BANKING ON POLITICS*

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Abstract

We present new data on the frequency with which former high-ranking politicians become bank directors for a large number of countries. Connections at this level are relatively rare but their frequency is robustly correlated with many important characteristics of banks and institutions. At the micro level, banks that are politically connected are larger and more profitable than unconnected ones, despite being less leveraged and less risky. At the aggregate level, we show that country-level connectedness is strongly negatively related to economic development. Controlling for this, the phenomenon is more prevalent where institutions are weaker and governments are more powerful but less accountable. Bank regulation tends to be more pro-banker and the banking system less developed where connectedness is higher. A benign, public-interest view is hard to reconcile with these patterns.

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1. **Introduction**

There is ample evidence that access to external financing is critical for the level and efficiency of investment, productivity, and ultimately growth, both at the firm and the aggregate level. Yet the availability of finance for firms varies widely across countries.[1] This raises two important questions: why do some countries not have a well developed financial system if it is so beneficial? And how do firms react to financial underdevelopment? A recent strand of financial development literature aims at answering both questions from a political economy standpoint.

Regarding the first question, this literature has complemented existing theories of financial development based on stable and largely predetermined factors (such as a country's legal origin, pattern of colonization, religion and culture, and social capital endowment) with a role for dynamic political economy considerations.[2] Private interests and politics appear to be relevant determinants of financial development, as suggested for instance by Rajan and Zingales (2003), Pagano and Volpin (2001), and Braun and Raddatz (2007, 2008). One possible channel though which this can happen is the regulatory effect of the interaction between politicians and financial-sector incumbents. The fact that regulators come from or end up in the regulated industry –a phenomenon termed the *revolving door* - has long been recognized as a potential determinant of regulation.[3] And indeed, the empirical work available, although still scarce, points to it having large social costs (see Kwhaja and Mian, 2005, and Dal Bó and Rossi, 2004).

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[1] See Levine (2006) for an extensive review of the literature on the subject.

[2] See LaPorta et al. (1997, 1998), Acemoglu and Johnson (2003), Stulz and Williamson (2003), and Guiso et al. (2004).

[3] See Dal Bó (2006) for a review of regulatory capture.

As for the second question, a number of recent papers have documented that politically connected firms seem to get preferential access to credit (Cull and Xu, 2005 and Khwaja and Mian, 2005) and better treatment by the government. In fact, these links between politics and business seem quite widespread (Faccio, 2006) and to add significant value to firms (Fisman, 2001).

This paper focuses on banks. We build a new dataset linking more than ten thousand politicians (cabinet members, financial sector regulators, and Central Bank governors) to around sixty thousand members of bank boards in a large number of countries. We then compare the names of bankers and those of the politicians in search of matches between the two groups. We use the frequency of these matches to compute a number of measures of the connection between bankers and politicians that provide useful bank and cross-country level variation in order to explore the role of political connectedness in this particular kind of firm. Banks, just like any other firm, may use these connections to improve their position, perhaps by affecting banking regulation. This would be more likely to happen where institutions are weak and the government is relatively more powerful yet less accountable. It may also carry large social costs in the form of more restricted access to credit. We are interested in knowing the extent to which banks are politically connected, where this is more prevalent, and whether this is associated with better outcomes for them. Given their critical role in the allocation of credit, the behavior of banks, unlike most firms, affects the entire economy.

The private-interest view of the presence of former politicians on banks' boards is, of course, not the only possibility. The fact that politicians and bankers are linked may simply be a way in which ability, knowledge, or experience is fruitfully shared between the private and public sectors. These links could also imply better outcomes for the firm without negative social effects. Banks could simply be lobbying to make a legitimate case to government officials or could consider these links more as consumption than as investment (see, for instance, Ansolabehere et al, 2003). The relative merit of these two types of views is ultimately an empirical question. In that sense, the stylized facts we provide in this paper may shed some light on which interpretation is more likely.

A number of stylized facts clearly stand out. At the micro level, banks that are politically connected are quite different from unconnected ones: they are larger, more profitable, less leveraged, and less risky. When we aggregate bank connectedness at the country level in a number of different ways, we find that it is strongly negatively related to GDP per capita. Controlling for this and for other traditional elements, countries where banks are more connected rank higher on corruption and government regulatory power, and lower on accountability. Moreover, overall regulation is less market friendly, bank regulation is generally more pro-banker, and the financial system is less developed in countries where the intersection between politicians and bankers is greatest.

This paper is closely related to a recent literature --exemplified by Faccio (2005), showing that firms that are politically connected appear to fare better than the rest. Our paper adds to this work in three main ways. The first is that we focus on banks in particular. We see this as an important contribution because of the likely effect this may have on the entire economy through the allocation of credit. We also differ in that, rather than determining whether political connections betters the connected firms, we delve deeper into the country characteristics and policy choices that are associated with these kinds of connections. Lastly, we look not just at current politicians but also at former ones.

The phenomenon we describe here focuses on the more subtle way in which the political and industry worlds relate to each other. A-priori, this is a kind of relationship that has a less clear interpretation. The empirical investigation is, therefore, particularly relevant.

Our paper is also related to the literature that looks into boards of directors in search of political experience (see, for instance, Agrawal and Knoeber, 2001, and Goldman et al, 2009). Similarly it is related to recent work on the relationship between connections and development, including banking sector development from a historical perspective (see, for instance, Haber 1991, Maurer 2000, Maurer et al 2005, and Razo forthcoming). Here the assembly of our dataset has allowed us to explore the issue consistently across a very large number of countries.

The rest of the paper is structured as follows. Section 2 describes the data and the matching procedure used to identify banker-politicians. It also discusses different ways of aggregating the results into a country-level connectedness variable. Section 3 shows how connected banks differ from unconnected ones, and in which kind of countries the phenomenon is more frequent. Section 4 presents the conclusion.

2. Measuring the connection between bankers and politicians

This section describes the methodology used to measure the connection between bankers and politicians in the data, presents some summary statistics from the resulting dataset, and introduces the different aggregate measures of the degree of connection across countries.

2.1 Building the data

The data on names of politicians were taken from various issues of the *Economist Intelligence Unit Country Reports*, which we revised twice a year for each country between 1996 and 2005. From this we obtained a total of 72,769 names of cabinet members and central bank governors. These names were complemented by a smaller set of 593 names of financial sector supervisors obtained from the 2000, 2002, 2003, and 2004 issues of Courtis (2005). These two data sets together provide extensive coverage for cabinet members and financial sector supervisors in 154 countries over ten years (see Table 1, Column (3)). After the data were cleaned and duplicate entries accounted for (as explained below) we ended up with an average of 72 unique politicians in each country, which is around seven per year. There is some variation across countries in this number but it is relatively small: 70% of the countries present between 40 and 100 names of politicians.

The names of banks' board members come from *Bankscope,* which has data on the most recent board composition of both listed and unlisted banks in nearly all countries. We collected these data for 2006, so the board composition is typically from December 2005. A total of 109,645 board member names from 4618 different banks were collected. After identifying duplicates, we ended up with 64,169 unique board member names. Although Bankscope is the most comprehensive source of bank data around the world, its coverage is not necessarily complete. The average number of banks with board composition data in Bankscope in 2001 is, however, similar to the total number of commercial banks reported by Barth et al (2003) for the same year (see Column (5)), which suggests that the coverage of Bankscope is close to universal. Although there is some variation in this figure across countries, in about 70% of these the difference between the numbers of banks in the two datasets falls within a 20% range. The banks for which we have board data represent on average 72% of the assets in each country and in about only one fourth of the countries the fraction is below 60% (Column (6)).

The process of finding coincidences between politicians and bankers' names involved four steps. First, we standardized the strings containing the names by converting them to lowercase only, and removing punctuations and titles (Sir, PhD, etc.). As a second step, we removed duplicate entries by determining in each of the datasets those observations that corresponded to different spellings of the same name (for instance, with and without the middle initial). As a third stage, we pooled the different datasets containing names of politicians and again identified those observations across the datasets that corresponded to the same individual. Once the names had been cleaned in this way, we compared the names included in the politicians and bankers datasets to obtain the matching observations.

To determine whether there was a matching name at each step, we used a *record-linkage algorithm* that forms all the possible pairs of names within each country and ranks the pairs based on three standard measures of string similarity used in record linkage literature: Bigram, Levenshtein, and Longest Common Subsequence.[4] The Bigram metric counts the number of consecutive pairs of characters that agree between two strings. The Levenshtein measure counts the minimal number of edits required to convert one text into the other. The allowable edit operations are the deletion of a single character, the insertion of a single character and the substitution of one character for another.

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[4] The record linkage software we use is *Merge Toolbox (MTB),* a Java based tool created by the members of the *Safelink* project (see Schnell et al (2004)).

Note that all the methods are based on the way names are written. If the difference between the way a name sounds and the way it is written varies across countries, so that mistakes are more prevalent in some than in others, these methods could be differentially effective and potentially induce bias. For these reasons, we used these algorithms only to restrict the sample of potential matches, as described below, but ultimately we visually identified the matches.

When comparing two strings containing names, each of these criteria results in a value between 0 and 1 that measures the likeliness of the two names. We kept all pairs with a minimum value of 0.8 in at least one of the three criteria, and visually checked all pairs to determine whether they corresponded to an actual match. Of course, one can think of alternative ways of restricting the set of pairs to be visually checked. We chose a relatively restrictive way because we preferred to err on the side of not finding many matches rather than being less certain that our matching of names really corresponded to the same individual. This was also the basic principle we used for the visual part.

Following the process above, after the second step our data contained 10,829 different politicians and 62,981 different bankers in 146 countries. The third step produced a total of 218 matching names across these two lists of people in this set of countries (see Column (4)). The mean (median) number of matches per country is 1.4 (1). The share of bankers that are politicians corresponding to 0.34% is quite small. This is partly because of the restrictive way in which we identified our matches. Also, the fraction of politician-bankers does not look as small when one considers the size of the populations from where these people are selected, as we will see below. However, the fraction of matches is unimpressive.

This most probably has to do with the fact that having high-ranking politicians on the board of banks is not the only way banks can be politically connected. Non-cabinet level politicians can certainly play an important role connecting banks. There are also more subtle forms of connection: a politician can be connected to a bank not only by sitting on the board himself, but also by having relatives or associates doing it,[5] or by supporting the appointment of directors or CEOs. There are also less subtle ones such as outright bribery and corruption. Our channel seems in fact to be a relatively rare form of connection when compared to the importance that other channels could have based on country case-studies and anecdotic evidence.[6] However, these other types of connections are much more difficult to document systematically across countries than the way we are looking at it. In this sense, rather than arguing that this is the only or the most important way in which bankers and politicians relate, we see the presence of high-level politicians on bank boards as a proxy for the general connection between politicians and bankers. As long as people do not completely specialize in one particular form of connection, the different ways of doing it are likely to be positively correlated. Since we are just considering the top posts in both politics and banking, what we are most likely finding here is the tip of the iceberg.

Instead of focusing on absolute magnitudes, we will later study how the variation in the relative importance of politicians sitting on bank boards relates to several bank and country characteristics. There are two sources of variation in our data: one between the countries where we found matches and countries where we did not (the extensive margin), and variation in the number of matches across the countries where we found at least one match (the intensive margin).

[5] See, for instance, Faccio (2006).

[6] See, for instance, Fisman 2001 for an account of Suharto's Indonesia.

In 72 of the 154 countries we found no matches. In most of the analysis that follows we drop these countries from our sample and concentrate on the variation across the ones where at least one match was found. There are two reasons behind this decision. First and most important, we are unsure of the reliability of the data for many of the countries with zero matches. For instance, while 60% of the countries with some matches meet the IMF's Special Data Dissemination Standard, only 20% on those with zero matches do. In fact, many of these countries are not typically included in systematic cross-country analyses.[7] Second, a large fraction of the countries with zero matches has a very small number of banks. One third of these countries have less than 3 banks in Bankscope in 2005, compared with 4 percent among banks with non-zero matches. Furthermore, the median number of banks with data in the first group is 5, while in the second is 16. Third, from a theoretical perspective, the zeroes give little information on whether the selection of bankers is biased toward former politicians. The reason is that, under reasonable assumptions, the probability of finding zero matches between bankers and politicians is high even if the bankers selection process is seriously biased to picking politicians instead of other equally qualified individuals.[8] In contrast, finding one match provides considerable information on the likely bias of the selection, since a match is typically a low probability event under the null of unbiased matching. Nevertheless, we also present results including banks with zero match but more than 2 banks (as an arbitrary cut to consider the zero a reliable one), and many of the correlations documented below remain unaffected.

7 For instance, 63 percent of these countries were not included in the cross-country analysis on bank regulation by Barth et al (2003). Some have been included in later rounds of the survey but their coverage is incomplete.

8 See the Appendix for a description of the distribution of matches under an unbiased selection process.

Of course, one could stretch this argument and further restrict the sample to those countries with more than one or two matches because a small number of matches may simply be fortuitous. Something that is less likely if one finds a significant number of matches. Although as previously argued, finding a single match is a very low probability event that is unlikely to occur by chance in most countries, we come back to this below and show that, even though the sample size drops quite rapidly, the results are not very different when further restricting the sample.

2.2 Measuring Connectedness at the aggregate level

There are a number of ways in which one can aggregate the information on individual matches to measure and compare how connected banks are in different countries, a concept we will refer as *connectedness*. Each has its own pros and cons and is more or less appropriate under different assumptions about the process that generates the matches between politicians and bankers. Instead of focusing on a single measure, we conduct all the analysis with five different metrics. These are presented for each country in Table 2. While the first three measures are straightforward, the last two are more elaborate because they address some shortcomings of the former. We compute all five measures considering the matches found in all kinds of banks (Panel A) and only those matches found in banks with no state ownership (Panel B).

The first measure, the *Fraction of connected banks*, henceforth *FRACBANKS,* is simply the number of banks that have at least one former politician as director divided by the total number of banks for which we have data on board members. The mean fraction of connected banks of 10% for all kinds of banks and 9% for private ones is much larger than the fraction of matches among individuals documented above. Indeed, when one we focus just on the countries with at least one match identified, the average share increases to around one fifth of the banks. There is interesting variation across countries. The countries with fewer connected banks are Switzerland, Japan, Italy, United States, and Germany, all with less than 2%. In Angola, Burundi, Madagascar, Gabon, Georgia, and Myanmar, more than two thirds of the banks are connected in this way. The picture is generally the same when considering all banks or just private banks; in fact, the correlation between the two measures is 0.86.

The rationale behind this first aggregation is that what determines a significant political link for a bank is whether the bank has at least one politician on their board. The higher the fraction of the banks in the system that are connected in this way, the larger the degree of connectedness between banking and politics. In particular, the issue is not about having a large number of people in both worlds but rather having people in the right place, even if their number is relatively small. In this sense this is more naturally interpreted as a measure of the institutional connection between banking and politics, rather than a personal matter perhaps related to the existence of a common set of skills.

A simple variation on the previous measure consists of computing the share of the total assets in the banking system that corresponds to banks that have a politician sitting on their board. This metric has the advantage of taking into account the fact that larger banks might be different than smaller ones in terms of their need or ability to connect to politics. Smaller banks may find free-riding on the goals of large banks more profitable than establishing their own connections. Also, this measure would probably be more relevant when looking at the likely effects of connectedness since it would be a measure of the amount of credit that is subject to these links. This metric is then more likely a proxy of the extent of power – both political and economic - these relationships might entail. On a more technical note, giving a higher weight to larger banks minimizes the potential problems induced by the smaller coverage we have for small banks.

The *Share of assets of connected banks (SHAREASSETS)*, is presented in the second column of each panel. As is shown in Table 3, it is strongly and significantly correlated to the previous one, both for all banks and just for the private ones. Focusing on countries with at least one match, the mean share is 25% and 18% for each kind of banks, respectively. The groups of countries that rank very high and very low are similar to those obtained using *FRACBANKS*. These figures suggest that the difference between large and small banks might not be very relevant. The correlation between the measures computed over all banks and over fully private banks is also quite high (0.79).

The third measure we consider is *Fraction of connected bankers (FRACBANKERS)*, which is the ratio of the number of matches to the number of bank directors in the data. Unlike the previous measure, this metric aims at measuring more the extent to which politicians populate bank boards. The average fraction of connected bankers across all countries is around 1%, and is close to 2% among countries with more than one match. These numbers suggest that the phenomenon is not particularly frequent. The correlation with the first two measures is small (0.34 and 0.38 for all banks) but statistically significant. Furthermore, the countries at both tails of the measure are similar to those at the tails of the previous two measures. Thus, despite the low level of the variable, its cross-country variation is capturing a similar concept to the previous two.

The first three measures of connectedness are easy to compute and natural in their interpretation. But they do not take into account that the expected number of banker-politicians may differ across countries even if the selection of bankers is not biased toward former politicians. In particular, countries with more matches might simply be countries where the number of individuals from which both bankers and politicians are selected is smaller. To be more precise about this, we derived the probability of obtaining a given number of matches under the assumption that the people needed to fill the politician and banker posts are selected randomly with replacement (at the sample level) from a common pool (see the Appendix). All individuals in the pool have the same probability of being selected for either position and there is no bias in favor of politicians in the selection of bankers. We use this probability to compute the expected number of matches one would find assuming the common pool is the entire population of each country (more on this below). The ratio of actual to expected matches (in logs) is what we call *PREVALENCE*. The correlation of this metric with the previous ones is not as strong as before, particularly with the fraction of connected bankers, but is still positive. The countries that rank highest in this connectedness measure are Myanmar, China, Bangladesh, India, and Mexico. The set of countries where the phenomenon is least prevalent include Luxembourg, France, Switzerland, and Norway.

For most countries the actual number of matches is many times larger than the expected one. This is the outcome of assuming that the pool from which officers are selected is the total population of a country. Since it is highly unlikely that every person has the same probability of being chosen for a politician or a banker post, the figures above are exaggerated. Nevertheless, the cross-country variation of this measure is the same that would be obtained by assuming that the pool where bankers and politicians are selected is a fixed fraction of a country's population. In fact, it can be shown that the expected number of matches is proportional to the size of the pool. Therefore,

$$PREVALENCE = PREVALENCE(ELITE) + \log(ELITE\ /\ POP)$$

where $PREVALENCE(ELITE)$ is the log ratio of actual to expected matches considering the true size of the elite, and $\log(ELITE\ /\ POP)$ is the log ratio of the size of the elite as a fraction of the population. Thus, as long as the elite are a fixed fraction of the population across countries, our measure of prevalence and the true prevalence would only differ in a constant.

The measure will be incorrect, however, if there is systematic variation across countries in the size of elite as a share of population. One way this may happen is if the elite is a relatively fixed number of people in all countries, so that its fraction of the population decreases as we move from smaller to larger countries. In the analysis we conduct we will be controlling for the size of the population in each country to control for this possibility.

Another possibility is that the size of the elite is related to the educated portion of the population. In fact, if one assumes that the pool is the number of people with tertiary educational attainment, the expected figures are more similar to the actual number of matches. This correction would incorporate the possibility that, in some of the countries where prevalence is highest, this is simply because they have very few people able to assume these posts. The correction, however, is not free of problems because it is not obvious that the relevant pool is the highly educated people. On one hand the pool may be too narrowly defined since not all the bankers and especially not all the politicians have tertiary education.[9] On the other, it may not be sufficiently small if a certain kind of economic or financial skill is shared between politicians in charge of economic cabinets and bankers. Most importantly, it may confound the interpretation of the results because it mixes in one variable two concepts –availability of human capital and connectedness - that may have independent (and opposite) effects on many country characteristics (e.g. real GDP per capita).

Given the uncertainty in the size of the pool of individuals where bankers and politicians are selected, we constructed a final measure. This was the *Maximum Share of Population for Randomness* (*MAXSHARE),* which corresponds to the largest pool (as a fraction of the population) where bankers and politicians would have to be selected so that the hypothesis that the selection is random could not be rejected at a five percent level (for the number of matches found in the data). It turns out that, in order not to reject this hypothesis, the size of the pool where bankers and politicians are drawn would have to be a very small fraction of the population in most countries. As expected, this variable is negatively correlated to the previous ones because it is measuring the inverse of the underlying concept. The usual groups of countries are at both extremes of the metric.

Overall, the different measures are significantly correlated, suggesting that they are likely to be different proxies for the same general concept. It is also clear that considering just the links to private banks makes no big difference, making it less likely that politicians sitting in state-owned banks drive the various measures.

[9] See Dreher et al. (2008) for data on the educational attainment of presidents. These data show that 30 percent of presidents worldwide since 1975 did not have higher education.

By looking at the groups of countries that rank the highest - Bangladesh, China, Mexico, India, and Russia - and the lowest - Luxembourg, Switzerland, Cyprus, Norway, and France - on the different connectedness measures[10], it is already apparent that they are different in other respects as well. The most obvious one is general economic development. Countries where the phenomenon is more prevalent are significantly poorer than countries where it is less so. Mean GDP per capita is 3,944 for countries with lower than median share of connected banks, while 18,958 for the rest. In other words, the fraction of connected banks in countries with lower than median per capita GDP is two and a half times larger than in more developed ones (28.2 vs. 11.4%). The general picture is about the same for the other measures and when only the private banks are considered.

The second distinctive feature is that countries where prevalence is higher also appear to have less developed institutions. For instance, countries with lower than median connectedness show control of corruption[11] figures that are one standard deviation higher than countries with higher prevalence. While the fraction of connected banks is 15.1% in countries with lower than median control of corruption, it is 26.5% in the rest. Finally, banking sector development is also quite different across the two groups of countries. Private credit to GDP is 3 times higher where connectedness measures are lower (76 vs. 25%), while the fraction of connected banks is almost twice as high in low banking sector development countries (26.5 vs. 15.1%).

Connectedness, then, does not seem to be equally distributed across countries but rather to cluster in countries where things do not work very well. In particular, where

[10] Giving equal weight to each of the five different connectedness measures.

[11] See definition below.

economic development is low, institutions are not very developed, and where the financial system is relatively underdeveloped. These are some of the relationships we look into more deeply in the following section.

3. The correlates of connectedness

In what follows we explore the correlates of connectedness first at the bank level and then at the cross-country level. We show that the different measures of connectedness introduced above are robustly correlated to important bank and country characteristics, and also to policy choices.

3.1 Bank Characteristics

In this section we compare connected and unconnected banks (i.e. those that have and do not have a former politician among their directors, respectively) in terms of several characteristics. In particular, we look at measures of size, profitability, leverage, riskiness and liquidity which were constructed directly from Bankscope data using bank statements at the end of 2004. The results are reported in Table 4.

The top panel of the table (Panel A) shows the average of these characteristics among connected and unconnected banks, their difference, and whether these differences are statistically significant according to a simple test of means. Clearly, connected banks are larger, more profitable, and less leveraged than unconnected ones. They also have a smaller share of gross loans corresponding to net charge-offs, suggesting that they take relatively less risk than unconnected ones, although when comparing them worldwide the difference is not significant. The sign and significance of these differences are maintained when looking only at fully private banks (Panel A.2).

The regressions in panel B further test whether these correlations are still present when comparing connected and unconnected banks within a country. To this end, we estimate the parameters of the following parsimonious specification

$$Y_{i,c} = \alpha + \beta \times CONNECTED_{i,c} + \gamma SIZE_{i,c} + \theta_c + \varepsilon_{i,c} \tag{1}$$

where $Y_{i,c}$ corresponds to the financial characteristics of bank i in country c, which include measures of size, profitability, riskiness, liquidity, and leverage; $CONNECTED_{i,c}$ is a dummy variable that takes the value one if at least one of the bank's directors has been a politician or bank supervisor, and zero otherwise, and $SIZE_{i,c}$ controls for (log) total assets (except when the left-hand-side variable itself is a measure of size). Finally, θ_c is a country fixed-effect that controls for cross-country differences in bank characteristics, and $\varepsilon_{i,c}$ is a residual term. Since these regressions exploit only within-country differences between connected and unconnected banks, and bank-level data are notoriously noisy, we measure all variables in logarithms to reduce the influence of outliers (variables corresponding to ratios that can plausibly take negative values are expressed as the logarithm of one plus the variable).[12] As in Panel A, we estimate the parameters of the benchmark model separately for all the banks (Panel B.1) and banks that have no public ownership (Panel B.2).

The coefficients confirm that connected banks tend to be the largest in a country (Column (1)). Assets of connected banks are about 34 percent larger. Similar results are obtained for other measures of size, such as loans and country ranking (not reported). Connected banks also tend to be more profitable and typically have a return on average

[12] This is not a major issue in the overall comparisons in Panel A which compute the average of each characteristic across all connected and all unconnected banks. In contrast, these regressions compare connected and unconnected banks within a country.

assets that is between 0.6 and 0.8 percent higher than the average bank (Column (2)). Regarding balance-sheet structure, leverage is significantly lower among connected banks (Column (3)). The ratio of equity to total assets is 2 percent higher in connected banks than in the average bank, and in the sample of fully privately owned banks this difference increases to 3 percent. Connected banks also seem to take on less risk in their operations since they tend to have a lower proportion of write-offs and impaired loans relative to gross loans and reserves (NCO/Average Gross Loans, Column (4)).

Overall, the results show that, across and within countries, connected banks are larger, more profitable, less leveraged, and less risky than unconnected ones, regardless of whether the government has some participation in their ownership.[13] Furthermore, we also built an intensive measure of a bank's political connection corresponding to the share of its directors that are former politicians (instead of the dummy variable described above) and re-estimated equation (1) using this measure. Interestingly, while the results are similar to those reported in panel B, they are weaker in statistical and economic terms (not reported). Thus, desirable bank characteristics are more strongly correlated with whether a bank has a former politician on its board than with the number of former politicians it has. It does not seem to be the case that politicians cluster in desirable banks.

3.2 Country Characteristics

As discussed in section 2, a simple look at the data seemed to suggest that banks were less politically connected in richer, more financially developed countries. The results in this section systematically test whether the degree of connectedness of banks is robustly

[13] These findings are robust to controlling for possible sample selection issues in the set of banks where there is director information using the standard Heckman (1979) two-step estimator (not reported).

correlated with various important country characteristics and whether these correlations survive when controlling for several straightforward omitted variables in a multivariate setting. To this end we relate country characteristics such as the level of development, quality of institutions, the extent of pro-banker regulation, and the development of the banking sector, to each of the five measures of connectedness by estimating the parameters of the following specification:

$$Y_c = \alpha + \beta \times CONNECTEDNESS_c + \gamma' X_c + \varepsilon_c \tag{2}$$

$Y_c = \alpha + \beta \times CONNECTEDNESS_c + \gamma' X_c + \varepsilon_c$ where Y is a measure of any of the country characteristics described above, and $CONNECTEDNESS$ is any of the five measures of connectedness discussed in section 2: the fraction of connected banks (*FRACBANKS*), the share of assets of connected banks (*SHAREASSETS*), the fraction of connected bankers (*FRACBANKERS*), the (log) actual to expected number of matches of bankers-politicians (*PREVALENCE*), and the maximum share of the population from where bankers and politicians would have to be selected so that the null of random selection cannot be rejected at a 5 percent level of significance (*MAXSHARE*). The variables in X control for other country characteristics that may be simultaneously related to both Y and $CONNECTEDNESS$.

3.2.1 Economic Development

The results, reported in Table 5, show a strong negative correlation between the degree of connectedness and GDP per-capita, both when considering all banks (Panel A) and only those that are fully private (Panel B). The correlation is particularly strong when no additional controls are included (columns (1) to (3)), but it survives controlling for log population and by the fraction of the population with tertiary education (columns (4) to

(6)), especially when focusing on fully private banks (Panel B). The latest control is especially important because it is a standard measure of a country's stock of human capital (which most theories relate to a country's per-capita GDP) and also may proxy for the size of the elite where politicians and bankers are selected (see section 2 above). The results are statistically stronger for the more elaborate measures of connectedness: *PREVALENCE* and *MAXSHARE*, which suggests that these measures have additional economic content with respect to the simpler ones. Nonetheless, results are qualitatively similar, whatever the measure. Furthermore, Figure 1 shows that the negative correlation between connectedness and development is not driven by a few outliers but is a robust pattern of the data.

The relation between connectedness and GDP per capita is economically large. For instance, the difference in (log) GDP per capita between Morocco and France is commensurate with their difference in *PREVALENCE*. Although lacking a good instrument one cannot attribute causality to this strong cross-country correlation. It is clear that the degree of connectedness is not neutral, but rather is associated to a country's overall level of development. The regressions below will show that connectedness is also associated with other country characteristics that have been causally related to level of development, even after controlling for the direct link between development and connectedness documented here.

3.2.2 Institutions

By correlating the different measures of connectedness with cross-country measures of institutional quality (from Kaufmann et al. (2004)), we find that connectedness is significantly higher in countries where institutions that that prevent corruption and limit the powers of the government vis-à-vis the citizens are less developed (blocks I and II of Table 6, respectively). The relation is present when considering the connectedness of all banks (Panel A) or only private ones (Panel B). Furthermore, in each of these cases, and regardless the measure, the relation between connectedness and institutional quality is significantly negative even after controlling for GDP per capita and population size (columns (4) to (6) and (10) to (12)). This is reassuring because of the widely documented link between institutions and development. Furthermore, it is even clearer than in the case of overall development that a few outliers do not drive the relation (see both panels of Figure 2). The magnitude of the estimated coefficient is also economically relevant: a one standard deviation increase in *PREVALENCE* (equivalent to the difference between Italy and Burkina-Faso) is associated with a decline of 0.4 in the control of corruption, corresponding to 25 percent of their difference in the control of corruption. Also, as shown in Figure 2, the difference in the control of corruption between Angola and Spain is commensurate with their difference in *PREVALENCE*.

3.2.3 Regulation

The results above show that prevalence is systematically related to bad institutions and underdevelopment. Here we test for a systematic relation between connectedness and banking sector regulation. As discussed in the introduction, political economy literature typically associates the links between regulators and regulated firms with private interest stories that critically depend on both parties having something to gain from colluding. Regulation that favors incumbents in the banking system is the obvious service that politicians can exchange for a seat on a bank's board.

Barth et al. (2003) provide data on the way countries regulate their financial systems using five dimensions: restrictions to bank activities, entry regulation, supervisory powers, private monitoring and self-regulation, and capital requirements. They assign an index to each of these broad ways of regulating that corresponds to the first principal component of the answers to surveys conducted by regulators in each country using each of these dimensions.

We use these indexes to construct an overall measure of the pro-banker characteristic of regulation across countries. This addresses the issue that some of the dimensions can be more easily thought as pro- or anti-banking incumbents, while for others the distinction is less clear. For instance, it is unclear whether the extent of restrictions on bank activities is pro or against incumbents. On the one hand, it constrains the ability of banking incumbents to expand into new lines of business. On the other hand, it also constrains other institutions from expanding into the banking business. Similarly, giving responsibility for the supervision and monitoring functions to the public or private sector may be pro or against bankers depending on what type of monitors may be more easily captured.

Instead of taking an arbitrary stance on whether each of these five dimensions is pro or against banking incumbents, we use cross-country data on the degree of rents in a country's banking sector (measured as the average net interest margin, also from Barth et al. (2003)) and built a de-facto index by running a regression between these rents and the five individual indices. We follow Burnside and Dollar (2000) and use the coefficients of this regression to weight the degree of pro or against bank incumbents of each of the individual indexes. The idea behind this procedure is to let the data speak: if a given dimension of regulation is more pro banker, an increase in its index should be associated with higher rents (and vice-versa). The regression yields the following result

$$\begin{array}{lllllllll} NIM & = & .30 \times ENT & -.32 \times CAP & +.51 \times ACT & -1.0 \times PRIV & -.05 \times OSP & R^2 = 0.28 \\ & & (.20) & (.31) & (.33) & (.38) & (.24) & \end{array}$$

where NIM is a country's banking sector average net interest margin, and ENT, CAP, ACT, PRIV, and OSP are the five principal component indexes of entry restrictions, capital requirements, activities restrictions, private monitoring, and overall supervisory power, described above (all standardized to have zero mean and unit variance so the magnitude of the coefficients reveal the relative importance of each dimension). According to the regression, average net interest margins are positively correlated to restrictions on entry and activity, and negatively correlated to capital requirements, the extent of private monitoring, and the power of the supervisor. In terms of magnitude and significance, the extent of private monitoring has the largest correlation with margins, followed by restrictions on activities, capital requirements, and entry restrictions. Surprisingly, the index of supervisory power has a negligible correlation with margins, both in terms of magnitude and significance.

In addition to this index, we use the Kaufman et al. (2004) index of regulatory quality, which measures the incidence of market-unfriendly policies such as price controls or inadequate bank supervision. We also checked the correlation between connectedness and each of the five individual dimensions of regulation (see Table A1 in the Appendix).

Table 7 presents the relation between the different measures of connectedness, our index of pro-banker regulation (columns (1) to (6)), and the index of overall regulatory quality (columns (7) to (12)). As in the previous tables, Panel A shows the results with the connectedness of all banks and Panel B with the connectedness of private banks only. Also, the first half of each block summarizes the unconditional regressions, and the second half the regression coefficients obtained after controlling for log real GDP per capita and log population. In each of the blocks and panels, with a few exceptions, there is a positive relation between connectedness, however measured, and the index of pro-banker regulation. There is also a strong negative correlation with the index of regulatory quality (the correlations with *MAXSHARE* have the opposite sign, as expected). The results are especially strong when connectedness is measured among private banks only, demonstrating again that politicians sitting in public banks do not drive the findings. Again, the economic magnitude of the effect is large: moving from the 10th to the 90th percentile of *PREVALENCE* is associated with a one standard deviation increase in the index of pro-bank regulation, an increase roughly commensurate with the difference between the index in Lithuania and Spain. Similarly, the same increase in *PREVALENCE* is associated with a more than one standard deviation decline in the index of regulatory quality, commensurate with the difference between Egypt and Japan.

Figure 3 shows that a few outliers are not driving the correlations with the regulatory index, although the relation is clearly not as strong as with the previous country-characteristics. This is partly due to the smaller sample available for regulatory variables, but is also most certainly due to the difficulty of aggregating the various indicators into a measure of pro-banker regulation. To check the robustness of the results, we also built the pro-banker index using the simpler indexes reported by Barth et al. (2003) for each dimension of regulation instead of the principal component indexes. The results are qualitatively similar, but significance is lost in several cases. We finally checked the results using data from Barth et al. (2006) to construct an index based on the 2001 and 2003 surveys that increases the cross-sectional dimension of the data. In this case we do not have the principal component indexes, but only the simple versions of the indexes. As before, the results are qualitatively similar but the significance is lost except for the unconditional regressions and the conditional regressions using *MAXSHARE* and *PREVALENCE*.[14]

3.2.4 Financial Development

The evidence above suggests that the connectedness of bankers and politicians is significantly and robustly correlated with the way the banking sector operates and is regulated. Insofar as these differences have no impact on the efficiency of the financial system, the issue would be of little public interest, and it would just be a matter of different preferences across countries. The case is different if the connection between bankers and politicians is correlated with the ability of the system to efficiently allocate funds. Here we test whether connectedness is related to the degree of development of the banking system. The specification is the same as above, with Y being now each country's log ratio of bank credit to the private sector to GDP. Also as before, we present univariate and multivariate regressions that control for per capita GDP and population, and by other standard determinants of financial development.

The results are presented in Table 8, which follows the same format as the previous tables. The coefficient of all measures of connectedness is negative (except, of course, for *MAXSHARE*, which is an inverse measure of connectedness) and almost always significant in univariate and multivariate regressions, and regardless of whether connectedness is

[14] Results are available upon request.

measured over all banks or private banks only. In fact, as in previous cases, the results are stronger when connectedness is measured over private banks only. Thus, connectedness is indeed associated with a lower degree of banking sector development. The relation is large in economic terms: moving from the 10th to the 90th percentile of prevalence is associated with a ratio of private credit to GDP 45 percentage points higher, an increase roughly commensurate with the difference between Brazil and Belgium. Figure 4 illustrates this relation and shows that a few outliers do not drive it.

The negative correlation between the measures of connectedness and financial development is not driven by the traditional measures used to explain financial development across countries such as the degree of protection granted to creditors, the quality of accounting practices, and investment opportunities measured with the decade's effective GDP growth rate (Block III).[15] Both creditor rights and accounting quality enter positively as expected (although not significantly).

3.3 Robustness

The previous results show that the connectedness of banks, however measured, is negatively correlated with economic development, the existence of less corrupt and more accountable institutions, and the development of the banking sector, and is positively correlated with the extent to which the regulation favors bank incumbents. As mentioned above, we do not have a good instrument for connectedness to make causal inferences, but we have checked that these reduced form relations are not trivially driven by some obvious third variables that may be simultaneously related to the connectedness measures and any

[15] When including the decadal growth rate of per-capita GDP we drop the log real per-capita GDP.

of the country characteristics we have analyzed, such as a country's overall development or size. The regressions reported in this section address some further robustness concerns.

As discussed in section 2, although the measure of *PREVALENCE* does not take a stance on what is the share of the total population where bankers and politicians are selected, it assumes that the share is constant across countries. This is a reasonable assumption, but it may also be the case that the elite are not proportional to the population but a fixed number of individuals. If this is the case, *PREVALENCE*, which is one of the most robust measures, could just be capturing the relation between cross-country differences in the size of the elite as a fraction of the population over several country characteristics. This is partially controlled by including the log population in the specifications, which does not eliminate the findings of unconditional regressions. Nevertheless, it is also possible that the size of the elite is not fixed but proportional to the fraction of the highly educated population. To check for this possibility, we added the log fraction of the population with tertiary education to each of our specifications.[16] The regressions summarized in Block I of Table 9 show that differences in the size of the elite as a fraction of the population do not drive the documented negative correlation of connectedness with institutions, financial development, and the positive correlation with pro-banker regulations. Although this is mainly a concern for the measure of prevalence, we also report the results using the share of assets of connected banks to show that

[16] As shown in section 2, *PREVALENCE* computed using the total population equals the *PREVALENCE* considering only the elite plus the log of the fraction of the population that the elite represent. Assuming that this log fraction is proportional to the share of the population with tertiary education, the true prevalence would be the prevalence with all population less the fraction of the population with tertiary education.

controlling for this additional variable does not change these results either. Results for other variables are similar and available upon request.

Another concern with the connected measures reported above is that, empirically, they are negatively correlated with the number of banks reporting to Bankscope. This number is an endogenous variable that may clearly be correlated with the development of the banking sector, but since the measures of connectedness may be mechanically related to this number by construction, the documented correlations could be spurious. To check for this possibility we re-computed the measures using only the 10 largest banks in a country (by total assets at the end of 2004). For countries with less than 10 reporting banks we kept the whole set of banks. This reduced in two orders of magnitude the cross-country variance of the number of banks used in the calculations of the measures of connectedness, and the resulting measures are not significantly correlated with the number of banks. Nevertheless, the results in Block II (columns (4) to (6)) show that the results obtained with these measures are quantitatively and qualitatively similar to those obtained with all banks. The significantly larger number of banks reporting in richer and more developed countries is not behind the documented correlations.

We restricted the analysis to those countries with at least one match, but it may still be argued that we are not being restrictive enough and that we may be over-interpreting the finding of one or two matches. To check this we restricted the analysis to countries with at least two matches (i.e. two matches is the baseline). The results, reported in columns (7) to (9) again follow the same pattern as before, which indicates that countries with more than one match drive the correlations. Further restricting the sample to include only countries with at least three matches yields qualitatively similar results, but some of the coefficients are not significant at a 10 percent level because of the reduction in the sample size (31 countries, not reported).

The regressions reported in blocks IV and V address a check for the influence of a few outliers on the results. Block IV takes an agnostic approach and simply uses a robust regression technique to reduce the influence of outliers.[17] As before, there is no important change in the results. The results reported in Block V control for the potential influence of former (and current) socialist countries. Although the different figures described above and the regressions in Block IV show that a few countries do not drive the correlations, it may be noticed that the group of former socialist countries tends to be at the extreme of the distribution of connectedness and, therefore, the correlations reported may just come from the difference between former socialist countries and the rest of the sample. To check for this without reducing the sample unnecessarily we added a dummy variable that takes the value 1 for countries with former and current socialist countries and zero elsewhere. Reassuringly, the sign and magnitude of all the reduced-form coefficients remains unaffected (the dummy for former socialist countries is typically significant and in the expected direction, e.g. lower financial development).

Finally, as discussed in section 2, we conducted all of the analysis dropping the countries with zero matches because we do not fully trust the quality of the information in many of these countries, and because finding a zero match provides very little information on the process driving the selection of bankers and politicians. Countries with zero matches are very heterogeneous and we do not have a good way of separating the zeroes resulting from data quality from the true ones. While we believe this is the right way of proceeding,

[17] Stata command rreg.

it would be troubling if the pattern of results qualitatively changed or even reversed when considering the zeroes. The regressions in Table 10 show that this is not the case. As a mild way of cleaning zeroes due to poor data from true ones, we included only the countries with zero matches and more than 2 banks. The unconditional regressions always result in significant coefficients of the same sign as those reported above, and the regressions controlling for log real GDP per capita and log population also show a similar pattern to that previously reported. The only major difference is that the coefficients for the degree of pro-banker regulation are no longer statistically significant for any measure. This is not fully surprising, considering that the relation with regulation is the most difficult to pin down and was the weakest among those reported in the baseline results. Including many diverse countries with the same value of connectedness (zero) clearly reduces the variance of the explanatory power and its ability to account for this country characteristic.

4 Concluding Remarks

This paper builds an extensive dataset to measure the extent to which banks are politically connected across countries. The measure is based on the fact that some high-rank politicians end up on the board of banks. Of course, this represents just one way in which relationships between bankers and politicians can be established. It may not even be the most important one, but is very likely to be correlated with other forms.

We compare politically connected banks to the ones that are not, and correlate several country-level measures of connectedness with a number of variables capturing the quality of institutions, bank regulation, and financial development.

Although we do not present a formal test and causality is not established, we believe that a private interest story better connects the different pieces of reduced-form evidence provided in the paper than a public interest explanation. First, connected banks do better than unconnected ones: they are larger and more profitable and this is not related to higher risk-taking. These results are quite consistent with previous ones that political economy literature has documented for non-bank firms. In this sense banks would not be any different. Although this could be partly consistent with a public interest view – for instance, politicians being attracted to good banks-, we do not find that the number of politicians on a bank's board is more correlated with desirable bank outcomes than the simple fact of having a politician on board. Second, the phenomenon is more prevalent where deals between bankers and politicians are likely to be less costly and more influential: connectedness correlates positively with corruption but negatively with government accountability. Third, these politician-banker relationships are associated with poorer outcomes for society in the form of lower overall and financial development. A likely mechanism for this result is regulatory capture which is supported by the fact that bank regulation seems to be more pro-banker and of lower quality where these links are more important.

If the direction of causality actually goes in the way we conjecture, a permissive institutional context allows banks to achieve better regulatory treatment by connecting themselves to politicians. These links allow banks to achieve higher profits without taking more risk or increasing efficiency. In the process, high social costs are incurred that work via hampering the development of the financial sector. All this would ultimately reduce access to financing to many firms in the economy. Imposing restrictions on this type of coalescence could therefore limit the ability of incumbent financiers to tilt regulations in their favor and restrict financial development. However, it is important not to take direct, partial equilibrium policy conclusions from this exercise. If this particular avenue is absent, the pressure of incumbents on regulators may simply manifest itself in a different way, such as outright bribes, that could be even more detrimental to the overall stability of the institutional framework.

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Appendix

A.1 Distribution of the number of matches under random draws.

Consider a population where there are N_P politicians and N_B bankers. The intersection of the two groups consists of N_{PB} banker-politicians. From the population of bankers and politicians we take two samples consecutively and with replacement at the sample level,[18] the first consisting of $n_B \leq N_B$ bankers and the second of $n_P \leq N_P$ politicians and match them. Let X be a random variable that counts the number of matches. This random variable will be distributed according to:

$$P(X = k) = \frac{\binom{N_{PB}}{k} \sum_{i=0}^{N_{PB}-k} \binom{N_{PB} - k}{i} \binom{N_B - N_{PB}}{n_B - k - i} \binom{N_P - k - i}{n_P - k}}{\binom{N_P}{n_P} \binom{N_B}{n_B}}$$

The denominator corresponds to the number of ways in which two samples of sizes n_P and n_B can be chosen from populations of sizes N_P and N_B respectively. The numerator has various components. The first term corresponds to the number of ways in which the k common elements can be chosen among the N_{PB} members of the intersection. The summation that follows counts the number of ways in which the remaining n_P - k and n_B - k terms can be chosen. The first term counts the manners in which i of those elements can be picked among the rest of the intersection. If i are chosen in this way, they can only be in one of the samples. For instance, assume that among the remaining $n_B - k$ components of n_B one also belongs to. N_{PB}. This one term

[18] This means that all individuals from the first sample are replaced in the population before taking the second sample, so that an individual from the intersection of the two samples can be drawn twice.

can be chosen in $\begin{pmatrix} N_{PB} - k \\ 1 \end{pmatrix}$ manners and the remaining n_B - k that are only bankers can be chosen in $\begin{pmatrix} N_B - N_{PB} \\ n_B - k - 1 \end{pmatrix}$ ways. Given that one of the terms in n_B - k belongs to the intersection, it cannot be selected in the remaining n_P - k draws from N_P, so we can choose those terms in $\begin{pmatrix} N_P - k - 1 \\ n_P - k \end{pmatrix}$ only.

We use this distribution to estimate the expected number of matches in a country considering the actual size of the samples of bankers and politicians available from the data, which pin down n_P and n_B, and assuming that both are drawn from a common pool corresponding to a country's total population. In the notation above, the assumption of a common pool corresponds to assuming that $N_P = N_B = N_{PB}$. In this case the probability of finding k matches simplifies to

$$P(X = k) = \frac{\begin{pmatrix} N \\ k \end{pmatrix} \begin{pmatrix} N - k \\ n_p - k \end{pmatrix} \begin{pmatrix} N - n_p \\ n_b - k \end{pmatrix}}{\begin{pmatrix} N \\ n_P \end{pmatrix} \begin{pmatrix} N \\ n_B \end{pmatrix}}$$

Table 1. Summary Statistics: Matches and Coverage by Country

Columns (1) and (2) show the number of banks with director data in Bankscope 2005 and the total number of individuals acting as directors in these banks (without duplications). Column (3) presents the number of persons that occupied a position as cabinet member, central bank director, or bank supervisor between 1996 and 2004. Column (4) summarizes the number of cases where the same individual appears among the list of bankers and the list of politicians (cases of bankers/politicians). Column (5) shows the ratio of the number of banks with director data in Bankscope in 2001 to the total number of commercial banks operating in the country that year according to Barth et al. (2003). Column (6) shows the fraction of the total assets of banks in Bankscope represented by those banks that report director information in 2004.

Country	Banks with director data in Bankscope (2005) (1)	Total number of directors (2)	Number of politicians (1996-2004) (3)	Matches (politician-bankers) (4)	(# Banks in bankscope)/ (# Commercial banks) (5)	(Assets in banks with director data)/ (All Bankscope (6)
Albania	2	14	111	0	0.64	0.82
Algeria	5	76	88	0	0.58	0.43
Angola	3	25	57	2	.	0.26
Argentina	81	358	83	1	1.16	0.56
Armenia	6	31	80	1	0.41	0.89
Aruba	2	23	35	0	0.80	0.41
Australia	45	408	56	1	1.25	0.96
Austria	61	940	50	3	0.23	0.8
Azerbaijan	5	9	51	0	0.25	0.04
Bahamas	4	36	39	0	.	0.13
Bahrain	11	157	43	0	1.10	0.96
Bangladesh	31	594	77	12	.	0.67
Barbados	2	37	31	0	.	0.9
Belarus	11	115	81	5	0.67	0.6
Belgium	53	619	50	5	0.88	0.97
Benin	4	51	69	0	1.00	0.81
Bermuda	3	66	53	0	.	0.68
Bolivia	4	90	139	0	1.00	0.61
Botswana	6	78	39	0	1.80	0.97
Brazil	43	506	110	4	0.98	0.66
Brunei Darussalam	2	14	24	0	.	0.6
Bulgaria	9	55	24	0	0.74	0.84
Burkina Faso	4	59	65	1	0.86	0.89
Burundi	6	73	101	6	0.71	0.95
Cambodia	3	32	50	0	0.17	0.37
Cameroon	2	27	78	1	.	0.26
Canada	25	536	92	2	1.06	0.91
Cape Verde	1	5	56	0	.	0.9
Cayman Islands	1	8	28	0	.	0.02
Chile	13	202	69	3	1.07	0.83
China	34	495	47	2	.	0.99
Colombia	10	153	103	2	1.34	0.29
Costa Rica	1	3	80	0	2.62	0.31
Croatia	19	177	98	5	0.91	0.7
Cuba	2	23	46	0	.	0.56
Cyprus	14	131	55	1	1.58	0.88
Czech Republic	28	352	85	0	0.89	0.98
Côte D'Ivoire	5	56	110	0	0.80	0.52
Denmark	67	685	60	2	0.60	0.97
Djibouti	1	6	41	0	.	.
Dominican Republic	7	69	82	1	.	0.43
Ecuador	1	3	170	0	1.57	0.06
Egypt	26	245	55	2	0.77	0.9
El Salvador	4	64	56	1	1.23	0.83
Estonia	5	49	77	0	1.00	0.67
Ethiopia	5	57	40	0	.	0.5
Finland	17	222	43	1	1.88	0.99
France	233	3484	76	1	1.11	0.69

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Country	Banks with director data in Bankscope (2005)	Total number of directors	Number of politicians (1996-2004)	Matches (politician-bankers)	(# Banks in bankscope)/ (# Commercial banks)	(Assets in banks with director data)/ (All Bankscope
	(1)	(2)	(3)	(4)	(5)	(6)
Gabon	3	42	51	4	.	0.63
Gambia	2	18	49	0	0.33	1
Georgia	1	25	87	2	.	0.8
Germany	532	9723	60	5	0.72	0.75
Ghana	18	166	100	0	1.24	0.98
Greece	20	211	74	0	0.43	0.71
Guatemala	2	21	89	0	1.22	0.13
Guyana	3	43	38	0	0.57	0.39
Haiti	2	35	97	0	.	1
Honduras	2	31	88	0	1.05	0.53
Hong Kong	64	745	49	5	0.77	0.91
Hungary	14	173	84	3	1.21	0.77
Iceland	13	90	25	2	3.00	0.97
India	75	1323	85	3	0.94	0.91
Indonesia	39	466	105	1	.	0.99
Iran, Islamic Republic Of	10	71	56	0	.	0.44
Ireland	54	447	51	0	1.11	0.99
Israel	12	173	100	1	0.73	0.99
Italy	315	4968	90	5	0.94	0.93
Jamaica	13	152	27	0	.	0.91
Japan	166	2725	122	1	3.61	0.73
Jordan	9	88	143	2	0.90	0.93
Kazakhstan	9	22	73	0	0.64	0.43
Kenya	30	276	93	0	0.85	0.96
Korea, Republic Of	33	458	143	5	1.60	0.99
Kuwait	11	150	67	3	2.71	0.82
Kyrgyzstan	1	2	75	0	0.30	0.55
Latvia	19	176	84	3	0.96	0.97
Lebanon	12	223	74	2	0.64	0.48
Lesotho	2	18	51	0	1.33	0.88
Libyan Arab Jamahiriya	2	30	75	0	.	0.63
Liechtenstein	9	146	4	0	0.88	0.73
Lithuania	7	36	93	1	0.77	0.54
Luxembourg	75	861	29	2	0.60	0.89
Macao	8	104	24	0	.	0.97
Macedonia, The Former Yugosla	7	68	113	1	0.71	0.92
Madagascar	3	32	94	2	1.17	0.88
Malawi	7	65	76	0	.	0.98
Malaysia	65	609	41	0	2.52	0.95
Mali	3	43	82	0	0.75	0.68
Malta	4	41	40	2	0.53	0.86
Mauritania	4	41	103	1	.	0.77
Mauritius	10	88	46	0	1.00	0.91
Mexico	25	347	63	6	1.63	0.82
Moldova, Republic Of	6	56	96	2	.	0.39
Mongolia	4	28	80	0	.	0.27
Morocco	9	131	73	4	0.79	0.76
Mozambique	5	46	59	0	.	0.97
Myanmar	1	16	58	3	.	.
Namibia	5	70	50	0	1.80	0.99
Nepal	11	104	109	1	.	0.96
Netherlands	61	601	50	3	0.95	0.93
New Zealand	8	66	70	0	0.59	0.78
Niger	2	13	106	0	0.43	0.52

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Country	Banks with director data in Bankscope (2005)	Total number of directors	Number of politicians (1996-2004)	Matches (politician-bankers)	(# Banks in bankscope)/ (# Commercial banks)	(Assets in banks with director data)/ (All Bankscope
	(1)	(2)	(3)	(4)	(5)	(6)
Nigeria	27	401	128	2	0.79	0.71
Norway	38	341	80	1	4.13	0.94
Oman	4	60	53	1	0.87	0.61
Pakistan	28	340	65	1	0.90	0.94
Panama	5	59	64	0	0.99	0.1
Papua New Guinea	2	23	91	0	0.60	1
Paraguay	7	64	98	0	1.05	0.57
Peru	8	172	131	3	1.27	0.48
Philippines	11	255	101	4	0.81	0.61
Poland	34	404	100	1	0.64	0.97
Portugal	27	365	95	1	0.72	0.94
Qatar	7	87	43	4	0.60	0.88
Romania	17	149	136	3	0.68	0.82
Russian Federation	83	805	108	8	0.12	0.86
Rwanda	4	42	71	2	0.83	0.29
Samoa	1	4	49	0	1.00	0.36
Saudi Arabia	13	211	52	0	1.55	0.57
Senegal	8	99	79	0	0.73	0.94
Serbia and Montenegro	10	135	112	2	0.59	0.65
Seychelles	2	7	21	0	0.33	0.84
Sierra Leone	3	27	132	2	.	0.92
Singapore	32	337	33	1	0.36	0.98
Slovakia	18	192	75	0	1.16	0.79
Slovenia	13	140	77	0	0.90	0.95
South Africa	47	591	52	3	1.05	0.99
Spain	86	1836	76	1	0.60	0.93
Sri Lanka	8	85	61	0	0.52	0.56
Sudan	10	144	72	2	0.60	0.84
Suriname	2	14	59	0	0.25	1
Swaziland	3	25	50	0	1.25	0.77
Sweden	36	436	48	0	5.00	0.83
Switzerland	194	2917	21	1	1.07	0.91
Syrian Arab Republic	1	6	93	0	.	1
Taiwan, Province Of China	35	793	10	3	1.80	0.75
Tanzania, United Republic Of	12	104	40	0	.	0.93
Thailand	18	344	104	2	1.29	0.75
Togo	3	58	74	0	0.57	0.88
Trinidad And Tobago	4	87	58	0	2.00	0.77
Tunisia	11	131	72	4	2.14	0.61
Turkey	37	546	163	3	0.83	0.86
Uganda	14	94	60	1	.	0.97
Ukraine	9	53	103	0	0.26	0.06
United Arab Emirates	19	229	40	7	0.51	0.97
United Kingdom	275	2814	63	3	0.97	0.97
United States	546	9145	86	7	0.17	0.6
Uruguay	14	213	69	0	2.27	0.29
Uzbekistan	5	38	77	2	.	0.37
Venezuela	6	157	105	0	2.95	0.65
Viet Nam	10	107	52	0	.	0.65
Yemen	6	24	73	1	.	0.88
Zambia	11	79	78	2	.	0.95
Zimbabwe	16	159	55	0	2.00	0.81
Total	28.16	416.68	72.24	1.42	1.05	0.72

Table 2. Measures of the Degree of Connectedness Across Countries

The various columns show different measures of the degree of connection between banks and politics across countries (connectedness). Panel A shows measures built considering all banks with data, and Panel B shows the same measures built considering only those banks with ownership data that were 100 percent private. In Panel A, Column (1) shows the fraction of banks with director data that had a former politician in their boards. Column (2) shows the fraction of the total assets of banks with director data in Bankscope that is represented by connected banks. Column (3) shows the fraction of bank directors that had a previous political position. Column (4) shows the (log) ratio of the actual to the expected number of matches, where the expected number is computed assuming no bias toward politicians in the selection of bankers, and assuming that both bankers and politicians are selected from the whole population of a country. Finally, Column (5) shows the largest fraction of a country's population from where politicians and bankers would have to be selected, so that the hypothesis that the selection of bankers is not biased toward politicians could not be rejected at the 5 percent level. Columns (6) to (10) in Panel B show the same information than columns (1) to (5) for the sample of fully private banks.

	All Banks					100% Private Banks				
Country	Fract. connected banks *FRACBANKS* (1)	Share of assets connected banks *SHAREASSETS* (2)	Fract. connected bankers *FRACBANKERS* (3)	log real to expected matches *PREVALENCE* (4)	Max. share of pop. for randomness (5)	Fract. connected banks *FRACBANKS* (6)	Share of assets connected banks *SHAREASSETS* (7)	Fract. connected bankers *FRACBANKERS* (8)	log real to expected matches *PREVALENCE* (9)	Max. share of pop. for randomness (10)
Albania	0	0	0	.	.	0	0	0	.	.
Algeria	0	0	0	.	.	0	0	0	.	.
Andorra	0	0	.	.	.	0	0	.	.	.
Angola	67	66	8	9.76	0.02	.	.	.	.	.
Antigua And Barbuda	0	0	.	.	.	0	0	.	.	.
Argentina	1	0	0	7.09	1.33	0	0	0	.	.
Armenia	17	11	3	7.15	1.47	20	11	4	7.36	1.17
Aruba	0	0	0	.	.	0	0	0	.	.
Australia	2	2	0	6.73	2.16	0	0	0	.	.
Austria	5	13	0	6.24	0.57	5	13	0	6.28	0.57
Azerbaijan	0	0	0	.	.	0	0	0	.	.
Bahamas	0	0	0	.	.	0	0	0	.	.
Bahrain	0	0	0	.	.	0	0	0	.	.
Bangladesh	35	23	2	10.44	0.00	35	11	2	10.27	0.01
Barbados	0	0	0	.	.	0	0	0	.	.
Belarus	45	84	4	8.59	0.04	38	62	4	8.52	0.04
Belgium	8	10	1	7.42	0.13	7	10	1	7.01	0.29
Benin	0	0	0	.	.	0	0	0	.	.
Bermuda	0	0	0	.	.	0	0	0	.	.
Bolivia	0	0	0	.	.	0	0	0	.	.
Botswana	0	0	0	.	.	0	0	0	.	.
Brazil	7	15	1	9.40	0.02	6	2	1	8.96	0.05
Brunei Darussalam	0	0	0	.	.	0	0	0	.	.
Bulgaria	0	0	0	.	.	0	0	0	.	.
Burkina Faso	25	16	2	7.98	0.64	50	16	5	8.97	0.21
Burundi	67	64	8	8.61	0.03	33	9	3	7.71	0.80
Cambodia	0	0	0	.	.	0	0	0	.	.
Cameroon	50	84	4	8.86	0.27	50	84	4	8.86	0.27
Canada	8	1	0	7.13	0.41	10	1	0	7.37	0.32
Cape Verde	0	0	0	.	.	0	0	0	.	.
Cayman Islands	0	0	0	.	.	0	0	0	.	.
Chile	23	30	1	8.09	0.09	25	30	2	8.11	0.09
China	6	16	0	11.58	0.00	0	0	0	.	.
Colombia	20	14	1	8.58	0.06	0	0	0	.	.
Costa Rica	0	0	0	.	.	.	.	.	.	.
Croatia	11	23	3	7.17	0.13	0	0	0	.	.
Cuba	0	0	0	.	.	0	0	0	.	.
Cyprus	7	3	1	4.65	11.57	8	3	1	4.87	10.00
Czech Republic	0	0	0	.	.	0	0	0	.	.
Côte D'Ivoire	0	0	0	.	.	0	0	0	.	.
Denmark	3	10	0	5.56	1.55	3	10	0	5.61	1.55
Djibouti	0	0	0	.	.	0	0	0	.	.
Dominican Republic	14	25	1	7.29	1.24	0	0	0	.	.
Ecuador	0	0	0	.	.	0	0	0	.	.
Egypt	8	6	1	9.15	0.05	8	2	1	9.36	0.14
El Salvador	25	37	2	7.45	1.09	0	0	0	.	.
Estonia	0	0	0	.	.	0	0	0	.	.
Ethiopia	0	0	0	.	.	0	0	0	.	.
Finland	6	.	0	6.29	3.34	8	.	1	6.45	2.51
France	1	4	0	5.40	8.30	1	4	0	5.45	7.61
Gabon	100	100	10	7.75	0.10	.	.	.	.	.
Gambia	0	0	0	.	.	0	0	0	.	.
Georgia	100	100	8	8.48	0.08	100	100	8	8.48	0.08
Germany	1	3	0	6.56	0.26	1	1	0	5.69	1.31
Ghana	0	0	0	.	.	0	0	0	.	.
Gibraltar	0	0	.	.	.	0	0	.	.	.
Greece	0	0	0	.	.	0	0	0	.	.
Grenada	0	0	.	.	.	0	0	.	.	.
Guatemala	0	0	0	.	.	0	0	0	.	.
Guyana	0	0	0	.	.	0	0	0	.	.
Haiti	0	0	0	.	.	0	0	0	.	.
Honduras	0	0	0	.	.	0	0	0	.	.

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Country	All Banks					100% Private Banks				
	Fract. connected banks	Share of assets connected banks	Fract. connected bankers	log real to expected matches	Max. share of pop. for randomness	Fract. connected banks	Share of assets connected banks	Fract. connected bankers	log real to expected matches	Max. share of pop. for randomness
	FRACBANKS	*SHAREASSETS*	*FRACBANKERS*	*PREVALENCE*		*FRACBANKS*	*SHAREASSETS*	*FRACBANKERS*	*PREVALENCE*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Hong Kong	11	16	1	6.81	0.12	10	14	1	6.87	0.12
Hungary	21	37	2	7.64	0.09	27	37	2	7.85	0.09
Iceland	15	60	2	5.52	1.63	14	37	2	5.31	9.21
India	4	22	0	10.20	0.01	4	1	0	10.29	0.02
Indonesia	3	0	0	8.34	0.31	3	0	0	8.58	0.31
Iran, Islamic Republic Of	0	0	0	.	.	0	0	0	.	.
Ireland	0	0	0	.	.	0	0	0	.	.
Israel	8	1	1	5.88	5.21	14	1	1	6.48	2.61
Italy	1	8	0	6.47	0.34	1	2	0	5.65	1.70
Jamaica	0	0	0	.	.	0	0	0	.	.
Japan	1	0	0	5.95	4.57	1	0	0	5.98	4.57
Jordan	22	5	2	6.64	0.64	22	5	2	6.64	0.64
Kazakhstan	0	0	0	.	.	0	0	0	.	.
Kenya	0	0	0	.	.	0	0	0	.	.
Korea, Republic Of	12	21	1	8.18	0.06	9	4	0	7.15	0.93
Kuwait	27	20	2	6.46	0.51	43	20	3	6.96	0.31
Kyrgyzstan	0	0	0	.	.	0	0	0	.	.
Latvia	11	24	2	6.19	0.60	7	20	1	6.05	1.21
Lebanon	17	23	1	6.25	1.00	17	23	1	6.25	1.00
Lesotho	0	0	0	.	.	0	0	0	.	.
Libyan Arab Jamahiriya	0	0	0	.	.	.	.	.	.	.
Liechtenstein	0	0	0	.	.	0	0	0	.	.
Lithuania	14	7	3	6.96	1.61	14	7	3	6.96	1.61
Luxembourg	3	11	0	3.54	14.88	1	4	0	2.91	.
Macao	0	0	0	.	.	0	0	0	.	.
Macedonia, The Former Yugosl	14	37	1	5.57	4.96	20	37	2	5.94	5.00
Madagascar	67	68	6	9.23	0.04	100	29	14	10.05	0.08
Malawi	0	0	0	.	.	0	0	0	.	.
Malaysia	0	0	0	.	.	0	0	0	.	.
Maldives	0	0	.	.	.	.	.	.	.	.
Mali	0	0	0	.	.	0	0	0	.	.
Malta	50	53	5	6.16	0.94	0	0	0	.	.
Mauritania	25	32	2	6.42	0.58	33	32	3	6.67	2.00
Mauritius	0	0	0	.	.	0	0	0	.	.
Mexico	4	3	2	10.19	0.01	0	0	0	.	.
Moldova, Republic Of	17	5	4	7.37	0.23	25	5	6	7.82	0.12
Monaco	0	0	.	.	.	0	0	.	.	.
Mongolia	0	0	0	.	.	0	0	0	.	.
Morocco	33	17	3	9.39	0.02	50	17	4	9.68	0.01
Mozambique	0	0	0	.	.	0	0	0	.	.
Myanmar	100	.	19	11.93	.	100	.	19	11.93	0.00
Namibia	0	0	0	.	.	0	0	0	.	.
Nepal	9	15	1	7.61	0.94	10	15	1	7.68	0.88
Netherlands	5	49	0	7.37	0.16	4	36	0	7.12	0.32
Netherlands Antilles	0	0	.	.	.	0	0	.	.	.
New Zealand	0	0	0	.	.	0	0	0	.	.
Niger	0	0	0	.	.	0	0	0	.	.
Nigeria	7	6	0	8.49	0.10	4	1	0	7.91	0.60
Norway	3	0	0	5.10	11.46	0	0	0	.	.
Oman	25	.	2	6.62	2.15	50	.	5	7.63	0.90
Pakistan	4	1	0	8.73	0.29	0	0	0	.	.
Panama	0	0	0	.	.	0	0	0	.	.
Papua New Guinea	0	0	0	.	.	0	0	0	.	.
Paraguay	0	0	0	.	.	0	0	0	.	.
Peru	38	29	2	8.14	0.09	29	12	1	7.88	0.13
Philippines	18	34	2	9.37	0.01	20	34	2	9.52	0.01
Poland	3	5	0	6.86	1.94	4	5	0	7.18	1.16
Portugal	4	1	0	5.68	6.13	4	1	0	5.75	5.00
Qatar	43	61	5	6.41	0.40	33	11	2	5.76	1.00
Romania	12	42	2	8.10	0.10	0	0	0	.	.
Russian Federation	7	58	1	9.51	0.01	6	7	1	9.17	0.02
Rwanda	50	52	5	8.51	0.10	50	52	4	8.37	0.40
Saint Kitts And Nevis	0	0	.	.	.	0	0	.	.	.
Saint Lucia	0	0	.	.	.	.	.	.	.	.
Samoa	0	0	0	.	.	0	0	0	.	.
San Marino	0	0	.	.	.	0	0	.	.	.
Saudi Arabia	0	0	0	.	.	0	0	0	.	.
Senegal	0	0	0	.	.	0	0	0	.	.
Serbia and Montenegro	20	.	1	7.19	.	22	.	2	7.22	0.30
Seychelles	0	0	0	.	.	0	0	0	.	.
Sierra Leone	33	12	7	7.94	0.18	50	12	11	8.34	0.11

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Country	All Banks: Fract. connected banks FRACBANKS (1)	Share of assets connected banks SHAREASSETS (2)	Fract. connected bankers FRACBANKERS (3)	log real to expected matches PREVALENCE (4)	Max. share of pop. for randomness (5)	100% Private Banks: Fract. connected banks FRACBANKS (6)	Share of assets connected banks SHAREASSETS (7)	Fract. connected bankers FRACBANKERS (8)	log real to expected matches PREVALENCE (9)	Max. share of pop. for randomness (10)
Singapore	3	.	0	5.88	4.93	3	.	0	5.93	4.93
Slovakia	0	0	0	.	.	0	0	0	.	.
Slovenia	0	0	0	.	.	0	0	0	.	.
South Africa	11	2	1	8.34	0.05	12	2	1	8.46	0.06
Spain	1	15	0	5.67	6.11	1	15	0	5.75	5.00
Sri Lanka	0	0	0	.	.	0	0	0	.	.
Sudan	20	23	1	8.70	0.05	25	23	2	8.87	0.05
Suriname	0	0	0	.	.	.	.	.	.	.
Swaziland	0	0	0	.	.	0	0	0	.	.
Sweden	0	0	0	.	.	0	0	0	.	.
Switzerland	1	0	0	4.77	12.11	1	0	0	4.96	10.00
Syrian Arab Republic	0	0	0	.	.	.	.	.	.	.
Taiwan, Province Of China	11	9	0	.	.	4	5	0	.	.
Tanzania, United Republic Of	0	0	0	.	.	0	0	0	.	.
Thailand	11	24	1	8.13	0.08	8	23	1	8.11	0.39
Togo	0	0	0	.	.	0	0	0	.	.
Trinidad And Tobago	0	0	0	.	.	0	0	0	.	.
Tunisia	27	44	3	8.30	0.04	0	0	0	.	.
Turkey	8	25	1	7.72	0.10	10	25	1	7.90	0.10
Uganda	7	27	1	8.31	0.36	7	27	1	8.31	0.40
Ukraine	0	0	0	.	.	0	0	0	.	.
United Arab Emirates	32	44	3	7.77	0.06	50	23	7	8.55	0.04
United Kingdom	1	0	0	6.90	0.28	2	0	0	6.98	0.30
United States	1	8	0	7.82	0.07	1	7	0	7.32	0.10
Uruguay	0	0	0	.	.	0	0	0	.	.
Uzbekistan	40	89	5	9.73	0.02	40	89	5	9.73	0.02
Venezuela	0	0	0	.	.	0	0	0	.	.
Viet Nam	0	0	0	.	.	0	0	0	.	.
Yemen	17	20	4	9.20	0.10	33	20	14	10.43	0.05
Zambia	18	17	3	8.06	0.15	22	17	3	8.24	0.10
Zimbabwe	0	0	0	.	.	0	0	0	.	.
Total	10	12	1	7.58	1.54	9	7	1	7.52	1.40

Table 3. Correlation among measures of connectedness

The table shows the pairwise correlations among the different measures of connectedness presented in Table 3 and their statistical significance. Correlations are computed including the countries with zero matches (for those measures that can take the value zero). *, **, and ***, denote statistical significance at the 10, 5, and 1 percent, respectively.

	All Banks					All 100% Private Banks				
Measures	Fract. connected banks *FRACBANK*	Share of assets connected banks *SHAREASSET*	Fract. connected bankers *FRACBANKERS*	log real to expected matches *PREVALENC*	Max. share of pop. for randomness *MAXSHARE*	Fract. connected banks *FRACBANK*	Share of assets connected banks *SHAREASSET*	Fract. connected bankers *FRACBANKER*	log real to expected matches *PREVALENC*	Max. share of pop. for randomness *MAXSHARE*
Fract. connected banks *FRACBANKS*	1									
Share of assets connected banks *SHAREASSETS*	0.88***	1								
Fract. connected bankers *FRACBANKERS*	0.92***	0.82***	1							
log real to expected matches *PREVALENCE*	0.40***	0.30***	0.43***	1						
Max. share of pop. for randomness *MAXSHARE*	-0.30***	-0.30***	-0.31***	-0.70***	1					
Fract. connected banks *FRACBANKS*	0.90***	0.71***	0.82***	0.38***	-0.26**	1				
Share of assets connected banks *SHAREASSETS*	0.72***	0.83***	0.63***	0.20	-0.20**	0.75***	1			
Fract. connected bankers *FRACBANKERS*	0.75***	0.54***	0.85***	0.38***	-0.22**	0.87***	0.55***	1		
log real to expected matches *PREVALENCE*	0.51***	0.34***	0.50***	0.96***	-0.68***	0.56***	0.30	0.57***	1	
Max. share of pop. for randomness *MAXSHARE*	-0.30**	-0.19**	-0.23**	-0.69***	0.90***	-0.32**	-0.17**	-0.25**	-0.66***	1.00***

Table 4. Differences between Connected and Unconnected Banks

Panel A compares the average of various bank-characteristics between connected and unconnected banks worldwide (those that have or do not have a politician in their board, respectively). Panel A.1 considers all banks with data, and Panel A.2 restricts the comparison to fully private banks. In each panel, the column labeled "Connected" shows the average of the characteristic listed in the row among connected banks, and "Unconnected" does the same for unconnected banks. The column labeled "Diff" shows the difference of that characteristic between connected and unconnected banks, as well as indicating the significance of the test of equality of means.

In Panel B, the dependent variable in each regression is reported at the top of each column. All dependent variables are in logs. Those corresponding to rations that can take negative values are measured as the log of one plus the corresponding ratio. Connected is a dummy variable that takes the value 1 if a bank has at least one former politician among its board members and 0 otherwise. All regressions included a country fixed effect, and all regressions, except the one reported in Column (1) also control for the (log) total assets. Robust standard errors in parentheses. * significant at 10%, ** 5%, *** 1%.

A. Worldwide Comparison of Average Bank Characteristics

(tests of equality of means)

A.1 All Banks

	Connected	Unconnected	Diff
Total Assets	9.72	8.60	1.12***
Return On Avg Assets (ROAA)	2.40	1.26	1.14***
Equity / Tot Assets	14.23	11.44	2.79***
NCO / Average Gross Loans	0.70	1.24	-0.54

A.2. Private Banks

	Connected	Unconnected	Diff
Total Assets	9.58	8.44	1.14***
Return On Avg Assets (ROAA)	2.46	1.19	1.27***
Equity / Tot Assets	15.20	11.17	4.02***
NCO / Average Gross Loans	0.66	1.11	-0.45

B. Within country comparison of bank characteristics

(regression analysis)

	Dependent Variable			
	Total Assets	Return On Avg Assets (ROAA)	Equity / Tot Assets	NCO / Average Gross Loans
	(1)	(2)	(3)	(4)
B.1 All Banks				
Connected	0.3358**	0.0062**	0.0225**	-0.0054**
	(0.1349)	(0.0025)	(0.0105)	(0.0023)
Obs	3312	3285	3311	1176
R2	0.635	0.150	0.329	0.294
B.2 Private Banks				
Connected	0.3131*	0.0079**	0.0284***	-0.0050*
	(0.1600)	(0.0031)	(0.0108)	(0.0026)
Obs	2845	2819	2845	1016
R2	0.611	0.145	0.324	0.239

Table 5: Connectedness and Development

The dependent variable is the log real GDP per capita (average 1995-2005 from Penn World Tables). Columns (1) to (3) show the estimated coefficients (with standard errors), the number of observations, and R2, respectively, of a series of separate regressions between the dependent variable and each of the five measures of connectedness listed in the "Measures" row: the fraction of banks that are connected (*FRACBANKS*), the fraction of total banking system assets owned by connected banks (*SHAREASSETS*), the fraction of bankers that have been politicians (*FRACBANKERS*), the (log) ratio of actual to expected number of matches between bankers and politicians (*PREVALENCE*), and the largest share of the population where bankers and politicians would have to be drawn, so that the null of random matching cannot be rejected at conventional levels (*MAXSHARE*). Columns (4) to (6) are analogous to (1) to (3), but the regressions reported in them include the log fraction of population with tertiary education and the log population. *, **, and *** denote statistical significance at the 10, 5, and 1 percent, respectively. Standard errors are robust to heteroskedasticity.

	log Real GDP per capita (PWT)					
	Controls: None			Controls: log population, log fraction of population with tertiary education		
	Coef/SE	N	R2	Coef/SE	N	R2
Measure	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: All Bankscope Banks						
FRACBANKS	-2.044***	79	0.136	-0.450	78	0.794
	(0.721)			(0.376)		
SHAREASSETS	-0.994**	76	0.047	0.146	75	0.788
	(0.479)			(0.250)		
FRACPOLITICIANS	-23.35***	79	0.192	-5.644	78	0.796
	(6.435)			(3.742)		
CONNECTEDNESS	-0.481***	79	0.383	-0.157**	78	0.805
	(0.0588)			(0.0600)		
MAXSHARE	0.163***	79	0.184	0.0319*	78	0.795
	(0.0214)			(0.0179)		
Panel B: 100% Private Banks						
FRACBANKS	-2.673***	64	0.215	-0.848*	63	0.814
	(0.678)			(0.433)		
SHAREASSETS	-1.425***	61	0.061	0.167	60	0.796
	(0.490)			(0.271)		
FRACPOLITICIANS	-20.72***	64	0.26	-8.004***	63	0.827
	(3.230)			(2.195)		
CONNECTEDNESS	-0.534***	64	0.436	-0.203***	63	0.829
	(0.0530)			(0.0717)		
MAXSHARE	0.197***	63	0.153	0.0562**	62	0.801
	(0.0340)			(0.0266)		

Table 6: Connectedness and Institutions

In columns (1) to (6) the dependent variable is Control of Corruption (average 1996-2002) and in columns (7) to (12) is Voice and Accountability (average 1996-2002). Columns (1) to (3) show the estimated coefficients (with standard errors), the number of observations, and R2, respectively, of a series of separate regressions between Control of Corruption and each of the five measures of connectedness listed in the "Measures" row: the fraction of banks that are connected (*FRACBANKS*), the fraction of total banking system assets owned by connected banks (*SHAREASSETS*), the fraction of bankers that have been politicians (*FRACBANKERS*), the (log) ratio of actual to expected number of matches between bankers and politicians (*PREVALENCE*), and the largest share of the population where bankers and politicians would have to be drawn, so that the null of random matching cannot be rejected at conventional levels (*MAXSHARE* Columns (4) to (6) are analogous to (1) to (3), but the regressions reported in them include the log of real GDP per capita (adjusted from purchasing power parity) and the log population. Columns (7) to (12) show the same information as (1) to (6) for Voice and Accountability as dependent variable.
In Panel A, the connectedness measures were built using data from all Bankscope banks, and in Panel B they were built using data from only 100 percet private banks. *, **, and *** denote statistical significance at the 10, 5, and 1 percent, respectively. Standard errors are robust to heteroskedasticity.

	Control of Corruption						**Voice and Accountability**					
	Controls: None			Controls: log real GDP, log population			Controls: None			Controls: log real GDP, log population		
	Coef/SE	N	R2	Coef/SE	N	R2	Coef/SE	N	R2	Coef/SE	N	R2
Measure	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: All Bankscope Banks												
FRACBANKS	-2.377***	79	0.21	-1.230***	79	0.72	-2.168***	79	0.23	-1.264***	79	0.58
	(0.435)			(0.371)			(0.556)			(0.440)		
SHAREASSETS	-1.575***	76	0.15	-1.012***	76	0.73	-1.539***	76	0.17	-1.076***	76	0.62
	(0.379)			(0.285)			(0.368)			(0.304)		
FRACPOLITICIANS	-25.19***	79	0.26	-13.30***	79	0.72	-22.42***	79	0.27	-13.19***	79	0.58
	(3.691)			(3.897)			(4.308)			(3.962)		
CONNECTEDNESS	-0.473***	79	0.43	-0.263***	79	0.73	-0.393***	79	0.38	-0.330***	79	0.63
	(0.0575)			(0.0636)			(0.0491)			(0.0718)		
MAXSHARE	0.174***	79	0.24	0.0613***	79	0.71	0.143***	79	0.21	0.0644***	79	0.56
	(0.0242)			(0.0201)			(0.0203)			(0.0222)		
Panel B: 100% Private Banks												
FRACBANKS	-2.317***	64	0.20	-0.573	64	0.73	-2.335***	64	0.28	-1.005	64	0.56
	(0.548)			(0.530)			(0.712)			(0.746)		
SHAREASSETS	-1.691***	61	0.12	-0.790***	61	0.74	-1.734***	61	0.15	-0.926**	61	0.59
	(0.404)			(0.283)			(0.458)			(0.394)		
FRACPOLITICIANS	-15.60***	64	0.19	-0.782	64	0.72	-14.51***	64	0.22	-2.784	64	0.54
	(3.943)			(3.699)			(4.448)			(4.916)		
CONNECTEDNESS	-0.474***	64	0.43	-0.146**	64	0.74	-0.367***	64	0.35	-0.250***	64	0.60
	(0.0543)			(0.0673)			(0.0555)			(0.0814)		
MAXSHARE	0.207***	63	0.21	0.0717**	63	0.73	0.171***	63	0.19	0.103***	63	0.58
	(0.0377)			(0.0290)			(0.0265)			(0.0313)		

Table 7: Connectedness and Regulation

In columns (1) to (6) the dependent variable is the Pro-Banker Regulation Index (from a regression of average net interest margins on the principal components of t regulatory dimensions described in Barth et al.(2003)), a higher value represents a more pro-banker regulation, and in columns (7) to (12) is the Kaufman and Kraay ind Regulatory Quality (average 1996-2002; a higher value denotes better quality). Columns (1) to (3) show the estimated coefficients (with standard errors), the numb observations, and R2, respectively, of a series of separate regressions between Pro-Banker Regulation and each of the five measures of connectedness listed in the "Meas row: the fraction of banks that are connected (*FRACBANKS*), the fraction of total banking system assets owned by connected banks (*SHAREASSETS*), the fraction of ba that have been politicians (FRACBANKERS), the (log) ratio of actual to expected number of matches between bankers and politicians (*PREVALENCE*), and the largest s of the population where bankers and politicians would have to be drawn, so that the null of random matching cannot be rejected at conventional levels (*MAXSHA* Columns (4) to (6) are analogous to (1) to (3), but the regressions reported in them include the log of real GDP per capita (adjusted from purchasing power parity) and th population. Columns (7) to (12) show the same information as (1) to (6) for Regulatory Quality as dependent variable. In Panel A, the connectedness measures were built data from all Bankscope banks, and in Panel B they were built using data from only 100 percet private banks. *, **, and *** denote statistical significance at the 10, 5, a percent, respectively. Standard errors are robust to heteroskedasticity.

	Pro-Banker Regulation Index						**Regulatory Quality**					
	Controls: None			Controls: log real GDP, log population			Controls: None			Controls: log real GDP, log population		
	Coef/SE	N	R2	Coef/SE	N	R2	Coef/SE	N	R2	Coef/SE	N	R2
Measure	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: All Bankscope Banks												
FRACBANKS	5.055***	51	0.25	1.733	51	0.49	-2.175***	79	0.29	-1.401***	79	0.68
	(1.456)			(2.142)			(0.456)			(0.362)		
SHAREASSETS	3.818***	48	0.26	2.360**	48	0.57	-1.593***	76	0.24	-1.190***	76	0.70
	(0.888)			(0.963)			(0.339)			(0.332)		
FRACPOLITICIANS	54.51***	51	0.33	28.71	51	0.52	-23.82***	79	0.38	-17.35***	79	0.72
	(18.31)			(25.83)			(3.833)			(3.721)		
CONNECTEDNESS	0.491***	51	0.25	0.362**	51	0.53	-0.349***	79	0.38	-0.241***	79	0.67
	(0.0968)			(0.170)			(0.0475)			(0.0739)		
MAXSHARE	-0.216***	51	0.14	-0.0709	51	0.49	0.116***	79	0.18	0.0352**	79	0.61
	(0.0501)			(0.0435)			(0.0178)			(0.0157)		
Panel B: 100% Private Banks												
FRACBANKS	4.444**	46	0.20	1.877	46	0.50	-2.170***	64	0.28	-1.004**	64	0.64
	(1.729)			(1.586)			(0.485)			(0.501)		
SHAREASSETS	4.561***	43	0.21	3.497***	43	0.60	-1.716***	61	0.19	-1.048**	61	0.65
	(1.463)			(1.219)			(0.418)			(0.469)		
FRACPOLITICIANS	55.28***	46	0.31	39.28**	46	0.55	-14.65***	64	0.26	-4.803	64	0.62
	(14.28)			(18.33)			(3.581)			(3.765)		
CONNECTEDNESS	0.612***	46	0.32	0.389**	46	0.54	-0.360***	64	0.40	-0.178**	64	0.64
	(0.108)			(0.170)			(0.0437)			(0.0787)		
MAXSHARE	-0.267***	46	0.16	-0.0997*	46	0.50	0.135***	63	0.14	0.0407	63	0.60
	(0.0555)			(0.0511)			(0.0286)			(0.0268)		

Table 8: Connectedness and Financial Development

The dependent variable is the (log) ratio of Private Credit to GDP (average 1995-2005 from Beck et al. (2000)). Columns (1) to (3) show the estimated coefficients (with standard errors), the number of observations, and R2, respectively, of a series of separate regressions between the dependent variable and each of the five measures of connectedness listed in the "Measures" row: the fraction of banks that are connected (*FRACBANKS*), the fraction of total banking system assets owned by connected banks (*SHAREASSETS* the fraction of bankers that have been politicians (FRACBANKERS), the (log) ratio of actual to expected number of matches between bankers and politicians (*PREVALENCE*), and the largest share of the population where bankers and politicians would have to be drawn, so that the null of random matching cannot be rejected at conventional levels (*MAXSHARE*). Columns (4) to (6) are analogous to (1) to (3), but the regressions reported in them include the log real GDP per capita and the log population. *, **, and *** denote statistical significance at the 10, 5, and 1 percent, respectively. Standard errors are robust to heteroskedasticity.

	Bank Development: (log) Private Credit to GDP (1995-2005)								
	I. Controls: None			II. Controls: log population, log real GDP per capita (PWT)			III. Controls: log population, creditor rights, accounting		
	Coef/SE	N	R2	Coef/SE	N	R2	Coef/SE	N	R2
Measure	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: All Bankscope Banks									
FRACBANKS	-2.905***	70	0.276	-0.844	70	0.63	-3.275***	59	0.382
	(0.512)			(0.526)			(0.575)		
SHAREASSETS	-2.189***	67	0.219	-1.039**	67	0.65	-1.961***	56	0.333
	(0.381)			(0.404)			(0.544)		
FRACPOLITICIANS	-33.95***	70	0.419	-15.13**	70	0.657	-34.57***	59	0.421
	(5.164)			(6.581)			(7.436)		
CONNECTEDNESS	-0.412***	70	0.268	-0.229**	70	0.651	-0.466***	59	0.413
	(0.0703)			(0.0870)			(0.0849)		
MAXSHARE	0.150***	70	0.128	0.0358	70	0.621	0.125***	59	0.262
	(0.0292)			(0.0226)			(0.0288)		
Panel B: 100% Private Banks									
FRACBANKS	-2.594***	58	0.301	-0.857*	58	0.69	-2.958***	49	0.528
	(0.466)			(0.441)			(0.437)		
SHAREASSETS	-2.216***	55	0.175	-1.155***	55	0.705	-1.677**	46	0.319
	(0.390)			(0.415)			(0.736)		
FRACPOLITICIANS	-21.18***	58	0.408	-9.147***	58	0.715	-23.94***	49	0.558
	(3.467)			(3.323)			(4.027)		
CONNECTEDNESS	-0.441***	58	0.327	-0.193**	58	0.701	-0.416***	49	0.506
	(0.0744)			(0.0813)			(0.0910)		
MAXSHARE	0.195***	58	0.138	0.0617**	58	0.681	0.154***	49	0.344
	(0.0428)			(0.0306)			(0.0433)		

Table 9: Robustness Exercises

In Panel A the dependent variable is the Kaufman and Kraay index of Control of Corruption (average 1996-2002), in Panel B is the index of Pro-Banker Regulation built by the authors using data from Barth et al. (2003), and in Panel C is the (log) ratio of Private Credit to GDP (average 1996-2002). Each block, from I to III show the estimated coefficients (with standard errors), the number of observations, and R2, respectively, of a series of separate regressions between the dependent variable listed in each panel and the main two measures of connectedness listed in the "Equation/Measures" row: the fraction of total banking system assets owned by connected banks (*SHAREASSETS*), and the (log) ratio of actual to expected number of matches between bankers and politicians (*PREVALENCE*). Regressions in all blocks control for log real GDP per capita and log population. Additionally, the regressions in Block I control for the log fraction of population over 25 with tertiary education, to control for the size of elites where bankers and politicians are drawn in each country. In Block II the measures of connectedness are built using only the information for the 10 largest banks in the country (measured by assets at the end of 2005). The regressions in Block III drop all countries where there is only 1 match. Block IV presents the results of robust regressions that control for the influence of outliers (stata command rreg). Finally, the regressions in Block V control for former socialist countries adding a dummy that takes the value 1 for countries with a socialist legal origin. *, **, and *** denote statistical significance at the 10, 5, and 1 percent, respectively. Standard errors are robust to heteroskedasticity.

	I. Controlling for tertiary education, log real GDP per capita, log population			II. Computing connectedness on 10 largest banks only.			III. Dropping countries with less than 2 matches Controls: log real GDP,			IV. Using Robust Regression. Controlling for log real GDP per			V. Controlling for log real GDP per capita, log population, and former		
	Coef/SE	N	R2	Coef/SE	N	R2	Coef/SE	N	R2	Coef/SE	N	R2	Coef/SE	N	R2
Equation/Measure	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Panel A: Dependent Variable is Control of Corruption															
SHAREASSETS	-0.988***	75	0.73	-0.956***	65	0.71	-1.066***	52	0.72	-1.119***	76	0.72	-0.828***	73	0.76
	(0.318)			(0.283)			(0.330)			(0.287)			(0.301)		
CONNECTEDNESS	-0.251***	78	0.74	-0.234**	65	0.68	-0.335***	52	0.73	-0.271***	79	0.70	-0.243***	76	0.77
	(0.0661)			(0.105)	0.711		(0.0890)			(0.0767)			(0.0643)		
Panel B: Dependent Variable is Pro-Banker Regulation Index															
SHAREASSETS	2.193**	48	0.57	2.081*	39	0.52	2.725**	36	0.55	2.427***	48	0.52	1.779**	48	0.62
	(0.952)			(1.073)			(1.024)			(0.896)			(0.871)		
CONNECTEDNESS	0.347**	51	0.55	0.599*	39	0.50	0.634**	36	0.53	0.322*	51	0.47	0.256*	51	0.59
	(0.164)			(0.300)			(0.234)			(0.174)			(0.149)		
Panel C: Dependent Variable is Financial Development															
SHAREASSETS	-1.035**	67	0.65	-1.082**	56	0.62	-1.347**	44	0.67	-1.122***	67	0.62	-0.697*	64	0.72
	(0.408)			(0.423)			(0.500)			(0.419)			(0.353)		
CONNECTEDNESS	-0.228**	70	0.65	-0.425***	56	0.64	-0.311**	44	0.64	-0.216**	70	0.62	-0.182**	67	0.73
	(0.0870)			(0.125)			(0.134)			(0.0947)			(0.0792)		

Table 10: Including Zeroes

In Block I the dependent variable is the Kaufman and Kraay index of Control of Corruption, in Block II is the index of Pro-Banker Regulation, and in Block III is the ratio of Private Credit to GDP. Each block, from I to III show the estimated coefficients (with standard errors), the number of observations, and R2, respectively, of a series of separate regressions between the dependent variable listed in each panel and four measures of connectedness listed in the "Measures" row: the fraction of banks that are connected (*FRACBANKS*), the fraction of total banking system assets owned by connected banks (*SHAREASSETS*), the fraction of bankers that have been politicians (*FRACBANKERS*), and the ratio of actual to expected number of matches between bankers and politicians (*PREVALENCE*). Regressions in all blocks control for log real GDP per capita and log population. All regressions include the observations with zero matches between bankers and politicians in those countries with more than 2 banks. *, **, and *** denote statistical significance at the 10, 5, and 1 percent, respectively. Standard errors are robust to heteroskedasticity.

	I. Control of Corruption			II. Pro-Banker Regulation Index			III. Financial Development		
	Coef/SE	N	R2	Coef/SE	N	R2	Coef/SE	N	R2
Measure	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
FRACBANKS	-1.429***	131	0.08	2.806**	74	0.07	-1.788***	110	0.10
	(0.256)			(1.345)			(0.407)		
SHAREASSETS	-0.819**	126	0.04	2.051**	71	0.07	-1.247***	107	0.07
	(0.317)			(0.928)			(0.362)		
FRACPOLITICIANS	-12.56***	131	0.10	33.95**	74	0.11	-22.51***	110	0.17
	(2.448)			(13.11)			(4.278)		
PREVALENCE	-0.301***	130	0.09	0.240*	73	0.03	-0.211**	109	0.04
	(0.0585)			(0.124)			(0.0929)		
FRACBANKS	-0.633**	126	0.64	0.0525	72	0.54	-0.734*	108	0.58
	(0.300)			(1.380)			(0.404)		
SHAREASSETS	-0.552**	123	0.64	1.207	69	0.56	-0.815**	105	0.59
	(0.254)			(0.976)			(0.327)		
FRACPOLITICIANS	-6.257**	126	0.64	5.338	72	0.54	-10.12**	108	0.60
	(2.956)			(13.92)			(4.425)		
PREVALENCE	-0.118*	126	0.64	0.0550	72	0.54	-0.145	108	0.58
	(0.0639)			(0.158)			(0.0891)		

Figure 1. Connectedness and Development

The scatter plot displays the relation between log real GDP per capita (average 1995-2005, from PWT) and the (log) ratio of actual to expected number of matches between bankers and politicians (*PREVALENCE*) (Panel B), controlling for the log fraction of population over 25 with tertiary education and log population. The bottom of the figure summarizes the coefficient of the connectedness measures in the multivariate regression against log real GDP per capita, its standard error, and the resulting t-statistic.

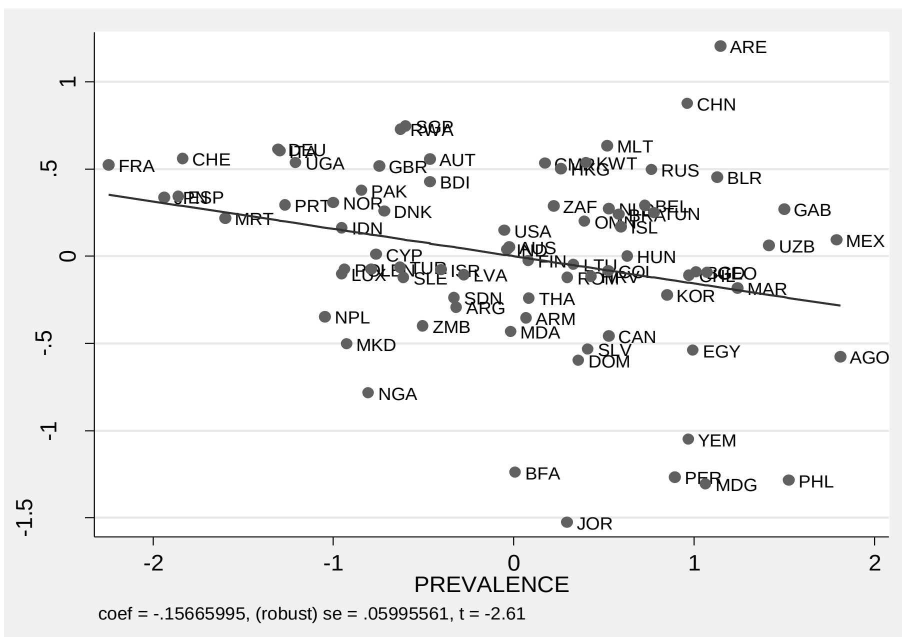
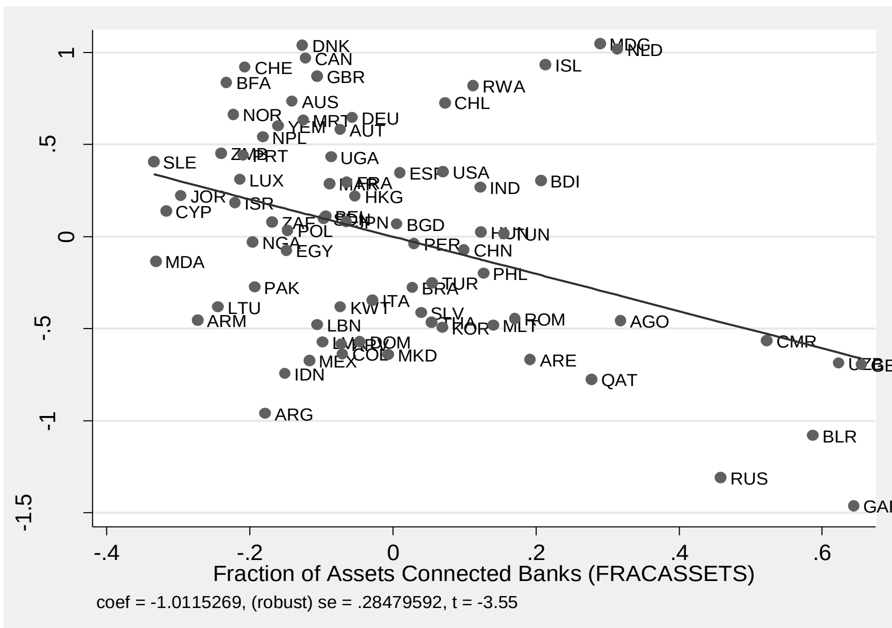


Figure 2. Connectedness and Institutions

The scatter plots display the relation between Control of Corruption (average 1996-2002), the fraction of total banking system assets owned by connected banks (*FRACASSETS*) (Panel A), and the (log) ratio of actual to expected number of matches between bankers and politicians (*PREVALENCE*) (Panel B), controlling for log of real GDP per capita (adjusted from purchasing power parity) and log population. The bottom of each figure summarizes the coefficient of each of the connectedness measures in the multivariate regression against Control of Corruption, its standard error, and the resulting t-statistic.

A. Fraction of Total Bank Assets in Connected Banks



B. Prevalence (log ratio of actual to expected number of matches)

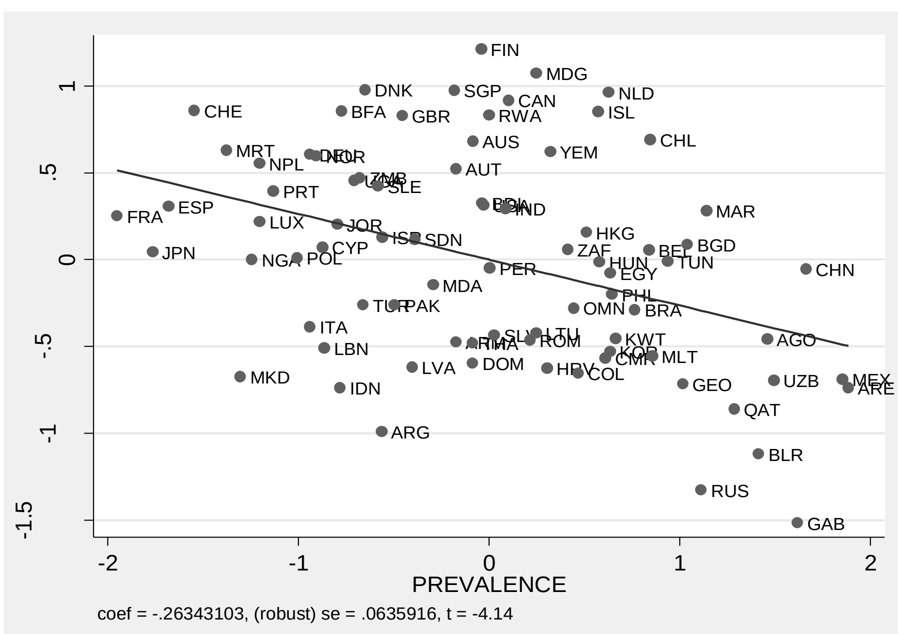
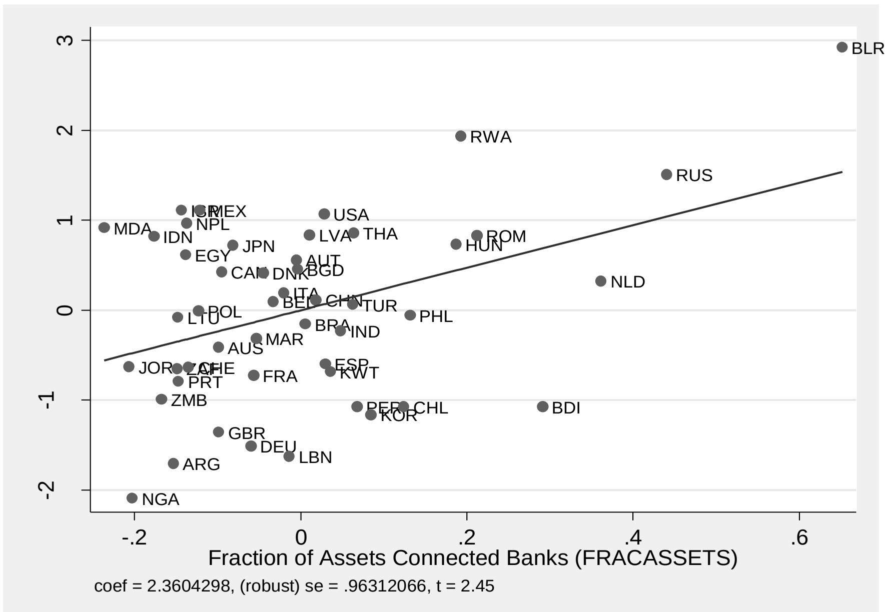


Figure 3. Connectedness and Pro-Banker Regulation

The scatter plots display the relation between the index of Pro-Banker Regulation, the fraction of total banking system assets owned by connected banks (*FRACASSETS*) (Panel A), and the (log) ratio of actual to expected number of matches between bankers and politicians (*PREVALENCE*) (Panel B), controlling for log of real GDP per capita (adjusted from purchasing power parity) and log population. The bottom of each figure summarizes the coefficient of each of the connectedness measures in the multivariate regression against Pro-Banker Regulation, its standard error, and the resulting t-statistic.

A. Fraction of Total Bank Assets in Connected Banks



B. Prevalence (log ratio of actual to expected number of matches)

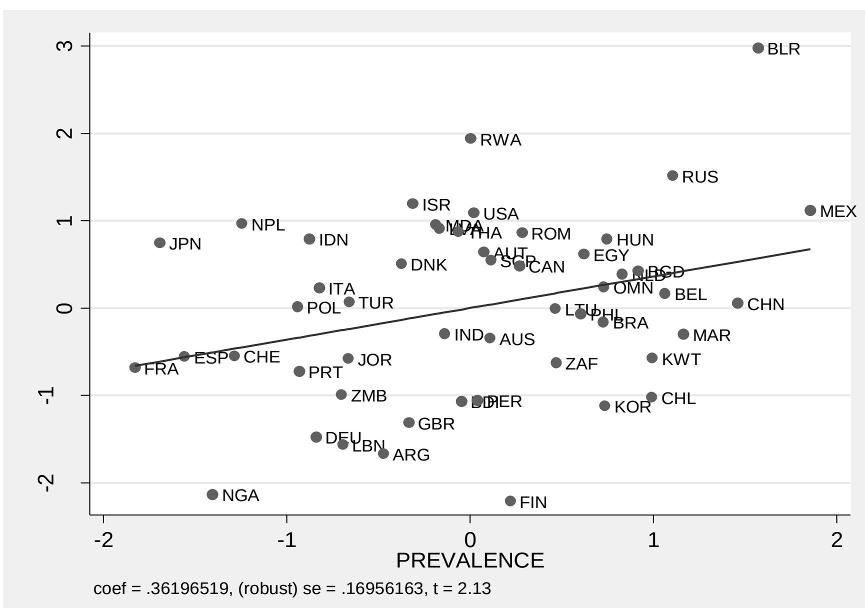
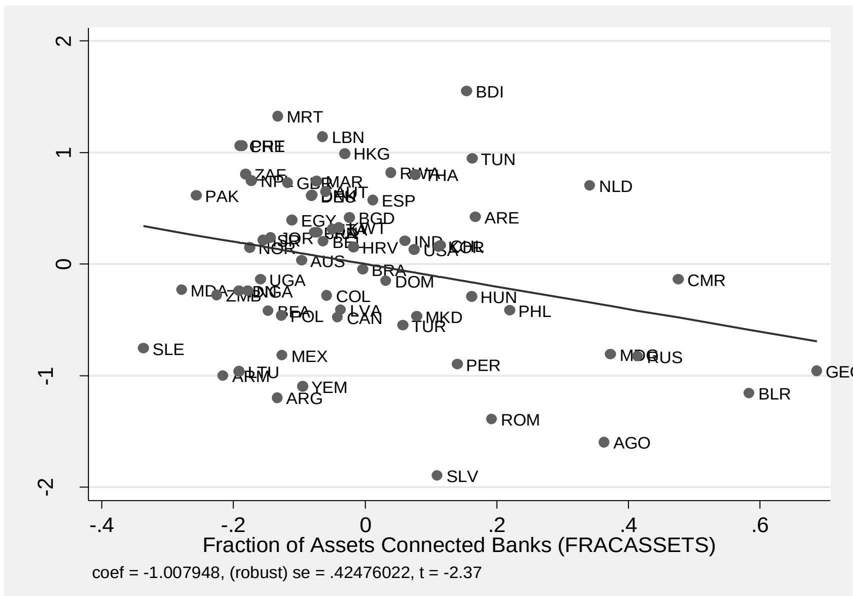


Figure 4. Connectedness and Financial Development

The scatter plots display the relation between the ratio of Private Credit to GDP (average 1995-2005) and the fraction of total banking system assets owned by connected banks (*FRACASSETS* (Panel A), and the (log) ratio of actual to expected number of matches between bankers and politicians (*PREVALENCE*) (Panel B), controlling for log of real GDP per capita (adjusted from purchasing power parity) and log population. The bottom of each figure summarizes the coefficient of each of the connectedness measures in the multivariate regression against Private Credit to GDP, its standard error, and the resulting t-statistic.

A. Fraction of Total Bank Assets in Connected Banks



B. Prevalence (log ratio of actual to expected number of matches)

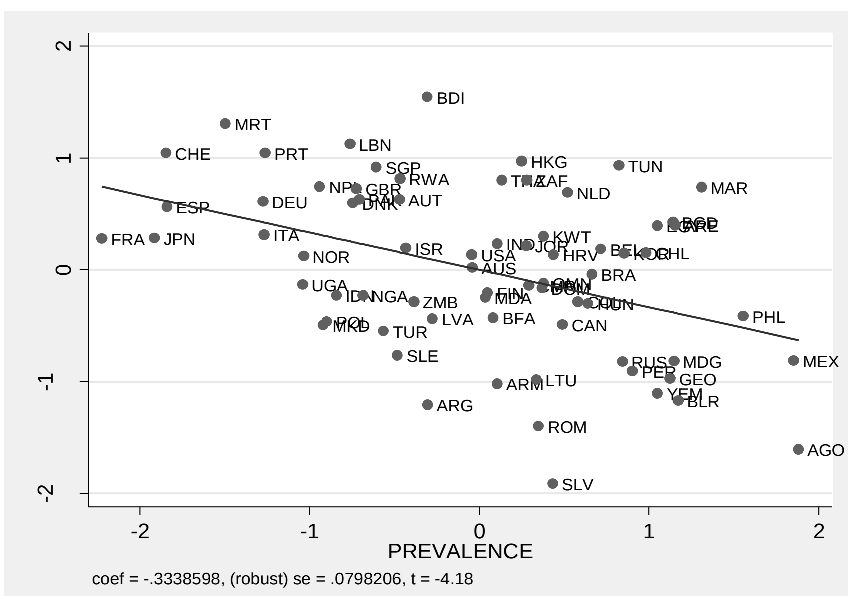


Table A1: Connectedness and Detailed Regulation

Each block from I to V show results from regressions where the dependent variable is each of the Barth et al. (2003) principal component indexes of five dimensions of bank regulation: the degree of restrictions to entry (I), the magnitude of capital requirements (II), the extent of restrictions to cross activities (III), the reliance of self monitoring (IV), and the overall authority of the regulator (V). In block I, Columns (1) to (3) show the estimated coefficients (with standard errors), the number of observations, and R2, respectively, of a series of separate regressions between the Entry Requirements index and each of the five measures of connectedness listed in the "Measures" row: the fraction of banks that are connected (*FRACBANKS*), the fraction of total banking system assets owned by connected banks (*FRACASSETS*), the fraction of bankers that have been politicians (*FRACBANKERS*), the (log) ratio of actual to expected number of matches between bankers and politicians (*PREVALENCE*), and the largest share of the population where bankers and politicians would have to be drawn, so that the null of random matching cannot be rejected at conventional levels (*MAXSHARE*).

Columns (4) to (6) are analogous to (1) to (3), but the regressions reported in them include the log of real GDP per capita (adjusted from purchasing power parity) and the log population. Each of the other blocks presents similar information for the other dependent variables. In Panel A, the connectedness measures were built using data from all Bankscope banks, and in Panel B they were built using data from only 100 percet private banks. *, **, and *** denote statistical significance at the 10, 5, and 1 percent, respectively. Standard errors are robust to heteroskedasticity.

	I. Entry Requirements						II. Capital Requirements						III. Activities Restrictions						IV. Private Monitoring						V. Overall Supervisory Power					
	Controls: None			Controls: log real GDP, log population			Controls: None			Controls: log real GDP, log population			Controls: None			Controls: log real GDP, log population			Controls: None			Controls: log real GDP, log population			Controls: None			Controls: log real GDP, log population		
	Coef/SE	N	R2	Coef/SE	N	R2	Coef/SE	N	R2	Coef/SE	N	R2	Coef/SE	N	R2	Coef/SE	N	R2	Coef/SE	N	R2	Coef/SE	N	R2	Coef/SE	N	R2	Coef/SE	N	R2
Measure	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)
Panel A: All Bankscope Banks																														
FRACBANKS	-0.334	52	0.002	-2.293	52	0.06	-0.842	52	0.017	0.00387	52	0.129	2.812***	51	0.153	2.655**	51	0.271	-3.227***	52	0.226	-0.994	52	0.391	0.310	52	0.002	0.360	52	0.059
	(1.059)			(1.646)			(0.725)			(1.010)			(0.747)			(1.072)			(1.018)			(1.470)			(1.022)			(1.511)		
FRACASSETS	0.0731	49	0	-0.276	49	0.026	-0.879	49	0.032	-0.542	49	0.133	1.211	48	0.05	0.665	48	0.23	-2.645***	49	0.265	-1.724**	49	0.478	-0.607	49	0.013	-0.741	49	0.052
	(0.689)			(0.792)			(0.609)			(0.606)			(0.751)			(0.842)			(0.602)			(0.662)			(0.909)			(0.924)		
FRACPOLITICIANS	3.187	52	0.002	-12.06	52	0.033	-8.900	52	0.021	-1.190	52	0.13	25.04***	51	0.137	24.68**	51	0.258	-35.31***	52	0.301	-17.65	52	0.414	-0.842	52	0	-4.211	52	0.059
	(10.05)			(13.12)			(5.792)			(8.839)			(8.104)			(11.83)			(12.58)			(17.24)			(8.829)			(13.97)		
CONNECTEDNESS	0.0203	52	0.001	-0.0795	52	0.026	-0.222**	52	0.127	-0.149	52	0.15	0.325***	51	0.221	0.298*	51	0.266	-0.233***	52	0.125	-0.169	52	0.403	0.131	52	0.031	-0.0293	52	0.058
	(0.0930)			(0.187)			(0.0847)			(0.130)			(0.0787)			(0.151)			(0.0865)			(0.129)			(0.0942)			(0.158)		
MAXSHARE	-0.0273	52	0.003	-0.00193	52	0.023	0.112***	52	0.09	0.0650*	52	0.154	-0.120**	51	0.085	-0.0478	51	0.209	0.103***	52	0.068	0.0202	52	0.382	-0.00670	52	0	0.0452	52	0.066
	(0.0589)			(0.0664)			(0.0323)			(0.0367)			(0.0451)			(0.0577)			(0.0339)			(0.0293)			(0.0678)			(0.0720)		
Panel B: 100% Private Banks																														
FRACBANKS	-0.178	46	0.000	-1.485	46	0.044	-0.180	46	0.001	0.269	46	0.109	3.276***	46	0.230	3.448***	46	0.331	-2.630*	46	0.150	-0.691	46	0.402	1.119	46	0.021	1.901	46	0.103
	(1.171)			(1.634)			(0.766)			(0.997)			(0.731)			(0.719)			(1.348)			(1.248)			(1.011)			(1.354)		
FRACASSETS	0.106	43	0.000	-0.379	43	0.027	-0.358	43	0.004	-0.380	43	0.103	1.309	43	0.036	1.086	43	0.210	-3.480***	43	0.252	-2.731***	43	0.529	-0.175	43	0.001	0.0633	43	0.041
	(1.268)			(1.409)			(0.675)			(0.702)			(1.051)			(1.129)			(0.976)			(0.702)			(1.509)			(1.621)		
FRACPOLITICIANS	8.438	46	0.009	0.414	46	0.026	-6.641	46	0.014	-7.130	46	0.115	27.26**	46	0.157	30.72*	46	0.270	-34.50***	46	0.254	-20.47	46	0.438	6.595	46	0.007	16.86	46	0.088
	(8.671)			(14.16)			(7.420)			(10.38)			(12.08)			(15.92)			(11.71)			(15.64)			(11.08)			(19.25)		
CONNECTEDNESS	0.0331	46	0.001	-0.0972	46	0.031	-0.238**	46	0.148	-0.194*	46	0.153	0.328***	46	0.191	0.273*	46	0.237	-0.340***	46	0.207	-0.202	46	0.430	0.188	46	0.048	0.0687	46	0.069
	(0.121)			(0.218)			(0.0947)			(0.114)			(0.0975)			(0.150)			(0.0744)			(0.130)			(0.121)			(0.188)		
MAXSHARE	-0.0283	46	0.002	0.00911	46	0.026	0.128***	46	0.109	0.0914**	46	0.153	-0.149***	46	0.101	-0.0825	46	0.200	0.132***	46	0.081	0.0268	46	0.398	-0.0385	46	0.005	0.0142	46	0.067
	(0.0683)			(0.0791)			(0.0355)			(0.0420)			(0.0495)			(0.0636)			(0.0419)			(0.0372)			(0.0948)			(0.101)		