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Real Effects of Bank Governance: Bank Ownership and Corporate Innovation

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ABSTRACT

In this paper we analyze the impact of government and private bank ownership on firms' probability to innovate. We estimate firms' decision to innovate and their selection of a main lender for a sample of 9000 German manufacturing companies. Since these two decisions may be simultaneously determined we use the number of private and government bank branches located in close geographic proximity to our sample firms as an instrument for the selection of each firm's main lender. We find that the probability of a firm to innovate is about 13 to 18 percent higher if the main lender is a private compared to a government bank (after controlling for firm characteristics and selectivity bias). The ownership type of the main lender is especially important for small firms since their access to finance is more dependent on the local supply of lenders. Thus, extensive government involvement in the allocation of credit comes at the cost of lower corporate innovation and thus economic growth.

JEL Codes: F34, F37, G21, G28, G33, K39.

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1. Introduction

During the current financial crisis governments have been forced to take over large parts of the banking system. Potentially this public sector involvement in the banking sector has considerable long run effects on all major industrialized countries. One of the most important functions of a financial system is that financial intermediaries select entrepreneurs with the best chances of developing new products which increases the rate of technological progress in an economy (King and Levine 1993; Levine and Zervos 1998; Beck, Levine, and Loayza 2000a; Levine 2005 for a survey).[1] Thus, banking development stimulates the introduction of innovations (Benfratello, Schiantarelli, and Sembenelli 2008). In this paper we examine whether public or private financial intermediaries are better in selecting promising innovative projects and thus foster technological progress. More specifically, we analyze the impact of government owned versus private owned banks on the innovation ability of corporations.

Theory is ambivalent about the effect of public bank ownership on technological progress. On the one hand, public banks might alleviate market failures associated with the process of innovation financing and thus foster growth. The most important market failures associated with the process of innovation financing are asymmetric information and moral hazard (Carpenter and Petersen 2002; Hall 2002)[2] as well as the existence of positive externalities associated with providing external finance for innovations.[3] The existence of such externalities might be a rationale for a government subsidy in the form of government financing (e.g. Hainz and Hakenes 2007).

[1]Beck, Levine, and Loayza (2000b) find a positive correlation between financial development and TFP growth.

[2]A new technology is less understood by third parties and during the development of the new technology few interim signals on its outcome can be verified (Goodacre and Tonks 1995). Furthermore, the salvage value from financing innovation is small leaving the entrepreneur with stronger incentives to add risk since a large proportion of the losses accrues to the outside financier.

[3]Such externalities are first of all technology spill-overs, but can also take the form of regional employment prospects etc. See Romer (1990), Aghion and Howitt (1992) or Aghion and Howitt (1997) for an overview.

On the other hand, government bankers' incentives can result in a misallocation of financial resources (La Porta, Lopez-De-Silanes, and Shleifer 2002; Sapienza 2004). The causes of resource misallocation associated with government financing are manifold: e.g. politicians tend to influence their bankers' financing decisions for their personal goals or government banks are reluctant to shut down unprofitable corporations to secure employment.[4] This political view of government bank ownership implies that government banks may not facilitate an efficient allocation of resources by preventing capital to be channeled to new innovative enterprises. Thus, there are diverging arguments about the effect of public bank ownership on corporate innovation. It is therefore an empirical question and evidence on this issue for industrialized countries is rare.

There are a number of recent papers that have shown that credit relationships may affect corporate innovation decisions. Herrera and Minetti (2007) find that a stronger relationship between lender and borrower, proxied by the duration of the credit relationship of the borrower and its main lender, promotes innovation. In a related paper, Benfratello, Schiantarelli, and Sembenelli (2008) show that local banking development matters for the probability of innovation of corporations. Atanassov, Nanda, and Seru (2005) document for a sample of large publicly traded US firms that more innovative firms actually prefer arm's length financing to relationship based borrowing.

Our paper differs in several dimensions from previous work in the field. Studies of bank governance mostly focus on developing countries (e.g. Khwaja and Mian 2005). In developing countries it is difficult to differentiate between particular institutional characteristics (e.g. corruption) of these economies and consequences of public bank ownership. Therefore, it is difficult to generalize these findings for industrialized coun-

[4]Following government deregulation of the French banking sector, Bertrand, Schoar, and Thesmar (2007) find that banks were less willing to bail out poorly performing firms and are more likely to support restructuring activities. Consequently, they observe an improvement in allocative efficiency across firms following deregulation. Khwaja and Mian (2005) present empirical evidence for For Pakistan. They find that government banks systematically favor political connected firms (i.e. firms whose director participates in an election) over non-connected firms even loans to connected firms have a 50 percent higher default rate. They estimate the economy wide costs of the rents associated with connected lending to be 0.3 to 1.9 percent of GDP every year.

tries. The German corporate landscape provides a good laboratory to examine the link between bank ownership and firms' innovation decision. First, because corruption is rather low, it is not the main driver of public bankers. Second, the German financial sector is bank-based and market-based financing is of secondary importance. Third, there exists a government banking sector that is about the same size than the private banking sector. Finally, the German economy is characterized as innovative[5] and innovations happens not only through large cooperations but a large share through medium sized enterprises.

We construct a unique dataset that allows us to observe individual corporate lending relationships. For a sample of 9 000 German manufacturing enterprises we determine their credit relationships for all loans exceeding 1.5 million Euros through the Bundesbank credit register for the years 1993 to 2006. Combining this dataset with patent information from the European and German Patent Office allows us to identify firms' innovation activity as well as the type of main lender.

Another novelty of our paper is that we model firms' selection of their main lender. A central concern for our study is a possible problem of endogeneity, namely that firms might choose a specific type of bank depending on their innovation ability. Thus, firms that plan to innovate in the future might choose a public or private bank depending on the banks' willingness to finance new technologies. We overcome this endogeneity problem by locating all existing bank branches in close distance of our sample firms. This measure is used as instrument (as discussed at length in section 4.1), because previous research has shown that geographic distance plays an important role in relationship banking (e.g. Degryse and Ongena 2005; Petersen and Rajan 2002). Especially small firms bear considerable costs if applying for external finance with non-regional banks.[6] Since private banks do not have branches in geographic proximity to all our sample firms, not all firms have a choice between private and public banks

[5]According to the OECD (2007) R&D spending in Germany is well above the OECD average in 2005.

[6]For large firms that have access to financial intermediaries nationwide as well as to national and international securities markets, local banking market development matters to a smaller extend (Benfratello, Schiantarelli, and Sembenelli 2008).

(or the choice of the private lender is associated with higher costs due to the distance between lender and borrower). This allows us to identify whether the ownership type of a bank itself has a causal effect on the innovation ability of a firm.

We argue that the type of lending relationship endogenously affects a firm's innovation ability. This raises the question why potentially innovative firms do not simply switch their main lender if e.g. private banks are better suited to finance new technologies. As mentioned before, asymmetric information and moral hazard are especially pronounced in the process of technology financing. A bank can moderate this moral hazard problem by gathering information on the new technology to be financed (Herrera and Minetti 2007). In this process a firm's main lender generally functions as a delegated monitor of the other lenders (Diamond 1984) and is therefore the main producer of information concerning the borrower. Once a firm is stuck in a relationship with a main lender it is difficult to switch to a new financier. The problem is that potential new financiers know that a firm's main lender has an informational advantage regarding the borrower. Consequently, switching the main bank is likely to be very costly either because the new lender lacks information or because of a bad signal switching the lender conveys (since the new lender may assumes that financing decision was refused by the old lender). This hold-up problem is especially pronounced for technology finance, since such projects tend to be informational opaque.

We find that a firm's probability to innovate is affected by the ownership of its main lender. The probability of a firm to innovate is about 13 to 18 percent higher if the main lender is a private compared to a government bank (after controlling for firm characteristics and selectivity bias). These findings are based on a bivariate probit model estimated with full maximum likelihood estimation. The ownership type of the main lender is especially important for smaller firms, since their access to finance is more dependent on the local supply of lenders. Among the innovating firms those with a private main lender tend to produce more innovations compared to firms with a government main lender. Our results are robust after controlling for a wide variety of possibilities.

The remainder of this paper is structured as follows. Section 2 describes the German banking system, the construction of our dataset and provides descriptive statistics. In Section 3 we introduce the empirical analysis we follow in this paper. Section 4 presents our results. Section 5 concludes.

2. Data and descriptives

2.1. The German banking sector

The Germany financial sector can be classified as bank-based, with a universal banking system. One of the particularities of the German banking sector is its so called three pillar structure, referring to the three different legal ownership forms of German banks. The three forms are public banks, private banks and credit cooperatives. While credit cooperatives mostly specialize on household and small business finance, private and public banks compete for enterprise financing. In the following, we focus on differences between public banks and private banks, these two groups hold together 84.5% of the total assets of German banks (39% held by private banks and 45.5% by public banks, see Table II).[7] While the market share of public banks in Germany is relatively high by European standards (Hartmann, Heider, Papaioannou, and Duca 2007), a high share of government involvement in the banking sector is not a uncommon phenomenon. Porta, Lopez-De-Silanes, and Shleifer (2002) find for a large sample of countries, that on average 30% of the banking sectors were controlled by governments in 1995.

The specific structure of the German banking sector has evolved historically. The first public saving banks were founded in the 18th/19th century in Germany in order to make a savings account accessible for everybody and the first joint stock banks were founded in the 19th century.[8] The structure of the public banking sector is the

[7]We restrict our analysis to these two groups, as credit cooperative are underrepresented in our sample. The reason is that credit cooperatives are typically very small and therefore are generally not the main lenders of our sample firms.

[8]See Hackethal (2004) and Brunner, Decressin, Hardy, and Kudela (2004) for more information on the German Banking market.

result of laws implemented at the beginning of the twentieth century and after the second world war in Germany. This so-called ‘Sparkassengesetz’ gave rise to a country wide community banking sector. Nowadays, public banks, also referred to as saving banks, are owned by local communities and state governments. The so-called regional principle demands from community banks to provide a comprehensive supply of local finance and prevents competition between public banks by forbidding them to serve customers beyond their community. The objectives of public banks as laid down in the respective laws (e.g. Sparkassengesetz 2008 and Sparkassengesetz 2005) are manifold: e.g. ensuring the availability of credit to enterprises, communities as well as facilitating individual savings.[9] The difference in objectives of public and private bankers is the main difference between the two groups of banks.

The strict legal setting for government banks in Germany translates into a rigid market. Germany is said to be overbanked with 2,277 banks and nearly 40,000 bank branches,[10] but still the legal framework prohibits consolidation between private and public banks. Consolidation can only take place within each of the pillars, so that competitive pressure through M&As is low for public banks. A typical example for the local distribution of private and public banks is shown in Figure 1 for the district of Karlsruhe. As can be seen in this graph, public banks possess a dense branch network in rural as well as urban areas. The strong presence of public banks in rural areas is a result of the aforementioned regional principle. As a consequence especially rural areas tend to be overbanked in Germany and private banks generally tend to concentrate their branches in urban areas.

[9]Commonly this legal framework includes a statement that profit maximization is not the main objective of public banks and that they have to serve common welfare. Other objectives are to provide a checking account to every private person independent of her income and the economic education of the youth (see the ‘Sparkassengesetze’, ‘Sparkassenordnung’ and ‘Landesbankgesetz’ of the Länder in Germany).

[10]Within Europe Germany is among the countries with the highest number of credit institutions, branches and bank employees, see European Central Bank (2007) for details.

2.2. Firm data and their innovation abilities

Time series information of financial statements of German corporations is obtained from Bureau van Dyck's Amadeus database. As a starting point we take all German manufacturing firms and obtain 9,310 firms and 32,839 firm year observations (for the period 1993-2006). A detailed description of the underlying data sets and the matching strategies can be found in Appendix A.

In order to measure the innovation ability of firms we collect data of successful patent applications for our sample firms. Patent applications have been used in several empirical studies to measure the innovation activity of firms (Seru 2007; Angrist and Krueger 1991) and have found to be the superior measure for innovation activity (Griliches and Mairesse 1991; Trajtenberg 1990a,b).[11] For our paper we collect patent information from two sources: the German patent office and the European patent office (EPO) extracted from the EP-CESPRI database. We have information on the number of patents per firm and year from both sources and information on the number of citations per year (as an indicator for the relevance of patents) from EPO (see Table III for a distribution of patent application and citations per industry). We use both the number of patents to measure innovation intensity as well as a binary variable classifying firms into innovators and non-innovators.[12]

We link financial statement information of our sample firms to the German credit register of the Deutsche Bundesbank. This allows us to identify the lenders of a firm and provides us also with historic data for lending relationships up to 1993. The credit register includes information on each credit relationship if the total outstanding amount of loans in a given quarter exceeds 1.5 million Euros.[13] We are therefore able to classify the firms based on their main lender (private or public), defining the main lender as the bank granting the highest share of loans to the firm. Finally, in order to

[11]In addition, according the German accounting standards (HGB) R&D expenditures include expenditures to purchase patents and copyright rights and are therefore not appropriate to measure the innovation activity of a firm (see Bessler and Bittelmeyer 2006, and Jeny and Stolowy 1999).

[12]For the definition of the variables see Table I.

[13]Please refer to Schmieder (2006) for a detailed description of the credit register of the Bundesbank.

control for different regional environments firms operate in (public banks tend to be more represented in rural areas), we also collect data on local community development (GDP per capita per region) and population density per community.

We have to control for the fact that the main lender choice of a firm may be endogenous, as will be discussed at length in Section 4.1. We therefore collect information on the ownership of the banks and branches close to the firms in our sample (within a radius of 3 km around each firm, a surface of about 28 km^2). As mentioned before distance matters in the relationship between firms and their lender. Our aim is to find a measure of local bank branch supply provided by private and public banks in close geographic proximity for all of our sample firms. Thus, we count the number of banks and branches in proximity to the firms (*total_banks*) and the number of private (*share_private*) and public banks (*public_banks*). Our instrument will be the share of private banks (to the sum of private and public banks). In addition we counted the number of private and public banks within a radius of 10 km (a surface of about 315 km^2).

All data sources are matched as described in Appendix A. We end up with a data set of 12,343 observations of 4,588 firms. About one third of all observations are from innovative firms (see Table IV), 1,362 of these observations have a public bank as main lender and 2,860 a private bank. Our sample firms have on average total assets of 265 million Euros and a debt to assets ratio of 28%. Turning to our aforementioned measure for bank services supply, the firms in our sample have on average 3 public banks and about 4 private banks in a radius of 3 km, this translates in a share of 40% of private banks.

In this paper we analyze if the ownership of the main lender affects the probability of a firm to innovate. In order to get some first insights, we present descriptive statistics for the two groups of firms (having either a public or a private bank as main lenders) and study the differences in means between them (columns (5) - (7) of Table IV and Table V, column (7) presenting results of a t-test of differences in means). We find that firms lending from private banks are with a higher probability innovative, the difference being fairly high with 10%. They furthermore apply on average for 1.5 patents more than costumers of public banks, supporting the hypothesis that these two groups differ substantially. On average, customers of private banks are somewhat larger and older. If a private bank serves as a main lender the number of total lenders is generally larger (Table V). Private bank costumers are settled in regions with a higher population density, a higher output per capita and a larger supply of bank branches in geographic proximity. Finally we can see evidence that geographic proximity matters for the formation of a lending relationship (Table V). Firms that have a lending relatinship with a private bank also have a higher number and share of private banks in a radius of 3 km around them.

We also compare innovative and non-innovative firms. The innovative firms in our sample are larger (measured by assets, sales or number of employees) and older than their not innovative counterparts (see column (4) of Table IV). Innovative firms have more bank branches, especially from private banks, in close geographic distance and are settled in more populated and economically more active regions (Table V).

3. Empirical analysis

We assume that a firm (i) has a choice to innovate or use an existing technology. This choice can be modeled as follows:

$$y_i = \alpha \cdot X_i + \delta \cdot F_i + u_i \qquad (1)$$

with y being our measure of innovation that takes the value of one if firm i decides for a new technology and zero otherwise. The decision to innovate is likely to depend on a series of firm specific characteristics such as industry sector, firm size and firm age that are summarized by the vector X_i. Whether the main lender of a firm is a government or private bank is captured by F_i, that takes the value of one if a public bank is the main lender and zero if the main lender is a private bank. Our coefficient of interest is δ that aims at measuring the sensitivity of ownership of the main bank to a firm's decision to innovate. We refer to specification 1 as our 'outcome' equation.

This interpretation of δ is, however, problematic if the choice of the Financier F_i and the decision to innovate is jointly determined. If a firm expects that one of the two types of banks is better suited to finance innovation, a firm might choose the bank that suits its preferences best. In this case, the average treatment effect δ would capture this choice of a firm and not an endogenous effect of the main bank's ownership type on its innovation progress.

In order to control for this selectivity bias, we introduce a bivariate probit model (Heckman 1978) in which a firm's decision to innovate is jointly determined by a firm's choice of the ownership of its main bank. The selection equation is as follows:

$$F_i = \beta \cdot X_i + \gamma \cdot Z_i + v_i \tag{2}$$

with Z_i being a vector of instruments. Equation 2 is referred to as our 'selection' equation.

Both decisions of the firm that we model (the innovation and the main bank selection) are binary, so that there are four states of the world. The likelihood function corresponding to this set of events is a bivariate probit model. A similar research design has been applied in several empirical studies such as Evans and Schwab (1995).

In a second step we also examine determinants of the innovation intensity among the innovators. We use the number of patents each innovator applies for as the dependent variable of the 'innovation' equation. In this case our two equation system corresponds to a classical treatment model. This model can be either estimated by full maximum likelihood or a two stage procedure (Imbens and Angrist 1994). We repeat these tests replacing the number of patents with the number of citations of a firms patents. This test allows us to measure the relative importance of the granted patents. Furthermore, we reestimate our main model by applying alternative definitions for a firm's main lender and alternative definition of our instrument.

4. Results

4.1. The choice between a government and private main lender

We start with the estimation of our 'selection' equation. We use the number of private bank branches to all bank branches located in a radius of 3 km around each firm as an instrument. For our instrument to be valid two conditions have to be met. First, it has to be an important determinant of a firm's decision to select its main lender. Second, it must not be a determinant of a firm's decision to innovate. The first condition can be easily tested by simply estimating the selection equation 2 individually and test for the explanatory power of the instrument.

Results are shown in Table VI. In the first column, we add the relative number of private banks to all banks (*share_private*) and the total number of banks (*total_banks*) in a radius of 3 km around each firm as instruments. Further, we add firm size, age as well as industry and year fixed effects as explanatory variables. Both of our instruments enter the probit model significantly. Firms that have a higher fraction of private banks and a higher number of branches in their surrounding are less likely to choose a government bank as their main bank. Furthermore, larger firms tend to have a relationship with a private bank and older firms with a government bank. Since government banks are more present in rural areas and private banks in urban areas as can be seen for example in Figure 1, the latter finding could be driven by differences in the population density of the firm location. Therefore, we include population density (*pop_density*) and regional development (*regional_GDP*) of the community a firm is located in (see Panel B column 1'). Both factors have an impact on the main bank selection. In more populated and developed areas, more private banks exist, and therefore firms are less likely to have a government bank as a main lender.

Second, the location of private bank branches in close geographic proximity of a firm may not be a determinant of a firm's innovation decision. One way to test for this is to include our instrument *share_private* in the outcome equation. This does not constitute a formal test since we have argued before that a bivariate probit is the correct specification. Nevertheless, this test allows us to analyze the correlation between the probability to innovate and the relative number of private branches in the proximity of a firm once controlling for other firm characteristics. As shown in Table VII, the estimated coefficient of *share_private* is statistically not significant. Even this is not a formal test for the validity of our instrument, no direct relationship between the bank-firm location and the probability to innovate is detected.

For our instrument to be meaningful, it is further important that bank as well as firm location is not endogenously determined (e.g. a certain bank type does not choose location based on innovation ability of firms and firms do not locate in proximity to a certain bank type based on their innovation ability). We are less concerned about endogeneity of bank branch location in Germany. As argued before the regional principle demands from public banks to establish a dense branch network in order to provide a areawide supply of finance (see Section 2.1). Consequently, rural areas tend to be overbanked and private banks concentrate their activities in urban areas. The observed distribution of private and public bank branches corresponds with these considerations (see Figure 1). Thus, while firm located in urban areas generally have a choice between private and public banks, firms located in rural areas generally only find public banks in their geographic proximity.

Arguing that firm location is not chosen endogenously is more difficult. In our sample of manufacturing firms, moving is not frictionless since it requires the relocation of manufacturing halls and machines. These frictions should be especially important for small firms and firms with a high fraction of tangible assets, since moving location is more costly. In order to see whether firm location is determined endogenously we reestimate our model only for firms with a fraction of tangible assets in the top quartile. Results are reported in the subsequent section (see Table XI).

Larger firms are likely to have better access to nationwide banking markets and therefore rely less on the conditions of their local banking market. Furthermore, larger firms may alternatively access market based finance. Consequently, our instrument should be more relevant for smaller firms. To test for this presumption we stepwise remove large firms from our sample and reestimate our selection equation for the remaining sample. Results are reported in Table VI, columns 2 to 5. In column 2 the largest 75^{th} percentile of firms are excluded from the sample. The coefficient *share_private* increases in magnitude. If we only estimate the selection model for the smallest 50^{th}, 25^{th} and 10^{th} percentile of firms this effect becomes more drastic. Therefore, we conclude that our instrument is more relevant for medium-sized and smaller firms. The coefficient is significant for all groups, but increases in magnitude, if we estimate the selection model for the smallest 50^{th}, 25^{th} and 10^{th} percentile of firms.

4.2. Government ownership and innovation

Table VIII presents coefficients of the outcome equation from the bivariate probit model. In column 1 we exclude community controls (*pop_density* and *regional_GDP*) from the selection equation, while these controls are included in the system presented in column 2. Having instrumented for the selection of a bank's choice of its main lender, the ownership type of the banker (F_i) has a significant impact on a firm's probability to innovate. The probability to innovate is 13 to 18 percent higher for firms with a private as compared to a government main lender (see marginal effects reported beside the coefficients). The coefficients of the firm characteristics suggest that older and larger firms are more likely to innovate. The marginal effects of these firm characteristics on the innovation probability are considerably smaller compared to the effect of the main lender's ownership type. The correlation between the error terms of the outcome and selection equation is denoted by ρ. As reported in the lower part of the table, we can reject the hypothesis that ρ is equal to zero, establishing the need for a bivariate estimation technique of our model.

Results for firms with a high fraction of tangible assets and thus high moving costs are reported in Table XI. Results are robust for estimation of this subsample.

The probability to innovate for a firm that is in a lending relationship with a public bank is actually even smaller.

We also present a different econometric model. If we ignore the bivariate nature of our endogenous variable, we can estimate our system with a two-stage procedure. The estimation technique is less demanding than the full maximum likelihood estimation of our bivariate model. Angrist (1991) has shown that instrumental variable estimation is a viable alternative to the bivariate probit model since the IV estimates of the average treatment effect δ are very close to the estimates obtained by a bivariate probit model. We choose the two-stage conditional maximum likelihood ($2SCML$) technique as proposed by Rivers and Vuong (1988). Thus, we estimate the selection equation by OLS and save the corresponding fitted residuals. In the second stage, we estimate a probit model of the outcome equation in which we include the fitted residuals as an additional regressor. An appealing feature of the $2SCML$ procedure is that the t-statistic of the fitted residuals provides a valid test of the null hypotheses that the selection of the main lender is exogenous (Wooldridge 2001). Results of the corresponding second-stage equation are presented in the first column of Table IX. Our main finding also holds for the two-stage procedure: if the main lender is a government bank as opposed to a private bank, a firm's probability to innovate is reduced. Since the coefficient of the fitted residuals from the first-stage regression are statistically significant, we can reject the null hypotheses that the selection of the main lender's ownership is exogenous. This result establishes the need for a bivariate (or two-stage) estimation technique.

Next, we use the two-stage estimation technique to test whether the impact of the main lender's ownership on a firm's probability to innovate varies by firm size. Therefore, we stepwise reduce our sample by dropping the largest firms measured by total assets. In column 2 of Table IX we estimate the same model as before but drop the largest 25^{th} percentile of firms from the sample. Here, results remain unaffected. If we further drop the largest firms from the sample (see columns 3 to 5) the coefficient of the *Financier* variable increases by magnitude. Thus, the negative effect of government bankers on a firm's innovation probability is larger for small firms. A rationale for this finding is that larger firm can also access financial markets nationwide while smaller firms are more dependent on local banks.

Finally, we test for the impact of the main lender's ownership on the number of innovations among innovating firms. In the previous analysis we modeled a firm's decision to innovate by a binary variable. In our underlying dataset, we have coded the number of patents each innovating firm has successfully applied for. Thus, we have a measure for the number of innovations for our sample firms. We estimate the same two equation system as before using the number of patents each innovator has been granted during our sample period as the outcome variable. Since in this system the outcome variable is not binary we can estimate the system with a treatment-effects model by using a two-step consistent estimator. The treatment-effects model considers the effect of an endogenously chosen binary treatment on another endogenous continuous variable. Results are reported in Table X. Among innovating firms, those firms with a private main lender tend to apply for more patents after controlling for firm characteristics and selectivity bias. This result is significant at the 99% hurdle. Thus, bank ownership has not only an effect on a firm's innovation decision, but also on the innovation intensity of a firm. Furthermore, we have information on the number of citations for each patent. Results are the number of patents as the dependent variable are shown in column (2) of Table X.

4.3. Robustness tests

So far, we have chosen each firm's largest lender as the main bank. Our definition of the main lender is based on Diamond (1984) who argued that the largest lender of a firm generally functions as a delegated monitor of the other lenders. In the relationship banking literature alternative definitions for the main lender are used. Memmel, Schmieder, and Stein (2007) require a bank to lend at least 80% of all all outstanding loans to a firm to name it its main lender. We test for the robustness of our findings by reestimation the bivariate probit model for alternative definitions for the main lender in Table XIV. In column 1, we require a bank to lend at least 80% and in column 2 at least 60% of all outstanding loans to be a firm's main lender. Results remain unaffected. A main government lender has a highly significant negative impact on a firm's innovation probability. The marginal effect is about 11 percent.

In all previous estimations we have chosen a radius of 3 km around each firm to define local banking supply. We replicated the analysis allowing for a wider radius of 10 km. Results are shown in Table XII. Furthermore we replicate the 2 SCML regressions (see Table XIII). Results remain unaffected by using this alternative definition of our instrument.

5. Conclusion

Providing external finance for corporate innovation is a key mechanism through which banks affect economic growth. We find that ownership (public versus private) of financial intermediaries has an impact on firms' innovation activity. Firms that have a public bank as a main lender are less likely to develop innovations compared to firms that have a lending relationship with a private bank. This finding is especially pronounced for smaller /medium-sized firms with limited access to nationwide financial markets. Among the innovators, firms that have their main lending relationship with a private bank apply for more patents compared to those that have a public bank as main lender.

These findings suggest that private banks are superior to public banks in selecting successful innovative projects. One reason why the private sector appears to be better at stimulating innovation is that private bankers have incentives to maximize shareholder value. Public bankers' incentives are manifold and, thereby may be less likely to support restructuring activities and more willing to allocate resources in old often less innovative firms. These findings have important policy implications for government ownership of banks. While a high degree of government involvement in banking is inevitable in view of the financial crises to stabilize the system, the present study suggest that government involvement in the allocation of credit to firms comes at the cost of lower innovation and thus growth.

References

Aghion, P., and P. Howitt, 1992, "A Model of Growth through Creative Destruction," *Econometrica*, 60, 323–51.

Aghion, P., and P. Howitt, 1997, *Endogenous Growth Theory*.

Angrist, J. D., 1991, "Instrumental Variables Estimation of Average Treatment Effects in Econometrics and Epidemiology," NBER Technical Working Papers 0115, National Bureau of Economic Research, Inc.

Angrist, J. D., and A. B. Krueger, 1991, "Does Compulsory School Attendance Affect Schooling and Earnings?," *The Quarterly Journal of Economics*, 106, 979–1014.

Atanassov, J., V. Nanda, and A. Seru, 2005, "Finance and Innovation: The Case of Publicly Traded Firms," Discussion paper.

Beck, T., R. Levine, and N. Loayza, 2000a, "Finance and the Sources of Growth," *Journal of Financial Economics*, 58, 261–300.

Beck, T., R. Levine, and N. Loayza, 2000b, "Financial Intermediation and Growth: Causality and Causes," *Journal of Monetary economics*, 46, 31–77.

Benfratello, L., F. Schiantarelli, and A. Sembenelli, 2008, "Banks and Innovation: Microeconometric Evidence on Italian Firms," *Journal of Financial Economics*, pp. 197–217.

Bertrand, M., A. Schoar, and D. Thesmar, 2007, "Banking Deregulation and Industry Structure: Evidence from the French Banking Reforms of 1985," *Journal of Finance*, 62, 597–628.

Bessler, W., and C. Bittelmeyer, 2006, "Intellectual Capital and the Long-run Performance of Technology Firms," Discussion paper, Center for Finance and Banking, Justus-Liebig-Universität Giessen.

Blasnik, M., 2007, "RECLINK: Stata module to probabilistically match records," Statistical Software Components, Boston College Department of Economics.

Brunner, A. D., J. Decressin, D. C. L. Hardy, and B. Kudela, 2004, "Germany's Three-Pillar Banking System: Cross-Country Perspectives in Europe," IMF Occasional Papers 233, International Monetary Fund.

Bundesbank, D., 2008, "Bankenstatistik Dezember 2008," .

Carpenter, R. E., and B. C. Petersen, 2002, "Capital Market Imperfections, High-Tech Investment, and New Equity Financing," *Economic Journal*, 112, F54–F72.

Degryse, H., and S. Ongena, 2005, "Distance, Lending Relationships, and Competition," *Journal of Finance*, 60, 231–266.

Diamond, D. W., 1984, "Financial Intermediation and Delegated Monitoring," *Review of Economic Studies*, 51, 393–414.

European Central Bank, 2007, *EU Banking Structures*, European Central Bank, Frankfurt a.M.

Evans, W. N., and R. M. Schwab, 1995, “Finishing High School and Starting College: Do Catholic Schools Make a Difference?,” *The Quarterly Journal of Economics*, 110, 941–74.

Goodacre, A., and I. Tonks, 1995, “Finance and Technological Change,” Discussion paper.

Griliches, Z., and J. Mairesse, 1991, “R&D and Productivity Growth: Comparing Japanese and U.S. Manufacturing Firms,” NBER Working Papers 1778, National Bureau of Economic Research, Inc.

Hackethal, A., 2004, “German Banks and Banking Structure,” in *The German Financial System*, Oxford University Press.

Hainz, C., and H. Hakenes, 2007, “The Politician and his Banker,” Discussion paper.

Hall, B. H., 2002, “The Financing of Research and Development,” *Oxford Review of Economic Policy*, 18, 35–51.

Hartmann, P., F. Heider, E. Papaioannou, and M. L. Duca, 2007, “The role of financial markets and innovation in productivity and growth in Europe,” Occasional Paper Series 72, European Central Bank.

Heckman, J. J., 1978, “Dummy Endogenous Variables in a Simultaneous Equation System,” *Econometrica*, 46, 931–59.

Herrera, A. M., and R. Minetti, 2007, “Informed finance and technological change: Evidence from credit relationships,” *Journal of Financial Economics*, 83, 223–269.

Imbens, G. W., and J. D. Angrist, 1994, “Identification and Estimation of Local Average Treatment Effects,” *Econometrica*, 62, 467–75.

Jeny, A., and H. Stolowy, 1999, “How Accounting Standards Approach and Classify Intangibles An International survey,” Discussion paper, HEC School of Management (Groupe HEC).

Khwaja, A. I., and A. Mian, 2005, “Do Lenders Favor Politically Connected Firms? Rent Provision in an Emerging Financial Market,” *The Quarterly Journal of Economics*, 120, 1371–1411.

King, R. G., and R. Levine, 1993, “Finance and Growth: Schumpeter Might Be Right,” *The Quarterly Journal of Economics*, 108, 717–37.

La Porta, R., F. Lopez-De-Silanes, and A. Shleifer, 2002, “Government Ownership of Banks,” *Journal of Finance*, 57, 265–301.

Levine, R., 2005, “Finance and Growth: Theory and Evidence,” in Philippe Aghion, and Steven Durlauf (ed.), *Handbook of Economic Growth*, vol. 1 of *Handbook of Economic Growth*, . chap. 12, pp. 865–934, Elsevier.

Levine, R., and S. Zervos, 1998, "Stock Markets, Banks, and Economic Growth," *American Economic Review*, 88, 537–58.

Memmel, C., C. Schmieder, and I. Stein, 2007, "Relationship lending: empirical evidence for Germany," Discussion paper.

OECD, 2007, "OECD Science, Technology and Industry Scoreboard 2007: Innovation and Performance in the Global Economy," Discussion paper.

Ongena, S., G. Tuemer-Alkan, and N. v. Westernhagen, 2007, "Creditor concentration: an empirical investigation," Discussion paper.

Parisi, M. L., F. Schiantarelli, and A. Sembenelli, 2006, "Productivity, innovation and R&D: Micro evidence for Italy," *European Economic Review*, 50, 2037–2061.

Petersen, M. A., and R. G. Rajan, 2002, "Does Distance Still Matter? The Information Revolution in Small Business Lending," *Journal of Finance*, 57, 2533–2570.

Porta, R. L., F. Lopez-De-Silanes, and A. Shleifer, 2002, "Government Ownership of Banks," *Journal of Finance*, 57, 265–301.

Rivers, D., and Q. H. Vuong, 1988, "Limited information estimators and exogeneity tests for simultaneous probit models," *Journal of Econometrics*, 39, 347–366.

Romer, P. M., 1990, "Endogenous Technological Change," *Journal of Political Economy*, 98, S71–102.

Sapienza, P., 2004, "The effects of government ownership on bank lending," *Journal of Financial Economics*, 72, 357–384.

Schmieder, C., 2006, "The Deutsche Bundesbank's Large Credit Database(BANKIS-M and MIMIk)," Discussion paper.

Seru, A., 2007, "Do Conglomerates Stifle Innovation," Discussion paper.

Sparkassengesetz, 2005, "Sparkassengesetz für Baden-Württemberg in der Fassung vom 19.Juli 2005," Gesetzblatt fr Baden-Württemberg.

Sparkassengesetz, 2008, "Sparkassengesetz Nordrhein-Westfalen vom 18. November 2008," Gesetz- und Verordnungsblatt des Landes Nordrhein-Westfalen.

Trajtenberg, M., 1990a, "A Penny for Your Quotes: Patent Citations and the Value of Innovations," *RAND Journal of Economics*, 21, 172–187.

Trajtenberg, M., 1990b, "Product Innovations, Price Indices and the (Mis)Measurement of Economic Performance," NBER Working Papers 3261, National Bureau of Economic Research, Inc.

Wooldridge, J. M., 2001, *Econometric Analysis of Cross Section and Panel Data*.

Appendix A. Description and construction of the data set

Amadeus database We use data from Bureau van Dyck, the Amadeus database for German firms. This database provides standardized annual account data and financial ratios. We restrain our sample to unconsolidated (in order to prevent double counting) annual account information of manufacturing firms.[14] We drop observations with turnover or assets reported as to be zero and firms with implausible financial data (negative values for debt). We therefore end up with an unbalanced panel of 9,309 German firms in the period from 1994 to 2007.

German credit register The Deutsche Bundesbank collects for regulatory purpose information for every credit granted in Germany when the sum of outstanding loans of a creditor exceed 1.5 Mio Euro. Information are collected on a quarterly basis and every credit exceeding the threshold once in the respective quarter has to be reported, thus entries in the credit register may be smaller than 1.5 Mio Euro. The credit register provides information about the borrower (name and address), the lender (name of the bank) and a classification of the credit. We focus on credits being on balance sheet positions in the years 1993 to 2006, taking the respective entry of the quarter in which balance sheet data in the Amadeus database is reported.

Having collected information on the credits of a firm from the credit register, we end up with mostly more than one observation from the credit register matched to one firm in the Amadeus database. We try to control if the sum of the loans taken from the credit register is in line with the indebtedness reported in the financial statements of the Amadeus database by calculating a coverage ratio (sum of loans as reported in the credit register divided by the indebtedness taken from the Amadeus database). This allows us furthermore to control if our matching procedure gives reasonable results. We find a median of 0.957 for this coverage ratio which is generally in line with those found by other studies using the German credit register (Memmel, Schmieder, and Stein 2007; Ongena, Tuemer-Alkan, and Westernhagen 2007) .

Innovation data The information on patents are part of the EP-CESPRI database, provided by Gianluca Tarasconi. This database is based on the information published by the European Patent Office (EPO) in Espace Bulletin and REFI. It covers all patents granted to German firms by the EPO from 1978-2006. The database includes a count of the patents granted and a count of citations of the patents by priority year[15] together with the firm name and address. Patents are assigned to the firm the innovator is working for at the moment of the patent application.

Bank branches data and geocoding procedure We collected data from the Banken-Verlag Medien GmbH about the branch network of German banks in 2007. This database provides us the addresses of all banks and bank branches (of German and foreign banks) in Germany.

[14]The three-digit US SIC codes from 200 to 399.

[15]Date of first application of the patent to any patent office, not the application date at the EPO.

For the calculation of the distance between bank branches and firms, we use geocodes (degrees of latitude and longitude). We add geocodes to our observations from the Amadeus database and to the addresses of the banks and their branches using the website MyGeoposition[16] and control the results via googlemaps. We use these geocodes to calculate the distance between firms and banks (using the great-circle-distance-method) and count the number of private and public banks in a certain distance to the firms. We used 3 km and 10 km as a radius around each firm, this equals an area of about $28km^2$ and $314km^2$.

Regional data We use data on the regional development (GDP, GDP per capita) and population density for German administrative districts (Landkreis)[17] from the statistical offices of the Federation and the Länder.

Matching procedure We link information from different data set that do not have a unique numeric identifier. Therefore, we matched these different data sources by the name, address and legal form of the respective firms.

For this procedure we apply the reclink-ado for STATA (Blasnik, 2007). It uses record linkage methods to match observations when no unique common identifier exists and gives a probability of matching correctness. Reclink uses a bigram string comparator to assess fuzzy matches of string variables and allows to match over more than one variable.

In order to improve the results of the matching procedure, we unify the spelling of the firm names. We drop all special characters use only uppercase letters. In a first step we match only those observations being in the same zip code area (we define zip code regions by the first two numbers of the zip code in case one data base reports the street zip code and the other post office box zip code. Then we group zip codes by steps of 5000, e.g. all observations with zip codes from 10000 to 15000 form one region). We manually control the results of the matching procedure to ensure the correctness of the matching results. In a second step, we further shorten the names by dropping common words and abbreviations and then match by the first letters of the firm-names and by zip code areas. We again inspect the results. In a last step we try to match all observations from the credit register not reporting any zip codes to the firms in the Amadeus database by only matching on the names. The data on innovation (patents) are matched to the Amadeus database in the same manner.

[16] www.mygeoposition.com

[17] As we use end-of-year-data for 2007, Germany was divided into 429 districts .

Appendix B. Regional distribution of private and public bank branches

Figure 1. Distribution of private and public bank branches in the community Karlsruhe

Notes: Data on bank branches from Banken-Verlag Medien GmbH for begin of 2007. The large map shows the district of Karlsruhe (Stadtkreis and Landkreis) in the south-west of Germany and the private and public banks and their branches in this area. Grey-shaded areas illustrate larger cities (more than 25,000 inhabitants) and their surface. All other cities displayed have more than 5,000 inhabitants. The small map in the down right corner shows Germany, the black area displays the district of Karlsruhe.

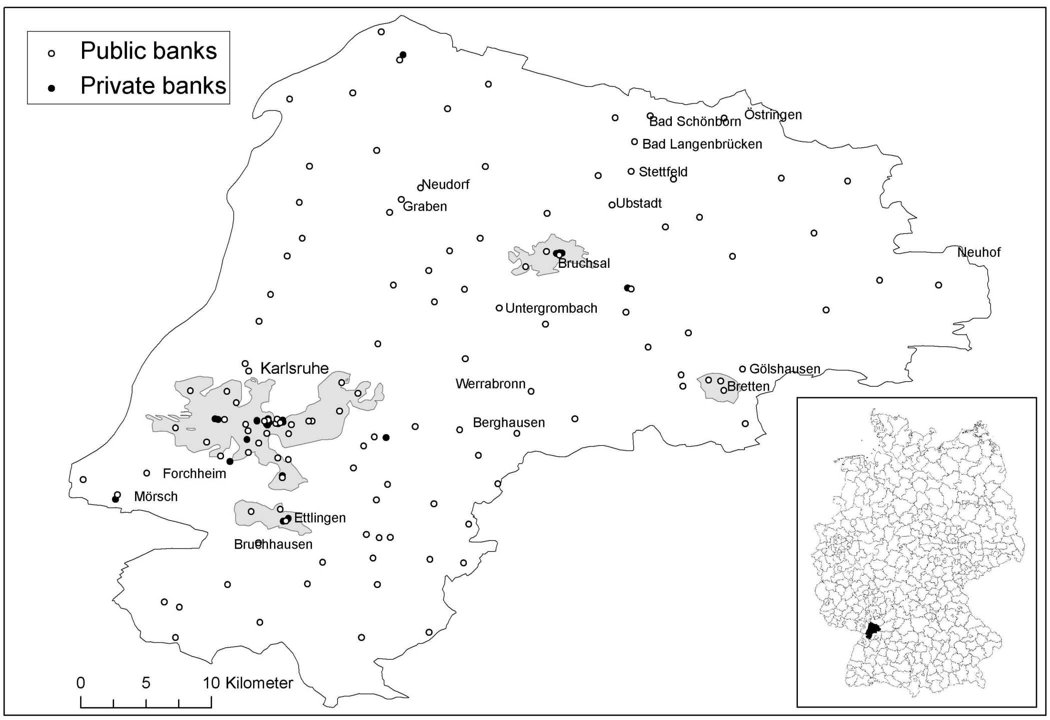

Table I
Description of Variables

Name	Description
Innovative	Dummy variable, 1 if firm applied at least once successfully for a patent at the EPO in the observation period (1996-2006), 0 else
Patents	Number of patent applications per year and firm (European Patent Office)
Patents_DPMA	Number of patent applications per year and firm (German Patent Office)
Citations	Number of citations of a patent
share_private	Number of private banks within a radius of 3 km for each firm
Public_banks	Number of public banks within a radius of 3 km for each firm
Total_banks	Number of all banks within a radius of 3 km for each firm
share_privatee	Share of private banks of all private and public banks within a radius of 3 km for each firm
Financier	Dummy variable, 1 if the main lender (highest amount of loans) is a public bank, 0 if main lender is private bank
Pop_density	Number of inhabitants per km^2
Regional_GDP	Regional GDP (in thousand) per capita
N_lender	Number of lenders of a firm reporting to the credit register
Share_main	Share of credit granted by the main lender, total credit taken from the credit register
Assets	Total Assets of the firm (in million Euro)
Age	Age of the firm
Employees	Number of employees of a firm
Sales	Sales of a firm (in million Euro)
ROA	Return on total assets (%)
Tangibility	Fixed assets over total assets
Debt	Total debt over total assets

Table II
Structure of the German banking market (2007)

Notes: Data from Bundesbank 2008

	Number of Institutes	Number of Branches	Share of Total assets
All Banks	2,277	39,833	100 %
Private banks	278	11,286	39.0 %
Public banks	458	14,109	45.5 %
Credit cooperatives	1,236	12,488	15.5 %

Table III
Number of patents and citations per industry

Notes: Number of patents and citations from the European Patent Office (EPO). *Innovative* is a dummy variable that takes the value of 1 if firm applied at least once successfully for a patent during the sample period and 0 otherwise. Industries grouped by two-digit SIC-codes, classification in high-tech and low-tech according to Parisi, Schiantarelli, and Sembenelli (2006). The number of observations (N) are reported in the last column.

	Patents Mean	Innovative Mean	Citations Mean	N
Low-tech industries				
Food and kindred products	0.010	0.054	0.006	1,082
Tobacco products	0.586	0.207	0.138	29
Textil mill products	0.050	0.166	0.003	319
Apparel and other finished products made from fabrics and similar materials	0.055	0.105	0.036	275
Lumber and wood products, except furniture	0.117	0.297	0.011	273
Furniture and fixtures	0.449	0.340	0.109	156
Paper and allied products	0.290	0.338	0.059	390
Printing, publishing and allied industries	1.078	0.087	0.124	460
Petroleum refining and related industries	0.211	0.232	0.011	95
Rubber and miscellaneous plastics products	1.293	0.383	0.409	699
Leather and leather products	0.000	0.125	0.000	16
Stone, clay, glass and concrete products	0.357	0.347	.120	499
Primary metal industries	0.427	0.289	0.033	838
Fabricated metal products, except machinery and transportation equipment	0.438	0.272	0.058	1,471
Miscellaneous manufacturing industries	0.226	0.290	0.048	186
High-tech industries				
Chemicals and allied products	10.947	0.452	6.189	957
Industrial and commercial machinery and computer equipment	1.841	0.446	0.220	2,226
Electronic and other electrical equipment an components, except computer equipment	2.031	0.476	0.281	1,085
Transportation equipment	10.162	0.496	2.863	815
Measuring, analyzing and controlling instruments; photographic, medical and optical goods; watches and clocks	1.909	0.557	0.081	472
All firms	2.340	0.342	0.784	12,343

Table IV: Descriptive statistics (Part I: Firm characteristics)

Notes: Means for firm characteristics by firms' innovation activity and main lending relationship. See Table I for definitions. Column 2 presents results for all firms, column (2) and (3) for innovative and not innovative firms (*Innovative*) and columns (5) and (6) for firms having as main lender a private or a public bank (*Financier*). The number of observations (N) of each variable is reported in parentheses below the respective mean values. Columns (4) and (7) present results of t-test for differences in means between the groups of firms, p-value below in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variable	All firms Mean (N)	No innovations Mean (N)	Innovators Mean (N)	(2)-(3) Difference (p-value)	Private Mean (N)	Public Mean (N)	(5)-(6) Difference (p-value)
Patents	2.339	0	6.839	-6.839	2.983	1.361	1.622
	(12,343)	(8,121)	(4,222)	(0.000)	(7,444)	(4,899)	(0.000)
Innovative	0.342	0	1		0.384	0.278	0.106
	(12,343)	(8,121)	(4,222)		(7,444)	(4,899)	(0.000)
Citations	0.784	0	2.292	-2.292	1.121	0.273	0.848
	(12,343)	(8,121)	(4,222)	(0.000)	(7,444)	(4,899)	(0.001)
Assets	265.455	98.540	586.515	-487.974	356.435	127.211	229.225
	(12,343)	(8,121)	(4,222)	(0.000)	(7,444)	(4,899)	(0.000)
Age	39.794	36.852	45.452	- 8.599	40.374	38.913	1.461
	(12,343)	(8,121)	(4,222)	(0.000)	(7,444)	(4,899)	(0.066)
Employees	1,687.341	764.822	2,788.211	- 2,023.390	2,010.801	986.714	1024.087
	(5,854)	(3,185)	(2,669)	(0.000)	(4,005)	(1,849)	(0.000)
ROA	6.137	6.173	6.068	0.104	6.364	5.793	0.571
	(12,334)	(8,114)	(4,220)	(0.692)	(7,436)	(4,898)	(0.025)
Sales	313.741	141.032	645.946	-504.914	421.217	150.431	270.786
	(12,343)	(8,121)	(4,222)	(0.000)	(7,444)	(4,899)	(0.000)
Tangibility	0.384	0.387	0.378	0.008	0.388	0.377	0.011
	(12,342)	(8,120)	(4,222)	(0.043)	(7,443)	(4,899)	(0.006)
Debt	0.280	0.325	0.204	0.121	0.237	0.347	-0.110
	(8,214)	(5,165)	(3,049)	(0.000)	(5,020)	(3,194)	(0.000)

Table V: Descriptive statistics (Part II: Lending relationship and regional data)

Notes: Means for firm characteristics by firms' innovation activity and main lending relationship. See Table I for definitions. Column 2 presents results for all firms, column (2) and (3) for innovative and not innovative firms (*Innovative*) and columns (5) and (6) for firms having as main lender a private or a public bank (*Financier*). The number of observations (N) of each variable is reported in parentheses below the respective mean values. Columns (4) and (7) present results of t-test for differences in means between the groups of firms, p-value below in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All firms	No innovations (a)	Innovators (b)	(a)-(b)	Private (c)	Public (d)	(c)-(d)
	Mean	Mean	Mean	Difference	Mean	Mean	Difference
Variable	(N)	(N)	(N)	(p-value)	(N)	(N)	(p-value)
Public_banks	3.251	3.061	3.618	- 0.558	3.469	2.920	0.549
	(12,343)	(8,121)	(4,222)	(0.000)	(7,444)	(4,899)	(0.000)
share_private	4.623	4.289	5.266	- 0.976	5.550	3.216	2.334
	(12,343)	(8,121)	(4,222)	(0.000)	(7,444)	(4,899)	(0.000)
share_privatee	0.405	0.393	0.427	- 0.034	0.438	0.355	0.082
	(11,116)	(7,190)	(3,926)	(0.000)	(6,758)	(4,358)	(0.000)
N_lender	2.647	2.031	3.833	- 1.802	2.829	2.370	0.458
	(12,343)	(8,121)	(4,222)	(0.000)	(7,444)	(4,899)	(0.000)
Share_main	0.795	0.833	0.722	0.111	0.779	0.820	-0.040
	(12,343)	(8,121)	(4,222)	(0.000)	(7,444)	(4,899)	(0.000)
Pop_density	831.446	752.599	983.108	- 230.510	951.528	648.982	302.547
	(12,343)	(8,121)	(4,222)	(0.000)	(7,444)	(4,899)	(0.000)
Regional_GDP	21.444	20.243	23.693	- 3.450	21.973	20.642	1.331
	(12,060)	(7,862)	(4,198)	(0.000)	(7,268)	(4,792)	(0.000)

Table VI
Determinants of the main bank relationship

Notes: The table reports estimates of the probit model $F_{it} = \beta \cdot X_{it} + \gamma \cdot Z_{it} + v_{it}$, where i indexes for firm and t for year. The dependent variable F_{it} is a dummy variable that takes the value of 1 if the main lender is a public bank and 0 if the main lender is a private bank. Firm specific characteristics are summarized by the vector X_{it}. A vector of instruments is denoted by Z_{it}. All variables are defined as in Table I. Standard errors are reported in parentheses. All regressions include year and industry fixed effects. The bottom line of the table states the number of observations of each estimation. *,**,*** indicates significance at the 10%, 5%, and 1%, respectively.

Panel A	(1)	(2)	(3)	(4)	(5)
Sample	All	75^{th} percentile	50^{th} percentile	25^{th} percentile	10^{th} percentile
Instrumental variables					
share_private	-0.290***	-0.438***	-0.615***	-0.826***	-0.853*
	[0.040]	[0.051]	[0.073]	[0.173]	[0.499]
total_banks	-0.002**	-0.005***	-0.007***	-0.004	-0.016
	[0.001]	[0.001]	[0.003]	[0.005]	[0.014]
Exogenous variables					
log(age)	0.092***	0.122***	0.099***	0.049	0.031
	[0.014]	[0.018]	[0.029]	[0.073]	[0.237]
log(assets)	-0.200***	-0.317***	-0.260***	0.013	0.297
	[0.008]	[0.017]	[0.033]	[0.081]	[0.201]
Year fixed effects	yes	yes	yes	yes	yes
Industry fixed effects	yes	yes	yes	yes	yes
Observations	11418	7007	3246	703	144
Pseudo R^2	8.87%	8.13%	8.22%	13.18%	40.56%

Panel B	(1')	(2')	(3')	(4')	(5')
Sample	All	75^{th} percentile	50^{th} percentile	25^{th} percentile	10^{th} percentile
Instrumental variables					
share_private	-0.159***	-0.232***	-0.388***	-0.545***	-1.153*
	[0.045]	[0.058]	[0.084]	[0.202]	[0.675]
total_banks	-0.002**	-0.003**	-0.004	0.003	-0.021
	[0.001]	[0.002]	[0.003]	[0.007]	[0.016]
pop_density	-0.177***	-0.270***	-0.325***	-0.341***	0.155
	[0.019]	[0.026]	[0.039]	[0.092]	[0.331]
regional_GDP	0.017***	0.020***	0.023***	0.014	0.008
	[0.002]	[0.002]	[0.004]	[0.009]	[0.042]
Exogenous variables					
log(age)	0.069***	0.083***	0.043	0.032	0.053
	[0.014]	[0.019]	[0.031]	[0.076]	[0.250]
log(assets)	-0.211***	-0.335***	-0.258***	-0.026	0.304
	[0.009]	[0.018]	[0.034]	[0.083]	[0.208]
Year fixed effects	yes	yes	yes	yes	yes
Industry fixed effects	yes	yes	yes	yes	yes
Observations	11171	6789	3127	663	125
Pseudo R^2	9.84%	9.59%	10.29%	14.93%	40.37%

Table VII
Testing for instrument viability

Notes: The table reports estimates of the probit model $y_{it} = \alpha \cdot X_{it} + \delta \cdot F_{it} + \gamma \cdot Z_{it} + u_{it}$, where i indexes for firm and t for year. The dependent variable y_{it} is a dummy variable that takes the value of 1 if firm has been innovative during our sample period and 0 otherwise. Firm specific characteristics are summarized by the vector X_{it}. F_{it} is a dummy variable that takes the value of 1 if the main lender is a public bank and 0 if the main lender is a private bank. A vector of instruments is denoted by Z_{it}. All variables are defined as in Table I. Standard errors are reported in parentheses. All regressions include year and industry fixed effects. The bottom line of the table states the number of observations of each estimation. *,**,*** indicates significance at the 10%, 5%, and 1%, respectively.

	(1)	(2)
Financier	-0.203***	-0.214***
	[0.027]	[0.028]
share_private	0.051	0.019
	[0.041]	[0.046]
total_banks	0.005***	0.001
	[0.001]	[0.001]
pop_density		-0.024
		[0.018]
regional_GDP		0.019***
		[0.002]
log(age)	0.170***	0.139***
	[0.014]	[0.014]
log(assets)	0.024***	0.021***
	[0.005]	[0.005]
	0.006	-0.007
Year fixed effects	yes	yes
Industry fixed effects	yes	yes
Observations	11418	11171
Pseudo R^2	11.84%	12.63%

Table VIII
Government banks and innovation progress - Bivariate probit estimations

Notes: The table reports estimates of the bivariate probit model described in Section 3. Coefficients are shown for the 'outcome' equation $y_{it} = \alpha \cdot X_{it} + \delta \cdot F_{it} + u_{it}$, where i indexes for firm and t for year. The dependent variable y_{it} is a dummy variable that takes the value of 1 if firm has been innovative during our sample period and 0 otherwise. Firm specific characteristics are summarized by the vector X_{it}. F_{it} is a dummy variable that takes the value of 1 if the main lender is a public bank and 0 if the main lender is a private bank. The 'outcome' equation is simultaneously estimated with the 'selection' equation $F_{it} = \beta \cdot X_{it} + \gamma \cdot Z_{it} + v_{it}$ by full maximum likelihood estimation. The vector of instruments is denoted by Z_{it}. All variables are defined as in Table I. Standard errors are reported in parentheses. All regressions include year and industry fixed effects. Marginal effects at the means (and the effect of a change from zero to one for dummy variables) are reported besides the coefficients. In column 1 control variables for the community each firm operates in are included in the 'selection' equation. The correlation between the error terms of the 'outcome' and 'selection' equation is denoted by ρ. The bottom line of the table states the value of the likelihood function and the number of observations of each estimation. *,**,*** indicates significance at the 10%, 5%, and 1%, respectively.

	(1)		(2)	
	coefficients	marginal effects	coefficients	marginal effects
Financier	-1.108***	-0.187	-0.832***	-0.133
	[0.077]		[0.141]	
log(age)	0.122***	0.036	0.111***	0.029
	[0.014]		[0.014]	
log(assets)	0.187***	0.003	0.230***	0.007
	[0.015]		[0.021]	
ρ	0.688		0.516	
$\chi^2(\rho = 0)$	49.155		14.769	
Year fixed effects	yes		yes	
Industry fixed effects	yes		yes	
Community controls	no		yes	
Log Likelihood	-12848		-12556	
Observations	11418		11171	

Table IX
Government banks and innovation progress - 2*SCML* estimations

Notes: The table reports estimates of a two-stage conditional maximum likelihood model. Coefficients are shown for the 'outcome' equation $y_{it} = \alpha \cdot X_{it} + \delta \cdot F_{it} + \eta \cdot Residuals + u_{it}$, where i indexes for firm and t for year. The dependent variable y_{it} is a dummy variable that takes the value of 1 if firm has been innovative during our sample period and 0 otherwise. Firm specific characteristics are summarized by the vector X_{it}. F_{it} is a dummy variable that takes the value of 1 if the main lender is a public bank and 0 if the main lender is a private bank. *Residuals* are fitted residuals obtain from on OLS estimation of the 'selection' equation $F_{it} = \beta \cdot X_{it} + \gamma \cdot Z_{it} + v_{it}$. The vector of instruments is denoted by Z_{it}. All variables are defined as in Table I. Standard errors are reported in parentheses. All regressions include year and industry fixed effects. The bottom line of the table states the number of observations of each estimation. *,**,*** indicates significance at the 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)
Sample	All coefficients	75th percentile coefficients	50th percentile coefficients	25th percentile coefficients	10th percentile coefficients
Financier	-0.074	-0.609**	-1.683***	-2.312**	-2.906
	[0.354]	[0.292]	[0.359]	[0.991]	[2.911]
Residuals	0.080	0.498*	1.493***	1.591	2.494
	[0.355]	[0.295]	[0.365]	[1.010]	[2.994]
log(assets)	0.307***	0.290***	0.025	-0.196**	-0.373
	[0.027]	[0.041]	[0.052]	[0.097]	[0.314]
log(age)	0.103***	0.096***	0.080**	0.046	-0.369
	[0.019]	[0.025]	[0.040]	[0.117]	[0.323]
Constant	-6.854***	-4.852***	-2.661***	-0.572	7.850*
	[0.735]	[0.685]	[1.032]	[1.395]	[4.102]
Year fixed effects	yes	yes	yes	yes	yes
Industry fixed effects	yes	yes	yes	yes	yes
Observations	11418	7007	2985	537	86
Pseudo R^2	20.20%	14.39%	9.07%	20.56%	42.65%

Table X
Government banks and the number of innovations - treatment-effects model

Notes: The table reports estimates of a treatment-effects model using a two-step consistent estimator for the innovative sample firms. Coefficients are shown for the 'outcome' equation $y_{it} = \alpha \cdot X_{it} + \delta \cdot F_{it} + u_{it}$, where i indexes for firm and t for year. The dependent variable y_{it} is the sum of all patents each innovative firm has been granted during the sample period. Firm specific characteristics are summarized by the vector X_{it}. F_{it} is a dummy variable that takes the value of 1 if the main lender is a public bank and 0 if the main lender is a private bank. The binary endogenous variable F_{it} is instrumented by Z_{it}. All variables are defined as in Table I. Standard errors are reported in parentheses. All regressions include year and industry fixed effects. The bottom line of the table states the number of observations of each estimation. *,**,*** indicates significance at the 10%, 5%, and 1%, respectively.

	(1)		(2)	
Dependent	log(Nr. of patents)		log(Nr. of citations)	
Sample	innovators		innovators	
	coefficients	marginal effects	coefficients	marginal effects
Financier	-2.407***	-0.910	-3.222**	-0.960
	[0.709]		[1.351]	
log(age)	0.181***		0.198***	
	[0.181]		[0.048]	
log(assets)	0.574***		0.551***	
	[0.035]		[0.037]	
ρ	0.860		0.880	
σ	1.690		1.879	
λ	1.454		1.944	
$\chi^2(\lambda=0)$	3.41		2.40	
Year fixed effects	yes		yes	
Industry fixed effects	yes		yes	
Observations	4027		2103	

Table XI
Effect of a government lending relationship for firms with high moving costs

Notes: The table reports estimates of a treatment-effects model using a two-step consistent estimator for the innovative sample firms. Coefficients are shown for the 'outcome' equation $y_{it} = \alpha \cdot X_{it} + \delta \cdot F_{it} + u_{it}$, where i indexes for firm and t for year. The dependent variable y_{it} is the sum of all patents each innovative firm has been granted during the sample period. Firm specific characteristics are summarized by the vector X_{it}. F_{it} is a dummy variable that takes the value of 1 if the main lender is a public bank and 0 if the main lender is a private bank. The binary endogenous variable F_{it} is instrumented by Z_{it}. All variables are defined as in Table I. Standard errors are reported in parentheses. All regressions include year and industry fixed effects. The bottom line of the table states the number of observations of each estimation. *,**,*** indicates significance at the 10%, 5%, and 1%, respectively.

Sample	tangibility > 0.5	
	coefficients	marginal effects
Financier	-1.302***	-0.238
	[0.071]	
log(age)	0.127***	0.043
	[0.024]	
log(assets)	0.184***	0.016
	[0.019]	
ρ	0.868	
χ^2 (ρ=0)	39.974	
Year fixed effects	yes	
Industry fixed effects	yes	
Observations	3463	

Table XII
Effect of a government lending relationship - Alternative definition of instrument 10 km radius

Notes: The table reports estimates of a treatment-effects model using a two-step consistent estimator for the innovative sample firms. Coefficients are shown for the 'outcome' equation $y_{it} = \alpha \cdot X_{it} + \delta \cdot F_{it} + u_{it}$, where i indexes for firm and t for year. The dependent variable y_{it} is the sum of all patents each innovative firm has been granted during the sample period. Firm specific characteristics are summarized by the vector X_{it}. F_{it} is a dummy variable that takes the value of 1 if the main lender is a public bank and 0 if the main lender is a private bank. The binary endogenous variable F_{it} is instrumented by Z_{it}. All variables are defined as in Table I. Standard errors are reported in parentheses. All regressions include year and industry fixed effects. The bottom line of the table states the number of observations of each estimation. *,**,*** indicates significance at the 10%, 5%, and 1%, respectively.

	(1)		(2)	
	coefficients	marginal effects	coefficients	marginal effects
Financier	-1.038***	-0.177	-0.721***	-0.115
	[0.086]		[0.163]	
log(age)	0.121***	0.035	0.109***	0.028
	[0.013]		[0.014]	
log(assets)	0.202***	0.008	0.248***	0.012
	[0.016]		[0.022]	
ρ	0.656		0.458	
$\chi^2(\rho=0)$	40.07		9.75	
Log Likelihood	-14138		-13823	
Observations	12623		12344	

Table XIII
Government banks and innovation progress - 2*SCML* estimations - Alterntive Definition of instrument

Notes: The table reports estimates of a two-stage conditional maximum likelihood model. Coefficients are shown for the 'outcome' equation $y_{it} = \alpha \cdot X_{it} + \delta \cdot F_{it} + \eta \cdot Residuals + u_{it}$, where i indexes for firm and t for year. The dependent variable y_{it} is a dummy variable that takes the value of 1 if firm has been innovative during our sample period and 0 otherwise. Firm specific characteristics are summarized by the vector X_{it}. F_{it} is a dummy variable that takes the value of 1 if the main lender is a public bank and 0 if the main lender is a private bank. *Residuals* are fitted residuals obtain from on OLS estimation of the 'selection' equation $F_{it} = \beta \cdot X_{it} + \gamma \cdot Z_{it} + v_{it}$. The vector of instruments is denoted by Z_{it}. All variables are defined as in Table I. Standard errors are reported in parentheses. All regressions include year and industry fixed effects. The bottom line of the table states the number of observations of each estimation. *,**,*** indicates significance at the 10%, 5%, and 1%, respectively.

Panel A	(1)	(2)	(3)	(4)	(5)
	All	75th percentile	50th percentile	25th percentile	10th percentile
share_private (10km)	-0.499***	-0.586***	-0.877***	-1.357***	-1.217*
	[0.051]	[0.064]	[0.096]	[0.219]	[0.690]
total_banks (10km)	-0.000	-0.001***	-0.001***	-0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.001]	[0.003]
log(age)	0.094***	0.132***	0.104***	0.043	-0.217
	[0.013]	[0.017]	[0.027]	[0.066]	[0.202]
log(assets)	-0.195***	-0.311***	-0.226***	-0.004	0.194
	[0.008]	[0.016]	[0.031]	[0.073]	[0.155]
Observations	12623	7847	3743	824	173
Pseudo R^2	0.09	0.08	0.09	0.13	0.32

Panel A	(1)'	(2)'	(3)'	(4)'	(5)'
	All	75th percentile	50th percentile	25th percentile	10th percentile
share_private (10km)	-0.357***	-0.397***	-0.711***	-1.280***	-1,005
	[0.058]	[0.074]	[0.114]	[0.261]	[0.839]
total_banks (10km)	0.000	-0.001	-0.001*	0.000	-0.002
	[0.000]	[0.000]	[0.001]	[0.002]	[0.006]
log(age)	0.073***	0.090***	0.039	-0.001	-0.194
	[0.013]	[0.018]	[0.029]	[0.068]	[0.208]
log(assets)	-0.209***	-0.327***	-0.222***	-0.006	0.161
	[0.008]	[0.017]	[0.032]	[0.074]	[0.157]
pop_density	-0.163***	-0.217***	-0.220***	-0.235*	0.092
	[0.024]	[0.033]	[0.050]	[0.129]	[0.449]
regional_GDP	0.016***	0.020***	0.026***	0.025***	0.008
	[0.002]	[0.002]	[0.004]	[0.009]	[0.027]
Observations	12344	7604	3603	777	154
Pseudo R^2	0.10	0.09	0.10	0.13	0.31

Table XIV
Relationship banks and innovations - Bivariate probit estimations

Notes: The table reports estimates of the bivariate probit model described in Section 3. Coefficients are shown for the 'outcome' equation $y_{it} = \alpha \cdot X_{it} + \delta \cdot F_{it} + u_{it}$, where i indexes for firm and t for year. The dependent variable y_{it} is a dummy variable that takes the value of 1 if firm has been innovative during our sample period and 0 otherwise. Firm specific characteristics are summarized by the vector X_{it}. In column 1 (2), F_{it} is a dummy variable that takes the value of 1 if a public bank provides at least 80 (60) percent of a firm's outstanding loans and 0 if a private bank provides at least 80 (60) percent of a firm's outstanding loans (and missing otherwise). The 'outcome' equation is simultaneously estimated with the 'selection' equation $F_{it} = \beta \cdot X_{it} + \gamma \cdot Z_{it} + v_{it}$ by full maximum likelihood estimation. The vector of instruments is denoted by Z_{it}. All variables are defined as in Table I. Standard errors are reported in parentheses. All regressions include year and industry fixed effects. Marginal effects at the means (and the effect of a change from zero to one for dummy variables) are reported besides the coefficients. The correlation between the error terms of the 'outcome' and 'selection' equation is denoted by ρ. The bottom line of the table states the value of the likelihood function and the number of observations of each estimation. *,**,*** indicates significance at the 10%, 5%, and 1%, respectively.

	(1)		(2)	
Relationship lender if	$>$ 80% of loans		$>$ 60% of loans	
	coefficients	marginal effects	coefficients	marginal effects
Financier	-0.761***	-0.116	-0.736***	-0.112
	[0.184]		[0.168]	
log(age)	0.113***	0.027	0.114***	0.027
	[0.020]		[0.018]	
log(assets)	0.227***	0.008	0.227***	0.007
	[0.030]		[0.026]	
ρ	0.409		0.420	
$\chi^2(\rho = 0)$	8.698		10.386	
Year fixed effects	yes		yes	
Industry fixed effects	yes		yes	
Community controls	no		no	
Log Likelihood	-7300.494		-8923.812	
Observations	6812		8207	