Stata module to perform full Mahalanobis and propensity score matching, common support graphing, and covariate imbalance testing.

Li L., Chen, J., Gao, H., Xie, L. (2019). The certification effect of government R&D subsidies on innovative entrepreneurial firms' access to bank finance: Evidence from China. *Small Business Economics* 52, 241-259.

Liberti, J., Mian, A., (2009). Estimating the effect of hierarchies on information use, *Review of Financial Studies* 22, 4057-4090.

Meuleman, M., De Maeseneire, W., (2012). Do R&D subsidies affect SMEs' access to external financing? *Research Policy* 41, 580-591.

Minnis, M., (2011). The value of financial statement verification in debt financing: Evidence from private U.S. firms. *Journal of Accounting Research* 49, 457-506.

Moro, A., Maresch, D., Fink, M., Ferrando, A., Piga, C., (2020). Spillover effects of government initiatives fostering entrepreneurship on the access to bank credit for entrepreneurial firms in Europe. *Journal of Corporate Finance* 62, 101603.

Neuhann, D., Saidi, F. (2018). Do universal banks finance riskier but more productive firms? *Journal of Financial Economics* 128, 66-85.

Ni, X., Yin, S. (2018). Shareholder litigation rights and the cost of debt: Evidence from derivative lawsuits. *Journal of Corporate Finance* 48, 169-186.

Olden, A. and Møen, J. (2022). The triple difference estimator. *Econometrics Journal*, in press.

Petersen, M., Rajan, R., (1994). The benefits of lending relationships: Evidence from small business data. *Journal of Finance* 49, 3-37.

Randelli, F., Boschma, R., (2012). Dynamics of industrial districts and business groups: The case of the Marche region. *European Planning Studies* 20, 1961-1974.

Rosenbaum, P. (2002). *Observational Studies*, 2nd Edition. New York: Springer.

Rosenbaum, P., Rubin, D., (1983). The central role of propensity score in observational studies for causal effects. *Biometrika* 70, 41-50.

Rubin, D., (2008). For objective causal inference, design trumps analysis. *The Annals of Applied Statistics* 2, 808-840.

Saidi, F., Žaldokas, A. (2020). How does firms' innovation disclosure affect their banking relationships? *Management Science* 67. 742-768.

Sikochi, A., (2020). Corporate legal structure and bank loan spread. *Journal of Corporate Finance* 64, 101656.

Söderblom, A., Samuelsson, M., Wiklund, J., Sandberg, R., (2015). Inside the black box of outcome additionality: Effects of early-stage government subsidies on resource accumulation and new venture performance. *Research Policy* 44, 1501-1512.

Vander Bauwhede, H., De Meyere, M., Van Cauwenberge, P., (2015). Financial reporting quality and the cost of debt of SMEs, *Small Business Economics* 45,149-164.

Wei, J., Zuo, Y., (2018). The certification effect of R&D subsidies from the central and local governments: Evidence from China. *R&D Management* 48, 615-626.

Wooldridge, J.M. (2010). *Econometric Analysis of Cross Section and Panel Data*. Cambridge, Mass., MIT Press.