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Article — Published Version

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Empirical Economics

Provided in Cooperation with:

Springer Nature

Suggested Citation: Raddant, Matthias; Takahashi, Hiroshi (2021) : Corporate boards, interorganizational ties and profitability: the case of Japan, Empirical Economics, ISSN 1435-8921, Springer, Berlin, Heidelberg, Vol. 62, Iss. 3, pp. 1365-1406, <https://doi.org/10.1007/s00181-021-02062-y>

This Version is available at:

<https://hdl.handle.net/10419/286864>

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Corporate boards, interorganizational ties and profitability: the case of Japan

Matthias Raddant^{1,2,3} · Hiroshi Takahashi³

Received: 29 August 2020 / Accepted: 17 April 2021 / Published online: 20 May 2021
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Abstract

We analyze the ties between 4000 Japanese corporations in the time period from 2004 until 2013. We combine data about the board composition with ownership relationships and indicators of corporate profitability. The board network exhibits some clustering, which can partly be explained by ownership relations, and a tendency to form ties to other corporations from the same sector. Connectivity in the board network (corporate board interlocks) and ownership network (shareholdings) does have an influence profitability. Firms that are linked to peers with above average profitability are more profitable than firms in other relationships. Hence, network effects partly explain why board interlocks and ownership ties are not always beneficial.

Keywords Corporate board interlock · Firm performance · Firm networks · Executive survival

JEL Classification L25 · G32 · M12 · C55

1 Introduction

We study the interorganizational networks of Japanese corporates from 2004 until 2013. We focus on corporate board interlocks and ownership ties. We investigate the network structure and we analyze if and under which conditions ties in either network are related to firm profitability.

An increasing amount of scholars in the fields of business and economics have recently put more emphasis on describing economic performance as the outcome of

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networked activity. This paradigm has been applied from a macroeconomic perspective, for example by Acemoglu et al. (2012), but also on the level of firms and sectors (Herskovic 2018; Ahern 2013; Aobdia et al. 2014) in the networks of production and trade. The interorganizational networks that are at the core of this approach have been analyzed by researchers from different fields, such as sociology, management and corporate finance, interdisciplinary physics, computer and network science. This has led to a literature that is partly segregated, despite dealing with closely related topics. This research is therefore also a step in connecting the different findings and viewpoints from these disciplines.

Board interlocks emerge when directors serve on the boards of more than one company. Most importantly, board interlocks and other interorganizational networks have been analyzed as influencing factor on firm profitability, strategy, managerial practice and corporate governance (see, e.g., Hermalin and Weisbach 2003; Mizruchi 1996; Gulati and Gargiulo 1999; Kramarz and Thesmar 1992). Cai et al. (2014) found significant interaction effects between connected corporate boards with respect to disclosure policies, Bizjak et al. (2009) found similar effects with respect to employee stock options, Chiu et al. (2013) found such effects with respect to earnings management.

In the sociological literature, firm connectivity is mostly regarded as necessary to provide opportunities for firms to develop (see, e.g., Uzzi 1996). The efficient creation of ties with other companies is thus expected to lead to an increase in corporate valuation. Yet, many studies also stress that ties should be carefully managed, since they can have positive as well as negative effects on firm performance (Barroso-Castro et al. 2016; Sullivan and Tang 2013).

Management science has analyzed board interlocks by applying agency theory, which tends to stress negative effects from board interlocks. Approaches that model resource considerations on the other hand tend to stress benefits (see Jensen and Meckling 1976; Pfeffer and Salancik 2003). The empirical results on the effects of board interlocks are similarly divided (see also Lamb and Roundy 2016). Positive effects on performance are found for example by Horton et al. (2012), while Devos et al. (2009) find negative ones. Zona et al. (2018) therefore try to combine different perspectives on board interlocks and find that effects likely depend on a firm's relative strengths and weaknesses. Our study contributes to this debate by looking at interaction effects between connected firms. Many of the above-mentioned studies analyze samples of limited size or focus on specific aspects of firm behavior. Our approach is comparably general and is applied to a large sample of firms. Although our approach differs from Zona et al. (2018), we find similar conditional effects of board interlocks and also of ownership ties. Our results thus strengthen the view that effects from interorganizational ties depend on firm characteristics and its position in the network.

A different facet of this debate, mostly in corporate finance, is the composition of the board. There is no consensus on the question if the appointment of outside board members is of any benefit to ensure good governance and accurate reporting (see the survey by Petra 2005). While an independent board is generally regarded as best practice, a link to performance can mostly not be established (Dalton and Dalton 2011). Nevertheless, we observe an increasing number of outside board members in Japan. While there is no evidence that this leads to significant differences in firm performance (Miwa and Ramseyer 2005), there is some evidence that foreign ownership has an

effect on firm valuation (Mian and Nagata 2015). We find support for this claim, since we observe a growing number of outside board members at firms with foreign shareholders.

Corporate interlocks are also an interesting phenomenon for social networks science, since the networks of directors with multiple mandates are (partly by construction) very dense and show high degrees of clustering, even though the average connectivity is very low (Conyon and Muldoon 2006; Davis et al. 2003; Battiston and Catanzaro 2004). Less research has focused on the dynamics of corporate interlocks, but it seems clear that some amplification mechanisms are in place that foster multiple mandates at highly capitalized firms and that imply replacement of very central directors with alike peers when board members retire or leave the company (Milaković et al. 2010; Bellenzier and Grassi 2014; Mariolis and Jones 1982; Raddant et al. 2017). In our analysis of the dynamic properties of corporate ties, we find similarly persistent structures in the Japanese case, and we also observe that firm growth is closely related to firm connectivity.

A topic that is specific for the Japanese economy are the fading effects of the so-called *keiretsu* (Lincoln and Shimotani 2001). This term describes six historic conglomerates of corporations that have dominated the Japanese economic landscape after the second World War. Studies found that today only very few traces of their former structure can be found, even though the names of the original concerns persist. Yet, risk sharing mechanisms within ownership structures have been identified as an influence on firm performance (see Schaeede 1995; Lincoln and Gerlach 2004; Nakano and Nguyen 2012; Lincoln et al. 1992). Our analysis of the different relationships in the board and ownership network can therefore also be seen as continuation of these studies.

In the following, we will first review the dataset and the methods that we have applied in Sect. 2. After this, we will discuss the board members and their ties in Sect. 3. Section 4 deals with the structure of the board network. In Sect. 5, we discuss board composition and the role of outside board members. At last, we will analyze dependencies between firm connectivity and profitability.

2 Materials and methods

2.1 Company data and network generation

The Japanese system of corporate boards used to be a very special one at least until the 1990s. Boards used to be large and had limited intend to care about international governance standards or even shareholder value. Really important decisions were taken within smaller groups of senior board members anyhow. The crisis of the 1990s lead to some change and influence from the US system. Following Sony, boards mostly shrank to a size of about 10 *corporate executive officers* plus 2 to 3 externals, including the auditor. An alternative system is the *company with committees*. In this system, additional to the board of directors, three committees would handle audit, nomination and remuneration duties (Buchanan and Deakin 2009). Hence, in our analysis, we look in the very large majority at cases where the board of directors consists of 6 to 15

corporate executive officers, 1–2 auditors and possibly 1 or 2 outside board members. Only few mainly very large corporations report up to 35 total board members.

For our analysis, we have collected data of all publicly listed companies in Japan. Most of these are listed at the Tokyo Stock Exchange (TSE). This means that our sample includes all the roughly 1700 firms of the so-called first section together with a similar amount of slightly smaller firms, totaling close to 4000 firms per year. We combine the data on the composition of corporate boards available from Toyo Keizai with financial data obtained from Nikkei Needs and Thompson Reuters Datastream. In particular, we use the information on market value, income, total assets, the business sector, largest shareholders and shareholder composition. This data is not available for the entirety of listed firms; hence, some parts of our analysis will be carried out using sub-samples of the data.

The information on the composition of the board is updated annually in the middle of the year. Besides the names of the board members, we have obtained information on the age, gender and role of the board member. The naming and numerical identifiers of board members are unanimous within each year, but not necessarily throughout the years. Hence, we have developed an algorithm to trace the destinies of board members over time based on parts of their names, date of birth and affiliations and have created our own identifier, which is unanimous for the entire sample period.¹ The financial data of the firms is matched using the same yearly frequency.

The basics of the treatment of the board composition data are simple. For each year, we observe a set of board members and a set of firms. Board members serve on the boards of one or more firms. This creates relationships (incidences) between the set of board members and the set of firms and resemble a bipartite graph. Incidences can be described by positive entries in a matrix I , where the dimensions of I are given by the number of firms and the number of board members within a year.

From the incidence matrix I , we can obtain an undirected network that describes the links between the boards of these firms by projecting $I'I = A_B$. A_B is a square matrix with as many rows and columns as we have firms in our sample. A positive entry A_{ij} describes a connection between the firms i and j that is given by at least one shared board members. In the following, we will refer to this network as the board network.²

2.2 The board network

The network that we look at naturally shows some churning over time, caused by entry and exit of firms as well as retirement and replacement of board members. Nevertheless, the basic statistics provided in Table 1 shows that the number of firms varies steadily between 3532 and 3943. (The number of distinct firm for all years is

¹ We have confirmed the validity of this algorithm by manual checks. The only known limitation of this method is that we may lose traces of board members who exit the dataset and re-appear at a later year at a different company. We are however confident that this problem applies only to a very limited number of board members who did not play a decisive role in the board member network anyhow.

² A different interpretation of the data would be the network derived by the projection $A_D = II'$. This adjacency matrix would describe relationships of board members who know each other from serving on at least one board together. This network is however not part of the following analysis.

Table 1 Network statistics

	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
Counts										
Nodes (firms)	3767	3849	3943	3887	3767	3672	3595	3543	3532	3545
b. members	42,175	42,635	43,121	41,998	39907	38,759	37,731	36,884	36,452	36,697
Mandates	45,119	45,760	46,257	44,991	42,693	41,461	40,318	39,458	39,103	39,503
Avg. board	11.98	11.89	11.73	11.57	11.33	11.29	11.22	11.14	11.07	11.14
Avg. mandates	1.070	1.073	1.073	1.071	1.070	1.070	1.069	1.070	1.073	1.076
Max mandates	11	9	8	8	8	8	7	7	7	7
Board network										
Edges	3221	3498	3415	3266	3045	2956	2883	2869	2984	3240
Density ⁻⁴	1.135	1.181	1.098	1.081	1.073	1.096	1.116	1.143	1.197	1.291
Mean degree	1.71	1.81	1.73	1.68	1.62	1.61	1.61	1.62	1.69	1.83
Max degree	27	27	25	25	26	24	27	26	23	22
Deg. assort.	0.6693	0.6854	0.6538	0.6543	0.6503	0.6191	0.6363	0.6398	0.6551	0.6620
Clustering	0.1483	0.1436	0.1333	0.1225	0.1201	0.1142	0.1112	0.1065	0.1061	0.1060
Local clust.	0.1581	0.1668	0.1579	0.1542	0.1476	0.1427	0.1431	0.1380	0.1357	0.1475
Nodes g.c.	1408	1571	1547	1495	1387	1383	1373	1380	1490	1625
Edges g.c.	2598	2931	2800	2633	2387	2343	2309	2303	2490	2779
Ownership network										
Edges	2574	2695	2880	2865	2918	3215	3408	3467	3542	3695
Density ⁻⁵	4.537	4.550	4.633	4.743	5.143	5.964	6.596	6.908	7.102	7.354
Mean degree	0.683	0.700	0.730	0.737	0.775	0.876	0.948	0.979	1.003	1.042

Table 1 continued

	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
Max degree	213	269	340	214	94	262	270	245	205	193
Deg. assort. $in \leftrightarrow out$	0.3865	0.3665	0.3264	0.3332	0.4479	0.2749	0.2773	0.2821	0.3001	0.2918
Clustering	0.0120	0.0118	0.0105	0.0133	0.0162	0.0182	0.0163	0.0158	0.0165	0.0166
Local clust.	0.0215	0.0178	0.0178	0.0198	0.0230	0.0320	0.0321	0.0331	0.0333	0.0348
Clustering <i>undir.</i>	0.0582	0.0530	0.0532	0.0593	0.0686	0.0906	0.0905	0.0941	0.0951	0.0965
Local clust. <i>undir.</i>	0.1581	0.1668	0.1579	0.1542	0.1476	0.1427	0.1431	0.1380	0.1357	0.1475
Nodes g.c.	1488	1543	1649	1632	1652	1766	1826	1822	1866	1948
Edges g.c.	2389	2484	2678	2618	2625	2925	3117	3154	3223	3363

This table shows annual statistics for the board members (top part), the board network created by board members (middle part), and the corresponding ownership network (bottom part). The board network becomes slightly less dense and less clustered over time. The number of companies and executives is slightly decreasing in the years after the financial crisis. The ownership network, which is a directed network, has a comparable density, which is increasing over time.

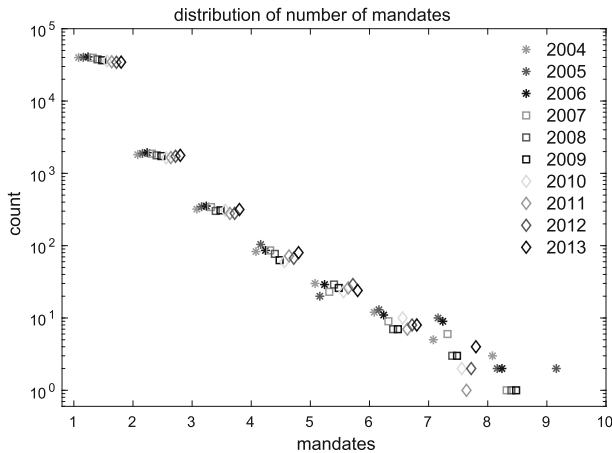


Fig. 1 Mandates statistics. We print the number of mandates with an offset and use a log-scale for the count. The tail of the distribution shows similarity to a power-law. The highest numbers of mandates are only observed until 2009

4505.) In the same time, the average number of board members is slightly declining from almost 12 in 2004 to 11.1 in 2013. The number of board members we observe per year lies around 40,000 (distinct: 95,192).

We can measure the survival of firms by looking at the stock identifier codes. We observe that the unconditional survival probability of the firms in our data set is very stable and lies around 96% (see also Table 7 in the “Appendix”). Slightly lower values are only observed around 2007, which is in line with the weak GDP growth at that time. The same exercise can be done for the board members. The survival rates for them are also rather stable and vary around 83%. Slightly lower figures are observed around 2007–2008 and slightly higher values are observed toward the end of the sample period (see also Table 8 in the “Appendix”).

The disparity between the average number of mandates and its maximum demands a short look at the distribution of the number of mandates. Figure 1 shows that this distribution is heavy-tailed. While around 40,000 board members have one mandate, only around 200 have three mandates, and only a handful of board members find themselves with eight or more. The degree distributions of the board networks are roughly in line with a power-law (see the left panel in Fig. 2). The estimated power-law exponents range from 3.2 to 3.6, which should be interpreted with caution given the low range of the degrees.

The middle part of Table 1 shows some statistics for the unweighted board network. The mean degree and the very low density reveal that in fact many firms do not share any board member. The correlation between a node’s degree and the average neighbor’s degree (i.e., the degree assortativity) is positive. The networks show transitivity. We find positive local clustering and a significantly positive (global) clustering coefficient (compared to a random network with identical degree sequence). To some extent, these effects result from ties between firm conglomerates, which can be confirmed by applying community detection algorithms to this network. We are not interested

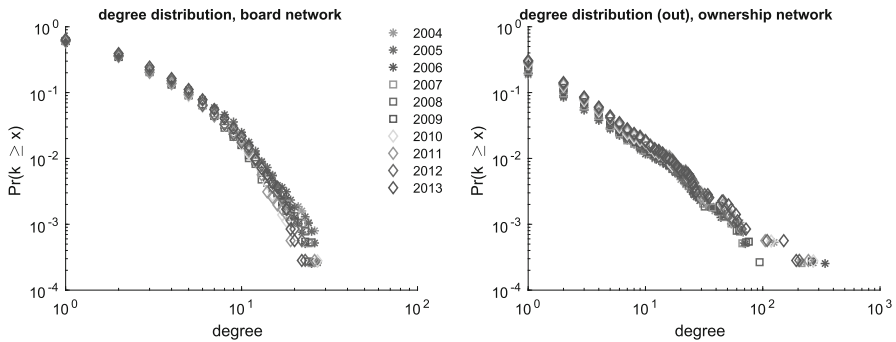


Fig. 2 Degree distributions (complementary cdfs). The degree distributions of the board network (left) are skewed and shows similarity to a power-law, yet the range for the degree is rather low. The degree distribution of the ownership network (right) shows a more typical power-law behavior

in the details of community structure in this study, yet one possible visualization of communities is provided in Fig. 10 in the “Appendix”.

While the board network shows some similarities with a social network, we also have to stress the differences. For example, the giant component never exceeds 50 percent of all the nodes in the network. This is caused by the fact that the size of a corporation influences its ability to create ties in both the board and the ownership network, because human resources and capital act as limiting factors. The size of the giant component in board networks therefore partly depends on the size of the dataset.

2.3 Ownership network

Links in the board network are to some extent of course the result of business relationships between firms. One example are relationships between producers and suppliers. For studies of such networks, we refer the reader to Krichene et al. (2019) and Chakraborty et al. (2018). For our purposes, the analysis of this level of connectivity would however delve too deeply into a very specific topic. However, business relationships that are more elaborate often result in some kind of shareholding or even cross-shareholding relationship. We have obtained data that reports the five largest shareholders and the percentage of shareholding for all of the firms in our sample. (This data is based on reporting required by law that is limited to the top five owners.) This might at first seem a little restrictive, yet in practice significant influence onto a company is unlikely to be performed by more than five owners. Also since this data is reported from the viewpoint of the owned company, this still results in a rather complete picture of the ownership network.

In the following, we will refer to the weighted networks based on ownership simply as the ownership networks. The ownership networks differ from the board networks by the fact that they are directed networks. The densities are however comparable, the ownership network in 2004 contains 2574 directed links, and we see a steady increase until 2013 when the network has 3695 links. The out-degree distributions of

these networks are more skewed (see the right panel of Fig. 2), and the power-law exponents lie around 2.2–2.3.

Links in the ownership network are (with negligible exceptions) not reciprocal and tendentially hierarchical. This has to do with the legal framework for reporting ownership relations.³ When calculating degree assortativity, it therefore makes sense to report the correlation of the average out-degree of neighbors with a node's in-degree. We find that this value fluctuates around 0.3. Different from the board network, this behavior translates only into negligible clustering since short directed loops are rare. If we were to ignore directionality for a moment and calculate clustering based on undirected ownership, this changes and we observe similar local clustering as in the board network. The global clustering in this case is lower than local clustering, and this difference is likely due to the just mentioned hierarchical structures and the fact that some nodes in this network have a much higher degree (compared to the maximum in the board network). This behavior is related to the diversified shareholding of some corporations, which does not produce much clustering.

The big hubs in the ownership network are mostly insurers and securities companies. Their shareholdership in a firm is normally small, but their activity is very spread out. In fact, much of their holdings are likely on behalf of their clients. A visualization of the ownership network in 2013 is shown in Fig. 11 in the "Appendix". It shows that communities in a classical sense do not exist, or vastly overlap. Not surprisingly, large corporations like Toyota, Mitsubishi, Fujitsu, Honda, Mitsui and Nippon Steel can be classified as smaller hubs in this network.

The ownership network is very stable, about 90 percent of the links survive from each one year to the next. However, the overlap between links in the firm network and the ownership network is with about 10 percent relatively small, as is shown in the left panel of Fig. 3.

One can condition this relationship on the level of shareholding. For this reason, we have binned pairs of firms with similar ownership percentage ($N = 30$) and have calculated how many of those are also linked in the board network.⁴ Results are shown in the right panel of Fig. 3. We can observe that the probability of having a board link increases with ownership and passes the unconditional probability once we reach about 10 percent ownership. Interestingly, at the high end when ownership reaches 50 percent this relationship slows down and might even slightly drop. It is likely that since this represents a majority ownership, there is less demand for control by shared board members once we reach this level of ownership.

³ When we calculate the giant component of the ownership network, we therefore consider the undirected version of this network.

⁴ For this comparison, we consider an undirected version of the ownership network. In the directed version of the network about 10 % of the links are reciprocal.

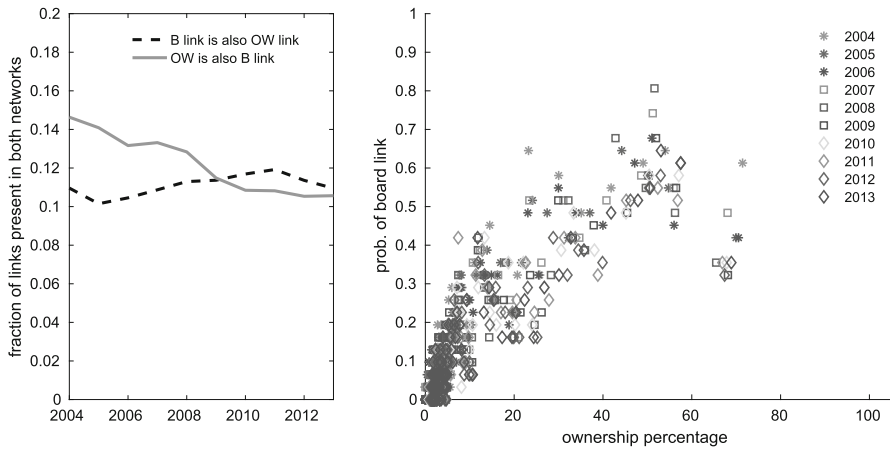


Fig. 3 Ownership statistics. The left panel shows the fraction of board links for which the respective link is also present in the ownership network, vice versa. The right panel shows the relationship between the percentage of ownership of two firms and the conditional probability of having a link in the board network. The calculation is based on subsamples of 30 firms with similar ownership

3 Dynamics of the board network

3.1 Determinants of board member survival

Since we have seen that some board members have multiple mandates, it is useful to investigate how the survival figures change when we condition the survival on the number of mandates that a board member has. These conditional survival probabilities are shown in Fig. 4. The probability for board members with one mandate differs only insignificantly from that of the entire population (83%). The likelihood to survive increases to around 93% with another mandate, further additional mandates only lead to marginal improvements. So even if directors with multiple mandates are of course more likely to survive, one can easily see that the losses of mandates are not independent.⁵

Based on these results about board member survival we can have a more detailed look at determinants of their destinies. Since the large number of board members prohibited us from collecting detailed information on each of their career paths, we have to confine ourselves to some of their basic characteristics together with details on the firms for which they work.

We can check if the role of a board member has an influence on his survival probability. We can further check if gender or the size of the company are important aspects of director survival, while we control for the number of mandates⁶ and age. Further, the performance of the firm should have an impact on survival. We can disentangle this

⁵ We can verify this by using the probability of survival with one mandate p_1 to calculate $(1 - p_2)$, the probability that a board member with two mandates loses both of them. Assuming independence, from the probability of losing one mandate we know $(1 - p_1) = 1 - 0.83 = 0.17$ and hence $1 - p_2 = (1 - p_1)^2 = 0.0289$, which would predict a survival probability of close to 97% for managers with two mandates.

⁶ In particular, the log of the deviation from the average number of mandates plus 1.

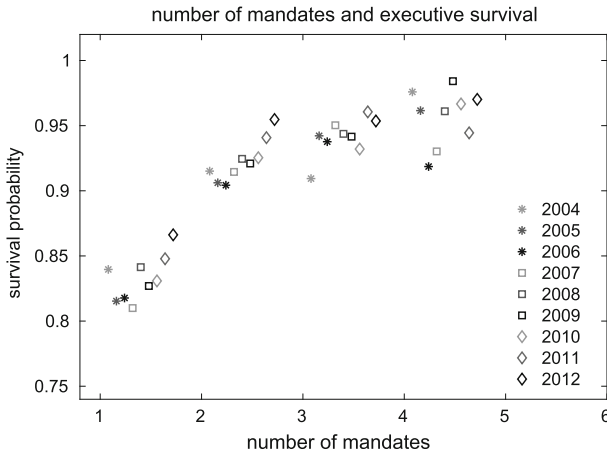


Fig. 4 Influence of number of mandates on survival. The figure shows the survival of board members with 1, 2, 3 and 4 mandates. The results are printed with an offset for the years 2004–2012

effect into two parts. First, we introduce a dummy variable for the case that a board member works for a firm that ceases to exist. Second, we calculate the difference in the market value for two consecutive years to capture the influence of the performance of firms that remain in business.⁷

Since survival is a binary variable this demands for a logistic regression where the observed survival or death (in the sense of leaving the data set) depends on the above mentioned variables. To confirm the robustness of the results with respect to the firm performance variables, we have also estimated the model while omitting these variables, and results are given in Table 9 in the “Appendix”.

The results in Table 2 indicate that most of the variables have a significant influence on the destinies of board members, yet the explanatory power is not very large, which hints at additional unobserved effects on the level of the individual board members. In general, the results are a bit more volatile in the first 4 years where we observe more changes in the sample composition, including the financial crisis, from 2009 on the results are remarkably stable.

The delisting of a firm and the number of previously held mandates are of course the most important influences in this analysis. The impact of age is mostly negative or insignificant, as expected, with some exceptions in the first years. Only very few women are serving as board members, less than 2%, and only at the end of our sample period, we see a slight tendency of higher survival. The market value (and thus also size) of a firm has a slight negative influence on survival; hence, smaller firms have slightly fewer changes in their boards. The influences of firm performance are mixed. Of course board members mostly disappear when a firm ceases to exist, but this influence is admittedly there mostly by construction. We cannot answer the question if the firm ceased to exist because of poor performance of the board or if other influences like

⁷ For board members with multiple mandates, these variables capture the largest firm for which they work. Data for the change in market value is available for about 80 % percent of the observations. We truncate mv change at 100% to dampen the influence of outliers.

Table 2 Determinants of board member survival

Year	2004–2005	2005–2006	2006–2007	2007–2008	2008–2009	2009–2010	2010–2011	2011–2012	2012–2013
MF R^2	0.1017	0.0837	0.1114	0.1374	0.1409	0.1215	0.1115	0.0977	0.0945
LR	3715	3355	4486	5508	4828	4255	3752	3066	2644
N	42,175	42,635	43,121	41,998	39,907	38,759	37,731	36,884	36,452
Survivors	35,589	34,998	35,488	34,276	33,769	32,266	31,548	31,469	31,764
Const	2.2967 (32.88)*	2.1642 (32.13)*	2.0330 (31.20)*	2.0199 (35.32)*	2.2420 (36.01)*	2.4157 (39.09)*	2.5712 (41.24)*	2.5002 (38.93)*	2.6905 (36.45)*
Firm delist	-5.2928 (-29.67)*	-4.8940 (-28.32)*	-5.1347 (-32.89)*	-5.4018 (-34.17)*	-5.5817 (-32.15)*	-5.6135 (-28.49)*	-5.7194 (-26.72)*	-5.5151 (-25.06)*	-5.81 (-22.33)*
$\log(\text{mand}_{t-1})$	0.6310 (11.49)*	0.7667 (14.88)*	0.6526 (12.77)*	0.7512 (13.52)*	0.7256 (11.97)*	0.7871 (13.56)*	0.7669 (13.10)*	0.8579 (13.00)*	0.9217 (12.61)*
Age	0.0003 (1.89)	-0.0384 (-23.03)*	0.0005 (3.81)*	0.0002 (1.67)	-0.0265 (-13.41)*	-0.0380 (-19.64)*	-0.0399 (-20.13)*	-0.0337 (-16.36)*	-0.0342 (-15.74)*
Female	0.3258 (2.05)	-0.1044 (-0.82)	0.0976 (0.76)	0.0985 (0.76)	0.1064 (0.7040)	0.5485 (3.27)*	0.3231 (2.11)	0.4690 (2.88)*	0.7197 (3.95)*
$\log(mv_t)$	-0.0398 (-6.08)*	-0.0243 (-3.80)*	-0.0178 (-2.91)*	-0.0158 (-2.97)*	-0.0033 (-0.54)	-0.0295 (-4.94)*	-0.0462 (-7.77)*	-0.0299 (-4.82)*	-0.0328 (-4.74)*
$\log(\frac{mv_t}{mv_{t-1}})$	0.0296 (0.57)	0.2038 (4.66)*	0.1113 (2.57)	0.1664 (3.39)*	0.2928 (5.24)*	0.1342 (2.29)	0.0551 (0.88)	0.3680 (5.74)*	-0.0442 (-0.70)
Outs. board	-0.4605 (-6.89)*	-0.4930 (-8.21)*	-0.3724 (-6.08)*	-0.5409 (-9.41)*	-0.4528 (-7.28)*	-0.2972 (-4.75)*	-0.1387 (-2.19)	-0.3615 (-6.01)*	-0.3318 (-5.39)*
Outs. audit	0.3002 (7.03)*	0.0943 (2.58)*	-0.0630 (-1.75)	0.3281 (8.24)*	0.3492 (8.00)*	0.0698 (2.28)	0.0794 (1.99)	0.2925 (6.68)*	0.3532 (7.46)*

This table shows the results of a logit regression. t values are shown in parentheses. Although survival is to a large part random, we find significant influence for holders of multiple mandates (mand), outside board members and outside auditors. The age, gender and the market value of the company are of changing importance. Significance levels: 0.1 ; 0.05 ; 0.01 *

mergers or restructuring are responsible. The influence of a change in market value is significant, yet the effect is small. Hence, the performance does influence the board in general, but admittedly our dataset does not identify specific responsibilities within the board which could explain these effects in more detail.

Rather clear however are the effects for board members who are not executives. Outside board members are being dropped with a higher likelihood throughout the sample period. This intuitively make sense since they are a more dispensable part of the board. On the other hand, it is common practice to stick to an auditing company once relations are established and thus outside auditors stay on the board longer than executives. The outlier in 2006/07 for the survival of auditors is at first sight puzzling, but is in fact easily explained by the ChuoAoyama PricewaterhouseCoopers accounting scandal (Skinner and Srinivasam 2012) that lead to a temporary increase in auditor replacement.⁸ In addition to the results presented in the table, we have checked if the existence of ownership ties increases the probability of board member survival. We could not find proof of such a relationship.

3.2 Tie survival

Another question is where the persistence of the network structure in the board network comes from. If it were just a matter of board members with multiple mandates at highly capitalized firms, then we should see higher survival rates of executives at these companies. We have however seen that this is not the case. This implies that there must be mechanism of upkeep of board network ties that go beyond the existence of central board members.

For this reason, we use the same method as in Raddant et al. (2017) and compute how many links between companies are being kept from one year to the next and look into how these links are maintained if board members retire. The findings are summarized in Table 3. We observe that only very few links are being lost because firms disappear. About 76% of the links survive from one year to the next and about 73% do so because at least one of the board members who was bridging the two boards is still there. Another 3% of links however is being kept because a new board member is replacing this function, in more than half of the cases he/she was already member of one of the boards. In any case, the board member was already a central player in the board network, with typically 2–3 mandates in the year before, much more than the average. We can thus conclude that one source of the persistence of the board network comes from the fact that board members with multiple mandates are being replaced by other board members that also hold multiple mandates.

Our findings are thus in line with those of Raddant et al. (2017) and Stearns and Mizruchi (1986) who find that about 14% of broken ties are being reconstituted by new directors.⁹ We cannot analyze the determinants of the reconstruction in this setting.

⁸ See also: The Economists, May 11th 2006, Auditors in Japan.

⁹ The first paper investigates time intervals of 6 years. The latter paper in fact reports almost the exact same percentage of reconstituted links that we observe. To compare our results in Table 3, we have calculated the percentage of *reconstituted* links as the ratio of links created by *new b. member* divided by the number of broken ties given by *firms alive* minus *same b. member*.

Table 3 Persistence of board network links over time

	2004–2005	2005–2006	2006–2007	2007–2008	2008–2009	2009–2010	2010–2011	2011–2012	2012–2013
Links _{<i>t</i>-1}	3221	3498	3415	3266	3045	2956	2883	2869	2984
firms alive _{<i>t</i>}	3207	3491	3405	3260	3035	2949	2879	2867	2978
links alive _{<i>t</i>}	2499	2569	2530	2519	2373	2272	2281	2343	2487
in %	77.58	73.44	74.08	77.13	77.93	76.86	79.12	81.67	83.34
Same b. member	2,376	2,423	2,398	2,401	2,259	2,176	2,184	2,250	2,399
in %	73.77	69.27	70.22	73.52	74.19	73.61	75.75	78.42	80.40
New b. member	123	146	132	118	114	96	97	93	88
in %	3.82	4.17	3.87	3.61	3.74	3.25	3.36	3.24	2.95
Reconstituted %	14.80	13.67	13.11	13.74	14.70	12.42	13.96	15.07	15.20
Mand _{<i>t</i>-1}	2.94	2.91	2.58	2.70	3.00	2.69	2.65	2.70	2.72
Former b. member	68	79	83	67	58	63	49	63	54
in %	55.28	54.11	62.88	56.78	50.88	65.63	50.52	67.74	61.36

The top part of the table summarizes how many of the links between two firms survive from one year to the next. Next, we summarize how many of these links are preserved by the same board members vs. new board members. In the bottom of the table, we report how many mandates those new board members held in the last year and how many of them have been part of at least one of the two companies' boards

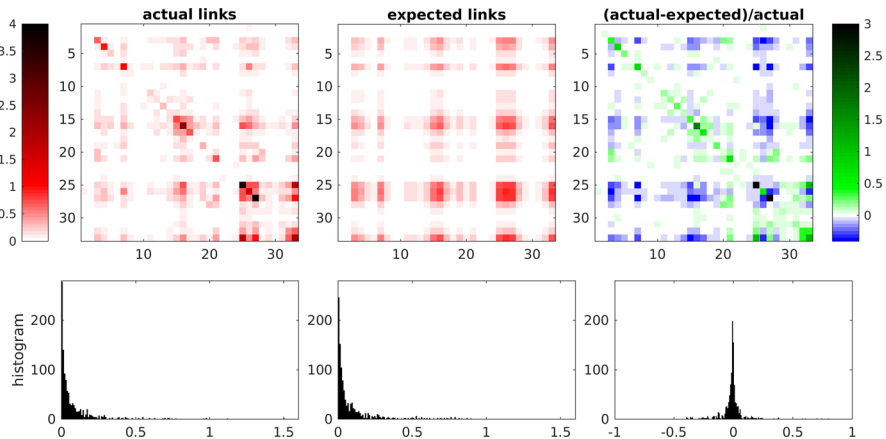


Fig. 5 Links in the board network based on sector classification. The top left panels show how the links are distributed within and between sectors of the economy (in percent). The middle panel shows the expected distribution given the number of firms in each sector and the respective average board sizes. The right panel shows a comparison. The bottom panels show matching histograms (abscissae clipped). The calculations are based on the 10-year averages

Yet, we can contribute to the debate about link reconstitution (Westphal et al. 2006) by confirming that in fact only a fraction of interlocks are being reconstructed. We can add that nevertheless this fraction contributes dis-proportionally to the overall connectivity, the persistence of the network structure over time and the tightly knitted networks between the most central board members.

4 Structure of the board network

When we speak about structure in the board network, one of the first questions has to be whether there are preferences with respect to the type of firms that are linked. One can ask if firms from certain sectors are more connected than others. For this reason, a closer look at the 33 TOPIX sector classifications is useful.

A complete list of the sector classification together with some statistics can be found in Table 12 in “Appendix”. The number of firms per sector varies, the sectors with the most number of companies are services, wholesale trade and retail trade (No. 33, 26 and 27). A color-coded matrix that shows the links between firms based on their sector affiliation is shown in the left panel of Fig. 5. When we assume that the number of links between sectors should only depend on the number of firms in each sector and the average number of board members we can calculate an expected number of links, which is shown in the middle panel. Overall, the qualitative resemblance between these two structures is rather good. The main difference is found on the main diagonal where we find more within-sector links than expected. On the other hand, there are cases where we find slightly fewer links than expected between sector from rather different parts of the economy like trade (26, 27) versus the traditional manufacturing

and construction industry (15, 16, 3). Another observation is a slight preference for links to the financial sector (28–31), which needs further investigation.

In order to quantify effects in the board network, we test two important hypotheses: The first one is to evaluate if firms tend to have more links to firms from the same sector. This would speak in favor of hiring board members that might bring some special expertise. The second hypotheses is that ties to the financial industry are reflected in additional ties. This would for example speak in favor of relationships of firms to a main bank who sends a board member to monitor the bank's exposure (see Lamb and Roundy 2016; Gulati and Gargiulo 1999; Kanamitsu 2013; Davis et al. 2003)

We have employed an exponential random graph model (Strauss and Ikeda 1990) to estimate these effects in the giant connected component of the board network. We assume that a firm's likelihood to form ties to another firm is proportional to the product of the number of board members of the two firms. We further assume that the level of ownership relations influence ties.¹⁰

In other words, our estimation tests the assumption that links within the same sector and to the financial sector are over-represented against the hypotheses that links are randomly distributed between firms and that their likelihood just depends on the number of members on the respective boards and ownership relationships.

We also investigate the possibility that there is an endogenous tendency of connected firms to share additional partners by estimating the so-called geometrically weighted edgewise shared partner statistic (gwesp), see Hunter (2007). This variable accounts for endogenous clustering that appears generally and is not explained by other variables. We did not find other significant endogenous network statistics in our network, which is likely due to the relative sparsity of our network (compared, for example, with the findings for the Japanese production network in Krichene et al. 2019).¹¹

Our results are shown in Table 4 and basically confirm both our hypothesis. There is a slight but constant tendency of links to the financial industry and a more obvious tendency for links to firms with the same TOPIX sector code. The latter effect is declining gradually. Hence, these two effects influence the structure of ties in the board network, but the results also show that the majority of links do not depend on them (and also not on board or firm size). We further confirm that there is a slight overlap between the ownership and the board network. However, this effect is small and roughly similar to that of within-sector ties. Some increase in the significance of the ownership effect and some decrease for the within-sector effect is observed over time. This might originate from the increase in ties in the ownership network and could be interpreted as a slight shift from informal ties in the board network toward more formal ties that incorporate also significant shareholding. The gwesp variable

¹⁰ The board size variable is measured as the deviation from its mean divided by 100. Ownership is a percentage value.

¹¹ We estimate gwesp with a fixed decay parameter of 0.25 for higher-order shared partners. We have also investigated the triangle statistics of our network but have found that estimation is plagued with model degeneracy. Estimating gwesp or triangles should however lead to very similar results in our case, despite the different conditioning of both statistics for identifying clustering. We note that our model aims at estimating the influence of observable economic determinants on connectivity in the board network. A comparisons of alternative endogenous mechanisms is outside the scope of this paper.

Table 4 Determinants of board network ties

Year	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
AIC	27,917	32,314	31,184	29,415	26,473	26,328	26,117	26,215	28,967	32,486
N	990,528	1,233,235	1,195,831	1,116,765	961,191	955,653	941,878	951,510	1,109,305	1,319,500
Links	2598	2931	2800	2633	2387	2343	2309	2303	2490	2779
Edges	-7.5566 (-186.01)	-7.6867 (-209.71)	-7.5892 (-201.69)	-7.5046 (-197.92)	-7.3983 (-195.79)	7.3331 (-193.53)	-7.2922 (-196.39)	-7.2787 (-193.13)	-7.2989 (-208.80)	-7.4142 (-215.65)
b size	0.1007 (14.20)	0.1469 (23.52)	0.1336 (20.78)	0.1443 (22.97)	0.1461 (30.61)	0.1398 (16.23)	0.1704 (23.39)	0.1609 (18.09)	0.1640 (17.10)	0.1766 (25.85)
Fin lk	0.1821 (4.79)	0.1632 (4.65)	0.1373 (3.54)	0.1870 (4.52)	0.2237 (5.08)	0.2579 (5.78)	0.1872 (4.30)	0.2246 (4.93)	0.1939 (4.71)	0.1916 (4.46)
Same sec	1.1425 (32.46)	1.0636 (31.28)	0.9823 (24.99)	0.9362 (21.01)	0.9890 (25.11)	0.9567 (19.30)	0.8453 (18.21)	0.9188 (19.78)	0.8644 (17.22)	0.8521 (17.72)
Owner lk	0.2209 (27.53)	0.1939 (27.30)	0.2029 (22.60)	0.2031 (35.69)	0.2031 (27.80)	0.1782 (25.73)	0.1744 (27.75)	0.1653 (27.04)	0.1545 (32.76)	0.1470 (31.94)
gwest	2.5656 (68.32)	2.6514 (82.79)	2.5669 (74.36)	2.4820 (70.16)	2.4020 (78.87)	2.3339 (64.30)	2.3191 (68.18)	2.2897 (64.31)	2.2786 (67.41)	2.3490 (71.91)

Results of the ERGM estimation. Z-scores in parenthesis. All variables are highly significant ($p < 10^{-4}$). Controlling for company board size (b size), we find that corporate boards have a tendency to form links to boards of other companies when ownership ties exist or if they come from the same sector (same sec). Also links to the financial sector are overrepresented (fin lk), yet to a lesser extend. Connected companies have a strong tendency to choose partners that are also partners of the connected company (gwest).

is significantly positive, indicating a tendency for clustering that is not explained by exogenous effects.

To check for the robustness of our results we have also estimated a model without endogenous clustering (*gvesp*) as well as one with fixed effects for each sector. Both did not influence our qualitative results, fixed sector effects only lead to negligible improvements in the fit. We also estimated versions with sector-to-sector interaction variables, but found that the gains in fit are small relative to the increase in the number of variables (measured by the AIC, material upon request). We have analyzed the goodness-of-fit of our model and found that simulated models based on our estimates are in agreement with the empirical network, see Fig. 12 and Table 10 in “Appendix”.

5 The role of outside board members and multiple mandates

We have already mentioned that the composition of Japanese corporate boards still differs noticeably from that in other western countries. Therefore, it is useful to have a look at changes in the composition of corporate boards, in particular the role of outside board members.

First, it is worth mentioning that the share of women on the boards of Japanese corporations is still very low. Even in 2013 less than 2% of board members are women. More change has happened with respect to outside board members. From 2004 until 2013, their share has doubled to 9.6%, for details see Table 11 in the “Appendix”.

Our dataset allows us to look more closely into which board rooms these additional outside members go. Therefore, we perform a Poisson regression in which our dependent variable is the number of outside board members in a firm. The number of outside members should depend on the size of the board, which is also a proxy for the size of the firm (which we therefore cannot account for in isolation). We test for the influence of the composition of a firm’s shareholders (see also Mian and Nagata 2015) and we test if the appointment of outside directors is related to the profitability of a firm, i.e., if the firm’s return on assets is related to the number of outside board members. For the case of shareholding, the data allows to differentiate between the percentage of shares held by financial institutions, by security companies, by other corporations and held by foreign corporations (the remainder is held by individual investors). Data on the distributions of shareholding is not available for some smaller companies, which limits the data set to 2432 to 2706 observations dependent on the year.

The results are summarized in Table 5. We show the results separately for each year, always with and without sector dummy variables. We calculate a pseudo R^2 value by calculating the ratio of correct predictions of the number of outside board members using the predictions rounded to integer values.

As expected, the number of outside board members varies with board size. More interestingly, the shareholder characteristics are highly significant. A high fraction of foreign shareholders increases the likelihood of having outside board members noticeably. The influence of shares held by other corporations is also significant, though slightly weaker.

These results hold when we include dummy variables for the most populated sectors according to the TOPIX classification. These variables add slightly to the explanatory

Table 5 Poisson regression results for the number of outside directors of a firm

	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
N	2628	2628	2702	2706	2640	2565	2502	2459	2432	2432
ps. R ²	0.4376	0.4817	0.4095	0.4534	0.4030	0.3372	0.3867	0.3269	0.3845	0.3233
disp.	1.23	1.21	1.23	1.21	1.19	1.16	1.14	1.13	1.12	1.08
const	-2.0060	-2.0458	-1.9420	-1.8778	-1.9240	-1.8455	-1.7810	-1.7549	-1.6112	-1.5247
board	(-21.75)	(-16.55)	(-21.54)	(-16.25)	(-21.85)	(-16.44)	(-20.80)	(-15.62)	(-19.40)	(-14.15)
sh corp	0.0664	0.0682	0.0780	0.0789	0.0785	0.0789	0.0728	0.0744	0.0734	0.0747
sh fin	1.8282	1.8073	1.5451	1.5206	1.4445	1.4630	1.3343	1.3994	1.3743	1.4754
sh for	3.3863	3.3245	3.1042	2.8838	2.9930	2.9233	2.8813	2.8548	2.7852	2.7149
sh sec	3.2923	3.2218	2.9422	2.8169	4.3988	4.2580	4.5128	3.8036	6.0419	5.9397
ROA	1.1096	0.8687	0.3910	0.4459	0.2628	0.3375	0.1647	0.1278	0.1209	0.1247
Constr	(-2.80)	(2.08)	(1.01)	(1.10)	(0.85)	(1.07)	(0.81)	(0.61)	(1.46)	(1.46)
Food	(-2.62)	(-3.65)	(-3.22)	(-3.69)	(-3.22)	(-3.22)	(-4.04)	(-5.27)	(-5.18)	(-5.82)
Text	(-0.86)	(-0.86)	(-1.21)	(-1.62)	(-0.74)	(-1.27)	(-1.19)	(-1.62)	(-0.88)	(-1.29)
Chem	(-0.1779)	(-0.2998)	(-0.3401)	(-0.3888)	(-0.3687)	(-0.4131)	(-0.3930)	(-0.3691)	(-0.74)	(-0.74)
Pharm	0.1470	0.1607	(-0.256)	(-0.51)	(-0.329)	(-0.374)	(-0.360)	(-0.349)	(-0.349)	(-0.349)
Glas	(-0.6444)	(-0.6368)	(-0.4920)	(-0.4313)	(-0.3650)	(-0.4298)	(-0.4298)	(-0.3865)	(-0.4110)	(-0.3964)
IronS	(-0.1864)	(-0.3622)	(-1.70)	(-2.47)	(-2.65)	(-2.76)	(-2.68)	(-3.06)	(-2.92)	(-2.77)
MetalIP	(-0.4020)	(-0.4248)	(-0.3528)	(-0.4953)	(-0.4133)	(-0.5043)	(-0.4423)	(-0.4290)	(-0.4423)	(-0.4694)
Mach	(-0.3078)	(-0.4842)	(-0.5904)	(-0.5522)	(-0.4919)	(-0.4996)	(-0.3766)	(-0.3949)	(-0.3286)	(-0.3230)
ElAppl	(-0.1093)	0.0492	0.1118	(-0.483)	(-0.436)	(-0.453)	(-0.353)	(-0.374)	(-0.30)	(-0.30)
TransE	(-0.8979)	(-1.0997)	(-1.1478)	(-0.92)	(-0.92)	(-1.27)	(-1.27)	(-1.77)	(-1.82)	(-1.75)
OtherP	(-5.25)	(-6.27)	(-6.49)	(-6.94)	(-6.49)	(-6.94)	(-6.94)	(-6.36)	(-6.02)	(-5.88)
LTrans	0.3432	(-2.66)	(-2.45)	(-2.84)	(-2.52)	(-2.61)	(-2.45)	(-2.45)	(-2.44)	(-2.38)
WHT	(-0.0769)	(-0.0081)	(-0.0750)	(-0.133)	(-0.104)	(-0.46)	(-0.46)	(-0.02)	(-0.22)	(-0.22)
	(-0.37)	(-0.04)	(-0.40)	(-1.14)	(-0.86)	(-1.37)	(-1.35)	(-0.90)	(-1.25)	(-1.46)

Table 5 continued

	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
IT	0.4025 (4.04)	0.3961 (4.36)	0.2115 (2.31)	0.2246 (2.54)	0.2583 (2.89)	0.2733 (3.10)	0.3624 (4.15)	0.3445 (3.99)	0.3386 (4.03)	0.2674 (3.31)
WTrade	-0.0871 (-0.81)	-0.1951 (-1.89)	-0.2083 (-2.07)	-0.2423 (-2.45)	-0.2213 (-2.22)	-0.3395 (-3.38)	-0.3818 (-3.76)	-0.2984 (-3.06)	-0.3302 (-3.30)	-0.2602 (-3.00)
RTrade	-0.2246 (-1.54)	-0.1826 (-1.39)	-0.1406 (-1.12)	-0.2364 (-1.90)	-0.1254 (-1.06)	-0.1951 (-1.59)	-0.1889 (-1.57)	-0.1165 (-1.02)	-0.2545 (-2.16)	-0.1849 (-1.74)
Banks	-0.4829 (-3.05)	-0.4418 (-2.86)	-0.3838 (-2.73)	-0.3537 (-2.69)	-0.2994 (-2.25)	-0.3254 (-2.41)	-0.3352 (-2.56)	-0.2347 (-1.91)	-0.2371 (-2.05)	-0.1219 (-1.18)
RealE	0.2646 (1.68)	0.0037 (0.02)	-0.0065 (-0.04)	-0.2825 (-1.87)	-0.2657 (-1.72)	-0.2124 (-1.47)	-0.0970 (-0.68)	-0.0608 (-0.42)	-0.0349 (-0.25)	-0.0525 (-0.39)
Serv	0.1344 (1.15)	0.1141 (1.05)	0.0988 (0.94)	0.0600 (0.60)	0.1381 (1.37)	0.1070 (1.08)	0.1342 (1.35)	0.0861 (0.86)	0.0886 (0.92)	0.0691 (0.76)

The Poisson regression explains the number of outside directors of a firm by the ratio of shares held by other corporations, shares held by financial institutions, shares held by foreign investors and shares held by security houses. We control for the firm's board size. For each year, we estimate this model and with and without additional controls for the (most populated) sectors based on the TOPIX classification in the odd and even columns. t values are shown in parenthesis.

power since in some sectors outside board members are still not that common. This includes firms from the sectors construction, glass, machinery, transportation equipment and (for most of the time) banks. On the other side of the spectrum, we find the IT industry, which for the entire sample period employs significantly more outside board members than the average.

The number of outside board members is on average higher at firms with higher profitability, yet this relationship is weak and fading over time.¹² Hence, while in the 2000s outside board members might have been an indicator for board efficiency and profitability, the wider adoption of outside board memberships has removed this relationship over time.

In general, our results are mostly in line with similar findings by Agrawal and Knoeber (1996) and Duchin et al. (2010), despite methodological differences. We can confirm that outside board membership has a sector-specific component and we observe that an increase in the number of outside board members does not necessarily lead to better performance. A likely explanation for the time variation of our results is that in the early phase of our sample, it was easier to find outside board members that had low costs in acquiring information about the firm they were appointed by (and were therefore effective) and that at the later stage of our sample a larger share of outside directors was appointed that served more of a window-dressing purpose.

6 Networks and firm profitability

6.1 Firm growth and connectivity

Over the ten years that our sample covers, some firms have, as discussed earlier, ceased to exist. Many others have seen profound changes in their business models or have for other reasons gained or lost in influence and size. We will therefore follow the 1798 firms that have survived and for which consistent data is available on their performance. We have calculated the percentage growth in total assets over the course of the 10 years and have grouped the firms into the top 25%, middle 50% and bottom 25% according to this criterion.

In Fig. 6, we show how these different groups develop. We observe that the firms from the weakest performing group do not only loose in terms of total assets but that these firms also loose connections in the board network and the ownership network (top left and bottom right panel). The top 25% on the other side have a high connectivity in both networks which is further growing, partially by hiring more outside board members and other board members with multiple mandates.¹³

Arguably, some of these developments are natural consequences of the growth and shrinkage of firms. (For more details, see also Fig. 14 in the “Appendix”, which shows

¹² Data on the ROA is not available for all the firms in the sample. As a robustness check, we have therefore alternatively estimated the model with reduced sample sizes of about two thirds of the firms. We have also estimated the model with the full sample while omitting the ROA variable. In both cases, the qualitative results were identical to those presented in Table 5 (material upon request).

¹³ Twelve firms which showed abnormal changes in total assets, mainly due to mergers and acquisitions, have been removed from this analysis.

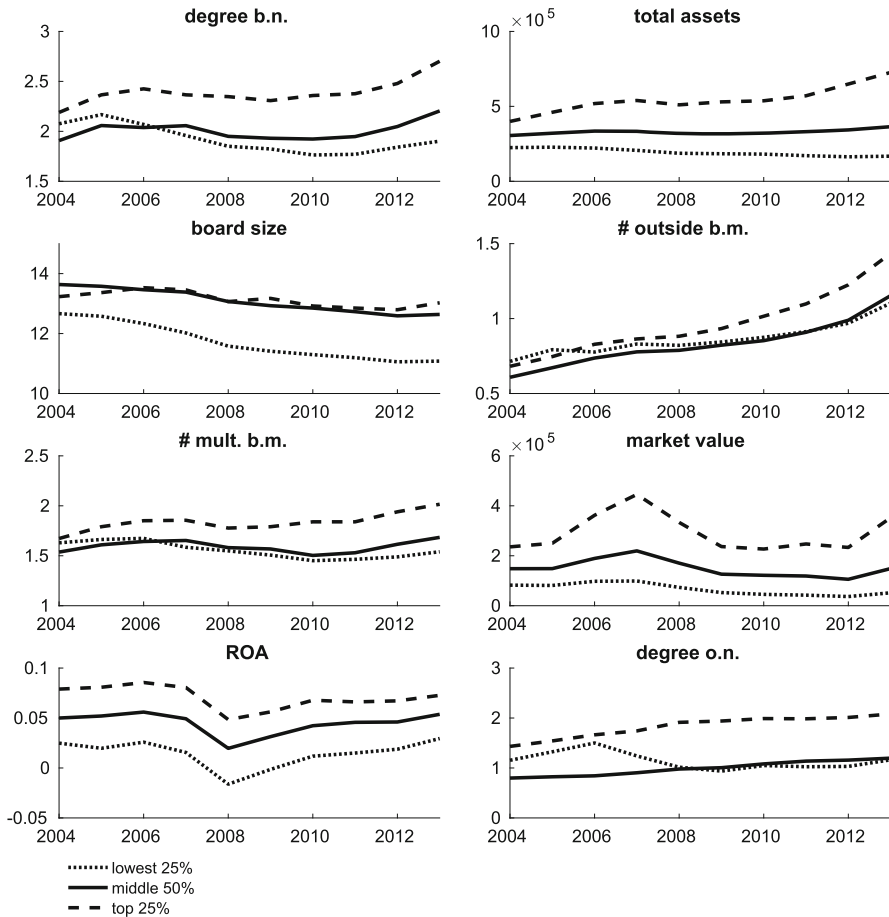


Fig. 6 Firm growth over time. This figure shows how the top 25% of firms with the highest total asset growth have developed compared to the lowest 25% and the rest. The figures show that firms that shrink (lowest growth) also lose connections in the board network and ownership network. Firms that grow gain interorganizational ties and gain more outside board members

the relationship of connectivity with other firm characteristics.) The fact however that the worst performing 25% of firms had a connectivity above average in the board network and the ownership network in 2004, which then successively dropped, suggests that some conditional feedback might exist from connectivity to profitability and growth. Those firms who performed worst lost more ties during the financial crisis than everybody else. This suggests that not the amount of ties but their quality is related to growth and profitability. We will elaborate on this in the following section.

6.2 Determinants of profitability

The structure of the top layer management of a corporation and how it is connected with the management of other corporations has implications for the long run success of a

company. Executives or other board members who can bring in experience from outside can be very valuable to navigate economic downturns or restructuring processes. On the other hand, board members who serve as a mere transmission channel for the needs of affiliated companies can slow down the effective management of a company (see also Davis and Cobb 2010; Carpenter and Westphal 2001). Similar effects occur in the case of ownership or equity ties between corporations. Connected firms can profit from these connections if they support a chain of value generating activities that would be hard to achieve without them. When ties exist for the mere sake of diversification of business activities the effects are often ambiguous (see also Anjos and Fracassi 2015).

In the case of Japan corporate ties however have a special history. Firm conglomerates, often referred to as *keiretsu*, used to have a huge influence on the economic system until the middle of the 20th century. Traces of them are still visible today, even if many argue that the economic downturn of the 1990s dissolved most. Studies on the long-run success of these conglomerates find that these structures go at hand with within-group interventions and risk sharing, a process that in general has been found to significantly lower the return on assets of conglomerate members. We will follow up on this finding and analyze if there are effects from firm connectivity on profitability by using variables from the board and ownership network together with some control variables. Similar to the work by Lincoln and Gerlach (2004), we measure profitability by the return on assets (ROA) and we use the total assets and the ratio of loans to total assets as controls.¹⁴ Data on these key financials is not consistently available for all the firms in our sample. This limits the sample for this part of the analysis to around 2000 firms in each year.¹⁵

Since the number of potential variables that describe network relationships, centrality, local connectivity or clustering is almost endless, we choose to break this analysis down into two steps. First, we employ a machine learning algorithm that we feed with data of the potential variables. From this process, we learn which variables seem to have an impact on the ROA. It also helps to identify variables that might interact. In any case, the results from the machine learning algorithm are then used to construct dummy variables which significance can be analyzed within a regression analysis.

We found that a regression tree model delivers satisfactory results in the first step. The output of this model consists in a regression tree, a hierarchical structure where at each branch the dataset is split into two parts depending on the value or state of the most important variable. An example of such a tree is shown in Fig. 13 in the “Appendix”. We have run the tree model separately for all the ten years of our dataset, and we have evaluated which variables, thresholds of variables, and combinations of variables repeatedly appear in the regression trees for all the ten years. We have supported this by calculating the importance scores for all the variables for all ten years. These results are shown in Fig. 7.

¹⁴ We found that the ROA is the variable that works best for a large sample comprised of firms from different sectors, including variables like sales into our model would necessitate either a much more complex model or a drastically reduced sample size.

¹⁵ We omit firms from the analysis which report a ROA that is outside the range $-20\% < ROA < 25\%$ since such results are typically not the result of continuing business activity.

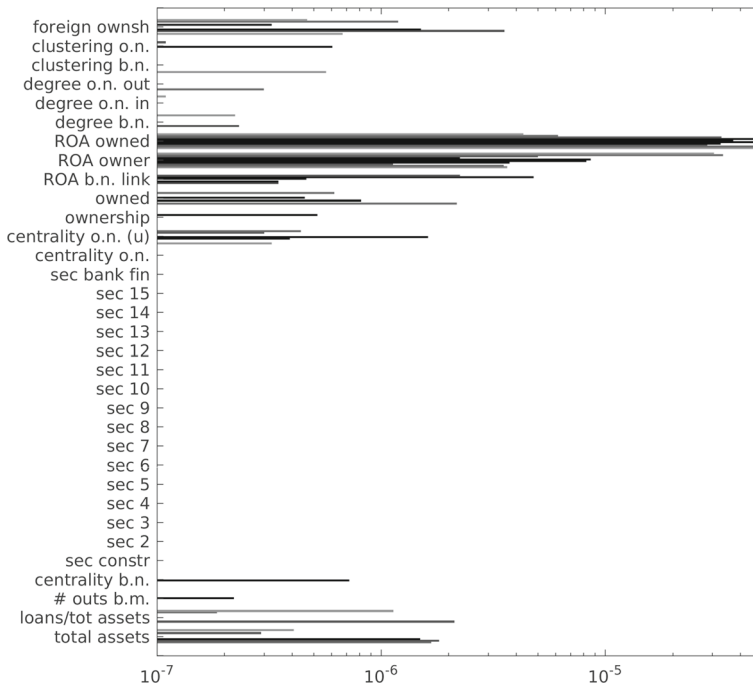


Fig. 7 Importance of variables in regression tree. The figure shows the importance scores of all our variables for all 10 years in a combined bar plot and on a log scale. Variables that are not used at any node in the regression tree will have a score of zero, while the score of other variables depends on the relative improvement to describe the data when the variable is used as either a primary or surrogate splitter

We have tested the following variables: log total assets, loans to total assets, number of outside directors, log eigencentrality in board network, sector dummies, log eigencentrality in ownership network, log eigencentrality in undirected ownership network, total ownership of other companies, fraction of company owner by other companies, average ROA of company linked to in board network, ROA of largest owner (min 3.8% ownership), average ROA of companies owned (min 2% ownership),¹⁶ degree in board network, in- and out-degree in ownership network, local clustering in board and ownership network, and foreign share ownership.

From this analysis, we learn that the ROA of owned firms as well as the ROA of the main owner have most influence on the firms' ROAs. The regression trees show us in fact even more, namely that these two variables often appear as two successive branches in the tree with predicted ROAs significantly different from the mean when both, the ROA of the owner as well as the average ROA of owned firms are greater than 3.5 percent. Also other variables from the ownership network have some importance, namely total ownership and the total share owned by other firms as well as centrality

¹⁶ The threshold of 2% is required to filter out diversified investments of institutional investors and other shareholders without significant influence on the owned firm. Filings for large shareholders are legally required at 5% ownership in Japan. In practice, this leads to many cases of shareholding slightly below this threshold which is why we chose a threshold of 3.8%.

(which are of course related). The degree itself is almost never important in any network. What is further interesting is that also the ROA of a firm which is linked by a shared board member is sometimes a significant influence.

In a second step, we can now test the significance of the influence of links in the ownership and board network by estimating the determinants of ROA. Since only some of the firms have a connection in the board and ownership network, we cannot use the ROA of connected firms as a variable directly. Also, in the case of the ownership network, both directions of ownership seem to be important. Hence, we set up two dummy variables. The board link dummy is 1 if the mean of the ROA of connected firms is larger than the mean of all firms plus 0.2 times the standard deviation. The dummy for the ownership network is 1 if both, the average ROA of owners and of owned firms is larger than the mean ROA minus 0.3 times the standard deviation.¹⁷ Hence, it signals that a firm is not sandwiched in between a badly performing owner and badly performing partly owned firms. We further test for the influence of the position of a firm in the ownership network by adding the variable *total ownership*, which describes the cumulative percentage shares held by other companies in the ownership network and *degree/total assets*, the number of companies of which a firm holds shares of divided by total assets. These specifications are chosen to make sure that these two variables do not correlate with *total assets* but give a measure of ownership relative to the size of a firm.

We now estimate three versions of this model.¹⁸ The first version uses only the just mentioned variables without any further differentiation for sectors or years. Since the thresholds for our ownership and board link ROA variables depend on the yearly averages of the ROA, a pooling for all 10 years should in principle be possible. The results for this model are shown in the left column of Table 6. Since the financial crisis of 2008 has probably led to more than just minor fluctuations it makes of course sense to employ individual constants for each year. As we can see, this does not change the estimation results much, yet it improves the explained variance quite a bit. Finally, we can add variables to classify the most populated Topix sectors. This should help to explain differences in ROA which are caused by sector-specific effects. We use 12 dummy variables for the sectors, yet in the table, we only show the most important ones. We note that the financial sector is a merged category that contains banks, insurances, and firms offering other financial services.

Interestingly, our analysis shows that ownership relations generally lead to slightly (yet significantly) lower ROAs. There are however two exceptions from this. Positive effects can be found when both the owner and the (partly) owned firms are profitable (signaled by the variable ROA owner net). Significantly positive effects can also be found from links in the board network (ROA board net), if connected firms have above average profitability.¹⁹

¹⁷ This results in a still slightly positive ROA. Note that this threshold level is derived from the regression tree analysis, but we now express it in terms of the mean and the standard deviation to accommodate for slight changes over time.

¹⁸ We note that the distributional properties of the data require a robust regression. This means that all our assessments of significance are based on t-distributed errors.

¹⁹ As a robustness check we have performed the same regression on a yearly basis and found similar results, although the ROA variables were not significant in all years. We have also left out the control variables total

Table 6 Determinants of ROA

Model	Simple pooled		Year dummy		Year and sector	
R^2	0.0464		0.0794		0.1107	
N	20,942		20,942		20,942	
Const	0.05467	(10.56)*				
Const 1–10						
Total assets	0.00077	(1.58)	0.00058	(1.22)	0.00150	(2.97)*
Loans/tot assets	-0.08289	(-10.89)*	-0.07927	(-10.58)*	-0.08662	(-11.04)*
Tot owned	-0.00166	(-7.41)*	-0.00168	(-7.63)*	-0.00132	(-5.92)*
Degree/tot assets	-0.05415	(-2.00)	-0.04806	(-1.80)	-0.06166	(-2.31)
ROA owner net	0.01647	(4.32)*	0.01696	(4.52)*	0.01502	(4.06)*
ROA board net	0.00820	(4.14)*	0.00816	(4.19)*	0.00695	(3.61)*
Sec constr					-0.01773	(-4.93)*
Sec chem					-0.00047	(-0.88)
Sec machinery					0.00317	(0.34)
Sec elec appl					-0.00674	(-2.20)*
Sec bank finance					-0.02019	(-3.23)*
Sec IT comm					0.01848	(5.49)*
Sec pharma					0.02718	(4.55)*
Sec 7–16						

This table shows the estimation results for three different models of influences on the return on assets. The simplest model in the left column only considers the main variables. The model in the middle column considers a dummy variable for each year. The model in the right columns considers a year dummy and 16 dummies for sectors, of which the results for the seven most important ones are given. *t* statistics based on *t* distributed errors are given in parenthesis. Significance levels: 0.1 ; 0.05 ; 0.01*

At last, the results on the effects of ownership deserve a closer look. We want to investigate if instead of referencing to connected firms' ROA structural features could be responsible for our results.

First of all, one could argue that in some cases we might see effects from minority shareholder relationships. Some authors claim that minority shareholders can be disadvantaged against controlling shareholder who enjoys private access. This can impact firm valuation and profitability (see, e.g., Guedes and Loureiro 2006; Claessens et al. 2002).

Second, our general result on negative effects from ownership relations is in fact in line with many studies on diversification. Although diversification as an instrument of risk management is often successful, many studies show that corporations which invest into companies that operate outside of their own area of expertise are likely to

Footnote 19 Continued

assets and loans/TA, this changes the results for the sector dummies but leaves other results qualitatively unchanged. Including further network measures does not improve the model and can lead to problems in the estimation since these variables tend to be related to the existing measures of degree. We note that foreign share ownership is correlated with total assets and also partly explained by the sector dummies and can thus not be included into this estimation.

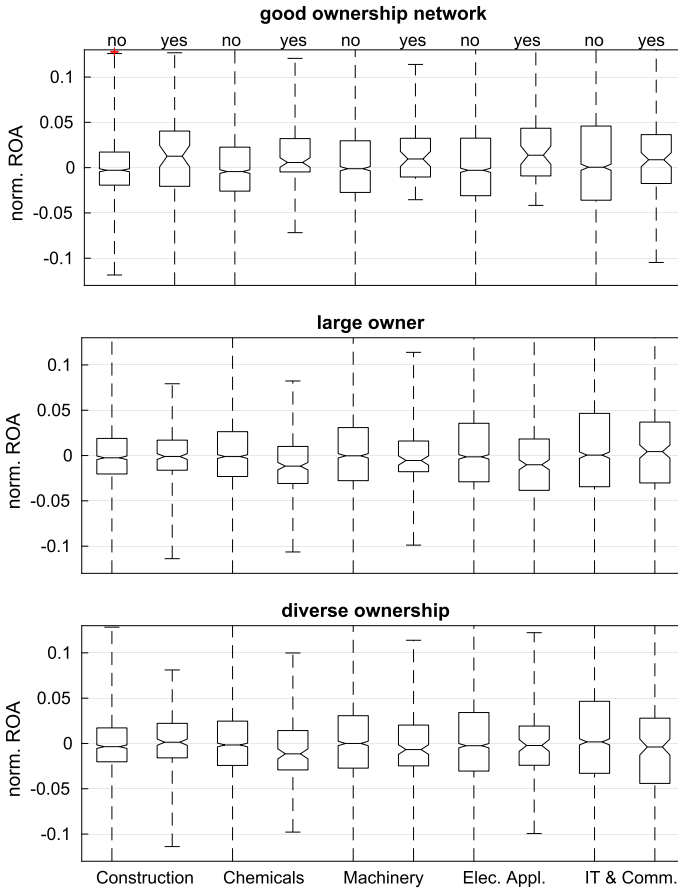


Fig. 8 Influences of ownership structures. This figure shows the differences in normalized ROA for firms from five large sectors and for three comparisons. The top panel compares firms with a ‘bad’ versus a ‘good’ ownership network. The middle panel compares firms with and without a large owner with at least 20 percent shareholdings. The bottom panel compares firms that have diversified through ownership of a company in another sector versus firms which do not diversify

negatively influence their own profitability (Berger and Ofek 1995; Schommer et al. 2019; Kawakami 2017).

In order to judge if any of these effects are related to our findings, we will look at subsamples of companies from the five most populated sectors, namely construction, chemicals, machinery, electrical appliances and IT and communications. We will compare firms with regard to the above-mentioned effects based on their ROA, which we normalize by the yearly group averages.

The results are presented in Fig. 8. We show box plots for three different comparisons for firms from five different sectors. The top panel shows the differences in the normalized ROA for our good ownership dummy variable as defined in our regression analysis and serves as a reference point. The averages of the bar plots labeled as ‘no’

and ‘yes’ are almost always significantly different, thus confirming that the results of our regression analysis can in principal be confirmed without further control variables.

We can now look at differences in between the same firms that might be caused by minority shareholding. The middle panel show a comparison where the firms are now grouped by the criterion whether they have an owner that controls at least 20 percent of the company. The results for this comparison are ambiguous. Firms from the sectors chemicals and electrical appliances do in fact have a significantly lower normalized ROA when they have one very large owner, for firms from other sectors this effect cannot be confirmed.

Finally, we group the firms by asking whether they own at least one percent of some other firm that is active in a sector different from their own. This aims at checking effects from diversification. At a first glance the results, presented on the bottom panel, appear unsystematic. For some sectors the difference is positive, for others negative. However, a pattern can be found once we go back to the sector-based dummy variables from our regression analysis in Table 6. In those sectors, where the average ROA is above or similar to the economy average (chemicals, machinery, IT) the average normalized ROA is lower for corporations which diversify to other sectors. For the two sectors where the average ROA is below economy average (construction, electrical appliances) diversifying into other sectors yields a slightly higher normalized ROA. These results are admittedly not in all cases significant, yet they show an interesting tendency. The benefits of diversification might depend on what the heritage of a corporation is and whether they can in the long run divert funding into activities in more lucrative fields.

Coming back to the question if our previous regression results are possibly remnants of minority shareholding or diversification effects, we can conclude that these do not explain our findings. The network effects on profitability that we have identified in the ownership network and through corporate board interlocks are of a more general kind and are caused by interdependencies of profitability rather than ownership relations alone. Our results can thus be viewed as complementary to that of Zona et al. (2018). While in their study they have found effects of board interlocks that depend on characteristics of the *ego* firm in a network, we have found effects that mainly depend on characteristics of the *alter* firms.

7 Conclusions

In this paper, we have analyzed dependencies between firm performance and the networks of board members and ownership from different viewpoints. We found that the survival of board members mostly depends on their role in the board. The feedback from the development of the market value on board members survival is small. Broken ties in the board network are reconstituted in many, but by far not in all cases. Yet, their reconstitution process contributes to the preservation of network structure and ties between the most central directors.

For the overall network structure, we observe a tendency for links within the same sector and an mild influence of ownership ties on board interlocks. The number of outside directors is increasing, yet their number depends mostly on the sector of the firm

and the influence of foreign shareholders. Their relationship with firm performance is mostly spurious.

We observe that variation in firm growth is connected to variation in connectivity in both the board and the ownership network. Most importantly, interaction effects in firm performance are found in both networks. Firms that are connected to peers with above average profitability are themselves more profitable.

Further research is needed on these effects of interorganizational ties. This however necessitates more fine-grain information on financial ties, including information on the main bank and borrowing relationships, as well as the inclusion of production networks. More research is also needed on the dynamics of board composition, especially the career paths of individual executives and the appointments of female board members.

Acknowledgements We thank Chieko Takahashi for help in compiling the board network data.

Funding Open Access funding enabled and organized by Projekt DEAL.

Data Availability Data available from Toyo Keizai, Nikkei Needs and Thompson Reuters Datastream. The authors do not have permission to share data.

Declarations

Funding Partial funding by JSPS KAKENHI, JP20K01751

Conflict of interest The authors declare that they have no competing interest.

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Appendix

See Figs. 9, 10, 11, 12, 13 and 14, Tables 7, 8, 9, 10, 11 and 12.

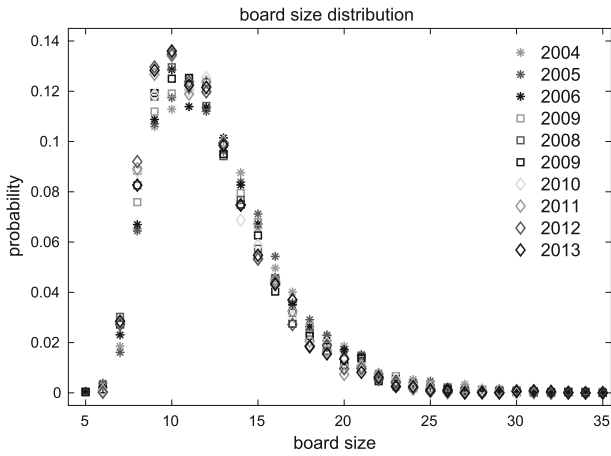


Fig. 9 Distributions of board size. The distribution of the board size shows only little variation over time. Since the board size is mostly determined by company size it shows a tail which for $x > 15$ shows similarity to a power-law

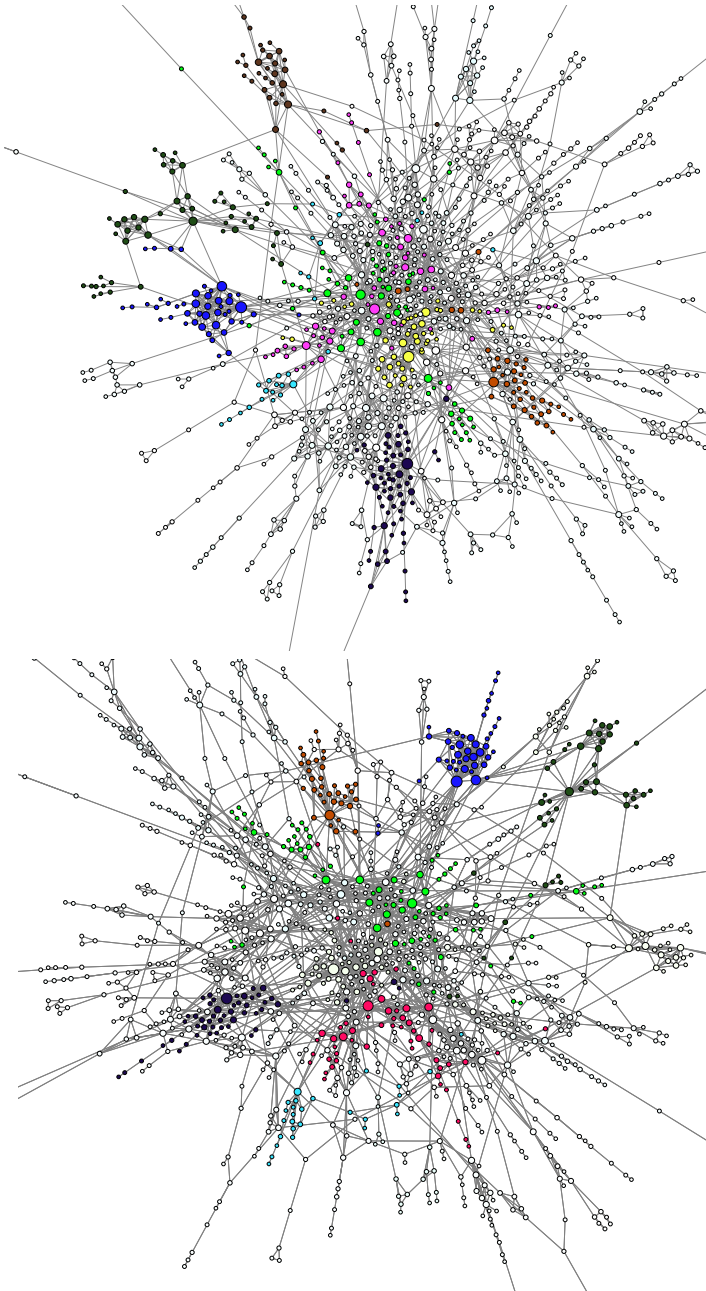


Fig. 10 Board networks. Visualization of the giant components of the board network in 2004 (left) and 2013 (right). The node size is proportional to the firm's degree. Colors represent communities. The visualization was performed in Gephi with the Force Atlas algorithm (see Jacomy et al. 2014). We used the 'fast unfolding' algorithm (Blondel et al. 2008) to identify communities. For 2004 we can find three rather obvious communities outside the center of the network. To the top left of the center we find one group which is arranged around the company Toyota (dark purple). On the right side of the network, we find a group (in blue) around Aeon. In the center of the network, we find companies arranged around Fuji Kyuko (red), Hitachi (brown), and Mitsubishi (green). In 2013, the clusters in the middle of the network overlap even more. In the right panel, we still see groups around Toyota, Aeon and Hitachi a bit distanced from the center of the network. In the center, we see (slightly changed) intertwined areas around Fuji Kyuko (pink), Tokyu (yellow) and Mitsubishi (green). In the periphery, some weaker structures exist around Softbank and SBI (beige), Rakuten (dark green), and Pioneer and Seiko Epson (brown). (We use the terms center and periphery here only with respect the position within this visualization). (Color figure online)

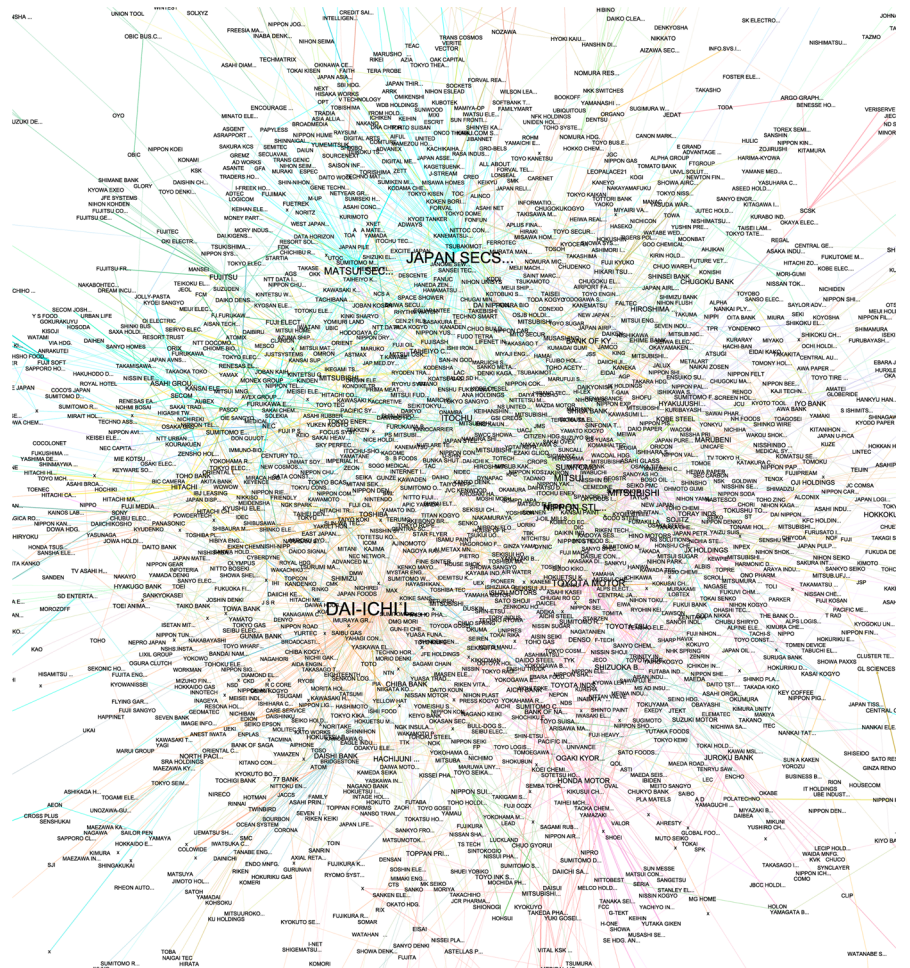


Fig. 11 Ownership network in 2013. This visualization shows the ownership network. The label size is proportional to the number of links. Color coding has been used to highlight the (overlapping and weak) community structures. The visualization is again based on the Force Atlas algorithm and the ‘fast unfolding’ algorithm for community detection. (Color figure online)

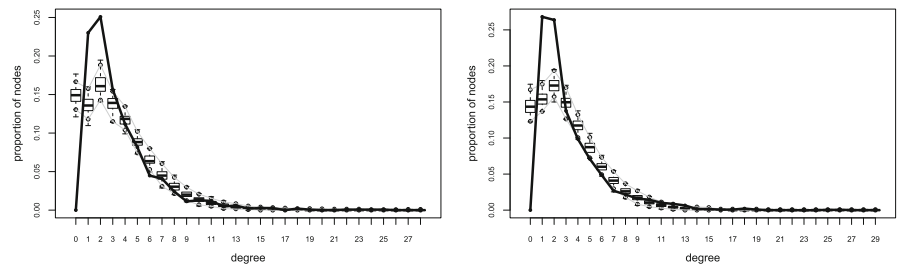


Fig. 12 Goodness of fit for degree distribution. This figure shows the degree distribution for 2007 (left) and 2010 (right) together with that of simulated networks based on estimation results. The degree distributions are in reasonable alignment for $k \geq 3$

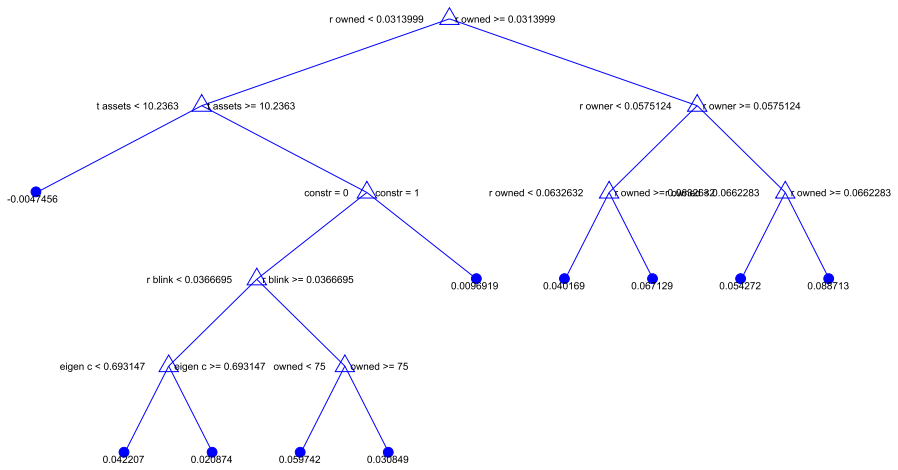


Fig. 13 Regression tree for 2010. This example shows prototypically the results of the regression tree analysis. Branches are labeled with the split variable and the split point value. End leaves show the expected resulting ROA for firms that fall into the category that is defined by the splits in the tree structure

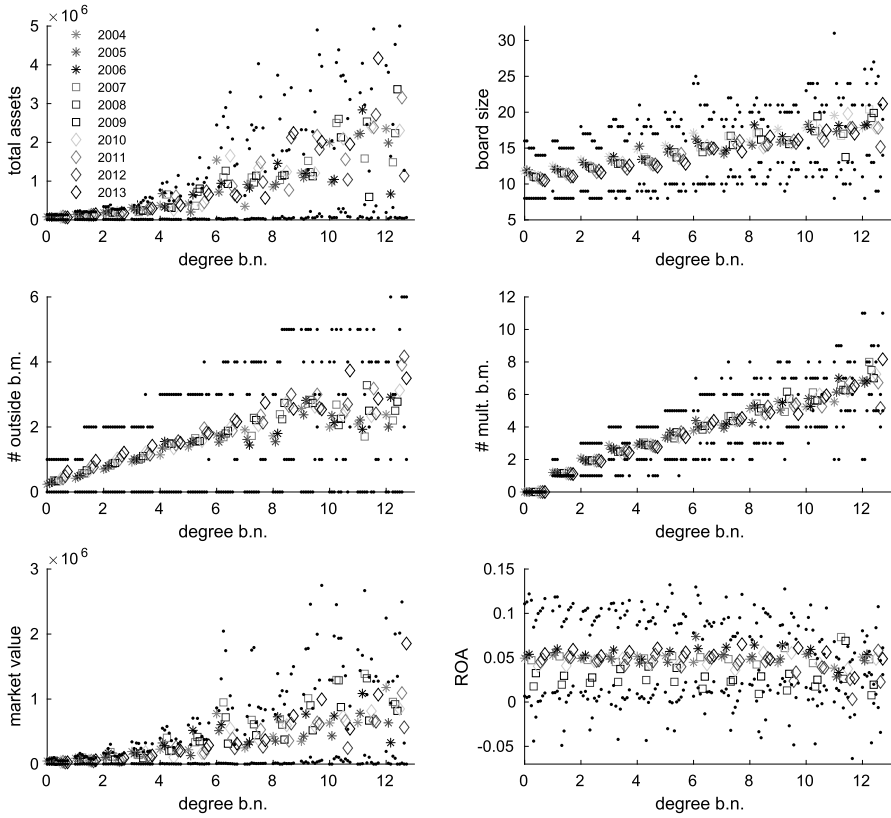


Fig. 14 Board connectivity and firm characteristics. This figure shows how different characteristics scale with the number of links in the board network. The averages for different years are printed with an offset. Black dots show the 75% interval for each year

Table 7 Board member survival

	$t + 1$	$t + 2$	$t + 3$	$t + 4$	$t + 5$	$t + 6$	$t + 7$	$t + 8$	$t + 9$
2004	0.8438	0.6855	0.5588	0.4508	0.3840	0.3175	0.2659	0.2263	0.1989
2005	0.8209	0.6685	0.5402	0.4542	0.3774	0.3155	0.2697	0.2345	
2006	0.8230	0.6665	0.5615	0.4601	0.3854	0.3282	0.2858		
2007	0.8161	0.6862	0.5665	0.4669	0.3976	0.3448			
2008	0.8462	0.6987	0.5779	0.4866	0.4230				
2009	0.8325	0.6886	0.5807	0.4997					
2010	0.8361	0.7065	0.6109						
2011	0.8532	0.7395							
2012	0.8714								

This table shows the survival probability of board members from one year to every other year based on the information in the Toyo Keizai database and our identification method described in Sect. 2.1

Table 8 Firm survival

	$t + 1$	$t + 2$	$t + 3$	$t + 4$	$t + 5$	$t + 6$	$t + 7$	$t + 8$	$t + 9$
2004	0.9750	0.9517	0.9180	0.8792	0.8482	0.8219	0.8004	0.7847	0.7730
2005	0.9771	0.9423	0.9000	0.8683	0.8410	0.8194	0.8030	0.7906	
2006	0.9650	0.9226	0.8907	0.8620	0.8385	0.8212	0.8088		
2007	0.9563	0.9233	0.8943	0.8691	0.8508	0.8377			
2008	0.9660	0.9360	0.9092	0.8898	0.8760				
2009	0.9692	0.9417	0.9218	0.9067					
2010	0.9716	0.9513	0.9355						
2011	0.9791	0.9630							
2012	0.9839								

This table shows the probability of survival for the firms from one to every other year, based on the existence of the stock identifier

Table 9 Determinants of board member survival without firm performance

Year	2004–2005	2005–2006	2006–2007	2007–2008	2008–2009	2009–2010	2010–2011	2011–2012	2012–2013
MF R^2	0.0071	0.0180	0.0068	0.0101	0.0108	0.0156	0.0148	0.0162	0.0183
LR	257.7	722.0	274.7	405.0	368.9	546.3	497.5	498.9	510.9
N	42,175	42,635	43,121	41,998	39,907	38,759	37,731	36,884	36,452
Survivors	35,589	34,998	35,488	34,276	33,769	32,266	31,548	31,469	31,764
Const	1.9569 (32.26)	1.8349 (28.86)	1.5866 (26.46)	1.3504 (26.92)	1.8192 (32.37)	1.9528 (34.70)	2.1018 (37.29)	2.2074 (37.20)	2.4642 (36.29)
$\log(\text{mand}_{t-1})$	0.5069 (10.51)	0.6577 (14.02)	0.5495 (12.18)	0.6095 (12.82)	0.5903 (11.46)	0.6800 (13.20)	0.6704 (12.74)	0.7582 (12.79)	0.7959 (12.20)
Age	0.0003 (1.82)	-0.0348 (-21.03)	0.0005 (4.32)	0.0002 (1.83)	-0.0185 (-10.49)	-0.0293 (-16.66)	-0.0286 (-15.85)	-0.0258 (-13.49)	-0.0286 (-13.98)
Female	0.3158 (2.13)	-0.0314 (-0.25)	-0.0888 (-0.80)	0.0260 (0.22)	0.1092 (0.80)	0.4961 (3.31)	0.2913 (2.10)	0.4529 (3.03)	0.6935 (4.08)
$\log(\text{mv}_t)$	-0.0228 (-3.87)	-0.0018 (-0.30)	0.0077 (1.35)	0.0251 (5.24)	0.0063 (1.16)	-0.0064 (-1.16)	-0.0201 (-3.64)	-0.0189 (-3.27)	-0.0287 (-4.35)
Outs. board	-0.4197 (-6.64)	-0.5002 (-8.72)	-0.4112 (-7.31)	-0.5475 (-10.36)	-0.4586 (-7.96)	-0.3224 (-5.56)	-0.2243 (-3.84)	-0.4197 (-7.43)	-0.2781 (-4.64)
Outs. audit	0.2885 (7.28)	0.0668 (1.92)	-0.0555 (-1.66)	0.2167 (6.19)	0.2633 (6.73)	0.0360 (0.99)	0.0209 (0.56)	0.2054 (5.03)	0.2771 (6.27)

This table shows the results of a logit regression. t -values are shown in parentheses. Although survival is a large part random, we find significant influence for holders of multiple mandates (mand), outside board members and outside auditors. The age, gender and the market value of the company (log MV) are of changing importance. The results are qualitatively similar to the findings in Table 2 although the R^2 is much lower when omitting the delist variable

Table 10 Goodness of fit for model

	2007					2010				
	Empirical	Min	Avg.	Max	P	Empirical	Min	Avg.	Max	P
Edges	2303	1993	2281	2624	0.76	2633	2256	2693	3060	0.78
b size	1036	609	959	1464	0.64	1356	1067	1555	2039	0.62
Fin lk	343	275	342	404	1.00	372	289	373	453	0.82
Same sec	377	304	363	450	0.58	467	392	488	564	0.74
Owner lk	5766	4464	5361	5913	0.16	6095	5504	6154	6678	1.00
gwesp	1607	1248	1583	1930	0.68	2008	1601	2083	2452	0.80

This table shows the statistics of networks generated based on the model estimates against the empirical (fitted) networks for 2007 and 2010. While the simulated models show some variability in the statistics, we observe that the average of the statistics are in agreement with the empirical data. The p-statistics confirm that the empirical network is not significantly different from the simulated ones based on this statistics

Table 11 Board composition

	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
b. members	42,175	42,635	43,121	41,998	39,907	38,759	37,731	36,884	36,452	36,697
female	439	506	533	515	493	514	536	571	623	713
% female	1.04	1.19	1.24	1.23	1.24	1.33	1.42	1.55	1.71	1.94
Avg. age	57.2	57.3	57.2	57.4	57.7	58.1	58.3	58.4	58.7	58.9
Avg. age f.	51.3	50.9	51.6	52.0	52.3	52.8	52.9	53.3	53.8	54.1
Outside b.m.	1823	2044	2194	2276	2214	2277	2355	2474	2603	3028
Mult b.m.	2268	2383	2423	2338	2194	2141	2039	2040	2108	2206
Both	527	554	593	591	571	569	545	564	596	678
% outside	5.57	6.06	6.34	6.64	6.73	7.11	7.39	7.86	8.32	9.60
% mult	11.03	11.50	11.41	11.26	11.06	11.14	10.90	11.09	11.50	12.00

The first 5 rows give information about the number of female board members and the average age of board members. The next three rows give the total numbers of board members who are labeled as an outside director have multiple mandates according to our data set, or where both applies. Rows 9 and 10 state the average percentage of outside board members and board members with multiple mandates in a corporate board

Table 12 Statistics on sectoral decomposition

Sector	2004			2013		
	N	< board >	Z	N	< board >	Z
1 Fishery and AF	11 (0)	13.27		11 (3)	12.27	
2 Mining	9 (5)	13.11		7 (5)	13.71	
3 Construction	223 (81)	13.21	-0.6423	174 (78)	11.93	-0.1146
4 Foods	157 (64)	12.66	-0.1934	131 (71)	11.93	-0.4192
5 Textiles and Ap.	87 (33)	11.34	-0.3991	56 (31)	11.16	-0.2239
6 Pulp Paper	29 (9)	12.62	-0.3251	26 (9)	11.65	-0.0908
7 Chemicals	216 (85)	12.53	-0.4017	215 (101)	11.61	-0.1378
8 Pharmac	54 (16)	12.06	-0.0477	61 (46)	11.44	-0.1777
9 Oil and CP	13 (6)	13.23		13 (8)	12.54	
10 Rubber P	21 (5)	12.38		19 (8)	11.63	
11 Glass and CP	72 (27)	11.24	-0.3105	62 (29)	10.66	0.0794
12 Iron Steel	56 (22)	13.07	-0.4619	49 (27)	11.59	-0.2133
13 Nonf Metals	39 (18)	11.74	0.0924	36 (19)	10.94	-0.2330
14 Metal P	100 (30)	11.43	-0.3620	91 (31)	10.73	-0.0318
15 Machinery	249 (84)	11.85	-0.4377	230 (95)	11.14	-0.2050
16 Electric A	305 (121)	12.05	-0.3506	273 (138)	11.23	-0.2521

Table 12 continued

Sector	2004			2013		
	N	< board >	Z	N	< board >	Z
17 Transp. Eq.	106 (46)	14.58	-0.4691	100 (49)	12.25	-0.3072
18 Precision I	51 (19)	11.27	-0.0962	50 (22)	11.20	-0.1170
19 Other Products	111 (37)	12.12	-0.3099	109 (41)	11.03	0.3016
20 Electric PG	25 (20)	18.80		23 (18)	15.91	
21 Land Transp	70 (44)	14.83	0.2076	65 (42)	14.31	0.1815
22 Marine Transp	19 (9)	13.11		16 (7)	11.75	
23 Air Transp	6 (6)	13.67		6 (4)	12.33	
24 Warehousing HT	43 (19)	13.33	-0.3223	41 (22)	12.66	0.2262
25 IT and Comm	306 (124)	10.79	-0.1196	349 (170)	10.08	-0.3540
26 W Trade	375 (106)	11.52	-0.3876	343 (120)	10.66	-0.0318
27 R Trade	375 (119)	11.10	-0.0214	342 (135)	10.58	-0.2151
28 Banks	96 (40)	14.40	-0.0903	93 (45)	15.14	0.0201
29 Securities CF	42 (19)	12.05	-0.1495	40 (22)	10.35	-0.2929
30 Insurance	11 (8)	16.27		12 (10)	12.25	
31 Other Financing	55 (34)	11.78	-0.1374	32 (19)	11.91	0.4810
32 Real Estate	110 (38)	10.65	0.1039	111 (50)	9.77	-0.3015
33 Services	325 (114)	10.66	-0.1265	359 (150)	10.06	-0.0237

This table shows the number of firms in each sector for 2004 and 2013 and their average board size. In parenthesis, we report the number of firms in the giant component. Further, we show estimation results for adding these firms to the estimation presented in Sect. 4

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