Lending in Social Networks

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Abstract

This paper employs a unique contract-level dataset on members of 211 social clubs in Germany over the period 1993-2011, and uses a quasi-experimental research design to investigate how social connections between banks and firms affect the allocation of credit. We find that banks provide significantly more credit to firms that are within their club than they do to firms that are members of other clubs. Interestingly, however, the credit supplied inside the club generates a lower return for the bank – banks earn 3.23 percent lower returns on club loans, compared to what they earn on loans given to firms that are members of other clubs. On examining the usage of funds, we find that club firms do not use these extra funds they receive from club banks to make new investments, but instead use these extra funds to pay out dividends. Overall, our results support a *favoritism* theory rather than a bright side *informational* or *enforcement* theory, with state-owned banks engaging most actively in what can be interpreted as 'crony' lending.

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1 Introduction

For a considerable fraction of corporate lending relationships lenders and borrowers are connected by social ties.[1] While proximity between lenders and borrowers can be useful in reducing informational asymmetries and increase the efficiency of credit allocation,[2] critics argue that proximity is a double edged sword and also has its ill effects.[3] In this paper, we investigate how social ties between firms and banks affect the allocation of credit. Specifically, we attempt to answer three questions. Do social ties matter for lending? If so, can we say something about the mechanism that generates this effect? Finally, how is the efficacy of credit allocation affected by the social ties?

Several challenges hinder empirical research in this area. The first obstacle relates to the selection problem. The formation of social networks is not random; people often self-select into social groups that have interests aligned with their own interests (Lazarsfeld and Merton 1954). In our context, firms which are part of social networks might share characteristics that distinguish them from firms that are not part of the same social network. The main identification challenge is to isolate the impact of social networks from spurious effects caused by selection.

The second obstacle relates to the availability of good quality data that allows one to examine the effect of social connections on lending. It is natural to expect that the benefits of social networks are more important for small and informationally opaque firms. Unfortunately, such granular micro-level data on small and medium-size enterprises and their network connections are very difficult to obtain and, when available, tend to be of poor quality.

Finally, the identification of the underlying mechanism that delivers the social network effect is challenging. After all, the identification of a link between social network and lending leads to an important question: how is the efficacy of credit allocation affected by the network effect? Do social networks, through better information and enforcement, improve the allocation of resources, or do forces such as favoritism, collusion, or social pressure inside the network distort credit allocation and generate inferior outcomes, compared with those that would be generated by a somewhat more arm's length contract?

[1] Karlan, Mobius, Rosenblat, and Szeidl (2009); own estimates

[2] The view that proximity is beneficial dates back to earlier work done by Gerschenkron (1962) and is at the heart of several more recent papers. According to the view, proximity may help alleviate informational and enforcement frictions, thus enhancing the efficiency of credit allocation.

[3] Critics often allege (Akerlof and Romer (1993)) that banks may provide preferential treatment to borrowers who they share proximity with and thus distort the allocation of credit (La Porta, Lopez-de Silanes, and Zamarripa (2003) and Khwaja and Mian (2005)).

Germany provides a nearly ideal setting to analyze social network effects for several reasons. First, the country has a strong culture of service clubs – clubs that bring together business and professional leaders to socialize on a regular basis. While these service clubs are organized through a global organization that is headquartered in the US, the individual service clubs operate locally in almost every city in Germany.[4] Membership to these service clubs is considered prestigious, and most individuals accept a membership invitation when offered one. Second, the Deutsche Bundesbank provides not only detailed contract-level information on all borrowers, available through its credit registry, but it also provides time-series financial statements of non-financial companies (USTAN).

We hand-collect data on members – both firms and banks – for 211 such service clubs, from 1993 to 2011, to capture both cross-sectional and time series variation in social proximity, and obtain very detailed contract-level financial data on these members from the Deutsche Bundesbank. We are thus able to create a unique dataset on social networks that provides very granular information on lending relationships combined with detailed accounting information on member firms.

We tackle the endogenous selection issue in several ways. At the outset, it should be noted that our analysis focuses on firms which are members of the same service club organization. Furthermore, our analysis does not compare firms which are members of the club with firms that are not members of the clubs. Instead, we compare firms that are members of a branch of a club with firms that are members of a different branch of the *same* service club in the same city.[5] Since members of these service clubs are selected with the same ideological criteria, this should alleviate most selection concerns to a significant extent. Moreover, a bank that is a club bank for one club is an outside bank for another club. By comparing the *same* bank's lending to firms which are members of its club (and therefore socially connected with each other) with firms it is not connected to, we are able to control for the time-invariant sources of unobserved bank heterogeneity that may bias the results.

We exploit three events to generate variation in the social proximity variable. One such event that leads to an increase in the degree of social connectedness is firms' entry to a service club. Clearly, the entrance of firms to these clubs might seem a bit problematic, since entrance may be driven by unobservable, firm-specific characteristics. For instance, clubs may elect 'stars' (i.e., the better-performing firms) as members, and so the expansion in lending is not an outcome of being in a club, but of selection into the club. While this seems like a plausible story, we believe that this is unlikely to be the case in our empirical

[4]Larger cities have several service clubs in close geographic proximity.

[5]Henceforth, when we use the expression clubs, we are actually referring to a club branch.

setting. Entry of firms, in our set-up, is driven by some pre-defined rules, such as the 'one member per industry' rule. By statute, only one representative of each industry sector can be a member in a given service club branch.[6] This restriction has been put in place to prevent competition and collusion in a club. Furthermore, due to capacity constraints, the entry of a new member to the club usually only takes place when an existing member retires or leaves the club. This gives us an exogenous source of variation in the timing of firms' entry to the clubs. So the firms that enter the club would have fulfilled the criteria to enter a club before and, in many cases, even had lending relationships with club banks but, since their industry sector slot is not vacant, they cannot join the club unless the existing member retires from the club. Additionally, it should be noted that membership of a club is an outcome of a complex voting mechanism that is in place to elect members, and it can largely be considered exogenous from the perspective of an individual firm or bank.

An additional source of variation comes from the formation of new clubs in Germany. Forming a new club is a highly regulated process, driven by pre-specified rules. The district governor, who is the local head of the service clubs, appoints a district extension committee, tasked mainly with identifying communities that are currently without clubs or communities that have existing clubs, but where an additional club is beneficial. The communities must meet the population criteria requirement for chartering a new club. In addition, for communities that have existing clubs, it is the job of the extension committee to ensure that the establishment of the additional club does not negatively affect the existing club(s). Given this process, the formation of a new club can be considered to be exogenous from the perspective of an individual firm.

The final source of identification comes from mayoral elections. In Germany, the mayor of a district is often directly appointed as the chairman of the supervisory board of a local savings bank which is state-owned. While he is not explicitly involved in managing the bank, he often is the chairman of the banks' supervisory board, and therefore has a large influence on their loan-granting activity. While the elected candidate is always a member of the club, the degree of influence changes with the elections. Importantly, the mayoral election is independent of time series changes in firm characteristics. It is further independent of changes in bank quality that would be of concern in case of bank entry to a club. The mayoral election thus gives us an exogenous times series variation in this member's ability to access and approve funds, which allows us to identify changes in firms' borrowing structures in a setting free from other influences.

[6] See Section 2 for details. Members representing business segments already represented by an existing member can only join once the existing member has belonged to the club for 15 years or retires.

To quantify the effect of social proximity on lending, our empirical strategy, which is essentially a differences-in-differences methodology, compares for the same firm, quarter-by-quarter, the financing provided by club banks to that provided by outside banks. This empirical strategy thus controls for demand-side effects, such as changes in investment opportunities that may arise due to enhanced social connections.

The following facts emerge from our analysis. Our 'within city' comparison of service clubs reveals that club banks have a higher market share among members of their own service club, compared with members of other service clubs in the same city, by 18.35%. On average, entry of firms to clubs leads to a 10.03 percentage points increase in the fraction the firm borrows from the club bank. We further examine the dynamics of lending around the entrance event and find that our results are not driven by pre-treatment trends. Very similar results are obtained using the formation of new clubs as a source of identification – firms that are involved in the formation of a new club experience a 12.53 percentage points increase in their share of lending from the banks that participate in the club formation. On examining mayoral elections, we find that when a club member is elected as a mayor and becomes the head of the local state bank, the share of loans from the state bank increases by an additional 5.63 percentage points. The evidence on mayoral elections is reinforced by comparing firm lending around mayoral elections for which the mayor is not appointed as the chairman of the supervisory board of the local savings bank. Using this event as a placebo test, we can isolate the effect of the state bank proximity from the proximity to the mayor following the election. The placebo test illustrates that if a club member is elected as a mayor, there is no effect on the lending of firms whose CEO is member of the respective club.

On examining firms' total debt, we find that social networks significantly increase borrowers' total debt by 32.22%. This finding is confirmed when we examine around new club formations and mayoral elections. Additionally, we find no evidence of any pre-treatment trends. On examining the *intensive* and the *extensive* margins, we find that an increase in the degree of social connectedness leads not only to more lending to firms that already have an existing relationship with the bank, but it also increases the probability of forming a new relationship with this bank by 11.44% relative to outside banks.

We further investigate the underlying mechanism from the bank's perspective, by calculating the returns on loans (ROLs) that the banks generate from these club transactions vis-à-vis outside transactions. A simple informational or enforcement theory should lead to a better allocation of credit, thereby improving the profitability of the bank. A favoritism theory, on the other hand, predicts that the ROLs are lower for 'in-club' loans, compared to 'out-club' loans originated by the same bank.

We find that a given club bank generates a 3.23 percentage points lower return on loans made within the club when compared with loans granted to firms outside the club. In addition, for the *same* firm, ROL of club banks are significantly lower when compared with outside banks. The ROL that the same bank generates on loans provided to club firms *before* they join a club (before the mayoral election) is significantly higher than on loans originated once the firm and bank are socially connected. On investigating the drivers of this difference in ROLs, we find that the difference comes mostly from the difference in returns that are generated from lending to firms in financial distress. While the interest rates and recovery rates on loans are not much different for club loans when compared with loans made outside the club, club banks lend disproportionately more to firms that are closer to distress, and thus lose a lot more when the firm defaults. It is this excess continuation of firms as a going concern which stems from the *soft budget constraint* problem of club banks (Kornai 1986), especially state banks; that generates a lower ROL for club banks. Since we measure ex-post loan performance, all contract features that affect the banks' returns, e.g., differences in collateral, are accounted for in the ROL calculation. Thus, our analysis is robust to differences in contract features.

We next examine how firms deploy the extra financing they receive through their membership of the club. We find that firms *do not* use this extra financing to make new investments, something one would expect if social proximity to the lender relaxed financing constraints. Instead, firms use these funds to pay out dividends to existing shareholders, which in most cases means paying out to themselves, as most of these are relatively small, family-owned firms. Furthermore, the increase in bank credit leads to a significant increase in leverage. The debt to assets ratio increases by 6.17 percentage points after firms join the club.

We also investigate the differences in lending behavior across state and private banks and find that the effects are substantially more pronounced for state-owned banks. We find that entry of firms to a club increases their share of financing by 6.45 percentage points more if they are state-owned, compared to when they are private.[7] Furthermore, for clubs with both a state and a private banker among its members, we find that, after a firm's entry to the club, the share of state club bank loans of the total club bank loans increases by 14.26 percentage points for the *same* firm. Finally, we examine the difference in the behavior of clubs that have the mayor in the club. We find that the increase in the share of firms' borrowing after entering a club with a state banker is 12.83 percentage points higher when the mayor is also head of the local state bank's supervisory board and present in the club as

[7] Very similar results are obtained if we look at formation of new clubs.

well. On examining the ROL, we find that, while the main effects are present for both state and private banks, the ROL are significantly lower for state banks. More specifically, the ROL obtained by the state banks on their 'in-club' loans is significantly lower (compared to the private bank) than the ROL they obtain on 'out-club' loans.[8] All in all, we find that state banks not only grant more loans to firms that are part of their club, but they also generate a much lower ROLs made within the club. These results are consistent with the view espoused by several commentators that state banks, due to blunt incentives, are more likely to engage in 'crony' lending.

The paper connects several strands of literature. The literature on proximity and lending is an obvious starting point (Petersen and Rajan 1995).[9] It is often argued that proximity between banks and firms mitigates informational problems. Our results suggest that proximity can be a double-edged sword, and that too much proximity may not always be desirable. The paper thus contributes to this growing literature.

The findings of this paper also naturally resonate with the rent-seeking pattern that has been documented for connected firms in La Porta, Lopez-de Silanes, and Zamarripa (2003) and Khwaja and Mian (2005), with of course some key differences that are worth highlighting. Clearly, the nature of connections is very different. While Khwaja and Mian (2005) examine the effect of *political connections* on lending in Pakistan, whereas La Porta, Lopez-de Silanes, and Zamarripa (2003) investigate the consequences of *related lending* in Mexico. To our best knowledge, this paper explores the link between social connections and rent seeking in bank lending. Moreover, it does so in a developed economy, Germany, where corruption and other institutional ills are perceived to be very low.

While most of the existing literature has focused on the positive effects of social networks,[10] this paper uncovers a malign view of the effects of social network connections on bank-lending relationships. This paper also contributes to the growing empirical evidence on the interplay between social networks and firm performance. Hwang and Kim (2009) document that network connections can dominate efficiency considerations in decision-making, especially when it comes to the appointment and remuneration of CEOs. Kuhnen (2009)

[8]It should be stressed that this test controls for differences in objective functions that might exist between state- and privately owned banks. Since we are looking at the wedge in ROL between 'in-club' and 'out-club' loans, for the *same* bank, we automatically control for inherent differences in these different organizational forms.

[9]See also (Petersen and Rajan 2002, Mian 2006, Fisman, Paravisini, and Vig 2012, Engelberg, Gao, and Parsons (2012)) for more papers on this topic.

[10]Engelberg, Gao, and Parsons (2012) for better information flow or better monitoring; Burchardi and Hassan (2013) for economic growth; Freedman and Jin (2008) for peer-to-peer lending; and Cohen, Frazzini, and Malloy (2008) for fund managers and analysts; Greif (1993) for the interaction between social and economic institutions.

shows that, in business networks, the conflicting effects of favoritism and the mitigation of agency conflicts just cancel each other out.

In a broader sense our paper also connects to the literature on social networks and economic outcomes.[11] As shown by Burchardi and Hassan (2013) personal relationships can be an important determinant of regional economic growth. There is an influential literature that has focused on the role social networks play in the transmission of information.[12] This paper also contributes to the growing empirical evidence on the interplay between social networks and firm performance. Hwang and Kim (2009) document that network connections can dominate efficiency considerations in decision-making when it comes to the appointment and remuneration of CEOs. Kuhnen (2009) shows that, in business networks, the conflicting effects of favoritism and the mitigation of agency conflicts just cancel each other out. Banerjee and Munshi (2004) and Bandiera, Barankay, and Rasul (2009) document a negative effect of social connections on economic outcomes.

Finally, our paper contributes to the understanding of the difference between state and private financing (La Porta, Lopez-de Silanes, and Shleifer 2002). Governments around the world are taking ownership of large parts of the banking system and, potentially, this public-sector involvement in the banking sector may have considerable long-term effects on all major industrialized countries.[13]

Section 2 describes the data and offers background information on service clubs in Germany. Section 3 outlines our empirical strategy, Sections 4, 5, and 6 present the results. Section 7 discusses alternate explanations that may explain the results, and Section 8 offers a conclusion.

[11] Granovetter (2005) describes the relationship between social networks and economic outcomes in the sociology literature; Knack and Keefer (1997), Sacerdote (2001), and Fracassi (2011), and Shue (2013) for social networks influencing economic outcomes and individual behavior; Lerner and Malmendier (2011) for successful ventures, Jackson and Schneider (2010) on moral hazard, Gompers, Mukharlyamov, and Xuan (2012) find that venture capitalists make worse investment decisions when their decision to invest together is based on shared social traits.

[12] Engelberg, Gao, and Parsons (2012) for better information flow or better monitoring; Hochberg, Ljungqvist, and Lu (2007) for venture capitalists; and Cohen, Frazzini, and Malloy (2008, 2010) for fund managers and analysts; Greif (1993) for the interaction between social and economic institutions.

[13] Several papers have documented distortions in lending by government-owned banks and state-regulated banking sectors (Jayaratne and Strahan 1996, Sapienza 2004, Dinç 2005, Bertrand, Schoar, and Thesmar 2007). For theoretical evidence on this topic, see Krueger (1974), Shleifer and Vishny (1993, 1994), Bliss and Tella (1997), and Acemoglu and Verdier (2000).

2 Institutional Background and Data

2.1 Service Clubs in Germany

To identify social connections, we focus on membership information of an important service club organization in Germany.[14] While these service clubs are organized through a global organization that is headquartered in the United States, the individual service clubs operate locally in almost every city or county in Germany. These clubs bring together members, all of whom are local businesses (mostly SMEs) and professional leaders, to meet once a week over lunch or dinner to socialize. As part of the membership requirement, it is mandatory for each club member to attend the weekly club meetings on a regular basis.[15] While the stated objective of these service clubs is to raise funds for charitable work, having personal connections to other business leaders is often cited as an important membership prerequisite.

On average, local service clubs have about 50 members and generally there is one service club in each city of about 20,000 inhabitants. In larger cities, formation of additional clubs is common; Munich and surroundings, for example, has more than 30 clubs. Overall, there are about 1,000 clubs with about 50,000 members in Germany. There are strict membership criteria which new members have to fulfill that tend to be based on business or professional leadership.

Our sample area comprises all service clubs in southern Germany (the northern boundary is Saarbruecken, Frankfurt, Erfurt and Hof), which are located in cities (and the surrounding areas of these cities), during the period 1993 until 2011.[16] Further details on the data collection of club membership information are described in Appendix A. We gather membership information on all corporate CEOs and directors of bank branches for 211 clubs in this area (Table 1, Panel A).[17] This provides data for 1,091 corporate CEOs whose firms are listed in the German credit register. Out of these sample firms, 141 firms became insolvent during our sample period. We exclude firms (five in total) which are listed on the German stock market index (DAX), since these are very large firms with many lending relationships.

The process for a potential new member joining a club is as follows: an existing member

[14] For confidentiality reasons, we do not mention the name of the service club organization in this paper.

[15] Specifically, membership is taken away if a member misses four consecutive meetings or attends less than 50% of the meetings over a period of six months.

[16] The German credit register starts in the second quarter of 1993, and therefore this date marks the beginning of our sample period.

[17] A particular service club is included in our sample if there is at least one CEO whose firm has taken out a bank loan that is recorded in the credit register of the Deutsche Bundesbank. Our sample firms have the following legal structure: 944 are head of a limited liability firm (GmbH), 57 members are heads of a private firm (KG and OHG), and 90 are CEOs of publicly listed firms (AG).

suggests a new candidate to the other club members, who then decide by vote if the candidate can join the club. Since membership of service clubs is considered very prestigious, in general, most CEOs and bank directors accept membership invitations to a particular club. Each specific profession or business can only be represented once in each club, according to the 'one member per industry' rule. A candidate whose industry sector is already represented by an existing member can only join once the existing member completed 15 years.[18] Therefore, the timing of the entry of new members depends on the date when the industry sector slot of the candidate becomes available in the club. During our sample period, 474 out of the 1,091 CEOs entered a club.

There are distinct rules that govern the formation of new clubs. The district governor, who is the local head of the service clubs, appoints a district extension committee, tasked mainly with identifying communities that are currently without clubs or communities that have existing clubs, but where an additional club is beneficial. The communities must meet the population criteria requirement for chartering a new club. For instance, it is required that the clubs must have at least 25 businessmen or professionals from the local community. In addition, for communities that have existing clubs, it is the job of the extension committee to ensure that the establishment of the additional club does not negatively affect the existing club(s). During our sample period, 43 new clubs were created.

The 1,091 firms whose CEOs are club members take out loans from 542 distinct banks. We define a bank as a club bank if the director of the bank or local branch of a bank is a member of the club. In Germany, private banks have different organizational characteristics vis-à-vis state-owned banks. Private banks, for instance, are generally larger in size, and provide a wide array of transaction services to the customers. Furthermore, compared to state-owned savings banks and cooperatives that have more of a local presence, private banks operate in different geographical areas through their local bank branches (see Appendix B for an overview of the German banking sector). Given this, all private bankers in our sample are directors (heads) of a local branch of a larger bank, while directors of public and cooperative banks are generally heads of local banks. We identify 352 club bankers,[19] 173 of which are of a private bank, 138 of a state bank and 41 of a cooperative bank. Among the 1,091 firms, 182 take out loans only from the club bank and 393 only from banks outside the club, while 516 CEOs take out loans from banks within and outside the club.

[18] If a member reaches the age of 60 and has been a member of the club for at least 10 years, or reaches the age of 65 and has been a member of the club for at least five years, a new member of his industry spot may join.

[19] Some clubs have two bankers among their members because state and private banking are considered as two distinct industry spots. Further, some bankers have been connected to the club for more than 15 years and are considered to have made the industry sector slot available again for someone else to join.

Finally, there is an interesting feature of German saving banks that we exploit for identification in this paper. Since German savings banks are owned by local cities, the respective mayor is often also the chairman of their supervisory board. While he is not explicitly involved in managing the bank, he has a large influence on he banks' loan-granting activity.[20] The election of a mayor to the club thus generates a time series variation in the member's ability to approve funds. In our sample, we identify 20 cases in which an existing club member was elected as a mayor for the first time and subsequently became chairman of the club bank's supervisory board, in 16 cases an existing member is elected as a mayor and does not become head of the local state bank.

2.2 Loan and Financial Statement Data

We collect information on all individual lending relationships of our sample firms from the credit register of the Deutsche Bundesbank. The credit register provides contract-level information on all German firms, whose total outstanding loans in a given quarter exceed 1.5 million euros.[21] We define a loan as a club loan if both the CEO of the firm and the bank director of the specific bank or branch are part of the same service club. As shown in Table 1, Panel B, our sample contains 54,123 firm-quarter loan observations. The average loan amount per lending relationship is 6.4 million euros and the average outstanding loan amount per firm is 13.4 million euros. The firms have, on average, 3.72 different lending relationships throughout the entire sample period.

We match loan-level data, obtained from the credit register, with accounting information from the Deutsche Bundesbank's USTAN database. This gives us more detailed variables at the firm level.[22] This match yields a sample of 686 firms (5,474 firm year observations).[23] Panel B provides summary statistics on total assets, debt to assets, return on assets (ROA), cash to assets, and borrowing costs for this sample. We next report how our sample firms compare with the population of firms contained in the USTAN database. The average size of our sample firms is very similar compared with the mean of the population (92 million euros as opposed to 93 million euros); the debt to asset ratio is slightly higher for sample firm (25.3% compared with 24.6%). The average profitability is somewhat lower for our sample

[20] Since savings banks are, on average, small institutions, large loans bear a particular risk for these banks. Therefore these banks have a credit committee in place to approve loans. Mayors often have a significant say in these credit committees.

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

[22] Even though the credit register and the accounting information all come from the Deutsche Bundesbank, the two datasets need to be hand matched by company name and location of incorporation.

[23] Note that the loan-level information is available quarterly, while the balance sheet information is annual.

firms (6.2%) than for the population of firms (6.9%). Our sample firms show a very similar fraction of cash holding (6.3%) relative to the population (6.6%). Finally, we consider the ratio of interest paid by total loans outstanding (i.e., borrowing costs). Our sample firms paid, on average, 8.1% interest compared to 9.1% interest paid by the population firms. All in all, the variables are quite similar.

3 Empirical Strategy

Our basic identification strategy examines how perturbation in the degree of social connectedness between firms and banks affects the quantity of financing that a firm receives. To identify the the network effect, one essentially attempts to estimate the following regression specification:

$$q_{jt} = \alpha_j + \alpha_t + \varphi \cdot event_{jt} + \epsilon_{jt} \tag{1}$$

where q_{jt} is the total financing that firm j receives at time t; α_j and α_t denote firm and quarter fixed effects; $event_{jt}$ is an indicator variable that takes on a value of one when firm j enters a club, and zero otherwise. In our empirical strategy we also exploit the formation of a new club branch and mayoral election as an event. In the latter case, the $event_{ijt}$ dummy takes on a value of one for all member firms that share membership with the elected mayor, and zero otherwise. The parameter φ measures how social connections affect firms' ability to access external finance and ϵ_{jt} captures firm-level demand shocks. It is, however, important to note that changes in the degree of social connectedness, captured by the $event_{jt}$ variable, can also generate demand effects, such as increases in investment opportunities. Then, a potential bias in the estimate $\hat{\varphi} = \varphi + \frac{Cov(event_{jt}, \epsilon_{jt})}{Var(event_{jt})}$ is captured by the term: $\frac{Cov(event_{jt}, \epsilon_{jt})}{Var(event_{jt})}$.

To identify the supply side effect separately, we employ our contract-level data and compare, for the same firm, quarter by quarter, the quantity of loans granted by 'in-club' banks with the quantity of loans granted by 'out-club' banks, where the terms 'in-club' and 'out-club' denote whether the firm and the bank are members of the same club. This allows us to control for firm-specific shocks, such as demand shocks, that may coincide with enhanced social proximity. In a regression framework, we estimate the following specification:

$$q_{ijt} = \gamma_{jt} + \gamma_{it} + \gamma_{ij} + \Delta \cdot event_{ijt} + \epsilon_{ijt}, \tag{2}$$

where q_{ijt} is the quantity loan from bank i to firm j, γ_{ij} are relationship-level fixed effects that control for any time-invariant effects between firm j and bank i; γ_{jt} and γ_{it} are non-parametric controls for firm and bank-specific shocks. In this specification, Δ is the variable of interest - it measures how social connections affect firms' ability to access external finance. It should be noted that, for firms that have a single lending relationship, the coefficient Δ cannot be identified since $event_{ijt}$ is absorbed by γ_{jt}. Our identification thus compares for the *same* firm the quantity of loans granted by 'in-club' banks with the quantity of loans granted by 'out-club' banks around the event.

While the empirical strategy controls for firm-level demand effects, it generates an upward bias if firms substitute lending from the 'out-club' bank to the 'in-club' bank. To see this, consider two banks, i and i', where i is the 'in-club' bank and i' is the 'out-club' bank, both providing external financing to firm j. Assume that the perturbation in the degree of social connectedness, say by the entry event, generates a positive supply-side effect (Δ_1) from the club bank. This supply-side effect could come, for example, from a lower cost of financing that results from lower asymmetric information. A lower cost of financing would lead to more club financing, but also to less outside financing (outside financing is now relatively more expensive). Such a substitution effect, if present, is denoted by (Δ_2). This gives us the following system of equations:

$$\begin{aligned} q_{ijt} &= \gamma_{it} + \gamma_{jt} + \gamma_{ij} + \Delta_1 \cdot event_{ijt} + \epsilon_{ijt} \\ q_{i'jt} &= \gamma_{i't} + \gamma_{jt} + \gamma_{i'j} - \Delta_2 \cdot event_{ijt} + \epsilon_{i'jt}. \end{aligned} \tag{3}$$

Differencing the equations in (3) leads to: $q_{ijt} - q_{i'jt} = \gamma_{it} - \gamma_{i't} + \gamma_{ij} - \gamma_{i'j} + [\Delta_1 + \Delta_2] \cdot event_{ijt} + \epsilon_{ijt} - \epsilon_{i'jt}$, which can be empirically estimated in the regression framework:

$$\Delta q_{jt} = \gamma_{it} - \gamma_{i't} + \gamma_{ij} - \gamma_{i'j} + [\Delta_1 + \Delta_2] \cdot event_{ijt} + \epsilon_{ijt} - \epsilon_{i'jt} \tag{4}$$

It can be seen from equation (4) that estimation in differences may generate an upward bias in the coefficient of interest. Substitution of loans by firms from 'out-club' banks to 'in-club' banks would bias the estimated coefficient Δ upwards – the network effect is $\Delta_1 + \Delta_2$ instead of Δ_1. To deal with this bias, we transform the left-hand side variable to a firm's share of loans from its club bank to its total loans (henceforth, club bank share).

Shares of inside (i) and outside (i') banks are given by:

$$\begin{aligned}\frac{q_{ijt}}{\sum_i q_{ijt}} &= \alpha_{jt} + \alpha_{it} + \alpha_{ij} + \delta \cdot event_{ijt} + \epsilon_{ijt} \\ \frac{q_{i'jt}}{\sum_i q_{ijt}} &= \alpha_{jt} + \alpha_{i't} + \alpha_{i'j} - \delta \cdot event_{ijt} + \epsilon_{i'jt}\end{aligned} \tag{5}$$

Differencing equations in (5) and noting that the sum of shares by inside and outside banks equals one, we get:

$$\frac{2q_{ijt}}{\sum_i q_{ijt}} - 1 = \alpha_{it} - \alpha_{i't} + \alpha_{ij} - \alpha_{i'j} + 2\delta \cdot event_{ijt} + \epsilon_{i'jt} - \epsilon_{ijt}, \tag{6}$$

which by dividing by two yields:

$$\frac{q_{ijt}}{\sum_i q_{ijt}} = \frac{1}{2} + \underbrace{\frac{\alpha_{it} - \alpha_{i't}}{2}}_{=0 \text{ on average}} + \underbrace{\frac{\alpha_{ij} - \alpha_{i'j}}{2}}_{\beta_j} + \delta \cdot event_{ijt} + \underbrace{\frac{\epsilon_{ijt} - \epsilon_{i'jt}}{2}}_{\epsilon_{jt}} \tag{7}$$

Since computing club banks' shares collapses the relationship-specific information from the two equations in (5) into one firm-level observation, this simplifies to:

$$\frac{q_{ijt}}{\sum_i q_{ijt}} = \beta + \beta_j + \delta \cdot event_{jt} + \epsilon_{jt} \tag{8}$$

where the dependent variable is the share of the financing provided by the 'in-club' bank. It should be noted that the specification is quite stringent and already controls in a non-parametric way for firm-specific shocks (α_{jt}), such as an increases in investment opportunities etc. that may coincide with increased social proximity. Importantly, our set-up also takes care of bank-specific shocks. 'In-club' banks and 'out-club' banks are not two distinct groups of banks; the same bank is an 'in-club' bank to some and an 'out-club' bank to other firms. Thus, on average, $\alpha_{it} - \alpha_{i't}$ is approximately 0.

To sharpen the analysis further, we saturate the specification by adding quarter-fixed effects β_t in equation (9).[24] The augmented regression is thus:

$$\frac{q_{ijt}}{\sum_i q_{ijt}} = \beta + \beta_t + \beta_j + \delta \cdot event_{jt} + \epsilon_{jt} \tag{9}$$

The variable δ thus captures a supply effect that results from an increase in proximity to the club bank, provided that the covariance between $event_{jt}$ and ϵ_{jt} is zero, which our empirical strategy tries to ensure. Equation (7) highlights that the nature of a shock that may lead to a bias in δ would need to be a shock that is correlated with $event_{jt}$ and that affects the borrowing of firm j from 'in-club' bank i differently than its borrowing from 'out-club' bank i'. Our empirical strategy tries to ensure that the $event_{jt}$ variable is exogenous from such shocks. Specifically, we exploit time series variation in the proximity variable to quantify the magnitude of the social network effect, which is detailed in Section 2. We start by looking at the entry of firms to clubs that is driven by some pre-specified rules and conditions. In addition, we examine the network effect around the formation of new clubs in various cities. Here again, the formation of new clubs is driven by some pre-specified rules which lends credibility to the analysis.

Our main empirical strategy, however, exploits mayoral elections. In a subset of clubs, one of the existing members is elected as a mayor for the first time. As stated before, the mayor is, by statute, the head of the supervisory board of the local state bank and even though he is not explicitly involved in managing the bank, he is the chairman of the bank's supervisory board and has a big say in the loan-granting activity, especially for larger loans that explicitly require his approval. The election of a club member as a mayor changes the proximity between firms and the club bank in a manner that is orthogonal to firm-specific shocks, allowing us to identify changes in borrowing in a setting free of spurious effects.

4 Social Networks and Lending Patterns

4.1 Structure of Financing

We start this section by reporting the average share of credit in a club that is provided by the club bank. This is measured as the ratio of financing provided to club firms by club banks to the total financing provided to the club firms by all banks. It can be seen from Panel C of Table 1, club firms borrow 25.08% of their total loans from the club banks.

[24] We can even control for shocks to the local bank branch by adding quarter-county fixed effects. Our results remain unaffected by this alternation.

To understand this number better, we exploit a distinct feature of our framework: our sample cities have multiple club branches. This allows us to examine the share of credit provided by club banks to firms that are members of 'other' service clubs – instances where the bank and the firm do not belong to the same branch of the service club organization. The mean share these banks have within the other service club(s) within the same city is only 6.73%. The difference between these two shares (18.35%) is quite large and statistically significant. This difference uncovers an interesting pattern, namely: firms borrow substantially more from their club bank than they do from the outside banks. Since the same bank is a club bank for one club, but an outside bank for another club, this suggest that these correlations are not driven by differences in quality of banks. Moreover, the fact that firms are selected under the same ideological criteria mitigates selection concerns related to the endogenous matching of banks to firms. We next investigate these patterns more systematically.

4.2 Entry of Firms to Clubs and New Club Formations

We exploit firms' entry to a service club to generate variation in the social proximity variable. As outlined in Section 2, a new candidate can only join if his industry sector is not already represented by an existing member. This pre-specified rule gives us an arguably exogenous source of variation in the timing of firms' entry to the clubs.

A graphical depiction of the average share of credit in a club that is given by the club bank is provided in Figure 1.[25] As can be seen, we observe a sharp rise in the share of 'connected lending' subsequent to entry; an increase from 14% to 24%. In addition, we find no evidence of pre-event trends. The results from running specification (9) are summarized in Table 2. Columns I and II display the results for the entire sample of firms which joined a club, while Columns III and IV display findings only for those firms that join a service club through the formation of a new club branch. Considering all entries, the lending share of club banks increases by 8.90 percentage points (Column I). Controlling for time variation in club bank shares by adding quarter fixed effects leads to a slightly higher increase of 10.03 percentage points (Column II). If we focus on firms that join a club through the formation of a new club branch, the share of lending among members increases by more than 10.80 percentage points (Columns III and IV) as a response to the event.

[25] Additionally, we have plotted the mean club lending share restricting the sample to firms entering a club subject to the 'one member per industry' rule or through club formations. The resulting graphs look almost identical.

4.2.1 Firm Borrowing Channel

We documented that an increase in proximity altered the composition of financing towards more 'in-club' financing. Here, we explore the effects of social proximity on total firm financing and capital structure. Since the documented effects are consistent with a *supply-side* effect, it is thus natural to expect that proximity should lead to an increase in total firm borrowing.

To test for this, we replace the dependent variable in equation (9) by the log of aggregate firm borrowing per quarter. The results are gathered in Table 2, Columns V and VI. Total borrowing is, on average, 32.22% higher after firms enter the network, relative to the pre-entry period (Column V). The magnitude is almost identical for firms participating in club formation (38.06%, Column VI). On examining the capital structure, we find that entry to a club, increases the leverage ratio by 6.17 percentage points (Column VII).[26] For firms that participate in the formation of a new club branch, the leverage increases by 6.73 percentage points (Column VIII). Thus, the documented increase in total bank loans after entry is not explained by asset growth of firms after joining the club but rather depicts a change in firms' debt usage.

One concern is that clubs might be picking 'star' firms to join their club, so it is not the proximity that generates this result, but rather the 'star' status which generates the proximity. To illustrate this argument, consider a CEO of a small firm which has recently come up with an innovation that is the 'talk of the town'. Clearly, this CEO might become rich as a result of this, and his firm will certainly experience an increase in the demand for finance for development. If the CEO is invited to join the club, the entry to the club picks up a spurious correlation. If this argument holds, our findings could be driven by reverse causality. To begin with, we would like to add that the financial variables do not provide support to this view. For instance, we do not find any changes in firms' profitability after they enter the club.[27] To sharpen our analysis further, in the next section we exploit mayoral elections as an additional source of identification.

[26]We include the log of sales and the log of earnings before interest and taxes (EBIT) in the loans to assets regression as both are commonly found to affect firms' leverage. While the estimates for the coefficients of both control variables are significant, the coefficient of the loans to assets ratio is almost identical to the estimation without control variables.

[27]We discuss this is Section 5.2.

4.3 Mayoral Elections: A Sharper Test

In this section, we exploit mayoral elections as an additional source of identification. Essentially, the mayor, being the head of the local municipal government, is also the chairman of the supervisory board of the local state bank (savings bank). This position gives the mayor substantial executive powers to affect the banks' strategies going forward. The mayor not only has significant influence in the management board, but he also has a big say in the appointment of bank managers, in the distribution of banks' earnings and, in the case of large loans, he has to approve the disbursement of credit. In our sample, we identify 20 clubs in which an existing member is elected. We use this mayoral election to generate an exogenous variation in the degree of firms' connectedness with the state bank.

A graphical depiction of the dynamics of average share of credit in a club that is provided by the state bank, is depicted in Figure 2. As can be seen, we observe a sharp rise in the share of 'connected lending' subsequent to the mayoral election from 17% to 28%. In addition, we find no evidence of pre-event trends. In Table 3, we define the $event_{ij}$ to be one from the year of the mayoral election for the firms in the 20 clubs that experience a mayoral election. Interestingly, we observe that the share of state bank loans in total firm loans for affected firms increases by 5.78 percentage points following the election (Column I). Adding quarter fixed effects to control for time variation in the shares of the club banks leaves the results almost unchanged (Column II). We further examine whether the mayoral election has an impact on firms' total debt and their leverage ratio and find that the election of a club member as mayor in clubs with a state bank leads to an increase in total debt for club firms by 23.30% (Column III) and an increase of the leverage ratio by 4.97 percentage points (Column IV).

It is worth highlighting that mayoral election provides us with a exogenous times series variation in this member's ability to access and approve funds. It thus allows us to identify changes in firms' borrowing structures in a setting that is free from other influences, such as time series changes in firm characteristics. A remaining concern might be that change in the proximity with the mayor also affects the firms' demand for loans. We therefore provide a placebo test by exploiting 16 elections of an existing club member as a mayor where the newly elected mayor does not become head of the state bank (Columns V to VIII). Whether an elected mayor becomes the head of the local state bank's supervisory board depends on the relative size of the city to its surrounding county. If the county is relatively large, the county administrator generally becomes chairman of the supervisory board of the regional state bank.[28] There is effectively no change in the share of state bank loans in total firm loans (Columns V and VI), firms' total loans (Column VII) and their loans to assets ratio (Column VIII) around the mayoral elections that are not associated with the state bank chairman position. Thus, the change in proximity between the state bank and the other club members induced by the mayoral election (in case the mayor becomes chairman of the state bank) drives our previous findings.

4.4 Dynamics of Network Borrowing

We further empirically investigate the issue of reverse causality and CEO entry into clubs by focusing on the dynamics of CEO entry and the share of lending within the club. To do so, we replace the $event_{jt}$ dummy variable with five dummy variables – the event dummy, two leads and two lags – that capture the dynamics of network borrowing before and after the point of entrance. Results are reported in Table 4. Importantly, there is no significant pre-treatment trend for firms before entry (column I), which can be inferred from the small coefficient on the dummy variable that capture the dynamics of network borrowing before entry (0.90%), in contrast to the much stronger and statistically significant value on the dummy variable in the year of entry (3.88%). The other dummy variables that capture changes in club bank shares after firms' entry to the club are all positive and mostly statistically significant, further indicating that perturbation in social connectedness of firms and banks through entry to the club increases the share of loans that firms take out from the socially connected banks. As can be seen in columns II and III, the dynamics of network borrowing before the formation of new club branches and mayoral elections show very similar patterns.

Examining the corresponding dynamics for firms' total lending and capital structure around firms' club entry, formation of new clubs, and mayoral elections (columns IV to IX) indicates that there are no pre-treatment trends. All in all, joining a network not only affects the composition of financing, but it also increases the equilibrium amount of financing that a firm receives.

[28] The *absolute* difference in the size of cities whose mayor becomes head of the state bank and cities whose mayor does not become head of the state bank is rather small (the mean number of inhabitants is 60,000 for cities where the mayor becomes chairman of the savings bank vs. 50,000 inhabitants for cities where the mayor does not become chairman).

5 Mechanism

Having documented that membership of a service club changes the structure of financing (club firms borrow disproportionately more from club banks) and also increases the equilibrium amount of financing that a firm receives, we now investigate the precise mechanism which generates these results. As discussed earlier, these results are consistent with the positive view of social networks – social proximity mitigates informational and enforcement problems that stifle lending – as well as the negative view of social networks: related lending may distort the allocation of credit.

First, we investigate the return on loans (ROL) that banks generate on loans given out to firms that are members of their club, compared with loans given to firms that are members of other clubs. Realized ROL allows us to disentangle the two competing effects, since it takes into account the interest payments that are collected on the loans, as well as losses on loans if default takes place. We will elaborate more on this issue in Section 5.1.

Additionally, we examine the deployment of funds by firms. Examining the usage of funds allows us to investigate whether social networks generate information that enable club bankers to identify profitable projects to be financed within clubs. In this case, we should observe that firms increase their investments following entrance.

5.1 Return on Loans

We next investigate the return on loans (ROL) that banks generate for loans that are given to firms that are members of their club, compared with loans given to firms that are members of other clubs. We believe that realized ROL is a good metric to differentiate the bright-side information and enforcement effects from the adverse network effects, since it measures real returns to the bank accounting for the information and enforcement channels.

5.1.1 Methodology

To calculate the return on a loan made by bank i to firm j, we calculate the bank's return per one euro investment for the entire duration of the lending relationship:

$$ROL_{ij} = \sum_{t=1}^{T} \frac{\theta_t \cdot loan_{ijt}}{\sum_{t=1}^{T} \theta_t \cdot loan_{ijt}} \cdot \left[(1 - \mathbb{1}_{\{def=1\}}) \cdot r_{ijt} + \mathbb{1}_{\{def=1\}} \cdot (\kappa_{ijt} - 1)\right], \qquad (10)$$

where $\theta_t \cdot loan_{ijt}$ is the outstanding loan from bank i to firm j at the beginning of period t discounted at the risk-free rate.[29] Accordingly, $\frac{\theta_t \cdot loan_{ijt}}{\sum_{t=1}^{T} \theta_t \cdot loan_{ijt}}$ is the fraction of the discounted loan outstanding in the current period and the total volume of outstanding loans over the lending relationship from $t = 1$ to $t = T$. The indicator function $\mathbb{1}_{\{def=1\}}$ is one if the firm defaults in the period between t and t+1, and zero otherwise. The interest rate charged by bank i for firm j is denoted by r_{ijt}; the recovery rate is denoted by κ_{ijt}. Consequently, $(\kappa_{ijt} - 1)$ is the fraction of the loan forgone by the bank in the default period. The weighting is important since loans tend to have higher outstanding amounts in the beginning, and often, if a loan defaults, a considerable fraction of the loans is already repaid. Alternatively, we measure the return on loans as the loan's internal rate of return, which yields almost identical results qualitatively and also quantitatively.

The calculation can be understood using a simple example. Consider a scenario where a bank lends 3 million euro to a firm in period t=0. The outstanding balance at t=1 is 2 million euros, and 1 million euros at t=2. Assume that the bank charges interest rates of 5% in all periods. Further assume that the firm defaults in period t=2 and the recovery rate is 50% of the outstanding balance. In such a scenario, the bank earns 5% on the 3 million euro in the first period and the 2 million euro in the second period, and -50% on the 1 million euro in the third period. The resulting ROL is calculated as $\frac{5}{6} * 0.05 + \frac{1}{6} * (-0.50) = -0.0417$. While omitted here for simplicity, in the paper we discount outstanding loans with the risk-free rate to capture the time value of money.

Importantly, if a low ROL is generated on small loans and a high ROL on economically significant (large) loans, results could be biased by relying on the estimation of individual ROL, which weights all loans equally. To account for this, we also calculate the value-weighted ROL on the portfolio of loans granted to firms inside the bank's own club and compare this with the value-weighted ROL on portfolio of loans granted to firms in other clubs. The calculation is almost identical to equation (10). The only difference is that, before weighting a bank's earning over time, the quarterly earnings of the bank are calculated from its entire portfolio of loans. This provides us with one or two observations per bank (one observation if the bank either only lends to firms in its own club or outside its own club; two if it lends to both groups of firms).

To calculate contract-specific ROL, we require information on relationship-specific interest rates and recovery rates. Annual contract as well as relationship-specific interest rates can be obtained through matching the credit register with the financial accounting informa-

[29] The discounting is simply done to account for the time value of money. It should be noted that since most of our analysis is cross-sectional, the discounting has no significant effect on our results.

tion (see Appendix C for a detailed description of the calculation of interest rates). For the full sample period, the Deutsche Bundesbank credit register includes an indicator variable if a firm defaults. Starting in 2008, the credit register also reports the amount of quarterly write-downs in case of default at the lending relationship level. These write-downs allow us to compute the recovery rate of the loan. For the pre-2008 period, we simply take the average recovery rates from the post-2008 period, since recovery rates are only available post-2008.

5.1.2 Results

To begin with, we conduct our analysis at the relationship level and investigate how social connections affect ROL. Since the actual rate of return already incorporates the riskiness of the loans, it provides a good metric with which to compare loan performance.

Table 5 reports descriptive statistics of ROL and components thereof. Overall, banks earn a 6.37% return on loans provided to our sample firms (median: 6.32%). ROL are considerably higher for loans granted by banks outside the clubs (7.30%), compared with those granted by club banks (4.23%). For the value-weighted portfolios, the average return is slightly higher, at 6.83% (median: 6.42%). Again, a bank's return is higher on the portfolio of loans granted outside the club (7.49%), compared with the portfolio of loans granted inside the club (5.00%). The average recovery rate once a loan defaults is 41.81%, and this remains relatively similar for loans granted inside the club (38.24%) and those granted outside the club (43.69%). The annual default rate of loans is 1.81%, with a significant difference between loans made inside the club (4.04%) and those made outside the club (0.84%). The average interest rate on loans is 7.47% and is very similar for loans granted inside the club (7.03%) and loans granted outside the network (7.71%). While these descriptive results suggest that club banks tend to make poor lending decisions compared with outside banks, we now examine differences in ROL in detail to verify that the descriptive differences are not driven by selection concerns.

We statistically examine the effect of social connections on banks' ROL by estimating:

$$ROL_{ij} = \alpha_j + \beta \cdot \text{club bank}_{ij} + \epsilon_{ij}, \tag{11}$$

where subscript i indexes banks and j indexes firms, α_j represents firm fixed effects. The dependent variable ROL_{ij} measures the return on a loan given to firm j by bank i according to equation (10). The coefficient of interest β allows us to identify the mechanism that generates the increased financing that has been documented for firms that are members of the club. All other things being equal, the positive view of social networks should generate a higher ROL on loans made within clubs, whereas a favoritism story would predict a lower ROL on these loans.

Results are reported in Table 6. In Columns I to III, we focus on a subset of loans for which we were able to back out the interest rate charged on the loans. The observation that the interest rate charged to a given firm by a club bank is not substantially different from the interest rate charged by a bank outside the club allows us to estimate our regressions using the full sample, assuming identical interest rates on club loans and loans made outside the clubs in a given year in Columns IV to VI.[30] In Column I, we look at differences in ROL from a firm's perspective. We compare the ROL generated by club banks and banks outside the clubs for the same firm. Club banks generate a 2.02 percentage points lower ROL to the *same* firm compared with outside banks. In Column II, we re-estimate our regression specification with bank fixed effects instead of firm fixed effects. This allows us to compare the ROL generated by the same bank on loans given to firms that are members of the same club with those given to firms that are members of other clubs in the same city. A simple information or enforcement story would, if anything, predict a higher ROL on loans made within clubs. We find just the opposite. The ROL on inside loans is significantly lower, by 3.03 percentage points, relative to loans granted outside the clubs. In Column III, we replace the dependent variable by banks' portfolio returns on portfolios of loans within clubs and loans made outside the clubs. Taking into account the relative importance of loans (loan size and maturity) reveals an even higher degree of difference of 3.23% between the ROL on loans made outside the clubs and those made within the clubs.

The results are qualitatively identical when we redo this analysis on the entire sample. The magnitude is somewhat lower, which is consistent with the notion that the assumption of identical interest rates in a given year for the same firm is conservative. Using firm fixed effects, we find that the ROL on loans generated by club banks is 0.85 percentage points lower than the ROL generated by banks outside the clubs (Column IV). From the bank perspective (using bank fixed effects), we again find similar results: club loans generate a 1.75 percentage points lower ROL when compared with loans made outside the clubs (Column V). Finally, for value-weighted portfolios, the difference in ROL between loans made within clubs and loans made outside the clubs is 1.40% (Column VI).

Our sample spans 18 years of data. During this period, interest rates vary substantially. To check the robustness of our results, we verify that differences in ROL between loans made

[30]It is important to note that the assumption on equal interest rates is a conservative assumption, given the results we document. If anything, the interest rates charged by club loans are slightly lower, even though the difference is not statistically significant.

within clubs and those made outside the clubs are not affected by differences in interest rates over time. Instead of calculating the ROL of a loan based on actual interest rates, we calculate the spread that banks earn over the risk-free rate (FIBOR/EURIBOR). The spread over the risk-free rate is much more constant over time. We report the results in Table A.4. The results are qualitatively identical and similar in magnitude.

The results in Table 6 document that loans provided to socially connected firms relative to non-connected firms generate a lower ROL. To validate that our results are not driven by endogenous network formation, we examine whether a perturbation in social connectedness between firms and banks is associated with changes in ROL. Formally, we estimate:

$$ROL_{ijt} = \alpha_j + \beta_1 \cdot \text{club bank}_{ij} + \beta_2 \cdot event_{jt} + \beta_3 \cdot \text{club bank}_{ij} * event_{jt} + \epsilon_{ijt}, \qquad (12)$$

To analyze changes in ROL, we split all loans for each firm-bank pair into the loans originated before and after the event. We use the same three events ($event_{jt}$) (i.e., firm entry to a club, club formations, mayoral elections), as discussed in the previous section.[31] We compute the ROL (ROL_{ijt}) for the set of loans issued before and after the event separately. A negative estimate of β_3 provides evidence of a deterioration in loan performance for socially connected loans after the event, compared to the period before the event (diff-in-diff estimate).

Results of estimating equation (12) are gathered in Table 7. After firm CEOs enter a club, socially connected banks earn a 3.29 percentage points lower return when lending to the same firm, as compared to a non-connected bank, relative to the pre-event period (Column I). The estimate is similar with -3.53 percentage points once controlling for bank fixed effects (Column II). When comparing the performance of value weighted loan portfolios, the effect is even stronger (-4.96 percentage points, Column III). The effects are very similar with slightly higher magnitudes for club formations (Columns IV to VI). For mayoral elections, the relative deterioration in loan performance for loans generated by the state bank to in-club firms is large with 9.56 percentage points after controlling for firm fixed effects (Column VII) and 9.21 percentage points controlling for bank fixed effects (Column VIII). Weighting the loans in bank portfolios somewhat reduces the effect to -6.72 percentage points (Column IX). All together the results in Table 7 reinforce the interpretation that social connections between bank directors and CEOs result in a reduction of loan performance.

[31] When using mayoral elections as our event, *club bank*$_{ij}$ is replaced with the local state bank in which the mayor becomes head of the supervisory board.

5.1.3 Unpacking ROL

What generates a lower ROL on loans made within clubs? As documented, the interest rates charged by club banks to club firms are similar to those charged by banks outside the clubs. Furthermore, the financial contracts offered by 'in-club' banks are very similar to the ones offered by 'out-club' banks, leading to fairly similar recovery rates.[32] When we investigate further, we find the difference in ROL comes from the excess continuation of distressed firms by club banks. In other words, the lower ROL is an outcome of the *soft budget constraint* problem (Kornai 1986). This effect can be seen from Panel A of Figure 3, which plots the share of club banks in total firm loans as a firm approaches bankruptcy. The share of club banks rises as firms move closer to bankruptcy. This is particularly dramatic if the club bank also happens to be the firm's main lender. As can be seen, this pattern is peculiar to loans given to club firms. In the population of firms in the sample region, one does not find this pattern for the firms' main lenders. Thus, club banks continue to finance firms which are members of the club much longer or are reluctant to liquidate inefficient firms which are members of the club. This soft budget constraint problem generates the lower ROL on club loans and points to a *favoritism* story rather than an *informational* or *enforcement* story, since continuation on better information should generate higher returns.

5.2 Deployment of Funds

To investigate the deployment of funds, we substitute the dependent variable of specification (9) with investment to assets, as measured by capital expenditure. Since we can only obtain balance sheet information for a subset of firms from the USTAN database, the sample size for this test is limited to 686 firms, compared with the 1,091 firms from the full sample. Interestingly, we find that, while entry to a club leads to increased financing, it does not result in an increase in firms' investment. The effect of club membership on capital expenditure is statistically indistinguishable from zero (Column I of Table 8). When we investigate where the additional funds are channeled to, we find that firms use the extra money from the club banks to increase their liquidity position and pay out dividends. The results in Columns II and III show that firms increase cash holdings to assets by 2.71 percentage points and increase the dividends that they pay out to shareholders by 2.89 percentage points per year. Since most of the sample firms are SMEs, the CEO is often the owner of the firm. Thus, paying out dividends to shareholders typically means that CEOs pay out funds into their

[32] If anything, the recovery rates for 'in-club' lending relationships are lower compared to 'out-club' lending relationships (see Table 5).

own pockets.

The increase in dividend payouts, rather than using the funds for additional investment, leads to a change in firms' capital structure. After entry to a club, firms' debt to assets ratio increases by 6.17 percentage points (Column IV). This also confirms that the increase in bank loans that we observe is not explained by asset growth of firms after joining the club, but rather depicts a change in firms' financial structure. Moreover, we find that firms' profitability is virtually unaffected by entry to a club, further reducing concerns about club membership being related to changes in firm quality (Column V). Finally, we examine whether firms' costs of capital are significantly different after entering the club. We find that the average fraction of interest rates by debt decreases by 0.40 percentage points; however, the decrease is quantitatively only mild and statistically insignificant (Column VI). These findings are at odds with the bright side view, namely: social networks facilitate financing thereby relaxing financial constraints.

6 Further results

In this section we report two additional results. In Section 6.1, we compare the differential behavior of state and private banks while in Section 6.2, we employ contract level data to examine whether the increase in the share of club banks' lending, documented in Section 4, are driven intensive margin and/or extensive margin.

6.1 Exploring Heterogeneity Across Banks

It is often argued that private bankers have stronger incentives compared with state bankers and that these incentives may keep favoritism in check. By comparing the behavior of state and private banks when operating in the same environment (service clubs), we are also able to shed some light on the efficacy of these organizational forms.

6.1.1 Structure of Financing

To examine if the degree of preferential treatment varies across these two bank groups, we modify our specification (9) to compare the differential effect of firm entry on state and private banks in the same club. As well as classifying banks as being either inside or outside the club, we now also classify them by their ownership, that is, whether they are state- or privately-owned banks.

In a regression framework, this is achieved by estimating:

$$\frac{q_{ijt}}{\sum_i q_{ijt}} = \alpha_t + \alpha_{ij} + \delta_1 \cdot event_{ijt} + \delta_2 \cdot event_{ijt} \cdot state\ bank_i \tag{13}$$

As before, i indexes banks, j indexes firms and t indexes time in quarters. The dummy variable $state\ bank_i$ is one for state banks and zero for private banks.

In Table 9, we investigate the differential effect across different groups of banks. The results in Columns I to III indicate that the increase in borrowing from club banks is higher for firms entering clubs with only a state bank as a member (10.82 percentage points), relative to firms entering a club with only a private bank as a member (7.63 percentage points, shown in Column II) or a cooperative bank (4.72 percentage points, shown in Column III). The differential effect is statistically significant; 6.45 percentage points higher for state banks (Column IV). To alleviate concerns that the differences in the increase in club bank lending shares could be driven by differences in firm quality across clubs, we examine differences in state and private banks for the *same* firm.[33] This is possible since some clubs have a state and a private banker among its members. For firms in those clubs we can compare changes, quarter by quarter, in club loans for private and state banks. To avoid double counting (an increase in the share of lending from the state club bank leads to a decrease of the private club bank) we replace the dependent variable by the share of the state club bank in total loans of both club banks (state plus private bank loans). Even with this stringent specification, one observes that the lending shares of the state banks, relative to all bank loans within clubs, increase by 14.26 percentage points (Column V). Finally, we exploit the fact that, in some clubs, one of the members is the mayor of the respective city in which the club is located, and simultaneously heads the board of the local state bank. We expect that, in clubs in which those mayors are members and additionally have a state banker among its members, the incentives to provide additional loans to club members are even stronger. Indeed, clubs with a state banker see a 6.26 percentage points increase in the share of loans made within the club after firms enter the club, whereas there is an additional increase of 12.83 percentage points for clubs with a mayor among members (Column VI).

[33]The private banks could also include cooperatives. Dropping those banks from our sample does not affect the results.

6.1.2 Return on Loans

In the previous section, we documented a large increase in financing provided by state banks. While the increase in supply by state banks is consistent with state bankers being more vulnerable to favoritism due to blunter incentives (particularly when the main supervisor of the state bank, the mayor, is also involved in the club), it is also consistent with an informational or enforcement story. One could argue that state banks have poor screening and/or monitoring technologies, so the marginal benefit of proximity is much higher for them. Notably, however, this would not explain why the effect is stronger when the head of the state bank board is also among the club members. To investigate the underlying mechanism further, we classify banks into three different categories: state banks, private banks, and cooperatives, and compare the ROL generated by different lenders.

We find that, while both private banks and cooperatives generate an only slightly lower ROL on loans made within clubs relative to those made outside the club (1.87 and 0.26 percentage points, respectively, shown in Table 10, Columns II and III), the state banks' performance turns out to be quite dismal with a difference between ROL on loans within clubs and loans outside clubs of 5.64% (Column I). The state banks generate an almost 4 percentage points lower ROL on loans within clubs, compared with those made outside clubs, relative to private banks (Column IV). It is likely that better incentives in private banks keep a check on their loan portfolio and limit the tendency to engage in favoritism. It should be noted that the lower ROL of state banks comes from the soft budget constraint problem it faces. Not only are state banks reluctant to liquidate firms which are members of the same club, when compared with private banks, but they are also more reluctant to liquidate firms which are members of the same club than they are to liquidate firms which are not members of other branches of the same club organization. This comparison suggests that this continuation bias is not driven by differences in objectives of state banks vis-à-vis private banks. The incentive problem can be seen by looking at Panel B in Figure 3. While for private banks in clubs the increase in their share in total firm loans, before firms default where they are a main lender, is a relatively mild 4 percentage points within the last four years before the default quarter (gray line), the increase is significant for state banks at 16 percentage points (black line).

6.2 Intensive Margin and Extensive Margin

The documented increase in the share of club banks' lending could occur through existing relationships (intensive margin) and/or new relationships (extensive margin). In order to provide insights into this, we shift our analysis from the firm to the loan (relationship) level and estimate the following equation:

$$log\,(loans_{ijt}) \;=\; \alpha_t + \alpha_i \cdot \alpha_j + \omega \cdot event_{jt} + \delta \cdot club\ bank_{ij} \cdot event_{jt} + \epsilon_{ijt}. \qquad (14)$$

The dependent variable is the logarithm of individual loans from bank i to firm j. We include quarter (α_t) and relationship ($\alpha_i \cdot \alpha_j$) fixed effects. By including relationship fixed effects, we capture the change in lending following entry for the same lending relationship over time. Note that this implies that the identification of changes in loans only comes through relationships that already exist before and after the event (intensive margin). The parameter ω captures the effect of the event on 'out-club' banks and δ quantifies the additional effect if the bank is an 'in-club' bank. Thus, we compare how access to a network increases the amount of financing received from 'in-club' banks compared to 'out-club' banks. While we find no effect on the quantity of 'out-club' loans, the 'in-club' loans go up by 26.31% more (Table 11, Column I).

In column II, we saturate the specification by adding firm-event ($\alpha_j \cdot event_{jt}$) fixed effects. These additional fixed effects allow us to compare changes in loans from club banks and outside banks for the *same* firm (comparison is across banks for the same firm). Thus the interaction term $club\ bank_{ij} \cdot event_{jt}$ captures the difference in borrowing of the club bank relative to outside banks as a response to the entry event for the *same* firm. The *same* firm borrowing from club and outside banks experiences a 30.37% increase in lending from the club bank relative to lending by the outside banks.

The specification in Column II bears close resemblance to the lending channel specification employed in Khwaja and Mian (2008).[34] They collapse the dependent variable around the event into one observation per firm-bank relationship ($\Delta\ log(loans)_{ij}$) and then add firm fixed effects to control for firm demand. As a robustness test, we also present their specification in Table A.5, Column I and find a very similar effect (32.51%).

In Columns III to IV, we replicate this analysis for firms that enter a club through the formation of a new club branch. As can be seen, the magnitudes for this event are slightly higher. The basic specification shows an increase in lending of 37.73%, which increases to 56.93% when we saturate the specification by adding firm-event ($\alpha_j \cdot event_{jt}$) fixed effects. Using the Khwaja and Mian specification, we find that there is a 55.06% increase in credit supplied by 'in-club' banks compared to 'out-club' banks (Table A.5, Column II).

We also replicate our analysis for the intensive margin using mayoral elections as the

[34] The main exception is that the staggered nature of our events allows us an additional level of differencing.

event (Columns V and VI). Regarding the intensive margin we find that lending by state banks increases significantly (41.47%) after the election as compared to outside banks. As before, we saturate this specification by adding firm-event ($\alpha_j \cdot event_{jt}$) fixed effects, as this allows us to compare changes in loans from state banks and outside banks for the *same* firm. We find that *same* firm borrowing from state and outside banks experiences a 47.70% increase in lending from the state bank relative to the lending by outside banks.[35]

In Columns VII to XII we investigate the extensive margin. Specifically, we examine whether entry of firms to clubs results in the formation of a new lending relationship with an 'in club' bank compared with forming a relationship with a bank that is outside the club. We define a dummy variable that takes the value of one if a relationship is formed between a firm and a bank, and zero otherwise. For this test we treat every connection between a particular firm and each bank lending to at least one firm in the county as a potential relationship. We regress this new relationship dummy variable on the interaction of the $event_{jt}$ dummy variable and the $club\ bank_{ij}$ dummy variable using ordinary least squares.[36] As can be seen in Column VII, we find that the probability of forming a relationship with a club bank is higher by 11.44 percentage points after a firm joins a club relative to an outside bank, when compared with the period before entry.[37] The effect is even stronger for firms joining by club branch formation (14.72 percentage points, Column IX). The increase in the likelihood of forming a new relationship after the mayoral election is about 10 percentage points higher for club banks relative to outside banks (Column XI). Adding firm-event fixed effects to compare the probability of establishing a new relationship for the *same* firm does not alter our results (Columns VIII, X and XII).

Overall, our findings demonstrate that membership to a social network, such as a service club in our setting, is associated with an increase in the supply of credit both on the extensive and intensive margin, with the expansion driven by club bank financing.

[35]The Khwaja and Mian specification provides an estimate of 41.91% (Table A.5, Column III).

[36]The results are qualitatively and also quantitatively almost identical to running a probit model for the same specification.

[37]It should be noted that since the time window before and after a firm's entry to a club or participation in club formation is not the same, only the interaction term can be meaningfully interpreted. For instance, if the number of years post entry is larger than pre-entry, then this would increase the chances of forming a relationship in the post-period. The cross-sectional results do not, however, suffer from this bias. Consistent with this argument, the cross-sectional results are not affected when we focus on windows of similar durations both before and after the event.

7 Alternate Explanations

The broad array of results presented above provides support for the view that lenders tend to favor firms with which they share social proximity. It should be noted that in our identification strategy we compare, on a quarterly basis, the amount of credit that is provided by club banks with the credit which is provided by banks outside the club to the *same* firm. We now discuss and rule out some alternative stories that may seem consistent with our findings. It should be noted that alternative theories must be able to explain the following results: first, entry to a club increases the amount of financing within clubs and also overall financing, with large shifts documented for state banks and even larger effects when the mayor, who is also the head of the board of directors of the bank, is in the club. Second, club banks generate a lower ROL on loans made within clubs compared with the ROL they generate on loans made outside the club, with larger reductions noted for state banks. Third, firms use the extra financing they receive to pay out dividends, rather than to increase investment in the firm.

7.1 Statistical Discrimination

The informational story would predict that banks face higher informational constraints when they lend to firms outside their club than when they lend to firms within the club. Given this difference in the degree of asymmetric information, which is larger for 'out-club' firms, club banks, the argument goes, only lend to high-quality 'out-club' firms. This creates a selection issue: 'out-club' firms which receive financing are different from 'in-club' firms which receive financing, which leads to biased estimates. Furthermore, the argument continues, since 'out-club' firms should have better credit quality, banks should earn a higher ROL on these loans. It should be noted that this argument is similar to the argument in the *statistical* discrimination literature, as pioneered by Gary Becker (Becker 1957).

While the statistical discrimination argument makes sense in certain settings, the ROL measure is free from this critique. The simple reason is that contract terms adjust in such a way that they break the link between observed credit quality and the ROL. To illustrate this, consider a bank lending in a competitive[38] credit market where banks have to lend to two borrowers: one risky and the other less risky, but both being positive NPV loans. While the banks charge higher rates on risky loans, there is no reason why the ROLs should be higher for 'out-group' firms. If anything, the club banks may have an informational monopoly when

[38]This assumption is not critical to this argument.

they lend to club firms which, in turn, should generate them a higher ROL on loans made inside the club. We believe that the ROL differences are economically quite large to be explained by any such mechanism.

7.2 Differences in Objectives

We interpret our state vs. private banks result as suggesting that state banks engage more in *crony* lending than private banks do, perhaps due to blunt incentives of state-bank CEOs. It is often argued that state banks are more socialist and thus it is natural to expect that they earn lower ROL on loans. While it is true in the data that state banks generate a lower ROL on the loans that they originate, compared to private banks, in our tests we compare the ROL generated by a state bank inside the club to the ROL generated by the same state bank in other clubs in the same city. This within-comparison controls for any differences in objective functions between state and private banks.

7.3 Cross-selling by Banks and Transaction Costs

It is often argued that, in addition to granting loans, banks also provide a significant amount of transaction-related services. So while banks may earn a lower ROL made within clubs, they make up for it by earning higher returns from other services they provide to firms in the club. Furthermore, the firms, through referrals, may generate other business for the bank, which more than makes up for the lower ROL generated on a loan made within the club (Santikian 2011). While this proposition may appear plausible at first, it is unlikely for a number of reasons. First, as has been noted earlier, most of the drop in ROL for loans made within clubs (as compared with loans made outside the clubs) comes from state banks. The state banks, however, offer a very limited set of services to the borrower; most transaction-related services are offered by the *Landesbanken*. Since these transaction-related services are offered mostly by private banks in Germany, cross-selling is unlikely to be driving our results.

Second, we can directly test whether banks that earn lower ROL on loans made within clubs, as compared with those made outside the clubs, make higher overall profits. Since loans made within clubs represent only a fraction of the total loans granted by the banks, it might be the case that, while banks lose money on loans made within clubs, club membership generates more business for the bank and overall this increases the banks' profitability.

To rule out such alternative explanations, we test whether banks that earn lower ROLs on club loans, compared with loans to firms outside the club, make up for these shortfall elsewhere. To examine this, we investigate how this difference between the inside ROL vs. outside ROL for the same bank correlates with the overall returns for this bank. Interestingly, we find that banks that engage in more preferential lending (measure by the wedge between outside ROL and inside ROL), also earn significantly lower returns for their shareholders.[39] Specifically, going from the lowest decile of wedge to the highest decile results in approximately a 1 percentage point lower ROE for the bank. This is substantial, since this represents roughly 19% of their returns as the average ROE of state banks is about 5.4%. Thus, banks that have a bigger drop 'in-club' ROL, also generate lower returns on equity in general.

It is worth highlighting that these findings can be also used to rule out potential explanations based on lower transaction costs of 'in-club' loans. It can be argued that the lenders have to expend less effort in screening and monitoring borrowers and this lowers the cost of providing loans inside the club. Since the ROL calculation does not take these costs into account, it is likely to understate the ROL generated by club banks on 'in-club' loans. As we have shown, banks that have a higher wedge between the 'in-club' ROL and the 'out-club' ROL also generate lower returns on their loan portfolios. This would not be the case if they were actually saving on the transaction costs, which then would have shown up as no difference in the overall ROE.

7.4 Financial Crisis in Germany

As noted earlier, our analysis spans the years 1993 to 2011 and this period includes the recent financial crisis. While the German economy has mostly been insulated from this crisis, the economy did experience some slowdown after the Lehman Brothers debacle. To examine the effect of such extraneous events on our results, we repeat the analysis using only pre-crisis data. In Table A.6, we replicate the ROL estimations from Table 6, but split the sample into a post-2008 period (for which we can compute exact recovery rates) and a pre-2008 period (for which we can extrapolate recovery rates). For the post-2008 period club banks earn a 2.67 percentage points lower ROL for the *same* firm, compared with banks outside the clubs (Column I), and these same banks earn a 3.40 percentage points lower ROL on loans made inside the club (Column II). Interestingly, the magnitudes of the effect are about twice as high, compared with the pre-crisis period where club banks earned a 1.63 percentage points

[39] It should be noted that this analysis already controls for bankers' ability since the independent variable is the difference between the ROL that the bank earns on their own club loans vis-à-vis ROL they earn on outside club loans.

lower ROL for the same firm (Column III), and a 1.28 percentage points lower ROL on loans inside the club, compared with loans made outside the club (Column IV). It seems as though the financial crisis, falling into the post-2008 period which saw more defaults, magnifies the network effect. Furthermore, we repeat the same exercise for the value-weighted portfolios. Results appear to be somewhat stronger in the post-crisis period with 3.24 percentage points (Column V) than in the pre-crisis period with 1.47 percentage points (Column VI).

8 Conclusion

It is often believed that social proximity mitigates informational and enforcement problems that stifle lending. However, there is another possibility: proximity may result in nepotism and soft collusion. Favorable treatment might be driven by social pressure, as bank officials may face social sanctions for denying favorable treatment to members of the group. In addition, granting favors to friends may generate private benefits for the banker. Given these agency conflicts, the efficiency implications of social proximity are, a priori, not obvious, and despite the different theoretical arguments about the efficiency implications of social networks, empirical evidence on this question is rather scant.

In this paper, we have examined how social proximity between lenders and firms affects the allocation of bank credit. Using a unique detailed micro-level dataset of firms which are members of service clubs in Germany, we find that lenders not only grant more credit to firms within their clubs, but these loans also produce a much lower ROL for their club bank. Similarly, using firm fixed effects and doing a within-firm comparison, we find that club banks generate a lower ROL when lending to firms within their club than 'out-club' banks, with these effects being more pronounced for state banks. All in all, our results paint a picture of preferential treatment accorded to club firms by club banks, with more evident results noted for state banks, and with very real economic consequences.

We would like to conclude with a few final remarks. It is important to note that, while we uncover some ill effects of social proximity, we do not make any efficiency claims here. It has been well noted by scholars that, in some situations, bribes and corruption can improve welfare. The theory of second-best (Lipsey and Lancaster 1956) cautions us against any welfare claims. That being said, our analysis does suggest some evidence of inefficient allocation of resources. From the perspective of the bank, the allocation of these funds is not efficient. Furthermore, we find that the extra financing that firms receive is not used for new investments, but rather to pay out dividends to the shareholders.

It should be noted that, although the focus of this paper has been on the effect of social proximity on lending, this paper also contributes to a larger literature on relationship banking (Petersen and Rajan 1995). According to many of these papers, banks achieve the task of screening and monitoring borrowers by establishing lending relationships. By increasing proximity between lenders and borrowers, relationship-lending is argued to play an important role, reducing informational frictions that adversely affect lending. What we have shown in this paper is that proximity can be double-edged sword. While proximity between the lenders and borrowers can be useful in reducing informational problems, too much of proximity may have its unintended consequences. The paper thus highlights the importance of aligning incentives to harness the benefit of proximity.

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Table 1: Descriptive Statistics

	Mean	Median	Std.	Obs.
Panel A: Network Data				
No. of clubs	211			
No. of CEOs within clubs	1,091			
No. of bankruptcies by CEOs	141			
No. of club entries by CEOs	474			
No. of club formations	43			
No. of banks	542			
No. of club banks	352			
No. of private club banks	173			
No. of public club banks	138			
No. of cooperative club banks	41			
No. of CEOs borrowing only from club bank	182			
No. of CEOs borrowing only from outside bank(s)	393			
No. of CEOs borrowing from club and outside banks	516			
No. of club members being elected mayor and becoming chairman of local state bank	20			
No. of club members being elected mayor not becoming chairman of local state bank	16			
Panel B: Loan & Firm Level Data				
	Mean	Median	Std.	Obs.
Loan Data (based on 1,091 firms):				
Loan amount - loan level (thousand euro)	6,433	4,000	6,100	54,123
Loan amount - firm level (thousand euro)	13,440	5,555	24,247	25,908
Lending relationships per firm (sample period)	3.72	2.00	4.50	1,091
Firm Data (based on 686 firms):				
Total assets (thousand euro)				
Sample	92,102	14,165	249,376	5,474
Population	93,367	9,677	1,261,264	200,531
Debt/assets				
Sample	0.2525	0.2235	0.1944	5,474
Population	0.2464	0.2038	0.2104	200531
ROA				
Sample	0.0621	0.0509	0.0952	5,474
Population	0.0691	0.0550	0.0985	200,531
Cash/assets				
Sample	0.0629	0.0241	0.0891	5,474
Population	0.0662	0.0206	0.1228	200,531
Borrowing costs				
Sample	0.0811	0.0707	0.0504	5,474
Population	0.0911	0.0560	0.1084	200,531
Panel C: Bank Lending Shares				
Lending share in bank's club	0.2508			
Lending share in other clubs (same city)	0.0673			
Difference	0.1835			
t-statistic	[10.56]			

Panel A depicts the data on social clubs: the number of clubs and CEOs in those clubs, number of firms defaulting on a loan or filling for bankruptcy, number of firms joining a club during the sample period and number of club formations, the total number of banks in the sample, number of bankers whose director is a club member and ownership of those banks, the number of firms that only borrow from banks that are member of the same club (club banks), from banks not member of the same club (outside banks) or from both, and the number of club members elected as mayors. The top part of Panel B provides information on loan data from the Bundesbank credit register, the bottom part shows balance sheet data for sample firms and the population of non-sample firms from the same geographic area from the Bundesbank USTAN database. Panel C depicts banks' lending share in clubs where they are members (a bank's loans to all firms in a club divided by all loans to those firms), in clubs where the bank is not a member located in cities where the bank is club bank in at least one other club, and the difference between both numbers including the significance level.

Table 2: Club Entry by Firms and Club Formations

	I	II	III	IV	V	VI	VII	VIII
Dep. Var.:	$\left(\frac{Club\ bank\ loans}{Total\ firm\ loans}\right)_{jt}$				$log\,(Debt)_{jt}$		$\left(\frac{Debt}{Assets}\right)_{jt}$	
	Entry		Formation		Entry	Formation	Entry	Formation
$event_{jt}$	0.0890***	0.1003***	0.1080***	0.1253***	0.3222***	0.3806**	0.0617***	0.0673***
	[7.13]	[7.12]	[4.47]	[5.22]	[3.40]	[2.18]	[2.67]	[2.64]
Quarter FE	no	yes	no	yes	yes	yes	no	no
Year FE	no	no	no	no	no	no	yes	yes
Firm FE	yes	yes	yes	yes	yes	yes	yes	yes
Clustered SE	club	club	club	club	club	club	club	club
Observations	25908	25908	19320	19320	25908	19320	4364	3017
R-squared	0.537	0.538	0.523	0.525	0.734	0.727	0.762	0.749

The sample for this table comprises all 1091 firms from our sample. The dependent variable in columns I to IV is firm j's loans from its club bank divided by firm j's total loans. In columns V and VI it is the log of firm j's total loans, in columns VII and VIII it is firm j's loans to assets ratio. The variable $event_{jt}$ is a dummy variable taking the value of one from the year when firm j enters a club, and zero otherwise in columns labeled 'Entry'. It takes the value of one from the year when firm j joins a club through club formation and zero otherwise in columns labeled 'Formation', in those columns firms that enter an existing club during the sample period are excluded. For columns VII and VIII the sample comprises the firms for which balance sheet data is available and data is annual. Information on fixed effect is provided at the bottom of the table. Standard errors correct for clustering at the club level. We report t-statistics in parentheses.

Table 3: Mayoral Elections

	I	II	III	IV	V	VI	VII	VIII
	Mayoral Elections + Supervisory Board				Mayoral Elections + No Supervisory Board			
Dep. Var.:	$\left(\frac{State\ bank\ loans}{Total\ firm\ loans}\right)_{jt}$		$log(Debt)_{jt}$	$\left(\frac{Debt}{Assets}\right)_{jt}$	$\left(\frac{State\ bank\ loans}{Total\ firm\ loans}\right)_{jt}$		$log(Debt)_{jt}$	$\left(\frac{Debt}{Assets}\right)_{jt}$
$event_{jt}$	0.0578**	0.0563**	0.2330**	0.0497*	-0.0336	-0.0443	-0.0131	-0.0135
	[2.47]	[2.45]	[2.20]	[1.86]	[0.97]	[1.28]	[0.09]	[0.94]
Quarter FE	no	yes	yes	no	no	yes	yes	no
Year FE	no	no	no	yes	no	no	no	yes
Firm FE	yes	yes	yes	yes	yes	yes	yes	yes
Clustered SE	club	club	club	club	club	club	club	club
Observations	25908	25908	25908	4364	25908	25908	25908	4364
R-squared	0.530	0.532	0.732	0.760	0.530	0.532	0.732	0.759

The sample in this table comprises all 1091 sample firms. The $event_{jt}$ dummy takes the value of one from the year when an existing member is newly elected as a mayor and zero otherwise. In columns I to IV only elections after which the mayor also automatically becomes the head of the local state bank's supervisory board are considered, in columns V to VIII only elections after which the mayor does not become head of the local state bank's board are considered. The dependent variable in columns I, II, V, and VI is firm j's loans from the state bank divided by firm j's total loans, in columns III, and VII it is the log of firm j's total loans, in columns IV and VIII it is firm j's total loans scaled by assets. In columns IV and VIII the sample is reduced to the 686 firms for which balance sheet data is available and the data is annual. The bottom of the table provides information on the fixed effects included. Standard errors are corrected for clustering at the club level. We report t-statistics in parentheses.

Table 4: Perturbation in Social Connectedness - Dynamics

Dep. Var.:	I	II $\left(\frac{Club\ bank\ loans}{Total\ firm\ loans}\right)_{jt}$	III	IV	V $log(Debt)_{jt}$	VI	VII	VIII $\left(\frac{Debt}{Assets}\right)_{jt}$	IX
	Entry	Formation	Mayoral Election	Entry	Formation	Mayoral Election	Entry	Formation	Mayoral Election
$Before_2$	0.0185	0.0262	0.0155	0.0680	0.0910	-0.1116	0.0114	-0.0296*	0.0218
	[1.46]	[1.12]	[0.50]	[0.90]	[0.49]	[1.26]	[0.42]	[1.74]	[0.51]
$Before_1$	0.0090	-0.0168	0.0169	0.0633	0.1246	0.0823	-0.0065	-0.0407	-0.0111
	[1.25]	[1.02]	[0.80]	[1.13]	[1.41]	[0.65]	[0.31]	[1.18]	[1.48]
$Before_0$	0.0388***	0.0503***	-0.0060	0.1412**	0.1823*	0.0409	0.0443***	0.0759*	-0.0055
	[4.73]	[2.97]	[1.34]	[2.49]	[1.95]	[0.31]	[2.58]	[1.90]	[0.32]
$After_1$	0.0104	0.0313**	0.0645*	0.0819**	0.0586	0.1941**	0.0015	0.0269	0.0568*
	[1.49]	[1.99]	[1.80]	[2.40]	[0.74]	[1.98]	[0.11]	[1.23]	[1.83]
$After_2$	0.0487***	0.0571**	0.0114	0.0457	0.0441	0.0323	0.0207	0.0075	-0.0065
	[3.87]	[2.48]	[0.76]	[0.89]	[0.52]	[0.29]	[1.42]	[0.44]	[0.92]
Quarter FE	yes	yes	yes	yes	yes	yes	no	no	no
Year FE	no	no	no	no	no	no	yes	yes	yes
Firm FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Clustered SE	club	club	club	club	club	club	club	club	club
Observations	25908	19320	25908	25908	19320	25908	4364	3017	4364
R-squared	0.539	0.526	0.532	0.735	0.728	0.732	0.762	0.750	0.760

The sample for this table comprises all 1091 firms from our sample. The dependent variable in columns I to III is firm j's loans from its club bank(s) divided by firm j's total loans. In column III the 'club bank' is the state bank in which the mayor becomes head of the supervisory board through her election. In columns IV to VI the dependent variable is the log of firm j's total loans, in columns VII to IX it is the ratio of firm j's loans to assets. Data is quarterly in columns I to VI an annual in columns VII and IX. In columns labeled "Entry" the dummy variables are defined as follows: The dummy variable $Before_2$ ($Before_1$) takes the value of one from two years (one year) before the firm enters a club and zero otherwise, $Before_0$ takes the value of one from the year when the firm enter a club, $After_1$ ($After_2$) takes the value of one from the year (two years) after the firm enters a club. In columns labeled "Formation" and "Mayoral Election" the five dummy variables are defined the same way with respect to the year when firm j participates in a new club formation or an existing member is elected as a mayor and becomes head of the supervisory board of the local state bank. For columns VII to IX the sample comprises the firms for which balance sheet data is available. Each regression includes time and firm fixed effects. Standard errors are corrected for clustering at the club level. We report t-statistics in parentheses.

Table 5: Returns on Loans - Data

	Mean	Median	Std.	Obs.
Return on loan (equal weighted) :				
All loans	0.0637	0.0632	0.0714	681
Inside loans	0.0423	0.0585	0.0995	206
Outside loans	0.0730	0.0657	0.0524	475
Return on loan portfolio (value weighted) :				
All loans	0.0683	0.0642	0.0563	339
Inside loans	0.0500	0.0594	0.0671	89
Outside loans	0.0749	0.0695	0.0505	250
Recovery rates (subsample from 2008 : *I* − 2011 : *III*) :				
All loans	0.4181	0.3612	0.2826	126
Inside loans	0.3824	0.3494	0.2795	51
Outside loans	0.4369	0.4040	0.2846	75
Default rates :				
All loans	0.0181	0.0000	0.0911	681
Inside loans	0.0404	0.0000	0.1511	206
Outside loans	0.0084	0.0000	0.0414	475
Interest rates (contract level) :				
All loans	0.0747	0.0679	0.0474	6197
Inside loans	0.0703	0.0657	0.0445	2191
Outside loans	0.0771	0.0693	0.0487	4006

This table reports descriptive statistics relevant for the computation of banks' returns on loans. This comprises banks' return on individual lending relationships, recovery rates in case of loan defaults (available from 2008:I to 2011:III), loan default rates, contract-level interest rates, and the return on value-weighted loan portfolios.

Table 6: Returns on Loans - Results

	I	II	III	IV	V	VI
	Contract-Level Interest Rates			Firm-Level Interest Rates		
Dep. Var.: ROL_{ij}	Relationship		Portfolio	Relationship		Portfolio
club bank$_{ij}$	-0.0202**	-0.0303***	-0.0323***	-0.0085**	-0.0175**	-0.0140**
	[2.24]	[3.24]	[3.44]	[2.37]	[2.02]	[2.28]
Constant	1.0687***	1.0718***	1.0745***	1.0729***	1.0751***	1.0755***
	[391.27]	[315.03]	[266.57]	[1302.85]	[648.54]	[522.38]
Firm FE	yes	no	no	yes	no	no
Bank FE	no	yes	yes	no	yes	yes
Clustered SE	club	club	club	club	club	club
Observations	681	681	339	2082	2082	755
R-squared	0.731	0.376	0.749	0.789	0.183	0.802

This table summarizes the results for banks' returns on loans. In columns I to III the sample is limited to the 681 lending relationships for which it is possible to extract contract-level interest rates (see Appendix C). The sample in columns IV to VI consists of the 2082 bank-firm relationships for which loan and balance sheet data is available. For this sample we assume interest rates to be the equal for the same firm in the same year for all contracts. Columns I, II, IV, and V display the results for individual lending relationships, columns III and VI for value weighted loan portfolios. For each bank we compute the return on a value weighted portfolio of all loans within their club and loans to firms from outside their club separately. Thus, there are at most two observations per bank. The dependent variable ROL_{ij} is bank i's payoff per one dollar investment over the life time of the lending relationship with firm j (or the loan portfolio in columns III and VI). Detailed explanation of the computation of banks' returns on individual loans and loan portfolios can be found in the text. The dummy variable *club bank*$_{ij}$ is one if bank i and firm j are connected through membership in the same club, and zero otherwise. The bottom of the table provides information about fixed effects and level of clustering. We report t-statistics in parentheses.

Table 7: Returns on Loans around Events

	I	II	III	IV	V	VI	VII	VIII	IX
		Entry			Formation			Mayoral Election	
Dep. var.: ROL_{ij}	Relationship		Portfolio	Relationship		Portfolio	Relationship		Portfolio
$event_{jt}$	-0.0068	-0.0123	-0.0187*	0.0086	0.0004	-0.0107	-0.0047	-0.0049	0.0001
	1.08	1.52	-1.97	0.77	0.03	0.69	0.63	0.46	0.00
$clubbank_i$	-0.0006	-0.0159	-0.006	-0.0045	0.0147	0.0053	0.0127	0.0129	-0.0162
	0.06	1.23	-0.41	0.29	0.85	0.23	0.63	0.49	0.55
$event_{jt} * clubbank_i$	-0.0329***	-0.0353**	-0.0496***	-0.0393***	-0.0475**	-0.0613**	-0.0956***	-0.0921***	-0.0672**
	2.88	2.46	2.95	2.27	2.62	2.45	4.63	3.10	2.25
$Constant$	1.0725***	1.0810***	1.0892***	1.0784***	1.0673***	1.0814***	1.0678***	1.0674***	1.0689***
	195.12	154.36	137.69	108.77	98.97	78.82	216.24	156.80	144.56
Fixed Effects	firm	bank	bank	firm	bank	bank	firm	bank	bank
Clustered SE	club	club	club	club	club	club	club	club	club
Observations	411	411	304	174	174	141	232	232	130
R-squared	0.736	0.623	0.672	0.668	0.708	0.710	0.722	0.542	0.717

This table summarizes the results for banks' returns on loans for which it is possible to extract contract-level interest rates (see Appendix C) for firms that are affected by the respective event specified at the top of the table (club entry, club formations, mayoral elections). For each firm-bank pair we split the loans in two groups: those originated before the event and those originated after the event and compute the return per one dollar investment separately for both groups. Columns I, II, IV, V, VII, and VIII display the results for individual lending relationships, columns III, VI, and IX for value weighted loan portfolios. For the portfolio tests we compute the return on a value weighted portfolio of all loans within their club and loans to firms from outside their club separately for each bank. Thus, there are at most two observations per bank. The dependent variable ROL_{ij} is bank i's payoff per one dollar investment over the life time of the lending relationship with firm j (or the loan portfolio in columns III and VI). Detailed explanation of the computation of banks' returns on individual loans and loan portfolios can be found in the text. The dummy variable $club\ bank_{ij}$ is one if bank i and firm j are connected through membership in the same club, and zero otherwise. In columns VII to IX the 'club bank' is the local state bank in which the newly elected mayor becomes head of the supervisory board through her election. The bottom of the table provides information about fixed effects and level of clustering. We report t-statistics in parentheses.

Table 8: Firms' Usage of Capital

Dep. Var.:	I $\left(\frac{Investments}{Assets}\right)_{jt}$	II $\left(\frac{Cash}{Assets}\right)_{jt}$	III $\left(\frac{Payouts}{Assets}\right)_{jt}$	IV $\left(\frac{Debt}{Assets}\right)_{jt}$	V $\left(\frac{EBIT}{Assets}\right)_{jt}$	VI $\left(\frac{Interest\ exp.}{Debt}\right)_{jt}$
$event_{jt}$	-0.0063	0.0271***	0.0289***	0.0617***	0.0018	-0.0040
	[0.65]	[2.71]	[2.83]	[2.67]	[0.28]	[1.33]
Year FE	yes	yes	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes	yes	yes
Clustered SE	club	club	club	club	club	club
Observations	4751	5474	4751	4364	5474	5094
R-squared	0.402	0.698	0.379	0.762	0.558	0.404

This table depicts changes in firm-level variables for the subsample of 686 firms for which balance sheet data from the USTAN database is available. Information on the dependent variable of each regression is provided at the top of the table. The dummy variable $event_{jt}$ takes the value of one from the year when firm j joins a club and zero otherwise. All regressions include year and firm fixed effects. Standard errors are corrected for clustering at the club level. We report t-statistics in parentheses.

Table 9: Lending Shares of Club Banks - By Bank Groups

	I	II	III	IV	V	VI
Dep. Var.:	$\left(\frac{Club\ bank\ loans}{Total\ firm\ loans}\right)_{jt}$				$\left(\frac{State\ club\ bank\ loans}{Total\ club\ bank\ loans}\right)_{jt}$	$\left(\frac{Club\ bank\ loans}{Total\ firm\ loans}\right)_{jt}$
	State	Private	Cooperatives	One bank	Multiple banks	State
$event_{jt}$	0.1082***	0.0763***	0.0472	0.0592***	0.1426*	0.0626**
	[3.63]	[4.66]	[1.28]	[4.56]	[1.94]	[2.20]
$event_{jt} * state\ bank_k$				0.0645**		
				[2.34]		
$event_{jt} * mayor_k$						0.1283***
						[2.89]
Quarter FE	yes	yes	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes	yes	yes
Clustered SE	club	club	club	club	club	club
Observations	4214	6936	866	12016	12696	4214
R-squared	0.511	0.445	0.363	0.473	0.662	0.554

For the dependent variable in this table we divide firm j's loans from its club bank by firm j's total loans in columns I to IV and VI. The sample in columns I to IV is limited to clubs with only one club bank, which is either a state bank (column I), a private bank (column II) or a cooperative bank (column III). The sample in column V comprises all clubs that have two club banks one of which is a state club bank and one of which is a private or cooperative club bank. The dependent variable is replaced by firm j's state club bank loans divided by firm j's total loans from all club banks. The variable $event_{jt}$ is a dummy variable taking the value of one from the year when firm j enters a club, and zero otherwise. The $state\ bank_k$ dummy takes the value of one for firms associated to a club with a state banker and zero for firms associated with club that have no state banker among its members. For a subsample of clubs the mayor of the respective city is member of the club (and simultaneously heading the board of the state bank). For those clubs the $mayor_k$ variable takes the value of one, whereas for clubs with no mayor it takes the value of zero. The sample in column VI is restricted to clubs in which the club bank is a state bank. Each regression includes quarter and firm fixed effects. Standard errors are corrected for clustering at the club level. We report t-statistics in parentheses.

Table 10: Returns on Loans - By Bank Groups

Dep. Var.: ROL_{ij}	I State	II Private	III Cooperatives	IV All
club bank$_i$	-0.0564***	-0.0187**	-0.0026	-0.0166
	[2.88]	[2.02]	[0.16]	[1.40]
club bank$_i$ $*$ *state bank*$_i$				-0.0398**
				[2.11]
Constant	1.0680***	1.0744***	1.0866***	1.0745***
	[111.21]	[267.68]	[237.13]	[271.62]
Bank FE	yes	yes	yes	yes
Clustered SE	club	club	club	club
Observations	105	175	59	339
R-squared	0.671	0.744	0.982	0.761

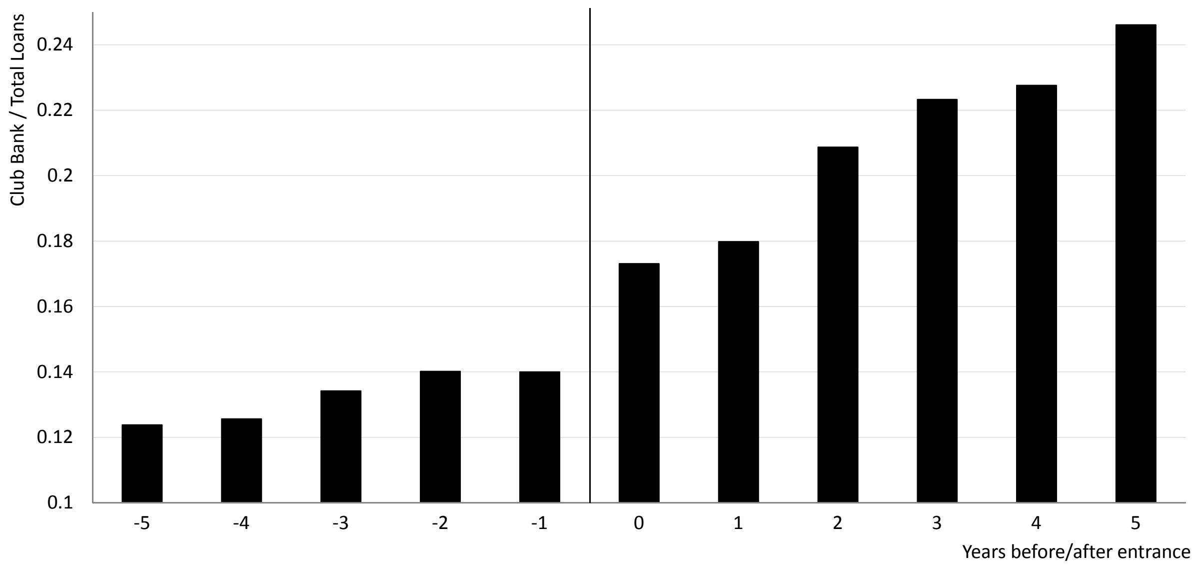
This table summarizes the estimation results for portfolio-level returns on loans for different bank groups. The sample comprises the firms for which contract-level interest rates can be computed (see Appendix C). We compute the return on a value-weighted portfolio separately for loans to firms within the club and firms in other clubs. Thus for each bank there are at most two observations (for banks who only borrow to firms in their own club or only to firms in other clubs there is only one observation). The dependent variable ROL_{ip} is bank i's payoff per one dollar investment over the life time of portfolio p. A detailed explanation of the computation of portfolio-level returns on loans can be found in the text. The dummy variable *club bank*$_{ij}$ is one if bank i and the firms in portfolio p are connected through membership in the same club, and zero otherwise. The *state bank*$_i$ dummy takes the value of one if bank i is a state bank, and zero otherwise. All regressions include bank fixed effects. Standard errors are corrected for clustering at the club level. We report t-statistics in parentheses.

Table 11: Bank Lending and Firm Borrowing Channel

	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII
	Intensive Margin						Extensive Margin					
Dep. var.:	$log(Loans)_{ijt}$						$New\ relationship_{ijt}$					
	Entry		Formation		Mayoral Election		Entry		Formation		Mayoral Election	
$event_{jt}$	0.0612		-0.0151		0.0349		0.0124***		0.0083***		-0.0115**	
	[0.83]		[0.15]		[0.26]		[3.46]		[3.08]		[2.42]	
$club\ bank_{ij}$							0.0709***	0.0709***	0.0691***	0.0713***	0.0151	0.159
							[5.94]	[5.90]	[3.42]	[3.49]	[0.57]	[0.59]
$event_{jt} * club\ bank_{ij}$	0.2631**	0.3037*	0.3773**	0.5693*	0.4147***	0.4770***	0.1144***	0.1143***	0.1472***	0.1428***	0.1076*	0.1059*
	[2.26]	[1.85]	[2.20]	[1.94]	[2.93]	[3.10]	[4.99]	[4.88]	[3.86]	[3.69]	[1.92]	[1.91]
Quarter FE	yes	yes	yes	yes	yes	yes	no	no	no	no	no	no
Firm FE	no	no	no	no	no	no	yes	yes	yes	yes	yes	yes
Firm-Bank FE	yes	yes	yes	yes	yes	yes	no	no	no	no	no	no
Firm-Event FE	no	yes	no	yes	no	yes	no	yes	no	yes	no	yes
Clustered SE	club	club	club	club	club	club	club	club	club	club	club	club
Observations	54123	54123	39145	39145	54123	54123	60334	60334	21176	21176	11796	11796
R-squared	0.737	0.744	0.716	0.761	0.735	0.736	0.098	0.151	0.081	0.118	0.051	0.080

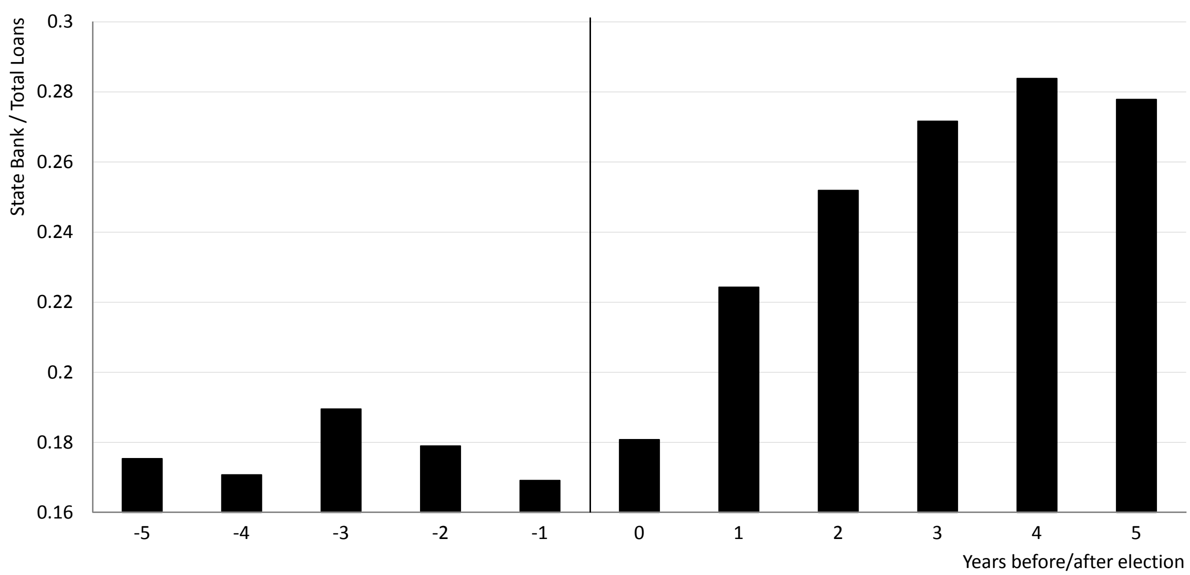
The sample for this table comprises all 1091 firms from our sample. The dependent variable in columns I to VI is the log of bank i's loans to firm j's. In columns VII to XII the dependent variable is replaced by a dummy variable that is one if bank i and firm j start a new lending relationship and zero otherwise. In columns VII to XII, there are two observations per firm-bank relationship, one for the period before the event and for the period after the event. Accordingly, the samples for this test are restricted to firms that are subject to the respective event during the sample period. In this test for each firm j every bank that provides a loan to at least one firm in the city in which firm j's club is located is considered as a potential lending relationship for firm j. The dummy variable $event_{jt}$ takes the value of one from the year when firm j joins a club and zero otherwise in columns labeled “Entry”, it takes the value of one from the year when firm j joins a club through new club formation in columns labeled “Formation”, and it takes the value of one after an existing club member is elected as mayor zero otherwise in columns labeled “Mayoral Election”. The dummy variable $club\ bank_{ij}$ takes the value of one if bank i is club bank to firm j, and zero otherwise. In columns labeled “Mayoral Election” the 'club bank' is the local state bank in which the mayor becomes the head of the supervisory board through her election. The bottom of the table depicts information on the fixed effects included. Standard errors are corrected for clustering at the club level. We report t-statistics in parentheses.

Figure 1: **Club Bank Share in Total Firm Lending Around Entry to a Club**



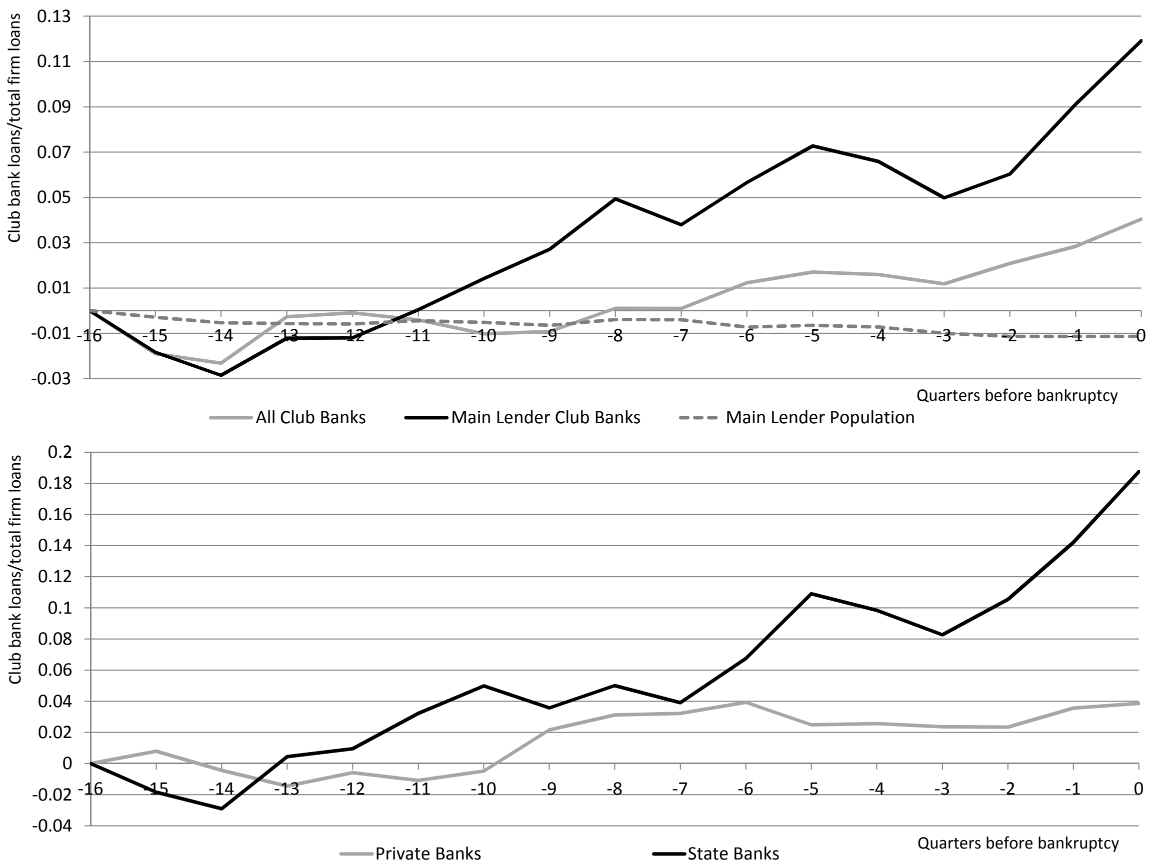
This figure depicts the share of loans from a firm's club bank divided by the firm's total loans for the sample of 474 firms that enter a club during the sample period. To compute the club bank shares on the y-axis we align firms around the year they enter a club and calculate the average club bank share for all firms with the same distance to club entry. The x-axis displays the distance to firms' entrance to a club in years. The value zero indicates the year in which the firm officially obtains member status in the club.

Figure 2: **State Bank Share in Total Firm Lending Around Mayoral Elections**



This figure depicts the share of loans a firm borrow's from the state bank divided by its total loans for the sample of 109 firms that are members of a club in which an existing member in elected as a mayor for the first time during the sample period and thereby becomes head of the local state bank's supervisory board. To compute the state bank shares on the y-axis we align firms around the year of the mayoral election and calculate the average state bank share for all firms with the same distance to the mayoral election.

Figure 3: **Bank Lending Shares before Bankruptcy**



Panel A of this figure plots the share of club bank loans in total firm loans in the sixteen quarters before firms' default on the y-axis (solid lines). We plot club bank shares relative to the share sixteen quarters before bankruptcy which we set to zero. The x-axis lists the distance to the official bankruptcy date in quarters. The gray solid line comprises all firms with a default event in the sample, whereas the black solid line only includes those firms for which additionally the club bank is their main lender. The gray dashed line depicts the share of loans from firms' main lender in total firm loans for the population of all firms in the sample region that are not club members (and therefore not part of our sample). Panel B plots the share of club bank loans in total firm loans for the firms with a default event whose club bank is the main lender separately for firms for which the club bank is a state bank (black line) and for firms for which the club bank is a private bank (gray line).

Appendix A. Data selection of service club members

This appendix describes the construction of the dataset on service club members. Many of these service clubs provide their entire membership section through their club website. Other service clubs only provide the names of current members and the official function within the club (e.g. president, vice-president, treasury), as well as the names of members that had an official function in the past. Since the clubs tend to be small (on average 50 members per club) and we are only interested in members that are either a firm's CEO or a bank director, we obtain most member names by this search strategy. We complete our sample by interviewing club members from our sample region.

Membership information includes an entrance date, as well as information on the member's profession. If the information regarding a member's profession is incomplete, we update our sample by internet research. Names of CEOs of limited liability and public firms can be obtained through the federal German corporate register (*elektronischer Bundesanzeiger*).[40] We also use the latter source to identify whether the firms in the service clubs filed for bankruptcy during our sample period. All sample banks list their regional directors on each bank's website.

Appendix B. The German banking sector

The German financial sector is bank-based with a universal banking system. One of the distinct features of the German banking sector is the so-called three-pillar structure which refers to the three different types of legal ownership of German banks - state owned banks (*Landesbanken* and *Sparkassen*), private banks, and credit cooperatives (39% of total banking assets are held by private banks, 45.5% by state banks, and 15.5% by cooperative banks (Bundesbank (2011)). The structure of the state banking sector is the result of laws ('Sparkassengesetz') implemented at the beginning of the twentieth century and after the Second World War, which gave rise to a country-wide community banking sector. The regional principle requires community banks to supply finance locally and prevents competition between state banks by prohibiting them from serving customers outside their community. The objectives of state banks, as laid down in the respective laws (e.g., SpGNRW and SpGBW), are manifold: e.g., ensuring the availability of credit to enterprises and communities, as well as facilitating individual savings.[41] The difference in objectives of state-owned and private

[40] https://www.ebundesanzeiger.de

[41] Commonly this legal framework includes a statement that profit maximization is not the main objective of state owned banks and that they are supposed to serve common welfare. Other objectives are to provide

banks 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.[42] The legal framework prohibits consolidation between private and state banks. Consolidation can only take place within each of the pillars, so that competitive pressure through M&As is low for state banks.

Appendix C. Computation of Interest Rates

Combining the quarterly Bundesbank credit register with annual firm-level accounting information from USTAN allows us to back out effective annual interest rates on the loan contract level.

Step 1: As a first step, we use quarterly information from the credit register on the bank-firm relationship level to identify individual loan contracts. From the repayment structure of the initial loan amount, we can infer the maturity of the loan contract (e.g., whether it is repaid at the end of the contract period; linearly or de/progressively). If the outstanding loan of a lending relationship increases, we identify a new loan contract. Some lending relationships include a current account for the client with a loan amount that fluctuates around a fairly stable mean. Therefore, we only identify a new loan contract if the increase in total loans per firm-bank relationship exceeds 33.33 percentage points. Following this procedure, we extract all individual loan contracts per firm from the credit register (see Table A.1, Panel A).[43]

a checking account to every private person independent of her income and the economic education of the youth (see the 'Sparkassengesetze', 'Sparkassenordnung' and 'Landesbankgesetz' of the Länder in Germany).

[42] Within Europe, Germany is among the countries with the highest number of credit institutions, branches, and bank employees; see ECB (2007) for details.

[43] The tables in this section help to guide the reader through the computation of interest rates by illustrating one hypothetical example.

Table A.1: Contract Extraction

A - Quarterly Data	I	II	III	IV	V
Quarter	Bank A	Bank B	Contract 1 (A)	Contract 2 (A)	Contract 3 (B)
1998 Q4	12000	-	12000	-	-
1999 Q1	10000	-	10000	-	-
1999 Q2	8000	-	8000	-	-
1999 Q3	6000	-	6000	-	-
1999 Q4	11000	-	4000	7000	-
2000 Q1	9000	-	2000	7000	-
2000 Q2	7000	-	-	7000	-
2000 Q3	7000	-	-	7000	-
2000 Q4	7000	-	-	7000	-
2001 Q1	7000	-	-	7000	-
2001 Q2	7000	-	-	7000	-
2001 Q3	7000	5000	-	7000	5000
2001 Q4	-	4000	-	-	4000
2002 Q1	-	3000	-	-	3000
2002 Q2	-	2000	-	-	2000
2002 Q3	-	1000	-	-	1000
B - Annualized Data	**I**	**II**	**III**	**IV**	**V**
Year	IR	Spread	Contract 1 (A)	Contract 2 (A)	Contract 3 (B)
1999	0.0700	0.0381	9000	-	-
2000	0.0853	0.0367	1500	7000	-
2001	0.0803	0.0399	-	7000	1250
2002	0.0800	0.0451	-	-	2500

Panel A of this table lists a firm's total loans from Bank A in column I and Bank B in column II derived from the credit register. Columns III to V display the contracts extracted from the quarterly loan information. Panel B depicts the annualized data. Column I shows the annual firm-level interest rate from balance sheet data, column II the spread of the interest rate over the EURIBOR. Columns III to V lists the average annual loan for Contracts 1 to 3. Details on the identification of loan contracts can be found in the text.

To match loan and balance sheet data, we annualize the loan data by averaging the loan amount over four quarters (December$_{t-1}$, March$_t$, June$_t$, September$_t$). We match contract-level information with interest payments derived from balance sheet information[44] (see Table A.1, Panel B). In rare cases, firms have interest-relevant debt in excess of bank loans. In this case, the sum of all bank loans from the credit register does not sum up to the amount of loans reported in a firm's balance sheet. We deal with this discrepancy by treating the difference as an additional lending relationship.

Step 2: The combination of both datasets allows us to compute contract-level interest rates by solving the equation system:

$$r_{jt} = \sum_{d=1}^{D} \frac{x_{djt}}{\sum_{d=1}^{D} x_{djt}} \cdot r_{dj}, \tag{C.1}$$
$$for\ t = t - int(D/2), ..., t, ..., t + int((D-1)/2)$$

[44] Annual firm-level interest rates are defined as interest expenses minus interest expenses to related firms (ap174-ap175) divided by the average loan amount in the same year.

where D is the number of relationships. The variable r_{jt} is the average interest rate paid by firm j in year t. We winsorize firm-level interest rates at the 5/95% quintile to account for unduly extreme outliers. The individual contract volume for firm j's contracts is denoted by x_{djt}, and thus, $\frac{x_{djt}}{\sum_{d=1}^{D} x_{djt}}$ is contract d's share in firm j's total borrowing. The variable of interest is r_{dj}, the interest rate on the individual loan contract.[45]

Each contract can either be a fixed or floating rate contract.[46] Equation system (C.1) can also be solved for floating rate contracts by replacing r_{dj} by $(s_{dj} + EURIBOR_t)$, where s_{dj} is the spread over the EURIBOR for contract d. As we do not have information about the type of contract, we allow all possible combinations for each firm at every point in time. For a firm with D contracts at a given point in time, we solve 2^{D} different equation systems. Additionally, for D contracts to solve the equation system for r_{dj}, D independent equations are required. Solving the equation system provides us with contract-specific interest rates/spreads (see Table A.2).

Step 3: To identify the correct combination of contract types, we first calculate the average absolute deviation from the mean interest rate/spread for each contract:

$$\sigma_{djt} \quad = \quad \frac{1}{T} \cdot \sum_{t=1}^{T} \left| r_{djt} - \sum\nolimits_{t=1}^{T} \frac{r_{djt}}{T} \right| \tag{C.2}$$

where T is the maturity of contract d in years. Next, we compute the average deviation for each of the 2^{D} equation systems as the average deviation over all contracts as ς_j. For each firm, we pick the combination of fixed and floating rate contracts that leads to the lowest value of ς_j (see Table A.2). Finally, we calculate the annual firm-bank relationship level interest rate as the value-weighted interest rate of all contracts of a firm-bank relationship for a given year. This approach allows us to compute firm-bank level interest rates for a subsample of lending relationships for which equation system (C.1) is solvable.

Step 4: To verify the validity of the computed interest rates we run several plausibility checks. From 2008 onwards, the credit register provides information about whether a loan is secured or unsecured. Additionally, banks transmit an estimated probability of default for each loan to Bundesbank. This allows us to check whether interest rates of the *same* firm in the same year differ depending on a bank's perceived risk of incurring a loss. This is particularly interesting as differences in interest rates for the *same* firm in the *same* year

[45] In the example from Table A.1, the equation system for the year 2000 with fixed interest rates is: $\begin{bmatrix} 0.0853 \\ 0.0803 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0.1765 & 0.8235 \end{bmatrix} \times \begin{bmatrix} r_1 \\ r_2 \end{bmatrix}$.

[46] In Germany, floating rate contracts use the FIBOR as base rate until 1998 and the EURIBOR as of 1999.

Table A.2: Solutions

	(r,r,r)	(s,s,s)	(r,s,s)	(r,r,s)	(r,s,r)	(s,r,r)	(s,r,s)	(s,s,r)
1999								
Contract 1 (A)	0.0700	0.0381	0.0700	0.0700	0.0700	0.0381	0.0381	0.0381
Contract 2 (A)	-	-	-	-	-	-	-	-
Contract 3 (B)	-	-	-	-	-	-	-	-
2000								
Contract 1 (A)	0.0700	0.0381	0.0700	0.0700	0.0700	0.0381	0.0381	0.0381
Contract 2 (A)	0.0886	0.0364	0.0400	0.0886	0.0400	0.0850	0.0850	0.0364
Contract 3 (B)	-	-	-	-	-	-	-	-
2001								
Contract 1 (A)	0.0700	0.0381	0.0700	0.0700	0.0700	0.0381	0.0381	0.0381
Contract 2 (A)	0.0886	0.0364	0.0400	0.0886	0.0400	0.0850	0.0850	0.0364
Contract 3 (B)	0.0339	0.0595	0.0395	-0.0065	0.0799	0.0540	0.0136	0.0999
2002								
Contract 1 (A)	-	-	-	-	-	-	-	-
Contract 2 (A)	0.0804	0.0390	0.0390	0.0794	0.0400	0.0804	0.0794	0.0462
Contract 3 (B)	0.0800	0.0451	0.0451	0.0451	0.0800	0.0800	0.0451	0.0451
σ(Contract 1 (A))	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
σ(Contract 2 (A))	0.0101	0.0031	0.0012	0.0113	0.0000	0.0057	0.0069	0.0120
σ(Contract 3 (B))	0.0345	0.0108	0.0042	0.0387	0.0001	0.0195	0.0236	0.0411
ς	0.0149	0.0046	0.0018	0.0166	0.0000	0.0084	0.0102	0.0177

The first line of the table indicates the combination of fixed rate contracts (r) and floating rate contracts (s). The optimal combination of contracts to solve the equation system is (r,s,r). The interest rate for Contract 1 is 0.08, the spread for Contract 2 is 0.04, and the interest rate for Contract 3 is 0.07. This leads to annual interest rates of 0.0700 in 1999, 0.0853 in 2000, and 0.0804 in 2001 for Bank A, and 0.0800 in 2001 and 2002 for Bank B.

Table A.3: Plausibility Tests

	Secured vs. unsecured			Firm risk		
Dep. Var.: IR_{ijt}	I	II	III	IV	V	VI
$secured_{ijt}$	-0.0052*	-0.0104***	-0.0175***			
	[1.88]	[3.33]	[3.56]			
$log(PD)_{ijt}$				0.0020*	0.0049***	0.0075**
				[1.77]	[2.74]	[2.23]
Year FE	yes	yes	-	yes	yes	-
Firm FE	no	yes	-	no	yes	-
Firm-Year FE	no	no	yes	no	no	yes
Observations	1093	1093	1093	636	636	636
R-squared	0.052	0.571	0.652	0.063	0.621	0.731

This table shows the results from the regression: $IR_{ijt} = \alpha + \beta \cdot secured_{ijt} + \epsilon_{ijt}$ in columns I to III, where IR_{ijt} is the relationship-level interest rate charged by bank i for firm j at time t and $secured_{ijt}$ is a dummy variable taking the value of one if the loan is secured and zero otherwise. In columns IV to VI the $secured_{ijt}$ dummy is replaced by $log(PD)_{ijt}$, the log of the probability of default assigned from bank i to firm j at time t. The bottom part of the table lists the fixed effects included. We report t-statistics in parentheses.

emerge from the computation of relationship-level interest rates only. We find that, in the cross-section, interest rates on secured loans are 0.52% lower than for unsecured loans (Table A.3, column I). By adding firm fixed effects, the difference is even larger, with 1.04% lower interest rates for secured loans (column II). The strictest specification with firm-year fixed effects yields differences in interest rates on secured loans that are 1.75% lower than for unsecured loans (column III). Additionally, in the cross-section of loans, interest rates are higher for riskier firms (column IV). After adding firm fixed effects, the difference is even stronger (column V). Adding firm-year fixed effects reveals that a bank that considers the same firm to be riskier in the same year (that is, reports a higher probability of default) charges higher interest rates (column VI). The results from the plausibility checks verify that the computed interest rates capture differences in interest rates across loan contracts correctly.

Appendix D. Additional Tables

Table A.4: Returns on Loans (Spread over FIBOR/EURIBOR)

Dep. Var.: ROL_{ij}	I	II	III
club bank$_i$	-0.0146*	-0.0336**	-0.0290***
	[1.72]	[2.58]	[3.01]
constant	1.0269***	1.0327***	1.0373***
	[399.70]	[262.35]	[253.69]
Firm FE	yes	no	no
Bank FE	no	yes	yes
Clustered SE	club	club	club
Observations	681	681	339
R-squared	0.821	0.348	0.746

This table summarizes the estimation results for portfolio-level returns on loans over the refinancing rate for lending relationships for which is it possible to back out contract-level interest rates (see Appendix C). The dependent variable ROL_{ij} is bank i's payoff per one dollar investment in the value-weighted loan portfolio with firm j in excess of the EURIBOR/FIBOR rate. Details on the computation of returns of loans can be found in the text. The dummy variable *club bank*$_{ij}$ is one if bank i and firm j are connected through membership in the same club, and zero otherwise. The bottom of the table provides information about fixed effects and level of clustering. We report t-statistics in parentheses.

Table A.5: Intensive Margin - Change in log of Loans

	I	II	III
Dep. Var.: Δ $log(Loans)_ijt$	Entry	Formation	Mayoral Election
$club\ bank_{ij}$	0.3251***	0.5506**	0.4191*
	[3.07]	[2.57]	[1.86]
Firm FE	yes	yes	yes
Clustered SE	club	club	club
Observations	289	63	92
R-squared	0.486	0.546	0.367

This table replicates the estimation framework from Khwaja and Mian (2008). The samples comprise the firms that have at least two lending relationships existing before and after the event that leads to perturbation in social proximity between firm j and bank i. In column I the event is firm j joining an existing club, in column II it is firm j joining a club through new club formation, in column III it is one of the members in firm j's club that has a state banker among its members being elected as a mayor for the first time during the sample period. The dependent variable is the change in log of average quarterly loans from bank i to firm j after compared to before the event. The dummy variable $club\ bank_{ij}$ is one if firm j and bank i are connected through membership in the same club, and zero otherwise. Each regression includes firm fixed effects, standard errors correct for clustering at the club level. We report t-statistics in parentheses.

Table A.6: Returns on Loans for Different Subsamples

	I	II	III	IV	V	VI
	Relationship				Portfolio	
Dep. Var.: ROL_{ij}	Post 2008		Pre 2008		Post 2008	Pre 2008
club bank$_{ij}$	-0.0267*	-0.0340**	-0.0163*	-0.0128*	-0.0324**	-0.0147**
	[1.73]	[2.28]	[1.93]	[1.88]	[2.20]	[2.16]
Constant	1.0687***	1.0718***	1.0745***	1.0729***	1.0638***	1.0774***
	[185.31]	[156.70]	[429.37]	[377.26]	[150.42]	[377.69]
Fixed Effects	firm	bank	firm	bank	bank	bank
Firm FE	yes	no	yes	no	no	no
Bank FE	no	yes	no	yes	yes	yes
Clustered SE	club	club	club	club	club	club
Observations	361	361	664	664	2082	755
R-squared	0.816	0.427	0.593	0.422	0.687	0.852

This table summarizes the estimation results for relationship and portfolio-level returns on loans for which it is possible to extract contract-level interest rates (see Appendix C). In columns I, II, and V the sample is restricted to the sample period from 1993:II to 2007:IV, in columns III, IV, and VI the sample period stretches from 2008:I to 2011:III. Columns I to IV display the results for individual lending relationships, columns V and VI for returns on value weighted loan portfolios. For each bank we calculate a return on the portfolio of loans within a club and loans to firms in other clubs separately. Thus for each bank there are at most two observations (for banks who only lend within a club or only to firms in other clubs there is only one observation). The dependent variable ROL_{ij} is bank i's payoff per one dollar investment over the life time of the lending relationship with firm j (or the loan portfolio in columns V and VI). The computation of relationship-level and portfolio-level returns on loans in outlined in detail in the text. The dummy variable *club bank*$_{ij}$ is one if bank i and firm j are connected through membership in the same club, and zero otherwise. The bottom of the table provides information about the fixed effects included and the level of clustering. We report t-statistics in parentheses.