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Government Ownership of Banks and Corporate Innovation

Monograph

Government Ownership of Banks and Corporate Innovation*

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Abstract

In this paper we analyze the impact of government and private ownership of banks on corporate innovation. We find that firms with more financing from government-owned banks are less (more) likely to initiate (exit) innovation. Among the innovators, firms that finance more through private banks have more innovative output. These findings could be driven by the selection of lending relationships based on firms' preferences to innovate or, alternatively, by the crowding out of innovation due to the presence of government-owned banks. To differentiate between these two explanations, we use the timing of government-owned bank distress events over the electoral cycle as an instrument. We show a remarkable increase in innovation following an exogenous decrease in government ownership of banks. Moreover, the allocation of credit is more responsive to the financing needs of future innovators among private banks, shedding light on the mechanism. Overall our results suggest that government involvement in the allocation of credit crowds out private banking and comes at the cost of lower corporate innovation.

Keywords: Corporate Innovation, Government subsidy, Government-owned Banks, Technological Change, Credit Allocation, Political Economy
JEL Classification: F34, F37, G21, G28, G33, K39

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1 Introduction

An important debate in economics is whether governments can spur economic activity by providing subsidies to innovative entrepreneurs. The presence of certain frictions associated with financing innovative projects, such as moral hazard, adverse selection or positive externalities (Benfratello, Schiantarelli, and Sembenelli (2008), Chava, Oettl, Subramanian, and Subramanian (2013), and Nanda and Nicholas (2014)), could be a rationale for such a government intervention. This motive might explain the substantial presence of government-owned financial intermediaries in many advanced economies around the globe. In this paper, we investigate empirically the ability of *government-owned* financial intermediaries to select promising innovative projects and foster technological progress. Further, we study whether the presence of government-owned financial intermediaries fosters aggregate corporate innovation, or alternatively, results in crowding-out innovation in the corporate sector.

Theory is ambivalent about the effect of government ownership of financial intermediaries on corporate technological progress. On the one hand, government-owned banks might alleviate market failures in financing innovation.[1] The most important market failures are asymmetric information and moral hazard (Carpenter and Petersen (2002), Hall (2002)),[2] as well as positive externalities generated by the provision of external finance for innovations.[3] The existence of such externalities might be a rationale for a subsidy in the form of government financing (Hainz and Hakenes (2012)).

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), Carvalho (2014)). 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 impede an ef-

[1] According to Lin, Srinivasan, and Yamada (2015) and Coleman and Feler (2015), government-owned banks can mitigate financial shocks, suggesting that lending markets are likely to be characterized by market failures.

[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 (Stoneman (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 (see also Herrera and Minetti (2007)). Moreover, the firm-specific assets that embody the new technology may not serve as good collateral in mitigating those moral hazard issues.

[3] Such externalities are first of all technology spillovers, but can also take the form of regional employment prospects. See Romer (1990), Aghion and Howitt (1992) or Aghion, Howitt, Brant-Collett, and García-Peñalosa (1998) for an overview.

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

ficient allocation of resources by preventing capital from being channelled to new and innovative enterprises. Furthermore, firms cannot easily get around this by switching to private banks. Such switch is likely to be hindered by severe information asymmetries and moral hazard issues associated with financing innovation. If this is the case, a strong presence of government-owned banks could potentially crowd out innovative investments since some firms are "stuck" in lending relationships with government-owned lenders.

Given these seemingly opposing arguments, the effect of government bank ownership on corporate innovation remains an empirical question that this paper tries to address. We construct a unique dataset that allows us to observe individual corporate lending relationships. For a sample of more than 200,000 German enterprises, we determine their credit relationships through the Bundesbank credit register from 1993. Merging this dataset with patent information from the European Patent Office, we can measure firms' innovation activities, as well as the ownership structure of their lenders.

The main finding is that government ownership of banks has a negative effect on firm innovation. We first document that government ownership of banks not only curbs the absolute amount of innovation, but also affects the probability that a firm starts or terminates innovation. With government-owned banks as its main lenders, a typical firm is around 20% less likely to initiate innovation and 25% more likely to cease innovation. We further document, in the intensive margins for innovators, the negative correlation between a higher share of financing from government-owned banks and the number of granted patents. Moreover, the number of patent applications, the number of quality-adjusted patents, and the success rate of patent applications, all decrease with more financing from government-owned banks.

The above correlation, albeit informative about the implications of government ownership of banks, are subject to endogeneity concerns. Firms might choose a specific type of banks according to their innovative activities. To circumvent the endogeneity problem, we use *the timing of government-owned banks' distress events in local electoral cycles* as an instrument for the local supply of capital from government-owned banks. In Germany, local government banks tend to cover pre-defined regions and local politicians have a strong influence over the operations of these banks. The timing of a distress event in the local electoral cycle determines the relative likelihood of a full bailout by the local politician versus restructuring by an insurance fund (Bian, Haselmann, Vig, and Kick (2018)), with the latter negatively impacting the local presence of government-owned banks.

To illustrate, consider two counties (A and B) in which the local government-owned banks experience similar distress events. One crucial difference is that the distress takes place right before the local election in county A while in county B the distress is far away from the next election. Due to his concern on the imminent re-election, the local politician refrains from bailing out the bank using tax payer's money in county A. Then the insurance fund is more likely to step in and impose a tight restructuring plan, which usually leads to a considerable reduction in the share of credit provided by government-owned banks in the local area. In county B, the politician tends to bailout the bank and keeps the bank at its original size. Therefore, county A experiences a negative shock in the presence of government-owned banks compared with county B. Using detailed information on 148 distress events of German local government banks, we indeed find that experiencing distress events right before elections leads to an eight percentage points decrease in the future share of loans extended by government-owned banks, corroborating the relevance of our instrument.

Using this identification strategy, we confirm our previous finding that more financing from government-owned banks leads to less innovation. A one percentage point instrument-induced reduction in the share of funding from government-owned banks results in an approximately 7% increase in the total number of granted patents in a typical affected county. Given that an average county in Germany receives around 30 patents per year, this translates into about two more patents per year. The negative impact of government bank ownership on innovation is persistent, with similar magnitude lasting more than five years. Importantly, the IV results also imply that the previous findings documented using OLS are not driven by the selection of lending relationships based on firms' preference to innovate. Moreover, by studying the nature of firms' innovation output, we find that following an exogenous increase in government bank funding, firms are in particular less likely to successfully develop innovative projects that are complex and exploratory.

To shed light on the mechanism, we provide evidence that the allocation of credit is more responsive to the financing needs of future innovators amongst private banks. Specifically, government-owned banks allocate 3.6% more credit to firms with high innovation potential compared with the rest of firms. In contrast, private banks allocate 7.5% more to future innovators. Overall our results indicate that government involvement in the allocation of credit crowds out private banking that are more effective in promoting innovation. As a result, investment in innovation and its output are negatively affected. Creative destruction is also impeded, suggesting another channel through which a higher government bank ownership leads to undesirable performance in innovation. Given that R&D is a crucial driver of economic growth, this paper casts doubt on government interventions in the banking industry.

We do a wide range of tests to support the validity of the instrument. We first make sure that the occurrence of savings bank distress events does not depend on the electoral cycle. We next examine covariate balance and parallel trends. There is no systematic relationship between the business cycle and the electoral cycle so that our results are not likely to be driven by election-induced business cycles. By focusing on the long-run effect following distress events, we also make sure that politician- or election-induced cyclicality, if any, is not likely to play a role. In the end, we try to rule out the alternative explanation that a politician may implement R&D

related policies right before an election to improve his chance of getting re-elected. Specifically, the distress events we exploit take place at county level while R&D policies are usually launched at a higher level.

The paper connects to several strands of literature. First, it is related to papers investigating the link between the financial sector and technological progress (see e.g. King and Levine (1993),Hall and Lerner (2010), Kogan, Papanikolaou, Seru, and Stoffman (2012)). Herrera and Minetti (2007) find that a stronger relationship between lenders and borrowers, proxied by the duration of the credit relationship between them, promotes innovation. Hombert and Matray (2017) argue that a negative shock to lending relationships deters innovation, especially for small and opaque firms. For a sample of large, publicly traded US firms, Atanassov (2015) documents that more innovative firms in fact prefer arm's length financing to relationship borrowing. Our paper diverges from the above literature by differentiating two categories of lending relationships: those formed with government-owned banks and those with private banks. We find that firms' decision to innovate and their innovation outcome strongly depend on the ownership structure of their lenders.

This article is also related to a broader literature investigating how to optimally finance innovation. Bank credit, as a source of financing for innovation, gradually draws attention in recent years.[5] Nanda and Nicholas (2014) highlight a negative relationship between bank distress and the level, quality and trajectory of firm-level innovation during the Great Depression. Amore, Schneider, and Žaldokas (2013) document the benefits brought by interstate banking deregulation to both the quantity and quality of innovation activities. Despite the common use of debt financing for innovative firms, Mann (2016) shows that patents are often pledged as collateral. The use of bank credit in supporting innovation is especially common in Germany, where the financial sector is bank-based. Exploiting the ownership structure of banks, we add to this literature by documenting heterogeneity across banks in promoting innovation.

This paper points out a new channel through which government ownership of banks can influence long-term economic growth, supplementing the literature pioneered by Beck, Levine, and Loayza (2000) and La Porta, Lopez-De-Silanes, and Shleifer (2002). These cross-country studies in general find a robust negative correlation between government ownership of banks and economic performance. Our paper provides evidence at the micro level by focusing on firms' innovative activities, which has long-term implications for the real economy. Our results are broadly in line with the political view of government bank ownership.

The remainder of this paper is organized as follows: Section 2 describes the German banking system, Section 3 explains the construction of our dataset, provides descriptive statistics, and

[5]Kerr and Nanda (2015) argue for the (surprising) importance of bank finance in innovation.

introduces the empirical strategy used in the following sections. In Section **??**, we presents the results and Section 7 concludes.

2 Institutional Background

2.1 The German Banking Sector

The German financial sector is bank-based, with a universal banking system. One of the particularities of the German banking sector is the so-called three pillar structure which refers to the three different legal ownership forms of German banks. The three forms are government-owned banks, private banks and credit cooperatives. While credit cooperatives mostly specialize in household and small business finance, private and government-owned banks compete for enterprise financing. In the following, we focus on the differences between government-owned banks and private banks. Together, these two groups hold 84.5% of the total assets of German banks (39% held by private banks and 45.5% by government-owned banks, see Table 1). While the market share of government-owned banks in Germany is relatively high by European standards (Hartmann, Heider, Papaioannou, Duca, and Marco (2007)), a high share of government involvement in the banking sector is not uncommon elsewhere. La Porta, Lopez-De-Silanes, and Shleifer (2002) find that, for a large sample of countries, on average 40% of the banking sectors were controlled by governments in 1995.

The specific structure of the German banking sector has evolved over time. The first public saving banks were founded in the 18th/19th century in Germany in order to make savings accounts accessible, and the first joint stock banks were founded in the 19th century.[6] The structure of the government-owned banking sector is the result of laws implemented at the beginning of the twentieth century and after the second world war. This so-called "Sparkassengesetz" gave rise to a country wide community banking sector. Nowadays, government-owned banks, also referred to as saving banks, are owned by local communities and state governments. The regional principle requires community banks to supply local finance and prevents competition between government-owned banks, by forbidding them to serve customers beyond their community. The objectives of government-owned banks as laid down in the respective laws (e.g. Sparkassengesetz (2005) and Sparkassengesetz (2008)) are manifold: e.g. ensuring the availability of credit to enterprises and communities as well as facilitating individual savings.[7] The difference in objec-

[6] See Krahnen and Schmidt (2004) and Brunner (2004) for more information on the German Banking market.

[7] Commonly this legal framework includes a statement that profit maximization is not the main objective of government-owned banks and that they have to serve common welfare. Other objectives are to provide a checking account to every private person, irrespective of their income, and the economic education of the youth (see the "Sparkassengesetze", "Sparkassenordnung" and "Landesbankgesetz" of the Länder in Germany).

tives of government-owned and private bankers is the main difference between the two groups of banks.

The German banking sector consists of 2,277 banks and nearly 40,000 bank branches.[8] The legal framework, however, prohibits consolidation between private and government-owned banks. Consolidation can only take place within each of the pillars, so that competitive pressure through M&As is low for government-owned banks. A typical example for the local distribution of private and government-owned banks is shown in Figure 1 for the district of Karlsruhe. As can be seen in this graph, government-owned banks possess a dense branch network in rural as well as urban areas. The strong presence of government-owned banks in rural areas is a result of the aforementioned regional principle. As a consequence, rural areas have an especially high branch density, so private banks generally tend to concentrate their branches in urban areas.

2.2 Distress and Bailouts among Government-owned Banks

To generate exogenous variation in the split of funding between government-owned banks and private ones, we exploit the distress events of saving banks and the subsequent bailout decisions. We first introduce the important institutional details on those distress events and the bailout regime.

German savings banks are owned by municipalities and the head of the respective municipal government, or the local politician, acts as the chairman of the local savings bank's supervisory board.[9] Their position as a chairman of the board gives local politicians a strong influence on the operations of the bank (e.g., the appointment of bank management and the allocation of earnings). While savings banks in distress will always be bailed out, there are two different ways in which the bailout can be organized: by the *saving bank association* that operates a safety net for these banks on the state level, or by the *local politician* who can inject tax payer's money into the distressed bank. Those two types of bailout regime imply divergent trajectories of post-bailout government-owned banks' presence. If the local politician organizes a bailout, the size of the regional bank remains the same or grows slightly larger in the following years. On the contrary, if the association imposes a restructuring plan, it either results in a downsizing or a distress merger with a neighbouring government-owned bank. Consequently, the share of loans provided by government-owned banks is drastically reduced in the respective area. Therefore, the bailout type is an important determinant of government-owned banks' future presence.

[8] Within Europe, Germany is among the countries with the highest number of credit institutions, branches and bank employees, see ECB (2016) for details.

[9] The supervisory board of a savings bank has about 15 members. The members besides the chairman are representatives from local authorities (in most cases politicians from the local parliament who account for about two thirds of the board members).

However, we cannot directly use the bailout type to instrument future presence of government-owned banks since their relation can suffer from endogeneity concerns. We address this issue by using the timing of distress events over the electoral cycle as an instrument instead. The intuition goes as follows: local politicians refrain from bailing out government-owned banks if the distress event occurs shortly before an election[10]. Combined with the strong correlation between bailout types and government-owned banks' future presence, we can then build a link between *the timing of distress events in the electoral cycle* and *the future presence of government-owned banks*. More specifically, if the distress takes place right before an election, we should expect lower presence of government-owned banks in the respective area since the association is likely to impose a restructuring plan on the bank.

The definition of state-owned bank distress events is based on Bian, Haselmann, Vig, and Kick (2018). Overall, we identify 148 distress events of German savings banks during our sample period from 1995 to 2010. Among these 148 distress event, more than one third (55 cases) was resolved by capital injections from the owner. The remaining 93 events were dealt with by the association. The regions exposed to those distress events and the firms located in those regions constitute the set of objects that we investigate to uncover the causal relationship between government-ownership of banks and innovation.

3 Data and Empirical Strategy

3.1 Data Sources

Data used in this paper are from multiple sources, which are briefly described below. Definition of key variables and details on the data sources can be found in the appendix.

Contract Level Loan Data. The credit register at the Deutsche Bundesbank provides contract-level information on all German firms, whose total outstanding loans in a given quarter exceed €1.5 million. We use the detailed loan data to calculate the lender composition and identify the top/main lender (state v.s. private) of a firm. The loan information is also collapsed at certain geographical levels to conduct analyses at the aggregate level.

Patent Data. Patstat provides information on patenting activities carried out by German firms. We use a disambiguated version of the Patstat named CRIOS-PatStat. The dataset allows us to measure innovation intensity, quality, and diversity in many different ways.

[10]More specifically, we find that the probability of bailout by local politicians is more than 30 percent less likely if the distress event occurs in the year before the election as compared with the years after the election.

Firm Balance Sheet Data. The firm level accounting information is collected from the Deutsche Bundesbank's USTAN[11] database. Firms covered by USTAN are then matched with loan-level information from the credit register and patent information from Patstat.

Distress Events and Election Variables. In order to generate exogenous variation in the presence of government-owned banks, we use the occurrence of distress events of government-owned banks over the electoral cycle as an instrument. Therefore, we collect information on distress events and city/county elections. Data on distress events utilizes information from several sources, including the Bundesbank's prudential data base for banking supervision (BAKIS), the monthly balance sheet statistics (BISTA), the borrowers' statistics, and the Bundesbank's data base on distress events. A detailed description of the those datasets and the method to identify distress events are available in Bian, Haselmann, Vig, and Kick (2018). Data of the election dates is obtained from the respective state election offices.

Macro Variables. In order to control for the different regional environments in which firms operate, we also collect information on macroeconomic variables from 16 German State Statistical Offices.

3.2 Measuring Innovation

To measure the innovation activities of firms, we collect data on the applications and grant of patents for our sample firms. Patent-based measures have been used in a wide range of empirical studies to evaluate innovation activities of firms and have been found to be superior to accounting figures as a proxy for corporate innovation (Griliches (1990), Trajtenberg (1990)).[12]

Using data from the European patent office (EPO), we calculate the number of patent applications filed in a given year that are later granted and the number of citations received by those patents. Citation counts may be subject to truncation problems since a patent tend to receive citations over a long period after publication. Therefore, for newly granted patents, the window to collect citations is shorter. Furthermore, patents in different technology fields may have divergent trajectories of citations, and this pattern is not accounted for when we use a simple citation count. To deal with these issues, we scale the number of citations received by each patent by the average number of citations received by all the patents that belong to the same technology field and are granted in the same year. [13] We further construct an indicator for high quality patents. It equals to one if a patent is in the top 10% of patents from the same

[11] See https://www.bundesbank.de/Redaktion/EN/Standardartikel/Bundesbank/Research_Centre/research_data_micro_data_ustan.html

[12] 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 (2008), and Hervé Stolowy and Anne Jeny-Cazavan (2001)).

[13] The International Patent Classification (IPC) divides technology into eight sections with approximately 70,000 subdivisions (see http://www.wipo.int/classifications/ipc/en/). We use 3-digit technology class.

year and technology class in terms of citations received. We use the application year rather than the grant year of a patent since previous studies have argued that the former is more likely to capture the actual time of innovation activities (Griliches (1990)). To avoid the truncation problem in patent counts due to lag between patent applications and patent grant, we limit the sample to 1993-2011[14]. We also construct a binary variable classifying firms into innovators and non-innovators based on a firm's patenting history. Table B1 provides more definition of variables.

3.3 Measuring Ownership of the Lenders

Lenders in the credit register are coded into two groups – government-owned and private-owned – based on information about their ownership structure. Next we construct three variables to measure the lender composition of each firm. The first measure, $State\_Share$, is the share of loans extended by government-owned banks in all loans received by a firm, and this is a continuous measure varying between 0 and 1. We also categorize firms according to the ownership structure of their top lender. The indicator $State\_Top$ equals to 1 if the top lender of a firm is government-owned. As argued by Diamond (1984), a firm's top lender generally functions as a delegated monitor for the other lenders. Therefore, $State\_Top$ conveys information not only on the most important funding source, but also its monitor and information producer. The third measure indicates whether a firm receives more than half of their loans from government-owned banks. The indicator $State\_Main$ equals to 1 if this is the case, suggesting that the firm relies mainly on government-owned banks for its financing. The correlation among the three measures is reasonably high. We use all of them to facilitate interpretation of the results and ensure the robustness of our findings.

3.4 Sample Construction and Descriptive Statistics

Our sample construction starts with all the firms in the credit register, which provides information about the type of corporation, industry, location, and lending relationships on a quarterly basis. The information on lending is then aggregated by year to facilitate matching to the annual data on patenting activities. The sample spans from *1993 to 2011* since credit register is available only from 1993 and the lag between patent application and grant suggests potentially incomplete information on patenting outcomes after 2011. To obtain firm-level accounting information, we further merge the dataset with USTAN. In the end, we have 287,605 firms in the full sample, out of which, 19,486 ever innovate, and 26,585 with detailed accounting information. We use different samples in our analysis to serve difference purposes. The full sample

[14] Although the data is until end of 2015, from 2011 the total number of patents applied and eventually granted by 2015 significantly decreases.

paints a more complete picture of the German economy. The subsamples allows us to focus on larger firms that are more likely to innovate, and include more firm-level control variables in the empirical tests. By focusing on firms with innovation history, we can explore more on the intensive margins.

Descriptive statistics are displayed in Table 2. Panel A provide information on the full sample, which includes all the credit registry firms. Panel B focuses on the subsample with balance sheet information (B/S subsample) while Panel C includes only firms that have ever patented. On average, a firm in Germany, regardless of its size and industry, applies for 0.188 patents a year, out of which 0.071 are eventually granted and receive 0.233 citations in total. Around 11% of all firm-year observations belong to firms defined as *Innovative*, or with patenting history during the sample period. A typical German firm receives bank loans of around €28.41 million, with roughly two banks involved. The government-owned banks provide slightly over 40% of the loans. Turning to the B/S subsample in Panel B, we observe significantly higher values in both the patent-related and loan-related variables. Firms are larger, more likely to innovate and have their patent applications approved. In the end, Panel C restricts the sample to innovators and those firms are also considerably larger (by total loan size) compared with a typical firm from the full sample. An average German innovator submit more than 1.7 patent applications per year and 0.66 of them are eventually granted. Those innovators only have 34.5% of their loans provided by government-owned banks, much lower than the share in the case of the full sample (40.7%) and the B/S subsample (37.1%). This simple comparison loosely illustrates the negative correlation between government-ownership of banks and innovation.

We further split firms into two subsamples based on the ownership structure of their main and top lender. We summarize the innovative output in Table 3. We use the full sample here, but the subsample with balance sheet information exhibits similar patterns. Panel A lists statistics for firms that obtain more or less than 50% of their credit from government-owned banks. In terms of innovation output, a firm with government-owned main lender receives 0.036 patents while a firm with private main lender more than doubles that amount. The same is true for the other patent-related measures. Firms with private main lenders are 30% (0.107 v.s. 0.078) more likely to be innovative. They also seem to be larger with a greater amount of total loans from more lenders. Moreover, all the differences between these two groups of firms are significant at 1% level. Categorizing firms based on top lender ownership rather than main lender ownership hardly changes any of the patterns documented above (Panel B of Table 3). The negative correlation between financing from government-owned banks and innovation is remarkable and merits further, more rigorous investigation. In the following subsection 3.5, we introduce our approach to establish causality between government ownership of banks and innovation.

3.5 Empirical Specification

The first step is to find out the correlation between ownership of lenders and innovation in a multivariate setting. To start with, we use the following Cox proportional hazards model to study how entry and exit of innovation relate to the ownership of lenders. The purpose is to understand if a firm's decision to initiate or terminate innovative activities is associated with the ownership patterns of lenders. A firm enters innovation when it first applies for a patent and exits when it stops applying for any patent.

$$Pr_{entry/exit_{i,t}} = \phi(\boldsymbol{\alpha_t} + \boldsymbol{\alpha_j} + \beta State\_Share_{i,t} + \boldsymbol{\phi' X_{i,t}} + \boldsymbol{\delta' C_{k,t}}) \tag{1}$$

Next we run the following fixed effects model to estimate the correlation between firms' innovative output and the ownership patterns of their lenders.

$$y_{i,t} = \boldsymbol{\alpha_t} + \boldsymbol{\alpha_j} + \beta State\_Share_{i,t} + \boldsymbol{\phi' X_{i,t}} + \boldsymbol{\delta' C_{k,t}} + \mu_{i,t} \tag{2}$$

where i indexes firm, t indexes time, j indexes industry, k indexes the geographical location of the firm. Variable $y_{i,t}$ stand for measures of firm-level innovation based on patenting activities. Time and industry fixed effects are captures by $\boldsymbol{\alpha_t}$ and $\boldsymbol{\alpha_j}$, respectively. Vector $\boldsymbol{X_{i,t}}$ and $\boldsymbol{C_{k,t}}$ stand for firm and local macro control variables. Our variable of interest, $State\_Share_{i,t}$ (or $State\_Top_{i,t}$, $State\_Main_{i,t}$) measures the composition of bank loans of a firm. The coefficient estimate on $State\_Share_{i,t}$, denoted by β, captures the effect of bank ownership on the amount of innovation. We include industry rather than firm fixed effects since the explanatory variable $State\_Share_{i,t}$ (or $State\_Main_{i,t}$, $State\_Top_{i,t}$) usually exhibits small within-firm variation.

Any correlation observed between the ownership patterns of banks and corporate innovation could be driven by the selection of lending relationships based on firms' preferences to innovate or, alternatively, by the differential implications of government versus private ownership of banks on corporate innovation. Our primary goal is to differentiate between these two explanations. The first explanation points to the selection bias underlying the previous fixed effects regression models. In particular, firms that plan to innovate in the future may choose a government-owned or private bank depending on the banks' willingness to finance new technologies. Ultimately, this is an omitted-variable bias. For a certain firm, its innovation potential or likelihood to patent is unobservable ex-ante. We can only observe innovation outcome, e.g. patents, ex-post. Moreover, the direction of such selection bias is unclear. If private banks are matched with firms that have higher innovation potential, the OLS coefficient is overestimated. However, if government-owned banks, through which governments implement their innovation stimulus agenda, provide credit to high potential firms, OLS may underestimate the true effect.

To overcome this selection issue, we exploit the exogenous variation in the presence of government-owned banks arising from electoral cycle and bank bailouts. Specifically, we adopt the following IV approach by using an instrument described in Section 2.2. We focus on the subsample of firms located in areas with government-owned bank distress events. We start by estimating the following first stage regression:

$$State\_Share_{i,t} = \boldsymbol{\alpha_t} + \boldsymbol{\alpha_j} + \theta PreElect_{k,t} + \boldsymbol{\phi_1'} \boldsymbol{X_{i,t}} + \boldsymbol{\delta_1'} \boldsymbol{C_{k,t}} + \mu_{1i,t} \tag{3}$$

In Equation 3, the instrumental variable from utilizing the electoral cycle is $PreElect_{k,t}$, which equals to one if the government-owned bank distress event takes place 0-12 months before the local election and zero otherwise. The underlying economic intuition for the instrument works as follows. The timing of distress event in the electoral cycle strongly affects the probability of capital injection organized by local politicians versus restructuring organized by savings bank associations, which shakes the future presence of government-owned banks in the respective area. As will be discussed in Section 5.1, the timing of the distress event and the following bailout in an electoral cycle can be considered as a shock since bankers or politicians do not have the opportunity to delay distress events under strong supervisory. This shocked-based instrument approach thus share the same advantages argued by Atanasov and Black (2016).

To estimate the effect of lenders' ownership on subsequent innovative activities of firms, we estimate the following second stage regression:

$$y_{i,t} = \boldsymbol{\alpha_t} + \boldsymbol{\alpha_j} + \beta \widehat{State\_Share}_{i,t} + \boldsymbol{\phi_2'} \boldsymbol{X_{i,t}} + \boldsymbol{\delta_2'} \boldsymbol{C_{k,t}} + \mu_{2i,t} \tag{4}$$

where $\widehat{State\_Share}_{i,t}$ is the predicted value of state loan share obtained from Equation 3. If indeed our instrument is a valid one, the coefficient of interest, β, captures the causal effect of bank ownership structure on firm innovation. Two stage least squares are used to estimate the equations. We double cluster the standard errors at the firm level and at the event-year level. The first cluster takes into account within firm standard error correlation across time and the second cluster takes into account within treatment unit correlation across firms. The detailed discussion on identifying assumptions is in Section 5.

4 Ownership Patterns of Banks and Corporate Innovation

We start with establishing the correlation between firms' innovative activities and the ownership structure of their lenders.

4.1 Extensive Margin: Entry and Exit of Innovators

We first study how a firm's choice to start or terminate innovative activities is associated with the ownership structure of its lenders. A dynamic and viable economy can be characterized by a larger number of innovative firms. Indeed, the OECD has called for policies towards less conditional R&D expenditure so that a larger number of firms or individuals could become innovators and promote the democratisation of innovation (see OECD (2014)). Therefore, it is important to understand the factors influencing the entry and exit of innovation. We estimate a Cox proportional hazards model with lenders' ownership as a key dependent variable.

We first focus on the decision to become an innovator. We find that at any given age, the probability to start innovation, i.e. hazard rate, is higher if private banks act as the main lender as opposed to government-owned banks (Figure 1a). The same is true when we compare firms with private top lender to those with government-owned top lender (Figure 1b).[15]

Equally important is a firm's decision to terminate innovation. We identify firms with patenting history and study whether the probability to exit innovation depends on the ownership structure of their main lenders. The results confirm the negative effect of financing from government-owned banks on innovation. At any given age, the likelihood to exit innovation is higher for firms with government-owned banks as the main lender relative to those with private banks (Figure 1c). Figure 1d reassures this finding when we compare firms with private top lender to those with government-owned top lender.

While Figure 1 graphically displays the difference between private and government-owned lenders in affecting a firm's choice to initiate or terminate innovation, Table 4 presents statistical evidence from Cox proportional hazards model. In column (1) of Panel A, Table 4, the continuous variable $State\_Share$ is used and the coefficient on it is negatively significant at 1% level. The magnitude is economically large: a standard deviation increase in $State\_Share$ is associated with roughly 10% lower probability of entry into patenting. When we use the indicator $State\_Main$ (or $State\_Top$) in column (2) (or column (3)), the results are similar: switching from a private main (top) lender to a government-owned one means that the firm is around 20% less likely to initiate innovation. Not surprisingly, large firms tend to have a higher probability of entry (size has a positively significant coefficient), since R&D usually requires considerable investment in equipment and application for patents itself can be costly for small firms[16]. Adding in time fixed effects barely changes the results, as shown in columns (4) to (6). The findings are robust

[15] When we turn to the subsample with balance sheet data in Figure A1a, the line for private main lender lie above the line for government-owned main lender, again suggesting a higher rate of entry into innovation for firms that financing mainly through private banks. Figure A1b exhibit similar patterns as compared with Figure 1b.

[16] The proxy for size is the log of total loans and this information is collected from the credit register. This is the only possible proxy of size given that the sample covers all firms, and most of which do not report their balance sheet information.

to using a more relevant sample where firms without balance sheet data are excluded.[17] We continue to explore the termination of innovation. The relevant coefficients and test-statistics are collected in Panel B of Table 4. In column (1), the coefficient on $State\_Share$ is 0.242 and it is significant at 1% level, indicating that a standard deviation increase in $State\_Share$ is associated with around 10% higher probability of terminating patenting activities. This effect is robust to alternative measures to gauge the importance of government-owned banks in a firm's financing (columns (2) and (3)), and to the inclusion of fixed effects (columns (4) to (6)).

Overall, the evidence in this section suggests a negative role of government-owned banks in supporting innovation. With more financing from government-owned banks, a firm is not only less likely to initiate innovation, but also more likely to cease innovation.

4.2 Intensive Margin: Innovator's R&D Outcome

Section 4.1 exhibits strong evidence at the extensive margins, and in the following subsection, we shift the focus to the intensive margins. Using the number of patents received by firms each year as the dependent variable, Table 5 reports the baseline regression results by estimating Equation 2. Columns (1) to (3) of Panel A include both the innovator and the non-innovators while columns (4) to (6) keep only the innovators. By focusing on innovators, namely firms with patenting history, we are able to not only examine the intensive margin, but also address the concern that our findings can be biased by the large number of observations with zero patents. The full sample covering all German firms with credit register record is used in Panel A. Regardless of the measure for the prominence of lending from government-owned banks, innovation seems to be negatively affected by more exposure to government-owned banks. In column (1), the point estimate suggests that a standard deviation increase in $State\_Share$ corresponds to a reduction in $lnN_{pt,gr}$ by 0.003. Considering that the mean of the dependent variable is 0.014 in the regression sample, it represents a decrease of more than 20%.[18] Note that this result is a mixture of the extensive margin and the intensive margin as we include all the firms regardless of their patenting history. We next focus exclusively on innovators in order to estimate the intensive margin. The coefficient on $State\_Share$ in column (4) is -0.068

[17] We use the more relevant B/S sample, which excludes firms without any balance sheet information, in columns (1) to (3) of Table B2. In this way, we make sure that our finding is not solely driven by small and insignificant firms. Furthermore, this allows us to control for time-varying firm characteristics. Nevertheless, the impact of government ownership of banks on firms' decision to start innovating is in the same direction and of similar magnitude when compared with the full sample. To be consistent with the specification in Table 4, we use total loans as a proxy for firm size, but substituting it with total sales or total assets hardly changes the findings.

[18] Here we cannot directly interpret the coefficient as percentage change since the mean value of patent counts is fairly small.

and significant at 1% level. In terms of magnitude, innovation output decreases by roughly 20% against its mean value with a standard deviation increase in $State\_Share$.[19,20]

While patent count is straightforward and easy to calculate, it cannot distinguish between revolutionary inventions and marginal technological improvements. To account for the differential values embedded in the vast universe of patents, we develop several alternative measures as the dependent variable, as displayed in Panel B of Table 5. The results here are obtained from investigating firms with patenting history, thereby, the innovators.

Column (1) of Panel B, Table 5 keeps the results using $lnN_{pt,gr}$ as the dependent variable to facilitate comparison across specifications. In column (2), we consider the number of patent applications, regardless of whether the application is successful or not. This variable may better capture the firm's innovation effort since the decision to grant a patent or not partly depends on the opinion of the patent office. Nevertheless, we observe a negative coefficient, significant at 1% level. In column (3), we study how a patent application's chances of being granted is affected by lender composition. While the other variables reveal information on the amount of innovation output, $grant\_rate$ allows us to investigate the efficiency of innovation. Importantly, the coefficient on $grant\_rate$ is negatively significant at 1% level, suggesting that more financing from government banks is associated with lower probability of success in patent applications. The magnitude is economically large: a 40% (roughly a standard deviation) increase in $State\_Share$ corresponds to a 12% lower probability of getting the patent approved. This finding suggests that firms obtaining credit from government-owned banks may be less creative and effective in their R&D projects.

Columns (4) to (6) turn to quality-adjusted measures. Column (4) exploits the citation information to calculate citation-weighted number of patents. The magnitude yielded by this specification is larger than that in column (1) where we use a simple count of patents. A standard deviation rise in $State\_Share$ corresponds around 15% drop in $lnN_{pt,gr}$ and close to 20% drop in $lncitN_{pt,gr}$. In column (5), we use technology class-year normalized citation measures as the dependent variable. The effect of $State\_Share$ is in the same direction and of similar magnitude when compared with column (4). In the end, we consider only the high-value patents, counting the number of patents in the top decile in terms of citations. The results in column (6) are consistent with our main findings. All the above results are robust to an alternative sample covering firms with balance sheet data and the inclusion of firm-level control variables, as shown by Table B4.

[19] This can be calculated by $(-0.068 \times 45.8\%)/0.155 = 20.1\%$.

[20] In Table B3, we add in controls for time-varying firm characteristics and re-run regressions using the subsample of firms with balance sheet information. Note that compared with the full sample, the average innovation output increases substantially: from 0.014 to 0.073 in column (1). Accordingly, the coefficient also scales up, and the magnitude remains comparable and economically large. For example, results in column (1) suggest that a 40% (roughly a standard deviation) increase in $State\_Share$ translates into a 15% drop in innovation output.

4.3 Switchers

Firms tend not to alter their lenders frequently, but for those that do change their main or top lender, an interesting pattern emerges. To be more specific, we focus on firms that have switched their main or top lender from government-owned banks to private ones, or vice versa. This allows us to graphically illustrate the dynamics of innovation around such switches.

Figure 2 displays the trends in innovation outcomes for two types of switchers in terms of the main or top lender: from government to private, and from private to government. Figure 2a focuses on the main lender switchers. The y-axis shows the average number of patents granted to such switchers. Both types of switchers seem to follow similar trends before the switching year, but they diverge after the switch. Firms switching from state main lenders to private ones have considerably more patents than firms switching in the opposite direction. The same pattern shows up when we study firms that have changed their top lender rather than main lender, see Figure 2b.[21] In addition, this pattern is robust to alternative measures of innovation, see Figure 2c for citation weighted count of patents and Figure 2d for citation counts scaled by technology-year mean value. Overall, we observe a coincidence of increased innovation and the switch into a private lender. It does not seem to be the case that innovating firms tend to choose private banks as the trend before the switching point is largely parallel. Thus, it is plausible that the financing from private banks induces innovation in these firms. In Section 5, we carefully examine if there is any causal relationship between the ownership structure of banks and innovation.

5 Does Government Ownership of Banks Stifle Corporate Innovation?

The evidence so far points to the undesirability of financing from government-owned banks in supporting innovation. These findings could be driven by the selection of lending relationships based on firms' preferences to innovate or, alternatively, by the crowding out of innovation due to the presence of government-owned banks. To differentiate between these two explanations, we need to identify the casual effect of government ownership of banks on corporate innovation. To this end, we use the timing of government-owned bank distress events in the electoral cycle to generate plausibly exogenous variation in the local presence of these banks. The instrument is introduced in Section 2.2 and the econometric specification is illustrated in Section 3.5. The intuition of this instrument works as follows. Local politicians refrain from bailing out government-owned banks using tax payer's money if the distress event occurs shortly before an

[21] Figure A2a and Figure A2b confirm similar findings in the subsample for firms with balance sheet information. These firms are larger and more active in R&D.

election. In these cases, it is more likely that the association steps in and implement a restructuring plan, which imposes tight restrictions on the operations of the bank and could, in the worst case, involve a distressed merger. Therefore, if the distress takes place right before an election, we should expect lower subsequent presence of government-owned banks in the respective area. In the following context, we start by arguing the validity of this instrument and then present the results.

5.1 Validity of the Instrument

For our instrument to be valid, it must first be an important determinant of local financing structure and thus affect the lender composition of a firm. Second, it must satisfy the exclusion restriction condition.

Relevance. The relevance of our instrument rests on the following two conditions: (1) strong dependence of the bailout type on the timing of distress in the electoral cycle; (2) significantly differential trends in the presence of government-owned banks following the two types of bailouts. The satisfaction of these two conditions are illustrated by Figure 3 and Figure 4a. Figure 3a shows that the distress events, irrespective of the type of the following bailouts, are distributed fairly equally over the electoral cycle. In contrast, Figure 3b shows that the frequency of bailouts by politicians display a clear pattern over the electoral cycle. In the 12 months before the election, the share of political bailouts in all distress events is considerably lower (15.4 %) than in the 12 months following the election (50.0 %). In fact, only one out of 55 cases of capital support by the politician occurs in the six months directly preceding an election. This suggests that politicians are reluctant to use taxpayers' money to support a distressed savings bank right before an election.

Figure 4a displays changes in the share of loans extended by distressed government-owned banks, in the years around the bailouts. Bailout decisions by local politicians seem to be associated with non-decreasing share of loans initiated by government-owned banks in the post-bailout years. On the contrary, restructuring imposed by the association seems to be followed by a considerable fall in the share of loans extended by government-owned banks. One rationale behind such shifts is that bailouts by the politicians tend to keep the distressed banks in operation while resolutions from the associations may result in branch mergers and closures.

In the reduced form, we can directly link the timing of distress events in the electoral cycle with future presence of government-owned banks. Figure 4b displays differential trends in the share of loans from government-owned banks that are subject to different types of bailouts. We find that, if the distress occurs before the election, which implies a higher chance of restructuring from the association, the share of loans from government-owned banks seems to decrease considerably. While in the case of a post-election distress, which implies a higher chance of bailouts by local politicians, the share slightly goes up. We further show statistical evidence from the first stage of the IV regressions in Table 7. The F-stat for the excluded instrument can also confirm the relevance of the instrument.

Exclusion Restriction. The exclusion restriction condition requires that the instrument should not affect the outcome variables through any channel other than its impact on the presence of government-owned banks. We take the following steps to address concerns on the exclusion restriction.

(1) *Distribution of distress events.* One important assumption for our identification strategy is that the occurrence of distress events per se does not depend on the electoral cycle. Figure 3a displays the distribution of all 148 distress events over the electoral cycle. We do not observe a clear relationship between bank distress events and the electoral cycle in Germany. This might be explained by a strong supervision of the banking sector, requiring the disclosure of monthly capital adequacy ratios. In such a supervisory environment bankers do not have the opportunity to delay distress events. We also confirm the irrelevance of the electoral cycle in influencing the occurrence of distress events by using a hazard model. Table B5 displays the model and results. The distress events are thus most likely to be driven by events that are uncorrelated with the electoral cycle. Indeed, most of the savings bank distress events are triggered by failure of big borrowers, which tends not to coincide with the electoral cycle.

(2) *Compare outcome variables.* We compare innovation outcomes prior to the treatment. In our setting the treatment corresponds to the distress event and the immediately followed bailouts. Table 6 shows that before the distress, there is no significant difference between innovation output for a firm exposed to pre-election distress and a firm exposed to post-election distress. Figure 5a and Figure 5b further presents the parallel trends in the pre-distress (or pre-bailout) period.

(3) *Covariate balance.* If our instrument is indeed exogenous, one should expect balance on pre-shock covariates. We examine whether there is a significant difference in the type of banks that experience distress events around the electoral cycle. To do so, we regress different bank characteristics in the year before the distress event on the electoral cycle indicator. We use all 148 distress banks in our sample. Results are shown in Panel A of Table B6. Banks that experience distress events before the election seem to not differ systematically in terms of absolute and relative size as compared with banks that experience distress events after the election. The same is also true with respect to customer loans to total assets ratio, deposit ratio, capital ratio, and profitability (measured by ROA). Turning to non-performing loans ratio and the ratio of loan loss provisions to customer loans, we also do not detect any significant differences. The banking sector

concentration level in areas exposed to pre- and post-election distress events is also similar, as indicated by comparable Herfindahl-Hirschman index. We then investigate whether the size of the bailout, or the severity of the bank distress, is correlated with the timing of the distress event in the electoral cycle. For example, politicians may find it easier to hide the failure of a relatively healthier bank. As a result, the size of bailout needed for post-election distress may be smaller than the pre-election ones. Using capital support over equity as the dependent variable, there seems to be no such correlation. The coefficient $D(0 - 12\ months\ before)$ is positively insignificant, suggesting that the severity of the distress, therefore the size of the bailout, is comparable for distress cases occurred before the election and those after.

(4) *Macro cycles.* Another potential concern could be that local politicians can influence regional economic conditions so that the outcome favours their probability of becoming re-elected. If this would be true, regional economic conditions would be correlated with the electoral cycle and this in turn may result in different prospects of firm innovation.To address this concern, we directly test whether the regional business cycle is correlated with the regional electoral cycle. In Panel B of Table B6, we find no significant differences between counties exposed to pre- and post-election distress events across a list of macro observables such as GDP per capita, GDP per capita growth, employment rate, employment growth, local government indebtedness, credit market growth and share of loans extended by state banks in the year before the distress and bailout event. The evidence confirms the balance of covariates for macro variables.

(5) *Long-run effect.* One may still be concerned about political business cycles that are not captured by the macro variables in Table B6. After all, the empirical evidence on this topic is inconclusive. While Julio and Yook (2012, 2016) and Jens (2017) document lower corporate investment in the election year, Drazen (2000) summarizes that there is little evidence of changes in economic activity before elections in the US or in any other OECD country. We take one more step to alleviate this concern. Studies supporting political business cycles usually examine how firm's behaviour changes *within* an electoral cycle. In contrast, we explore the *long-run* implications of the shake-up in the mix of government-owned banks and private ones. If the results are driven by other factors which covary with the electoral cycle, we are unlikely to observe significant long-run impact because any election-induced cyclicality tend to exist in the short term and within the electoral cycle. However, in Table 8, we find that the negative impact of higher government bank ownership, as a result of post-election distress events, remains highly significant even after five years.

(6) *County-level treatment.* One may argue that there can exist policies (such as R&D tax incentives) that target innovation, and politicians may adopt those policies before the

election to attract voters. However, this is unlikely to be the case since such policies are usually not made by the county-level government office.[22]. As a result, the local county-level elections are unlikely to be correlated with R&D policy changes.

5.2 Results: Instrumental Variable Estimation Using Local Electoral Cycles

As is evident from Figure 4b, having the distress events before the election (*Pre Election* group) results in considerably *weaker* presence of government-owned banks relative to having the distress events after the election (*Post Election* group). If indeed financing from government-owned banks is detrimental to innovation, we should expect faster growth of innovation in areas exposed to distress events that take place before the election. We first check whether this is true graphically. Figure 5a depicts the average successful patent applications for firms located in areas where the local government-owned banks experience distress events. We further split firms into two groups based on whether the distress events occur before or after the local election. For the *Post Election* group, there is not much variation over the event window. However, for the *Pre Election* group, we observe a substantial increase in the number of granted patents in the post-distress years, consistent with aforementioned conjecture. We then turn to the citation-weighted measure in Figure 5b and it shows that the number of citation-weighted patents is trending closely in parallel for *Post Election* and *Pre Election* groups in the years leading up to the event. However, in the post-event years, we find that innovations grows faster for the *Pre Election* group.

Corroborating Figure 5, Table 6 provides summary statistics supporting our identification strategy. We find that there is no difference between the *Pre Election* and *Post Election* group in the years before the treatment (column (3)), but the *Pre Election* group reaches a significantly higher amount of $N_{pt,gr}$ after the bailout event. The diff-in-diff estimator is significantly positive. The same remains true if we adjust $N_{pt,gr}$ by time trend, as shown in columns (4) to (6) or if we change the variable of interest to the citation-weighted measure, as shown in Panel B. Taken together, Figure 4, Figure 5 and Table 6 illustrate the negative consequences of increased government ownership of banks on corporate innovation. Furthermore, by exploiting savings bank distress and the following bailouts, the results also directly imply that bailouts organized by governments could be harmful for innovative activities in the corporate sector.

Both Figure 5 and Table 6 suggest that the reduced form of our IV approach works well. More importantly, the pre-event trend of the outcome variables confirms that our shock (the timing of the distress event and the following bailout in an electoral cycle) is likely to be random. With comfort in our IV method, we continue to report regression results from IV specifications

[22]Before 2012 there is no R&D tax incentives for a long period in Germany. OECD (2014) discusses the initiatives launched by the federal government.

in Table 7. First-stage regression results are reported in column (1). We find that the share of credit from government-owned banks is strongly influenced by the timing of the distress event in the electoral cycle. The coefficient on $PreElect$ is negatively and significant at 1% level. Firms located in areas where government-owned bank distress events take place before elections experience an eight percentage points drop in the share of loans provided by government-owned banks, assuring the relevance of our instrument. The reduced form results in column (2) are consistent with both Figure 5 and Table 6.

Column (3) of Table 7 exhibits the second stage regression results from IV. The coefficients on $State\_Share$ is negative and significant at 5% level. The instrument-induced ($PreElect$ from 0 to 1 or vice versa) exogenous variation in $State\_Share$ is around eight percentage points (column (1)), and this translates into a change in the outcome variable by 0.007 (0.08×0.091), which is around 50% of the mean value. The magnitude is consistent with the estimation in Table 6; corporate innovation in regions exposed to *Pre Election* distress experiences roughly a 50% increase (0.061 *v.s.* 0.04 or 0.165 *v.s.* 0.112), while that in regions exposed to *Post Election* distress is insignificant. Although the magnitude in percentage terms is remarkably large, but it is economically plausible. Given that there are on average 400 firms in each county, the total number of granted patents increases roughly from 16 to 24 for a county shocked by *Pre Election* distress events.[23] Therefore, financing from government-owned banks seem to severely impede innovation after we control for endogeneity problems. Columns (4) and (5) uses alternative explanatory variables $State\_Main$ and $State\_Top$, and the results are similar to those in column (3). Panel B takes the quality of innovation into account by employing a citation-weighted measure, and the results barely change. Note that the F-stat is above the rule-of-thumb (see Stock, Wright, and Yogo (2002)) critical value of 10 in all specifications, which corroborates the relevance of the instrument in explaining the endogenous independent variable.

Another concern is that the strong negative effect from the distress-induced higher presence of government-owned banks exists only in the short term so that our findings reflects only transitory changes. We study the dynamics of this effect in Table 8. Column (1) represents the average effect in all the years after the distress/bailout event while columns (2) to (4) show the dynamics of this effect over time. Importantly, the coefficients on $State\_Share$ varies little over columns (2) and (4). It remains strong and significant five years after the event. Overall, the negative impact of financing from government-owned banks seems to be highly persistent.

[23] This is calculated by using the estimation in Table 6. The average number of granted patents in *Pre Election* County is 0.04 before the distress/bailout, and increases to 0.061 afterwards. We further multiply those two numbers by the average number of firms (roughly 400) to calculate the change in aggregate innovation levels.

5.3 Discussion and Additional Results

A. Using Patents to Measure Innovation. One concern over the use of patenting information to measure innovation is that the number and quality of patents may not capture all the R&D effort and output of a firm. Firms carefully decide between patenting, thereby disclosing critical information on their technology, and keeping it secret (See Moser (2005) and Moser (2012)). Most relevantly, Saidi and Zaldokas (2017) propose that patents may act as a substitute for lending relationships. Therefore, if a firm changes its lender, it may choose to patent more to produce information. Applying this argument to our setting, firms in areas exposed to pre-election distress, which corresponds to restructuring, are more likely to experience a change of lenders and hence patent more. We argue that this is unlikely to drive our findings. First, firms that switched from private lender to government-owned lender should also patent more to fix the information asymmetry problem between them and their new lenders. However, we do not observe this in Figure 2. In fact, those private-to-government switchers tend to produce fewer patents after they switch. Secondly, the level of information asymmetry between the firms and the banks decreases with the duration of the lending relationship. As a result, the incentive to disclose information via patenting diminishes over time. However, we detect a long-run impact of changes in lenders' composition on patenting activities in Section 5.2, Table 8, which seems to contradict the argument above. Taken together, the observed negative correlation between government ownership of banks and patenting activities is not likely to be driven by the incentive to provide information for new lenders.

B. Additional Measures of Patenting Activities. In addition to quantity and quality of patents generated, we also construct four other measures to capture the nature of a firm's patenting output. In particular, we compute the "originality", "generality", "exploration" and "diversification" score for each firm's patent portfolio.[24] From the results in Table 9, we find that the coefficients on $State\_Share$ are all negatively significant across four specifications. Specifically, a lower originality and generality score for firms with more government bank funding indicates a narrower set of innovations, combining information from and contributing to fewer technology fields. A lower exploration score shows that those firms' patents are less likely to learn from technologies outside the firm's existing knowledge base. Finally, firms that finance more through government-owned banks have a less diversified patent portfolio. Overall, the evidence suggests that following an exogenous increase in the presence of government owned banks, firms are less likely to successfully develop innovative projects, in particular the ones that are complex and exploratory in nature.

[24] A description of the construction procedure is provided in Table B1.

6 Mechanism

In Section 4 and Section 5, we document a strong, negative impact of government ownership of banks on corporate innovation. It remains challenging to answer what is the underlying economic mechanism driving this relation. What makes private banks better in promoting innovation? In the following context, we take a first step to unveil potential driving forces.

6.1 Allocation of Credit to Innovative Firms

The political view of government bank ownership suggests that government-owned banks may not direct credit to high-potential innovative and disruptive firms compared with private banks. Government bankers care about stability and may depress restructuring as they are more willing to allocate resources to safe, less innovative projects. Government bankers might also engage in preferential lending and are subject to regulatory capture, potentially preventing capital from being deployed to finance innovative projects. Khwaja and Mian (2005) and **?** both document the undesirable features of political involvement in bank credit allocation. In the following tests, we focus on bank-level allocation of credit to innovative and non-innovative firms. A bank that is superior in promoting innovation should provide funds for high potential firms and help those firms convert their potential in R&D into intangible assets, such as patents. Accordingly, if private banks are more effective in eliciting high quality innovation, they are expected to allocate more credit to firms in the years preceding their successful patent applications.

To test the above conjecture, we first compare the share of credit allocated to firms that have successfully applied for patents amongst both government-owned and private-owned banks. Figure 6 exhibits a substantial difference. Government-owned banks on average allocate less than 10% of their total credit to innovating firms while private banks allocate more than 20%.

We then verify statistically whether government-owned banks are indeed less likely to extend credit to high-potential future innovators. Exploiting detailed loan contract level data, we run the following regression. The dependent variable is log loan amount for every bank-firm pair, measured by the end of each year. The dummy variable, $Future\ Innovator$, equals to 1 if a firm has at least one patent granted in the next five years and zero otherwise. The coefficient on this variable indicates how different types of banks respond to firms' innovativeness in their loan allocation decisions. Bank-firm fixed effects are included so that the coefficients pick up only within-relationship changes. Bank level shocks are absorbed by bank-year fixed effects.

In column (1) of Table 10, we find that government-owned banks allocate 3.6% more credit to future innovators. However, private banks allocate significantly more, around 7.5% more in column (2). The difference (3.6%-7.5%=-3.9%) is significant at 1% level, as indicated in column (3). Using more restrictive B/S or innovator subsamples does not change the above finding, as shown in columns (4) to (9). The allocation of credit within private banks tends to better promote innovation as they direct more credit to high potential future innovators. Government-owned banks, on the other hand, may not be able to fulfil the expanding financing requirement of future innovators. Moreover, this is unlikely to be driven by differential attitudes towards risk-taking within government-owned and private banks. More often than not, the presence of government protections induces higher risk-taking. Those banks are characterized by higher operating risk and lower default risk, as documented in Iannotta, Nocera, and Sironi (2013). Therefore, the difference in risk aversion is unlikely to drive our results.

Heterogeneity across industries in the negative impact of government-owned banks is consistent with the above political view. In industries that rely more on external financing and face more severe information asymmetry, the cost of switching lenders is higher, which may prevent firms from choosing the most appropriate financier subject to its innovation needs. As a result, future innovators may stuck with government-owned banks and are not able to obtain enough financing to convert their R&D investment into successful patent applications. If this is true, the negative impact of government funding on innovation is expected to be more pronounced in industries characterized by high cost of switching lenders. We exploit the following two cross-sectional variations to test this conjecture.

The first cross-sectional variation we examine pertains to firms' external financial dependence (EFD). Firms that rely more on external finance rather than their own cash flow are more likely to be affected by their lenders when making investment decisions. We investigate whether this argument is true when it comes to innovation decisions. We divide our sample into two subsamples based on whether the industry to which the firm belongs to has an EFD above the median.

We calculate EFD for each industry in the same approach as Rajan and Zingales (1998). We then separately study the role of financing from government-owned banks for both firms with low and high external financial dependence. The results are displayed in Table 11. Columns (1) and (2) use the log of patent counts as the dependent variable. Consistent with our conjecture, the coefficient on $State\_Share$ is close to zero for the low EFD group, while for the high EFD group, it is negative and significant at 1% level. The difference between those two coefficients is significant with a p-value of 0.017. We do not detect any significantly negative effect of financing from government-owned banks for firms that rely less on external finance across all other specifications (see columns (3), (5), and (7)). However, the negative impact remains large and significant among firms that rely heavily on external finance (see columns (4), (6), and (8)). This finding suggests that the detrimental impact of government funding on innovation is especially pronounced for industries with high financial dependence. As those industries also tend to be more research-intensive, the role of the ownership structure of financiers in determining innovation becomes even more crucial.

Next we examine how the technology opaqueness affects the negative effect of government ownership of banks on firm innovation. There are huge differences across industries in their technology: some industries use technologies that are easy to understand by the lenders, while in some other industries, their technology can be extremely complicated and specialized so that information collection and comprehension become costly for the lenders. In industries where the technology is more informationally opaque[25], it becomes rather costly to switch to new lenders. We then partition our sample into two subsamples based on whether the industry to which a firm belongs to is classified as more informationally opaque. We then separately study the role of financing from government-owned banks for both firms with low and high technology opaqueness. The results are collected in Table 12. Log of patent counts is used as the dependent variable in columns (1) and (2). The coefficient on *State_Share* is close to zero in the low technology opaqueness group, while for the high technology opaqueness group, it is negative and significant at 1% level. Using other outcome variables (columns (3) to (8)) mimics this finding. The evidence implies that financing from government-owned banks hinders innovation in technology fields that are more informationally opaque.

Overall, private banks seem to be superior to government-owned banks in identifying and financing high potential innovative projects.

6.2 Creative Destruction

Apart from less innovation by existing firms, the differential performance in innovation can also be driven by fewer disruptive entry and exit activities. Table 13 presents the estimations on firm births and deaths. In column (1) of Panel A, we find that the fraction of new-born firms is significantly lower in areas where the share of government bank financing is higher. The magnitude is considerable. Given that the average annual firm birth rate is approximately 8%, the instrument-induced increase in *State_Share* (around 8 percentage points) leads to a decrease in birth rate by 0.4 percentage points or 5% of the average birth rate.

The same pattern shows up for firm death. In column (1) of Panel B, the coefficient on *State_Share* is again negative and significant, indicating that firms die less frequently in areas with stronger presence of government-owned banks. The magnitude is even larger. The instrument-induced increase in *State_Share* leads to a decrease in firm death rate by 0.5 percentage points or 10% of the average death rate. Columns (2) to (4) of both Panel A and B show the persistence of the negative impact on creative destruction.

[25] We classify chemicals, machinery, computers, electrical machinery, TV–radio, medical apparels, means of transport as technologies that are more informationally opaque. The less technology intensive industries are in the less informationally opaque group.

Our findings on firm births and deaths point to a less dynamic macroeconomic environment (in line with Schumpeter's concept of creative destruction) as a consequence of more government bank financing. The results are consistent with the view that government bankers' incentives are manifold and thereby may be less willing to support creative destruction and more willing to allocate resources to old, often less innovative firms.

7 Conclusion

Providing external finance for corporate innovation is a key mechanism through which banks affect economic growth. We find that ownership (government versus private) of financial intermediaries has an impact on firms' innovation activity. These findings suggest that private banks are superior to government-owned banks in selecting successful innovative projects. One reason why the private sector appears to be better at stimulating innovation could be that private bankers have incentives to maximize shareholder value. Government bankers' incentives are manifold and thereby may be less likely to support restructuring activities and more willing to allocate resources to 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 suggests that government involvement in the allocation of credit to firms comes at the cost of lower innovation and thus lower growth.

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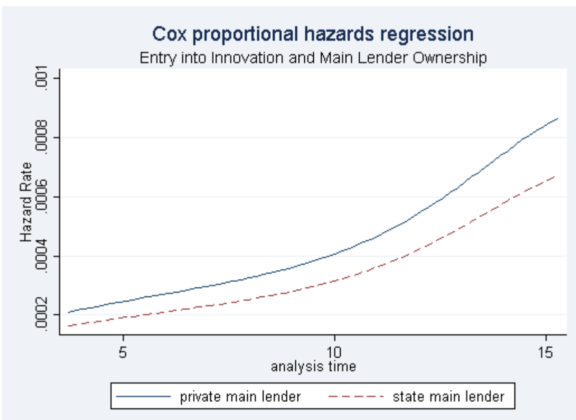
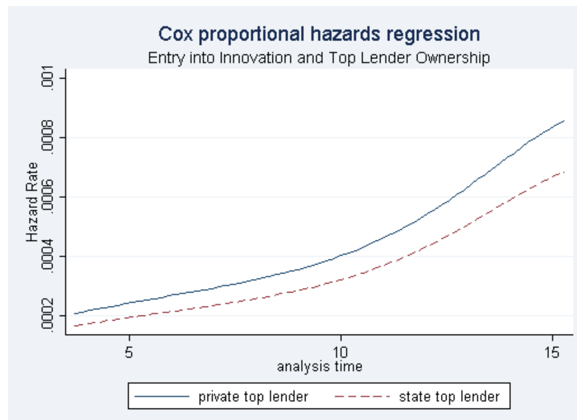
Table 1: Structure of the German Banking Sector

	Number of Institutes	Number of Branches	Share of Total Assets
All Banks	2,277	39,833	100%
Private Banks	278	11,286	39%
Government-owned Banks	458	14,109	45.50%
Credit cooperatives	1,236	12,488	15.50%

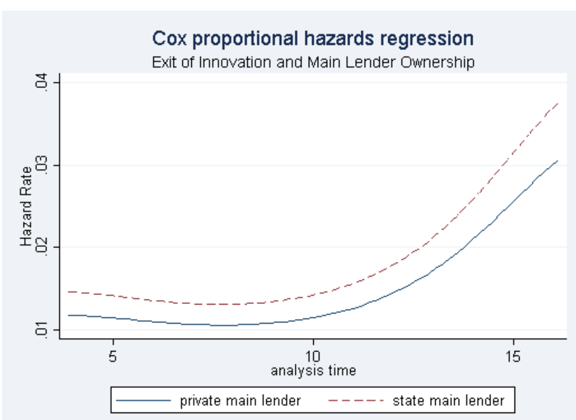
The table shows the structure of the German banking sector as of 2007. Information source: monthly balance sheet statistics (BISTA) from Bundesbank.



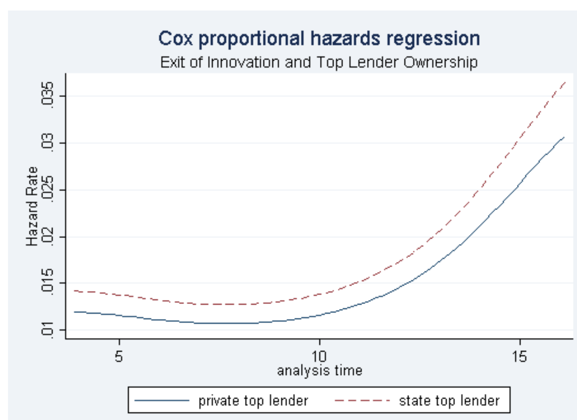
(a) Main Lender Ownership, Full Sample



(b) Top Lender Ownership, Full Sample



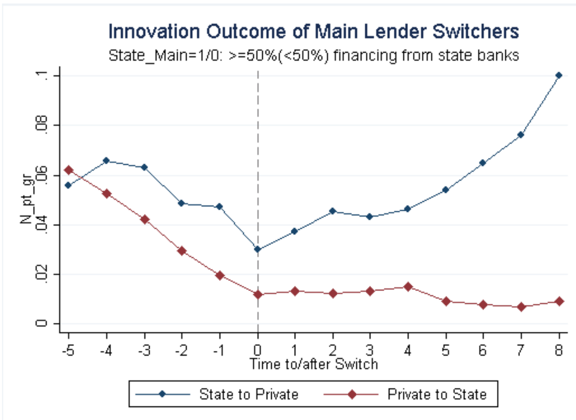
(c) Main Lender Ownership, Full Sample



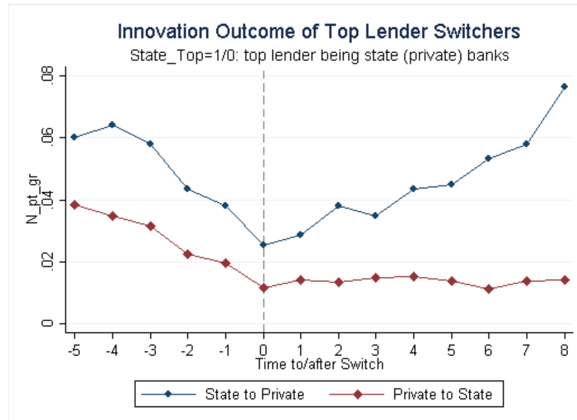
(d) Top Lender Ownership, Full Sample

Figure 1: Hazard Rate: Entry/Exit Innovation

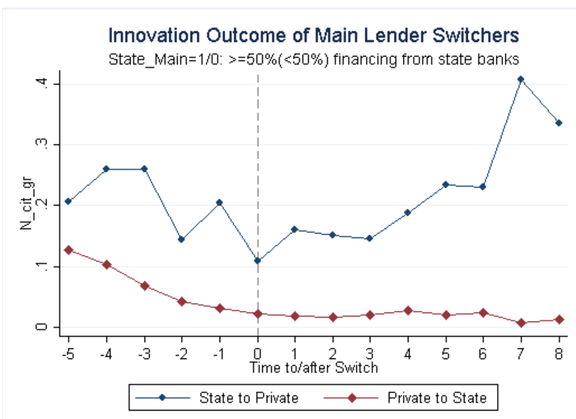
Figure 1 plots the probability of initiating/terminating innovation, i.e. hazard rate, for the firms with government-owned main/top lender (red/bottom dashed line) and private-owned main/top lender (blue/top solid line), at any given age. Figure 1a and Figure 1b study the entry into innovation while Figure 1c and Figure 1d study the termination of innovation. A firm with government-owned (private) main lender means that more than 50% of the firm's bank credit is from a government-owned (private) bank. A firm with government-owned (private) top lender means that the firm's biggest lender is a government-owned (private) one. Full sample covers all the firms with bank credit in Germany.



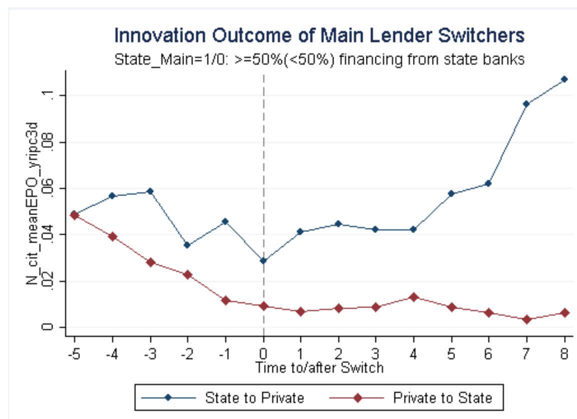
(a) Main Lender Switchers, Full Sample



(b) Top Lender Switchers, Full Sample



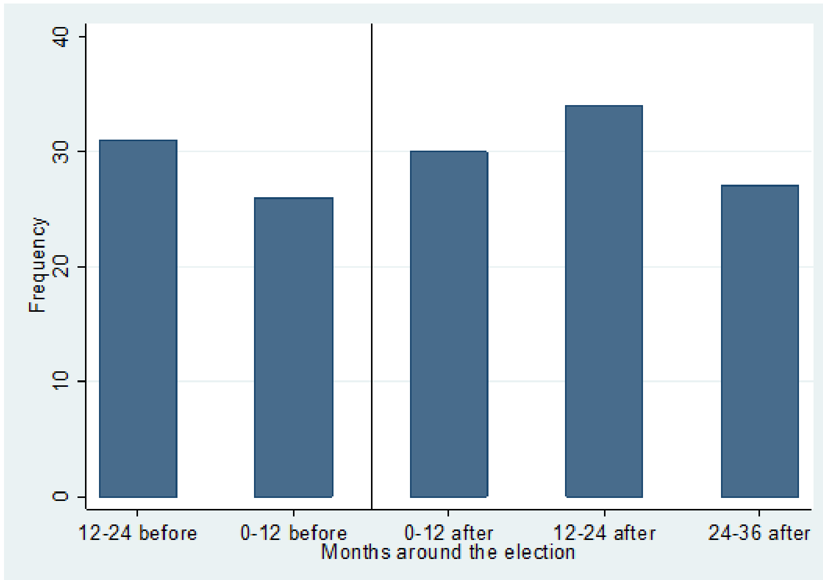
(c) Main Lender Switchers, Full Sample



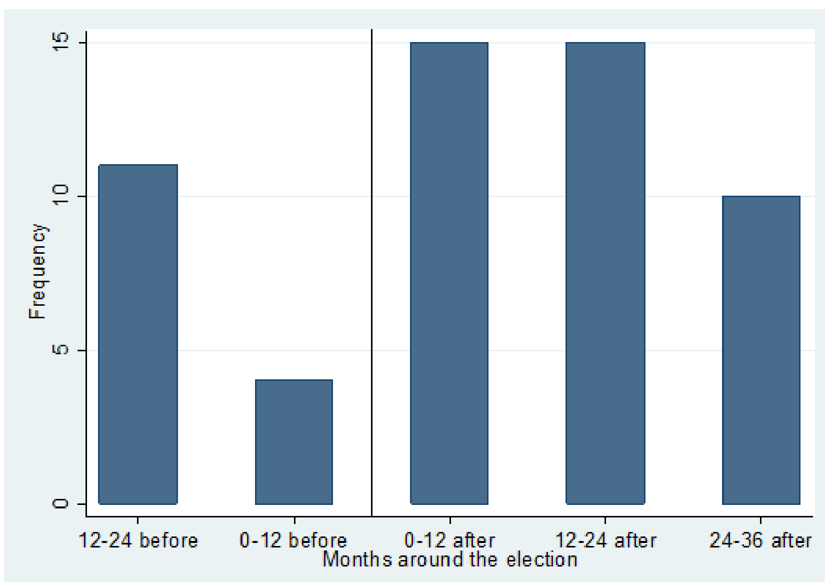
(d) Main Lender Switchers, Full Sample

Figure 2: Main/Top Lender Switchers and Their Innovation Outcome

Figure 2 illustrates the innovation outcome of main/top lender switchers in the years around the switch. In Figure 2a and Figure 2b, the outcome variable is number of patents granted to a firm in the respective year. In Figure 2c the outcome variable is the number of citations received by the patents granted to a firm (or citation-weighted patent count) in the respective year. In Figure 2d, the outcome variable is the *technology class-year* scaled number of citations received by the firms' newly granted patents. The blue (circle) line stands for the those switching from government-owned main/top lenders to private ones. The red (diamond) line stands for the those switching from private main/top lenders to government-owned ones.



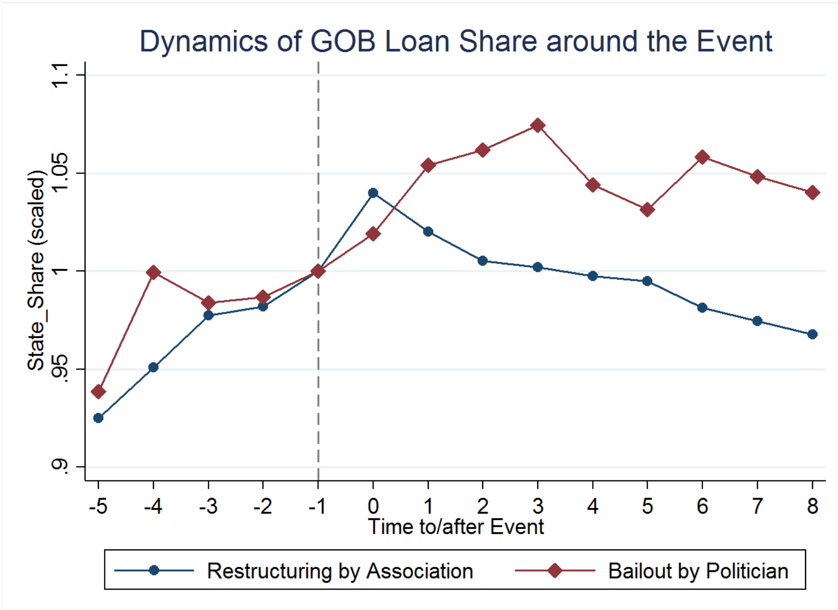
(a) Distribution of all distress events (all bailouts)



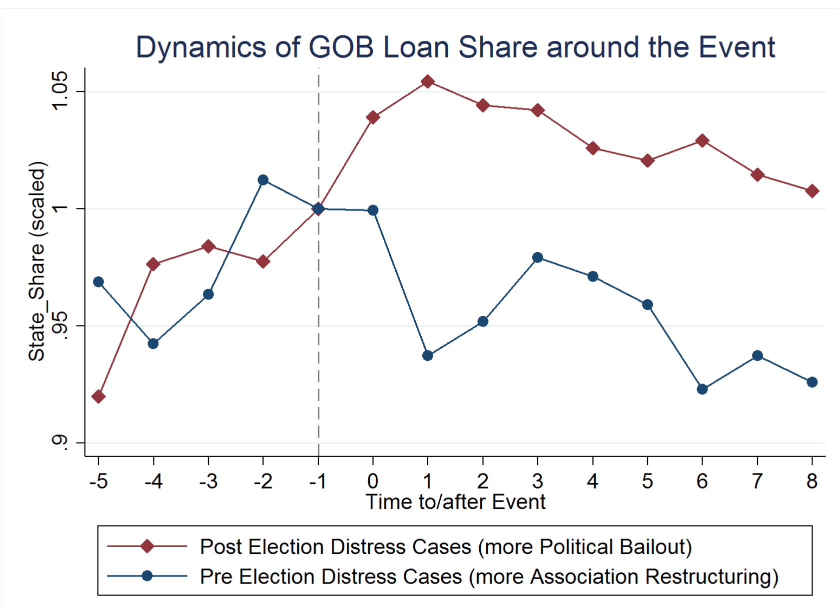
(b) Distribution of bailouts from politicians

Figure 3: Bank Bailout Types and Electoral Cycle.

Figure 3 illustrates how the number of bank distress (or bailouts) and the number of bailouts from politicians vary over the electoral cycle, where the vertical black line indicates the election date.



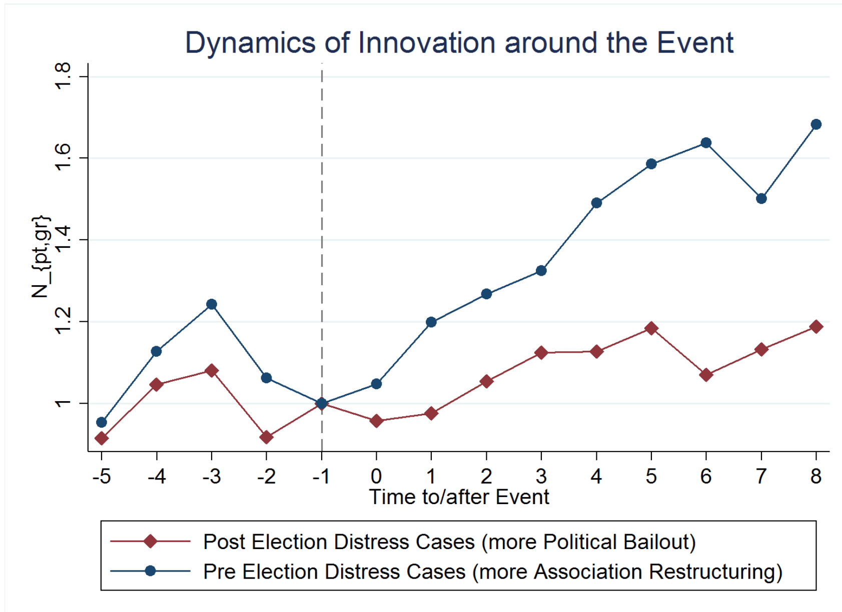
(a) Partitioned by Type of Bailouts



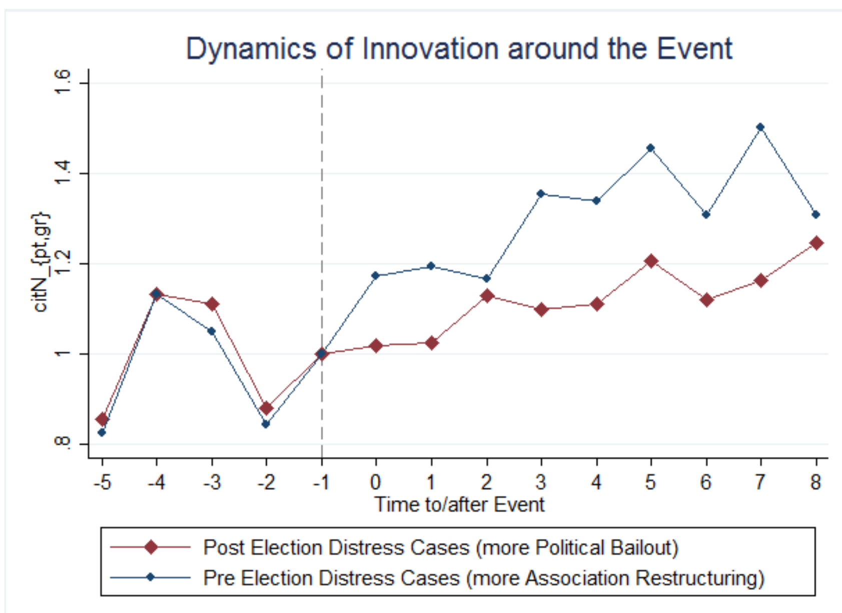
(b) Partitioned by the Timing of Distress in the Electoral Cycle

Figure 4: Share of Loans by Government-owned Banks around Bailouts.

Figure 4 illustrates changes in share of loans extended by government-owned banks (GOB) in the years around the bailout event. The x-axis shows the year to/after the bailout event. The share of loans extended by government-owned banks is normalized to have value 1 in the year preceding the bailout or election event. In Figure 4a the blue (circle) line stands for restructuring by association and the red (diamond) line stands for bailouts by the politician. In Figure 4b the blue (circle) line stands for cases where distress/bailouts take place before the election and the red (diamond) line stands for cases where distress/bailouts take place after the election.



(a) Number of Patents around Bailouts



(b) Number of Citation-weighted Patents around Bailouts

Figure 5: Innovation Outcomes around Bailouts.

Figure 5a illustrates changes in the number of patents for firms located in areas with government-owned bank distress events, around the bailouts. Figure 5b illustrates changes in the number of citation-weighted patent counts for firms located in areas with government-owned bank distress events, around the bailouts. The x-axis shows the year to/after the bailout event. The innovation outcome is normalized to have value 1 in the year preceding the election event. The blue (circle) line stands for cases where distress/bailouts take place before the election and the red (diamond) line stands for cases where distress/bailouts take place after the election.

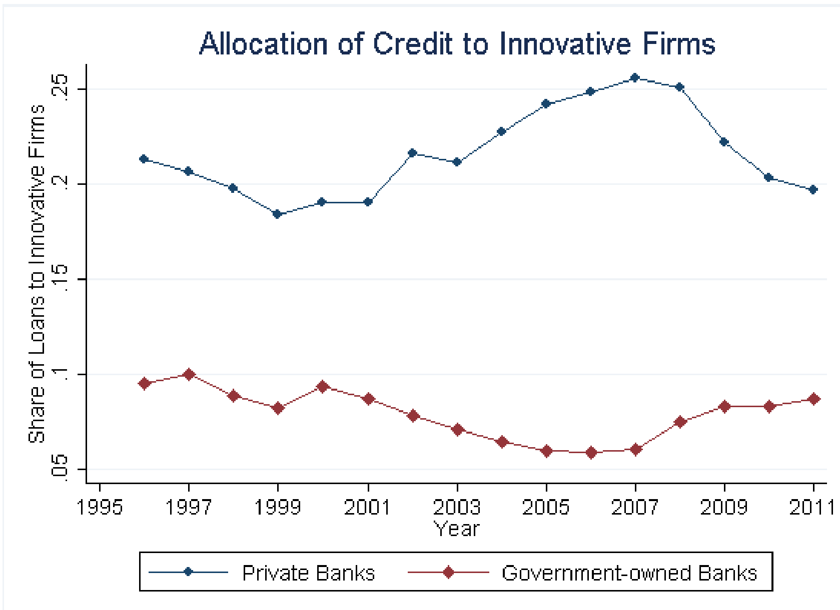


Figure 6: Allocation of Credit to Innovative Firms.

Figure 6 illustrates the percentage of credit assigned to firms that ever innovates by government-owned banks and private banks overtime. The blue (circle) line stands for private banks and the red (diamond) line stands for government-owned banks.

Table 2: Summary Statistics

Panel A: Full sample, 1993 - 2011

Variable	**Mean**	**S.D.**	**Median**	**P25**	**P75**	**Obs**
$N_{pt,gr}$	0.071	2.582	0.000	0.000	0.000	2,081,168
$N_{pt,ap}$	0.188	7.768	0.000	0.000	0.000	2,081,168
$citN_{pt,gr}$	0.233	10.763	0.000	0.000	0.000	2,081,168
$citN_{pt,gr}^{time-tech}$	0.060	2.207	0.000	0.000	0.000	2,081,168
$N_{pt,gr}^{top10}$	0.006	0.299	0.000	0.000	0.000	2,081,168
Innovative (=1 for patentees)	0.108	0.311	0.000	0.000	0.000	2,081,168
Total Loans (€m)	28.41	1160.5	1.524	0.158	4.816	2,047,768
N_lender	1.953	2.347	1.000	1.000	2.000	2,047,768
$State\_Share$	0.407	0.458	0.035	0.000	1.000	1,831,914
$State\_Main$	0.402	0.490	0.000	0.000	1.000	1,831,914
$State\_Top$	0.410	0.492	0.000	0.000	1.000	1,831,914

Panel B: B/S Sample, 1993 - 2011

Variable	**Mean**	**S.D.**	**Median**	**P25**	**P75**	**Obs**
$N_{pt,gr}$	0.262	5.255	0.000	0.000	0.000	368,926
$N_{pt,ap}$	0.656	15.102	0.000	0.000	0.000	368,926
$citN_{pt,gr}$	0.773	17.146	0.000	0.000	0.000	368,926
$citN_{pt,gr}^{time-tech}$	0.214	4.121	0.000	0.000	0.000	368,926
$N_{pt,gr}^{top10}$	0.020	0.438	0.000	0.000	0.000	368,926
Innovative (=1 for patentees)	0.331	0.470	0.000	0.000	1.000	368,926
Total Loans (€m)	17.95	330.7	2.409	0.746	7.495	359,211
N_lender	3.087	6.799	2.000	1.000	3.000	359,211
$State\_Share$	0.371	0.415	0.175	0.000	0.840	339,143
$State\_Main$	0.357	0.479	0.000	0.000	1.000	339,143
$State\_Top$	0.379	0.485	0.000	0.000	1.000	339,143
Age	43.015	40.715	30	16	57	210,139
Assets (€m)	124.63	1764.3	12.020	4.875	37.089	210,139
Sales (€m)	103.81	1187.5	17.444	6.606	47.170	210,139
Leverage	0.764	0.197	0.809	0.654	0.921	210,139
Profitability	0.061	0.110	0.040	0.006	0.103	210,139
Cash	0.053	0.088	0.018	0.003	0.063	210,139

Panel C: Innovator Sample, 1993 - 2011

Variable	**Mean**	**S.D.**	**Median**	**P25**	**P75**	**Obs**
$N_{pt,gr}$	0.660	7.827	0.000	0.000	0.000	225,148
$N_{pt,ap}$	1.738	23.559	0.000	0.000	0.000	225,148
$citN_{pt,gr}$	2.151	32.660	0.000	0.000	0.000	225,148
$citN_{pt,gr}^{time-tech}$	0.556	6.691	0.000	0.000	0.000	225,148
$N_{pt,gr}^{top10}$	0.059	0.909	0.000	0.000	0.000	225,148
Innovative (=1 for patentees)	1.000	0.000	1.000	1.000	1.000	225,148
Total Loans (€m)	41.02	2134.0	2.015	0.361	6.804	191,748
N_lender	3.030	3.371	2.000	1.000	4.000	191,748
$State\_Share$	0.345	0.414	0.075	0.000	0.788	174,082
$State\_Main$	0.329	0.470	0.000	0.000	1.000	174,082
$State\_Top$	0.352	0.478	0.000	0.000	1.000	174,082

The table reports summary statistics for variables listed in the first column. Panel A includes all the firms in German credit register from 1993 to 2011. Panel B is a subsample covering firms with balance sheet data. Panel C is a subsample covering firms that ever innovate during our sample period. The definition of the variables are listed in Table B1.

Table 3: Descriptives: Innovation Outcome by Main/Top Lender Ownership

Panel A: Categorized by Main Lender Ownership, Full sample, 1993-2011								
	$State\_Main$=1			$State\_Main$=0			Difference	
	Mean	S.D.	Obs	Mean	S.D.	Obs	Diff	T-stat
$N_{pt,gr}$	0.036	2.498	735,663	0.078	2.718	1,096,251	-0.043	10.764
$N_{pt,ap}$	0.089	6.647	735,663	0.215	8.700	1,096,251	-0.126	10.543
$citN_{pt,gr}$	0.102	7.494	735,663	0.250	11.919	1,096,251	-0.149	9.520
$citN_{pt,gr}^{time-tech}$	0.029	1.938	735,663	0.066	2.332	1,096,251	-0.037	11.214
$N_{pt,gr}^{top10}$	0.003	0.201	735,663	0.007	0.340	1,096,251	-0.004	9.568
Innovative	0.078	0.268	735,663	0.107	0.309	1,096,251	-0.029	65.379
Total Loans (€m)	16.41	394.2	735,663	42.06	1552.7	1,096,251	-25.65	13.871
N_lender	1.766	2.037	735,663	2.239	2.686	1,096,251	-0.473	128.22

Panel B: Categorized by Top Lender Ownership, Full sample, 1993-2011								
	$State\_Top$=1			$State\_Top$=0			Difference	
	Mean	S.D.	Obs	Mean	S.D.	Obs	Diff	T-stat
$N_{pt,gr}$	0.046	2.938	751,367	0.072	2.396	1,080,547	-0.026	6.572
$N_{pt,ap}$	0.122	9.335	751,367	0.193	6.803	1,080,547	-0.071	5.959
$citN_{pt,gr}$	0.127	8.258	751,367	0.235	11.617	1,080,547	-0.108	6.957
$citN_{pt,gr}^{time-tech}$	0.038	2.247	751,367	0.061	2.137	1,080,547	-0.023	7.038
$N_{pt,gr}^{top10}$	0.004	0.225	751,367	0.007	0.331	1,080,547	0.003	6.784
Innovative	0.082	0.274	751,367	0.104	0.306	1,080,547	-0.023	52.083
Total Loans (€m)	25.44	732.8	751,367	36.16	1476.0	1,080,547	-10.72	5.817
N_lender	1.907	2.385	751,367	2.148	2.501	1,080,547	-0.241	65.396

The table reports mean, standard deviation and number of observations of variables listed in the first column by their main/top lender ownership. Panel A groups firms by ownership of their main lender, and Panel B groups firms by ownership of their top lender. *State_Main* equals to 1 (0) when a firm obtains more than 50% of it bank credit from government-owned (private) banks. *State_Top* equals to 1 (0) when a firm's top lender is a government-owned (private) bank. The definition of other variables are listed in Table B1. * indicates statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 4: Decisions to Start/Exit Innovation and Ownership of Lenders

Panel A: Cox Hazard, Forecasting *Entry* into Innovation						
	(1)	(2)	(3)	(4)	(5)	(6)
State_Share	-0.284***			-0.262***		
	(0.031)			(0.030)		
State_Main		-0.254***			-0.237***	
		(0.029)			(0.028)	
State_Top			-0.223***			-0.206***
			(0.028)			(0.028)
Size	0.141***	0.139***	0.141***	0.118***	0.117***	0.119***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Year FE	NO	NO	NO	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
No. of Firms	204,710	204,710	204,710	204,710	204,710	204,710
Obs	1,449,877	1,449,877	1,449,877	1,449,877	1,449,877	1,449,877
Pseudo R2	0.052	0.052	0.051	0.084	0.084	0.083

Panel B: Cox Hazard, Forecasting *Exit* of Innovation						
	(1)	(2)	(3)	(4)	(5)	(6)
State_Share	0.242***			0.262***		
	(0.040)			(0.040)		
State_Main		0.214***			0.231***	
		(0.034)			(0.034)	
State_Top			0.176***			0.190***
			(0.033)			(0.033)
Size	-0.113***	-0.112***	-0.114***	-0.117***	-0.115***	-0.118***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Year FE	NO	NO	NO	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
No. of Firms	11,214	11,214	11,214	11,214	11,214	11,214
Obs	61,412	61,412	61,412	61,412	61,412	61,412
Pseudo R2	0.012	0.012	0.012	0.022	0.022	0.022

The table reports regression results from cox hazards models to forecast the entry into innovation and the exit of innovation. In columns (1) and (4), the key independent variable is *State_Share*. In columns (2) and (5), the key independent variable is *State_Main*. In columns (3) and (6), the key independent variable is *State_Top*. Full sample is used and Panel A studies entry decision while Panel B studies exit decision. Year and industry fixed effects are included. Robust standard errors clustered at firm level are denoted in parentheses. * indicates statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 5: Innovation Outcome and Ownership of Lenders

OLS

Panel A: Full Sample, Dep. Var.: $lnN_{pt,gr}$						
	(1)	(2)	(3)	(4)	(5)	(6)
Subsample	All: Innovator + Non-Innovator			Innovator Only: Intensive Margin		
State_Share	-0.007***			-0.068***		
	(0.000)			(0.006)		
State_Main		-0.008***			-0.062***	
		(0.001)			(0.005)	
State_Top			-0.006***			-0.050***
			-0.001			(0.005)
Size	0.004***	0.004***	0.004***	0.030***	0.029***	0.030***
	(0.000)	(0.000)	(0.000)	(0.002)	(0.002)	(0.002)
Dep. Var. Mean	0.014	0.014	0.014	0.155	0.155	0.155
Year FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
No. of Firms	238,492	238,492	238,492	13,596	13,596	13,596
Obs	1,755,351	1,755,351	1,755,351	153,584	153,584	153,584
Adj R2	0.022	0.022	0.022	0.036	0.036	0.035

Panel B: Full Sample, Innovator Only, Alternative Dependent Variables						
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	$lnN_{pt,gr}$	$lnN_{pt,ap}$	*grant_rate*	$lncitN_{pt,gr}$	$lncitN_{pt,gr}^{time-tech}$	$lnN_{pt,gr}^{top10}$
State_Share	-0.068***	-0.120***	-0.028***	-0.084***	-0.054***	-0.011***
	(0.006)	(0.008)	(0.002)	(0.008)	(0.005)	(0.002)
Size	0.030***	0.045***	0.009***	0.035***	0.025***	0.007***
	(0.002)	(0.003)	(0.001)	(0.003)	(0.002)	(0.001)
Dep. Var. Mean	0.155	0.277	0.093	0.185	0.115	0.023
Year FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
No. of Firms	13,596	13,596	13,596	13,596	13,596	13,596
Obs	153,584	153,584	153,584	153,584	153,584	153,584
Adj R2	0.036	0.046	0.022	0.034	0.029	0.013

The table shows how firms' innovation depends on the ownership structure of their lenders. In Panel A, the dependent variable is the natural logarithm of one plus a firm's total number of patents filed and eventually granted in a year. Columns (1) to (3) include all the firms, irrespective whether they have ever patented or not. Columns (4) to (6) keeps only firms with patenting history (those firms are denoted as innovators). In Panel B, only firms with patenting history are included. Different measures of innovation are used and the definition of those dependent variables from columns (1) to (6) are listed in Table B1. Year fixed effects and industry fixed effects are included. Robust standard errors clustered at firm level are denoted in parentheses. * indicates statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 6: Innovation Outcome and Timing of Distress in the Electoral Cycle

Reduced form diff-in-diff descriptives

Panel A: Number of Granted Patents

	(1)	(2)	(3)	(4)	(5)	(6)
Var.	$N_{pt,gr}$			$N_{pt,gr}$, time trend adjusted		
	Pre Election (Association$\nearrow$) (GOB$\searrow$)	*Post Election* (Politician$\nearrow$) (GOB$\nearrow$)	Diff	*Pre Election* (Association$\nearrow$) (GOB$\searrow$)	*Post Election* (Politician$\nearrow$) (GOB$\nearrow$)	Diff
Before Bailout	0.051	0.057	-0.006	0.040	0.043	-0.004
	(0.004)	(0.003)	(0.005)	(0.004)	(0.003)	(0.005)
After Bailout	0.052	0.040	0.012***	0.061	0.048	0.013***
	(0.004)	(0.002)	(0.004)	(0.004)	(0.002)	(0.004)
Diff-in-Diff			0.018***			0.017***
			(0.006)			(0.006)
Obs	145,815	549,554		145,815	549,554	

Panel B: Number of Citation-weighted Granted Patents

	(1)	(2)	(3)	(4)	(5)	(6)
Var.	$lncitN_{pt,gr}$			$citN_{pt,gr}$, time trend adjusted		
	Pre Election (Association$\nearrow$) (GOB$\searrow$)	*Post Election* (Politician$\nearrow$) (GOB$\nearrow$)	Diff	*Pre Election* (Association$\nearrow$) (GOB$\searrow$)	*Post Election* (Politician$\nearrow$) (GOB$\nearrow$)	Diff
Before Bailout	0.169	0.183	-0.013	0.112	0.109	0.003
	(0.014)	(0.008)	(0.017)	(0.014)	(0.008)	(0.017)
After Bailout	0.115	0.080	0.035***	0.165	0.124	0.040***
	(0.009)	(0.004)	(0.009)	(0.009)	(0.004)	(0.009)
Diff-in-Diff			0.049***			0.037**
			(0.018)			(0.018)
Obs	145,815	549,554		145,815	549,554	

The table shows descriptive statistics for firms' innovation in areas where the savings bank distress events occur before and after the election. *Pre Election* stands for the group of firms located in areas where the savings bank distress events occur just before the local election. *Post Election* stands for the group of firms located in areas where the savings bank distress events occur after the local election. *Before Bailout* groups years before the distress/bailout event. *After Bailout* groups years after the distress/bailout event. Columns (1) to (3) use the raw value of patent counts while columns (4) to (6) use the patent counts adjusted by time trend. In Panel A the variable of interest is $N_{pt,gr}$, or the number of granted patents. In Panel B the variable of interest is $citN_{pt,gr}$, or the number of citation-weighted granted patents. Standard deviation (standard errors) are denoted in parentheses. * indicates statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 7: Innovation Outcome and Ownership of Lenders
IV results

Panel A: Number of Granted Patents

	(1)	(2)	(3)	(4)	(5)
Dep. Var.			$lnN_{pt,gr}$		
Model	First Stage	Reduced	IV	IV	IV
State_Share			-0.091**		
			(0.038)		
State_Main				-0.090**	
				(0.038)	
State_Top					-0.091**
					(0.039)
PreElect	-0.081***	0.007**			
	(0.011)	(0.003)			
F-stat			52.825	49.711	48.395
Year FE	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES
No. of Firms	37,927	37,927	37,927	37,927	37,927
Obs	204,404	204,404	204,404	204,404	204,404
Adj R2	0.04	0.023	-	-	-

Panel B: Number of Citation-weighted Granted Patents

	(1)	(2)	(3)	(4)	(5)
Dep. Var.			$citN_{pt,gr}$		
Model	First Stage	Reduced	IV	IV	IV
State_Share			-0.113**		
			(0.045)		
State_Main				-0.112**	
				(0.045)	
State_Top					-0.113**
					(0.046)
PreElect	-0.081***	0.009***			
	(0.011)	(0.004)			
F-stat			52.825	49.711	48.395
Year FE	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES
No. of Firms	37,927	37,927	37,927	37,927	37,927
Obs	204,404	204,404	204,404	204,404	204,404
Adj R2	0.04	0.016	-	-	-

The table shows how firms' innovation depends on the ownership structure of their lenders using an instrumental variable approach. First stage regression results are reported in column (1) where the dependent variable is *State_Share*. In column (2) we report the reduced-form results from regressing the outcome variable directly on the instrument. Column (3) exhibits the second stage IV results where *State_Share* is instrumented by the timing of government-owned bank distress in the local electoral cycle, or *PreElect*. Columns (4) and (5) further show the second stage IV results where *State_Main* and *State_Top* are instrumented by *PreElect* respectively. F-stat are reported from columns (3) to (5). From columns (2) to (5) the dependent variable is the natural logarithm of one plus a firm's total number of patents filed and eventually granted in a year in Panel A and citation weighted measure is used in Panel B. Year fixed effects and industry fixed effects are further included. Adjusted R2 is not provided for IV models as it has no statistical meaning in the context of 2SLS/IV. Robust standard errors double clustered at firm level and event-year level are denoted in parentheses. * indicates statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 8: Innovation Outcome and Ownership of Lenders

Dynamics

Panel A: Number of Granted Patents

	(1)	(2)	(3)	(4)
Dep. Var.	$lnN_{pt,gr}$			
Window	$T = 0+$	$T = 0$ to $T = 2$	$T = 3$ to $T = 5$	$T = 5+$
State_Share	-0.091**	-0.080**	-0.063*	-0.106**
	(0.038)	(0.037)	(0.037)	(0.043)
Size	0.003***	0.002***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
F-stat	52.825	31.329	31.004	48.424
Year FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
No. of Firms	37,927	21,485	20,433	27,649
Obs	204,404	52,514	48,275	103,615

Panel B: Number of Citation-weighted Granted Patents

	(1)	(2)	(3)	(4)
Dep. Var.	$citN_{pt,gr}$			
Window	$T = 0+$	$T = 0$ to $T = 2$	$T = 3$ to $T = 5$	$T = 5+$
State_Share	-0.113**	-0.080**	-0.095*	-0.113**
	(0.045)	(0.037)	(0.049)	(0.046)
Size	0.002***	0.002***	0.002***	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)
F-stat	52.825	31.329	31.004	48.424
Year FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
No. of Firms	37,927	21,485	20,433	27,649
Obs	204,404	52,514	48,275	103,615

The table shows how firms' innovation depends on the ownership structure of their lenders using an instrumental variable approach. We focus on the dynamics of the effect and only second stage IV results are reported here. *State_Share* is instrumented by the timing of government-owned bank distress in the local electoral cycle, or *PreElect*, in all specifications. In column (1) we keep all the post-bailout years ($T = 0+$). In column (2) we include only three years after the bailout ($T = 0$ to $T = 2$). Column (3) focuses on the next three years ($T = 3$ to $T = 5$). Any year after year 5 ($T = 5+$) are included in column (4). The dependent variable is the natural logarithm of one plus a firm's total number of patents filed and eventually granted in a year in Panel A and citation weighted measure is used in Panel B. Year fixed effects and industry fixed effects are further included. Adjusted R2 is not provided as it has no statistical meaning in the context of 2SLS/IV. Robust standard errors double clustered at firm level and event-year level are denoted in parentheses. * indicates statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 9: Innovation Outcome and Ownership of Lenders

Other measures: nature of innovation output

	(1)	(2)	(3)	(4)
Dep. Var.	originality	generality	exploration	diversity
State_Share	-0.011**	-0.006**	-0.041**	-0.016**
	(0.005)	(0.002)	(0.016)	(0.008)
Size	0.000***	0.000**	0.002***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
F-stat	52.825	52.825	52.825	52.825
Year FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
No. of Firms	37,927	37,927	37,927	37,927
Obs	204,404	204,404	204,404	204,404

The table shows how the nature of firms' innovation output depends on the ownership structure of their lenders using an instrumental variable approach. Second stage IV results are reported. *State_Share* is instrumented by the timing of government-owned bank distress in the local electoral cycle, or *PreElect*, in all specifications. The definition of dependent variables is in Table B1. Year fixed effects and industry fixed effects are further included. Adjusted R2 is not provided as it has no statistical meaning in the context of 2SLS/IV. Robust standard errors double clustered at firm level and event-year level are denoted in parentheses. * indicates statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 10: Credit Allocated to Future Innovators: Government-owned v.s. Private Banks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dep. Var.					ln(loans)				
		Full sample			B/S sample			Innovator sample	
	State	Private	All	State	Private	All	State	Private	All
Future Innovator	0.036*	0.075***	0.075***	0.060**	0.091***	0.091***	0.092***	0.138***	0.138***
	(0.022)	(0.020)	(0.007)	(0.024)	(0.013)	(0.009)	(0.018)	(0.011)	(0.011)
Future Innovator X State			-0.039***			-0.031**			-0.047**
			(0.013)			(0.015)			(0.021)
Bank-Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Bank-Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
No. of Banks	688	2,864	3,552	618	912	1,530	593	1,185	1,778
Obs	1,399,949	1,916,490	3,437,884	315,208	510,009	825,217	158,171	306,260	464,431
Adj R2	0.805	0.77	0.785	0.714	0.65	0.674	0.685	0.645	0.658

The table shows how the flow of credit to high-potential innovative firms depends on the ownership structure of their lenders. The observation is at bank-firm-year level. The dependent variable is $ln(loans)$. $Future\ Innovator$ is an indicator which equals to one if a firm has successfully filed for at least one patent in the following five years and zero otherwise. $State$ is an indicator which equals to one if the bank is a government-owned one and zero otherwise. Columns (1) to (3) use the full sample. Columns (4) to (6) keep only firms with balance sheet information while columns (7) to (9) keep firms that ever innovate in our sample period. In columns (1), (4), (7), we focus at state banks while in columns (2), (5), (8), we focus at private banks. In columns (3), (6) and (9), we study the differential patterns between the state and private banks in allocating funds to future innovators by adding in the interaction term $Future\ Innovator$ X $State$. Bank-firm (relationship level) and bank-year fixed effects are included. Robust standard errors clustered at bank level are denoted in parentheses. * indicates statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 11: Innovation Outcome and Ownership of Lenders

Heterogeneity by External Financial Dependence

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.	$lnN_{pt,gr}$		$lnN_{pt,ap}$		$grant\_rate$		$lncitN_{pt,gr}$	
	Low	High	Low	High	Low	High	Low	High
State_Share	-0.019	-0.101***	-0.044	-0.151***	-0.01	-0.034***	-0.026	-0.112***
	(0.024)	(0.025)	(0.033)	(0.034)	(0.010)	(0.010)	(0.032)	(0.032)
Size	0.045***	0.063***	0.060***	0.086***	0.014***	0.016***	0.056***	0.078***
	(0.011)	(0.010)	(0.013)	(0.012)	(0.002)	(0.002)	(0.013)	(0.013)
Leverage	-0.202***	-0.231***	-0.347***	-0.305***	-0.087***	-0.099***	-0.308***	-0.381***
	(0.057)	(0.084)	(0.087)	(0.109)	(0.023)	(0.028)	(0.076)	(0.109)
Cash	0.06	0.07	0.071	0.087	0.002	0.026	0.046	-0.014
	(0.098)	(0.132)	(0.141)	(0.167)	(0.036)	(0.048)	(0.127)	(0.165)
Profitability	0.135*	0.280***	0.182*	0.360***	0.055*	0.038	0.179*	0.440***
	(0.070)	(0.106)	(0.093)	(0.136)	(0.031)	(0.036)	(0.094)	(0.133)
p (diff)	0.017		0.022		0.090		0.058	
chi (diff)	5.708		5.228		2.866		3.591	
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Age FE	YES	YES	YES	YES	YES	YES	YES	YES
No. of Firms	1,413	1,518	1,413	1,518	1,413	1,518	1,413	1,518
Obs	16,268	16,995	16,268	16,995	16,268	16,995	16,268	16,995
Adj R2	0.054	0.117	0.064	0.144	0.023	0.040	0.046	0.099

The table examines how firms' innovation depends on the ownership structure of their lenders using subsamples partitioned on external financial dependence. *Low* includes firms in industries below median external financial dependence while $High$ includes firms in industries above median external financial dependence. Different measures of innovation are used and the definition of those dependent variables from columns (1) to (8) are listed in Table B1. All the firms with balance sheet data and patenting history, thereby the innovators, are included. Firms are classified into five groups based on their age and age fixed effects are added. Year fixed effects and industry fixed effects are further included. $p(diff)$ reports p-value of the difference between the coefficients yielded by the *Low* and $High$ subsamples. Robust standard errors clustered at firm level are denoted in parentheses. * indicates statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 12: Innovation Outcome and Ownership of Lenders

Heterogeneity by Technology Opaqueness

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.	$lnN_{pt,gr}$		$lnN_{pt,ap}$		$grant\_rate$		$lncitN_{pt,gr}$	
	Low	High	Low	High	Low	High	Low	High
State_Share	-0.009	-0.100***	-0.035	-0.142***	-0.014	-0.030**	-0.021	-0.102***
	(0.020)	(0.029)	(0.028)	(0.039)	(0.009)	(0.012)	(0.027)	(0.038)
Size	0.038***	0.077***	0.052***	0.105***	0.012***	0.019***	0.047***	0.096***
	(0.008)	(0.014)	(0.010)	(0.016)	(0.002)	(0.003)	(0.009)	(0.018)
Leverage	-0.161***	-0.304***	-0.254***	-0.435***	-0.074***	-0.123***	-0.242***	-0.492***
	(0.048)	(0.097)	(0.071)	(0.128)	(0.021)	(0.032)	(0.060)	(0.128)
Cash	0.034	0.052	0.043	0.054	0.005	0.006	0.004	-0.027
	(0.092)	(0.138)	(0.132)	(0.177)	(0.038)	(0.048)	(0.115)	(0.176)
Profitability	0.140**	0.340***	0.194**	0.426***	0.058**	0.045	0.185**	0.530***
	(0.066)	(0.120)	(0.090)	(0.150)	(0.029)	(0.040)	(0.091)	(0.148)
p (diff)	0.010		0.025		0.068		0.079	
chi (diff)	6.706		5.013		3.325		3.080	
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Age FE	YES	YES	YES	YES	YES	YES	YES	YES
No. of Firms	1,634	1,294	1,634	1,294	1,634	1,294	1,634	1,294
Obs	18,455	14,757	18,455	14,757	18,455	14,757	18,455	14,757
Adj R2	0.074	0.105	0.086	0.133	0.026	0.037	0.060	0.091

The table examines how firms' innovation depends on the ownership structure of their lenders using subsamples partitioned on technology opaqueness. *Low* includes firms in industries where the technology is less opaque while *High* includes firms in industries where the technology is more opaque. Different measures of innovation are used and the definition of those dependent variables from columns (1) to (8) are listed in Table B1. All the firms with balance sheet data and patenting history, thereby the innovators, are included. Firms are classified into five groups based on their age and age fixed effects are added. Year fixed effects and industry fixed effects are further included. $p(diff)$ reports p-value of the difference between the coefficients yielded by the *Low* and *High* subsamples. Robust standard errors clustered at firm level are denoted in parentheses. * indicates statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 13: Creative Destruction and Ownership of Lenders

Panel A: Firm Birth

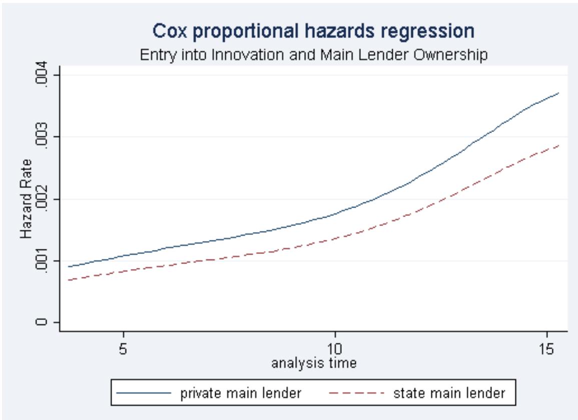
	(1)	(2)	(3)	(4)
Dep. Var.	I_{birth}			
Window	$T = 0+$	$T = 0$ to $T = 2$	$T = 3$ to $T = 5$	$T = 5+$
$State\_Share$	-0.047*	-0.080**	-0.018	-0.081**
	(0.026)	(0.037)	(0.039)	(0.037)
Size	-0.014***	0.002***	-0.014***	-0.013***
	(0.000)	(0.001)	(0.001)	(0.000)
F-stat	52.825	31.329	31.004	48.424
Year FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
No. of Firms	37,927	21,485	20,433	27,649
Obs	204,404	52,514	48,275	103,615

Panel B: Firm Death

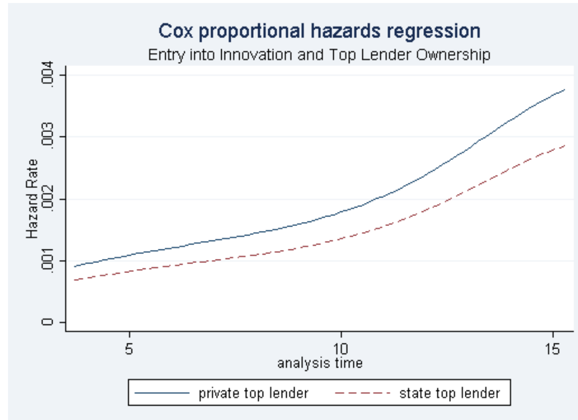
	(1)	(2)	(3)	(4)
Dep. Var.	I_{death}			
Window	$T = 0+$	$T = 0$ to $T = 2$	$T = 3$ to $T = 5$	$T = 5+$
$State\_Share$	-0.062***	-0.080**	-0.091***	-0.080***
	(0.020)	(0.037)	(0.024)	(0.031)
Size	-0.009***	0.002***	-0.008***	-0.012***
	(0.001)	(0.001)	(0.001)	(0.001)
F-stat	52.825	31.329	31.004	48.424
Year FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
No. of Firms	37,927	21,485	20,433	27,649
Obs	204,404	52,514	48,275	103,615

The table shows how firm birth and death depend on the ownership structure of their lenders using an instrumental variable approach. We focus on the dynamics of the effect and only second stage IV results are reported here. $State\_Share$ is instrumented by the timing of government-owned bank distress in the local electoral cycle, or $PreElect$, in all specifications. In column (1) we keep all the post-bailout years ($T = 0+$). In column (2) we include only three years after the bailout ($T = 0$ to $T = 2$). Column (3) focuses on the next three years ($T = 3$ to $T = 5$). Any year after year 5 ($T = 5+$) are included in column (4). The dependent variable is a dummy variable indicating birth of a firm in Panel A and a dummy variable indicating death of a firm is used in Panel B. Year fixed effects and industry fixed effects are further included. Adjusted R2 is not provided as it has no statistical meaning in the context of 2SLS/IV. Robust standard errors double clustered at firm level and event-year level are denoted in parentheses. * indicates statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

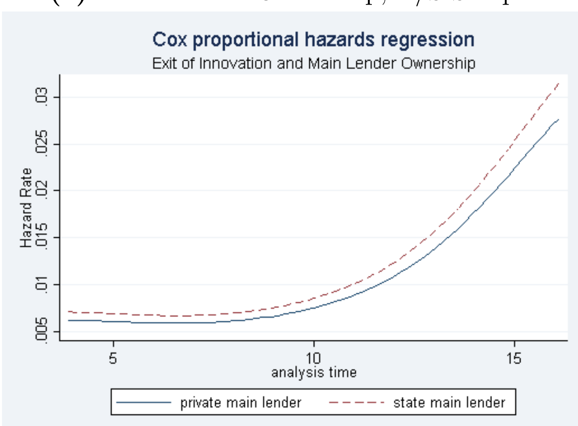
A Appendix: Additional Figures



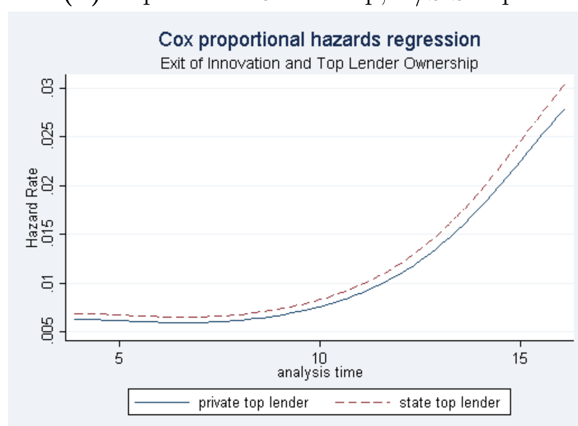
(a) Main Lender Ownership, B/S Sample



(b) Top Lender Ownership, B/S Sample



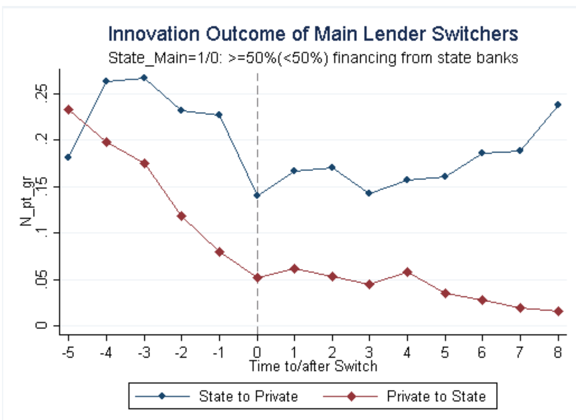
(c) Main Lender Ownership, B/S Sample



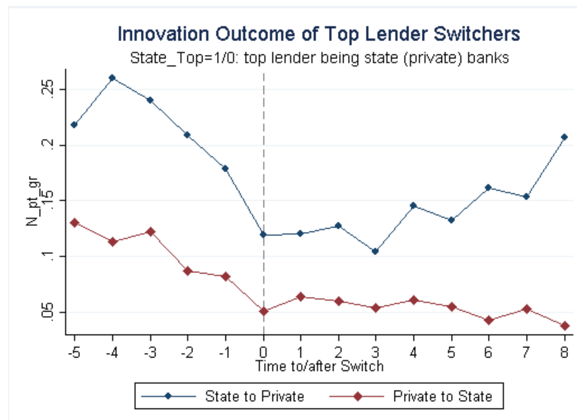
(d) Top Lender Ownership, B/S Sample

Figure A1: Hazard Rate: Enter/Exit Innovation
B/S sample

Figure A1 plots the probability of initiating/terminating innovation, i.e. hazard rate, for the firms with government-owned main/top lender (red/bottom dashed line) and private-owned main/top lender (blue/top solid line), at any given age. Figure A1a and Figure A1b study the entry into innovation while Figure A1c and Figure A1d study the termination of innovation. A firm with government-owned (private) main lender means that more than 50% of the firm's bank credit is from a government-owned (private) bank. A firm with government-owned (private) top lender means that the firm's biggest lender is a government-owned (private) one. B/S sample includes only firms with balance sheet data.



(a) Main Lender Switchers, B/S Sample



(b) Top Lender Switchersrship, B/S Sample

Figure A2: Main/Top Lender Switchers and Their Innovation Outcome
B/S sample

Figure A2 illustrates the innovation outcome of main/top lender switchers in the years around the switch. The sample includes firms for which balance sheet data is available. In Figure A2a and Figure A2b, the outcome variable is number of patents granted to a firm in the respective year. The blue (circle) line stands for the those switching from government-owned main/top lenders to private ones. The red (diamond) line stands for the those switching from private main/top lenders to government-owned ones.

B Appendix: Additional Tables

Table B1: Description of Variables

Name	Description
N_lender	Number of lenders of a firm reporting to the credit register
$ln(loans)$	ln(total amount of loans from all the private and government-owned banks)
$State\_Share$	Share of loans extended by government-owned banks in all bank loans
$State\_Top$	Dummy variable, =1 if the top lender of a firm is a government-owned bank, =0 otherwise
$State\_Main$	Dummy variable, =1 if a firm obtains more than half of its bank credit from a government-owned bank, =0 otherwise
$ln(N_{pt,gr})$	ln(# of granted patents+1), successful patent applications per year (European Patent Office)
$ln(N_{pt,ap})$	ln(# of applied patents+1), patent applications per year, regardless of whether the patent gets granted or not
$ln(citN_{pt,gr})$	ln(# of citation-weighted granted patents+1)
$ln(citN_{pt,gr}^{time-tech})$	ln(# of citation-weighted granted patents+1), corrected for time truncation and for technology class
$ln(N_{pt,gr}^{top10})$	ln(# of granted patents with top 10% citations+1)
$Innovative$	Dummy variable, =1 if a firm ever patents, =0 otherwise
$grant\_rate$	The proportion of patent applications that eventually get granted
$originality$	Measures how original the patent portfolio is, = 1 - Herfindahl-Hirschman Index (HHI) of backward citations across technology classes
$generality$	Measures how widely applicable the patent portfolio is, =1 - HHI of forward citations across technology classes
$exploration$	Measures how explorative the patent portfolio is
	=fraction of patents that are not based on a firm's existing knowledge (own patents or previously cited patents)
$diversity$	Measures how diversified the patent portfolio is, = 1- HHI of all granted patents across technology classes
$Sales$	Sales of a firm (in million Euro)
$Assets$	Total Assets of a firm (in million Euro)
Age	Age of a firm
$Leverage$	Total debt over total assets
$Cash$	Total cash holdings over total assets
$Profitability$	Earnings before interest and taxes of a firm (in million Euro)
$Political\ Bailout$	Dummy variable, =1 if the the government-owned bank distress is resolved by a local politician, =0 otherwise
$PreElect$	Dummy variable, =1 if the government-owned bank distress occurs 0-12 months before a local election, =0 otherwise

Table B2: Decisions to Start/Exit Innovation and Ownership of Lenders

Hazard model, B/S sample

	(1)	(2)	(3)	(4)	(5)	(6)
	Entry			Exit		
State_Share	-0.239***			0.275***		
	(0.060)			(0.086)		
State_Main		-0.184***			0.150**	
		(0.050)			(0.067)	
State_Top			-0.181***			0.112*
			(0.049)			(0.065)
Size	0.187***	0.185***	0.189***	-0.118***	-0.116***	-0.118***
	(0.016)	(0.016)	(0.016)	(0.014)	(0.014)	(0.014)
Leverage	-0.516***	-0.526***	-0.525***	1.076***	1.086***	1.089***
	(0.132)	(0.131)	(0.131)	(0.190)	(0.190)	(0.190)
Cash	0.561**	0.567**	0.560**	-0.743*	-0.720*	-0.703*
	(0.273)	(0.273)	(0.273)	(0.394)	(0.394)	(0.393)
Profitability	0.630***	0.628***	0.630***	-1.331***	-1.352***	-1.354***
	(0.233)	(0.233)	(0.234)	(0.283)	(0.283)	(0.282)
Year FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Age FE	YES	YES	YES	YES	YES	YES
No. of Firms	19,674	19,674	19,674	3,134	3,134	3,134
Obs	141,493	141,493	141,493	21,643	21,643	21,643
Pseudo R2	0.120	0.120	0.120	0.037	0.036	0.036

The table reports regression results from cox hazards models to forecast the entry into innovation and the exit of innovation. Columns (1) to (3) study entry decision while columns (4) to (6) study exit decision. The B/S sample, which includes firms with balance sheet data is used. Columns (1) to (3) include all the firms, irrespective whether they have ever patented or not. Columns (4) to (6) keeps only firms with patenting history (those firms are denoted as innovators). Firms are classified into five groups based on their age. Age fixed effects are added in Panel B where the information on age is available. Year fixed effects and industry fixed effects are further included. Robust standard errors clustered at firm level are denoted in parentheses. * indicates statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table B3: Innovation Outcome and Ownership of Lenders

OLS, B/S sample

	(1)	(2)	(3)	(4)	(5)	(6)
Subsample	All: Innovator + Non-Innovator			Innovator Only: Intensive Margin		
Dep. Var.	$lnN_{pt,gr}$	$lnN_{pt,gr}$	$lnN_{pt,gr}$	$lnN_{pt,gr}$	$lnN_{pt,gr}$	$lnN_{pt,gr}$
State_Share	-0.025***			-0.053***		
	(0.004)			(0.014)		
State_Main		-0.025***			-0.043***	
		(0.004)			(0.012)	
State_Top			-0.019***			-0.028**
			(0.004)			(0.012)
Size	0.026***	0.025***	0.026***	0.052***	0.051***	0.052***
	(0.002)	(0.002)	(0.002)	(0.006)	(0.006)	(0.006)
Leverage	-0.142***	-0.142***	-0.143***	-0.248***	-0.249***	-0.252***
	(0.016)	(0.016)	(0.016)	(0.041)	(0.040)	(0.041)
Cash	0.054*	0.054*	0.054*	0.078	0.077	0.073
	(0.028)	(0.028)	(0.028)	(0.071)	(0.071)	(0.071)
Profitability	0.081***	0.081***	0.081***	0.133***	0.134***	0.135***
	(0.020)	(0.020)	(0.020)	(0.050)	(0.050)	(0.050)
Dep. Var. Mean	0.073	0.073	0.073	0.222	0.222	0.222
Year FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Age FE	YES	YES	YES	YES	YES	YES
No. of Firms	13,983	13,983	13,983	4,138	4,138	4138
Obs	139,444	139,444	139,444	45,790	45,790	45,790
Adj R2	0.060	0.060	0.059	0.068	0.068	0.067

The table shows how firms' innovation depends on the ownership structure of their lenders. The dependent variable is the natural logarithm of one plus a firm's total number of patents filed and eventually granted in a year. The B/S sample, which includes firms with balance sheet data is used. Columns (1) to (3) include all the firms, irrespective whether they have ever patented or not. Columns (4) to (6) keeps only firms with patenting history (those firms are denoted as innovators). Firms are classified into five groups based on their age. Age fixed effects are added in Panel B where the information on age is available. Year fixed effects and industry fixed effects are further included. Robust standard errors clustered at firm level are denoted in parentheses. * indicates statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table B4: Innovation Outcome and Ownership of Lenders

Alternative measures, B/S sample

	B/S Sample, Innovator Only: Intensive Margin					
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	$lnN_{pt,gr}$	$lnN_{pt,ap}$	$grant\_rate$	$lncitN_{pt,gr}$	$lncitN_{pt,gr}^{time-tech}$	$lnN_{pt,gr}^{top10}$
$State\_Share$	-0.053***	-0.085***	-0.023***	-0.067***	-0.040***	-0.007*
	(0.014)	(0.019)	(0.006)	(0.018)	(0.012)	(0.004)
Size	0.052***	0.071***	0.014***	0.064***	0.045***	0.013***
	(0.006)	(0.007)	(0.001)	(0.007)	(0.006)	(0.002)
Leverage	-0.248***	-0.371***	-0.096***	-0.366***	-0.198***	-0.046***
	(0.041)	(0.054)	(0.015)	(0.053)	(0.035)	(0.013)
Cash	0.078	0.1	0.002	0.028	0.067	0.019
	(0.071)	(0.093)	(0.026)	(0.089)	(0.064)	(0.021)
Profitability	0.133***	0.160**	0.042**	0.217***	0.146***	0.042***
	(0.050)	(0.065)	(0.020)	(0.066)	(0.044)	(0.013)
Dep. Var. Mean	0.222	0.352	0.125	0.273	0.165	0.033
Year FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Age FE	YES	YES	YES	YES	YES	YES
No. of Firms	4,138	4,138	4,138	4,138	4,138	4,138
Obs	45,790	45,790	45,790	45,790	45,790	45,790
Adj R2	0.068	0.085	0.032	0.059	0.057	0.034

The table shows how firms' innovation depends on the ownership structure of their lenders. Different measures of innovation are used and the definition of those dependent variables from columns (1) to (6) are listed in Table B1. The B/S sample, which includes firms with balance sheet data is used. Firms are classified into five groups based on their age. Age fixed effects are added in Panel B where the information on age is available. Year fixed effects and industry fixed effects are further included. Robust standard errors clustered at firm level are denoted in parentheses. * indicates statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table B5: Instrument Verification

Hazard model for government-owned bank distress events

Sample	all government-owned bank distress events (1995-2010)					
	(1)	(2)	(3)	(4)	(5)	(6)
PreElect	0.198	-0.060	0.027	-0.079	0.012	-0.099
	(0.274)	(0.315)	(0.355)	(0.347)	(0.432)	(0.425)
Cons. Bank Chairman					2.434***	2.249***
					(0.332)	(0.355)
Competitive County					-0.059	0.227
					(0.235)	(0.288)
Total Assets / GDP			0.165	-0.032	-0.019	-0.307
			(0.122)	(0.122)	(0.185)	(0.278)
Capital Ratio			-0.017	-0.092	0.072	-0.027
			(0.110)	(0.105)	(0.130)	(0.147)
ROA			-0.254*	-0.225*	-0.164	-0.102
			(0.132)	(0.137)	(0.142)	(0.174)
NPL Ratio			-0.001*	-0.013	-0.000**	-0.000**
			(0.000)	(0.025)	(0.000)	(0.000)
Market Share			-0.011***	-0.014***	-0.004	0.001
			(0.004)	(0.005)	(0.007)	(0.006)
Deposit Ratio			-0.031***	-0.006	-0.043***	-0.035***
			(0.006)	(0.007)	(0.010)	(0.012)
GDPPC Growth			0.019	0.002	0.012	0.002
			(0.026)	(0.031)	(0.033)	(0.036)
Log(GDPPC)			0.124	-0.415	0.911**	0.465
			(0.244)	(0.264)	(0.395)	(0.391)
Time FE	NO	YES	NO	YES	NO	YES
Obs	1,174	1,174	1,169	1,169	1,169	1,169
Number of Distress	148	148	148	148	148	148

The table shows results from estimating the following exponential hazards model:

$$h_i(t) = exp(\alpha_t + \beta_1' \cdot PreElect_{i,t} + \beta_0' \cdot X_{i,t})$$

where $X_{i,t}$ denotes a vector of covariates. The dummy variable $PreElect$ indicates whether the distress event takes place 0-12 months before the election. Two political variables, the ideology of the politician and the political competition within the county, are added in columns (5) and (6). The regression further includes bank-level control variables and regional control variables, and those independent variables are self-explanatory. All control variables are lagged by one period. Columns (2), (4) and (6) include time dummies for the four election cycles in our sample (begin of sample-1998, 1999-2003, 2004-2008, 2009-end of sample). Robust standard errors are denoted in parentheses. * indicates statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table B6: Instrument Verification

Are Pre-election and Post-election Cases Different? (covariates balance)

	D (0-12 months before)	Observations	R-squared
Panel A: Bank Charactersistics and Size of Bailout			
Log (Total assets)	0.136	148	0.003
	(0.229)		
Log (Number of employees)	0.091	148	0.002
	(0.193)		
Number of branches	-1.424	148	0.000
	(8.749)		
Market share (in %)	-0.843	148	0.000
	(3.529)		
Customer loans to Total assets (in %)	-1.996	148	0.003
	(3.321)		
Deposit ratio (in %)	-0.043	148	0.000
	(2.544)		
Capital ratio (in %)	-0.194	148	0.007
	(0.197)		
ROA (in %)	-0.045	148	0.000
	(0.131)		
NPL ratio (in %)	0.312	148	0.000
	(0.920)		
LLP ratio CL (in %)	0.060	148	0.000
	(0.164)		
Local banking sector HHI (0-10000)	13.848	148	0.000
	(164.310)		
ln (Capital injection)	-0.909	148	0.003
	(1.488)		
Capital injection to total equity (in %)	2.326	148	0.001
	(7.847)		
Panel B: Local Macro and Other Variables			
Log (GDPPC)	-0.020	148	0.000
	(0.689)		
GDPPC growth (in %)	-0.573	148	0.002
	(0.785)		
Employment rate (in %)	-3.082	145	0.009
	(2.642)		
Employment growth (in %)	0.000	145	0.000
	(0.289)		
Government debt to GDP (in %)	0.310	131	0.003
	(0.487)		
Government debt to revenue (in %)	3.801	132	0.004
	(5.689)		
Total loan growth (in %)	0.032	140	0.000
	(2.321)		
State loan share (in %)	0.846	140	0.000
	(2.885)		

Each row of this table represents a univariate regression of the variable in the first column on the dummy indicating the timing of distress in the electoral cycle. $D(0-12\ months\ before)$ equals to one if the distress event occurs 0 to 12 months before the election and zero otherwise. Panel A examines bank characteristics and bailout size. Panel B examines local macroeconomic and loan-related variables. The variables are measured in the year before the distress event. Robust standard errors are denoted in parentheses. * indicates statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.