Corporate governance networks and financial performance *

Annalisa Tonetto [†]

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[†]University of Cambridge, Judge Business School, Trumpington Street, Cambridge CB2 1AG, United Kingdom e-mail: *a.tonetto@jbs.cam.ac.uk* .

Abstract

I investigate the impact of two different corporate governance network connectedness measures on financial performance of firms. I consider both ownership connectedness, defined as the number of connections to other firms through common shareholders, and boardroom connectedness, that is the number of connections to other firms through common directors. In panel regressions, I find that firms with higher shareholder overlap but lower directors overlap with other firms have higher ROA. These relations are statistically significant and economically meaningful: ceteris paribus, 200 additional common institutional shareholders have a +0.7% impact on ROA, while one additional common female director has a -0.6% impact on ROA. Using changes in the Russell 1000 and Russell 2000 indices constituents as a source of exogenous variation in ownership connectedness, I establish that the relation for ownership connectedness is causal: higher institutional shareholder connectedness imply higher ROA. Firms benefit from sharing institutional investors. In fact, given their size and scope, they act like a super entity between the firms they have in their portfolios, facilitating the exchange of best practices among connected firms. On the other hand, I provide evidence that female directors sitting on multiple boards adversely affect firm performance, most likely because of the overboarding issue associated with women sitting on US boards.

Keywords: ownership, boards, network analysis, indexing, corporate governance, institutional investors, financial performance

1 Introduction

Networks represent the environment in which corporations operate and they act as conduits for multiple type of flows. Networks' links are channels to communicate information, to exchange resources, to create new relationships. Researchers have long been studying the nature and consequences of networks from a social[1], financial[2], and commercial perspective. Traditionally, the different type of relations connecting firms have been studied in isolation without accounting for multiple types of connections between firms.

In this paper, I study the impact on firm performance of two main corporate governance measures of connectedness: ownership and boardroom. Ownership links are represented by common shareholders between firms while boardroom links are represented by shared directors. To date, the net effect of these two types of connectedness on firm performance has received scant attention, and we are unable to disentangle the net effect on firm operating performance of the ownership and board connectedness.

Institutional ownership has grown in the last decades, and its composition has moved towards passive fund ownership[3]. So far, researchers are still debating on the effects of passive funds on firms' governance and the discussion about their role has primarily focused on their incentive to engage with the firms for which they hold shares. Some papers argue that passive funds lack on incentives to stay engaged[4], while others provide evidence that they have among the strongest direct financial incentives to become informed[5]. Passive funds are also well known to push broad based reforms, especially to increase board gender diversity[6], opening a debate on the consequences of an *elite* of women directors serving on multiple boards[7] (also known in the literature as "overboarded" or "busy" directors).

To address overboarding concerns, in the past five years, BlackRock, Vanguard, State Street, ISS, and Glass Lewis updated their proxy voting guidelines related to what they consider "overboarded" directors. Some of these investors, may withhold votes where a director sits on more than three public company boards. They generally recommend a vote against executive officers who sit on more than

[1]For background on social networks see: Watts (2003) and Laumann (1973).

[2]For background on how networks are studied in finance and their role see, Fracassi and Tate (2012), Larcker, So, and Wang (2013) and Vitali, Glattfelder, and Battiston (2011).

[3]Corum, Malenko, and Malenko (2022)

[4]Lund (2018)

[5]Kahan and Rock (2020)

[6]Gormley, Gupta, Matsa, Mortal, and Yang (2021)

[7]Seierstad and Opsahl (2011)

two public company boards. Given the percentage of the shares owned by institutional investors in the aggregate of any US public company, the impact of voting policies on director elections is vast. These overboarding policies explicitly state that shareholders will take into account public commitments by directors to step down. Therefore, if a director finds herself a potential candidate for a no-vote, the director should consider whether she intends to step down from any of the public company boards on which she serves and ensure that such plans are adequately communicated and disclosed. Institutional investors also reiterate that companies for which they have shares, are encouraged to discuss their governance practices more generally. Director skills, experience and the director selection process are aspects on which institutional investors are particularly engaged.

In this paper I explore the extent to which the interconnectedness of shareholders and boards affect firm performance. I contribute to existing literature[8] by showing that these two different types of connections have opposite implications on firm profitability. I test empirically such relations on a large sample of US companies in the period 2013-2018.

Empirically, I use ORBIS data to analyze patterns of ownership connectedness between US firms and BoardEx data for boardroom connectedness. In contrast to prior studies, I find that a firm benefits from having common shareholders, while it is detrimental to share directors with other firms. In panel regressions, I find that firms with higher shareholder overlap but lower directors overlap have higher ROA. These relations are statistically significant and economically substantial: ceteris paribus, 200 additional common institutional shareholders (average number of additional common shareholders when a large institutional investor buys a share in the company) have a +0.7% impact on annual ROA, while one additional shared female director has a -0.6% impact on ROA.

My second contribution to the literature is to study how ownership connectedness varies by investor type and how boardroom connectedness varies by gender type. Considering subnetworks created only either from institutional investors connections or female directors connections, I find that only for these subnetworks the connectedness measure remain significant for ROA. These results are consistent with the interpretation of institutional shareholders' links serving as information channel, thus leading to better firm performance. On the other hand, board connectedness, through female directors appears to be detrimental for performance, probably because too few women are on too many boards thus producing a degree of busyness that penalizes the board work and eventually the firm return.

[8] Azar (2022)

As a third contribution, I provide causal analysis using the Russell 1000/2000 setting in a regression discontinuity design (RDD) to examine the effect of institutional investor ownership connectedness on firm performance. In fact, the yearly allocation to Russell 1000 and Russell 2000 indexes drives a quasi random exogenous change in institutional ownership, and consequently, in ownership connectedness: the largest firms in the Russell 2000 are characterized by an increase in numbers of institutional investors and therefore ownership links to other firms.

This paper highlights the significant opportunities for the simultaneous use of data to measure and identify more accurately which channels are relevant to better understand the role of firms connectedness. Taken together my findings indicate that: both ownership and boardroom connections have an impact on firms outcome, and should be considered jointly.

This paper also contributes to the indexing and corporate governance literature. First, by using these two measures of connectedness, I identify mechanisms associated to busyness of female directors and to share of best practices among institutional shareholders. Second, I clearly identify which channels have a positive and a negative effect on firm performance. Third, I show that my results have a causal interpretation by using a discontinuity that has never been applied to the context of networks before. Finally, I show that there is the need to include more channels when studying flows - of resources, information - between firms.

The rest of the paper is organized as follows. Section 2 reviews the relevant literatures. Section 3 describes the data, while section 4 contains the panel regression results and their discussion. Section 5 discusses the causal interpretation of the above results by introducing appropriate exogenous shock to ownership. Section 6 presents robustness checks and section 7 a discussion of the main results. Conclusions appear in section 8.

2 Literature review

This paper relates to the literature on indexing and corporate governance. Indexed investment strategies are increasingly popular, the percent of fund assets that are indexed has increased fourfold over the last 20 years. The ”Big Three” (Vanguard, BlackRock, State Street) dominate this market, holding on average about 16% of a U.S. public company’s equity. They account for 25% of votes cast for

S&P500 firms[9]. This indexing growth raises many questions such as what impact does this ownership shift have on stewardship, or does the resulting increase in common ownership matter. Focusing on the governance implications, a first question is on the impact of ownership and boardroom structures' on firm performance. The channels through which ownership structures could impact firm performance are multiple. In particular, indexers might weaken governance for lack of engagement[10], or they might strengthen it because of their more active monitoring role[11], scale and scope[12]. Answering this question is challenging because ownership structures are not exogenous. To overcome the challenge, many recent papers rely on index ownership variation induced by Russell 1000 and Russell 2000 inclusion.

There is evidence on direct impact that Big Three voice matters[13]. For example, index ownership is associated with corporate governance improvements[14], including board gender diversity[15]. On the other hand, evidence suggests limits to their influence. They successfully use low cost approaches to push broad based reforms, but managers seem to take advantage of index tracking institutions' weaker monitoring[16].

Other papers attempt to explain a possible indirect impact on governance. Even if index-tracking institutions are less able to engage in high-cost monitoring, they might help others do it: ownership blocks might lower expected costs of activism by others, and their presence might increase likelihood of success. Evidence suggests as indirect impact the improvement of activists' ability to discipline managers[17]. Moreover, new work finds evidence that indexers do actually monitor, but not as much as actively managed funds[18] do. Some still question whether indexers monitor at all[19].

Several empirical papers explore the extent to which common ownership affects governance[20]. Common ownership is increasing, and growth of indexing is a key driver. There are many potential

[9] Bebchuk and Hirst (2019)
[10] Lund (2018)
[11] He, Huang, and Zhao (2019)
[12] Corum, Malenko, and Malenko (2022)
[13] Azar, Duro, Kadachb, and Ormazaba (2021)
[14] Appel, Gormley, and Keim (2016)
[15] Gormley, Gupta, Matsa, Mortal, and Yang (2021)
[16] Schmidt and Fahlenbrach (2017)
[17] Appel, Gormley, and Keim (2019)
[18] Evidence suggests they are not passive in proxy fights, but they are less likely to support activist (Brav, Jiang, Li, and Pinnington (2021)), that they focus on firms where they can have biggest impact but do less research overall (Iliev, Kalodimos, and Lowry (2021)).
[19] Heath, Macciocchi, Michaely, and M. (2022)
[20] See Azar, Schmalz, and Tecu (2018), Kempf, Manconi, and Spalt (2017) and Azar, Raina, and Schmalz (2022) for background.

problems with the argument that indexers hurt competition. It is still unclear what is the mechanism by which they influence prices and quantities of goods, if it is plausible that indexers solve this as an optimization problem, whether we should expect the growth in index ownership to shift managers' incentives to internalize externalities. Theory and data suggests small impact on incentives. In fact, accounting for investor inattention casts doubt on idea that indexing significantly shifts managers' incentive to internalize externalities[21]. So far, the empirical investigation of the relationship between index inclusion and incentives has proven inconclusive and the most recent evidence also casts doubt on early findings[22].

Evidence suggests institutional investors use low-cost ways to push broad-based changes (for example: board gender diversity). Some hypotheses have been made on what is their motivation, increasing fund performance[23] or staving off regulation[24] for example. Another relevant question is if it does matter where voting power resides. Voting responsibility can reside with centralized in-house proxy voting group or with individual funds or their investors. The Big Three have typically centralized their voting. Fund families typically vote as a block[25] and this likely gives family more influence[26]. Through an analysis of proxy vote records[27] there is evidence that the Big Three do utilize coordinated voting strategies and hence follow a centralized corporate governance strategy. Moreover, empirical patterns of shareholders' voting behavior suggest that proxy advisors' recommendations may not be a suitable benchmark for evaluating the votes of asset managers[28].

The still unanswered question is: what is the net impact of institutional investors, in particular, indexers on firm performance? Can we assess indexing's net impact on performance?

I have highlighted the fact that index ownership has focused a lot on board gender diversity campaigns during the past years. Specifically, considering board of directors' as a channel that impact firm performance, the other unanswered question is: are we able to identify which is the hidden mecha-

[21] Gilje, Gormley, and Levit (2020)

[22] Lewellen and Lowry (2021), Dennis, Gerardi, and Schenone (2021), Koch, Panayides, and Thomas (2021), Eldar (2019).

[23] Lewellen and Lewellen (2022)

[24] Kahan and Rock (2019)

[25] Choi, Fisch, and Kahan (2013)

[26] Kahan and Rock (2020)

[27] Fichtner, Heemskerk, and Garcia-Bernardo (2017)

[28] Malenko, Malenko, and Spatt (2021)

nism? Possible alternative explanations include: information flow[29], reciprocity[30], weaker monitoring[31], busyness[32].

This paper uses network framework to identify the mechanism(s) through which ownership structure and board of directors affect firm performance, and to estimate their net impacts.

Recent empirical work[33] supports the hypothesis that institutional shareholders have an active influence on the board of directors of publicly traded US firms, by presenting evidence on the relationship between measures of common ownership and interlocking directorships. Specifically, a gravity equation model for the probability that a pair of firms will have a common director, as a function of the geographic distance between the firms, their sizes, and a set of covariates, including measures of common ownership between the firms, is estimated. The main result is that, firm pairs with higher levels of common ownership are associated with a higher likelihood of sharing directors, which can be interpreted as institutional shareholders having at least some power to influence who will be on the board of the firms in which they hold blocks of stock.

Two prominent papers map ownership control around the world[34] and find that transnational corporations form a giant bow-tie network structure where a large portion of control flows to a small tightly-knit core of financial institutions, which can be seen as an economic super-entity[35].

More generally, a vast literature in organizational sociology, economics, and finance highlights both potential benefits and costs associated to well-connected boards. Yet, there are decidedly mixed results from the empirical assessments of the value of independent directors[36].

The effect of women on corporate performance is also a matter of debate. Analysts have explored the effects of board diversity on profitability, stock price informativeness[37] and stock valuation[38]. The majority of contributions supports the view that gender diversity inhibits performance.

[29] Watts (2003)

[30] Clark (1982)

[31] Fracassi and Tate (2012)

[32] Falato, Kadyrzhanova, and Lel (2014)

[33] Azar (2022)

[34] Aminadav and Papaioannou (2020)

[35] Vitali, Glattfelder, and Battiston (2011)

[36] For example, Larcker, So, and Wang (2013) interpret the positive connectedness-return relation as evidence that, all things equal, firms benefit from having a well-connected board and that there is equity price under-reaction to this information, instead, Fracassi and Tate (2012) identify external network connections between directors and CEOs to find that CEO-director ties reduce firm value, particularly in the absence of other governance mechanisms to substitute for board oversight. Moreover, firms with more CEO-director ties engage in more value-destroying acquisitions.

[37] Gul, Srinidhi, and Ng (2011)

[38] Dobbin and Jung (2011)

3 Data

I collect the following data for US listed firms from 2000 to 2020 from different sources: ownership data from ORBIS, directors data from BoardEx, institutional investors data from WRDS SEC 13F holdings, balance sheet data from Compustat, Russell 1000 and Russell 2000 constituents from Datastream, and finally stock prices and SIC codes from CRSP.

Nevertheless, in the empirical analysis I consider only the years 2013-2018 as the quality and the coverage of the ORBIS ownership data is much lower before that date. Table 1 presents a recap on the number of firms from Orbis and BoardEx databases analyzed in isolation, and after the union of the two databases. For all the years in analysis (2013-2018), more than 2,000 firms are included for each year, for a total of 15,179 observations. Additional samples are presented in the robustness checks.

Table 1: Orbis and BoardEx number of firms 2013-2018

	Orbis	**BoardEx**	**Orbis and BoardEx**
2013	3,093	3,425	2,172
2014	3,557	3,525	2,425
2015	3,630	3,579	2,373
2016	3,648	3,514	2,617
2017	3,630	3,535	2,784
2018	3,686	3,539	2,808
Total	**21,244**	**21,117**	**15,179**

Reported numbers refer to the number of firms in analysis, by year and by database. Column one reports the number of firms from ORBIS, column two from BoardEx and column three from the merge of the two databases.

Table 2 reports the SIC codes distribution of the sample. It is representative of the US economy, in fact, the majority of the firms are allocated to Manufacturing (40%) and Finance, Insurance and Real Estate (26%) sectors. After merging ORBIS and BoardEx databases, a representation of US firms for the most important sectors still holds in my sample.

The ownership network is created using data from ORBIS, which only records voting shares. The data from ORBIS that is used in this research includes only information on connections formed by direct ownership (links indicating that entity A owns a certain percentage of company B) and cut-off of 1% (only direct ownership links greater or equal to 1% are included). This cut-off level is applied in order to include the largest amount of data, and in the robustness checks I consider different cut-offs

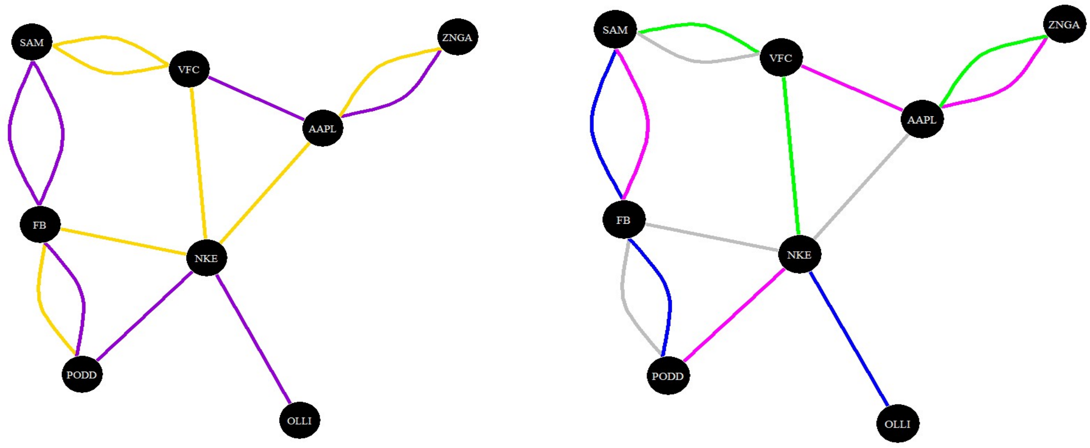
Table 2: Industry representation in the sample

SIC	Freq.	Percent
Construction	216	1
Finance, Insurance and Real estate	3,932	26
Manufacturing	6,043	40
Mining	563	4
Nonclassifiable	39	0
Retail Trade	733	5
Services	2,218	15
Transportation, Communications, Elect...	971	6
Wholesale Trade	464	3
Total	**15,179**	**100**

Reported figures for the frequency and percentage of the observations by SIC code from Compustat. The industry with highest frequency is Manufacturing.

levels. Dataset are merged using Ticker. Shareholders are required to disclose a holding above 5% of the firm' market capitalization via Schedule 13D, for this reason, WRDS SEC 13F holdings files have been checked to determine whether an investor is institutional or not.

Figure 1: Network with 2 and 4 layers



(a) Network with 2 connection types (b) Network with 4 connection types

Representation of networks with multiple connection types. Figure (a) displays the ownership (yellow) and boardroom (purple) links, while Figure (b) displays the links of: male directors (blue), female directors (pink), non institutional investors (green) and institutional investors (grey).

For every year in my sample I then create a second inter-firm network using BoardEx data, where the nodes are the firms and links are generated by directors sitting on many boards of firms through their joint employment in different firms during the same year. These are referred to as *board interlock networks* and they are essentially *firm-to-firm 1-mode networks*, using the terminology of networks.

The nodes are represented by US firms and edges are represented by common shareholders between firms (for the ownership network, in yellow), and common directors between firms (for boardroom network, in purple). Figure 1 (a) is the representation of a network with overlapping connections on ownership and boardroom, where the firms are connected between them through shareholder edges and/or directors edges. In this way, the simplified network represented in the graph is accounting for both ownership (yellow) and social ties (purple). To further investigate the network characteristics, the ownership network is split by institutional and non institutional investors and the boardroom network by males and females directors. These splits increase the complexity of the network structure, by considering four types of edges. As it can be seen in Figure 1 (b), the blue lines represent links deriving from male directors, the pink lines represent links deriving from female directors, green lines from non institutional owners and grey lines from institutional investors. In Section 4 I identify which are the relevant links for a firm to have a better ROA.

3.1 Network diagnostics

In this paper I assess how prominent a firm is within the ownership and boardroom network, through connectedness measures.

Formally, a network consists of a set of nodes (also commonly called vertices) and a set of links (also commonly called edges). In finance, the nodes are usually people or firms, and links represent social or economic relationships between nodes.

For each year in the sample, I estimate a connectedness measure for the ownership networks using all the firms in the ORBIS database. This allows to generate an unbalanced panel of network connectednesses. All the ownership networks are: *i)* undirected, as the links do not point into a specific direction, *ii)* without loops, as no links from the same firm to the same firm, *iii)* unweighted, that is connections between firms with multiple links do not have higher weight, but *iv)* have not bipartite nodes, that is their nodes are not divided into two disjoint sets.

Table 3: Ownership topology measures 2013-2018

	Years					
	2013	**2014**	**2015**	**2016**	**2017**	**2018**
	Panel A. All investor types					
Nodes	4,697	5,814	6,065	6,218	6,306	6,628
Total links	736,128	1,368,581	735,736	636,898	590,618	653,070
Density	0.07	0.08	0.04	0.03	0.03	0.03
Transitivity	0.80	0.78	0.67	0.70	0.74	0.73
Transitivity_random	0.03	0.03	0.02	0.01	0.01	0.01
Average path length	2.52	2.57	2.69	2.88	2.91	2.89
Average path length_random	2.09	2.03	2.25	2.32	2.37	2.35
Small World Index	21.95	18.24	32.50	39.74	48.03	46.07
	Panel B. Institutional investors only					
Nodes	2,456	3,121	3,124	3,064	3,089	3,188
Total links	717,554	1,330,560	694,204	592,470	547,004	603,737
Density	0.22	0.27	0.14	0.13	0.11	0.12
Transitivity	0.80	0.78	0.67	0.71	0.74	0.74
Transitivity_random	0.10	0.12	0.06	0.06	0.05	0.05
Average path length	2.27	2.21	2.38	2.45	2.57	2.55
Average path length_random	1.81	1.77	1.91	1.94	1.98	1.96
Small World Index	6	5	9	10	11	11
	Panel C. Non institutional investors only					
Nodes	3,791	4,903	5,239	5,413	5,460	5,828
Total links	18,574	38,021	41,532	44,428	43,614	49,333
Density	0.0026	0.0032	0.0030	0.0030	0.0029	0.0029
Transitivity	0.88	0.78	0.77	0.79	0.79	0.78
Transitivity_random	0.0005	0.001	0.001	0.001	0.001	0.001
Average path length	5.94	6.73	5.53	6.32	6.87	5.69
Average path length_random	12.88	6.08	6.05	5.81	5.98	5.70
Small World Index	3,902	837	1,048	870	863	956

For all the years, standard topology measures are reported: nodes, links, density, transitivity, and the Small World Index, to study trends or evolution in the ownership network. Panel A reports the ownership network statistics including all investor types, Panel B including institutional investors only, and Panel C including non institutional investors only.

I also study if the ownership and board networks are 'small networks'. The categorical distinction between 'small world network' and 'not small world network' is driven by two key network features. In fact, small world networks are characterized by a tightly interconnected clusters of nodes and a shortest mean path length similar to a matched random graph (with the same number of nodes and edges). Therefore, I use a precise measure of 'small-world-ness' based on the trade off between high local clustering and short path length.

Table 4: Boardroom topology measures 2013-2018

	Years					
	2013	**2014**	**2015**	**2016**	**2017**	**2018**
			Panel A. All directors			
Nodes	5,847	5,959	6,198	6,052	5,992	5,959
Total links	85,780	84,933	85,015	86,002	78,754	77,333
Density	0.0050	0.0048	0.00443	0.00470	0.00439	0.00436
Transitivity	0.4601	0.3812	0.3124	0.3037	0.2617	0.2509
Transitivity_random	0.0008	0.0008	0.0008	0.0008	0.0007	0.0008
Average path length	5.71	5.71	5.67	5.61	5.72	5.71
Average path length_random	5.84	5.83	5.80	5.78	5.92	5.90
Small World Index	605	506	426	405	363	344
			Panel B. Male directors only			
Nodes	5,839	5,950	6,186	6,038	5,981	5,942
Total links	71,668	71,375	71,101	70,472	64,690	62,187
Density	0.0042	0.004	0.0037	0.0039	0.0036	0.0035
Transitivity	0.518	0.442	0.372	0.366	0.324	0.319
Transitivity_random	0.001	0.001	0.001	0.001	0.001	0.001
Average path length	6	6	6	6	6	6
Average path length_random	6	6	6	6	7	7
Small World Index	779	680	590	585	547	547
			Panel C. Female directors only			
Nodes	2,962	3,122	3,411	3,476	3,598	3,806
Total links	13,867	13,327	13,684	15,237	13,773	14,794
Density	0.0032	0.0027	0.0024	0.0025	0.0021	0.002
Transitivity	0.96	0.93	0.85	0.82	0.69	0.66
Transitivity_random	0.001	0.001	0.0005	0.0005	0.0004	0.0004
Average path length	8	15	16	11	11	10
Average path length_random	13	16	16	15	19	18
Small World Index	2,798	1,842	1,876	2,305	2,961	2,755

For all the years, standard topology measures are reported: nodes, links, density, transitivity, and the Small World Index, to study trends or evolution in the boardroom network. Panel A reports the boardroom network statistics including all directors, Panel B including male directors only, and Panel C including female directors only.

I summarize the most important ownership network topology measures. Table 3 - Panel A, shows an overall increasing number of nodes over the years, and a stable overall average path length across the years. The Small World Index[39] indicates that the overall ownership networks are small. I do not detect any particular patterns during the six years in analysis.

Then, I construct the two sub-networks where a link between two firms is present only if *i)* they

[39] A formal definition of the Index is given in Appendix A.2. In the network literature, a network is considered ”small” when the Index is greater than 3.

share at least one institutional investor (Panel B), or *ii)* non-institutional investor (Panel C). The majority of the ownership network' links are created by institutional investors and non institutional investors network is a much "smaller world", with longer average path length.

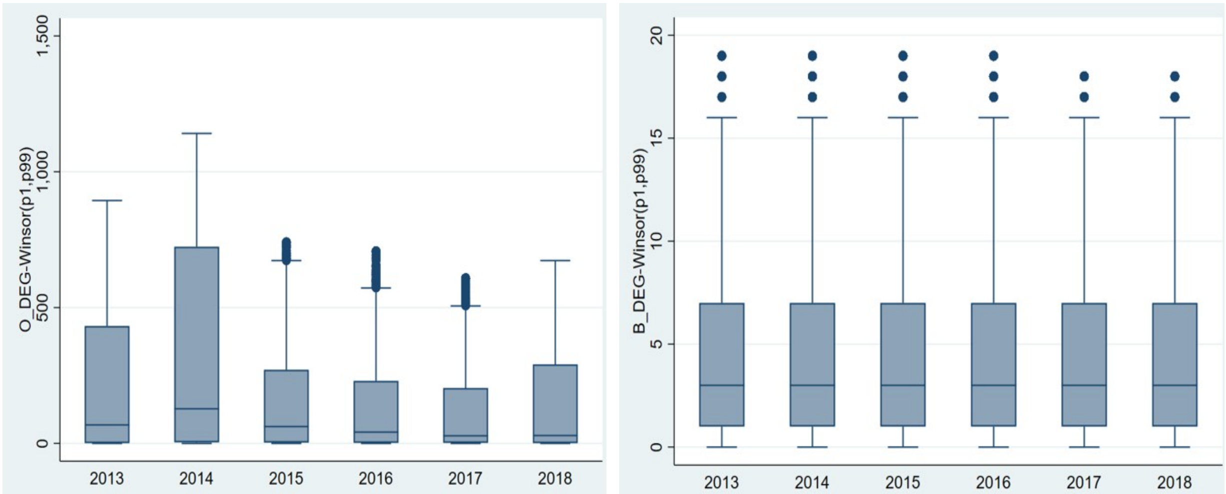
I estimate the same connectedness measure in the BoardEx network for all the firms in the sample to create an unbalanced panel of boardroom connectedness measure, and summarize them in Table 4. Panel A reports estimates including all directors, Panel B considers the subnetwork with links formed by male directors only, while Panel C considers female directors only. Statistics for networks formed by all directors are very stable across the years, only transitivity and Small World Index decrease from 2013 to 2018. Interestingly, the network of female directors is much smaller compared to males, although the number of firms and links are increasing across the years. This means that boardrooms are becoming more inclusive with regard to female directors. Average path length is longer, and the small world index reaches the highest values reported into this paper. Transitivity decreases for both genders across the years, but female directors networks show higher transitivity compared to males. Insight that female directors are more willing to create partnerships among their group.

Comparing Table 3 - Panel A and Table 4 - Panel A, boardroom networks are smaller compared to ownership networks, moreover, density is much lower (indicating that these are less connected networks), average path length is longer, and boardroom network statistics are more stable across the years.

3.2 Connectedness measures: descriptive statistics

In this paper, I consider the simplest and easier to interpret connectedness measure, namely degree connectedness, which counts the number of firms to which a firm is connected (via either board members or shareholders). I start by presenting the descriptive statistics of ownership and boardroom degree connectedness measures. Figure 2 compares the distribution of ownership degree connectedness (Panel (a)) with the distribution of boardroom degree connectedness (Panel (b)). Across all years, the average ownership connectedness is 179, with average median of 46, standard deviation of 248, skewness of 1.6, and kurtosis of 4.8. The average boardroom degree connectedness is 4.5, with average median of 3, standard deviation of 4.2, average skewness of 1.2, and kurtosis of 4.1. The scale of boardroom connectedness is different from the ownership connectedness, and the former looks more stable across the years in analysis.

Figure 2: Distribution of degree connectedness by year



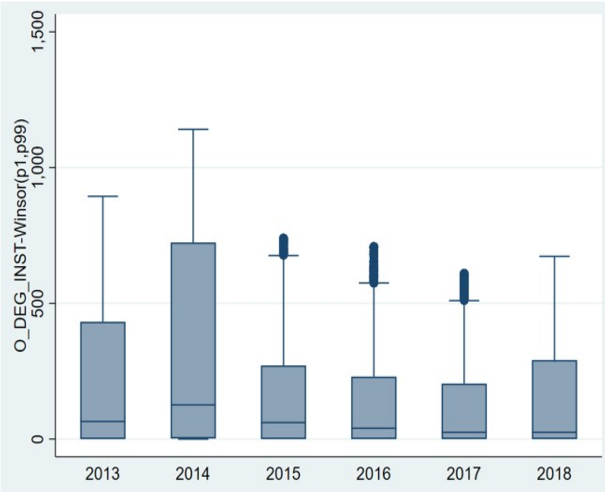
(a) Ownership degree distribution (b) Boardroom degree distribution

Comparison of degree connectedness distributions in the two networks.

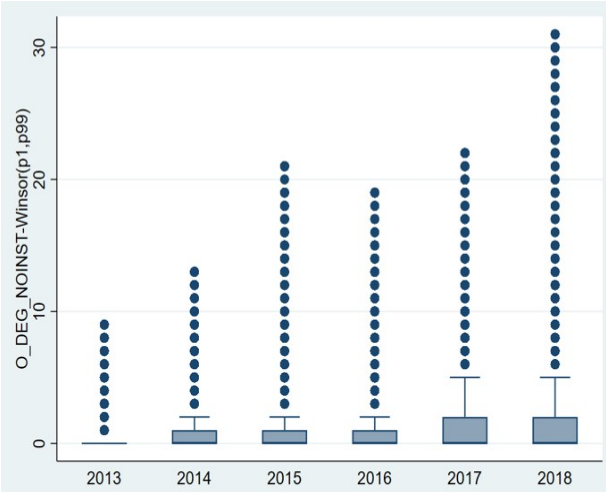
Figure 3 (a) presents the distribution of ownership degree connectedness for the network of institutional investors only. The average value of this connectedness measure across all years is 177, with average median of 42, standard deviation of 248, average skewness of 1.6 and kurtosis of 4.8. These results do not differ much from those of the overall ownership network. Figure 3 (b), plots the distribution of non institutional investors ownership degree connectedness. The average connectedness measure across all years is very small and equal to 1.6, with average median of 0. A value 0 for the non-institutional ownership connectedness of a company means that there are no common non-institutional investors with other companies owning more than 1% shares in one company or another. The average standard deviation is 4, the average skewness is 3.7 and the kurtosis 20. Over the years, there is an increasing trend in the right tail of this connectedness denoting an increase in the number of large non-institutional investors.

Finally, I present the distributions of boardroom connectedness measures split by gender. Figure 4 (a) shows the distribution of female boardroom degree connectedness, that is the number of firms to which a firm is connected via female directors only, the average connectedness measure across the years is very small, it is 0.7 (with average median of 0). The average standard deviation is 1.3, the

Figure 3: Ownership degree distribution by investor type



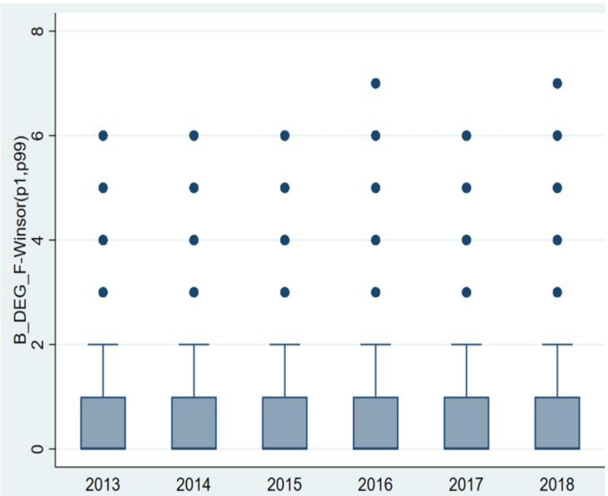
(a) Ownership degree distribution - institutional investors



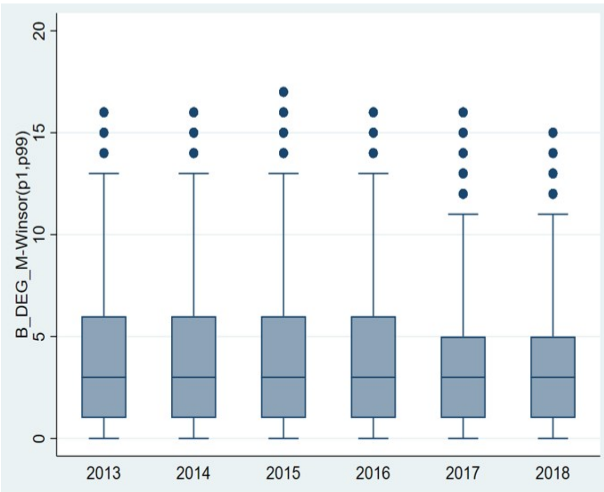
(b) Ownership degree distribution - non-institutional investors

Comparison of degree distributions in the ownership network by investor type.

Figure 4: Boardroom degree distribution by gender



(a) Boardroom degree distribution - females

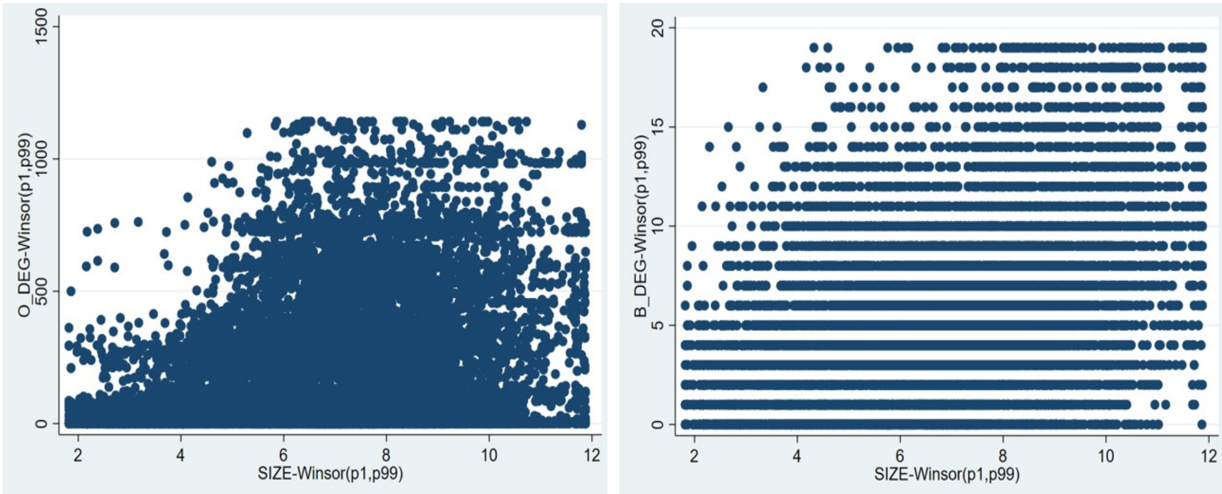


(b) Boardroom degree distribution - males

Comparison of degree distributions in the boardroom network by gender.

average skewness is 2.1 and the kurtosis is 7.5. This clearly shows that female directors network is very small and stable. Moreover, Figure 4 (b) reports the distribution of boardroom degree connectedness for males. The average connectedness measure across the years is 3.7 (with average median of 3). The average standard deviation is 3.6, the average skewness is 1.2 and the kurtosis is 4.2.

Figure 5: Scatterplots connectedness measures/size



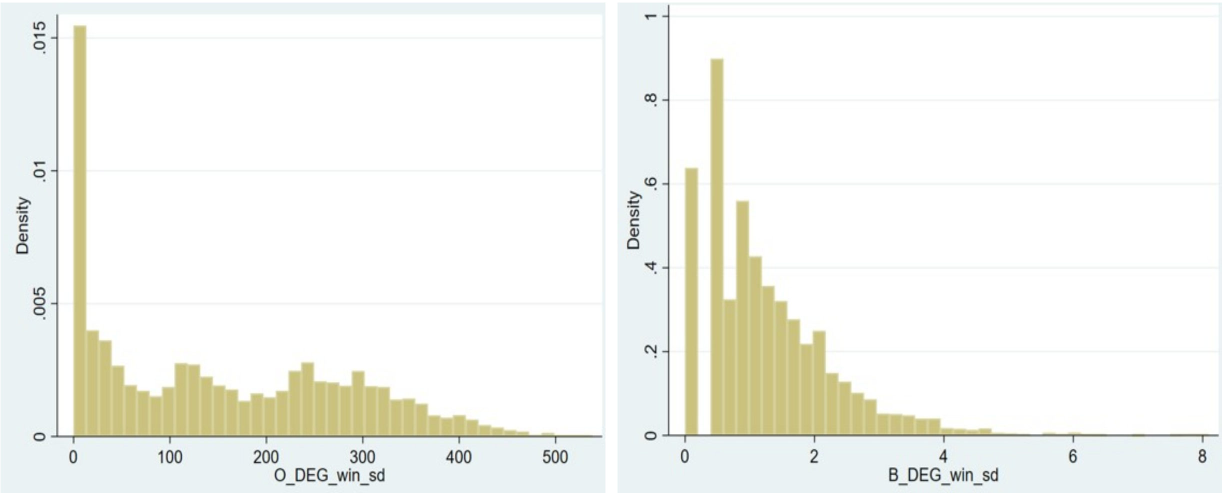
(a) Scatterplot ownership connectedness/size (b) Scatterplot boardroom connectedness/size

Comparison of the scatterplots of ownership connectedness and boardroom connectedness with size.

A potential concern could be that connectedness captures a size effect, in the sense that bigger firms naturally have more connections within a network and therefore a connectedness measure is simply a proxy for the size of the firm. Although this issue is addressed in the panel regressions by including size as a control, here I study the relationship between these measures. Figure 5 (a) (resp. (b)) shows that the scatterplot between ownership (resp. boardroom) degree connectedness and size is dispersed. As expected, regressions of ownership connectedness and boardroom connectedness on size, size^2, size^3, and $1/$size (the latter four terms are included to capture non-linearity) show that size has a positive and statistically significant impact on both connectedness measures. Nevertheless, the R-squared is relatively small (approximately 8%), meaning that connectedness variables and firm size have some orthogonal components, and both might help explaining changes ROA across firms and time.

Figures 6 (a) and (b) represent the distribution of the within-firm standard deviation of ownership

Figure 6: Within firm std. dev. histogram - Ownership and Boardroom connectedness

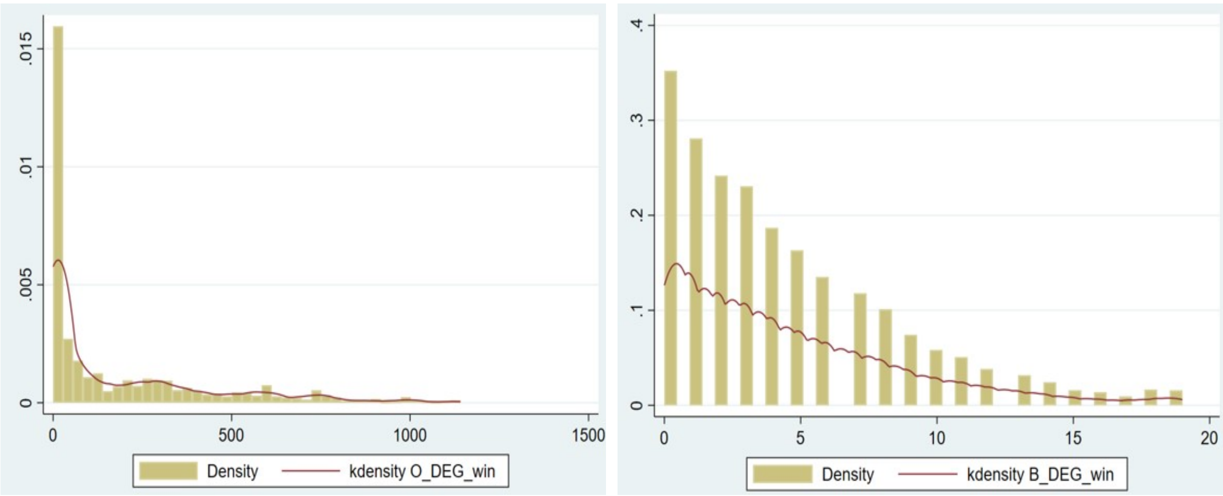


(a) Within firm std. dev. histogram - Ownership connectedness

(b) Within firm std. dev. histogram - Boardroom connectedness

Comparison of the within firms std. dev. histograms of ownership connectedness and boardroom connectedness.

Figure 7: Cross sectional distribution - Ownership and Boardroom connectedness



(a) Cross sectional distribution of ownership connectedness

(b) Cross sectional distribution of boardroom connectedness

Comparison of cross sectional distributions of ownership connectedness and boardroom connectedness.

and boardroom degree connectedness, respectively[40]. For ownership (resp. boardroom) connectedness, a non-negligible number of companies have value 0 - corresponding approximately to 10% - that is their connectedness is not changing over time. The majority of the companies in our sample have values well distributed between 1 and 500 (resp. 1 and 6), denoting a large variability over time for the same company.

Figure 7 (a) and (b) display the cross sectional distribution of ownership and boardroom connectedness, respectively. For both the connectedness measures the highest density value is at 0 and then a decrease in density with the increase in the connectedness measure is displayed.

The correlation between ownership degree connectedness and boardroom degree connectedness is 0.18[41]. It is worth noting that the correlation between ownership degree connectedness and the institutional investors degree connectedness is 0.99, confirming the previous comment that most of the results in the main analysis on ownership are driven mainly by institutional investors. Moreover, it is important to note that my ownership connectedness measure is not simply the number of institutional investors. The two measures are positively, but not perfectly, related: their correlation is 0.5.

3.3 Network examples

I hereby present a relevant example for each network. I select the firm AbbVie (Ticker: ABBV) as example on board of directors (BoD) connectedness. This is a relevant case study from chemicals industry, in fact, in October 2011 Abbott Laboratories announced its plan to separate into two publicly traded companies. The new Abbott Laboratories, specializing in diversified products including medical devices, diagnostic equipment and nutrition products, and AbbVie operating as a research-based pharmaceutical manufacturer. The separation was effective in January 2013 when AbbVie was officially listed on the New York Stock Exchange.

The overall number of AbbVie directors has increased from 9 to 15 during the years 2013 to 2018, this growth comes more from female than male directors. In fact, in 2013 there is only one woman director (Roxanne Austin), that brings three links (with Abbott, Target Corporation, Teledyne Technologies Inc.). This remains largely unchanged until 2016. In 2017, another woman director joins

[40] That is, for each company I compute the standard deviation of a connectedness measure using all the time series observations available for that company only, and then I represent the histogram of all these company-specific standard deviations.

[41] See Table 28 in the Appendix.

the board of directors (Melody Meyer) bringing connections with National Oilwell Varco. Finally, in 2018, a third woman director joins the Company (Rebecca Roberts) bringing connections with Black Hills Corporation, Enbridge, Mine Safety appliances on top of the additional connection from Roxanne Austin (CrowdStrike).

During the six years in analysis, nine male directors have been sitting on the BoD while only three female directors. In Table 5, the average number of directorships is 2 for males and 2.8 for females. These statistics show that women are underrepresented in this firm' BoD although this have become more female inclusive over time, and there is a stronger evidence of overboarded directorships for women than for men. I show in the Appendix, Figures 18 and 19, that the additional connections for AbbVie come primarily from women, meaning that the connectedness of AbbVie firm has increased thanks to the combined effect of more female directors on its board and more connections coming from these. The fact that these women directors simultaneously sit on many boards, amplifies the increase in connectedness of AbbVie.

Digi International (Ticker: DGII), from the industrial sector, is taken as example for the ownership network. This is a technology company headquartered in Minnesota that went public in 1989. During the years in analysis the ranking on Russell 2000 index varies from 1299 to 1599, with associated weights of 0.019 and 0.013. Ownership connectedness for this firm varies between 201 and 775,

Table 5: AbbVie number of directorships by year

Gender	Director name	2013	2014	2015	2016	2017	2018	Average 2013 2018
Male	Brett Hart	0	0	0	1	1	1	1.0
Male	Ed Liddy	4	4	4	4	4	4	4.0
Male	Ed Rapp	2	2	2	2	2	2	2.0
Male	Glenn Tilton	4	3	3	3	3	3	3.2
Female	Melody Meyer	0	0	0	0	2	2	2.0
Male	Professor Doctor Robert Alpern	2	2	2	2	2	3	2.2
Female	Rebecca Roberts	0	0	0	0	1	4	2.5
Male	Rick Gonzalez	1	1	1	1	3	1	1.3
Male	Rick Waddell	2	2	2	2	4	3	2.5
Female	Roxanne Austin	4	4	3	4	0	5	4.0
Male	Roy Roberts	1	1	1	1	0	0	1.0
Male	Willie Burnside	1	1	1	1	1	1	1.0

This table reports AbbVie BoD evolution by gender for years 2013-2018.

Table 6: Digi International number of shareholders' other firms owned - years 2013 vs 2018

Shareholder name	**2013**	**2018**	**Diff. 2018-2013**
Black Rock Inc	591	292	-299
Dimensional fund advisors Lp	66	332	266
Edgepoint investment group Inc	4	3	-1
Riverbridge partners Llc	11	0	-1
Royce and associates Llc	188	0	-188
Vanguard group Inc	0	268	268
Total	**860**	**895**	**35**

This table reports a comparison of number of connections by shareholder for years 2013 and 2018 for Digi International.

primarily due to institutional investors. The institutional owner that brings more links is BlackRock Inc., in fact the number of additional connections coming from it are in the range from 292 to 591. BlackRock Inc. has direct ownership from 8.9% to 12.4% of Digi International during these years. A new institutional shareholder brought 268 additional connections in 2018 (Vanguard Group Inc.), representing a 5.2% of direct ownership and causing an increase in Digi connectedness on ownership network.

The majority of the variations of Digi ownership connectedness derive from the change in the number of additional links brought from institutional investors and by the addition of new institutional investors as direct shareholders of the firm. A comparison of number of links by shareholder for years 2013 and 2018 is presented in Table 6.

4 Panel regressions results and discussion

In this paper, I use operating profitability as performance measure. The reason for choosing ROA is because it is a proxy of asset profitability that captures firm value creation. Also, the major contributions to the topic focus on this performance measure[42]. The results using ROA as dependent variable, are confirmed when using ROA industry adjusted. To minimize the effects of outliers, I winsorize all variables at the 1st and 99th percentiles in all the panel regressions presented.

I use linear unobserved effects models for unbalanced panel data, with five different estimators

[42]see: Larcker, So, and Wang (2013), Fracassi and Tate (2012) and Malmendier and Tate (2009)

(pooled OLS, fixed effects, two-way fixed effects, Arellano and Bond, Blundell and Bond). Given the persistence over time of ROA, I am more interested in the last two linear dynamic models including lags of the dependent variable as covariates.

The dynamic panel-data model used has the form:

$$ROA_{i,t} = \sum_{j=1}^{p} \rho_j ROA_{i,t-j} + \beta_1 ODEG_{i,t} + \beta_2 BDEG_{i,t} + \sum_{k=1}^{K} \phi_k \cdot controlvar_{k,it} + c_i + u_{i,t} \quad (1)$$

I run panel regressions for years 2013-2018 using POLS estimator, controlling for a vector of firm characteristics that may affect a firm's performance (size, leverage, asset tangibility). In the first model specification, I include ownership connectedness and boardroom connectedness separately as explanatory variables in the regressions, while in the second specification, I include both connectedness measures. I find consistent results: connectedness measures are always statistically significant, ownership connectedness coefficient is positive and boardroom connectedness coefficient is negative. These preliminary results suggest that ownership connectedness is associated with a higher ROA in the same year, while boardroom connectedness is associated with a lower ROA. Therefore, the first main result is that connectedness is not always good for a firm. In fact, my results show that there's a good connectedness (ownership) and a bad connectedness (boardroom). Moreover, since these two connectedness measures remain statistically significant when they are both included, this indicates that these two channels are both relevant in determining firm performance and they impact on performance through different mechanisms.

I hereby present figures on different types of shareholders from the data set in use. Tables 7 and 8 show that the average number of different firms owned is higher for institutional investors than non institutional. Moreover, within institutional investors, I observe heterogeneity: not all institutional investors have high number of firms owned, some institutional investors own a low number of firms. The process followed to identify institutional investors is through manual match of the shareholder name from ORBIS database and SEC 13F schedule from WRDS.

In order to further understand if the effect on ROA of ownership connectedness is driven or not by institutional investors, I re-estimated the ownership connectedness measures splitting the network into institutional investors only and non institutional investors only. This procedure creates two networks of ownership based on shareholder type (institutional/non institutional) from the initial one network of ownership with all shareholder types.

Table 7: Average of Shareholder - Direct %

Average of Shareholder - Direct %	2013	2014	2015	2016	2017	2018
Institutional	7.6	7.5	6.7	7.1	7.3	7.1
Non Institutional	9.1	8.8	8.9	8.2	8.4	8.3
All	**8.5**	**8.2**	**7.4**	**7.8**	**8.0**	**7.9**

Reported figures show the average shareholder percentage split by investor type for the years in analysis.

In Table 9, I report the percentage of directors by gender and year. It can be noticed that the percentage of female directors is increasing across years. The gender has been attributed to directors names using genderize.io software.

Table 10 reports the comparison of panel regressions using five different estimators: POLS including SIC2 level dummies, Fixed Effects, Two Way Fixed Effects, Arellano and Bond, Blundell and Bond. The standard errors are robust, for heteroskedasticity and serial correlation. The panel regressions for years 2013-2018 control for size, leverage, asset tangibility, industry dummies and four measures of connectedness (institutional ownership, non institutional ownership, female boardroom, male boardroom).

Institutional ownership connectedness and female boardroom connectedness are statistically significant using Pooled OLS, Fixed Effects, Arellano and Bond, Blundell and Bond estimators. They have positive and negative sign, respectively. These regressions estimate the same coefficient signs for connectedness measures as the panel regressions including only one connectedness measure: negative effect on ROA for boardroom connectedness and positive effect on ROA for ownership connectedness. The additional information is that the significant ownership connectedness is institutional investors and the significant boardroom connectedness is female directors.

To account for the potential correlation between a central firm and its size, I include size as a control variable. I report a significant statistical relation between size and connectedness, but still connectedness measure captures additional information than size variable does. Both connectedness measures are persistent across time, this has been checked by creating their lagged versions and regressing them against the original connectedness measures. Omitted variables correlated with both a firms' connectedness and ROA could bias these results. Another potential concern is that firms with

Table 8: Average number of different firms owned %

Avg. firms %	2013	2014	2015	2016	2017	2018
Institutional	5.9	6.2	5.9	5.4	4.9	5.3
min	*1*	*1*	*1*	*1*	*1*	*1*
max	*497*	*592*	*331*	*345*	*281*	*295*
Non Institutional	1.1	1.1	1.1	1.1	1.1	1.5
All	**1.7**	**1.7**	**1.7**	**1.6**	**1.6**	**1.6**

Reported figures show the average firms percentage split by investor type for the years in analysis.

Table 9: Percentage of directors by gender and year

Gender	2013	2014	2015	2016	2017	2018
Female	12%	13%	14%	15%	16%	17%
Male	87%	87%	86%	85%	84%	82%

Reported figures show that the percentage of female directors has increased during the years in analysis.

better prospects for operating performance may attract more institutional investors, resulting in reverse causality. I address these issues in the next section proposing an identification strategy.

4.1 Alternative specifications

In this subsection I report the results from different specifications of the ROA panel regressions for years 2013-2018 using Blundell and Bond estimator. In all the specification analyzed, two additional control variables have been included: number of institutional investors and sales growth. Table 11, first column, includes the interaction between the original variables institutional ownership connectedness and female boardroom connectedness, the second column uses the number of achievements as proxy of director busyness and includes their interaction with dummies ”Core-Periphery” for institutional and non institutional investors.

The introduction of interaction between female boardroom connectedness and institutional ownership connectedness, reported in Table 11 shows that there is still a positive joint effect on ROA from having common institutional shareholders and common female directors on boards. This effect is statistically significant and relates to the common practice of institutional investors to increase gender equality within boards of firms for which they own shares. It seems that the presence of institutional

Table 10: ROA panel regressions 2013-2018

	OLS (1)	**Fixed effects (2)**	**Two way fixed effects (3)**	**Arellano Bond (4)**	**Blundell Bond (5)**
Inst. Own. Connectedness	0.22***	0.33***	0.03	0.24***	0.20***
	(0.06)	(0.04)	(0.05)	(0.06)	(0.06)
Non Inst. Own. Connectedness	-42.48***	-9.20	2.34	7.06	11.04
	(6.56)	(6.19)	(6.11)	(6.61)	(7.41)
Female Board. Connectedness	-1.12***	-0.56***	-0.05	-0.54**	-0.60**
	(0.14)	(0.20)	(0.20)	(0.27)	(0.29)
Male Board. Connectedness	-0.62***	-0.09	-0.15	0.01	0
	(0.06)	(0.1)	(0.1)	(0.13)	(0.15)
Size	6.16***	11.75***	14.19***	21.80***	21.15***
	(0.18)	(0.90)	(10.12)	(1.72)	(1.67)
Leverage	-0.26***	-0.14*	-0.16**	-0.25**	-0.23**
	(0.08)	(0.08)	(0.08)	(0.11)	(0.11)
Asset Tangibility	9.12***	-17.27***	-15.50***	-14.66**	-9.76
	(1.35)	(5.34)	(5.21)	(6.52)	(8.87)
ROA L1				0.09	0.19***
				(0.09)	(0.05)
R^2	0.38	0.22	0.23		
Prob $> \chi^2$				0	0
Observations	15,179	15,179	15,179		

Reported figures refer to ROA panel regressions for years from 2013 to 2018. The presented results use five different estimators: Ordinary Least Squares, Fixed Effects, Two Way Fixed Effects, Arellano and Bond, Blundell and Bond. Variables are rescaled.

investors, which increase institutional ownership connectedness, mitigates the negative effect of female directors busyness. For a hypothetical company with an average (resp. 30% and 90% quantile) value of institutional ownership connectedness, the impact on ROA of an additional female director, changes from -0.6 to -0.09 (resp. -0.001 and -0.29).

I now introduce two different measures of directors busyness: number of announcements and number of achievements. Information on directors' announcements and achievements has been retrieved from BoardEx at director level, for all the dates within a certain year. Announcements refer to becoming member of a committee, taking on new roles, for example. Achievements refer to general admissions, awards, prizes, fellowships, honors, general recognition, for example. Individual information have been then aggregated by gender and firm, to obtain these variables: number of announcements females, number of announcements men.

I constructed two "Core-Periphery" dummies, for institutional ownership connectedness and non

Table 11: ROA panel regressions 2013-2018 including interactions and additional control variables using Blundell and Bond estimator

	Original centr. measures	**Achievement**
Inst. Own. Connectedness	0.15*	0.25***
	(0.09)	(0.08)
Non Inst. Own. Connectedness	11.49	11.72*
	(7.35)	(7.35)
Male Board. Connectedness	-0.009	-
	(0.15)	(-)
Female Board. Connectedness	-0.57*	-
	(0.31)	(-)
Individual Achievement Male	-	2.25
	(-)	(1.84)
Individual Achievement Female	-	1.82
	(-)	(1.15)
Interaction Female Institutional	8.54**	-
	(3.89)	(-)
Interaction Female Achievement CP Own.Inst.	-	-3.12**
	(-)	(13.15)
Size	20.26***	20.20***
	(1.73)	(1.72)
Leverage	-0.22**	-0.22**
	(0.11)	(0.11)
Asset Tangibility	-7.20	-7.17
	(8.64)	(8.70)
Number of Institutional Investors	-0.08	-0.09
	(0.12)	(0.12)
Sales Growth	4.21***	4.23***
	(0.84)	(0.85)
ROA L1	0.22***	0.22***
	(0.05)	(0.05)
Prob $> \chi^2$	0	0
Observations	11,608	11,608

Reported figures refer to ROA panel regressions for years from 2013 to 2018 including interaction between female directors and institutional investors. Additional control variables have been included. The second column uses a different variable to proxy busyness: number of achievements, and its interaction with a dummy variable called Core Periphery ownership institutional. The presented results use Blundell and Bond estimator. Variables are rescaled.

institutional ownership connectedness. These dummies provide more interpretable coefficients when computing the interactions between female/male announcements and institutional/non institutional connectedness. Core-Periphery non institutional gives value 0 to firms below the 85% percentile of the non institutional ownership variable, while gives value 1 to firms above the 85% percentile. Firms that are highly connected in the non institutional ownership network, have a value 1 for this dummy, representing the core. Similarly, Core-Periphery institutional gives value 0 to firms below the 85% percentile of the institutional ownership variable, while gives value 1 to firms above the 85% percentile. Firms that are highly connected in the institutional ownership network, have a value 1 for this dummy, representing the core.

The second column of Table 11 shows that the interaction between number of achievements for female directors and the Core-Periphery dummy of institutional ownership is generating the negative effect of busyness on ROA.

I tried the specification with announcements as proxy of busyness, and I obtain similar results, but not statistically significant coefficients.

5 Causality analysis: exogenous shocks to connectedness measures

In this section an identification strategy to detect causality in the results from section 4 is presented. Change in constituents from Russell 1000 and Russell 2000 indexes has been chosen as exogenous shock for ownership connectedness.

Recent papers start from observing that the yearly allocation to Russell 1000 and Russell 2000 indexes drives a quasi random exogenous change in institutional ownership. The Russell 1000 and 2000 stock indexes comprise the first 1000 and next 2000 largest firms ranked by market capitalization. Characteristics of firms near the index cutoff are similar, except that firms in the top of the Russell 2000 have discontinuously higher proportional institutional ownership than firms in the bottom of the Russell 1000 primarily due to indexing and benchmarking strategies. Small changes in the capitalizations of firms ranked near 1000 move them between these indexes. Because the indexes are value-weighted, more money tracks the largest stocks in the Russell 2000 than the smallest in the Russell 1000.

This discontinuity is used to examine the effects of institutional ownership on firms information and trading environments[43], moreover, findings show that additions to the Russell 2000 result in price increases and deletions result in price declines and then identify time trends in indexing effects and the

[43] Boone and White (2015)

types of funds that provide liquidity to indexers[44].

In this section, I implement a regression discontinuity design (RDD) for evaluating causal effects. There are papers reviewing some of the practical and theoretical issues in implementation of RDD methods[45], and the use of graphical analysis has been strongly advocated because it provides both easy presentation and transparent validation of the design[46].

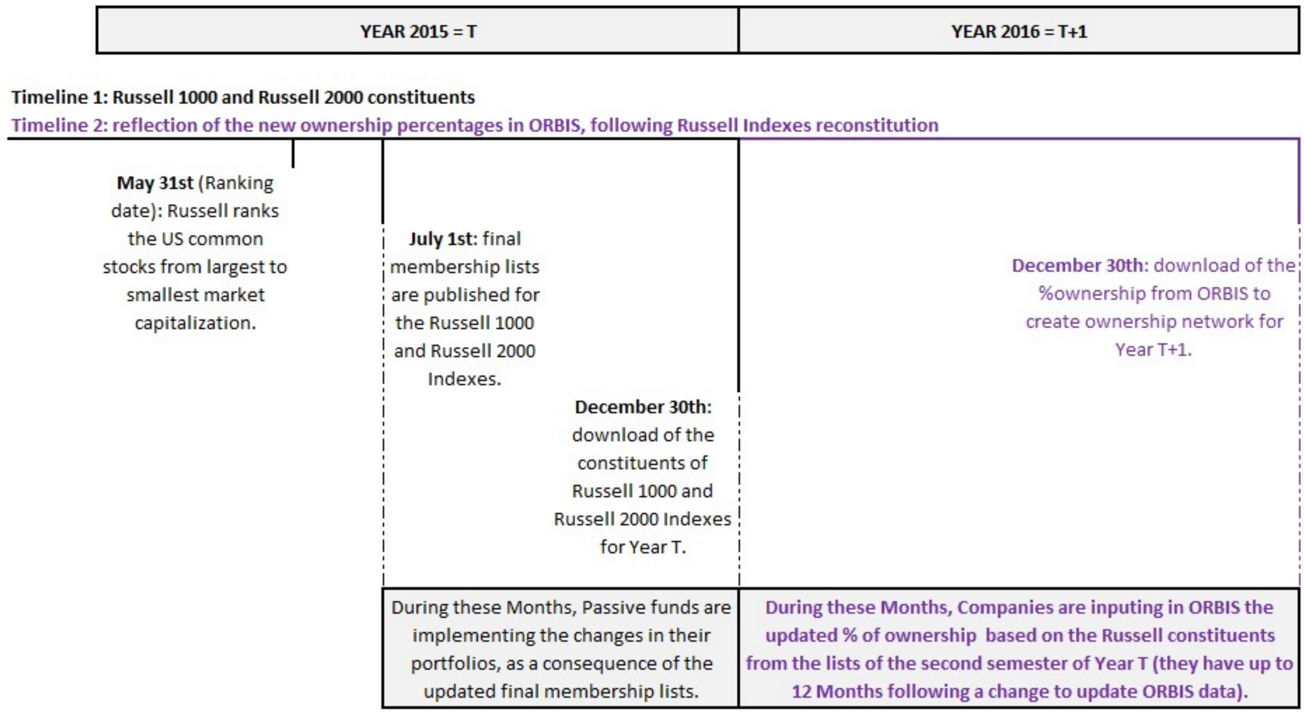
All units have a score, a treatment is assigned to the units whose value of the score is above the cutoff while the treatment is not assigned to units with score below the cutoff. The probability of receiving the treatment changes abruptly at the threshold. The discontinuous change in this probability can be used to learn about the local causal effect of the treatment on an outcome of interest using scores barely below the cutoff as counterfactuals for units with scores barely above it. The three fundamental components[47] in the design are: score, cutoff, treatment.

It is important to highlight a key methodological issue. Figure 8 presents the timeline of the Indexes Russell 1000 and Russell 2000, which is linked to the updated figures of ownership in ORBIS database. Every year the final membership lists are published for both Indexes in July. Passive funds use the following few months to reflect these changes into their portfolios. Companies have up to 12 months to report changes into the ownership structure into ORBIS database. For this reason, the data downloaded from ORBIS database on year T+1, reflect the info contained on the list of constituents from the second half of the prior year. This happens every year so that there is a delay of one year from the exogenous shock caused by the change of Russell indexes composition and the consequent ownership structure reported into ORBIS.

Figure 9 (a) illustrates the large discontinuity in the relative weighting for firms around the threshold (1000th firm with larger market capitalization). The firms in the bottom of the Russell 1000 have small portfolio weighting while firms in the top of the Russell 2000 receive a higher relative index weight, this is by Index construction. Figures 9 (b), 10 (a) and (b) show the function form and a fitted regression curve of the ownership connectedness, BIG3[48] ownership connectedness, and ROA at T+1 around the Russell 1000/2000 threshold for the years 2013-2017. The line represents a third-order polynomial regression curve. The statistical significance of the discontinuities is commented in the

[44]Chang, Hong, and Liskovich (2015)
[45]Imbens and Lemieux (2008)
[46]Calonico, Cattaneo, and Titiunik (2015)
[47]Cattaneo, Idrobo, and Titiunik (2017)
[48]BlackRock, Vanguard, State Street

Figure 8: Sample timeline for Russell 1000 and Russell 2000 index reconstitution and consequent reflection on ORBIS.



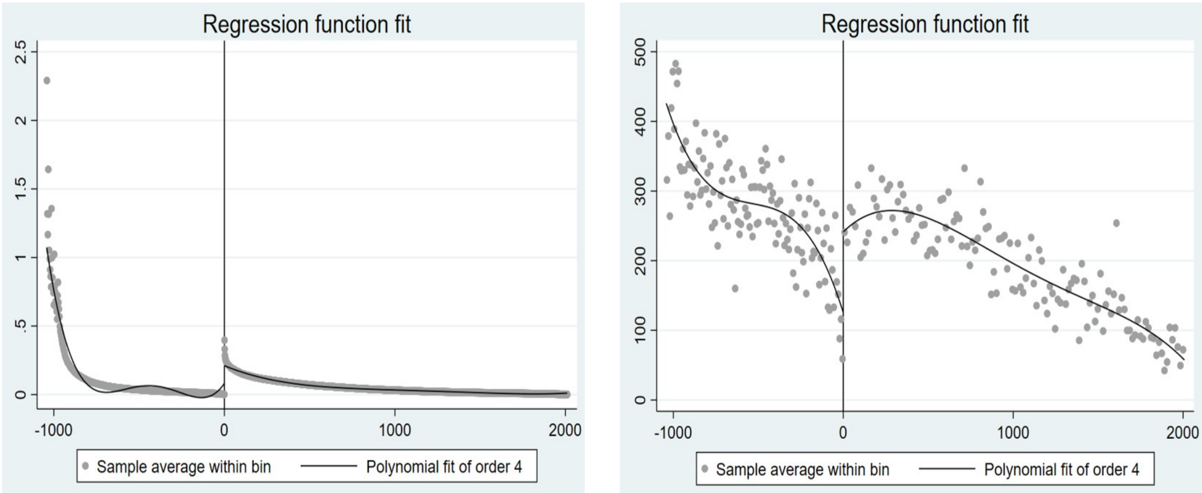
This picture represents the timeline from the definition of firms constituting Russell 1000 and Russell 2000, to the reflection of these indexes into ORBIS database.

next tables.

I explore similarities or differences between firms on either side of the cutoff by comparing means for a set of fixed bandwidths. I also report the optimal rule of thumb bandwidth. This is a selection procedure that corrects for the bias in the distributional approximation of subjective bandwidth choices. Standard statistical tests for significance are also included.

Table 12 reports institutional ownership (general institutional investors and BIG3 only) at time T+1 for firms around the Russell 1000/2000 threshold at time T. A comparison on the mean percentage of shares held by institutions for three different fixed bandwidths (+/-200, +/-300, +/-400) is reported in Panel A, where bandwidth is the number of firms on either side of Russell 1000/2000 threshold. A bias-corrected regression discontinuity treatment coefficient τ presented in Panel B (average causal effect of assignment to the Russell 2000 index on institutional ownership) is estimated fitting a local third-order polynomial estimate using a triangular kernel to the left and right of the Russell 1000/2000 threshold. I present the τ coefficients based on the rule of thumb bandwidth selection procedure

Figure 9: Discontinuity at the threshold



(a) Discontinuity in Russell 1000 and Russell 2000 weights

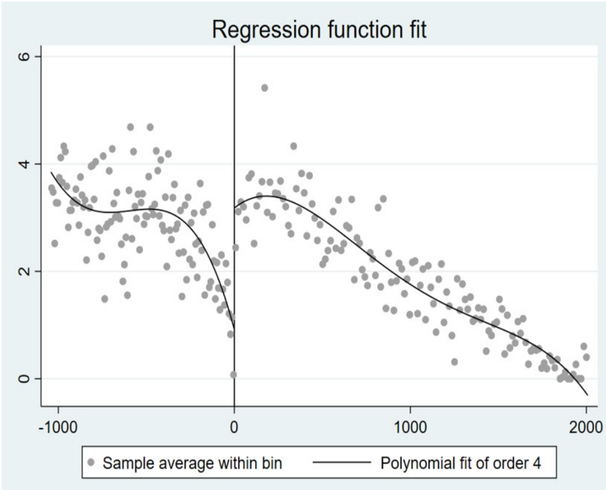
(b) Discontinuity in ownership connectedness at time T+1

Representation of discontinuity around the threshold for Russell 1000 and Russell 2000 weights, and ownership connectedness at time T+1.

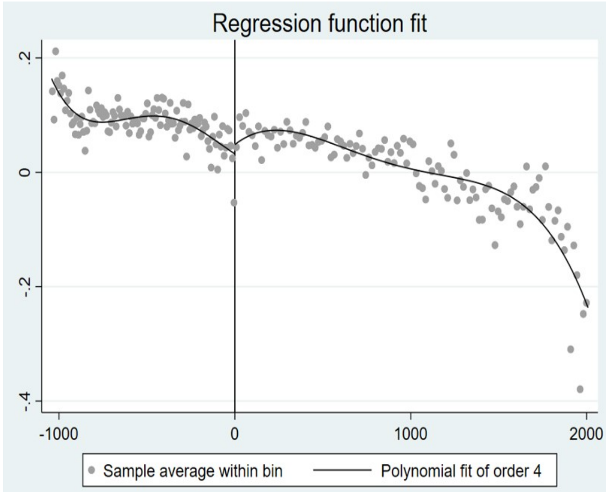
and for the same three fixed bandwidths around the Russell 1000/2000 threshold as in Panel A. The differences in mean values (Panel A) or the treatment coefficients (Panel B) are significantly different from zero for the BIG3 institutional investors considering both the optimal and fixed bandwidths. Firms at the top of the Russell 2000 exhibit discontinuously higher institutional ownership than those in the bottom of the Russell 1000 index. The estimated treatment effect of being assigned to the top of the Russell 2000 is 1.82% greater BIG3 institutional ownership within the optimal bandwidth one year after reconstitution. The majority of variation in institutional ownership is due to the BIG3.

Referring to ownership connectedness, Table 13 shows in Panel B that the τ coefficient for connectedness at time T+1 is statistically significant and the size of the jump at the rule of thumb bandwidth is 101 more connections in the ownership network. Table 14 shows in Panel B that the τ coefficient for ROA at time T+1 is statistically significant and the size of the jump at the rule of thumb bandwidth is 5%. The validity of this research design relies on any discernible variation in ROA being attributable to change in the ownership structure arising from index assignment rather than differences in firm attributes. Firms cannot manipulate the inclusion into one index versus another, for this rea-

Figure 10: Discontinuity at the threshold



(a) Discontinuity in BIG3 ownership connectedness at time T+1



(b) Discontinuity in ROA at time T+1

Representation of discontinuity around the threshold for BIG3 ownership connectedness at time Y+1, and ROA at time T+1.

Table 12: Recap RDD results institutional ownership

Panel A. Univariate Analysis of institutional ownership (percent ownership of common shares)

	Bandwidth +/- 200		Bandwidth +/- 300		Bandwidth +/-400	
	R1000	R2000	R1000	R2000	R1000	R2000
Institutional ownership T+1	5.36	5.9	5.29	5.9	5.28*	5.84*
BIG3 T+1	1.96*	3.4*	2.14*	3.38*	2.35*	3.4*

Panel B. Regression discontinuity analysis of percentage institutional ownership

	Rule of thumb bandwidth			Fixed bandwidth		
	Treatment τ	Z-stat	Bandwidth	τ +/-200	τ +/-300	τ +/-400
Intitutional ownership T+1	0.15	0.2	239	0.06	0.28	0.41
BIG3 T+1	1.82	6.18	398	1.83*	1.82*	1.82*

Panel A reports the univariate analysis of institutional ownership at time T+1 for three fixed bandwidths. Panel B reports the regression discontinuity analysis of the percentage of institutional ownership at time T+1, treatment tau are presented using the rule of thumb bandwidth and fixed bandwidths.

Table 13: Recap RDD results Connectedness

Panel A. Univariate Analysis of connectedness

	Bandwidth +/- 300		Bandwidth +/- 400	
	R1000	R2000	R1000	R2000
Connectedness T+1	205*	267*	218*	270*

Panel B. Regression discontinuity analysis of connectedness

	Rule of thumb bandwidth			Fixed bandwidth	
	Treatment τ	Z-stat	Bandwidth	τ +/-300	τ +/-400
Connectedness T+1	101	4.65	369	109*	98*

Panel A reports the univariate analysis of connectedness at time T+1 for two fixed bandwidths. Panel B reports the regression discontinuity analysis of the percentage of connectedness at time T+1, treatment tau are presented using the rule of thumb bandwidth and fixed bandwidths.

Table 14: Recap RDD results ROA

Panel A. Univariate Analysis of ROA

	Bandwidth +/- 100		Bandwidth +/- 200		Bandwidth +/- 300		Bandwidth +/- 400	
	R1000	R2000	R1000	R2000	R1000	R2000	R1000	R2000
ROA T+1	0.045*	0.082*	0.0528*	0.069*	0.06	0.067	0.068	0.067

Panel B. Regression discontinuity analysis of ROA

	Rule of thumb bandwidth			Fixed bandwidth	
	Treatment τ	Z-stat	Bandwidth	τ +/-300	τ +/-400
ROA T+1	0.05	2.77	332	0.05*	0.04*

Panel A reports the univariate analysis of ROA at time T+1 for four fixed bandwidths. Panel B reports the regression discontinuity analysis of the percentage of ROA at time T+1, treatment tau are presented using the rule of thumb bandwidth and fixed bandwidths.

son the research design is valid (firms are like-randomized above and below the threshold). To avoid concerns of index assignment manipulation, I verify that firm characteristics prior to the annual reconstitution are similar on each side of the cutoff. Table 15 indicates that firms are comparable near the

Table 15: Recap RDD ex-ante firm characteristics

Panel A. Univariate Analysis of baseline firm characteristics

	Bandwidth +/- 200		Bandwidth +/- 300		Bandwidth +/- 400	
	R1000	R2000	R1000	R2000	R1000	R2000
Size	8.27*	7.89*	8.34*	7.79*	8.4*	7.7*
Leverage	1.34	0.77	1.18*	0.74*	1.34	0.85
Asset Tangibility	0.21	0.18	0.21	0.18	0.21*	0.18*

Panel B. Regression discontinuity analysis of baseline firm characteristics

	Rule of thumb bandwidth			Fixed bandwidth		
	Treatment τ	Z-stat	Bandwidth	τ +/-200	τ +/-300	τ +/-400
Size	-0.13	-1.35	322	-0.18	-0.15	-0.11
Leverage	-1.93	-2.61	177	-2.09	-1.85	-1.69
Size	-0.06	-2.32	279	-0.08	-0.05	-0.04

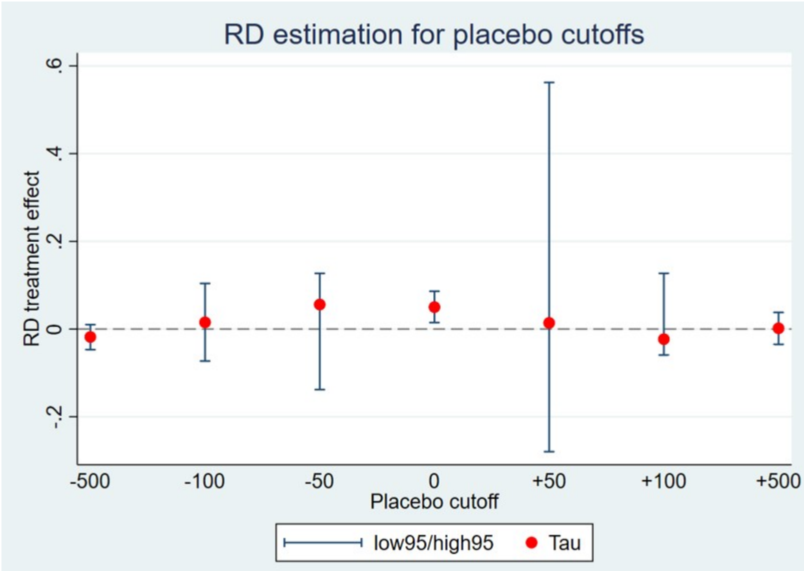
Panel A reports the univariate analysis of baseline firm characteristics (size, leverage and asset tangibility) for three fixed bandwidths. Panel B reports the regression discontinuity analysis of baseline firm characteristics, treatment tau are presented using the rule of thumb bandwidth and fixed bandwidths.

threshold, which supports the suitability of the sample and setting for our research designs. I therefore attribute differences in ROA to variation in connectedness driven by institutional ownership rather than discontinuities in other pre-assignment firm characteristics.

I introduce a falsification test to verify that the above RDD results are robust. When implementing an RDD design, the identifying assumption is the continuity (or lack of jumps) of the regression functions for treatment and controls at the cutoff in absence of treatment. I empirically investigate if the estimable regression functions for control and treatment units are continuous at points different from the cutoff. The validity of the RDD design would be less strong if there was evidence of discontinuities away from the cutoff in the data. To implement this test, I replace the true cutoff value by other values at which the treatment status does not change, and I perform estimation and inference using this placebo cutoff points. Artificial cutoffs or placebo cutoffs are defined such that the treatment did not actually change in these points.

In figure 11 the true cutoff value is called ”baseline”, and refers to the firm that has the 1000th ranking on the Russell 1000 Index. The alternative cutoff points are: +/-50, +/-100, +/-500. In this

Figure 11: Placebo cutoffs



Representation of the treatment effect for placebo cutoff values (from -500 to $+500$).

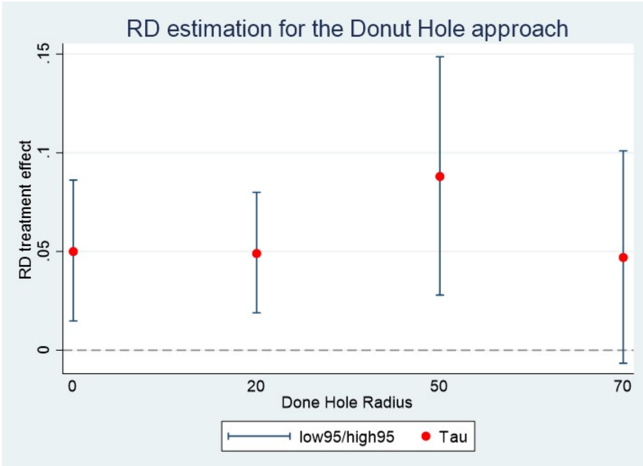
way, I check if there are discontinuities when considering as cutoff points the following firm rankings: 500, 900, 950, 1050, 1100, 1500. As shown in Table 16, the p-values are all greater than 0.05 for all cutoff points, except the cutoff 1000 and this is consistent with the conclusion that the outcome of interest does not jump at the artificial cutoff points. I include a graphical illustration of the main results from this falsification test.

Table 16: Placebo cutoffs

Ranking	Altern. cutoff	MS optimal bandw.	RD estim.	p-value	Num. obs. left	Num. obs. right	low95	high95	Tot. obs.
500	-500	153	-0.018	0.21	1357	1429	-0.05	0.01	2786
900	-100	62	0.015	0.74	2492	294	-0.07	0.10	2786
950	-50	81	0.056	0.12	2646	140	0.14	0.13	2786
1000	**0**	**332**	**0.050**	**0.01**	**2785**	**6016**	**0.01**	**0.09**	**8801**
1050	+50	115	0.014	0.51	151	5865	-0.28	0.56	6016
1100	+100	147	-0.023	0.21	307	5709	-0.06	0.13	6016
1500	+500	140	0.002	0.93	1588	4428	-0.04	0.04	6016

Reported figures refer to alternative cutoff points (from -500 to +500) and related info: MS optimal bandwidth, RD estimator, p-value, number of observations on the left and right of the cutoff, low95 and high95 percentile, and the number of total observations.

Figure 12: Sensitivity to observations near the cutoff



Representation of the treatment effect using different levels of hole radius.

Table 17: Sensitivity to observations near the cutoff

Donut hole radius	MSE Optional bandwidth	RD estimator	p-value	low95	high95
0	**332**	**0.050**	**0.006**	**0.01**	**0.09**
20	216	0.049	0.002	0.02	0.09
50	205	0.088	0.004	0.03	0.15
70	244	0.047	0.085	-0.01	0.10

Reported figures refer to different donut hole radius and the relative MSE optimal bandwidth, RD estimator, p-value, low95 and high95 percentile.

I hereby present another falsification approach to understand how sensitive the results are to the response of units located very close to the cutoff. Even if in this research design there is no suspect of score manipulation, this strategy (also known as ”donut hole approach”) is useful to assess the sensitivity of the results to the unavoidable extrapolation involved in local polynomial estimation, as the few observations closest to the cutoff are likely to be the most influential when fitting the local polynomials. In figure 12, are reported the cases in which the units with score lower than 20, 50 and 70 are excluded from the analysis. Table 17 presents similar results to what obtained before, showing that the conclusions from the analysis are robust also when excluding the few observations closest to the cutoff. The MSE optimal bandwidth changes from 332 in the original analysis to 244 in the analysis that excludes units with a distance of 70 rankings from the cutoff. The exclusion of these observations changes the point estimate from 0.050 to 0.047. The conclusion of the analysis remains largely unchanged, however, since both the original and the new estimated effect are significant. In practice, it is natural to repeat this exercise a few times to assess the actual sensitivity for different amounts of excluded units. These falsification tests follow those presented in literature[49].

6 Robustness checks

In this section of the paper I present the robustness checks. Both connectedness measures have been re-estimated for all the years in analysis without including links from the financial sector. These links are likely to have a relevant role, in fact, previous studies have shown that including or excluding ownership links from the financial sector changes firm connectedness within a network, underlying the role played by the financial sector in the strength of the ownership network' links[50].

After removing the links from the financial sector, I would expect to see a sharp decrease in the number of ownership relations among firms. This is confirmed in the data, as financial intermediaries are well integrated in the network and hold many ownership shares in companies belonging to both the non-financial and the financial sector. Nevertheless, the main results from ROA panel regressions (in terms of statistically significant relevance and impact) are consistent also when excluding financial firms from network nodes. The main results are confirmed meaning that they are not driven by ownership links created by financial companies.

Another robustness check regards industry dummies. Initially, only SIC1 dummies where included when running the panel regressions with OLS estimator meaning that there could be very different types of firms included, while SIC2 codes capture an industry effect. For this reason, SIC2 dummies have been then included in the panel regressions instead of SIC1 dummies. The results of the panel regressions do not change and remain significative also including SIC2 industry dummies. Networks only using Manufacturing industry data have been created (that is the biggest industry represented in the sample) and I report the same conclusions on the effect of the connectedness measures on ROA, limitating my network only on Manufacturing firms.

[49] Cattaneo, Idrobo, and Titiunik (2017)
[50] Vitali and Battiston (2013)

Table 18: ROA panel regressions 2013-2019

	OLS (1)	Fixed effects (2)	Two way fixed effects (3)	Arellano Bond (4)	Blundell Bond (5)
Inst. Own. Connectedness	0.30***	0.40***	0.06	0.25***	0.21***
	(0.05)	(0.04)	(0.05)	(0.06)	(0.06)
Non Inst. Own. Connectedness	-10.13***	-3.83***	0.32	-0.17***	0.08
	(1.35)	(1.08)	(1.08)	(1.46)	(1.53)
Female Board. Connectedness	-1.21***	-0.64***	-0.04	-0.7**	-0.76***
	(0.12)	(0.16)	(0.16)	(0.25)	(0.26)
Male Board. Ceonnectedness	-0.69***	-0.04	-0.14	0.11	0.10
	(0.05)	(0.09)	(0.09)	(0.12)	(0.13)
Size	6.49***	10.74***	13.40***	22.13***	21.23***
	(0.16)	(0.80)	(0.90)	(1.64)	(1.53)
Leverage	-0.28***	-0.14**	-0.17**	-0.24**	-0.22**
	(0.07)	(0.07)	(0.07)	(0.1)	(0.1)
Asset Tangibility	9.09***	-19.70***	-15.08***	-20.37***	-14.34**
	(1.25)	(4.66)	(4.56)	(5.60)	(7.30)
ROA L1				0.19**	0.21***
				(0.08)	(0.04)
R^2	0.39	0.22	0.24		
Prob $> \chi^2$				0	0
Observations	18,043	18,043	18,043		

Reported figures refer to ROA panel regressions for years from 2013 to 2019. The presented results use five different estimators: Ordinary Least Squares, Fixed Effects, Two Way Fixed Effects, Arellano and Bond, Blundell and Bond. Variables are rescaled.

The results presented in the previous sections are obtained by applying a cut-off on ownership at 1%. The reason for this is to include as many firms as possible when merging the different data sources. I check if there is an impact on the results driven by this assumption. Therefore, I consider only the ownership links generated by an ownership level greater than 2% and 5% and then re-run the estimations of ownership connectedness measures. The same results as those presented into this paper are robust to the specification with 2% cut-off, while also retail investors connectedness is statistically significant and with a positive effect in the specification with 5% cut-off.

An additional investigation has been performed on institutional investors. Specifically, the institutional investors network is split into two: BIG3 and other institutional investors. The a-priori is that the results driven by institutional investors are potentially driven by the major funds with passive strategies (where the BIG3 are: BlackRock, Vanguard, State Street). Creating an ownership network only for the BIG3 and with 1% cut-off, I confirm that these three big passive funds have a positive and

Table 19: ROA panel regressions 2013-2020

	OLS (1)	**Fixed effects (2)**	**Two way fixed effects (3)**	**Arellano Bond (4)**	**Blundell Bond (5)**
Inst. Own. Connectedness	0.26***	0.14***	-0.03	0.01	-0.02
	(0.05)	(0.03)	(0.04)	(0.05)	(0.05)
Non Inst. Own. Connectedness	-8.27***	-3.64***	0	1.21	2.04
	(0.89)	(0.95)	(0.94)	(1.48)	(1.41)
Female Board. Connectedness	-12.31***	-0.82***	-0.15	-0.75**	-0.72***
	(0.11)	(0.14)	(0.14)	(2.63)	(0.24)
Male Board. Connectedness	-0.64***	0.01	-0.12	0.19	0.16
	(0.15)	(0.08)	(0.08)	(0.14)	(0.13)
Size	6.33***	10.23***	13.17***	23.11**	21.19***
	(0.15)	(0.69)	(0.78)	(1.54)	(1.36)
Leverage	-0.29***	-0.11*	-0.12**	-0.2*	-0.19**
	(0.06)	(0.06)	(0.06)	(0.1)	(0.09)
Asset Tangibility	8.52***	-22.08***	-16.41***	-26.83***	-20.05***
	(1.12)	(3.80)	(37.81)	(5.72)	(6.69)
ROA L1				0.47***	0.25***
				(0.09)	(0.04)
R^2	0.39	0.22	0.24		
Prob $> \chi^2$				0	0
Observations	20,928	20,928	20,928		

Reported figures refer to ROA panel regressions for years from 2013 to 2020. The presented results use five different estimators: Ordinary Least Squares, Fixed Effects, Two Way Fixed Effects, Arellano and Bond, Blundell and Bond. Variables are rescaled.

statistically relevant effect on ROA. The other institutional investors still have a positive and statistically significant effect on ROA, but less significant than the BIG3. Also with this modified network, board connectedness is statistically significant and with negative sign. Given these additional results I conclude that the positive effect of ownership connectednesss on ROA is due to institutional investors, mainly the BIG3.

Two additional years of data have been added to the analysis on this paper, 2019 an 2020. In this section, I present the results for the same specifications of section 4, using different sample sizes. In Table 18 are presented the results for years 2013-2019: ownership connectedness measures are statistically significant for both type of investors but only institutional investors have a positive sign. Female boardroom connectedness is statistically significant and with negative sign. The same conclusions hold for the Arellano and Bond estimator, while with the Blundell and Bond estimator there is statistically significance for female boardroom connectedness only and institutional investors ownership. In Table

Table 20: ROA panel regressions 2002-2020

	OLS (1)	**Fixed effects (2)**	**Two way fixed effects (3)**	**Arellano Bond (4)**	**Blundell Bond (5)**
Ownership Connectedness	0.38***	0.23***	-0.04	0.05	0.04
	(0.03)	(0.02)	(0.04)	(0.04)	(0.04)
Boardroom Connectedness	-1.16***	-0.26***	-0.22***	-0.16*	-0.29***
	(0.04)	(0.52)	(0.05)	(0.09)	(0.10)
Size	6.42***	5.87***	8.34***	24.65***	22.25***
	(0.12)	(0.41)	(0.56)	(13.74)	(1.25)
Leverage	-0.29***	-0.08	-0.11**	-0.12	-0.11
	(0.05)	(0.05)	(0.05)	(1.37)	(0.09)
Asset Tangibility	13.13***	-17.96***	-15.90***	-31.21***	-22.54***
	(0.79)	(2.97)	(3.00)	(6.47)	(6.78)
ROA L1				0.22***	0.17***
				(0.05)	(0.03)
R^2	0.25	0.16	0.19		
Prob $> \chi^2$				0	0
Observations	31,225	31,225	31,225		

Reported figures refer to ROA panel regressions for years from 2002 to 2020. The presented results use five different estimators: Ordinary Least Squares, Fixed Effects, Two Way Fixed Effects, Arellano and Bond, Blundell and Bond. Variables are rescaled.

19 are presented the results for years 2013-2020: fixed effect estimator confirms the results obtained also in the previous sample, while the Arellano and Bond, Blundell and Bond estimators detect only female boardroom connectedness as statistically significant (and with negative sign). In Table 20 are presented the results for years 2002-2020. For this longer time period, the split by investor type and gender is missing. OLS and FE estimators confirm sign and statistical significance for ownership and boardroom connectedness. Blundell and Bond estimator, instead, just confirms the statistical significance of boardroom connectedness. In all these three different samples, the lagged ROA variable is positive and statistically significant. The last ones are relevant results because there are no papers reporting importance of connectedness measures for panels of 19 years.

Table 21 includes two additional control variables that are commonly used in papers on board of directors: board size and percentage of independent directors. The conclusions for the connectedness measures analyzed in this paper remain unchanged, except from the fact that female boardroom connectedness is statistically significant at 13%.

Table 21: ROA panel regressions 2013-2018 including board size and percentage of independent directors

	Blundell Bond
Inst. Own. Connectedness	0.23***
	(0.08)
Non Inst. Own. Connectedness	11.57
	(7.36)
Female Boardroom Connectedness	-0.44
	(0.29)
Male Boardroom Connectedness	-0.01
	(0.15)
Size	20.26***
	(1.72)
Leverage	-0.22**
	(0.12)
Asset Tangibility	-7.18
	(8.65)
Number of Institutional Investors	-0.08
	(0.12)
Sales Growth	4.21***
	(0.84)
Board Size	-0.01
	(0.16)
Percentage Independent Directors	0.76
	(3.24)
ROA L1	0.22***
	(0.05)
Prob $> \chi^2$	0
Observations	11,608

Reported figures refer to ROA panel regressions for years from 2013 to 2018 including board size and percentage of independent directors as control variables. The presented results use Blundell and Bond estimator. Variables are rescaled.

7 Discussion

In this paper I refer to crucial changes in the financial markets such as the rise of large blockholdings and social evolution impacting the structure of firms' boards composition. Twenty years ago, researchers started to study what appeared to be a new American system of financial capitalism. This was associated to a distinctive system of corporate ownership in which a small number of investment funds had ownership positions in hundreds of corporations simultaneously. At that time it was premature to speculate and formalize a theory on institutional ownership. Lately, there has been a significant growth of influence from financial institutions on the economy as a whole. Researches have investigated on the impacts of an increasing trend on a long-lived capitalism in US because in this country, a unique evolution on the number of big investors has been historically documented, with the continuous rise of ownership especially concentrated on the BIG3 institutional investors (Black Rock, Vanguard, State Street). In recent years in fact, large passive index funds have concentrated more ownership, becoming the most significant corporate owners in the United States. The effects of this new finance capitalism could have been positive or negative for the economy. Some of the negative implications refer to common ownership, as example: reduced product market competition, large influence and high pressure to companies to adopt targets.

The results of my research, instead, identify these large institutional owners as the drivers of positive effects for the owned firms. With this paper, I show that the rise of institutional investors brings positive effects to owned firms, that could potentially be: increased shared best practices and increased information flow across owned firms. Institutional investors, through investment stewardship departments[51], could act like a financial entity that connects and brings closer the firms in the whole economy.

Another profound social change of the last decades is the reduction of the gender gaps in the labor force and in executive posts. Changes toward a more inclusive and diverse society, alongside regulatory changes in the vast majority of the countries have impacted firms' board composition. The standard and most common procedure to account for women participation on board of directors it is through indicators that simply count the absolute number or percentage of women on boards. The reason for using connectedness of women directors to measure the impact of gender on firm performance, is because connectedness measures capture not only the relationships between firms driven by directors, but also they measure how much specific directors sit on multiple boards (overboarded directors). My results show that the inclusion of women in corporations translates into overboarded, and consequently busy, female directors leading to a negative impact on firm performance.

This research highlights some possible implications of the recent practices from the industry. For example, some of these investors may withhold votes where a director sits on more than three public company boards, given that they generally recommend a vote against an executive officer who sits on more than two public company boards. Consequently, in the next years we could potentially report a

[51]For background on investment stewardship reports refer to these examples:
https://www.blackrock.com/corporate/about-us/investment-stewardship,
https://www.ssga.com/library-content/pdfs/asset-stewardship/asset-stewardship-report-2020.pdf.

decrease in the number of ”overboarded” directors. If this will be the case, I would expect companies to show an increase in ROA. In fact, the impact on director election results for directors that exceed the number of acceptable public company boards under these new policies may be significant, as common directors could be in a position to choose for which company retain the director position. On the other hand, referring to board diversity and the objective of including more women on boards, there could be a decrease in the number of busy female directors in the future, leading to a reduction of the so called ”Golden Skirts” phenomenon[52] or tokenism[53].

There are some limitations related to this research. For example, the panel regressions results for years from 2000 to 2020 only use boardroom networks and ownership networks without splitting by gender and investor type. Moreover, the overall results focus on American firms, and it would be worth checking if the same conclusions hold for a global data set. USA is a very specific market in which there is a high percentage of ownership concentrated in few large institutional investors, and it is not the same for other countries. It would be important to investigate if the net impacts of ownership and boardroom structures lead to the same conclusions also in European countries, or if the results of my research are country specific.

My results pave the way o further research questions. To further support the ”busyness directors” hypothesis, a deeper analysis should be conducted on the number of meetings attended by directors with multiple appointments. It would be useful to estimate how much busy are overboarded directors, to effectively quantify how less time they dedicate to each firm they have a director position. More research should be conducted on female directors network, to assess whether the ”female busyness directors” hypothesis is supported and to give an economic interpretation to this phenomenon. I conduct research on this topic in my second working paper observing that California was the first US state to impose a binding gender quota on boards. In September 2018 a quota for corporate boards was passed (CA Senate Bill 826) requiring quotas on female board members for all publicly held firms headquartered in the State starting from the end of 2019, and this is just one of the many examples of regulations that have been introduced in the last 20 years to increase gender diversity in board of directors composition; little is known on the effects of these quotas introductions to directors' busyness. In that paper, I document an increase in firms with overboarded female directors, following the introduction

[52] Seierstad and Opsahl (2011)
[53] Gormley, Gupta, Matsa, Mortal, and Yang (2022)

of CA Senate Bill. Moreover, the causal effect of quota introduction on directors' busyness is tested using Synthetic Control Methodology. In panel regressions, I find that overboarded female directors are associated to lower ROA and lower ES rating.

Additional future research could be conducted on the asset pricing implications of the results presented in this paper. Some preliminary evidence is already presented in the appendix, where I create long short portfolios of stocks based on ownership and board connectedness. Interestingly, a strategy based on boardroom connectedness can outperform the market and can generate significant abnormal returns.

Finally, more research should focus on what are the resources exchanged by institutional investors, to support the "institutional investors best practices" hypothesis. It would be useful to list these practices and try to identify and estimate which are the ones more relevant for corporations.

8 Conclusions

Firms should not be studied in isolation, every firm is in fact part of complex financial and social networks. In this paper I investigate if the position of a firm in two different networks has an impact on firm performance. Using US common stocks I estimate yearly connectedness measures from ORBIS and BoardEx databases for the period 2013-2018 and I provide evidence that there is a positive (ownership connectedness) and a negative (boardroom connectedness) impact on the operating performance. Ownership connectedness is desirable for firms as it increases firm performance measured as ROA. These results on ownership network are driven by institutional investors suggesting that firms benefit from having common shareholders with other firms as they act like a channel for best practices exchange and information flow[54]. On the other hand, boardroom connectedness is detrimental for firm performance, this effect appears to be mainly driven by female directors. Although the percentage of female directors is slowly increasing from 12% in 2013 to 17% in 2018, their network is particularly small compared to male directors network. One possible reason for this is that firms have increased the number of female directors in recent years due to external social pressure or rules on quotas increasing busyness of directors[55], thus penalizing the board and firm performance.

[54] Laumann (1973) and Marsden (1987)

[55] In another working paper, I study the effect of the introduction of gender quota on board of directors busyness, within a network framework.

This paper complements existing literature[56] examining simultaneously two connectedness measures to account for more complexity and to assess two different networks on the same sample and on the same firms. Panel regressions with different estimators have been proposed and a number of robustness checks have been performed to confirm the results.

This paper exploits the annual Russell 1000 and 2000 index reconstitution setting as exogenous shock for ownership connectedness. Applying a Regression Discontinuity Design, I find evidence that a shock that increases ownership connectedness (especially driven by passive funds) positively affects the firm performance. Firms benefit from having common institutional shareholders, as they have among the strongest direct financial incentives to spread best practices across their portfolio of firms. On the other hand, directors that serve on multiple boards inhibit firm performance, and this is particularly true for women, due to recent broad based reforms aiming to increase board gender diversity.

[56] Azar (2022)

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A Appendix

A.1 Variables definition

Variables included in the panel regressions:

1. ROA: NI/AT where AT is total assets in millions and NI is net income in millions,
2. Size: ln(AT),
3. Leverage: (DLTT+DLC)/SEQ where DLTT is long term debt total in millions, DLC is debt in current liabilities total in millions and SEQ is Total Parent Stockholders' Equity in millions,
4. Asset Tangibility: PPENT/AT where PPENT is Property, Plant and Equipment - Total (Net) in millions,
5. Number of institutional investors: count of institutional investors owning shares of a given firm,
6. Sales Growth: sales increase/decrease vs last year (percentage),
7. Board size: count of the number of board members of a given firm,
8. Percentage independent directors: ratio between the number of independent directors on total directors for a given firm (expressed in percentage),
9. Individual Achievement: directors' achievements for a given firm (average),
10. Individual Announcement: directors' announcements for a given firm (average),
11. Core Periphery institutional: value 0 to firms below the 85% percentile of the institutional ownership connectedness measure, and 1 to firms above the 85% percentile (dummy),
12. Core Periphery non institutional: value 0 to firms below the 85% percentile of the non institutional ownership connectedness measure, and 1 to firms above the 85% percentile (dummy).

A.2 Networks terminology

I introduce some basic knowledge on networks which will be used during the description of the estimates and the discussion of the results. What is a network, or graph? Formally, a graph G = (V, E) is a mathematical structure consisting of a set V of vertices (also commonly called nodes) and a set E of edges (also commonly called links), where elements of E are unordered pairs u, v of distinct vertices u, v $\in$ V. In finance, the vertices are usually people or firms, and links represent social or economic relationships between vertices.

Networks need to depict complicated relational structures so they require a specific type of data storage. In network analysis, the fundamental piece of information is a relationship (tie) between two members of a network. There are two ways to store the network information: sociomatrix and edgelist. Sociomatrix (or adjacency matrix) is a square matrix where 1 indicates a tie between two nodes and 0 indicates no tie. The convention is that rows indicate the starting node, and columns indicate the receiving node. Edge list format depicts network information by simply listing every tie in the network. Each row corresponds to a single tie, that goes from the node listed in the first column to the node listed in the second column.

By examining the location of individual network members, we can assess the prominence of those members. Networks affect their members based on where those members are located in the networks. High connectedness estimate means high central position/actor prominence.

I briefly discuss now some notions used in network topology. Of all the basic characteristics of a network, density is among the most important. The density of a graph is the frequency of realized edges relative to potential edges. It is a ratio than can range from 0 to 2 (for undirected graphs). The closer to 2 the density is, the more interconnected is the network. For an undirected network, the maximum number of possible ties among k actors is $k \cdot (k-1)/2$ (because non-directed ties should only be counted once for every dyad, or pair of nodes), so the formula for the density is: $2L/(k \cdot (k-1))$ where L is the number of observed ties in the network. Density, as defined here, does not allow for ties between a particular node and itself (called a loop). Average path length is the mean of the shortest distance between each pair of nodes in the network. One of the fundamental characteristics of networks is the presence of clustering, or the tendency to form closed triangles. Transitivity is defined as the proportion of closed triangles (triads where all three ties are observed) to the total number of open and closed triangles (triads where either two or all three ties are observed). Transitivity (also called clustering coefficient) is a ratio that can range from 0 to 1, and typically refers to the quantity: $3\tau(G)/\tau_3(G)$ where $3\tau(G)$ is the number of triangles in the graph G and $\tau_3(G)$ is the number of connected triples. Note that this is a measure of global clustering, summarizing the relative frequency with which connected triples close to form triangles.

Small-World models where introduced by Watts and Strogatz (1998), these authors were intrigued by the fact that many networks in the real world display high level of clustering, but small distances between most nodes. The notion of a small-world network may be quantified with $S_G > 1$, defined as follows: $S_G = \gamma_G/\lambda_G$ where: L_G is the mean shortest path length of network G, L_{RAND} is the mean shortest path length of E-R random graph, C_G is the clustering coefficient of network G, C_{RAND} is the clustering coefficient of E-R random graph, $\gamma_G = C_G/C_{RAND}$ and $\lambda_G = L_G/L_{RAND}$.
The network G is said to be a small-world network if $L_G \geq L_{RAND}$ and $C_G \gg C_{RAND}$.
Densely connected networks trivially have a small mean path lengths and high clustering coefficients.

A.3 Model specification and estimators

To assess how a firms' connectedness relates to its ROA I estimate unbalanced panel regressions. In this section I explain the theoretical framework from which the empirical results will follow. I hereby define linear unobserved effects models for unbalanced panel data.

Firstly, I include in one specification ORBIS connectedness measure and control variables as explanatory variables, and in the other specification I also include dummy for industries.

$$ROA_{i,t} = \alpha + \beta_1 ODEG_{i,t} + \sum_{k=1}^{K} \phi_k \cdot controlvar_{k,it} + c_i + u_{i,t} \tag{2}$$

$$ROA_{i,t} = \alpha + \beta_1 ODEG_{i,t} + \sum_{k=1}^{K} \phi_k \cdot controlvar_{k,it} + \sum_{j=1}^{9} \theta_j \cdot dummyind_{ij} + c_i + u_{i,t} \tag{3}$$

Secondly, I focus on BoardEx connectedness measure only, the same specifications follow:

$$ROA_{i,t} = \alpha + \beta_1 BDEG_{i,t} + \sum_{k=1}^{K} \phi_k \cdot controlvar_{k,it} + c_i + u_{i,t} \tag{4}$$

$$ROA_{i,t} = \alpha + \beta_1 BDEG_{i,t} + \sum_{k=1}^{K} \phi_k \cdot controlvar_{k,it} + \sum_{j=1}^{9} \theta_j \cdot dummyind_{ij} + c_i + u_{i,t} \quad (5)$$

Finally, I include both the connectedness measures as explanatory variables in both the specifications:

$$ROA_{i,t} = \alpha + \beta_1 ODEG_{i,t} + \beta_2 BDEG_{i,t} + \sum_{k=1}^{K} \phi_k \cdot controlvar_{k,it} + c_i + u_{i,t} \quad (6)$$

$$ROA_{i,t} = \alpha + \beta_1 ODEG_{i,t} + \beta_2 BDEG_{i,t} + \sum_{k=1}^{K} \phi_k \cdot controlvar_{k,it} + \sum_{j=1}^{9} \theta_j \cdot dummyind_{ij} + c_i + u_{i,t} \quad (7)$$

where $t = 1, \ldots, T$ (time), $i = 1, \ldots, N$ (firms), $j = 1, \ldots, 10$ (industries) and $k = 1, \ldots, K$ (control variables).

In all the above specifications, the term c_i refers to firm fixed effects and it is usually called unobserved effect or individual heterogeneity. It is view as random variable, which may or may not be correlated with the $controlvar_{k,it}$. $controlvar_{k,it}$ can contain variables that change across *i* only, or across *i* and *t*, $u_{i,t}$ are the idiosyncratic errors, traditionally were assumed to be homoskedastic and serially uncorrelated, $v_{i,t} = c_i + u_{i,t}$ is the composite error at time *t*, $v_{i,t}$ is serially correlated and could be heteroskedastic. There are several possible estimators of β, I will use the pooled OLS estimator, the Fixed Effects estimator, Two-way fixed effects estimator, Arellano and Bond estimator, Blundell and Bond estimator.

The pooled OLS estimator leaves c_i in the error term, pool the observations across *i* and *t* and apply OLS:

$$ROA_{i,t} = \alpha + \beta_1 ODEG_{i,t} + \sum_{k=1}^{K} \phi_k \cdot controlvar_{k,it} + v_{i,t} \quad (8)$$

consistency is ensured by $Cov(x_{it}, u_{it}) = 0$ and $Cov(x_{it}, c_i) = 0$ for $t = 1, \ldots, T$.

The Fixed Effects estimator, average across *t* to get a cross section equation:

$$\overline{ROA_{i,t}} = \alpha + \beta_1 \overline{ODEG_{i,t}} + \sum_{k=1}^{K} \phi_k \cdot \overline{controlvar_{k,it}} + \overline{u_{i,t}} \quad (9)$$

then subtract off the time averages:

$$ROA_{i,t}-\overline{ROA_{i,t}} = \alpha+\beta_1\cdot(ODEG_{i,t}-\overline{ODEG_{i,t}})+\sum_{k=1}^{K}\phi_k\cdot(controlvar_{k,it}-\overline{controlvar_{k,it}})+u_{i,t}-\overline{u_{i,t}} \tag{10}$$

to obtain the time-demeaned equation, also called the within transformation, where c_i is absent. Then the pooled OLS is applied to the demeaned equation, this is the FE estimator or within estimator. The weakest exogeneity condition for consistency is $\sum_{t=1}^{T} E[(x_{it} - \overline{x}_i)'u_{it}] = 0$, sufficient for $t = 1, \ldots, T$ (contemporaneous and strict exogeneity) $E[(x_{it})'u_{it}] = 0$, $E[(\overline{x}_i)'u_{it}] = 0$. The relationship between c_i and $controlvar_{k,it}$ is unrestricted and the ideal assumptions rule out serial correlation and heteroskedasticity in u_{it}.

Many applied researchers use the two-way fixed effects estimator to adjust for unobserved unit-specific and time-specific confounders at the same time. A recent paper demonstrates that the ability to simultaneously adjust for these two types of unobserved confounders critically relies upon the assumption of linear additive effects. Another common justification is based on the fact that this estimator is equivalent to the difference-in-differences estimator under the simplest setting with two groups and two time periods Kosuke and K. (2020). This is the two-way fixed effects specification where f_t are the time specifics effects:

$$ROA_{i,t} = \alpha + \beta_1 ODEG_{i,t} + \beta_2 BDEG_{i,t} + \sum_{k=1}^{K}\phi_k \cdot controlvar_{k,it} + c_i + f_t + u_{i,t} \tag{11}$$

As is well known, including unit fixed effects in a linear regression is identical to removing unit-specific time averages and applying pooled ordinary least squares (OLS) to the transformed data. Including time fixed effects then removes changes in the economic environment that have the same effect on all units.

Linear dynamic panel-data models include p lags of the dependent variable as covariates and contain unobserved panel-level effects, fixed or random. By construction, the unobserved panel-level effects are correlated with the lagged dependent variables, making standard estimators inconsistent. Arellano and Bond (1991) derived a consistent generalized method of moments (GMM) estimator for the parameters of this model. This estimator is designed for datasets with many panels and few periods. It requires no autocorrelation in the idiosyncratic errors. A dynamic panel-data model has the form:

$$ROA_{i,t} = \sum_{j=1}^{p} \rho_j ROA_{i,t-j} + \beta_1 ODEG_{i,t} + \beta_2 BDEG_{i,t} + \sum_{k=1}^{K} \phi_k \cdot controlvar_{k,it} + c_i + u_{i,t} \quad (12)$$

When the variance of the individual effect term across individual observations is high, the GMM estimator which was suggested by Arellano and Bond (1991) is known to be rather inefficient because in this case instruments are weak since they use the information contained in differences only. Blundell and Bond (1998) derived a condition under which it is possible to use an additional set of moment conditions that can be used to improve the small sample performance of the Arellano and Bond estimator. In their paper, Blundell and Bond (1998) suggest making use of additional level information beside the differences. The combination of moment restrictions for differences and levels results in an estimator which was called GMM system-estimator.

A.4 Exogenous shocks for board of directors' networks

The identification strategy used for the boardroom network uses data on the directors dates of death. After identifying the firms that lost connections in the directors network due to a director decease, I perform a causal analysis with a staggered adoption design that combines Propensity Score Matching (PSM) and DiD model to find adequate controls for the treated units.

There are few papers that use information on directors deaths in the context of causal analysis. Falato, Kadyrzhanova, and Lel (2014) use the deaths of directors and chief executive officers as a natural experiment generating exogenous variation in the time and resources available to independent directors at interlocked firms. These are attention shocks and the authors find that busyness is detrimental to board monitoring quality and shareholder value. The methodology used in this paper is similar to the one documented by Dettman, Giebler, and Weyh (2020). It is a non parametric flexible conditional Difference in Differences estimator (DiD) which aims to consider problems associated with heterogeneous treatment effects in a panel data context. This approach incorporates the observation time information from the panel data into the matching process, defines different different observation periods for the outcome comparisons to consider a dynamic treatment effect. There is a limit of the potential partners for every treated unit to those observed just at the individual matching date, then the matching algorithm selects one or more statistical twins among these pre-selected units.

Matching is based on a combined statistical distance function. Based on this matching process, the average treatment effect (ATT) for the treated is estimated.

The identification strategy adopted to assess causality of Boardroom connectedness on firm performance uses BoardEx information on the dates in which directors deceases happened. I use this data to study if the changes in the boardroom network (that is: missing links) consequent to directors deceases have an impact on firm performance. Death is used as an exogenous shock to boardroom network. The numbers of directors deceases that happened every year are reported in Table 22. Only deaths of directors that created links among firms are taken into account. For this reason, the final number of director deceases included in the analysis reported in Table 23, are only nine. The number of shocks included does not allow to present statistically robust results. To conduct the analysis, treatment group has been identified as the firms that experienced a director decease that created links with other firms, and control group as the firms that experienced a director decease but that did not create links with other firms. Data have been pre-processed with the following matching variables: size and asset tangibility, then the treatment effect has been estimated for the treated with different matching approaches. Estimation results based on the flexible conditional DiD approach for the executed matching procedure find a partner for 9 out of the 9 treated units. The means of all the matching variables are balanced, the pvalues of the Kolmogorov-Smirnov test show that the variable distributions between the treated and the control group are not significantly different. The quantile-quantile plots in Figure 13 compare the distributions in both groups by means of the plotted quantiles. The 45 degrees-line represents identical distributions, small deviations from the 45 degrees-line for all displayed variables, mostly at the tails of the distributions.

The estimation result for average treatment effect for the treated using the estimator ”nearest neighbor matching”, the statistical distance function as the distance metric, the number of the treated observations and unique controls included in the estimation (9 treated and 2 controls) and the mean number

Table 22: All directors deceases by year 2013-2018

	2013	**2014**	**2015**	**2016**	**2017**	**2018**
Number of deceases	846	990	1035	1100	1204	1043

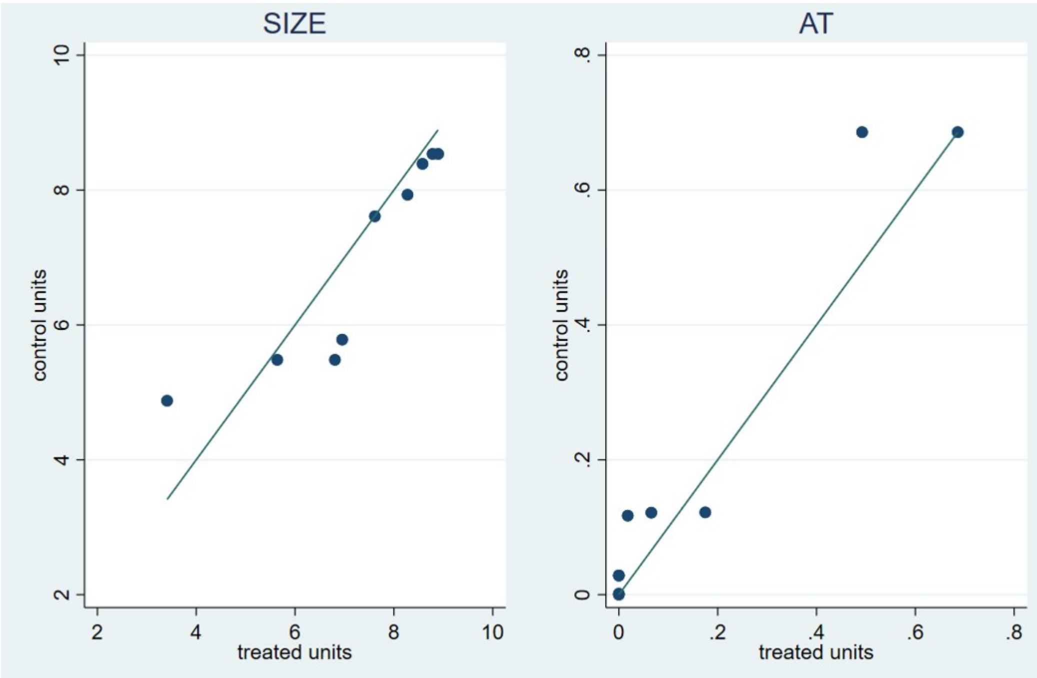
This table reports the number of directors deceases for the years in analysis.

Table 23: Directors deceases by year 2013-2018 - only directors generating links

	2013	2014	2015	2016	2017	2018
Number of deceases	0	1	1	3	3	1

This table reports the number of directors who created a link in the boardroom network for the years in analysis.

Figure 13: Quantile-quantile plots - matching variables at matching time



Representation of the Q-Q plots of the matching variables at matching time.

of matches per treated (one) are then obtained. I document a positive development of firm performance (ROA) both for the treated and the controls. The mean difference in the ROA between treated and controls is 0. The pvalue indicates that the difference is not significant.

This new Difference in Differences approach to access causality of the results does not provide enough statistically robust results to conclude on the effect of BoardEx connectedness on firm performance. I envise a future development of this tecnique on another paper with a longer sample of years including just the firms from BoardEx database (without merging this database with ORBIS and dramatically reduce the number of firms in analysis) to conclude on boardroom causality.

A.5 Empirical Asset Pricing application

The main part of this paper follows the standard corporate finance literature where ROA is a proxy of firm operating performance. However, in the empirical asset pricing exercise presented in this section, I verify if firms that are more central in the network (ownership or boardroom) earn higher or lower stock returns than firms that are less central. The objective is to provide a perspective on network connectedness and the cross section of stock returns. The Factor Zoo phenomenon calls for answers as to which risk factors are capable of providing independent information on the cross-section of expected excess returns. Asset pricing literature has produced hundreds of candidates, some of these candidates relate to institutional investors, but none of them refer to connectedness and especially boardroom connectedness [57]. Based on the analysis on the previous sections, I create factors based on firm characteristics ownership connectedness and boardroom connectedness, which can be considered firm specific characteristics and I investigate whether these are capable of explaining cross-section returns.

Firstly, I discuss the creation of the ownership connectedness factor during the period 2012-2018, because this is the data range that allows me to include a relevant number of firms for every year. I create 3 portfolios on yearly ownership degree connectedness characteristics (breakpoints: 0.33 and 0.66 percentiles allowing for extreme values), using monthly stock returns from CRSP and I estimate the Fama and French five factor model (Fama and French (2015)). Is ownership degree connectedness a price characteristic in the cross section of monthly stock returns? I hereby explain the approach used. I start calculating the breakpoints to divide the sample into portfolios computing the percentiles for the ownership connectedness which are time varying for every year (because the ownership connectedness characteristic changes at yearly frequency). I use these breakpoints to form the portfolios and I compute the average value of the outcome variable (returns) within each portfolio for each month (since I use monthly returns). Each month, all stocks in the sample are sorted into 3 portfolios based on ascending sort of ownership degree connectedness with breakpoints set to the percentiles of ownership degree in the given month. I follow the same procedure to compute the time series average excess returns of each portfolio. In this section, stock returns are excess stock returns. All standard errors are adjusted following Newey and West (Newey and West (1987)).

[57] Among the 410 factors reported by Chen, those related to institutional investors are the following ones: residual institutional ownership, institutional ownership among high short interest, breadth of ownership, shareholder activism.

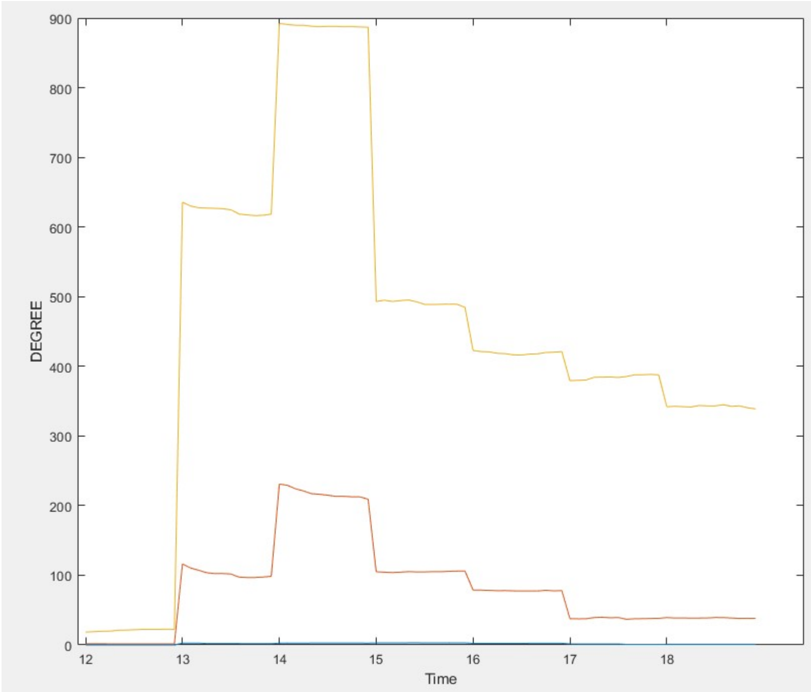


Figure 14: Avg. degree VW portfolios formed on ownership connectedness

All the results shown are related to value weighted portfolios, using weights determined by the market capitalisation at every time t. To obtain the market capitalisation, I use data downloaded from CRSP database. I report two set of results: one includes all the firms available for ownership or boardroom database for the considered years, the second one (which I call 'merged') is including the firms that are available in both the ownership and boardroom databases for every year. Just to give an idea of how these portfolios are constructed, on the after merge factor, the total number of firms included is 3227, portfolio 1 has 812 average number of firms, 634 minimum and 936 maximum; portfolio 2 has 693 average number of firms, 186 minimum and 915 maximum; portfolio 3 has 717 average number of firms, 313 minimum and 925 maximum. Figure 14 shows the average degree connectedness on ownership for the three value weighted portfolios.

The first two lines in Table 24 show that the long short portfolio (3-1) has positive excess return, but it is not statistically significant for both the full dataset and the dataset after merge. Similarly, I find a positive but not statistically significant intercept of the time series regressions of my factor on the 5 Fama and French factors. Which implies that a strategy based on ownership connectedness

Ownership factor: 2012-2018 full dataset

Value Weighted on Degree

	PT1	PT2	PT3	3-1	
Avg Excess Return	17.1	17.1	17.6	0.5	‡
T-stat Excess Return	4.12	3.75	4.06	0.28	

Value Weighted 5F model

	PT1	PT2	PT3	3-1	
Intercept	4.9	5.2	5.1	0.3	‡
Gamma MKT	1.00	0.99	1.01	0.01	
Gamma SMB	0.05	0.18	(0.08)	(0.12)	
Gamma HML	0.04	(0.03)	(0.01)	(0.05)	
Gamma RMW	(0.01)	(0.26)	0.06	0.07	
Gamma CMA	(0.02)	0.17	(0.18)	(0.16)	
T-stat Intercept	4.12	3.64	5.06	0.15	
T-stat Gamma MKT	28.29	29.13	32.78	0.10	
T-stat Gamma SMB	1.00	3.87	(2.48)	(1.87)	
T-stat Gamma HML	0.51	(0.52)	(0.35)	(0.53)	
T-stat Gamma RMW	(0.12)	(2.81)	0.97	0.66	
T-stat Gamma CMA	(0.20)	2.03	(2.59)	(1.07)	

Ownership factor: 2012-2018 after merge

Value Weighted on Degree

	PT1	PT2	PT3	3-1	
Avg Excess Return	16.4	17.6	17.5	1.1	‡
T-stat Excess Return	3.75	3.93	4.01	0.54	

Value Weighted 5F model

	PT1	PT2	PT3	3-1	
Intercept	4.2	6.2	5.3	1.1	‡
Gamma MKT	1.01	0.95	0.99	(0.02)	
Gamma SMB	0.08	0.21	0.03	(0.06)	
Gamma HML	0.01	(0.06)	(0.07)	(0.08)	
Gamma RMW	(0.10)	(0.31)	0.15	0.25	
Gamma CMA	0.14	0.19	(0.18)	(0.32)	
T-stat Intercept	3.57	3.59	4.65	0.60	
T-stat Gamma MKT	24.26	23.49	24.27	(0.29)	
T-stat Gamma SMB	1.62	3.87	0.60	(0.70)	
T-stat Gamma HML	0.21	(0.88)	(1.57)	(1.03)	
T-stat Gamma RMW	(1.42)	(2.54)	2.00	2.14	
T-stat Gamma CMA	1.58	2.07	(2.70)	(2.62)	

‡ in percentage and annualized

Table 24: Portfolios formed on ownership connectedness

cannot outperform the market and cannot generate significant abnormal returns [58]. This is consistent with what found in the panel regressions. Infact, since portfolio 3 is the one with firms with highest ownership connectedness, and portfolio 1 with the least central firms: a zero-investment strategy of buying stocks with high-percentile ownership connectedness and selling low-percentile ones cannot generate significant abnormal returns, but at least generates positive excess returns on average.

I discuss the creation of the boardroom connectedness factor, considering years 2012-2018. I create 3 portfolios on yearly boardroom degree connectedness characteristics (breakpoints: 0.33 and 0.66 percentiles allowing for extreme values), using monthly stock returns from CRSP and I estimate the Fama and French 5 factor model. Also in this case, is boardroom degree connectedness a price characteristic in the cross section of monthly stock returns? On the after merge factor, the total number of firms included is 3226, portfolio 1 has 885 average number of firms, 485 minimum and 1110

[58] Similar results are obtained for the Fama and French 3 factors model, available on request.

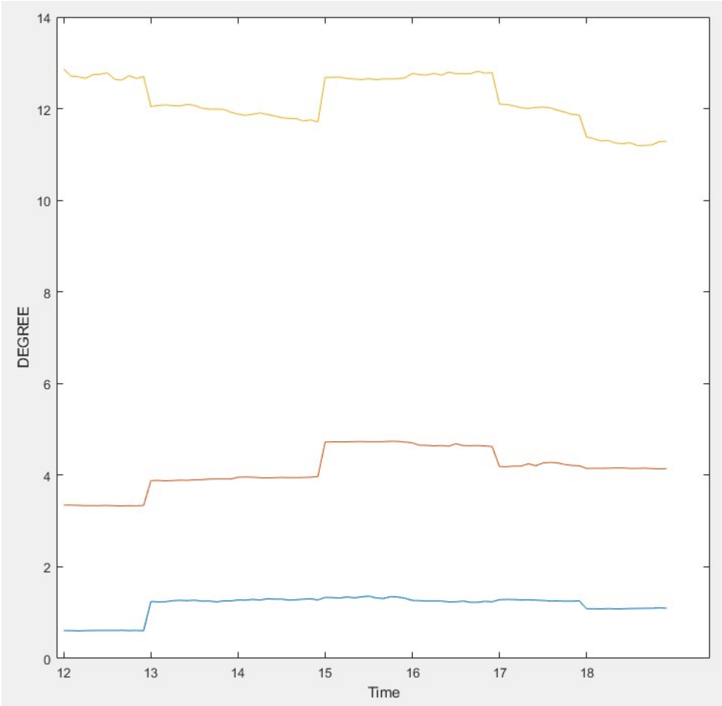


Figure 15: Avg. degree VW portfolios formed on boardroom connectedness

maximum; portfolio 2 has 660 average number of firms, 478 minimum and 828 maximum; portfolio 3 has 678 average number of firms, 414 minimum and 875 maximum. Figure 15 shows the average boardroom degree for the value weighted portfolios.

The first two lines in Table 25 show that the long short portfolio (3-1) has negative excess return, but it is not statistically significant for both the full dataset and the dataset after merge. Similarly, I find a negative but not statistically significant intercept of the time series regressions of my factor on the 5 Fama and French factors. Which implies that a strategy based on boardroom connectedness cannot outperform the market and cannot generate significant abnormal returns [59]. Again, I find that this is consistent with what found in the panel regressions. In fact, since portfolio 3 is the one with firms with highest boardroom connectedness, and portfolio 1 with the least central firms: a zero-investment strategy of buying stocks with high-percentile boardroom connectedness and selling low-percentile ones cannot outperform the market and generate significant abnormal returns, and moreover generates negative excess returns on average.

I create 3 portfolios formed on both ownership and boardroom connectedness. Given the findings

[59] Similar results are obtained for the Fama and French 3 factors model, available on request.

Boardroom factor: 2012-2018 full dataset

Value Weighted on Degree

	PT1	PT2	PT3	3-1
Avg Excess Return	17.6	15.9	16.4	(1.2) ‡
T-stat Excess Return	4.12	3.68	4.33	(0.70)

Value Weighted 5F model

	PT1	PT2	PT3	3-1
Intercept	6.6	4.2	4.5	(2.1) ‡
Gamma MKT	0.93	0.97	0.97	0.04
Gamma SMB	0.34	0.18	(0.00)	(0.34)
Gamma HML	0.08	(0.14)	(0.08)	(0.16)
Gamma RMW	(0.07)	(0.02)	0.07	0.13
Gamma CMA	(0.02)	0.13	0.10	0.12
T-stat Intercept	5.16	3.20	8.64	(1.76)
T-stat Gamma MKT	30.99	27.23	55.10	1.57
T-stat Gamma SMB	5.95	3.59	(0.17)	(6.05)
T-stat Gamma HML	0.99	(2.05)	(3.52)	(1.94)
T-stat Gamma RMW	(0.73)	(0.28)	2.38	1.60
T-stat Gamma CMA	(0.24)	1.38	2.69	1.17

Boardroom factor: 2012-2018 after merge

Value Weighted on Degree

	PT1	PT2	PT3	3-1
Avg Excess Return	17.7	16.4	17.3	(0.4) ‡
T-stat Excess Return	4.04	3.68	4.09	(0.22)

Value Weighted 5F model

	PT1	PT2	PT3	3-1
Intercept	6.8	4.6	5.0	(1.7) ‡
Gamma MKT	0.92	0.97	1.00	0.07
Gamma SMB	0.36	0.18	(0.00)	(0.36)
Gamma HML	0.12	(0.17)	(0.03)	(0.15)
Gamma RMW	(0.08)	(0.10)	0.06	0.14
Gamma CMA	(0.11)	0.12	(0.02)	0.09
T-stat Intercept	5.17	3.12	6.74	(1.24)
T-stat Gamma MKT	28.89	26.64	35.98	1.80
T-stat Gamma SMB	6.31	3.04	(0.09)	(5.58)
T-stat Gamma HML	1.62	(2.22)	(1.13)	(2.10)
T-stat Gamma RMW	(0.90)	(1.31)	1.34	1.59
T-stat Gamma CMA	(1.15)	1.15	(0.53)	0.80

‡ in percentage and annualized

Table 25: Portfolios formed on boardroom connectedness

from the panel regressions, I build 3 portfolios using yearly ownership and boardroom degree conenctedness characteristics. Are both ownership and boardroom degree connectedness price characteristics in the cross section of monthly stock returns? The long short portfolio is built as in Figure 16, where LOHB stays for portfolio of firms with low ownership connectedness measure and high boardroom connectedness measure, while HOLB is the opposte (high ownership connectedness measure and low boardroom connectedness measure).

The total number of firms included is 3221, portfolio LOHB has 164 average number of firms, 114 minimum and 216 maximum; portfolio HOLB has 212 average number of firms, 60 minimum and 302 maximum. Figure 17 shows the breakpoints for both the connectedness measures to create the double sorted portfolios.

Compatibly with the two previous set of results, the first two lines in Table 26 show that this strategy has positive excess return, but it is not statistically significant. Similarly, I find a positive but

Value Weighted on Degree

	LOHB	HOLB	2-1	
Avg Excess Return	16.1	17.5	1.4	‡
T-stat Excess Return	3.70	3.88	0.53	

Value Weighted 5F model

	LOHB	HOLB	2-1	
Intercept	3.7	6.8	3.1	‡
Gamma MKT	1.01	0.91	(0.10)	
Gamma SMB	(0.04)	0.37	0.41	
Gamma HML	0.02	0.14	0.12	
Gamma RMW	(0.13)	0.03	0.16	
Gamma CMA	0.17	(0.06)	(0.23)	
T-stat Intercept	2.58	3.08	1.1	
T-stat Gamma MKT	18.69	15.60	(1.14)	
T-stat Gamma SMB	(0.65)	4.67	3.72	
T-stat Gamma HML	0.23	0.96	0.98	
T-stat Gamma RMW	(1.44)	0.23	0.85	
T-stat Gamma CMA	1.64	(0.38)	(1.20)	

‡ in percentage and annualized

Table 26: Results from double sorted portfolios

not statistically significant intercept of the time series regressions on the 5 Fama and French factors, which implies that this strategy cannot outperform the market and cannot generate significant abnormal returns [60].

The previous three analysis have been conducted using the sample 2012-2018 based on the discussion of the poor data quality of ownership database before 2012 and for compatibility of the sample with the ROA regressions. As data quality is not an issue for years prior to 2012 for BoardEx database,

[60] Similar results are obtained for the Fama and French 3 factors model, available on request.

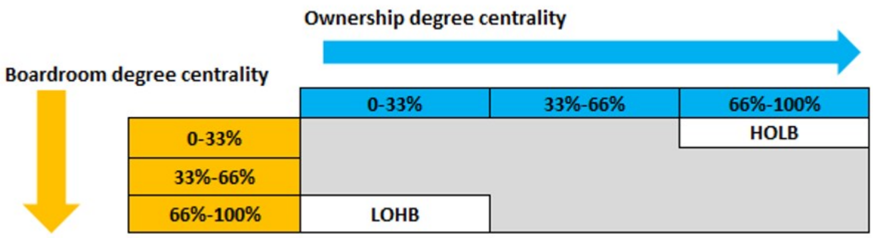


Figure 16: Portfolios formed on both connectedness measures

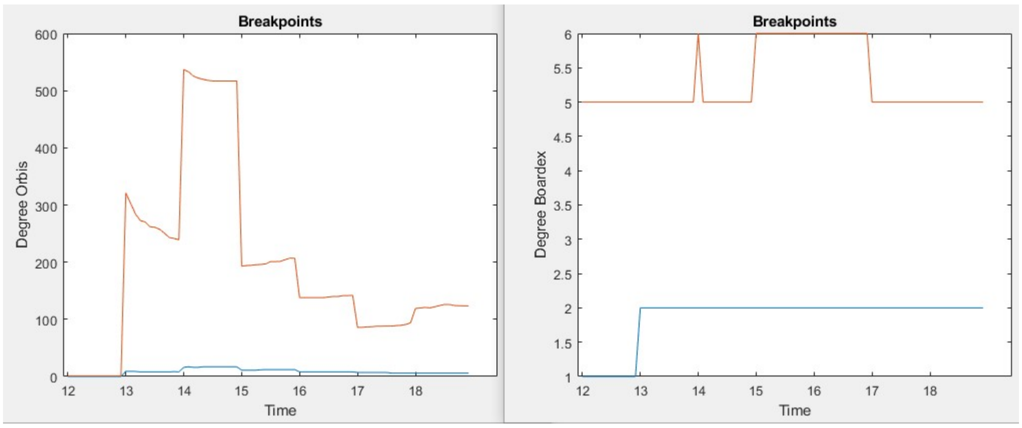


Figure 17: Breakpoints to create double sorted portfolios

it is worth to consider a longer sample to look at the performance of the strategy based on boardroom connectedness.

In the last section of this section I discuss the creation of the boardroom connectedness factor for a longer time horizon, from year 2003 to 2018. I create 3 portfolios on yearly boardroom degree connectedness characteristics (breakpoints: 0.33 and 0.66 percentiles allowing for extreme values), using monthly stock returns from CRSP and I estimate the five factor model. Since I have seen that the previous boardroom factor was very close to be statistically significant, I now include more data to see whether I can improve the significance of my results. The total number of firms included is 6562, portfolio 1 has 1157 average number of firms, 792 minimum and 1551 maximum; portfolio 2 has 906 average number of firms, 521 minimum and 1293 maximum; portfolio 3 has 851 average number of firms, 492 minimum and 1125 maximum. The first two lines in Table 27 show that the long short portfolio (3-1) has negative excess return, and it is statistically significant. Similarly, I find a negative and statistically significant intercept of the time series regressions of my factor on the 5 Fama and French factors. Which implies that a strategy based on boardroom connectedness (buying stocks with high-percentile boardroom connectedness and selling low-percentile ones) can outperform the market and can generate significant abnormal returns, for completeness I report also the results for CAPM and Fama and French 3 factor model.

To enrich these results I also implemented some of the most recent asset pricing models like: Q5 factor model (Kewei, Xue, and Zhang (2015)), BS6 factor model (Barillas and Shanken (2018)), DHS factor model (Daniel, Hirshleifer, and Sun (2020)). These pricing models confirm the previous results.

Value Weighted on Degree

	PT1	PT2	PT3	3-1	
Avg Excess Return	18.0	17.8	13.9	(4.1)	‡
T-stat Excess Return	4.11	4.21	4.02	(2.62)	

Value Weighted CAPM

	PT1	PT2	PT3	3-1	
Alpha	8.3	8.4	5.6	(2.7)	‡
Beta	1.10	1.06	0.94	(0.16)	
T-stat alpha	5.93	6.85	10.84	(1.96)	

Value Weighted 3F model

	PT1	PT2	PT3	3-1	
Intercept	8.6	8.2	5.7	(2.9)	‡
Gamma MKT	0.98	1.01	0.95	(0.03)	
Gamma SMB	0.39	0.31	(0.07)	(0.45)	
Gamma HML	0.13	(0.14)	0.03	(0.10)	
T-stat Intercept	8.32	8.41	10.33	(3.41)	
T-stat Gamma MKT	24.49	44.24	55.59	(0.94)	
T-stat Gamma SMB	11.50	8.00	(3.44)	(11.54)	
T-stat Gamma HML	2.17	(3.21)	1.45	(1.50)	

Value Weighted 5F model

	PT1	PT2	PT3	3-1	
Intercept	8.5	8.2	5.4	(3.1)	‡
Gamma MKT	0.98	1.01	0.96	(0.02)	
Gamma SMB	0.40	0.30	(0.05)	(0.45)	
Gamma HML	0.16	(0.16)	0.04	(0.13)	
Gamma RMW	0.05	(0.03)	0.08	0.03	
Gamma CMA	(0.10)	0.06	(0.01)	0.09	
T-stat Intercept	8.71	8.10	10.16	(3.37)	
T-stat Gamma MKT	24.40	42.57	59.96	(0.61)	
T-stat Gamma SMB	12.14	8.09	(2.44)	(12.53)	
T-stat Gamma HML	2.00	(3.59)	1.27	(1.51)	
T-stat Gamma RMW	0.60	(0.41)	3.30	0.45	
T-stat Gamma CMA	(0.88)	0.82	(0.22)	0.91	

‡ in percentage and annualized

Value Weighted HXZ model

	PT1	PT2	PT3	3-1	
Intercept	0.01	0.01	0.00	(3.5)	‡
Gamma MKT	0.95	0.95	0.96	0.00	
Gamma RME	0.36	0.24	(0.05)	(0.41)	
Gamma RIA	0.07	(0.11)	0.03	(0.04)	
Gamma ROE	(0.17)	(0.17)	0.01	0.18	
Gamma REG	0.00	0.00	(0.00)	(0.01)	
T-stat Intercept	7.71	8.55	9.75	(3.28)	
T-stat Gamma MKT	29.99	30.81	61.07	0.10	
T-stat Gamma RME	9.65	6.14	(2.27)	(8.53)	
T-stat Gamma RIA	0.94	(1.70)	1.06	(0.55)	
T-stat Gamma ROE	(1.28)	(2.86)	0.20	2.04	
T-stat Gamma REG	0.03	0.04	(0.13)	(0.11)	

Value Weighted BS6 model

	PT1	PT2	PT3	3-1	
Intercept	0.01	0.01	0.00	(3.0)	‡
Gamma MKT	0.95	0.97	0.95	(0.00)	
Gamma RME	0.38	0.26	(0.06)	(0.44)	
Gamma RIA	(0.09)	(0.04)	(0.01)	0.07	
Gamma ROE	0.02	(0.17)	0.05	0.04	
Gamma HMLM	0.23	(0.11)	0.06	(0.17)	
Gamma UMD	0.05	(0.04)	(0.00)	(0.05)	
T-stat Intercept	7.48	8.05	9.33	(3.18)	
T-stat Gamma MKT	43.14	36.87	61.09	(0.09)	
T-stat Gamma RME	10.05	6.31	(2.86)	(10.26)	
T-stat Gamma RIA	(0.98)	(0.55)	(0.50)	0.89	
T-stat Gamma ROE	0.35	(2.39)	1.87	0.61	
T-stat Gamma HMLM	3.24	(2.23)	2.87	(2.32)	
T-stat Gamma UMD	0.97	(0.92)	(0.11)	(1.15)	

Value Weighted DHS model

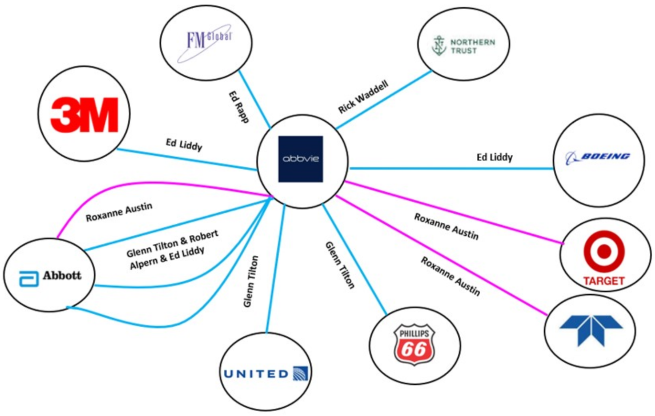
	PT1	PT2	PT3	3-1	
Intercept	0.01	0.01	0.00	(3.8)	‡
Gamma MKT	1.05	1.01	0.95	(0.11)	
Gamma PEAD	(0.17)	(0.03)	(0.04)	0.13	
Gamma FIN	(0.08)	(0.17)	0.04	0.12	
T-stat Intercept	6.37	7.42	10.15	(2.59)	
T-stat Gamma MKT	19.24	34.30	73.29	(2.02)	
T-stat Gamma PEAD	(1.33)	(0.44)	(1.10)	1.24	
T-stat Gamma FIN	(1.37)	(3.97)	3.14	2.15	

Table 27: Boardoom factor results on sample 2003-2018

So far, I have been able to confirm the effects that I have detected on ROA performance of ownership and boardroom connectedness in a stock returns framework. I have done an additional analysis: portfolios formed on connectedness measures at time T, do not predict returns at time T+1. For this reason, the results on portfolio returns are just shown in the appendix as additional confirmation/contribution to what has been presented in section 4, but the long short portfolios I built on connectedness measures cannot be properly considered factors since they have no predictive power.

A.6 Supporting charts and tables

Figure 18: ABBVIE connectedness in 2013 boardroom network



Representation of ABBVIE connectedness in 2013 boardroom network, with details on links from female directors in pink and male directors in blue.

Figure 19: ABBVIE connectedness in 2018 boardroom network

Representation of ABBVIE connectedness in 2018 boardroom network, with details on links from female directors in pink and male directors in blue.

	Ownership connectedness	**Ownership connectedness institutional**	**Ownership connectedness non institutional**	**Boardroom connectedness**	**Boardroom female connectedness**	**Boardroom male connectedness**	**ROA**	**Size**	**Lev.**	**Asset Tang.**
Ownership connectedness	1.00									
Ownership connectedness institutional	1.00	1.00								
Ownership connectedness non institutional	-0.06	-0.07	1.00							
Boardroom connectedness	0.18	0.18	0.07	1.00						
Boardroom female connectedness	0.14	0.14	0.00	0.57	1.00					
Boardroom male connectedness	0.17	0.17	0.08	0.93	0.33	1.00				
ROA	0.16	0.16	-0.18	0.05	0.08	0.05	1.00			
Size	0.30	0.30	-0.13	0.41	0.33	0.37	0.48	1.00		
Lev.	0.02	0.02	-0.02	0.06	0.03	0.05	0.08	0.19	1.00	
Asset Tang.	0.03	0.03	-0.05	0.05	0.04	0.04	0.10	0.07	0.02	1.00

Table 28: Correlations