Banking on Politics: When Former High-ranking Politicians Become Bank Directors

Matías Braun and Claudio Raddatz

Abstract: New data are presented for a large number of countries on how frequently former high-ranking politicians become bank directors. Politician-banker 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 other banks, despite being less leveraged and having less risk. At the country level, this connectedness is strongly negatively related to economic development. Controlling for this, the analysis finds that the phenomenon is more prevalent where institutions are weaker and governments 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.

Keywords: Banking sector development, institutions, political economy.

JEL codes: G15, G21, P16

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

On the first question, the literature complements theories of financial development based on stable and largely predetermined factors (such as the origins of a country's legal system, pattern of colonization, religion and culture, and social capital endowment) with a role for dynamic political economy considerations (LaPorta and others 1997, 1998;

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

Acemoglu and Johnson 2005, Stulz and Williamson 2003, and Guiso, Sapienza, and Zingales 2004). 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, 2005), and Braun and Raddatz (2007, 2008). One channel through which this could occur is the regulatory effect of the interaction between politicians and financial sector firms.[2] That regulators come from or end up in the regulated industry—the revolving door phenomenon—has long been recognized as a potential determinant of regulation.[3] And indeed, the empirical work, although still scarce, points to its having large social costs (see Kwhaja and Mian 2005 and Dal Bó and Rossi 2006.)

As for how firms react to financial sector underdevelopment, several recent papers have documented that politically connected firms seem to get preferential access to credit (Cull and Xu 2005; Khwaja and Mian 2005) and better treatment by the government. These links between politics and business seem quite widespread (Faccio 2006) and seem to add considerable value to firms (Fisman 2001).

This article focuses on banks. Because of their critical role in allocating credit, the behavior of banks, unlike that of most other types of firms, affects the entire economy. A new dataset linking more than 10,000 politicians (cabinet members, financial sector regulators, and central bank governors) and some 60,000 members of bank boards in a large number of countries is used to compare the names of bankers and of politicians to search for matches. The frequency of these matches is then used to compute measures of the connection between politicians and bankers to explore the role of political connectedness. Banks, 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 powerful yet less accountable. It may also carry large social costs, through more restricted access to credit. The article examines the extent to which banks are politically connected, where this connectedness is more prevalent, and whether it is associated with better outcomes for banks.

This private-interest view of the presence of former politicians on bank boards is, of course, not the only possibility. Links between politicians and bankers may be a way of fruitfully sharing ability, knowledge, and experience between the public and private sectors. These links could 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, de Figueiredo, and Snyder 2003). The merit of these two perspectives is ultimately an empirical question. In that sense, the stylized facts provided in this article may shed some light on which interpretation is more likely.

Several stylized facts stand out. At the micro level, politically connected banks are different from unconnected banks: they are larger, more profitable, less leveraged, and less risky. When aggregated at the country level in various ways, bank connectedness is found to be strongly negatively related to GDP per capita. After controlling for this and for other

[2] Financial sector incumbents are defined as the people and firms that form part of the financial sector at a given time, as opposed to those interested in entering the sector.

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

traditional elements, countries where banks are more connected are shown to rank higher on corruption and government regulatory power and lower on accountability. Overall regulation is less market friendly, bank regulation is generally more pro-banker, and the financial system is less developed.

This article is closely related to the recent literature showing that politically connected firms appear to fare better than the rest (see, for example, Faccio 2006; and Faccio, Masulis, and McConnell 2005.) This article adds to this work in three main ways. It focuses on banks, an important contribution because of the likely effect bank connectedness may have on the entire economy through credit allocation. Rather than determining whether political connections improve outcomes for the connected firms, it delves deeper into the country characteristics and policy choices associated with these kinds of connections. And it looks at former politicians as well as incumbents.

The article is also related to the literature on the search for political experience by boards of directors (see, for instance, Agrawal and Knoeber 2001 and Goldman and others 2009). Similarly, it is related to recent work on the relationship between connections and development, including banking sector development from a historical perspective (Haber 1991; Maurer 2002; Maurer and Gomberg 2005; Milanovic, Hoff, and Horowitz forthcoming; and Razo forthcoming). In this article, the assembly of the new dataset has allowed consistent exploration of the issue across a large number of countries.

The article compares politically connected banks to banks that are not connected and correlates several country-level measures of connectedness with variables capturing the quality of institutions, bank regulation, and financial development. Section I describes the data and the matching procedure used to identify banker-politicians. It also discusses ways of aggregating the results into a country-level connectedness variable. Section II shows how connected banks differ from unconnected ones and explores the characteristics of countries where the phenomenon is more frequent. Section III presents conclusions and implications.

I. Measuring the Connection between Bankers and Politicians

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

Building the Data

The data on names of politicians came from the Country Reports of the Economist Intelligence Unit, which were revised twice yearly for each country for 1996–2005. This review yielded 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 editions of *How Countries Supervise their Banks, Insurers, and Securities Markets* (Central Bank Publications ,various years). These two data sets together provide extensive coverage for cabinet members and financial sector supervisors in 154 countries over 10 years (see supplemental appendix table S1, column 3, available at http://wber.oxfordjournals.org/). Once cleaned (as explained below), the data yielded an average of 72 politicians in each country, which is around 7 a year. There is some variation across countries, but it is small: 40–100 names of politicians were found for 70 percent of the countries.

The names of bank board members are from Bankscope (Bureau van Dijk 2006), which has data on the most recent board composition of both listed and unlisted banks in nearly all countries. The data were collected for 2006, so the board composition is typically from December 2005. Once duplicates were identified among the 109,645 board member names found for 4,618 banks, 64,169 unique board member names remained. Although Bankscope is the most comprehensive source of bank data around the world, its coverage is not necessarily complete. It is close to universal, however, as evidenced by the correspondence between the average number of banks with board composition data in Bankscope in 2001 and the total number of commercial banks reported by Barth, Caprio, and Levine (2003) for the same year (see column 5 in supplemental appendix table S1). Although there is some variation across countries, the difference between the number of banks in the two datasets falls within a 20 percent range in about 70 percent of countries. The banks for which board data are available account, on average, for 72 percent of the assets in each country; in only about a fourth of the countries is the fraction below 60 percent (see column 6).

Because data on bank directors are from the December 2005 issue of Bankscope and data on politicians cover the period 1996–2005, matches between the two datasets typically consist of former politicians who later sit on a bank board. This is the convention followed in the rest of the article, which refers to these individuals as “former politicians.” There are a few caveats with this terminology. First, the entire history of each individual is unknown. Thus, some of them may have been bankers before 1996 (the first observation of the politician dataset). Second, how long a director has been sitting on the board is also unknown. For instance, the data do not show whether a politician who is on a board in 2005 and whose term in government ended in 2004 was already sitting on the board in 2003. Third, matches between politicians who are in their political positions in 2005 correspond to cases where the politicians simultaneously hold both positions. Fourth, a given issue of Bankscope reports the latest director data available. In more than two-thirds of cases, this corresponds to December 2005, but in a few cases the data are from earlier years. Thus, to be more precise, “former politicians” refer to individuals who were politicians at some point during 1996–2005 and who were on a bank board in December 2005.

Finding matches between politicians’ and bankers’ names involved four steps. First, the strings containing the names were standardized by converting them to lowercase and removing punctuations and titles (Sir, PhD, and so on). Second, duplicate entries were removed by identifying observations that were simply different spellings of the same name (for instance, with and without the middle initial). Third, the datasets containing names of politicians were pooled and duplicate observations across the datasets were identified. Once the names had been cleaned in this way, the names in the politician and banker datasets were compared to obtain the matching observations.

At each step, a record-linkage algorithm was used to find matching names. The algorithm forms all possible pairs of names within each country and ranks the pairs on three standard measures of string similarity from the record-linkage literature: bigram, Levenshtein, and longest common subsequence [cite the sources for each of these].[4] The bigram metric counts the number of consecutive matching pairs of characters between two strings. The Levenshtein measure counts the minimal number of edits required to convert one string into the other. Allowable edit operations are the deletion of a single character, the insertion of a single character, and the substitution of one character for another. The longest common subsequence counts the number of consecutive characters that are present in two strings, and keeps the largest number.

All three 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 countries than in others, these methods could be differentially effective and could potentially induce bias. For these reasons, the algorithms were used only to restrict the sample of potential matches, as described below. Ultimately, the matches were visually identified.

When two strings containing names are compared, each of these criteria results in a value between 0 and 1 that measures the likeliness of the two names being the same. All pairs with a minimum value of 0.8 in at least one of the three methods were retained and visually checked to determine whether they matched. While alternative ways could have been used to restrict the set of pairs to be visually checked, this relatively restrictive way was chosen so as to err more on the side of failing to find true matches than of falsely identifying matches. This was also the basic principle used for the visual verification.

After step two, the data contained 10,829 politicians and 62,981 bankers in 146 countries. Step three yielded 218 matching names across these two lists (see column 4 in table S1). The mean number of matches per country was 1.4, and the median was 1.0. At 0.34 percent, the share of bankers who are politicians is quite small and unimpressive. The dearth of matches reflects in part the restrictive way that the matches were identified. On the other hand, the fraction of politician-bankers does not seem as small in the context of the size of the populations from where they were drawn (see below).

Having high-ranking politicians on the board of banks is not the only way banks can be politically connected. Non-cabinet level politicians can also play an important role connecting banks. And there are more subtle forms of connection: a politician can be connected to a bank by having relatives or associates on the board (Faccio 2006) or by supporting the appointment of directors or chief executive officers. There are also less subtle ways, such as outright bribery and corruption. Politicians sitting on bank boards seem to be a relatively rare form of connection compared with some other channels, to judge by country case studies and anecdotal evidence.[5]

However, these other types of connections are much more difficult to document systematically across countries. Rather than arguing that a direct presence on the board is the only or the most important way politicians and bankers relate, the article considers 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

[4] The record linkage software used was Merge Toolbox, a Java-based tool created by the members of the Safelink project (see Schnell, Bachteler, and Bender 2004).

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

particular form of connection, the different ways of connecting are likely to be positively correlated. Since the analysis here looks only at the top posts in both politics and banking, the results are likely just the tip of the iceberg.

Instead of focusing on absolute magnitudes, the article looks at how variations in the importance of politicians sitting on bank boards links to several bank and country characteristics. There are two sources of variation in the data: variation between countries with matches and those without (the extensive margin) and variation in the number of matches for the countries with at least one match (the intensive margin).

The 72 of 154 countries for which no matches were found were dropped from the sample for most of the analyses, for several reasons. Most important is concern about the reliability of the data for many countries with zero matches. For instance, while 60 percent of countries with some matches meet the International Monetary Fund's Special Data Dissemination Standard (IMF 2009), only 20 percent on those with zero matches do (many of these countries are not generally included in systematic cross-country analyses).[6] Second, many countries with zero matches have very few banks. A third had fewer than three banks in Bankscope in 2005, compared with just 4 percent among countries with matches. And the median number of banks with data is 5 in the no-matches group but 16 in the group with at least one match. Third, the zeroes give little information on whether the selection of bankers is biased toward former politicians. Under reasonable assumptions, the probability of finding zero matches between bankers and politicians is high even if banker selection is seriously biased toward picking politicians.[7] In contrast, finding even one match provides considerable information on the likely bias of the selection, since a match is typically a low probability event under the null hypothesis of unbiased matching. Nevertheless, results are also presented for analyses that include countries with zero matches but more than two banks (as an arbitrary cutoff for considering the zero as reliable), and many of the correlations documented below remain unaffected.

Of course, this argument could be stretched to restrict the sample to countries with more than one or two matches because finding a small number of matches may simply occur by chance, something that is less likely if a more substantial number of matches are found. Although finding a single match is a very low probability event that is unlikely to occur by chance in most countries, the article returns to this issue below to show that, even though the sample size drops quite rapidly, the results are not very different when the sample is further restricted.

Measuring Connectedness at the Aggregate Level

There are several ways to aggregate the information on individual matches to measure and compare the connectedness between banking and politics in different countries. Each method has pros and cons and is more or less appropriate under different

[6] For instance, 63 percent of these countries were not included in the cross-country analysis of bank regulation by Barth, Caprio, and Levine (2003). Some were included in later rounds of the survey, but coverage is incomplete.

[7] See the appendix for a description of the distribution of matches under an unbiased selection process.

assumptions about the process that generates the matches between politicians and bankers. Instead of focusing on a single measure, the analysis is conducted with five different metrics (table 1). Three measures are straightforward, and two are more elaborate because they address some shortcomings of the other three. The five measures are computed twice: once for matches found for all Bankscope banks (public, private, and mixed), and once only for matches for fully private banks.

{TABLE 1 HERE}

FRACTION OF CONNECTED BANKS. The fraction of connected banks *(FRACBANKS)* is the number of banks with at least one former politician on the board of directors divided by the number of banks for which there are data on board members. The mean fractions of connected banks of 10 percent for all kinds of banks and 9 percent for private banks are much larger than the fraction of matches among individuals documented above. Indeed, when only countries with at least one match are considered, the average share increases to about a fifth of the banks. There is interesting variation across countries. The countries with fewest connected banks are Germany, the United States, Italy, Japan, and Switzerland, all with less than 2 percent of banks connected in this way. In contrast, more than two-thirds of the banks are connected in Gabon, Georgia, Myanmar, Angola, Burundi, and Madagascar. The picture is generally the same whether considering all banks or just private banks; the correlation between the two groups 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 its 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. The issue is not about having a large number of people in both worlds but rather about having people in the right place, even if their number is small. In this sense, *FRACBANKS* is more naturally interpreted as a measure of the institutional connection between banking and politics, rather than a personal matter related perhaps to the existence of a common set of skills.

SHARE OF ASSETS OF CONNECTED BANKS. A simple variation on the *FRACBANKS* measure consists of computing the share of total banking system assets in banks that have a politician on their board. This metric, the share of assets of connected banks *(SHAREASSETS),* has the advantage of acknowledging that larger banks might differ from smaller ones in their need or ability to connect to politics. Smaller banks may find free-riding on the connections 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 for the extent of power—both political and economic—that 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 for small banks.

SHAREASSETS is strongly and significantly correlated with *FRACBANKS*, both for all banks and for private banks (table 2). For countries with at least one match, the mean share is 25 percent for all banks and 18 percent for private banks. The groups of countries that rank very high and very low are similar to those for the *FRACBANKS* measure. These results 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 private banks is also quite high (0.79).

{TABLE 2 HERE}

FRACTION OF CONNECTED BANKERS. The third measure, fraction of connected bankers *(FRACBANKERS)*, is the ratio of the number of matches to the number of bank directors in the dataset. This metric looks at the extent to which politicians populate bank boards. The average fraction of connected bankers across all countries is around 1 percent and is close to 2 percent for 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 for *FRACBANKS* and 0.38 for *SHAREASSETS* 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 captures a similar concept to the previous two.

PREVALENCE. 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 with fewer people from which both bankers and politicians are selected. For greater precision, the probability of obtaining a given number of matches was derived 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). Everyone in the pool has the same probability of being selected for either position, and there is no bias in favor of politicians in the selection of bankers. This probability is then used to compute the expected number of matches assuming that the common pool is the entire population of each country (more on this below). This ratio of actual to expected matches (in logs) is called *PREVALENCE*. The correlation of this metric with the previous ones is not as strong as for the others, particularly with *FRACBANKERS*, but it is still positive. The countries that rank highest in this connectedness measure are Myanmar, China, Bangladesh, India, and Mexico (see table 1). The 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 number because of the assumption that the pool from which directors are selected is the total population of a country. Since it is highly unlikely that every person has the same probability of being chosen as a politician or a banker, the results for this measure are exaggerated. Nevertheless, the cross-country variation in this measure is the same as it would be if it were assumed that the selection pool for bankers and politicians 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,

$$PREVALENCE = PREVALENCE(ELITE) + \log\left(\frac{ELITE}{POP}\right) \quad (1)$$

where $PREVALENCE(ELITE)$ is the log ratio of actual to expected matches considering the true size of the elite, and $\log\left(\frac{ELITE}{POP}\right)$ 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, the *PREVALENCE* measure and true prevalence would differ only in a constant.

The measure will be incorrect, however, if there is systematic variation across countries in the elite as a share of population. This could happen if the number of elite is relatively fixed in all countries, so that the elite decline as a fraction of the population from smaller to larger countries. The analysis considers the size of the population in each country to control for this possibility.

MAXIMUM SHARE OF POPULATION FOR RANDOMNESS. Another possibility is that the size of the elite is related to the educated portion of the population. If one assumes that the pool is the number of people with a tertiary education, the expected figures are closer to the actual number of matches. This correction incorporates the possibility that *PREVALENCE* is highest in some countries simply because there are so few people in those countries who are capable of assuming these posts. The correction, however, is not free of problems because it is not obvious that the relevant pool is the group of highly educated people. On the one hand, the pool may be too narrowly defined since not all the bankers and politicians have a tertiary education.[8] On the other, the pool might not be sufficiently small if a certain kind of economic or financial skill is shared between politicians working in economic spheres within the government and bankers. Most important, such a correction might confound the interpretation of the results because one variable mixes two concepts—availability of human capital and connectedness—that may have independent (and opposite) effects on many country characteristics (such as real GDP per capita).

The final measure, maximum share of population for randomness (*MAXSHARE),* takes into consideration the uncertainty about the size of the pool of individuals from which bankers and politicians are selected. *MAXSHARE* corresponds to the largest pool (as a fraction of the population) from which bankers and politicians are selected so that the hypothesis that the selection is random could not be rejected at the 5 percent level (for the number of matches found in the data). For most countries, in order not to reject this hypothesis, the size of the pool turns out to be a very small fraction of the population. As expected, this variable is negatively correlated with the previous ones because it measures the inverse of the underlying concept. The usual groups of countries are at both extremes of the metric.

CONNECTEDNESS AND COUNTRY CHARACTERISTICS. 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 links solely to private banks makes little difference, suggesting that politicians sitting on the boards of state-owned banks do not drive the findings for the various measures.

[8] See Dreher and others (2009) for data on the educational attainment of presidents. These data show that 30 percent of presidents worldwide since 1975 did not receive a higher education.

Countries that rank highest on the connectedness measures[9] (Bangladesh, China, Mexico, India, and the Russian Federation) and those that rank lowest (Luxembourg, Switzerland, Cyprus, Norway, and France) clearly differ in many other respects as well. The most obvious is economic development. Countries where connectedness is more prevalent are significantly poorer than countries where it is less prevalent. Mean GDP per capita is $3,944 for countries with higher than the median share of connected banks, and $18,958 for the others. The share of connected banks in countries with lower than median per capita GDP (28.2 percent) is two and a half times larger than the share in more developed countries (11.4 percent). The picture is about the same for the other measures and when only private banks are considered.

The second distinctive feature is that countries where the prevalence of connectedness is higher also appear to have less developed institutions. For instance, countries with lower than median connectedness have control of corruption indicators (defined below) that are one standard deviation higher than countries with higher prevalence. While the share of connected banks is 15.1 percent in countries with higher than median control of corruption, it is 26.5 percent in the rest. Finally, banking sector development differs considerably across the two groups of countries. The ratio of private credit to GDP (from Beck, Demirguc-Kunt, and Levine 2000) is 3 times higher where connectedness measures are lower (76 percent) than where they are higher (25 percent), while the share of connected banks is almost twice as high in countries where banking sector development is low (26.5 percent) than in those where it is high (15.1 percent).

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, connectedness is higher where economic development is low and where institutions and the financial system are underdeveloped. These are some of the relationships examined more deeply in the following section.

II. The Correlates of Connectedness

This section explores the correlates of connectedness first at the bank level and then at the cross-country level. It shows that the measures of connectedness introduced above are robustly correlated to important bank and country characteristics and also to policy choices.

Bank Characteristics

Connected and unconnected banks can be compared on several characteristics. Here, they are compared on measures of size, profitability, leverage, riskiness, and liquidity, which were constructed from Bankscope data using bank statements at the end of 2004.

Table 3 shows averages for these characteristics for connected and unconnected banks, their differences, and whether the differences are statistically significant according to a simple test of means. Clearly, connected banks are larger, more profitable, and less

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

leveraged than are unconnected banks. They also have a smaller share of net charge-offs to gross loans, suggesting that they take less risk than unconnected banks, although on a worldwide comparison, the difference is not significant. The sign and significance of these differences remain unchanged when only fully private banks are considered.

{TABLE 3 HERE}

The regressions in table 4 further test whether these correlations hold when connected and unconnected banks are compared within a country. The parameters of the following parsimonious specification are estimated:

$$Y_{i,c} = \alpha + \beta \times CONNECTED_{i,c} + \gamma SIZE_{i,c} + \theta_c + \varepsilon_{i,c} \quad (2)$$

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 a value of 1 if at least one of the bank's directors has been a politician or bank regulator, and 0 otherwise; $SIZE_{i,c}$ controls for (log) total assets (except when the left-side variable is itself a measure of size); 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, all variables are measured 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).[10] As in table 3, the parameters of the benchmark model are estimated separately for all banks and for banks with no public ownership.

{TABLE4 HERE}

The coefficients confirm that connected banks tend to be the largest banks in a country, with total assets about 34 percent larger than those of the average unconnected bank (see table 4, column 1). 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 to have a return on average assets 0.6–0.8 percent higher than the average unconnected bank (column 2). Leverage is significantly lower among connected banks; the ratio of equity to total assets is 2 percent higher in connected banks than in the average bank, a difference that increases to 3 percent in the sample of privately owned banks (column 3). Connected banks also tend to have a lower proportion of write-offs and impaired loans relative to average gross loans and reserves, suggesting that they take on less risk (column 4).

Overall, the results across and within countries show that connected banks are larger, more profitable, less leveraged, and less risky than unconnected banks, regardless of

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[10] This is not a major issue in the overall comparisons in table 3, 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.

whether there is any government ownership.[11] In addition, to see whether bank characteristics are correlated with the share of former politicians on a bank's board, equation (2) was reestimated using that share (a measure of the intensity of banks' political connections) instead of the dummy variable described previously. While the results are similar to those reported in table 4, 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 does not seem that politicians cluster in banks with desirable characteristics.

Country Characteristics

As discussed in section I, a simple look at the data suggested that banks were less politically connected in richer, more financially developed countries. The results reported here systematically test whether the degree of connectedness of banks is robustly correlated with important country characteristics and whether those correlations survive when controlling for several straightforward omitted variables in a multivariate setting. Country characteristics, such as development level, institutional quality, extent of pro-banker regulation, and banking sector development, were related to the five measures of connectedness by estimating the parameters of the following specification:

(3) $$Y_c = \alpha + \beta \times CONNECTEDNESS_c + \gamma' X_c + \varepsilon_c$$

where Y is a measure of any of the country characteristics described above for country *c*, and $CONNECTEDNESS$ is any of the five measures of connectedness discussed in section I: the fraction of connected banks (*FRACBANKS*), the share of assets of connected banks (*SHAREASSETS*), the fraction of connected bankers (*FRACBANKERS*), the (log) of actual to expected number of matches of bankers-politicians (*PREVALENCE*), and the maximum share of the population from which bankers and politicians are 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 $CONNECTEDNESS$.

Economic Development

The results show a strong negative correlation between the degree of connectedness and GDP per capita, whether considering all banks or only those that are fully private (table 5). The correlation is particularly strong when no additional controls are included (columns 1–3), but it survives after controlling for log population and for the fraction of the population with tertiary education (columns 4–6), especially when focusing on fully private banks. Educational attainment is particularly relevant as a standard measure of a country's stock of human capital (which most theories relate to a country's per capita GDP), but it is also important as a proxy for the size of the pool of elite from which politicians and bankers are selected (see section I). The results are statistically stronger for the more complex

[11] These findings are robust to using the standard Heckman (1979) two-step estimator to control for possible sample selection issues in the set of banks with information on directors (not reported).

measures of connectedness: *PREVALENCE* and *MAXSHARE*. This suggests that these measures have greater economic content than the simpler ones. Nonetheless, results are qualitatively similar, whatever the measure.

{TABLE 5 HERE}

Furthermore, figure 1 shows that the negative correlation between connectedness and development is not driven by a few outliers but reflects a robust pattern of the data. The relation between connectedness and GDP per capita (from Heston, Summers, and Aten 2006) is economically large. For instance, the difference in (log) GDP per capita between Morocco and France is commensurate with their difference in *PREVALENCE*. Although causality cannot be attributed to this strong cross-country correlation without a good instrument, it is clear that the degree of connectedness is not neutral but is associated with a country's level of development. The regressions discussed below show that connectedness is also associated with other country characteristics that have been causally related in the literature to level of development, even after controlling for the direct link between development and connectedness documented here.

{FIGURE 1 HERE}

Institutions

Correlating the five measures of connectedness with cross-country measures of institutional quality (from Kaufmann, Kraay, and Mastruzzi 2004) shows that connectedness is significantly higher in countries with less developed institutions for preventing corruption and limiting the power of the government over its citizens (voice and accountability; table 6). The relation holds for all banks and for private banks. For all measures, the relation between connectedness and institutional quality is significantly negative even after controlling for GDP per capita and population size (columns 4–6 and 10–12). This is reassuring because of the widely documented link between institutions and development and because the measures of connectedness may be correlated with population size. With these correlations, it is not surprising that the estimated coefficient changes according to the unconditional specification. However, all the coefficients maintain their sign and statistical significance, which shows that the relations between connectedness and a country's level of development and population size are not qualitatively driving the findings.[12]

It is even clearer than for the case of overall development that a few outliers do not drive the relations between connectedness and institutional quality (figure 2). The magnitude of the estimated coefficient is also economically relevant: a one standard

[12] To capture nonlinearities, specifications were also estimated that included a quadratic term for log GDP per capita in addition to log GDP per capita and log population. The results, available on request, are qualitatively and quantitatively similar to those obtained with the baseline control set. This exercise was repeated for all the regressions reported in this section, with similar results.

deviation increase in *SHAREASSETS* (equivalent to the difference between Luxembourg and Philippines) is associated with a 0.4 decline (around half a standard deviation) in the control of corruption, corresponding to 25 percent of the difference in control of corruption between the two countries. Also, as shown in the bottom panel of figure 2, the difference in control of corruption between Angola and Spain is commensurate with their difference in *PREVALENCE*.

{TABLE 6 HERE}

{FIGURE 2 HERE}

Regulation

The results so far have shown that prevalence is systematically related to underdevelopment and weak institutions. The next test is for a systematic relation between connectedness and banking sector regulation. As discussed in the introduction, the political economy literature typically associates the links between regulators and regulated firms with private interests that depend critically 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, Caprio, and Levine (2003) use using five dimensions of financial regulation to show how countries regulate their financial systems: restrictions on 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 banks that corresponds to the first principal component of the answers to surveys conducted by regulators in each country.

To address the ambiguity inherent in some of these dimensions, these indexes were used to construct an overall measure of the pro-banker leaning of financial regulations across countries. For instance, it is unclear whether restrictions on bank activities are pro- or anti-incumbents. On the one hand, restrictions constrain the ability of banking incumbents to expand into new lines of business. On the other hand, restrictions constrain other institutions from expanding into the banking business. Similarly, whether giving responsibility for supervision and monitoring to the public or private sector is pro- or anti-bankers depends on what type of monitors are more easily captured.

Instead of taking an arbitrary stance on whether each of these five dimensions of financial regulation is pro- or anti-banking incumbents, cross-country data on the degree of rents in a country's banking sector (measured as the average net interest margin, also from Barth, Caprio, and Levine 2003) are used to build a de facto index by regressing these rents on the five individual indexes. Burnside and Dollar's (2000) methodology was used to construct an index of the pro-banker intensity of regulation by weighting each index by its estimated elasticity to rents. The intention 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

(4)

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

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 as described above: entry restrictions, capital requirements, activities restrictions, private monitoring, and overall supervisory power (all standardized to have zero mean and unit variance so that the magnitude of the coefficients reveal the relative importance of each dimension). According to the regression, average net interest margins are positively correlated with restrictions on entry and activity and negatively correlated with capital requirements, the extent of private monitoring, and the power of the supervisor. In terms of magnitude and significance, 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, in both magnitude and significance.

In addition to this index, the Kaufmann, Kraay, and Mastruzzi (2004) index of regulatory quality was also used (the index measures the incidence of market-unfriendly policies such as price controls or inadequate bank supervision), and the correlation between connectedness and each of the five individual dimensions of regulation was checked (see table A1 in the appendix).

Table 7 shows the relation between the measures of connectedness and the index of pro-banker regulation (columns 1–6) and the index of overall regulatory quality (columns 7–12) for all banks and for private banks only, both unconditionally and after controlling for log real GDP per capita and log population. 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 between connectedness and 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 on boards 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 more than a one standard deviation decline in the index of regulatory quality, commensurate with the difference between Egypt and Japan.

{TABLE 7 HERE}

The correlations with the regulatory index are not driven by a few outliers (figure 3), although the relation is not as strong as that with country characteristics. This is due partly to the smaller sample for regulatory variables, but also to the difficulty of aggregating the indicators into a measure of pro-banker regulation. To check the robustness of the results, the pro-banker index was also built using the simpler indexes reported by

Barth, Caprio, and Levine (2003) for each dimension of regulation instead of the principal component indexes. The results are qualitatively similar, but significance is lost in several cases. Finally, the results were checked using data from Barth, Caprio, and Levine (2006) to construct a simple index (rather than a principal components index) based on surveys in 2001 and 2003, which increases the cross-sectional dimension of the data. As before, the results are qualitatively similar, but the significance is lost except in the unconditional regressions and the conditional regressions using *MAXSHARE* and *PREVALENCE*.[13]

{FIGURE 3 HERE}

Financial Development

The evidence presented above suggests that the connectedness of bankers and politicians is significantly and robustly correlated with how the banking sector operates and is regulated. Insofar as these differences have no impact on the efficiency of the financial system, the issue would simply be a matter of diverse preferences across countries. The importance rises, however, if the connection between bankers and politicians is correlated with the ability of the system to allocate funds efficiently. This section tests whether connectedness is related to the degree of development of the banking system. The specification is the same as above, with Y now being each country's log ratio of bank credit to the private sector to GDP. Also as before, univariate and multivariate regressions are presented that control for per capita GDP and population size and for other standard determinants of financial development.

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 regardless of whether connectedness is measured over all banks or private banks only (table 8). In fact, as before, the results are stronger when connectedness is measured over private banks only. Thus, connectedness is 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 Philippines and Japan. Again, a few outliers do not drive the results (figure 4).

{TABLE 8 HERE}

{FIGURE 4 HERE}

The negative correlation between the measures of connectedness and financial development is not driven by the traditional measures used to explain financial

[13] Results are available on request.

development across countries, such as the degree of protection of creditors, the quality of accounting practices, and investment opportunities measured using the decade's effective GDP growth rate (columns 7–9).[14] Both creditor rights and accounting quality enter positively as expected (although not significantly).

Robustness

The results have shown that the connectedness of banks, however measured, is negatively correlated with economic development, the existence of less corrupt and more accountable institutions, and development of the banking sector and is positively correlated with the extent to which regulation favors bank incumbents. As mentioned, without a good instrument for connectedness, causal inferences cannot be made, but it has been shown 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 of the country characteristics analyzed, such as a overall development or population size. The regressions reported here address some further robustness concerns.

As discussed in section I, although the *PREVALENCE* measure takes no stance on the share of the population from which bankers and politicians are selected, it assumes that the share is constant across countries. This is a reasonable assumption, but it may be that the elite are not a fixed share of the population but rather a fixed number of people. If so, *PREVALENCE*, one of the most robust measures, could simply 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 the unconditional regressions. Nevertheless, it is also possible that the size of the elite is not fixed but proportional to the share of the highly educated population. To check for this possibility, the log share of the population with tertiary education was added to each specification.[15] The regressions 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 and financial development or the positive correlation with pro-banker regulations. Although this is mainly a concern for the *PREVALENCE* measure, results are also reported using the share of assets of connected banks to show that controlling for this additional variable does not change these results either. Results for other variables are similar and available on request.

{TABLE 9 HERE}

[14] When the decadal growth rate of per capita GDP is included, log real per capita GDP is dropped.

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

Another concern with the connectedness measures 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 banking sector development, 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, the measures were recomputed using only the 10 largest banks in a country as measured by total assets at the end of 2004 (columns 4–6 in table 9). All banks were included for countries with fewer than 10 reporting banks. This reduced by two orders of magnitude the cross-country variance in the number of banks used in calculating the measures of connectedness, and the resulting measures are not significantly correlated with the number of banks. Nevertheless, the results obtained with these measures are quantitatively and qualitatively similar to those obtained when all banks are included. Thus the significantly larger number of banks reporting in richer and more developed countries is not behind the documented correlations.

The analysis was restricted to countries with at least one match, but it could be argued that that was not restrictive enough and that the finding of one or two matches might be an overinterpretation. To check this, the analysis was restricted to countries with at least two matches (making two matches the baseline). The results follow the same pattern as before (columns 7–9), indicating that countries with more than one match drive the correlations. Further restricting the sample to include only countries with at least three matches (31 countries) 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 columns 10–15 address a check for the influence of outliers on the results. Columns 10–12 take an agnostic approach and simply use a robust regression technique to reduce the influence of outliers.[16] As before, there is no important change in the results. Columns 13–15 control for the potential influence of socialist countries. Although figures 1–4 and the regressions reported in columns 10–12 show that a few countries do not drive the correlations, they also show that the group of formerly socialist countries tends to be at the extreme of the distribution of connectedness. Thus, the correlations reported may come from the difference between former socialist countries and the rest of the sample. To check for this without unnecessarily reducing the sample, a dummy variable was added that takes a value of 1 for formerly socialist countries and 0 otherwise. Reassuringly, the sign and magnitude of all the reduced-form coefficients remain unaffected (the dummy for formerly socialist countries is typically significant and in the expected direction, for example, with lower financial development).

Finally, because the quality of the information in many countries with zero matches cannot be trusted and the finding of a zero match provides very little information on the process driving the selection of bankers and politicians, the analyses were conducted again after dropping countries with zero matches. Countries with zero matches are very heterogeneous, and there is no good way of separating the zeroes resulting from data quality from the true zeroes. While this seems to be the right approach, it would be troubling if the pattern of results changed qualitatively or was even reversed when the

[16] Stata command rreg.

zeroes were considered. That was not the case (table 10). As a mild way of separating zeroes resulting from poor data from true zeroes, only the countries with zero matches and more than two banks were included.

{TABLE 10 HERE}

The unconditional regressions always result in significant coefficients of the same sign as those reported previously, and the regressions controlling for log real GDP per capita and log population size also show a similar pattern to those 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 so 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.

III. Concluding Remarks

This article 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-ranking politicians end up on bank boards of directors. Of course, this represents just one way of establishing relationships between bankers and politicians. It may not even be the most important one, but it is likely to be correlated with other forms. Although formal tests are not presented and causality is not established, the article presents pieces of reduced-form evidence that hold together better as a private interest story than as a public interest story. First, connected banks do better than unconnected ones: they are larger and more profitable, and these characteristics are not related to higher risk taking. These results are consistent with those for nonbank firms documented in the political economy literature. While a public interest view is still possible (say if politicians were attracted to good banks), in that case politicians would be expected to cluster in the best banks, which should result in a strong relation between the share of politicians on a bank's board and the bank's performance. But no such relationship was found: once a bank is connected, having more politicians on the board is not associated with better performance.

Second, connectedness 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 is regulatory capture, a conjecture supported by the finding that bank regulation is more pro-banker and of lower quality where these links are more important. If that is the direction of causality, 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 boosting efficiency, in the process incurring high social costs in the form of inhibited financial sector development and reduced access to financing for many firms. Restricting these types of connections could limit the ability of incumbent financiers to tilt regulations in their favor and impede financial sector development. It is important, however, not to draw direct, partial equilibrium policy conclusions from this exercise. If this particular avenue of connection is absent, incumbents might instead pressure regulators some other way, such as through outright bribes, that could be even more detrimental to the institutional framework.

APPENDIX. DISTRIBUTION OF THE NUMBER OF MATCHES UNDER RANDOM DRAWS.

Consider a population with N_P politicians and N_B bankers. The intersection of the two groups consists of N_{PB} banker-politicians. Two samples are taken consecutively and matched from the population of bankers and politicians with replacement at the sample level,[17] the first consisting of $n_B \leq N_B$ bankers and the second of $n_P \leq N_P$ politicians. Let X be a random variable that counts the number of matches and is 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 ways the two samples of sizes n_P and n_B can be chosen from populations of sizes N_P and N_B. 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 to choose the remaining $n_P - k$ and $n_B - k$ terms. The first term counts the ways to choose the i terms of those elements can be picked from among the rest of the members of the intersection. If the i terms are chosen in this way, they can be in only 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 can be chosen in $\binom{N_{PB} - k}{1}$ ways, and the remaining $n_B - k$ terms, which are bankers only, can be chosen in $\binom{N_B - N_{PB}}{n_B - k - 1}$ 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 those terms can be chosen in $\binom{N_P - k - 1}{n_P - k}$ only.

This distribution is used 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

[17] 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.

common pool corresponds to assuming that $N_P = N_B = N_{PB}$. In this case the probability of finding k matches simplifies to

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

APPENDIX

[TABLE A1 HERE]

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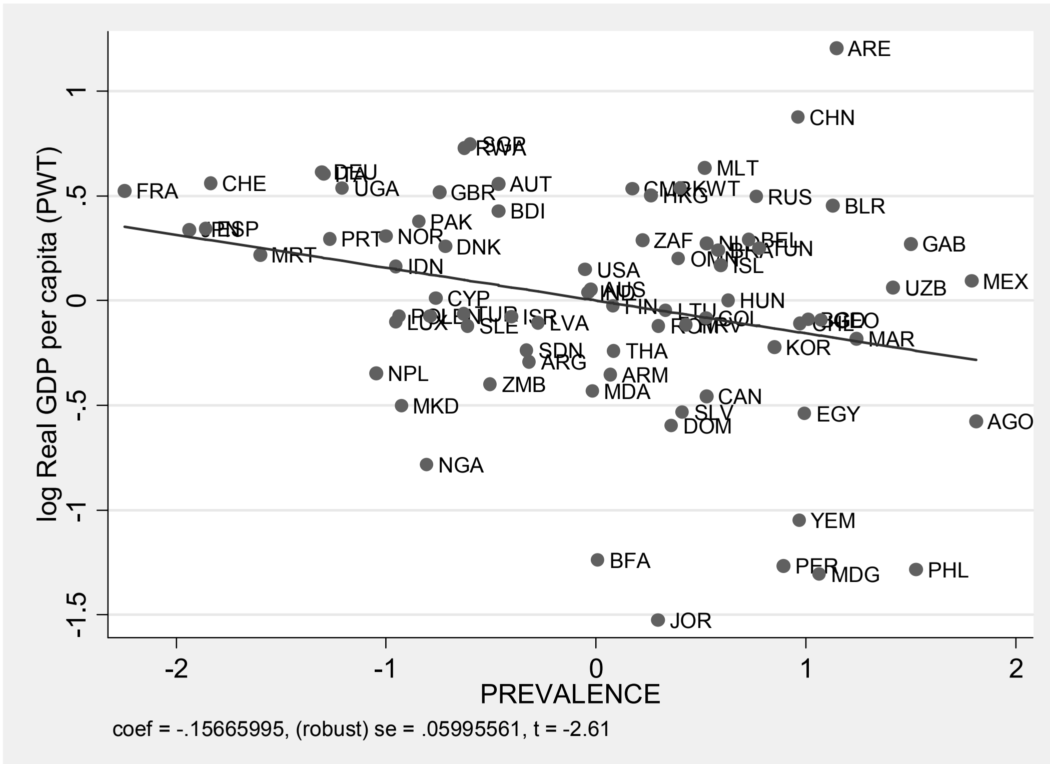
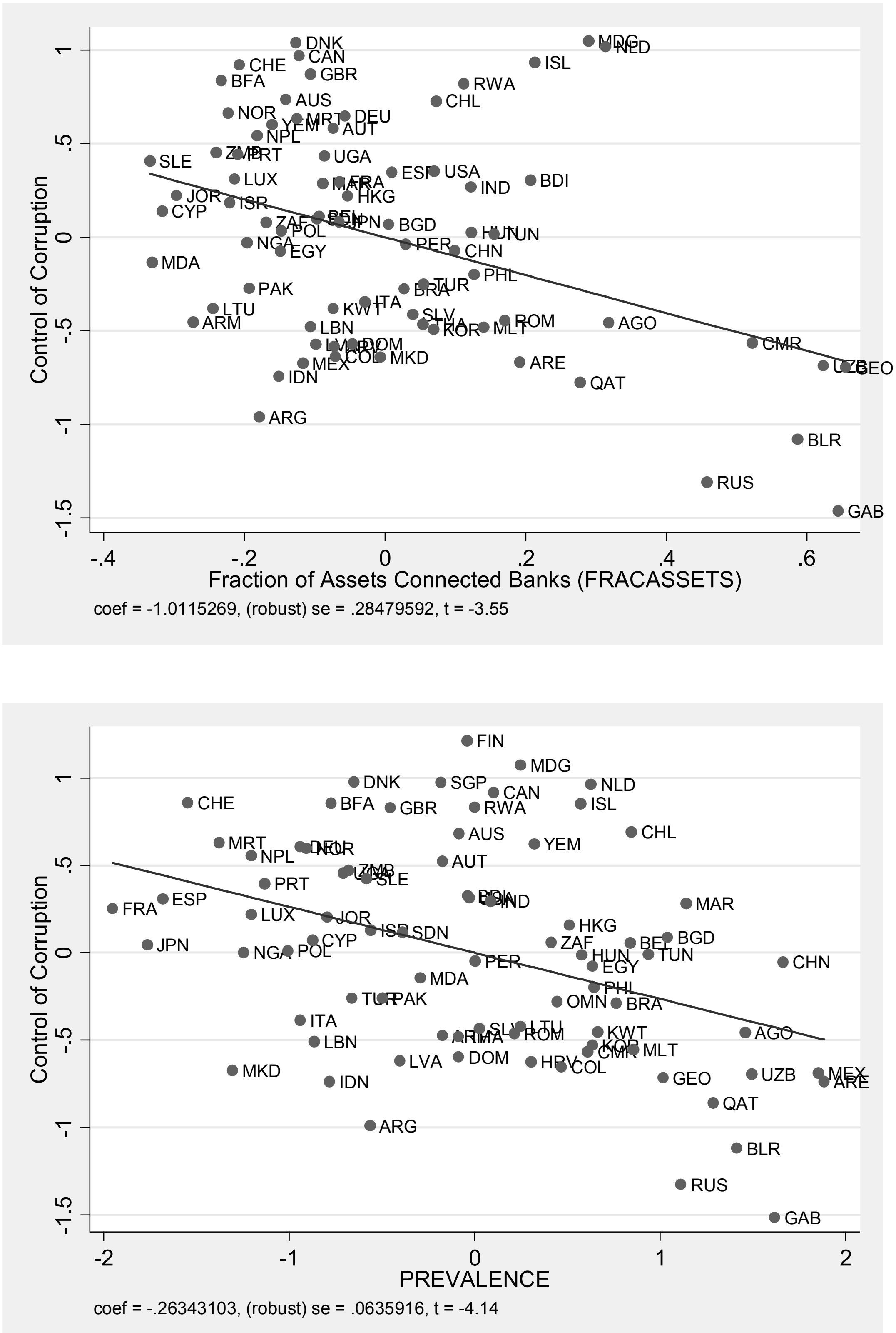
FIGURE 1. Connectedness and Development



Note: Figure shows the relation between (log) average real 1995–2005 GDP per capita (from Heston, Summers, and Aten 2006) and (log) ratio of actual to expected number of matches between bankers and politicians (*PREVALENCE*), controlling for (log) fraction of population over age 25 with a tertiary education and log population. The displayed coefficient is the value for the *PREVALENCE* measure of connectedness in the multivariate regression against log real GDP per capita. Country observations are labeled according to the World Bank's codification system (see Table 1.)

Source: Authors' analysis based on data described in the text.

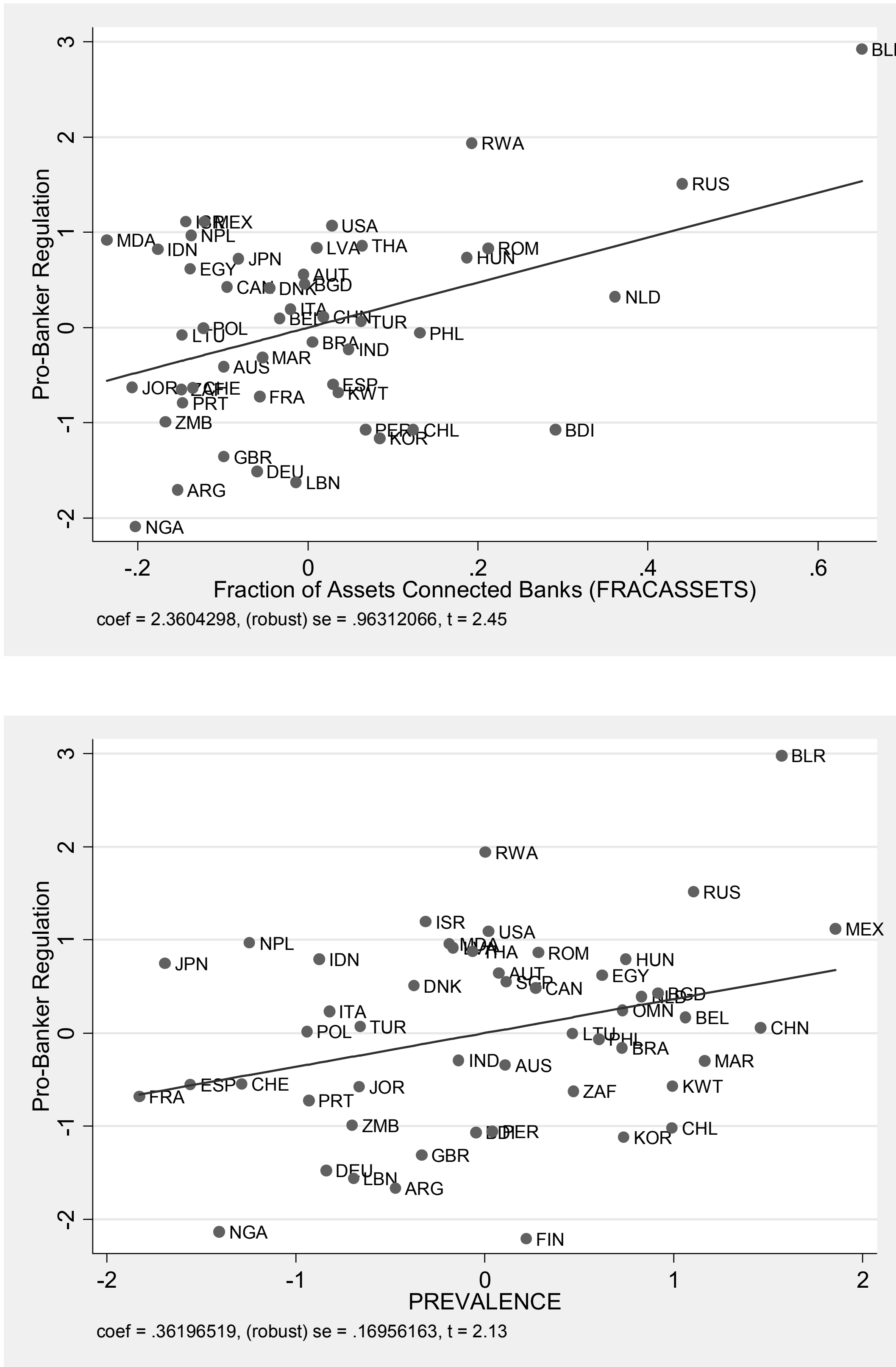
FIGURE 2. Connectedness and Institutions



Note: Figures show the relation between control of corruption (average 1996–2002 from Kaufmann, Kraay, and Mastruzzi 2004) and the fraction of total banking system assets owned by connected banks (*FRACASSETS*; top panel) and the (log) ratio of actual to expected number of matches between bankers and politicians (*PREVALENCE*; bottom panel), controlling for (log) real GDP per capita (adjusted for purchasing power parity) and log population. The displayed coefficients are the values for the two connectedness measures in the multivariate regression against control of corruption.

Source: Authors' analysis based on data described in the text.

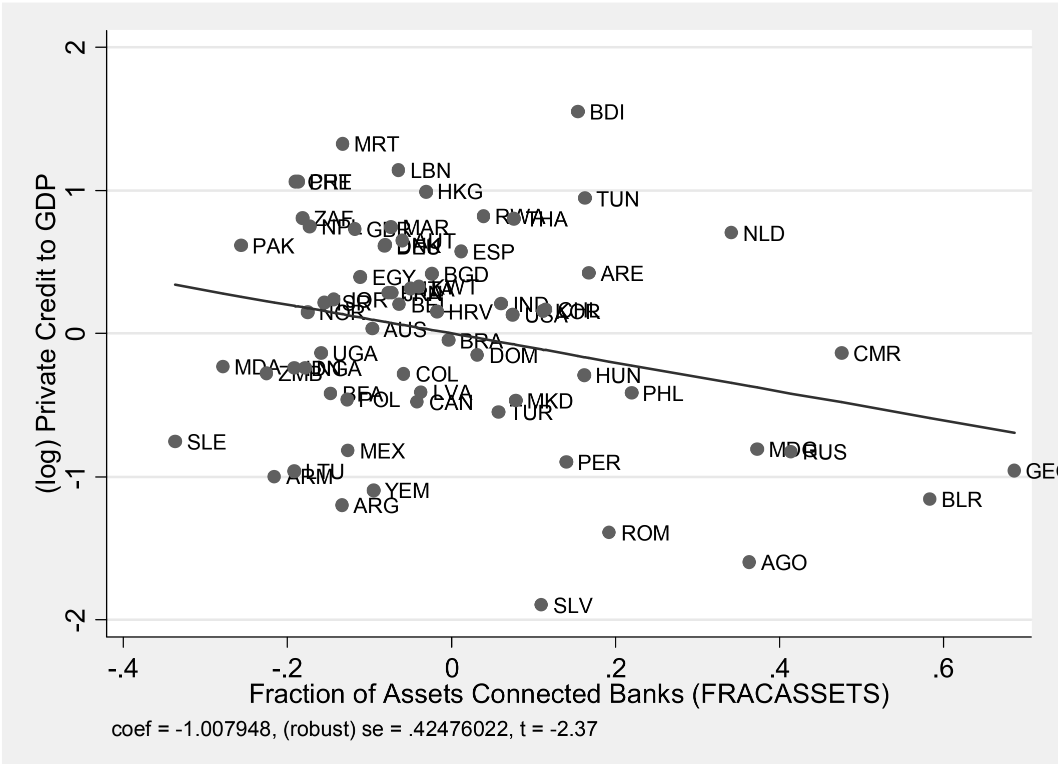
FIGURE 3. Connectedness and Pro-Banker Regulation

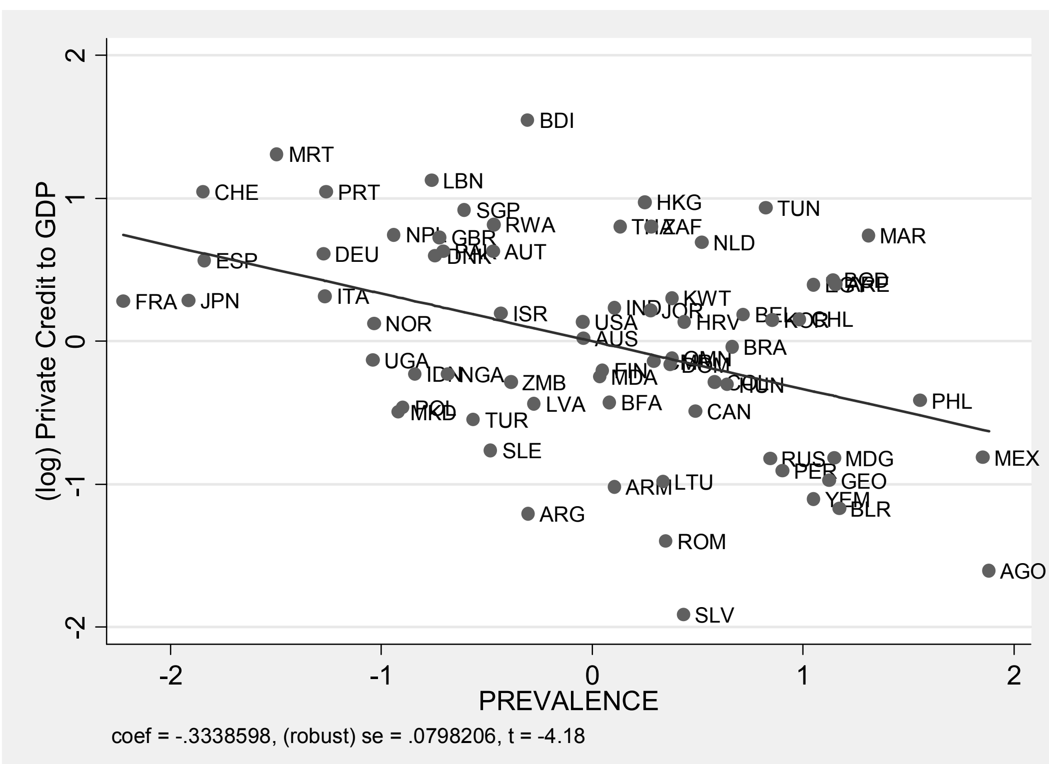


Note: Figures show the relation between the index of pro-banker regulation and the fraction of total banking system assets owned by connected banks (*FRACASSETS*; top panel) and the (log) ratio of actual to expected number of matches between bankers and politicians (*PREVALENCE;* bottom panel), controlling for (log) real GDP per capita (adjusted for purchasing power parity) and log population. The displayed coefficients are values for the two connectedness measures in the multivariate regression against pro-banker regulation.

Source: Authors' analysis based on data described in the text.

FIGURE 4. Connectedness and Financial Development





Note: The figures show the relation between the ratio of average 1995–2005 private credit to GDP and the fraction of total banking system assets owned by connected banks (*FRACASSETS*; top panel) and the (log) ratio of actual to expected number of matches between bankers and politicians (*PREVALENCE;* bottom panel), controlling for (log) real GDP per capita (adjusted for purchasing power parity) and log population. The displayed coefficients are the values for the two connectedness measures in the multivariate regression against private credit to GDP.

Source: Authors' analysis based on data described in the text.

TABLE 1. Measures of the Degree of Connectedness across Countries between Banks and Politicians

Country	World Bank Country Code	All Banks					Fully Private Banks Only				
		FRACBANKS	*SHAREASSETS*	*FRACBANKERS*	*PREVALENCE*	*MAXSHARE*	*FFRACBANKS*	*SHAREASSETS*	*FRACBANKERS*	*PREVALENCE*	*MA*
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	
Gabon	GAB	100	100	10	7.75	0.1	-	-	-	-	
Georgia	GEO	100	100	8	8.48	0.08	100	100	8	8.48	
Myanmar	MMR	100	-	19	11.93	-	100	-	19	11.93	
Angola	AGO	67	66	8	9.76	0.02	-	-	-	-	
Burundi	BDI	67	64	8	8.61	0.03	33	9	3	7.71	
Madagascar	MDG	67	68	6	9.23	0.04	100	29	14	10.05	
Cameroon	CMR	50	84	4	8.86	0.27	50	84	4	8.86	
Malta	MLT	50	53	5	6.16	0.94	0	0	0	-	
Rwanda	RWA	50	52	5	8.51	0.1	50	52	4	8.37	
Belarus	BLR	45	84	4	8.59	0.04	38	62	4	8.52	
Qatar	QAT	43	61	5	6.41	0.4	33	11	2	5.76	
Uzbekistan	UZB	40	89	5	9.73	0.02	40	89	5	9.73	
Peru	PER	38	29	2	8.14	0.09	29	12	1	7.88	
Bangladesh	BGD	35	23	2	10.44	0	35	11	2	10.27	
Morocco	MAR	33	17	3	9.39	0.02	50	17	4	9.68	
Sierra Leone	SLE	33	12	7	7.94	0.18	50	12	11	8.34	
United Arab Emirates	ARE	32	44	3	7.77	0.06	50	23	7	8.55	
Kuwait	KWT	27	20	2	6.46	0.51	43	20	3	6.96	
Tunisia	TUN	27	44	3	8.3	0.04	0	0	0	-	
Burkina Faso	BFA	25	16	2	7.98	0.64	50	16	5	8.97	
El Salvador	MRT	25	37	2	7.45	1.09	0	0	0	-	
Mauritania	OMN	25	32	2	6.42	0.58	33	32	3	6.67	
Oman	SLV	25	-	2	6.62	2.15	50	-	5	7.63	
Chile	CHL	23	30	1	8.09	0.09	25	30	2	8.11	
Jordan	JOR	22	5	2	6.64	0.64	22	5	2	6.64	
Hungary	HUN	21	37	2	7.64	0.09	27	37	2	7.85	
Colombia	COL	20	14	1	8.58	0.06	0	0	0	-	
Serbia & Montenegro	SDN	20	-	1	7.19	-	22	-	2	7.22	
Sudan	YUG	20	23	1	8.7	0.05	25	23	2	8.87	
Philippines	PHL	18	34	2	9.37	0.01	20	34	2	9.52	
Zambia	ZMB	18	17	3	8.06	0.15	22	17	3	8.24	
Armenia	ARM	17	11	3	7.15	1.47	20	11	4	7.36	
Lebanon	LBN	17	23	1	6.25	1	17	23	1	6.25	

Moldova, Rep.	MDA	17	5	4	7.37	0.23	25	5	6	7.82
Yemen	YEM	17	20	4	9.2	0.1	33	20	14	10.43
Iceland	ISL	15	60	2	5.52	1.63	14	37	2	5.31
Dominican Republic	DOM	14	25	1	7.29	1.24	0	0	0	-
Lithuania	LTU	14	7	3	6.96	1.61	14	7	3	6.96
Macedonia, FYR	MKD	14	37	1	5.57	4.96	20	37	2	5.94
Korea, Rep.	KOR	12	21	1	8.18	0.06	9	4	0	7.15
Romania	ROM	12	42	2	8.1	0.1	0	0	0	-
Croatia	HRV	11	23	3	7.17	0.13	0	0	0	-
Hong Kong, China	HKG	11	16	1	6.81	0.12	10	14	1	6.87
Latvia	LVA	11	24	2	6.19	0.6	7	20	1	6.05
South Africa	ZAF	11	2	1	8.34	0.05	12	2	1	8.46
Taiwan, China	TWN	11	9	0	-	-	4	5	0	-
Thailand	THA	11	24	1	8.13	0.08	8	23	1	8.11
Nepal	NPL	9	15	1	7.61	0.94	10	15	1	7.68
Belgium	BEL	8	10	1	7.42	0.13	7	10	1	7.01
Canada	CAN	8	1	0	7.13	0.41	10	1	0	7.37
Egypt, Arab Rep.	EGY	8	6	1	9.15	0.05	8	2	1	9.36
Israel	ISR	8	1	1	5.88	5.21	14	1	1	6.48
Turkey	TUR	8	25	1	7.72	0.1	10	25	1	7.9
Brazil	BRA	7	15	1	9.4	0.02	6	2	1	8.96
Cyprus	CYP	7	3	1	4.65	11.57	8	3	1	4.87
Nigeria	NGA	7	6	0	8.49	0.1	4	1	0	7.91
Russian Federation	RUS	7	58	1	9.51	0.01	6	7	1	9.17
Uganda	UGA	7	27	1	8.31	0.36	7	27	1	8.31
China	CHN	6	16	0	11.58	0	0	0	0	-
Finland	FIN	6	-	0	6.29	3.34	8	-	1	6.45
Austria	AUT	5	13	0	6.24	0.57	5	13	0	6.28
Netherlands	NLD	5	49	0	7.37	0.16	4	36	0	7.12
India	IND	4	22	0	10.2	0.01	4	1	0	10.29
Mexico	MEX	4	3	2	10.19	0.01	0	0	0	-
Pakistan	PAK	4	1	0	8.73	0.29	0	0	0	-
Portugal	PRT	4	1	0	5.68	6.13	4	1	0	5.75
Denmark	DNK	3	10	0	5.56	1.55	3	10	0	5.61
Indonesia	IDN	3	0	0	8.34	0.31	3	0	0	8.58
Luxembourg	LUX	3	11	0	3.54	14.88	1	4	0	2.91
Norway	NOR	3	0	0	5.1	11.46	0	0	0	-
Poland	POL	3	5	0	6.86	1.94	4	5	0	7.18
Singapore	SGP	3	-	0	5.88	4.93	3	-	0	5.93

Australia	AUS	2	2	0	6.73	2.16	0	0	0	-
Argentina	ARG	1	0	0	7.09	1.33	0	0	0	-
France	FRA	1	4	0	5.4	8.3	1	4	0	5.45
Germany	DEU	1	3	0	6.56	0.26	1	1	0	5.69
Italy	ITA	1	8	0	6.47	0.34	1	2	0	5.65
Japan	JPN	1	0	0	5.95	4.57	1	0	0	5.98
Spain	ESP	1	15	0	5.67	6.11	1	15	0	5.75
Switzerland	CHE	1	0	0	4.77	12.11	1	0	0	4.96
United Kingdom	GBR	1	0	0	6.9	0.28	2	0	0	6.98
United States	USA	1	8	0	7.82	0.07	1	7	0	7.32
Albania	ALB	0	0	0	-	-	0	0	0	-
Algeria	DZA	0	0	0	-	-	0	0	0	-
Andorra	ADO	0	0	0	-	-	0	0	-	-
Antigua & Barbuda	ATG	0	0	0	-	-	0	0	-	-
Aruba	ABW	0	0	0	-	-	0	0	0	-
Azerbaijan	AZE	0	0	0	-	-	0	0	0	-
Bahamas	BHS	0	0	0	-	-	0	0	0	-
Bahrain	BHR	0	0	0	-	-	0	0	0	-
Barbados	BRB	0	0	0	-	-	0	0	0	-
Benin	BEN	0	0	0	-	-	0	0	0	-
Bermuda	BMU	0	0	0	-	-	0	0	0	-
Bolivia	BOL	0	0	0	-	-	0	0	0	-
Botswana	BWA	0	0	0	-	-	0	0	0	-
Brunei Darussalam	BRN	0	0	0	-	-	0	0	0	-
Bulgaria	BGR	0	0	0	-	-	0	0	0	-
Cambodia	KHM	0	0	0	-	-	0	0	0	-
Cape Verde	CPV	0	0	0	-	-	0	0	0	-
Cayman Islands	CYM	0	0	0	-	-	0	0	0	-
Costa Rica	CRI	0	0	0	-	-	-	-	-	-
Côte d'Ivoire	CIV	0	0	0	-	-	0	0	0	-
Cuba	CUB	0	0	0	-	-	0	0	0	-
Czech Republic	CZE	0	0	0	-	-	0	0	0	-
Djibouti	DJI	0	0	0	-	-	0	0	0	-
Ecuador	ECU	0	0	0	-	-	0	0	0	-
Estonia	EST	0	0	0	-	-	0	0	0	-
Ethiopia	ETH	0	0	0	-	-	0	0	0	-
Gambia, The	GMB	0	0	0	-	-	0	0	0	-
Ghana	GHA	0	0	0	-	-	0	0	0	-
Gibraltar	GIB	0	0	0	-	-	0	0	-	-
Greece	GRC	0	0	0	-	-	0	0	0	-

Grenada	GRD	0	0	0	-	-	0	0	-	-
Guatemala	GTM	0	0	0	-	-	0	0	0	-
Guyana	GUY	0	0	0	-	-	0	0	0	-
Haiti	HTI	0	0	0	-	-	0	0	0	-
Honduras	HND	0	0	0	-	-	0	0	0	-
Iran, Islamic Rep.	IRN	0	0	0	-	-	0	0	0	-
Ireland	IRL	0	0	0	-	-	0	0	0	-
Jamaica	JAM	0	0	0	-	-	0	0	0	-
Kazakhstan	KAZ	0	0	0	-	-	0	0	0	-
Kenya	KEN	0	0	0	-	-	0	0	0	-
Kyrgyz Republic	KGZ	0	0	0	-	-	0	0	0	-
Lesotho	LSO	0	0	0	-	-	0	0	0	-
Libya	LBY	0	0	0	-	-	-	-	-	-
Liechtenstein	LIE	0	0	0	-	-	0	0	0	-
Macao	MAC	0	0	0	-	-	0	0	0	-
Malawi	MWI	0	0	0	-	-	0	0	0	-
Malaysia	MYS	0	0	0	-	-	0	0	0	-
Maldives	MDV	0	0	0	-	-	-	-	-	-
Mali	MLI	0	0	0	-	-	0	0	0	-
Mauritius	MUS	0	0	0	-	-	0	0	0	-
Monaco	MCO	0	0	0	-	-	0	0	-	-
Mongolia	MNG	0	0	0	-	-	0	0	0	-
Mozambique	MOZ	0	0	0	-	-	0	0	0	-
Namibia	NAM	0	0	0	-	-	0	0	0	-
Netherlands Antilles	ANT	0	0	0	-	-	0	0	-	-
New Zealand	NZL	0	0	0	-	-	0	0	0	-
Niger	NER	0	0	0	-	-	0	0	0	-
Panama	PAN	0	0	0	-	-	0	0	0	-
Papua New Guinea	PNG	0	0	0	-	-	0	0	0	-
Paraguay	PRY	0	0	0	-	-	0	0	0	-
Saint Kitts & Nevis	KNA	0	0	0	-	-	0	0	-	-
Saint Lucia	LCA	0	0	0	-	-	-	-	-	-
Samoa	WSM	0	0	0	-	-	0	0	0	-
San Marino	SMR	0	0	0	-	-	0	0	-	-
Saudi Arabia	SAU	0	0	0	-	-	0	0	0	-
Senegal	SEN	0	0	0	-	-	0	0	0	-
Seychelles	SYC	0	0	0	-	-	0	0	0	-
Slovakia	SVK	0	0	0	-	-	0	0	0	-
Slovenia	SVN	0	0	0	-	-	0	0	0	-

Sri Lanka	LKA	0	0	0	-	-	0	0	0	-
Suriname	SUR	0	0	0	-	-	-	-	-	-
Swaziland	SWZ	0	0	0	-	-	0	0	0	-
Sweden	SWE	0	0	0	-	-	0	0	0	-
Syrian Arab Rep.	SYR	0	0	0	-	-	-	-	-	-
Tanzania	TZA	0	0	0	-	-	0	0	0	-
Togo	TGO	0	0	0	-	-	0	0	0	-
Trinidad & Tobago	TTO	0	0	0	-	-	0	0	0	-
Ukraine	UKR	0	0	0	-	-	0	0	0	-
Uruguay	URY	0	0	0	-	-	0	0	0	-
Venezuela, RB	VEN	0	0	0	-	-	0	0	0	-
Vietnam	VNM	0	0	0	-	-	0	0	0	-
Zimbabwe	ZWE	0	0	0	-	-	0	0	0	-
Total		10	12	1	7.58	1.54	9	7	1	7.52

Note: Countries are sorted in decreasing order by fraction of banks with data on board of directors that had a former politician on their boards; countries with the same values are listed alphabetically. *FRACBANKS* is the fraction of banks with Bankscope data on board of directors that had a former politician on their boards. *SHAREASSETS* is the share of the total assets of banks with Bankscope data on board of directors that is represented by connected banks. *FRACBANKERS* is the fraction of bank directors that had a previous political position. *PREVALENCE i*s 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. *MAXSHARE* is the largest fraction of a country's population from which 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. Not available is coded as "-".
Source: Authors' analysis based on data described in the text.

TABLE 2. Correlation among Measures of Connectedness

Measures	All Banks					Fully Private Banks Only				
	FRACBANKS	*SHAREASSETS*	*FRACBANKERS*	*PREVALENCE*	*MAXSHARE*	*FRACBANKS*	*SHAREASSETS*	*FRACBANKERS*	*PREVALENCE*	*MAXSHARE*
FRACBANKS	1.00					1.00				
SHAREASSETS	0.88***	1.00				0.75***	1.00			
FRACBANKERS	0.92***	0.82***	1.00			0.87***	0.55***	1.00		
PREVALENCE	0.40***	0.30***	0.43***	1.00		0.56***	0.30	0.57***	1.00	
MAXSHARE	-0.30***	-0.30***	-0.31***	-0.70***	1.00	-0.32**	-0.17**	-0.25**	-0.66***	1.00***

*Significant at the 10 percent level; ** significant at the 5 percent level; *** significant at the 1 percent level.

Note: Correlations are computed including the countries with zero matches (for those measures that can take the value zero). *FRACBANKS* is the fraction of banks with Bankscope data on board of directors that had a former politician on their boards. *SHAREASSETS* is the share of the total assets of banks with Bankscope data on board of directors that is represented by connected banks. *FRACBANKERS* is the fraction of bank directors that had a previous political position. *PREVALENCE i*s 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. *MAXSHARE* is the largest fraction of a country's population from which 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.

Source: Authors' analysis based on data described in the text.

TABLE 3. Differences between Connected and Unconnected Banks, Worldwide Comparison of Average Bank Characteristics (tests of equality of means)

Bank characteristics	Connected	Unconnected	Difference
All Bankscope Banks			
Total assets	9.72	8.60	1.12***
Return on average assets	2.40	1.26	1.14***
Equity / Total assets	14.23	11.44	2.79***
Net charge-off / Average gross loans	0.70	1.24	-0.54
Fully Private Banks Only			
Total assets	9.58	8.44	1.14***
Return on average assets	2.46	1.19	1.27***
Equity / Total assets	15.20	11.17	4.02***
Net charge-off / Average gross loans	0.66	1.11	-0.45

***Significant at the 1 percent level on a simple test of means.
Source: Authors' analysis based on data described in the text.

TABLE 4. Differences between Connected and Unconnected Banks, Within-Country Comparison of Bank Characteristics (regression analysis)

	Total assets (1)	Return on average assets (2)	Equity / Total assets (3)	Net charge-off / Average gross loans (4)
All Bankscope Banks				
Connected	0.3358**	0.0062**	0.0225**	-0.0054**
	(0.1349)	(0.0025)	(0.0105)	(0.0023)
Number of observations	3,312	3,285	3,311	1,176
R^2	0.635	0.150	0.329	0.294
Fully Private Banks Only				
Connected	0.3131*	0.0079**	0.0284***	-0.0050*
	(0.1600)	(0.0031)	(0.0108)	(0.0026)
Number of observations	2,845	2,819	2,845	1,016
R^2	0.611	0.145	0.324	0.239

*Significant at the 10 percent level; ** significant at the 5 percent level; *** significant at the 1 percent level.

Note: Number in parentheses are robust standard errors. All dependent variables are in logs. Ratios that can take negative values are measured as the log of one plus the corresponding ratio. *Connected* is a dummy variable that takes a value of 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 for total assets also control for (log) total assets

Source: Authors' analysis based on data described in the text.

TABLE 5. Connectedness and Development

	No controls			Controls: log population, log fraction of population with tertiary education		
Measure	Coefficient (1)	Number of observations (2)	R^2 (3)	Coefficient (4)	Number of observations (5)	R^2 (6)
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)		
PREVALENCE	-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)		
Fully Private Banks Only						
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)		
PREVALENCE	-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)		

*Significant at the 10 percent level; ** significant at the 5 percent level; *** significant at the 1 percent level.

Note: The dependent variable is the average 1995–2005 log real GDP per capita (from Heston, Summers, and Aten 2006). Standard errors (in parentheses) are robust to heteroskedasticity. *FRACBANKS* is the fraction of banks with Bankscope data on board of directors that had a former politician on their boards. *SHAREASSETS* is the share of the total assets of banks with Bankscope data on board of directors that is represented by connected banks. *FRACBANKERS* is the fraction of bank directors that had a previous political position. *PREVALENCE i*s 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. *MAXSHARE* is the largest fraction of a country's population from which 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.

Source: Authors’ analysis based on data described in the text and table.

TABLE 6. Connectedness and Institutions

	Control of corruption[a]						Voice and accountability[a]					
	No controls			Controls: log real GDP, log population			No controls			Controls: log real GDP, log population		
	Coefficient	Number of observations	R^2	Coefficient	Number of observations	R^2	Coefficient	Number of observations	R^2	Coefficient	Number of observations	R^2
Measure	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
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)		
PREVALENCE	-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)		
Fully Private Banks Only												
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)		
PREVALENCE	-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)		

*Significant at the 10 percent level; ** significant at the 5 percent level *FRACBANKS* is the fraction of banks with Bankscope data on board of directors that had a former politician on their boards.

Note: Standard errors (in parentheses) are robust to heteroskedasticity. *FRACBANKS* is the fraction of banks with Bankscope data on board of directors that had a former politician on their boards. *SHAREASSETS* is the share of the total assets of banks with Bankscope data on board of directors that is represented by connected banks. *FRACBANKERS* is the fraction of bank directors that had a previous political position. *PREVALENCE* is 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. *MAXSHARE* is the largest fraction of a country's population from which 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.

a. Average for 1996–2002, from Kaufmann, Kraay, and Mastruzzi (2004)

Source: Authors’ analysis based on data described in the text and table.

TABLE 7. Connectedness and Regulation

	Pro-banker regulation index[a]						Regulatory quality[b]					
	No controls			Controls: log real GDP, log population			No controls			Controls: log real GDP, log population		
	Coefficient	Number of observations	R^2	Coefficient	Number of observations	R^2	Coefficient	Number of observations	R^2	Coefficient	Number of observations	R^2
Measure	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
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)		
PREVALENCE	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)		
Fully Private Banks Only												
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)		
PREVALENCE	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)		

*Significant at the 10 percent level; ** significant at the 5 percent level; *** significant at the 1 percent level.

Note: A higher number indicates more pro-banker regulation or better regulatory quality. Standard errors (in parentheses) are robust to heteroskedasticity. *FRACBANKS* is the fraction of banks with Bankscope data on board of directors that had a former politician on their boards. *SHAREASSETS* is the share of the total assets of banks with Bankscope data on board of directors that is represented by connected banks. *FRACBANKERS* is the fraction of bank directors that had a previous political position. *PREVALENCE* is 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. *MAXSHARE* is the largest fraction of a country's population from which 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.

a. Index built from Barth, Caprio, and Levine (2003) using the methodology of Burnside and Dollar (2000).

b. Average for 1996–2002 from Kaufmann, Kraay, and Mastruzzi (2004).

Source: Authors' analysis based on data described in the text and table.

TABLE 8. Connectedness and Financial Development

	No controls			Controls: log population, log real GDP per capita			Controls: log population, creditor rights, accounting standards, per capita GDP growth		
	Coefficient	Number of observations	R^2	Coefficient	Number of observations	R^2	Coefficient	Number of observations	R^2
Measure	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
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)		
PREVALENCE	-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)		
Fully Private Banks Only									
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
FRACPOLITICIANS	-21.18***	58	0.408	-9.147***	58	0.715	-23.94***	49	0.558
	(3.467)			(3.323)			(4.027)		
PREVALENCE	-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)		

*Significant at the 10 percent level; ** significant at the 5 percent level; *** significant at the 1 percent level.

Note: Standard errors (in parentheses) are robust to heteroskedasticity. The dependent variable is the (log) ratio of average 1995–2005 private credit to GDP (from Beck, Demirguc-Kunt, and Levine 2000). *FRACBANKS* is the fraction of banks with Bankscope data on board of directors that had a former politician on their boards. *SHAREASSETS* is the share of the total assets of banks with Bankscope data on board of directors that is represented by connected banks. *FRACBANKERS* is the fraction of bank directors that had a previous political position. *PREVALENCE i*s 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. *MAXSHARE* is the largest fraction of a country's population from which 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.

Source: Authors' analysis based on data described in the text and table.

Table 9. Robustness Exercises

	Controls: tertiary education, log real GDP per capita, log population			Computing connectedness on 10 largest banks only; controls: log real GDP, log population			Dropping countries with fewer than two matches; controls: log real GDP, log population			Using robust regression; controls: log real GDP per capita and log population			Controls: log real GDP per capita, log population, and former socialist countries		
	Coefficient	Number of observations	R^2	Coefficient	Number of observations	R^2	Coefficient	Number of observations	R^2	Coefficient	Number of observations	R^2	Coefficient	Number of observations	R^2
Dependent variable and measure	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Dependent variable: control of corruption[a]															
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)		
PREVALENCE	-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)		
Dependent variable: pro-banker regulation index[b]															
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)		
PREVALENCE	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)		
Dependent variable: financial development[c]															
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)		
PREVALENCE	-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)		

*Significant at the 10 percent level; ** significant at the 5 percent level; *** significant at the 1 percent level.

Note: Standard errors (in parentheses) are robust to heteroskedasticity. *SHAREASSETS* is the share of the total assets of banks with Bankscope data on board of directors that is represented by connected banks. *PREVALENCE i*s 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.

a. Average for 1996–2002, from Kauffman, Kraay, and Mastruzzi (2004).

b. Index built from Barth, Caprio, and Levine (2003) using the methodology of Burnside and Dollar (2000)..

c. Log ratio of average 1996–2002 private credit to GDP (from Beck, Demirguc-Kunt, and Levine 2000).

Source: Authors' analysis based on data described in the text

TABLE 10. Robustness Exercise Including Countries with Zero Matches

	Control of corruption[a]			Pro-banker regulation index[b]			Financial development[c]		
	Coefficient	Number of observations	R^2	Coefficient	Number of observations	R^2	Coefficient	Number of observations	R^2
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)		
FRACBANKERS	-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)		
FRACBANKERS	-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)		

*Significant at the 10 percent level; ** significant at the 5 percent level; *** significant at the 1 percent level.

Note: Standard errors (in parentheses) are robust to heteroskedasticity. All regressions include the observations with zero matches between bankers and politicians in countries with more than two banks, and all regressions control for log real GDP per capita and log population. *FRACBANKS* is the fraction of banks with Bankscope data on board of directors that had a former politician on their boards. *SHAREASSETS* is the share of the total assets of banks with Bankscope data on board of directors that is represented by connected banks. *FRACBANKERS* is the fraction of bank directors that had a previous political position. *PREVALENCE i*s 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..

a. Index of control of corruption, average 1996–2002, from Kauffman, Kraay, and Mastruzzi (2004).

b. Built by the authors using data from Barth and others (2003).

c. Log ratio of average 1996–2002.private credit to GDP(from Beck, Demirguc-Kunt, and Levine 2000).

Source: Authors' analysis based on data described in the text.

Table A1. Connectedness and Detailed Regulation

	Entry requirements						Capital requirements				
	No controls			Controls: log real GDP, log population			No controls			Controls: log real GDP, l	
	Coefficient	Number of observations	R2	Coefficient	No. of observations	R2	Coefficient	No. of observations	R2	Coefficient	No. of observatio
Measure	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
<u>All Banks</u>											
FRACBANKS	-0.334	52	0.002	-2.293	52	0.06	-0.842	52	0.017	0.00387	52
	(1.059)			(1.646)			(0.725)			(1.010)	
SHAREASSETS	0.0731	49	0	-0.276	49	0.026	-0.879	49	0.032	-0.542	49
	(0.689)			(0.792)			(0.609)			(0.606)	
FRACBANKERS	3.187	52	0.002	-12.06	52	0.033	-8.900	52	0.021	-1.190	52
	(10.05)			(13.12)			(5.792)			(8.839)	
CONNECTEDNESS	0.0203	52	0.001	-0.0795	52	0.026	-0.222**	52	0.127	-0.149	52
	(0.0930)			(0.187)			(0.0847)			(0.130)	
PREVALENCE	-0.0273	52	0.003	-0.00193	52	0.023	0.112***	52	0.09	0.0650*	52
	(0.0589)			(0.0664)			(0.0323)			(0.0367)	
<u>Fully Private Banks Only</u>											
FRACBANKS	-0.178	46	0.000	-1.485	46	0.044	-0.180	46	0.001	0.269	46
	(1.171)			(1.634)			(0.766)			(0.997)	
FRACASSETS	0.106	43	0.000	-0.379	43	0.027	-0.358	43	0.004	-0.380	43
	(1.268)			(1.409)			(0.675)			(0.702)	
FRACPOLITICIANS	8.438	46	0.009	0.414	46	0.026	-6.641	46	0.014	-7.130	46

	(8.671)			(14.16)			(7.420)			(10.38)	
CONNECTEDNESS	0.0331	46	0.001	-0.0972	46	0.031	-0.238**	46	0.148	-0.194*	46
	(0.121)			(0.218)			(0.0947)			(0.114)	
MAXSHARE	-0.0283	46	0.002	0.00911	46	0.026	0.128***	46	0.109	0.0914**	46
	(0.0683)			(0.0791)			(0.0355)			(0.0420)	

Table A1. Connectedness and Detailed Regulation (continued)

	Activities restrictions						Private monitoring				
	No controls			Controls: log real GDP, log population			No controls			Controls: log real GDP, log p	
Measure	Coefficient (13)	No. of observations (14)	R2 (15)	Coefficient (16)	No. of observations (17)	R2 (18)	Coefficient (19)	No. of observations (20)	R2 (21)	Coefficient (22)	No. observations (23)
All Banks											
FRACBANKS	2.812***	51	0.153	2.655**	51	0.271	-3.227***	52	0.226	-0.994	52
	(0.747)			(1.072)			(1.018)			(1.470)	
SHAREASSETS	1.211	48	0.05	0.665	48	0.23	-2.645***	49	0.265	-1.724**	49
	(0.751)			(0.842)			(0.602)			(0.662)	
FRACBANKERS	25.04***	51	0.137	24.68**	51	0.258	-35.31***	52	0.301	-17.65	52
	(8.104)			(11.83)			(12.58)			(17.24)	
CONNECTEDNESS	0.325***	51	0.221	0.298*	51	0.266	-0.233***	52	0.125	-0.169	52
	(0.0787)			(0.151)			(0.0865)			(0.129)	
PREVALENCE	-0.120**	51	0.085	-0.0478	51	0.209	0.103***	52	0.068	0.0202	52
	(0.0451)			(0.0577)			(0.0339)			(0.0293)	
Fully Private Banks Only											
FRACBANKS	3.276***	46	0.230	3.448***	46	0.331	-2.630*	46	0.150	-0.691	46
	(0.731)			(0.719)			(1.348)			(1.248)	
FRACASSETS	1.309	43	0.036	1.086	43	0.210	-3.480***	43	0.252	-2.731***	43
	(1.051)			(1.129)			(0.976)			(0.702)	
FRACPOLITICIANS	27.26**	46	0.157	30.72*	46	0.270	-34.50***	46	0.254	-20.47	46

	(12.08)			(15.92)			(11.71)			(15.64)	
CONNECTEDNESS	0.328***	46	0.191	0.273*	46	0.237	-0.340***	46	0.207	-0.202	46
	(0.0975)			(0.150)			(0.0744)			(0.130)	
MAXSHARE	-0.149***	46	0.101	-0.0825	46	0.200	0.132***	46	0.081	0.0268	46
	(0.0495)			(0.0636)			(0.0419)			(0.0372)	

Table A1. Connectedness and Detailed Regulation (continued)

	Overall supervisory power					
	No controls			Controls: log real GDP, log population		
Measure	Coefficient (25)	No. of observations (26)	R2 (27)	Coefficient (28)	No. of observations (29)	R2 (30)
All Banks						
FRACBANKS	0.310 (1.022)	52	0.002	0.360 (1.511)	52	0.059
SHAREASSETS	-0.607 (0.909)	49	0.013	-0.741 (0.924)	49	0.052
FRACBANKERS	-0.842 (8.829)	52	0	-4.211 (13.97)	52	0.059
CONNECTEDNESS	0.131 (0.0942)	52	0.031	-0.0293 (0.158)	52	0.058
PREVALENCE	-0.00670 (0.0678)	52	0	0.0452 (0.0720)	52	0.066
Fully Private Banks Only						
FRACBANKS	1.119 (1.011)	46	0.021	1.901 (1.354)	46	0.103
FRACASSETS	-0.175 (1.509)	43	0.001	0.0633 (1.621)	43	0.041

FRACPOLITICIANS	6.595 (11.08)	46	0.007	16.86 (19.25)	46	0.088
CONNECTEDNESS	0.188 (0.121)	46	0.048	0.0687 (0.188)	46	0.069
MAXSHARE	-0.0385 (0.0948)	46	0.005	0.0142 (0.101)	46	0.067

*Significant at the 10 percent level; ** significant at the 5 percent level; *** significant at the 1 percent level.

Note: Standard errors (in parentheses) are robust to heteroskedasticity. The dependent variable are the Barth, Caprio, and Levine (2003) principal component indexes of five dimensions of bank regulation: the degree of restrictions to entry, the magnitude of capital requirements, the extent of restrictions to cross activities, the reliance of self monitoring, and the overall authority of the regulator. All regressions include the observations with zero matches between bankers and politicians in countries with more than two banks, and all regressions control for log real GDP per capita and log population. *FRACBANKS* is the fraction of banks with Bankscope data on board of directors that had a former politician on their boards. *SHAREASSETS* is the share of the total assets of banks with Bankscope data on board of directors that is represented by connected banks. *FRACBANKERS* is the fraction of bank directors that had a previous political position. *PREVALENCE i*s 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. *MAXSHARE* is the largest fraction of a country's population from which 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.

Source: Authors' analysis based on data described in the text and table.