OLD-BOY NETWORKS, CAPITAL INJECTION, AND BANKS' RETURNS: EVIDENCE FROM JAPANESE BANKS

KAZUKI ONJI, TAKESHI OSADA, AND DAVID VERA*

Abstract. We present a novel analysis of the relation between a board's network structure and mandatory reorganization in the context of Japanese banks. Using a unique data set containing biographical information of banks' board members, we construct affiliated networks based on alma mater and hometown. We find that bank capital injections disrupt both alma mater and hometown networks: the board networks of banks that receive capital injections experience a larger drop in average number of connections and in density than those of banks with no capital injections. We also find that capital injections have negative effects on banks' returns. We circumvent the endogeneity of banks' returns and capital injections by using the proportion of former employees of the Bank of Japan and the Ministry of Finance on the boards to instrument for capital injections. Our findings suggest that capital injections negatively affected bank performance of Japanese banks in the late 1990s and early 2000s.

Keywords: Recapitalization program, Japanese banks, board network.

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Onji: Graduate School of Economics, Osaka University, E-mail kazuki.onji@econ.osaka-u.ac.j; Osada: School of Economics Graduate School of Humanities and Social Sciences Saitama University, E-mail takeshiosada@mail.saitama-u.ac.jp; Vera (corresponding author): Department of Economics, California State University, E-mail dvera@csufresno.edu. We are grateful to seminar participants at WEIA Conference (2019), International Christian University, and Hitosubashi University for their useful feedback. Vera acknowledges support from the Japan Society for the Promotion of Science International Fellowship. All remaining errors are our own.

1. Introduction

We present a novel analysis of the relation between a board's network structure and mandatory reorganization in the context of Japanese banks. Using a unique data set on the characteristics of individual board members, we estimate affiliated networks based on alma mater and hometown. Looking at hometown and alma matter network, we answer the following questions: (1) Can we find evidence of old-boy networks (OBN) in Japanese banks based on their board members' alma mater and hometown and, if so, (2) does government intervention in the form of capital injections disrupt these networks?

Also using board member's employment history data, we identify the board members whom were previously employed by either Bank of Japan (BoJ) and/or the Ministry of Finance (MoF). Exploiting this aspect of old-boy-network in Japanese, we answer the following question: (3) What is the effect of capital injections on bank performance?

Our findings are as follows: (1) There is evidence of strong affiliation networks based on members' alma mater and on their hometowns. (2) Capital injections disrupt both networks; we find that the board networks of banks that receive capital injections experience a larger drop in average number of connections and in density than those of banks with no capital injections. (3) We find that, overall, capital injections negatively affect bank performance (we consider alternative measures of banks' returns on assets and returns on equity). We circumvent the endogeneity of banks' returns and capital injections by using the proportion of former employees on the boards of the BoJ and MoF to instrument for capital injections. Our findings are robust to different subsamples of Japanese banks (a matched sample and regional banks).

Previous findings suggest that banks that receive capital injections may not meet all goals as expeditiously as intended by the regulators (Hoshi & Kashyap [2005], Onji et al. [2012]). Our results seem to support these findings.

Our study makes two contributions. We add to the literature that formally shows the existence of OBNs among board members of Japanese banks. Here, we show that the board network structure in Japanese banks is affected by capital injections. Second, our findings on bank networks, capital injections, and bank returns add to the recent literature on corporate networks and finance (El-Khatib et al. [2015], Fracassi [2016], Fracassi & Tate [2012], Kramarz & Thesmar [2013], Khanna et al. [2015]).

The remainder of this paper is organized as follows. In Section 2, we discuss the institutional background, and in Section 3, we describe the data set and stylized facts. In section 4, we describe the networks, present our empirical analysis, and check the robustness of our results using alternative samples of Japanese banks. In Section 5, we analyze the effect of capital injections on bank performance. Lastly, Section 6 concludes the paper.

2. Institutional Background

2.1. **OBN History:**

Japanese society is well known as being centered on academic credentialism, where graduates of select universities are believed to perform better in the labor market. In this context, previous studies (Kawaguchi & Ma [2008]) have found that OBNs may be a factor in the correlation between university selectivity and labor-market performance.

According to Amano (1992), OBNs began to play a role in Japan at the end of the 19th century. After the shogunate system ended in 1867, in order to catch up with Western countries, the Japanese government founded its first university in 1877 during the Japanese Modernization period. Tokyo University, as it was named, later became the current University of Tokyo. At the time, Tokyo University was the only "university" among the country's higher education institutions. Other such institutions at the time were run by the private and public sectors. For example, Keio University and Waseda University were prominent private institutions, as they still are today. However, they were not allowed to add the word "university" to their names or confer BA degrees to graduates. As a result, Tokyo University was the only university where students could obtain a BA degree until the Kyoto Imperial University was founded in 1897.

In 1886, the Japanese government launched the examination system for central government officers, from which BA graduates only were exempt. Thus, posts in the central government were monopolized by graduates from Tokyo University, resulting in a strong OBN in the Japanese public sector. In 1893, the exemption was abolished and all applicants were required to take a qualification exam. However, by then, the university's OBN had already been established in parts of the central government. As evidence, the proportion of graduates from Tokyo University to total successful applicants during the period 1894–1901 was about 60%. This trend remains in place today. For example, the proportion of Tokyo University graduates in 2015 was about 23%, which is significantly higher than that of Kyoto University in second place (8%).

Amano (1992) has established that OBNs in the banking sector were formed in the early 20th century, about 30 years after the first four commercial banks were founded in Japan in 1872. By 1880, 150 private banks were operating within Japan (Ohnuki [2005]). However, during the 19th century, not all bankers had necessarily completed a higher education. Often, bookkeeping skills were sufficient, which meant banks did not need someone with higher education. The private sector continued to grow, forming zaibatsu conglomerates, and its social status gradually improved. As a result, companies began demanding managerial staff with a higher education (e.g., being skilled in a foreign language). From the labor supply side, most government-affiliated positions were dominated by Tokyo University, forcing other graduates to work in the private sector. For example, Mitsui Bank was the first private company to hire large numbers of highly educated staff. Between 1891 and 1895, Mitsui Bank hired 20 Keio alumni, most of which took place through personal connections (the OBN), because the recruitment officer at Mitsui Bank was also an alumnus of Keio University. In this way, companies and industries began to establish their own

OBNs, which remain powerful today. For example, Waseda's OBN is known to be powerful in the media and journalism industry, whereas Keio's OBN is dominant in business.

Schaede (1995) examines the relationships between the government and firms in Japan in terms of OBNs, showing how many former government employees end up working for Japanese firms after retirement from civil service. She finds that the practice of hiring former government employees in Japan was more pervasive in the 1990s than it was in the late 1970s. Furthermore Schaede (1995) suggests that "old boys" play important roles in Japanese firms, such as allowing access to regulatory information, smoothing the firm–regulator relationship, and lobbying for the interests of firms.

As noted earlier, OBNs are a characteristic of the Japanese economy, helping to facilitate Japan's rapid economic growth during the 20th century. However, during the long-term economic slump in the 1990s and 2000s, it is possible that the nepotism embedded in OBNs decreased the efficiency of the labor market, thus preventing talented people from succeeding and worsening the Japanese economy.

2.2. **Corporate Governance and Board Structure in Japan:**

Since the late 1990s, when the Japanese economy experienced a severe financial crisis, Japanese firms have been restructuring their boards of directors. One notable change has been a reduction in the number of board members. According to Miyajima and Kasai (2010), the average number of board members for non-financial companies listed on the Tokyo Stock Exchange dropped from 15.80 to 9.01 between 1997 and 2007. For example, Sony Corporation reduced the size of its board from 40 to 10 in 1997.

Another aspect of this restructuring has been the employment of outside personnel as directors. Prior to the 1980s, almost all board members were internal personnel, promoted from within the company. Although some "external" directors existed, they were usually appointed from the "main banks" or from within the relevant "keiretsu" (a group of inter-linked firms). For example, in 1997, Sony Corporation appointed two external executives as directors. As a result, two of the 10 board members (20%) of the company were external members, which was much higher than the average number in the 1980s.

These structural reforms of Japanese firms were partly due to law amendments related to corporate boards, such as the revision of the Commercial Code in 2002 and the enactment of the Companies Act in 2005, and partly a response to the economic recession. In the past, the boards of Japanese companies had a limited monitoring function, and were primarily titular bodies. However, in response to the economic crisis, companies began changing the corporate governance of their boards, after which, the laws were amended. Sony Corporation was one of the pioneers of such changes.

2.3. **Recent Literature on Board Networks, Corporate Structure, and Returns:**

There is a stream of empirical work that examines the effects of personal connections among board members on firms' financial outcomes (Chidambaran et al. [2010], Fracassi & Tate [2012], Khanna et al. [2015], Nguyen et al. [2016]). The findings of these studies are mixed, suggesting that personal connections among board members may have positive or negative effects on a firm's financial outcomes by affecting internal governance related to the board's decision-making. On the one hand, personal connections between board members may allow them to gather information more efficiently, thus improving their decisions. On the other hand, personal connections could prevent board members from making appropriate decisions in an independent manner.

Chidambaran et al. (2010) employ firm-level US data on financial fraud for the period 2000 to 2006, finding a significant relation between the probability of fraud and CEO–board connectedness. The nature of the relationship between board members may be professional or non-professional. Non-professional connectedness (sharing educational and/or non-business antecedents) increases the probability of fraud, whereas professional connections based on common prior employment decrease the likelihood of fraud. The authors also examine how connections between board members were affected by a change in federal law, namely, the Sarbanes–Oxley Act of 2002 (SOX Act). Their findings suggest that the effects of professional connections persisted after the passing of the SOX Act, whereas those of non-professional connections lost significance. Fracassi and Tate (2012) employ biographical information on the directors of S&P 1500 companies for the period 2000 to 2007, and find that CEO–director ties weaken the intensity of board monitoring and reduce firm value. Their main measure of network ties is the social network index (SNI), which aggregates the number of the following connections between outside directors and the CEO: current employment, prior employment, education, and other activities. Khanna et al. (2015) use data for the period 1996 to 2006 on appointment-based CEO connectedness, measured as the fraction of top corporate leaders, executives, and directors appointed during the tenure of the current CEO. Their findings suggest this connectedness increases the risk of corporate fraud. Nguyen et al. (2016) examine the financial outcomes of board members' personal connections in the banking industry. They employ data on regulatory enforcement actions issued by the three main US banking supervisory authorities (FDIC, FRB, and OCC) for the period 2000-2013. Their findings show that a board's monitoring and advisory capacity are both effective in preventing misconduct in banks. They measure the quality of board monitoring using the fraction of directors who were appointed before the current CEO assumed office, and the quality of a board's advice using the number of connections a director has with those of other firms at any given time. The aforementioned two studies (Chidambaran et al. (2010), Fracassi & Tate (2012)) examine the effects of boards' education-based networks, as we do. Recent financial literature shows that various education-based networks, in addition to those within a board, affect financial decision-making and performance (Cohen et al. [2008], Shue [2013], El-Khatib et al. [2015], Fracassi [2016], Gompers et al. [2016]). Cohen et al. (2008) examine the connections between mutual fund managers and corporate board members via shared education networks. They find that portfolio managers make larger investments in connected firms, and that these perform significantly better than their holdings in non-connected firms. Their data are based on mutual fund holdings and the biographical information of managers of US equity funds and portfolios for the period 1990 to 2006. Their results suggest that social networks may be important mechanisms through which information flows into asset prices. Shue (2013) uses a historical random assignment of MBA students to sections at the Harvard Business School (HBS), and finds that executive peer networks are important determinants of managerial decision-making. Within an HBS class, firm outcomes are more similar among graduates from the same section than among graduates from different sections, with the strongest effects evident in executive compensation and acquisitions strategies. The HBS executive sample covers MBA alumni who graduated between 1949 and 2008 and who were executives of S&P 1500 firms in the period 1992 to 2008. El-Khatib et al. (2015) employ biographical information on S&P 1500 CEOs related to their educational background and prior employment, as well as their social relationships with directors and executives of U.S. public companies from 1999 to 2008. As such, they examine the effects on M&A outcomes of CEO network centrality, which measures the extent and strength of a CEO's personal connections. Their findings suggest that the effects are negative in that high-centrality CEOs use their power and influence to increase their entrenchment and to reap private benefits. Fracassi (2016) uses information on the social, educational, and professional ties between key executives and directors of S&P 1500 companies for the period 1999 to 2009, and finds that companies' capital investments become more similar as the number of connections they share increases. Gompers et al. (2016) employ investment data on individual venture capitalists for the period 1973 to 2003, and find that venture capitalists who share the same ethnic, educational, or career background are more likely to syndicate with each other. This homophily reduces the probability of investment success, and the detrimental effect is most prominent for early-stage investments. The cost of affinity is most likely attributable to poor decision-making by high-affinity syndicates after an investment is made. These results suggest that such collaboration effects can be costly.

3. Data

The main source of data on board members' alma mater, hometown, and previous employment is Toyo Keizai's *Directors' Data*, which contain individual-level information on board member characteristics. Information on education background is based on the highest qualification attained by individuals, and includes the names of universities/schools, departments within universities, and years of graduation. Information on hometown is based on that reported by each individual. Information on previous employment includes whether a board member was previously employed at the BoJ or the MoF. The *Directors' Data* covers publicly traded companies, companies registered on the over-the-counter market, and other prominent organizations. The data are available for 1993, 1996, 1998, 2003, 2006, and 2008.

4. Empirical Analysis

4.1. **Description of Banks' Board Networks:**

Using biographical information on Japanese banks' board members, we estimate two networks for each bank's board: an alma mater or school network (based on where the members obtained their highest degree), and a hometown network (based on where members were born). Because we analyze how board members of a given bank are connected directly through either school affiliation or hometown, we convert the two-mode network data to one-mode network data.[1] The advantage of examining a one-mode affiliation network between board members is that we can employ methods for analyzing such networks using

[1]The original data set on the school and hometown affiliations of each bank's board of directors can also be used to build two-mode networks. However, because our interest is the bank itself, it is more relevant to build one-mode networks, allowing us to identify connections between board members within a bank.

a bank's board as the unit of analysis. In our case, two nodes are connected in a school network if both board members attended the same alma mater; similarly, two nodes are connected in a hometown network if both members are from the same region. The networks are undirected; that is, a network simply indicates whether two nodes are connected, regardless of the direction of the connection.

In a network, each node represents a member of the board of directors, and is numbered from one to the number of board members (23, in some cases). The CEO is assigned the number one, the CFO is number two, and so on. We use the rank of the board member (e.g. CEO, CFO) as a measure of the size of a node in each network graph. In each network, node number one (the CEO) is also the largest.

A network can be presented as a sociomatrix, with equal numbers of rows and columns, each representing a board member of a bank (in identical order). An entry in the sociomatrix codes an affiliation from the row actor to the column actor. When two board members of a given bank have the same alma mater (or the same hometown), the entry in the sociomatrix takes the value one, and zero otherwise.

The information from the sociomatrix can be illustrated graphically. As Wasserman and Faust (1994) point out, graphs are useful in network analyses because they provide the vocabulary necessary to denote the social structure and its properties. Graph theory provides the mathematical background for quantifying the properties of a network; that is, a graph is a model (albeit a simplified one) of the network.

Figures 1–9 show the evolution of the banks' school networks. For example, Figure 1 depicts the network for the board members of Hokuriku Bank for 1993, 1998 (pre-injection), and 2003 (post-injection). The network for Hokuriku Bank appears to change over time. Although somewhat well connected in 1993, the school network becomes less "dense" and less "connected" over time, and shrinks after the capital injection. The school networks for the other banks follow similar patterns.

Figures 10–18 show the evolution of the banks' hometown networks. For example, Figure 10 depicts the network for Hokuriku Bank for 1993, 1998 (pre-injection), and 2003 (post-injection). Overall, the hometown networks of the banks that received capital injections appear to be denser than their school networks. However, as in the case of the school networks, the hometown networks appear to shrink, becoming less "dense" and less "connected" after the capital injection.

4.2. **Network Features:**

The board member networks are examples of a nondirectional affiliated network. The modeling unit is the board of the financial institution, where the actors are the boards members of a bank, and the affiliations are determined either by alma mater or hometown. The network maps or graphs presented here are useful for identifying and illustrating the changes in the network structures over time. However, specific network metrics can allow us to track further changes in each network, as well as make statistical comparisons between the networks of banks that received capital injections and those that did not.

In order to compare the evolution of the networks over time, we estimate the following properties for each network: size, density, and mean degree. Before discussing the summary statistics, we briefly define each property.

The number of nodes in a network (i.e., the number of board members) determines the **size** of the network.

As described by Jackson (2014), network density is the most basic global property of a network. Global features of networks play important roles in diffusion and social learning. The **density** of a network is defined as:

$$\text{Density} = \frac{\text{Actual Connections}}{\text{Potential Connections}},$$

where potential connections $= \frac{n*(n-1)}{2}$, where n is the number of nodes.

Density is 100% if the actual connections between nodes is the same as the number of potential connections.

In undirected networks, the degree is the number of connections of a node. For example, the degree of node i (a given board member in a given network) is the number of connections it has within the board. The **mean degree** is the average number of connections in a network per node.

Table 1 provides the summary statistics for the alma mater (school) network properties for all banks, injected banks, and non-injected banks, averaged over all years (1993, 1996, 1998, 2003, 2006, 2008). Based on Toyo Keizai's *Directors' Data*, we identify 602 networks based on alma mater or school affiliation, of which 59 correspond to injected banks and 543 to non-injected banks. Injected banks' networks are slightly smaller than those of non-injected banks (16.44 vs. 18.69, respectively). While the average density of injected and non-injected school networks is the same (0.10) for both sets of banks, the school networks of injected banks have a lower mean degree than that of non-injected banks (1.55 vs. 2.1, respectively).

Table 2 provides the summary statistics for the hometown network properties for all banks, injected banks, and non-injected banks, averaged over all years (1993, 1996, 1998, 2003, 2006, 2008). Based on Toyo Keizai's *Directors' Data* we have 473 networks based on hometown affiliation, of which 46 correspond to injected banks and 427 to non-injected banks. Injected banks' networks are smaller (15.61 vs. 17.79, respectively) and have a lower density (0.48 vs. 0.57, respectively) and mean degree (6.75 vs. 8.73, respectively) than those of non-injected banks.

4.3. **Empirical Model:**

To motivate our empirical approach, we present the evolution of the networks of capital inject and non injected of banks graphically. Figure 19 presents the average size, average density, and mean degree for the school network for injected and non-injected banks over time. In Figure 19(a), we can see that the average sizes of all banks decrease over time. However, the effect is stronger for injected banks, starting in 2003. The effect on density shown in Figure 19(b) is more difficult to gauge because the average network densities of injected and non-injected banks follow somewhat different patterns. Figure 19(c) appears to suggest that, starting in 2003, the mean degrees of non-injected bank networks decrease by more than those of injected banks. However, the effect is not as strong as that for network size.

Figure 20 presents the average size, average density, and mean degree for the hometown network, based on members' reported hometowns. Figure 20(a) shows a similar pattern to that shown in Figure 19(a).

The capitalization of banks (or injection of capital into Japanese banks) occurred in two rounds. The amounts were proportional to a bank's size, and not all banks were capitalized in both rounds. Our empirical approach aims to capture the differential effects of the capital injection on each network for injected versus non-injected banks, taking into account some of the complexity of the capitalization process. The following model is akin to a difference-in-differences estimation that compares injected and non-injected banks, and accounts for heterogenous treatments among the injected or treated banks (in terms of timing and intensity):

$$y_{it} = \beta_0 + \beta_1 \text{injection measure} + \alpha_i + \tau_t + \epsilon_{it} \tag{1}$$

where y_{it} is a network feature (i.e., size, density, or mean degree) for the board of bank i at time t. The coefficient β_1 on **injection measure** captures the effect of the capital injection on a given board's network feature. α_i accounts for bank specific fixed effects. τ_t accounts for the year fixed effects to control for changes that may have impacted all banks (e.g., changes in board culture),[2] and ϵ_{it} is a heteroskedastic error with no serial correlation, clustered at bank level.

The bank capital injections in Japan were implemented through two programs: the Financial Functions Stabilization Act (FFSA) of 1998, and the Early Strengthening Act (ESA) between 1999 and 2002. Thus, to better assess the effect of a capital injection on a bank's board network, we use the following alternatives to **injection measure**:

(1) **injection**: A dummy variable, set equal to one after the first round of injections (capital injections under the FFSA).

(2) $\mathbf{injection}_{t-1}$: Lagged **injection**. In this case, we assume that a capital injection from the FFSA may affect the network with a lag and at the same time as a capital injection from ESA.

(3) **intensity**: To capture the strength of an injection, we create the following variable: $\mathbf{intensity} = \frac{\mathbf{injection\ amount}}{\mathbf{total\ assets}}$. In this case, we set intensity equal to the average injection under both programs (FFSA & ESA).

(4) $\mathbf{intensity}_{t-1}$: The intensity variable is lagged to capture the potential delayed effect of the average injection.

(5) $\mathbf{intensity}_{1998}$: Captures the effect of the FFSA capital injection only.

(6) $\mathbf{intensity}_{2003}$: Captures the effect of the ESA capital injection only.

(7) $\mathbf{intensity}_{1998}^{lagged}$: Captures the potential delayed effect of the FFSA injection only.

[2]One of the important changes was the amendment to the Commercial Code in 2002, which aligned the Japanese corporate structure with that of the United States. However, many banks had already adopted the American corporate structure earlier than this. We are grateful to one of the reviewers for pointing this out.

4.4. **Results:**

School network

We start by examining the effects of the capital injection on the school network features using the simplest version of the injection variable (dummy variable). Table 4 presents the results from model 1 for size, density, and mean degree. Columns (1)–(3) of Table 4 show that the contemporaneous effect of the capital injection is negative for all network features, but only statistically significant in the case of size. The coefficient on injection in column (1) suggests that banks that received a capital injection shed two additional board members compared with those banks that did not receive an injection. Columns (4)–(6) of Table 4 show the results of the lagged injection dummy on all network features. The coefficient in column (4) is now larger, suggesting that the boards of injected banks have at least three fewer board members compared with banks that did not receive an injection. The sign of the coefficient on the lagged injection in the case of mean degree is also negative, albeit non-significant.

Table 5 presents the results for the alternative versions of the capital-injection variable. The overall finding on school network size (see Columns (1), (4), (7), and (10)) suggests that the decrease in board network size of injected banks is robust to alternative specifications of the injection variable. The capital injections appear to have reduced the number of board members significantly, with estimates ranging from a decrease of between one and 16 board members. The mean degree (see Columns (3), (6), (9), and (12)) also seems sensitive to the capital injection. Here, it appears that the board networks of banks that received a capital injection experienced a decrease in the number of connections between board members, regardless of size.

Hometown network

Next, we turn to the effects of the capital injection on the hometown network features.

Table 6 presents the results for model 1 for size, density, and mean degree. Columns (1)–(3) of Table 6 show that the contemporaneous effect of a capital injection is negative for all network features, and is statistically significant in the case of size and density. Columns (4)–(6) show the result for the lagged injection dummy on all network features. These results are negative for all network features, and are statistically significant in the case of size and mean degree.

Table 7 presents the results for the alternative versions of the capital-injection variable. The overall findings on network size (see Columns (1), (4), (7), and (10)) suggest that the decrease in the board network size of injected banks is robust to the alternative specification of the injection variable. Capital injection appears to have reduced the number of board members significantly, with estimates ranging from one to eight board members. Results on density (see Columns (2), (5), (8), and (11)) are negative for all estimations, but only statistically significant in the case of *intensity*, which captures the strength of the injection. The results on mean degree (see Columns (3), (6), (9), and (12)) are also negative for all estimations and statistically significant in the case of $intensity_{t-1}$ and $intensity_{2003}$.

It appears that the board networks of banks that received a capital injection experienced a decrease in the number of connections between board members in terms of the hometown network.

4.5. **Comparison with a Matched Sample:**

Our findings from the previous section suggest that, for the school network, the size and the mean degree of capital-injected banks decreased during the injection period, 1998–2003, as compared with non-injected banks. We consider these findings as a baseline scenario, where neither injected banks (treated) nor non-injected banks (control) were selected randomly. It is possible that injected banks differ from non-injected banks in ways that make government rescue more likely, and that will also lead to biased results when comparing changes in the networks. For instance, it is possible that banks with a high-density network have a prevailing OBN mentality, where nepotism and connections determine who becomes part of the network. If banks with an OBN structure are more likely to be run less efficiently, they are also more likely to require government support through a capital injection. In this scenario, the coefficient of an injection will be biased.

As an additional robustness check, we create a more comparable group of non-injected banks using propensity-score matching. Here, we identify a sample of non-injected banks that are similar to the injected banks across many dimensions before a capital injection occurs. The propensity score estimates the likelihood that a financial institution will receive a capital injection. The estimate is based on observable characteristics prior to the injection period. We estimate the propensity score for each bank using the following set of covariates: workers' average age, return on assets, bank size, number of workers, and number of job applicants.[3]

School network

Table 8 and Table 9 present the results for the matched sample. The effect of injections on the size of the hometown network is still significant under the alternative specifications (see Table 8, Column (4), and Table 9, Columns (1), (4), (7), and (10)). In contrast to our results on the full sample, only the lagged capital injection of 1998 seems to have a significant effect on the mean degree in the matched sample (see Table 9, Column (12)).

Hometown network

Table 10 and Table 11 present the results for the matched sample for the hometown network. The effect of the injections on the hometown network size is still significant under the alternative specifications (see Table 10, Columns (3) and (4), and Table 11, Columns (1), (3), (4), (7), (9), (10), and (12)). In contrast to our results on the full sample, we do not have significant results for *density*. In addition, we find positive and significant effects of $intensity^{lagged}_{1998}$ on *mean degree* in the match sample (see Table 11, Column (12)).

[3]Onji et al. (2017) use a similar procedure to identify a controlled sample.

4.6. **Regional Banks Only:**

An important aspect of the Japanese banking system is the difference between city and regional banks. City banks are larger and tend to be more diversified than regional banks. In addition to being smaller, most of the assets of regional banks are based on regional credit provision. During the capitalization program, all city banks received a capital injection, either during wave one or wave two. However, not all regional banks received capital injections. In spite of our finding being robust to a matched sample analysis, it is still possible that the heterogeneity in a sample that includes both city and regional banks could bias the results. For instance, a few city banks as outliers could drive our findings on the effect of capital injections on the banks' board networks. Therefore, we estimate this effect for regional banks only. The findings mirror those for the sample of all banks and the matched sample. Overall, capital injections appear to reduce the size of the board network in banks that received a capital injection for both school and hometown networks. [4]

5. Effect of Capital Injections on Bank Performance

Thus far, we have examined how capital injections affected the board networks of Japanese banks, and found that they disrupted the networks of those banks that received a capital injection. These findings have an important economic implication. However, we have not yet examined the link between capital injections and bank performance in the context of the network features. In order to investigate this relationship, we use additional information contained in Toyo Keizai's *Directors' Data* on directors' previous employment. Our analysis is motivated by the Japanese labor market practice of "Amakudari". This is a common practice in the Japanese labor market, akin to a "golden parachute," where retired regulators join the board of directors of a bank (as well as the boards of non-financial

[4] These results are available upon request.

firms). Amakudari officers can facilitate a relationship between a bank and regulatory agencies. In the case of Japanese banks these are board members who previously worked for the main bank regulators: the Bank of Japan (BoJ) and/or the Minister of Finance (MoF). In our analysis we look at the proportion of board members who previously worked for the BoJ and/or the MoF.

Table 3 provides the summary statistics for the ratio of former BoJ and MoF officers to total board members, averaged over all years in the sample. The sample contains 556 networks, of which 71 correspond to injected banks and 485 are non-injected banks.
Injected banks have a higher ratio of former BoJ and MoF officers on their boards than do non-injected banks in terms of the mean value (6% vs. 5.1%, respectively). Thus, it's possible that injected banks have a stronger connection with the BoJ and MoF than non-injected banks do. In order to determine the effect of a capital injection on bank performance, we posit that the presence of former BoJ and MoF officers in a board may facilitate the restructuring plans set between regulators and a bank, thus we can use it to instrument for capital injections.[5]

We estimate the following two-stage least squares model. In the first stage, we estimate the relation between our various injection measures and the proportion of BoJ and MoF members, as follows:

$$1^{st} - \text{stage} : \text{injection measure}_{it} = \alpha_0 + \alpha_1 \text{Fraction of BOJandMOF members}_{it} + \eta_i + \delta_t + \upsilon_{it}.$$

In the second stage, we use the fitted value of the injection measure from stage 1 to determine how a capital injection affects bank performance.

[5]The underlying assumption is that bank's returns are uncorrelated with the proportion of former BoJ and MoF officers in the bank's board. As we discuss in detail in this section, this is the exclusion condition in the 2SLS approach.

$$\text{Performance}_{it} = \beta_0 + \beta_1 \widehat{\text{injection measure}}_{it} + \eta_i + \delta_t + \epsilon_{it}, \quad (2)$$

where Performance_{it} is a performance measure for bank i at time t, $\widehat{\text{injection measure}}_{it}$ is the fitted value from the first stage, η_i is a bank fixed effect, and δ_t accounts for the year fixed effects to control for changes that may have impacted all banks. Both υ_{it} and ϵ_{it} are stochastic error terms.

In the second stage, we consider four measures of Performance: ordinary income over assets (ROA), net business income (ordinary income - non-performing loans written off) over assets (ROANET), ordinary income over equity capital (ROE), and net business income over equity capital (ROENET).

As shown in the 1^{st} – stage, we circumvent the endogeneity of banks' returns and our injection measure by using the proportion of former employees of the BoJ and MoF on a bank's board .

Our underlying assumptions are (1) a higher proportion of former employees of the BoJ and MoF on a bank's board is a determinant of capital injection (inclusion condition); (2) a higher proportion of former employees of the BoJ and MoF on a bank's board does not directly affect bank performance (exclusion condition).

We cannot test the exclusion condition empirically, as pointed out in the literature (Shaede (1995) notes that "amakudari" board members or former government employees helped access regulatory information and with lobbying) because these board members may not have been directly involved in the management of the firm and, thus, may not have affected the banks' performance. Furthermore, the results documented in the literature indicate that the effect of " amakudari" board members on a bank's risk is non-significant (Konishi & Yasuda [2004]).[6] With regard to the inclusion condition, Figure 21 shows that

[6]Konishi and Yasuda (2004) show theoretically that the effect of "amakudari" on a bank's risk-taking can be positive or negative. On the one hand, by facilitating and improving the efficiency of risk-relevant

injected banks appointed more former BoJ and MoF officers than non-injected banks did, and that this difference pre-dates any capital injections.

We now discuss the results of the 2SLS for all banks in the sample.[7]

Table 12 presents the estimates for the effect of capital injections on the ROA. Among the six capital-injection specifications, we have two significant results (Columns (1) and (4)), both showing that capital injections have significant and negative effects on ROA. Table 13 presents the results for the effect of a capital injection on the ROANET. The effect is negative and significant for four of the measures of capital injections.
As an alternative to the return on assets measures (ROA and ROANET), we estimate the effect of a capital injection on return on equity (ROE) and on return on equity using net business income (ROANET). Table 14 shows that capital injections reduced the ROE, and that the effect is negative for all six measures of injections and significant for four of the measures. Table 15 shows that capital injections decreased the ROENET, and that this result is consistent across the measures of capital injections.

Overall our results suggest that a capital injection has a negative effect on bank performance, on average, and that these results are robust for a matched sample and for a sample containing regional banks only. We hypothesize that the negative effect of a capital injection on bank performance is possibly caused by a delay in the injected banks implementing the restructuring plans, which has a negatively effect on their financial health.

information to regulators, an " amakudari" officer may provide incentives to reduce risk-taking behavior. On the other hand, it is possible that "amakudari" officers reduce the monitoring intensity by regulators, thus increasing risk-taking behavior. Their results suggest that the first effect dominates the second. Thus, "amukadari" officers do not increase banks' risking-taking behavior.

[7]The results for the matched sample and the regional banks are consistent. These additional results are available upon request.

6. Conclusion

Using data on alma mater affiliations and the hometowns of board members, we construct the networks of the boards of Japanese banks. We provide evidence supporting the existence OBNs; that is, the alma mater and hometown seem to be important factors in determining board membership. However, the importance of alma mater affiliation and, to a lesser extent, hometown seem to have decreased over time.

We considered three features of board networks: the size, density, and mean degree of both the school network and the hometown network. Our findings show that the network sizes of banks that received an injection decreased compared with those of other banks. We find no significant difference between the network density of injected and non-injected banks. The results for the mean degree of injected banks are mixed. If we assume that a capital injection has a delayed effect, it is possible that the mean degree of injected banks decreased compared with that of non-injected banks. Our findings are robust for a matched sample and for a sample containing regional banks only.

The findings on network size suggest that a capital injection may have strong effects on the corporate board structure in Japanese banks, thus disrupting the OBN structure.

Furthermore, we use the proportion of board members previously employed by the BoJ and MoF to determine how capital injections affect bank performance. In order to circumvent the endogeneity of banks' returns and capital injections, we estimated two-stage least-squares models using the aforementioned proportion to instrument for capital injections. Our findings suggest that, overall, capital injections had a negative effect on Japanese banks' performance (e.g., ordinary income over assets (ROA), net business income (ordinary income - non-performing loans written off) over assets (ROANET), ordinary income over equity capital (ROE), and net business income over equity capital (ROENET)).

Consistent with the existent literature (Hoshi and Kashyap [2005] and Onji, Vera and Corbett [2012], Onji, Osada and Vera [2017]), banks that participated in capital injection programs may have delayed or may not have acted as expeditious at implementing structural reforms to improve their financial health.

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Table 1. Summary of School Network Properties

Panel A: All Banks					
Statistic	N	Mean	St. Dev.	Min	Max
Size	595	18.55	8.06	2	75
Density	595	0.10	0.08	0.00	0.51
Mean degree	595	2.05	2.55	0.00	25.23
Panel B: Injected Banks					
Statistic	N	Mean	St. Dev.	Min	Max
Size	59	16.44	5.48	7	29
Density	59	0.10	0.06	0.00	0.28
Mean degree	59	1.55	0.96	0.00	5.59
Panel C: Non-injected Banks					
Statistic	N	Mean	St. Dev.	Min	Max
Size	536	18.79	8.26	2	75
Density	536	0.10	0.08	0.00	0.51
Mean degree	536	2.11	2.67	0.00	25.23

TABLE 2. Summary of Hometown Network Properties

Panel A: All Banks					
Statistic	N	Mean	St. Dev.	Min	Max
Size	587	18.51	8.09	2	74
Density	587	0.55	0.29	0.03	1.00
Mean degree	587	8.69	4.57	0.36	20.00
Panel B: Injected Banks					
Statistic	N	Mean	St. Dev.	Min	Max
Size	59	16.44	5.48	7	29
Density	59	0.47	0.28	0.06	1.00
Mean degree	59	7.05	4.24	0.50	18.00
Panel C: Non-injected Banks					
Statistic	N	Mean	St. Dev.	Min	Max
Size	528	18.74	8.30	2	74
Density	528	0.56	0.29	0.03	1.00
Mean degree	528	8.88	4.57	0.36	20.00

TABLE 3. Ratio of Former Bank of Japan (BoJ) and Minister of Finance (MoF) Officers to the Total Banks Board Members

Statistic	N	Mean	St. Dev.	Min	Max
All banks	704	0.05	0.06	0.00	0.26
Injected banks	71	0.06	0.07	0	0.26
Non-injected banks	633	0.04	0.06	0.00	0.23

Table 4. Effect of Capital Injection on School Network

	Dependent variable:					
	size	density	mean degree	size	density	mean degree
	(1)	(2)	(3)	(4)	(5)	(6)
injection	-4.387**	-0.005	-0.690**			
	(0.879)	(0.016)	(0.249)			
injection_{t-1}				-5.946**	-0.004	-0.640*
				(1.914)	(0.025)	(0.281)
Constant	20.311**	0.121**	2.526**	20.419**	0.121**	2.544**
	(0.265)	(0.004)	(0.098)	(0.273)	(0.004)	(0.101)
Observations	595	595	595	595	595	595
R-squared	0.470	0.096	0.203	0.454	0.096	0.190
Number of Banks	128	128	128	128	128	128

Note: *p < 0.1; **p < 0.05; ***p < 0.01. Robust standard errors in parentheses.

Table 5. Effect of Capital Injection on School Network Using Intensity Measures

	Dependent variable:											
	(1) size	(2) density	(3) mean degree	(4) size	(5) density	(6) mean degree	(7) size	(8) density	(9) mean degree	(10) size	(11) density	(12) mean degree
intensity	-5.369**	-0.008	-0.666**									
	(1.397)	(0.023)	(0.247)									
intensity_{t-1}				-5.070**	-0.004	-0.545*						
				(1.937)	(0.022)	(0.250)						
intensity_{1998}							-7.505**	0.019	-0.890*			
							(1.889)	(0.012)	(0.386)			
intensity_{2003}							-1.916**	-0.008	-0.244+	-1.800**	-0.008	-0.236+
							(0.531)	(0.013)	(0.130)	(0.499)	(0.013)	(0.129)
$\text{intensity}_{1998}^{lagged}$										-10.714**	0.039**	-0.976**
										(0.542)	(0.008)	(0.177)
Constant	20.387**	0.121**	2.540**	20.428**	0.121**	2.545**	20.343**	0.121**	2.535**	20.405**	0.121**	2.543**
	(0.270)	(0.004)	(0.101)	(0.277)	(0.004)	(0.101)	(0.259)	(0.004)	(0.100)	(0.264)	(0.004)	(0.101)
Observations	595	595	595	595	595	595	595	595	595	595	595	595
R-squared	0.457	0.096	0.193	0.435	0.096	0.188	0.486	0.099	0.197	0.505	0.102	0.195
Number of Banks	128	128	128	128	128	128	128	128	128	128	128	128

Note: The regressions include bank and year fixed effects. Robust standard errors in parentheses.
$^{+}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 6. Effect of Capital Injection on Hometown Network

	Dependent variable:					
	size	density	mean degree	size	density	mean degree
	(1)	(2)	(3)	(4)	(5)	(6)
injection	-3.521**	-0.019	-0.859+			
	(0.761)	(0.033)	(0.514)			
injection$_{t-1}$				-4.162**	-0.039	-0.933
				(1.347)	(0.063)	(0.962)
Constant	20.322**	0.549**	9.610**	20.412**	0.550**	9.632**
	(0.268)	(0.012)	(0.215)	(0.275)	(0.011)	(0.212)
Observations	587	587	587	587	587	587
R-squared	0.455	0.009	0.220	0.432	0.009	0.217
Number of Banks	127	127	127	127	127	127

Note: *p < 0.1; **p < 0.05; ***p < 0.01. Robust standard errors in parentheses.

Table 7. Effect of Capital Injection on Hometown Network Using Intensity Measures

	Dependent variable:											
	(1) size	(2) density	(3) mean degree	(4) size	(5) density	(6) mean degree	(7) size	(8) density	(9) mean degree	(10) size	(11) density	(12) mean degree
intensity	-4.682**	-0.068	-1.863**									
	(1.250)	(0.050)	(0.621)									
intensity_{t-1}				-3.853**	-0.069	-1.581*						
				(1.450)	(0.055)	(0.681)						
intensity_{1998}							-6.067**	0.010	0.289			
							(1.625)	(0.017)	(0.394)			
intensity_{2003}							-1.800**	-0.040	-1.109**	-1.717**	-0.041	-1.118**
							(0.561)	(0.028)	(0.300)	(0.536)	(0.028)	(0.296)
$\text{intensity}_{1998}^{lagged}$										-10.551**	0.016	0.939
										(0.963)	(0.038)	(0.738)
Constant	20.340**	0.549**	9.607**	20.380**	0.549**	9.623**	20.299**	0.549**	9.621**	20.352**	0.549**	9.619**
	(0.264)	(0.011)	(0.213)	(0.269)	(0.011)	(0.213)	(0.258)	(0.012)	(0.213)	(0.263)	(0.011)	(0.212)
Observations	583	583	583	583	583	583	583	583	583	583	583	583
R-squared	0.449	0.018	0.222	0.425	0.015	0.215	0.465	0.020	0.225	0.471	0.020	0.226
Number of Banks	127	127	127	127	127	127	127	127	127	127	127	127

Note: The regressions include bank and year fixed effects. Robust standard errors in parentheses.
$^{+}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 8. Effect of Capital Injection on School Network (Matched Sample)

	Dependent variable:					
	size	density	mean degree	size	density	mean degree
	(1)	(2)	(3)	(4)	(5)	(6)
injection	-3.591**	-0.009	-0.537			
	(1.192)	(0.029)	(0.445)			
injection_{t-1}				-3.281*	-0.010	-0.394
				(1.321)	(0.031)	(0.345)
Constant	20.084**	0.128**	2.515**	20.135**	0.128**	2.523**
	(0.498)	(0.007)	(0.185)	(0.497)	(0.007)	(0.187)
Observations	251	251	251	251	251	251
R-squared	0.521	0.174	0.255	0.501	0.174	0.248
Number of Banks	47	47	47	47	47	47

Note: *p < 0.1; **p < 0.05; ***p < 0.01. Robust standard errors in parentheses.

Table 9. Effect of Capital Injection on School Network Using Intensity Measures (Matched Sample)

	Dependent variable:											
	(1) size	(2) density	(3) mean degree	(4) size	(5) density	(6) mean degree	(7) size	(8) density	(9) mean degree	(10) size	(11) density	(12) mean degree
intensity	-3.513**	-0.005	-0.436									
	(1.226)	(0.027)	(0.299)									
intensity_{t-1}				-2.773*	-0.005	-0.290						
				(1.072)	(0.024)	(0.244)						
intensity_{1998}							-13.440**	0.004	-3.153			
							(3.544)	(0.045)	(2.421)			
intensity_{2003}							-1.350*	-0.003	-0.116	-1.238*	-0.004	-0.116
							(0.561)	(0.014)	(0.156)	(0.575)	(0.015)	(0.154)
$\text{intensity}_{1998}^{lagged}$										-13.632**	0.053	-2.098**
										(1.773)	(0.065)	(0.622)
Constant	20.120**	0.128**	2.521**	20.139**	0.128**	2.523**	20.058**	0.128**	2.505**	20.113**	0.128**	2.520**
	(0.490)	(0.007)	(0.186)	(0.497)	(0.007)	(0.187)	(0.484)	(0.007)	(0.181)	(0.487)	(0.007)	(0.187)
Observations	251	251	251	251	251	251	251	251	251	251	251	251
R-squared	0.515	0.173	0.250	0.496	0.173	0.246	0.543	0.174	0.273	0.525	0.175	0.253
Number of Banks	47	47	47	47	47	47	47	47	47	47	47	47

Note: The regressions include bank and year fixed effects. Robust standard errors in parentheses.
$^{+}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

TABLE 10. Effect of Capital Injection on Hometown Network (Matched Sample)

	Dependent variable:					
	size	density	mean degree	size	density	mean degree
	(1)	(2)	(3)	(4)	(5)	(6)
injection	-3.060*	-0.071	-1.671+			
	(1.196)	(0.055)	(0.909)			
injection_{t-1}				-2.525+	-0.061	-0.791
				(1.447)	(0.080)	(1.276)
Constant	20.097**	0.534**	9.812**	20.141**	0.535**	9.838**
	(0.489)	(0.017)	(0.341)	(0.489)	(0.017)	(0.341)
Observations	242	242	242	242	242	242
R-squared	0.519	0.040	0.259	0.501	0.029	0.243
Number of Banks	47	47	47	47	47	47

Note: $^{+}$p < 0.1; **p < 0.05; ***p < 0.01. Robust standard errors in parentheses.

Table 11. Effect of Capital Injection on Hometown Network Using Intensity Measures (Matched Sample)

	Dependent variable:											
	(1) size	(2) density	(3) mean degree	(4) size	(5) density	(6) mean degree	(7) size	(8) density	(9) mean degree	(10) size	(11) density	(12) mean degree
intensity	-2.911*	-0.087	-1.946*									
	(1.283)	(0.058)	(0.749)									
intensity_{t-1}				-2.006+	-0.080	-1.563+						
				(1.148)	(0.060)	(0.837)						
intensity_{1998}							-12.916**	0.017	-0.797			
							(3.554)	(0.044)	(2.030)			
intensity_{2003}							-1.139+	-0.045	-0.978*	-1.069+	-0.047	-1.049**
							(0.601)	(0.030)	(0.373)	(0.603)	(0.030)	(0.363)
$\text{intensity}_{1998}^{lagged}$										-14.251**	0.191**	5.305**
										(1.186)	(0.061)	(0.741)
Constant	20.132**	0.534**	9.830**	20.144**	0.535**	9.838**	20.071**	0.535**	9.831**	20.128**	0.535**	9.840**
	(0.484)	(0.017)	(0.333)	(0.489)	(0.017)	(0.336)	(0.479)	(0.017)	(0.335)	(0.483)	(0.017)	(0.333)
Observations	242	242	242	242	242	242	242	242	242	242	242	242
R-squared	0.512	0.045	0.261	0.498	0.036	0.250	0.538	0.046	0.261	0.521	0.050	0.266
Number of Banks	47	47	47	47	47	47	47	47	47	47	47	47

Note: The regressions include bank and year fixed effects. Robust standard errors in parentheses.
$^{+}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 12. Effect of Capital Injection on Ordinary Income over Assets (ROA)

	Dependent variable:					
	(1)	(2)	(3)	(4)	(5)	(6)
	ROA	ROA	ROA	ROA	ROA	ROA
injection	-1.666**					
	(0.251)					
injection_{t-1}		0.079				
		(0.468)				
intensity			-0.681+			
			(0.377)			
intensity_{1998}				-3.366**		
				(0.514)		
intensity_{2003}					0.089	
					(0.204)	
intensity_{t-1}						-0.021
						(0.464)
Observations	575	575	575	575	575	575
R-squared	0.089	0.000	0.007	0.086	0.000	0.000
Number of Banks	122	122	122	122	122	122

Note: The regressions include bank and year fixed effects.
Robust standard errors in parentheses, clustered at bank level.
$^{+}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

TABLE 13. Effect of Capital Injection on Net Business Income Over Assets (ROANET)

	Dependent variable:					
	(1) ROANET	(2) ROANET	(3) ROANET	(4) ROANET	(5) ROANET	(6) ROANET
injection	-0.182**					
	(0.066)					
injection_{t-1}		-0.139				
		(0.116)				
intensity			-0.079			
			(0.094)			
intensity_{1998}				-0.662**		
				(0.132)		
intensity_{2003}					0.046	
					(0.051)	
intensity_{t-1}						-0.127
						(0.115)
Observations	574	574	574	574	574	574
R-squared	0.017	0.003	0.002	0.052	0.002	0.003
Number of Banks	122	122	122	122	122	122

Note: The regressions include bank and year fixed effects.
Robust standard errors in parentheses, clustered at bank level.
$^{+}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

TABLE 14. Effect of Capital Injection on Ordinary Income Over Equity (ROE)

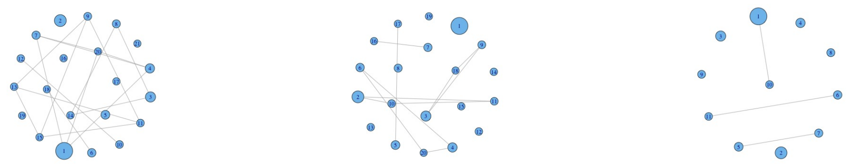
	Dependent variable:					
	(1) ROE	(2) ROE	(3) ROE	(4) ROE	(5) ROE	(6) ROE
injection	-30.816**					
	(8.567)					
injection_{t-1}		-45.535**				
		(14.885)				
intensity			-24.483*			
			(12.157)			
intensity_{1998}				-48.693**		
				(17.615)		
intensity_{2003}					-7.501	
					(6.555)	
intensity_{t-1}						47.573**
						(14.743)
Observations	573	573	573	573	573	573
R-squared	0.028	0.020	0.009	0.017	0.003	0.023
Number of gid	122	122	122	122	122	122

Note: The regressions include bank and year fixed effects.
Robust standard errors in parentheses, clustered at bank level.
$^{+}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

TABLE 15. Effect of Capital Injection on Net Business Income Over Equity (ROENET)

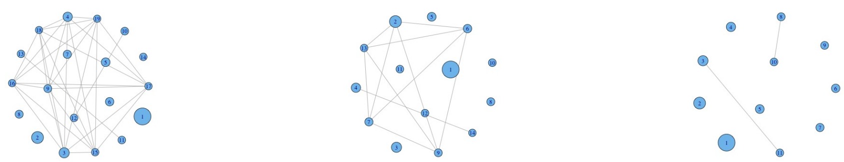
	Dependent variable:					
	(1) ROENET	(2) ROENET	(3) ROENET	(4) ROENET	(5) ROENET	(6) ROENET
injection	-6.559** (2.062)					
injection_{t-1}		-7.603* (3.591)				
intensity			-6.909* (2.912)			
intensity_{1998}				-20.316** (4.153)		
intensity_{2003}					-1.219 (1.574)	
intensity_{t-1}						-6.308+ (3.566)
Observations	573	573	573	573	573	573
R-squared	0.022	0.010	0.012	0.050	0.001	0.007
Number of Banks	122	122	122	122	122	122

Note: The regressions include bank and year fixed effects.
Robust standard errors in parentheses, clustered at bank level
$^{+}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.



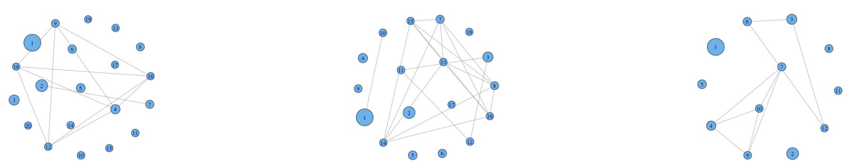
(a) 1993 (b) 1998 (c) 2003

Figure 1. Evolution of Hokuriku Bank Board School Network



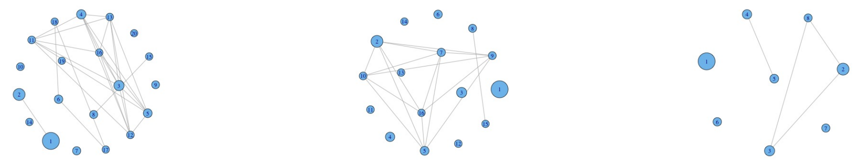
(a) 1993 (b) 1998 (c) 2003

Figure 2. Evolution of Ryukyus Bank Board School Network



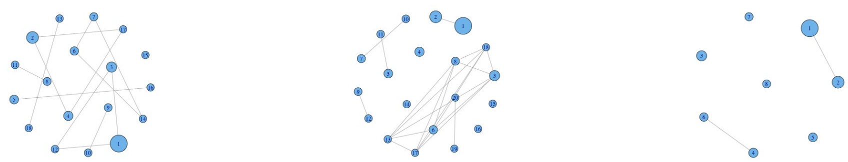
(a) 1993 (b) 1998 (c) 2003

Figure 3. Evolution of Kumamoto Bank Board School Network



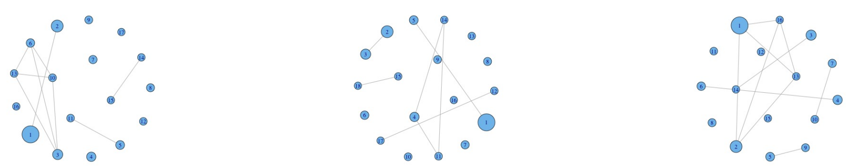
(a) 1993 (b) 1998 (c) 2003

Figure 4. Evolution of Hokkaido Bank Board School Network



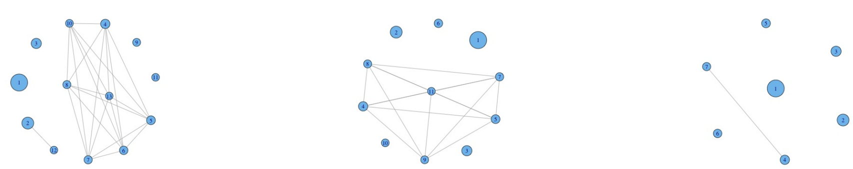
(a) 1993 (b) 1998 (c) 2003

Figure 5. Evolution of Chiba Kogyo Bank Board School Network



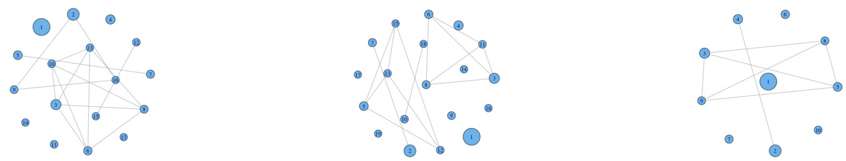
(a) 1993 (b) 1998 (c) 2003

Figure 6. Evolution of Higashi Niho Bank Board School Network



(a) 1993 (b) 1998 (c) 2003

Figure 7. Evolution of Gifu Bank Board School Network

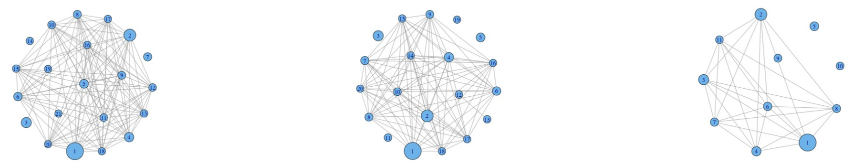


(a) 1993 (b) 1998 (c) 2003

Figure 8. Evolution of Fukuoka City Bank Board School Network

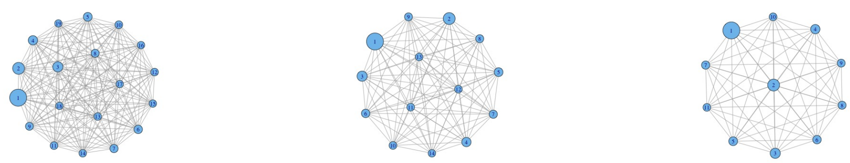
(a) 1993 (b) 1998

Figure 9. Evolution of Yokohama Bank Board School Network



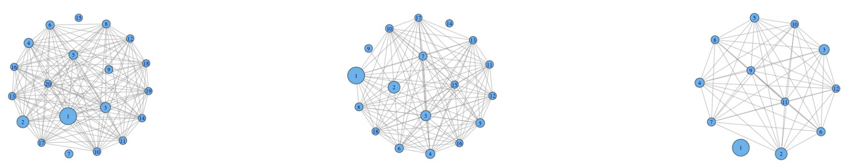
(a) 1993 (b) 1998 (c) 2003

FIGURE 10. Evolution of Hokuriku Bank Board Hometown Network



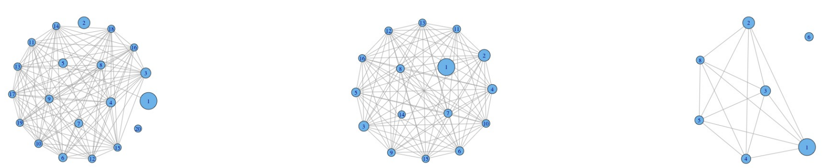
(a) 1993 (b) 1998 (c) 2003

FIGURE 11. Evolution of Ryukyus Bank Board Hometown Network



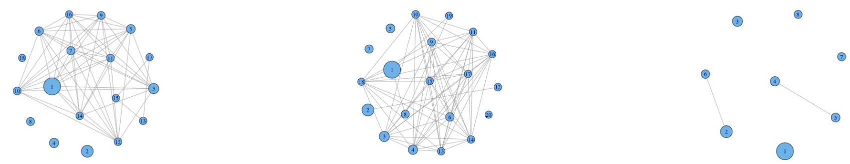
(a) 1993 (b) 1998 (c) 2003

FIGURE 12. Evolution of Kumamoto Bank Board Hometown Network



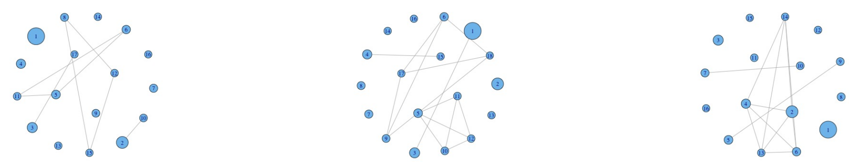
(a) 1993 (b) 1998 (c) 2003

FIGURE 13. Evolution of Hokkaido Bank Board Hometown Network



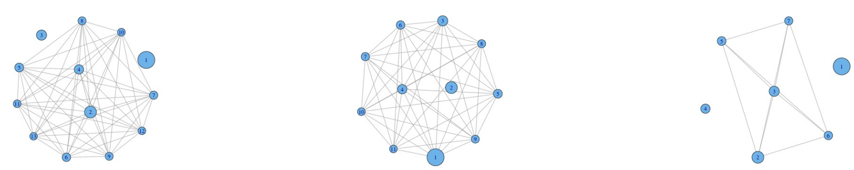
(a) 1993 (b) 1998 (c) 2003

FIGURE 14. Evolution of Chiba Kogyo Bank Board Hometown Network



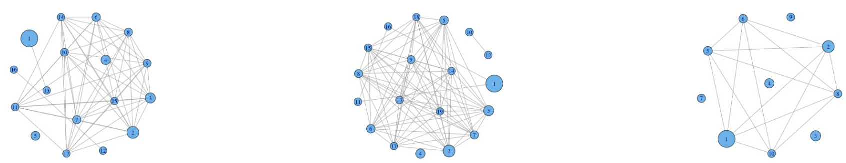
(a) 1993 (b) 1998 (c) 2003

FIGURE 15. Evolution of Higashi Niho Bank Board Hometown Network



(a) 1993 (b) 1998 (c) After Injection 2003

FIGURE 16. Evolution of Gifu Bank Board Hometown Network



(a) 1993

(b) 1998

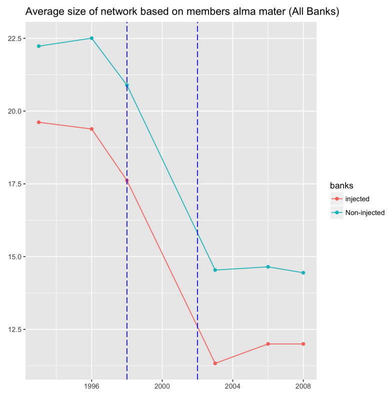
(c) After Injection 2003

Figure 17. Evolution of Fukuoka City Bank Board Hometown Network

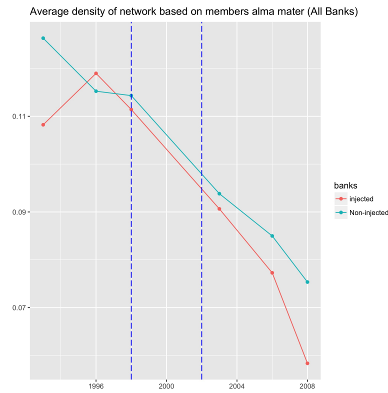
(a) 1993

(b) 1998

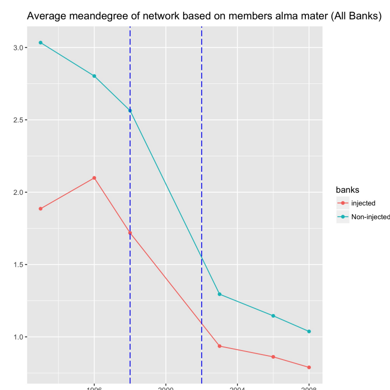
Figure 18. Evolution of Yokohama Bank Board Hometown Network



(a)

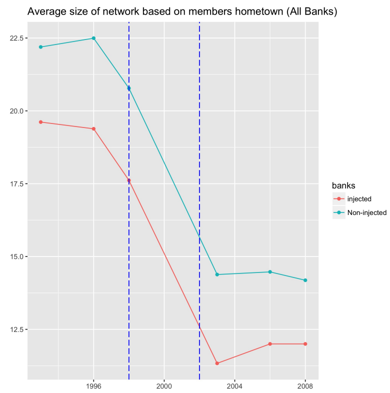


(b)

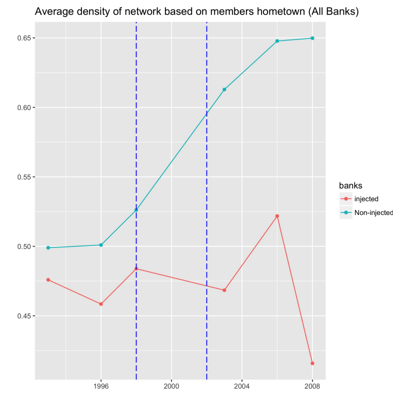


(c)

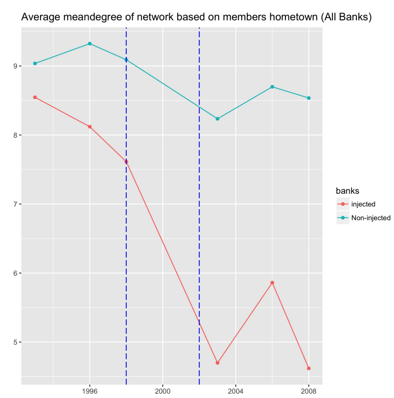
FIGURE 19. Comparing Average Features of Injected and Non-Injected Banks' School Networks



(a)



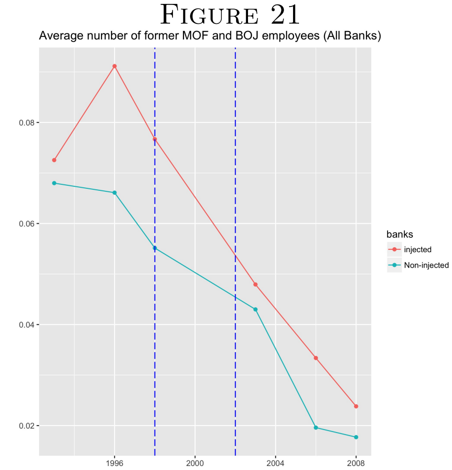
(b)



(c)

FIGURE 20. Comparing Average Features of Injected and Non-Injected Banks' Hometown Networks

Figure 21


Average number of former MOF and BOJ employees (All Banks)
0.08
0.06
0.04
0.02
1996
2000
2004
2008
banks
injected
Non-injected