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JEL Classification: D57, G14, G32, L14

Keywords: firms networks, Natural Experiment, executives' compensation

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The Value of Firm Networks: A Natural Experiment on Board Connections*

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April 14, 2020

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1. Introduction

Boards of directors play a crucial role in advising and monitoring corporate decisions. A large literature is devoted to understanding the impact of boards' characteristics on firms' outcomes. Establishing a causal link between board characteristics and firm value is, however, difficult since the board composition is an equilibrium outcome of a mechanism design problem (see Adams et al., 2010, for an overview).

In this paper we consider the role of inter-firm networks arising from shared (interlocking) directorships. By analyzing their causal effects on firm value we take a step forward in this research agenda. Networks, and in particular the centrality of firms in the boardroom network, are important since personal relationships are a salient feature of many economic exchanges: They shape the information flow between firms, facilitate resource exchange, and promote interpersonal and inter-organizational linkages.

Our main contribution lies in the use of exogenous variation in firms' network centrality arising from a regulatory shock to the board composition of Italian listed companies. This event, a ban of interlocking directorships directed at financial and insurance companies, allows us to address endogeneity concerns that are pervasive in the literature.

We provide causal evidence on the interaction between boardroom networks and economic outcomes, and find that firms' stock market valuations increase when firms' centrality in the boardroom network rises in response to the reform. Besides that, firms also become more insulated from shocks hitting other firms. Hence, we resolve existing uncertainty regarding the true effect of networks from the previous literature[1] that is likely stemming from the difficulty in addressing the endogeneity of governance and board structures. We also show that board connections are rewarded: directors' compensation increases as well for firms whose centrality rises after the reform. This is due to rent sharing and/or improved directors' outside options.

The ban of interlocking directorships was enacted in December 2011 and was primarily targeted at banks and insurance companies. Despite this, it has had an impact at large on

1 See Fracassi and Tate (2012) and Cohen et al. (2008), who address endogeneity concerns using past social networks.

the firms' networks due to historically pervasive and tight links between many companies and the service industry. To perform our analysis, we hand-collect data on the composition of corporate boards of listed firms, our boardroom network, as well as the compensation of each member from the firms' mandatory filings for the years 2009–2014. Those data are then matched with firm stock returns and accounting data. We measure changes in the network graphs before and after the reform and compute different proxies for network centrality (degree, Katz centrality, betweenness, and closeness).[2] We exploit the regulatory change on interlocking directorships to simulate and isolate the effect of the reform on firms' locations in the boardroom network. While some firms lose centrality after the reform, some, due to the non-linear nature of our network measures, become more central. We verify that the reform has a significant and long-lasting impact on the network that is forecastable by investors.

In the baseline specification the three-day announcement return, centered around the policy announcement, is regressed on the predicted change in network centrality induced by the reform. We find that a standard deviation increase in predicted centrality determines a 90 basis points rise in stock returns. This result is robust under different time windows around the announcement, with respect to different centrality measures, and with different sets of controls. Not only firms that become more central gain in market value, but they become also better hedged against market shocks (their beta falls) and against shocks of closely connected firms.[3]

Next, we investigate which economic forces drive our results. We start by testing the presence of an information channel. We conjecture that stock values increase and hedging abilities improve for central firms as they have better access to information. If so, firms that have less access to external information might benefit more from boardroom centrality. We verify this conjecture by sorting firms according to three proxies for the access to external information, namely analyst coverage, market valuation disagreement, and volatility of earnings forecasts. We find that firms for which external information is less extensive or

2 We use principal components of the four metrics to avoid collinearity and reduce dimensionality. See for example Hochberg et al. (2007), Larcker et al. (2013), El-Khatib et al. (2015) or Fracassi (2017).

3 The latter is defined by the number of intermediate steps between two firms in the boardroom network. For example, we consider firms sharing a director as being more more closely connected than firms that share a director in a third firm but whose boards are not interlocking. See Section 4.7 for details.

precise benefit more from boardroom centrality. This evidence confirms theories of incentive-compatible information sharing among competitors, such as Stein (2008).

Next, we find a relation between firms' fragility and the breadth of the benefits from boardroom connections. Firms with lower performance and growth prospects benefit more from the flow of information passing through the board. Intriguing insights are gained by exploring possible complementarities with other firms' networks, specifically input-output production linkages and cross-ownership. Firms that operate in industries that are more central in the input-output network benefit more from boardroom centrality. This is so since those firms are more exposed to upstream shocks, hence the flow of information passing through the boardroom allows them to better hedge. This result has further reaching implications, as it shows that the shock amplification uncovered in the literature on the micro origins of aggregate fluctuations[4] can be mitigated through other types of connections. In parallel, we also find that firms with lower cross-ownership centrality benefit the most from boardroom connections. Common ownership can be an effective coordination device (see Azar et al., 2018) and thus can act as a substitute for board connections.

Finally, as firms' surpluses are shared between owners and executives, we explore the impact of network centrality on directors' compensation, a topic which has attracted increasing attention (see literature review) due to the extraordinary rise in executive compensation in recent years. Unlike previous work, we focus on board networks. Using hand-collected data on directors' pay, including top executives, we find a positive and significant impact of board connections on compensation. Perhaps surprisingly, we find that all board members, and not only the top executives, benefit from network centrality. The relation is due to rent sharing or improvements in executives' outside options as arising from the larger sphere of influence. In addition, we find evidence that firms that are more closely connected in the boardroom network display a higher similarity in their pay-setting policy consistent with theories of imitation or poaching.

This paper is organized as follows. Section 2 relates our paper to existing research. Section 3 discusses the institutional setting and describes the construction of our boardroom-network

4 See among others Gabaix (2011), Acemoglu et al. (2012), and Carvalho and Gabaix (2013).

measures and instrumental variable strategy. Section 4 presents results. Section 5 presents results on director compensation.

2. Related Literature

Our work is related to the literature that tries to establish the effects of board characteristics, and more specifically of board network centrality, on firm outcomes. A commonly used empirical strategy is based on the idea of constructing networks from social, educational, or professional connections predating the current relationship (Cohen et al., 2008, 2010; Kuhnen, 2009; Engelberg et al., 2012, 2013; Kramarz and Thesmar, 2013). This helps to avoid confounding networks with current firm performance. Other authors exploit changes in network centrality arising from the appointment of existing board members to other boards (Larcker et al., 2013; Hann et al., 2019; Burt et al., 2019). In contrast to this literature, we focus on a previously unexplored exogenous regulatory shock in Italy specifically aimed at the boardroom network structure rather than the general board composition. For the purpose of identification, a strength of our approach is that we can validate it by showing that both stock market valuations and board centrality do not appear to exhibit any pre-trends prior to the announcement of the policy. Besides, most other papers examine the role of bilateral connections between individuals (see, e.g., Cohen et al., 2008; Engelberg et al., 2012; Fracassi and Tate, 2012; Fracassi, 2017; Shue, 2013) whereas causal evidence on the effects of boardroom connections through interlocking board members is sparse.

In terms of economic channels, more central firms have been shown to benefit from increased information flows in the context of venture capital (Hochberg et al., 2007), mutual fund investments (Cohen et al., 2008), analyst recommendations (Cohen et al., 2010), borrowing (Engelberg et al., 2012), corporate investment (Fracassi and Tate, 2012), and R&D expenditures (Faleye et al., 2014). Evidence in the context of M&A is more mixed (El-Khatib et al., 2015; Chikh and Filbien, 2011; Stuart and Yim, 2010). Board connections may also have a detrimental role due to a reduction in monitoring intensity (Fracassi and Tate, 2012), distortions in director selection (Kuhnen, 2009), voting behavior of mutual funds (Butler and Gurun, 2012), corporate investment (Güner et al., 2008), and option backdating (Bizjak et al., 2009). Hence, whether boardroom connections, and network centrality in particular, reduce or increase firms' value is ex ante unclear. Our natural experiment can provide a more definite answer. In addition, we contribute to the growing literature on the importance of directors as advisers rather than just monitors (see, e.g., Dass et al., 2013).

Some of our results have also broader implications and provide insights for related fields and other strands of the literature. We show that there is complementarity between boardroom and input-output networks. This result speaks to the literature on intersectoral input–output linkages as multipliers of firms' idiosyncratic shocks (see Gabaix, 2011; Acemoglu et al., 2012; Carvalho and Gabaix, 2013, among others). We also find evidence of a substitutability between the boardroom network and co-ownership. This result has important implications for the industrial organization literature and the social costs of hidden market power (see Azar et al., 2018). Like co-ownership, interlocking boards also act as an information coordination device and so they are substitutes. Finally, our paper sheds new light on the role of a firm's network position on the compensation of its directors and executives (see also Engelberg et al., 2013; Brick et al., 2006; Hwang and Kim, 2009; Balsam et al., 2017). Directors' compensation, and especially that of CEOs, has received vast attention also given its exponential growth in recent years. A large amount of literature has attempted to examine the origins of this growth, varying from luck (Bertrand and Mullainathan, 2001) and assortative matching (Gabaix and Landier, 2008) to rent sharing in a knowledge economy (Garicano and Rossi-Hansberg, 2008). We contribute to this literature by showing that boardroom connections have a substantial effect on compensation, both for top executives and for directors.

3. Institutional Setting

3.1. Institutional Setting

In December 2011, the Italian government presented a piece of legislation commonly known as the "Save Italy" decree. It was primarily a package of fiscal adjustments designed as a response to investors' concerns about the sustainability of the Italian debt.[5] Beyond its main

5 See for example "Saving Italy", The Economist, December 10, 2011.

goal, the decree also contained a ban on interlocking directorships for all competing firms in the finance and insurance sector, which was sudden and unexpected.

Most listed Italian companies adopt a two-tier governance structure with the two bodies being the board of directors (*Consiglio d'Amministrazione*) and the audit committee (*Collegio Sindacale*). The ban on interlocking boards applies to members of both bodies.[6] As a result of this law, numerous directors had to leave some of their posts. Hence the regulation was binding, as we further argue below. The deadline for a decision on which post to leave or to maintain was set to be April 27, 2012. After this date a non-compliant director would have to step down from all her seats.

A number of features make this policy particularly well-suited as a natural experiment. Although the scope of the reform was targeted to the finance and insurance sectors, it proved to be quite effective in dispersing the boardroom network between listed firms for two reasons. First, the finance industry historically has had a central role in the network of firms, with the same directors often being in both banks' and firms' boardrooms. Second, the definition of competing companies was strict and unambiguous. It indeed established that all banks or insurance companies were subject to the ban as long as they had a single branch in the same province. Given the nationwide presence of the banks and insurance companies in our sample of large, listed firms, the law had a de facto impact on all firms in these industries as long as they shared at least one director. This guaranteed full and broad compliance with the law. This stands in contrast to similar legislative acts, such as the Clayton Act in the U.S. that has been rarely enforced due to a lack of a well-defined classification of competing firms.[7] In contrast, the Italian law induced full compliance.

Figure 1 illustrates the effects of the ban on interlocking directorships for the network of Italian companies at large. It plots the graph density, i.e., the number of observed links over the number of all possible links of the boardroom network at an annual frequency for the sample period 2009-2014. It shows that network density has experienced a sharp decrease following the reform in 2011.

6 We will, for brevity, refer to members of the audit committee as directors as well.

7 For example, Apple and Google shared two directors, including Google's CEO Eric Schmidt, for three years, before the Federal Trade Commission forced them to break the tie (See "Google and Apple Eliminate Another Link Tie", New York Times, October 12, 2009).

The content of the decree, and the provision on interlocking directorates, became known to investors only when the decree was presented to the parliament, becoming immediately effective, on December 6. The provision was, arguably, unexpected by investors. This is confirmed by the fact that press coverage of this issue was completely absent before December 6. We searched the web archive of *Sole 24 Ore*, the main daily financial newspaper, using the tag "interlocking directorates." The first article examining the implications of the provision appeared on December 7 [8] whereas no article on the topic appeared in the year leading up to the decree.

3.2. Measures of Network Centrality

We derive our information on director networks from board data on Italian listed companies available at the website of the *Italian Companies and Exchange Commission* (CONSOB). The reporting frequency on board composition is biannual. We collect name and position of each board member and manually match firm names to Compustat Global to obtain financial data. Using these data, we construct an undirected and unweighted firm network. We define two firms as being connected if they share at least one board member.

Other interpersonal and non-professional connections formed in more informal contexts (education, club membership, etc.) might extend beyond the network of shared directorates. However, as noted in Hwang and Kim (2009) and Larcker et al. (2013), there is most likely some degree of strategic complementarity between the social and the boardroom network. Moreover, unlike members in common clubs shared directors are guaranteed to interact on economically relevant topics during mandatory meetings.

In our empirical analysis, we construct several network centrality metrics. The advantage over the use of simpler measures (e.g., a raw count of the number of firm connections) is that we can capture both direct and indirect links among firms. Network centrality is a multi-dimensional object that encompass several forms of interactions, including the one we will be mainly focusing on, namely the information transmission. Firms have more influence on the flow of information if they have a more central position in the boardroom network as

8 See "Le regole di Monti sui pluri-banchieri", Sole 24 Ore, December 7, 2011.

measured by the extent of their relationships, direct or indirect, with others. (Hochberg et al., 2007; Fracassi, 2017). We follow previous work (e.g. Hochberg et al., 2007; Larcker et al., 2013) and measure the firms' relative position in the network using four simple statistics.[9]

Degree centrality is the simplest measure of a firm's network position and counts the number of direct ties of a firm to other firms, i.e., whether they share at least one director. The more connections a firm possesses, the more channels it has to access information and leverage its connections in economic exchanges.

The same motive is also captured by *Katz centrality*.[10] Unlike degree centrality, which accounts only for first-degree connections, this measure takes into account the centrality or *importance* of firms with which the firm shares a director. Being connected to others that are themselves central increases the centrality of the firm itself. The relative centrality of firms that are only indirectly connected to most central firms is dampened by an attenuation factor.[11] As such, Katz centrality better captures a firm's power or prestige (Fracassi, 2017) and especially does so in its vicinity. This measure is particularly well suited in quantifying the quality and the amount of the information flows, since it focuses on firms which are both more central and more indirectly connected.

The extent of indirect information transmission is well captured by *closeness centrality*. It is constructed from the inverse average distance between a given firm and any other firm in the network. Intuitively, it is large when only a few shared directors are needed for the information flow to reach a firm.

The last metric we consider is *betweenness centrality*. It measures how much control a given firm has over the information flow between any other two firms. More technically, it measures how often a given firm lies on the shortest path of information flow between two

9 See Appendix A for a more formal definition of each measure.

10 We propose using Katz centrality instead of the more commonly used eigenvector centrality (Hochberg et al., 2007) in order to consistently measure the centrality of firms located in unconnected components (i.e. a smaller set of firms not connected to the rest of the corporate network). For these unconnected components eigenvector centrality is 0 and small changes in board composition over time could lead to the instability of eigenvector centrality over time.

11 When the attenuation factor α converges to 0 Katz centrality is constant for all firms; when α converges to an upper bound Katz centrality coincides with eigenvector centrality. We make a very conservative choice and set $\alpha = 0.05$.

other firms in the network. Intuitively, the directors of firms with high betweenness centrality can pass information from otherwise unconnected parts of the network.

Since these centrality measures are potentially correlated, our main results are based on their first principal component, henceforth simply labeled *centrality*.[12]

3.3. Illustrative Example

To fix ideas, in Figure 2 we describe the potential impact that a policy like the one considered here can have on a stylized network with two banks and six firms. Circles represent the firms (nodes), lines between nodes (edges) are created if two firms share a director and the size of the nodes is proportional to the value of our centrality measure. In Panel (a), both Bank A and Bank B are very central in the network. They have a high degree and Katz centrality (see Table 1). Katz centrality exhibits more variation and differs across companies with the same degree centrality; i.e., Company A and B have two direct connections, but Company A has higher Katz centrality since it is connected to Bank A, which is, in turn, very central.

Enforcement of the regulatory shock results in a ban of the link between Bank A and Bank B. In addition, we assume that the shared director between both banks is also on the board of Company A, and that she decides to leave the board of Bank A. Hence, the latter loses ties to both Bank B and Company A. This has significant implications for the overall network structure, visible from the changes of the four centrality measures and in the overall network density. In addition, although firms rank fairly similarly across all measures prior to the shock, the effect of the shock is heterogeneous across firms and measures.

Bank A was initially the most central according to all measures. After the shock, it instead has the same centrality as Bank B (according to degree and Katz centrality). In terms of information transmission, Company C and D play a more important role after the shock, well captured by the change in betweenness. Intuitively, both companies become ex post pivotal for information transmission from the nodes connected to Bank B (i.e., Companies A and B) to the nodes connected to Bank A (i.e. Companies E and F). If it were not for the connections of Company C and D information transmission would be inhibited. A significant

12 See also El-Khatib et al. (2015) or Larcker et al. (2013) for similar techniques to reduce dimensionality in the context of corporate networks.

change is also seen for closeness centrality. This is especially the case for companies in the periphery (A, B, E, F), as well as for both banks. The reason is that the severed tie between Bank A and Bank B inhibits the information flow by increasing the distance to the periphery.

3.4. Predicting Network Centrality

Our empirical strategy exploits the exogenous change in firm network centrality induced by the reform to identify its causal effects on firm value. Importantly, we only use information available to investors at the time of the announcement of the policy, and identify the component of the change in firm centrality that was forecastable by investors.

We use the boardroom network in June 2011 (before the reform) to simulate the change in the network structure due to breaks in the ties between the firms affected by the reform. To this end, we first select all directors that create an interlock between banks or insurance companies. Next, we choose a simple criterion to predict which boards each of the selected directors are more likely to leave. We assume that high-ranking executives, i.e. CEO, president, vice-president, and general director,[13] are more likely to remain in the firm where they hold this position. We further assume that the position of ordinary board member is more highly valued than the ones in an auditing committee. We solve remaining tie-breaks by assuming that directors remain at the firm where they earned more in 2010.

Comparing predicted resignations to actual resignations from the press releases (all mentioning the regulation as the reason) we correctly predict 68% of the resignations. This suggests that our criterion for selecting boards is reasonable. Based on the above, the predicted change in centrality Δ is defined as the difference between predicted and actual centrality:

$$\Delta = \overline{Centrality}_{i,06/2011} - Centrality_{i,06/2011}, \tag{1}$$

where $\overline{Centrality}$ is the simulated and $Centrality$ the actual network centrality of a given firm i.

13 *Direttore generale* is a role present only in few firms. This is effectively equivalent to a Chief Operating Officer but in Italy is often as important, if not more important, then the CEO.

4. Network Centrality and Firm Value

We build on our hand-collected data of board members by hand-matching firm names to corresponding Compustat Global identifiers. For any inconsistencies we cross-referenced the hand-collected data on board composition and financial data from Compustat with data from annual reports to ensure proper matching. We get data on daily stock prices as well as firm-level financial and balance sheet variables for all companies listed on the Milan Stock Exchange from Compustat Global. We further match firms with Datastream to obtain data on market capitalization. Analyst coverage and earnings forecasts are obtained from IBES. Description of the procedure for collecting information on directors' compensation, that is used in the next section, is described in Section 5.2 and, more detailed, in Appendix B.[14]

4.1. Effects on Network Centrality

At the time of the policy announcement, investors can anticipate only in part how the firm network will evolve as a result of the reform. At first we test whether the reform has a significant effect on the configuration of the board network and whether the effect is persistent. Both conditions need to be satisfied to have a significant stock market reaction.

We use data on board composition at the annual level and estimate:

$$y_{i,t} = \beta \times \Delta_i \times Post_t + \eta_i + \delta_t + \varepsilon_{i,t} \tag{2}$$

where y is a network centrality measure, *Post* is a dummy equal to 1 after December 2011, and zero otherwise. η and δ are the firm and year fixed effects, respectively, and ε is the error term.

Δ is the predicted change in firm i's network centrality, constructed by simulating the network after breaking the ties among firms connected prior to the reform (see Section 3.4 for details). We estimate the model over the 12/2009–12/2014 period including all firms that have at least one observation before and one after the reform.

Table 3 reports estimates of the coefficient β. As expected, in column 1, where the dependent

14 Definitions of all other variables used can be found in Appendix-Table A1

variable is our measure of network centrality, the coefficient is large and significant, with a t-statistic of 6.10. In columns 2 through 5, we test whether any of the four components of our network centrality measure are driving this positive association. We find that coefficients are indeed all positive and, except for closeness (t-statistics= 1.48), large and significant: the coefficients on degree, Katz, and betweenness (columns 2 through 4) have t-statistics equal to 5.06, 10.91, and 2, respectively.

We also perform an event study analysis by replacing $\Delta \times Post$ with a vector of interactions between Δ and time dummies, omitting the coefficient corresponding to the last pre-reform year, 2011. In Figure 2, the coefficients are small and insignificant for the years 2009 and 2010 whereas they increase significantly in the post-reform years 2012 through 2014. Hence, there is no evidence of a pre-trend in changes in network composition. Moreover, there is no apparent reversion after the reform. This suggests that the firms whose ties with other firms have been broken by the reform were unable to recover their centrality in the firm network.

4.2. Baseline Results

We now turn to the main point of our analysis, the impact of the reform on firms' market values through changes in the network. In Table 3, we estimate the following equation:

$$CAR_i = \beta \times \Delta_i + \gamma X_i + \varepsilon_i \tag{3}$$

CAR is the cumulative abnormal return of firm i over a three-day window surrounding the announcement date. Daily abnormal returns are either raw (i.e., net of the risk-free rate) or risk-adjusted using either the market model or the Fama French three-factor model.

β is our main coefficient of interest. It captures the impact of the predicted change in the principal component of the four centrality measures. We standardize it by demeaning and dividing by its standard deviation to facilitate interpretation. The vector X includes our control variables, namely size, defined as Log(total assets), and ROA, defined as income divided by lagged total assets. We choose those since they are consistently observed for the entire sample. We nevertheless check that results are unaffected if we include additional controls or no controls at all (see Table 4). X also includes industry dummies, defined using the Fama-French 17 industries classification.[15] ε is an error term.

In Column 1 of Table 3 we use the raw stock return as dependent variable and find that a one-standard deviation change in predicted centrality is associated with a 90 basis points increase in stock returns. The coefficient on Δ is statistically significant at the 5% level (t-statistic$= 2.23$). This result does not depend on the particular benchmark used to adjust for risk. In column 2 we use the market return as benchmark, and in column 3 we use the three Fama-French factors. The coefficients and the statistical significance are virtually identical.

As a first robustness test, we run our baseline regression separately for the daily return on day $t-5$ and the buy-and-hold return between day $t-5$ to $t-4$, $t-5$ to $t-3$, and so on, until $t+5$. The purpose of this exercise is to test whether there is any "pre-trend" in the change of valuation preceding the announcement of the interlocking ban, and whether we find any evidence of reversion to the mean. We can confirm that this is not the case. Figure 3 plots the estimated coefficients for these regressions along with 95% confidence intervals. The coefficients are close to 0 for the days before the reform and increase around and after its announcement, indicating that the timing of the change in market valuation coincides with the announcement of the policy.

4.3. Robustness Tests

In this section we verify the robustness of our results across different specifications. In Table 4 we present several variations of the baseline specifications of Table 3. For brevity, in all the tests that follow we use the market model to adjust stock returns, but results are similar with different benchmarks. Columns 1 through 3 examine whether the effect of network centrality on stock market valuations vanishes over time. In addition to our baseline -1,+1 window, results are shown for a five-day (column 2) or seven-day (column 3) window around the announcement date. Point estimates and standard errors are similar. With a -2,+2

15 We have also used the 12, 30, 38, and 49 industries classification, finding similar results.

window the coefficient on Δ is 1.02, and it rises to 1.19 with a -3,+3 window. In both cases coefficients are significant at the 5% level.

In columns 4 through 7, we regress the three-day cumulative abnormal return on the four different components of our main centrality measure, standardized as usual. There is no evidence that our results are driven by a specific proxy. All the coefficients are positive and economically large, with the only exception of betweenness centrality. Results are the strongest for the Katz and closeness centrality measures, whereby estimated coefficients are 1.20 and 0.79, respectively, both significant at the 1% level. The coefficient on degree centrality is 0.74 and significant at the 10% level. Only the coefficient on betweenness centrality appears small and more noisily estimated.

In columns 8 and 9 we test whether any of the control variables are driving our results. In column 8 we exclude all controls except the industry dummies. In this case the coefficient rises to 1.24 and is significant at the 1% level. In column 9 we include standard predictors of stock returns, beyond ROA and size, the logarithm of market capitalization and Tobin's Q. The coefficient and the statistical significance are, again, similar to those found in our benchmark estimates. We conclude that results are robust.

In the four sections that follow, we put under the microscope the economic channels behind our results. We start with the role of information, and move to examine complementarities with other firms' connections, namely input-output and cross-holdings. We then analyze the importance of firm profitability and growth opportunities.

4.4. The Role of Information

One of the economic channel considered as the most plausible driving force behind the role of the boardroom network is the transmission of information. Overall we find that the information transmitted through boardroom networks can increase firm value. A more connected boardroom promotes information transmission to outside investors and improves the quality and availability of information for directors and advisers.

Our strategy consists of identifying the firms that may benefit the most from information transmission and test whether the impact of the change in network centrality is stronger for them. Our hypothesis is that network centrality can substitute for other sources of information. Hence, for firms whose access to external information is scant market valuations should react more to changes in network centrality. To this purpose, we construct three proxies for the breadth and depth of the external access to information: idiosyncratic volatility (IVOL), analyst coverage, and the dispersion of analyst earnings forecasts. We use them to sort firms and analyze how they interact with network centrality.

Following Hirshleifer et al. (2013) IVOL is estimated by regressing, for each firm, the daily excess stock return on the equity premium over the 12 months that precede the announcement (i.e. from December 2010 to November 2011 included). We then extract the standard deviation of the residuals. Analyst coverage captures, instead, access to external reporting (Hong et al., 2000). Because analyst coverage is strongly correlated with firm size, a potential confounding factor, we regress the logarithm of one plus the number of analysts covering the firm in the previous calendar year over the logarithm of total market capitalization and its squared value. We then sort firms according to the estimated error from this regression. Finally, we use the dispersion of analyst earnings forecasts as a measure of disagreement about firms' market valuation. This captures well the degree of heterogeneity in investors' beliefs (Johnson, 2004). Disagreement is constructed as the standard deviation of net income forecasts for 2010 (available from IBES) standardized by the book value of assets.[16]

In Table 5 we estimate Equation (3) for two different sub-samples. We sort firms according to whether they are below or above the sample median of each proxy discussed above. As hypothesized, results are much stronger in firms with higher idiosyncratic volatility, lower residual analyst coverage, and higher dispersion of analyst forecasts. In these subsamples, the coefficients of interest are 1.49, 1.24, and 2.16, respectively. All are significant at the 5% level. In the other subsamples, the effect of changes in network centrality is positive but insignificant at conventional levels. Hence, firms whose market values are less uncertain or for which there is ample and more clear external reporting appear to benefit less from boardroom connections.

16 Since about half of the firms have no coverage, estimates are based on a smaller sample of 124 observations.

4.5. Input-Output and Ownership Networks

Boardroom networks are one way, among many others, in which firms are connected. Alternatives include input-output production networks and cross-ownership connections. It is of interest to examine possible complementarities or substitutions between various form of connections. As before, we sort firms according to their centrality in other networks. We then verify whether the impact of exogenous changes in the boardroom network is stronger or more muted depending on their centrality with respect to other types of networks.

We start with value-chain connections that have recently attracted a considerable amount of attention also in the firms' dynamics and macro literature (see, among others, Acemoglu et al., 2012; Carvalho and Gabaix, 2013). The focus of this literature is on the propagation of idiosyncratic shocks through the production network. We are instead interested in studying whether the strength of the boardroom information transmission varies depending on the firm's position in the input-output network. Firms that are more central in the input-output network are more susceptible to shocks regardless of whether these are upstream technology shocks or downstream demand shocks (see Barrot and Sauvagnat, 2016; Gabaix, 2011). Due to their fragility, we expect these firms to benefit more from the flow of information provided by a more central position in the boardroom network.[17]

Input-output data for the year 2010, aggregated to 62 NACE industries,[18] are provided by the *Istituto Nazionale di Statistica* (ISTAT). We match sample firms to (potentially multiple) NACE codes using official crosswalks available from Eurostat's RAMON database[19] to Compustat's NAICS code.[20] We then compute industry-level network centrality for both a weighted and unweighted directed[21] input-output network, where the weights in the former

17 A similar insight emerges in previous evidence by Dass et al. (2013), who show that companies are better isolated from industry shocks and have a shorter cash conversion cycle when they share directors with firms in related upward or downstream industries.

18 We exclude home production.

19 RAMON — Reference And Management Of Nomenclatures available under `https://ec.europa.eu/eurostat/ramon`

20 We match them based on 6-digit NAICS codes and impute any shorter NAICS codes only if they map uniquely into a NACE category. Wherever this is not possible, we used NACE classifications provided by AMADEUS. If a 6-digit NAICS code maps into more than one of the NACE codes, we compute firms' network centrality as the average of the corresponding NACE industry centrality.

21 Directed implies that links between industries are not bi-directional, but rather reflect the flow of inputs from industry i to j and inputs provided by industry j to industry i respectively. In terms of the adjacency matrix entries (i,j) and (j,i) now differ.

are the input flow from sector i to j relative to total input demand of sector j. For the unweighted network we define two industries i and j to be connected if i's output exceeds 1 percent (Carvalho, 2014) of j's total input purchases. We then compute Katz centrality[22] of this network and estimate Equation (3) for two sub-samples identified by whether a firm operates in an industry that is below or above the sample median centrality in the input-output network.

Results are displayed in Table 6. As conjectured a change in boardroom centrality has bigger impact on stock values when firms operate in more central, downstream industries. In this case estimated coefficients of interest are equal to 1.66 and 1.77, depending on whether we use the weighted or unweighted network measure. On the other hand, the coefficients drop to 0.12 and 1.04 in industries that are less central, with only the latter being significant. Hence investors deem a firm that is more central in the boardroom network as better able to isolate itself from shocks originated in upstream industries.[23]

Next, we examine the complementarity with cross-ownership networks as a source of information. This dimension is also insightful since it has been so far overlooked. Data on cross-ownership of Italian firms is collected from mandatory filings with CONSOB and manually matched to our board data. Our sample includes all Italian listed companies as well as unlisted Italian and foreign (listed or unlisted) companies reported as owners. We exclude all institutional owners. We compute Katz centrality for an un-directed, weighted cross-ownership network using the ownership stakes as weights[24] and for an un-directed, unweighted ownership network, selecting only stakes that are above either 1% or 2%. We re-estimate our baseline specification for two sub-samples identified by whether firms' centrality in the ownership network is below or above the sample median. Results in Table 7 indicate that firms benefit more from a central position in the boardroom network when they are less central in the ownership network. For the weighted network (column 1 and 2), the coefficient on Δ is a significant 1.43 for firms characterized by low centrality, and 0.55 (insignificant) for

22 See also Carvalho (2014) for a structural interpretation of Katz centrality in the context of input-output networks.

23 Estimated coefficients are statistically significant for both weighted and unweighted networks, though they are lower in the first case.

24 Past literature on cross-ownership considered directed networks in the context of corporate control (Glattfelder and Battiston, 2009). This is a less relevant aspect for our analysis.

firms with high centrality in the ownership network. Results are very similar when using unweighted networks regardless of whether we choose 1% (column 3 and 4) or 2% (column 5 and 6) as a cutoff. To sum up, firms that are less central in the ownership network benefit more from boardroom centrality. This echoes the previous findings of complementarity with the production networks. Cross-ownership can reduce information asymmetry (Brooks et al., 2018) and serve as an important coordination device (Azar et al., 2018). Thus, firms that cannot take advantage of these linkages benefit more from the information flows channelled through the boardroom.

4.6. Profitability and Growth Opportunities

We bring our strategy of detecting the economic channels through firms' sorting one step forward. We now rank firms according to their degree of profitability or their growth prospects and see whether they respond differently to the same exogenous change in the boardroom.[25] Opposite forces might be operating in this case. On the one side, firms with ample growth opportunities are less sensitive to shocks and may not need boardroom centrality. On the other side, the information channeled through boardroom connections might benefit more innovative, and hence more profitable, firms. Those might indeed be better equipped to extract added value from the information flow.

We proxy past profitability using ROA and growth opportunities using Tobin's Q and Sales Growth, all measured with one-year lag. We then again estimate Equation (3) in two subsamples, identified by whether a firm is below or above the sample median. Table 8 shows that firms with low ROA, sales growth and Tobin's Q benefit the most from increased network centrality. The coefficients on Δ range between 1.37 and 1.90 for this group of firms, and are significant at the 1% or 5% level. Coefficients for the set of firms that exhibit better ex ante performance or growth opportunities are smaller in magnitude and occasionally negative. This evidence indicates that boardroom connections are especially valuable for firms facing downturns or in need of finding profitable investment opportunities.

25 Fracassi (2017), Larcker et al. (2013),Hann et al. (2019) also study the effects of boardroom connections on firms' investment policies.

4.7. Returns Co-Movement and the Hedging Role of Information

So far we have measured the impact of the shock on firms' stock values. To cross-validate our results we now examine other performance indicators. If more central firms are better able to exploit information flows, they should also be better hedged against shocks hitting other firms. As a result their returns should be less correlated with the market.

To this purpose we regress firms' exposure to general market movements on their centrality. As before, to address concerns of endogenous network formation, we use the expected change in network centrality Δ interacted with a "Post reform" dummy as an instrument for centrality. While the previous event study included the instrument directly in the reduced form, here an IV strategy is adopted (see Section 3.4 for details). Firm's market exposure is the beta $\beta_{i,t}$ from a standard market model. The latter is obtained by regressing daily returns net of the risk-free rate over the market return on a yearly basis from 2009 until 2014.[26] We focus on a sample of firms that exhibit at least 200 return observations in a given year.

Our econometric specification reads as follows:

$$\beta_{it} = \theta \times Centrality_{i,t} + \eta_i + \delta_t + \varepsilon_{i,t}, \tag{4}$$

where the dependent variable is the market exposure of firm i in year t and *Centrality* is instrumented by the expected change in the network induced by the reform, Δ, interacted with the "Post reform" dummy, as in Equation (2). Firm and year fixed effects are captured by η and δ, respectively. ε is an error term. We cluster standard errors at the firm level.

To appreciate the novelty and strength of our IV strategy we consistently display results for both the OLS estimation[27] and for the IV regressions. As it will become evident, results might be largely diverging in some instances. Results are in Table 9. Coefficients in column 1, the OLS estimates are negative and imprecisely estimated. Coefficients in column 2, the IV estimates, are highly significant. The negative estimate confirms our conjecture: Firms

26 Here we use the broader FTSE All Italia index instead of the Fama-French European market return since the first is more likely to reflect common shocks to the network of Italian firms.
27 Whereby *Centrality* is our previously constructed principal component.

central in the boardroom can use the information flow to hedge themselves from market movements.

Next, we take our analysis to a more granular level and check whether firms can also hedge shocks originating in other firms that are closely connected to them. We measure hedging in this case as the correlation of returns for every possible permutation of firm pairs on an annual basis. As before we use either raw returns or residuals from the market model and focus on firms that have at least 200 daily return observations in a given year. Two firms are defined as more closely connected if the path between them across the boardroom is shorter.[28] The variable *Board Proximity* is defined so that larger values indicate shorter paths. The econometric specification includes an instrument constructed in the usual way.

The econometric specification reads as follows:

$$\rho_{ij,t} = \lambda \times \textit{Board Proximity}_{ij,t} + \eta_{ij} + \delta_t + \varepsilon_{ij,t}, \tag{5}$$

where the dependent variable is the correlation between company i and j in year t and *Board Proximity* is the negative of the shortest path between i and j in year t. η and δ are firm-pair and year fixed effects, respectively, and ε is an error term. Standard errors are clustered at the firm-pair level.

Results are displayed in table 9. Correlations in column 3 and 4 are based on raw returns. Both OLS and IV coefficients are precisely estimated but deliver opposite conclusions. Once we control for the potential network endogeneity (column 4) the sign of the estimated coefficient reverts. The IV estimates confirm the negative relation between the correlation in stock returns and firms' proximity. In comparison the returns of two firms that are an additional board-step away, have a 1.3 percentage point higher correlation. This is sizeable relative to a sample average correlation of 15.5%. Results are similar when we consider the correlation of abnormal returns in columns 5 and 6. In this case OLS regressions are imprecisely estimated whereas IV estimates are significant. Effects are even larger in this case considering that the mean correlation of abnormal returns is now 2.7%. To sum up, the

28 To fix ideas consider the following example. One step is needed to go from firm A to firm B if each of them has at least one director on the board of firm C. The shortest path is one in this case. The path length then rises as the number of indirect steps in the network pathway increases.

information flow between two firms that are nearby in the boardroom network makes each one less sensitive to shocks occurring to the other.

5. Director Compensation

Firms' surplus is shared between owners and directors. Network centrality and the flow of information can affect the latter too through various channels, which we highlight below. In recent years a large literature has examined the determinants of cross-sectional and time-series variation of directors' compensation.[29] The interest was justified mainly because of its unprecedented growth. None has so far examined the role of boardroom centrality. We do so through our natural experiment setting.

5.1. Isolating the Effect on Compensation: Empirical Design

Boardroom centrality can affect directors' compensation first and foremost through rent sharing. As centrality raises firms' surplus so too does directors' compensation. Besides this, better connected directors can leverage on better outside options. This improves their bargaining position within the firm.[30]

We adapt our baseline specification by using the logarithm of directors' annual compensation as dependent variable and account for the endogeneity in the usual way. [31]

The econometric specification reads as follows:

$$log(Compensation_{i,j,t}) = \lambda \times Centrality_{i,t} + \eta_{ij} + \delta_t + \varepsilon_{i,j,t} \tag{6}$$

where the dependent variable is the logarithm of director j, employed at firm i in year t, and *Centrality* is our usual proxy instrumented as before. η and δ are director-firm and year fixed effects and ε is an error term. We double-cluster standard errors at the director and firm level to account for two potential layers of autocorrelation.

29 See Edmans and Gabaix (2016) for an extensive review.

30 See also Liu (2014).

31 Engelberg et al. (2013) studies the role of CEOs connections for their compensation. Our analysis addresses the endogeneity concerns through the experiment setting and uses a broader network measure which includes also links to all directors.

Our data sample consist of 13,066 directors, whose compensation is hand-collected from mandatory governance filings, so-called *Relazioni sulla Remunerazione*. Those are filed annually with the Italian stock exchange (*Borsa Italiana*). Since these only became mandatory in 2011, we hand-collect compensation data from annual reports for the years 2009-2010.[32] Like the DEF14A filings in the US, reports contain data on fixed compensation (*compensi fissi*), bonus payments (*bonus*), non-monetary benefits (*benefici non monetari*), and other compensation (*altri compensi*).[33] Stock and option grants are reported separately. Reporting consistency is achieved through the typical "Execucomp" methodology, by which all grants are re-evaluated using hand-collected data on the number of stocks/options, grant-date share price, grant date, and, for option grants, the strike price and the expiration date.[34]

5.2. Network Centrality and Compensation

Table 10 shows the causal effect of network centrality on directors' compensation. A one-standard deviation increase in centrality induces a large and statistically significant increase in compensation, corresponding to a 12% pay raise (column 1). The F-statistic is 47.16 suggesting that our instrument is very strong. Columns 2 and 3 tell apart the effects for high-rank directors (CEO, chairman, and vice-chairman) and low-rank directors (all the others). The coefficients are both large and positive but insignificant for high-rank directors possibly due to small sample size.

Columns 4 through 6 replicate the tests above, however, compensation is now measured taking the firm-year average. The advantage of this specification is that each firms is weighted equally and independently of the number of its directors. This alternative specification also allows us to control for possible attrition effects from directors' turnover. The previous specification featured firm-director fixed effects. This implies that an executive who is part of a firm board only before or only after the appointment will not enter the sample because of collinearity.

32 While coverage is almost universal for all listed companies starting in 2011, there are some companies for which annual reports or compensation information is missing for the 2009 or 2010.

33 To improve consistency reporting is harmonized across firms by assigning alternative definitions of compensation components to one of the above categories.

34 Details on specific assumptions are in Appendix B

In columns 4 through 6, we indeed find larger and more precise coefficients on the centrality variable. The coefficient is equal to 0.33 when all directors are included. When we split directors according to their rank, we find coefficients equal to 0.32 and 0.41 for high- and low-rank directors, respectively. All these estimates are statistically significant at the 5% or 1% level.

5.3. Peer Effects and Compensation

Next we examine whether direct and indirect board connections between firms influence the pay-setting process. There are potentially two reasons. First, simple peer effects: Learning about the compensation that a connected firm is paying to its directors might induce imitation.[35] Second, two firms that are only a few steps away in the boardroom network might share the same information about directors' talents and abilities and attempt to poach each other's directors.

To capture potential peer effects, the similarity in compensation policy for any two firms i and j is measured as follows (see Fracassi, 2017; Shue, 2013)[36]: We first regress the logarithm of the average compensation of directors and executives at the firm-year level (as in column 4-6 of Table 10) on year and firm fixed effects from 2009-2014:

$$log(Compensation_{i,t}) = \eta_i + \delta_t + \Psi_{i,t}, \tag{7}$$

where the dependent variable is the logarithm of average compensation at firm i in year t. Firm and year fixed effects are captured by η and δ. Ψ is the unexplained part of observed compensation.

35 Similarly Hayes and Schaefer (2009) argue that one reason for the observed increase in CEO compensation is that no company wants to signal that their CEO is worse than the average by paying him below the average.

36 What differentiates us from their finding is that, unlike Shue (2013) who uses random assignment of CEOs to the same section at the Harvard Business School MBA, we can focus on the compensation of all executives and directors; unlike Fracassi (2017), who uses past social ties of directors and executives, we can account for endogenous network formation through our IV strategy.

Based on the residuals of the first-stage (Ψ), the variable of interest *Policy Similiarity* is then defined for each possible firm pair (i, j) and every year t as

$$\textit{Policy Similiarity}_{ij,t} \equiv -\log\left(1 + |\Psi_{it} - \Psi_{jt}|\right), \tag{8}$$

where higher values of *Policy Similarity* correspond to smaller differences in the unexplained part of the average compensation between the two firms.

If indeed firms that are more closely connected influence each other's pay-setting, positive peer effects are reflected in greater similarity for firms located closer to each other in the network. We test this conjecture by regressing *Policy Similarity* on our *Board Proximity* variable (as in Section 4.7) using again our IV strategy. The specification reads more formally:

$$\textit{Policy Similiarity}_{ij,t} = \gamma \times \textit{Board Proximity}_{ij,t} + \eta_{ij} + \delta_t + \varepsilon_{ij,t}, \tag{9}$$

with observations at the firm pair (i, j) level in each year t. *Policy Similarity* measures the difference in observed differences in compensation and *Board Proximity* is instrumented as in the previous section. η and δ capture firm-pair and year fixed effects and ε is an error term. Standard errors are clustered at the firm-pair level.

Results are displayed in Table 11. To provide a full picture, column 1 shows results for the policy similarity based on observed differences in (i.e. based on $log(Compensation)$), while results in column 2 are based on the residuals (i.e. Ψ) as defined in Equation (9). The F-statistic is well over 200, and estimated coefficients are negative and highly significant. Hence, more connected firms have more similar compensation policies. An additional intermediate step between two firms would raise similarity by 8% to 10%. Similarities in pay policies might also be due to similarities in firms' business activity. We exclude this possibility in column 3 and 4 by rerunning regression excluding firm pairs that operate in the same industry.[37] Results are again highly significant and quantitatively similar. We therefore conclude that either imitation or poaching are plausible forces behind our results.

37 We again use the Fama-French 17 industry classification.

6. Conclusion

This paper presents causal evidence on the effects of firms' centrality in the network of shared boardrooms on firm value and pay setting. To this end, we leverage a change in Italian corporate governance legislation that rules out interlocking directorships between banks and insurance companies. The reform was fully unexpected and out of the firms' span of control. Hence, it qualifies well as a natural experiment.

Upon verifying that the reform has a meaningful impact on network connections, we document that firms whose boardroom network centrality rises after the reform experience positive abnormal returns around the announcement date. This effect is robust to the use of alternative return risk adjustments, when controlling for different firm-level observables and industry fixed effects, or when using several measures of network centrality. More central firms also become better hedged against market shocks or shocks from other closely-connected firms. Further, since the increase in firms' surplus is typically shared with directors, firms becoming more central pay significantly higher compensations to their executives. We also find evidence that imitation or poaching are additional plausible forces behind firms' pay setting as we find more closely connected firms to have a more similar compensation policy.

We find that the value-enhancing effects of increases in network centrality are due to information spillovers. Abnormal returns are especially high for firms with higher idiosyncratic risk, lower analyst coverage, and higher disagreement among analysts. Hence, firms with more uncertain market valuations or with lower external coverage benefit more from boardroom centrality. At last, we uncover a complementarity between boardroom networks and input-output networks on one side and cross-ownership on the other. Hence our results have broader outreach for lateral fields such as the study of production networks and firms' competitive advantages.

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7. Figures

Figure 1
Graph Density around the Event

Figure 1 displays the the annual "graph density" of the firm network. Density is the number of observed links normalized by the total number of all possible links in a given year. The horizontal dashed line corresponds to the reform year.

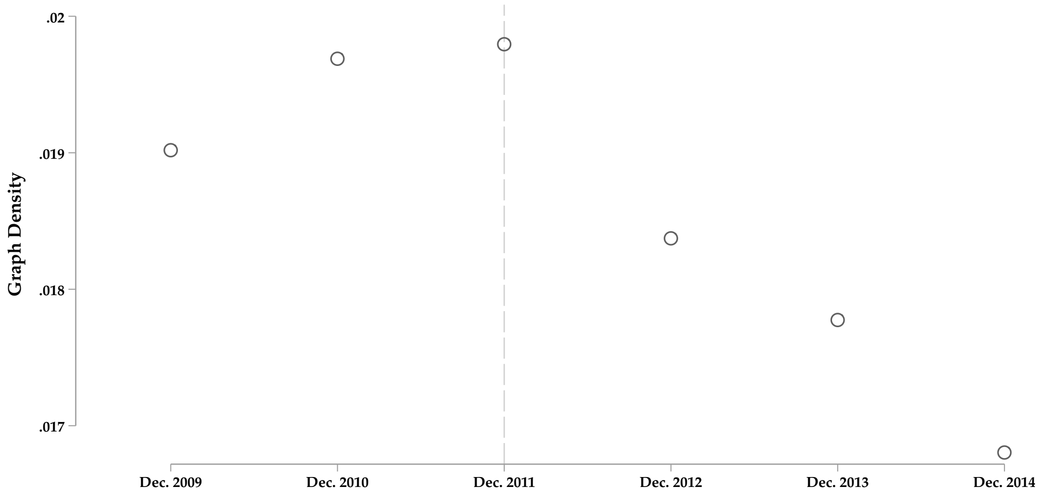
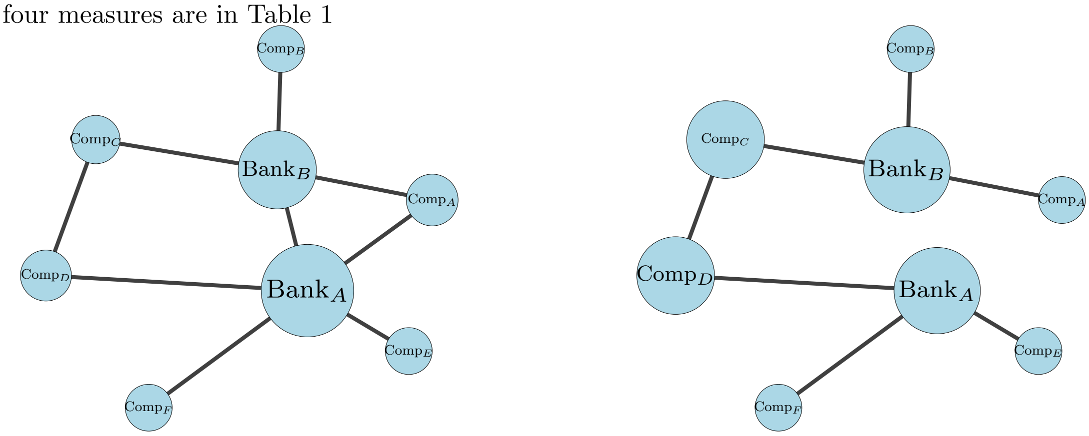


Figure 2
Fictional Corporate Network and Potential Effect of Regulation

Figure 2 shows an illustrative example of a potential boardroom network structure before and after simulating the effects of enacting the reform. We assume a director to be on the board of Bank A, Bank B, and Company A, and that the director steps down from his position at Bank A, hence also severing the tie between Company A and Bank A. The size of the nodes scales with the principal component of the four network measures (Degree, Katz, Closeness, Betweeness) as used in our main analysis. Actual values for each of the four measures are in Table 1



(a) Before **(b) After**

Figure 2
Event Study: Network Centrality

Figure 2 shows coefficients from regressing Centrality (PCA) on firm and year fixed-effects, and year dummies multiplied by the predicted change in Centrality Δ. The coefficients β_t associated to the year dummies interacted with Δ are plotted together with the 95% confidence intervals. Standard errors are clustered at the firm level. $t = 0$ corresponds to the reform year 2011, and β_0 is normalized to zero.

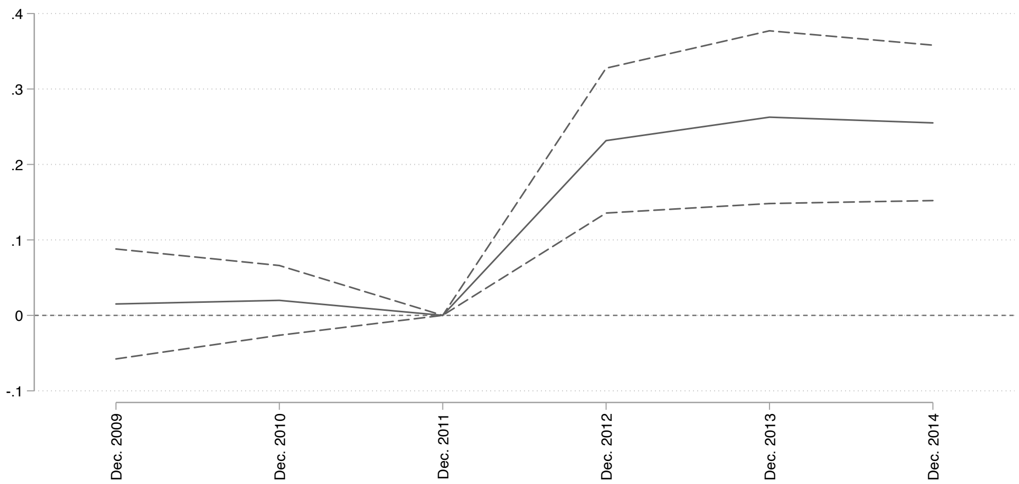
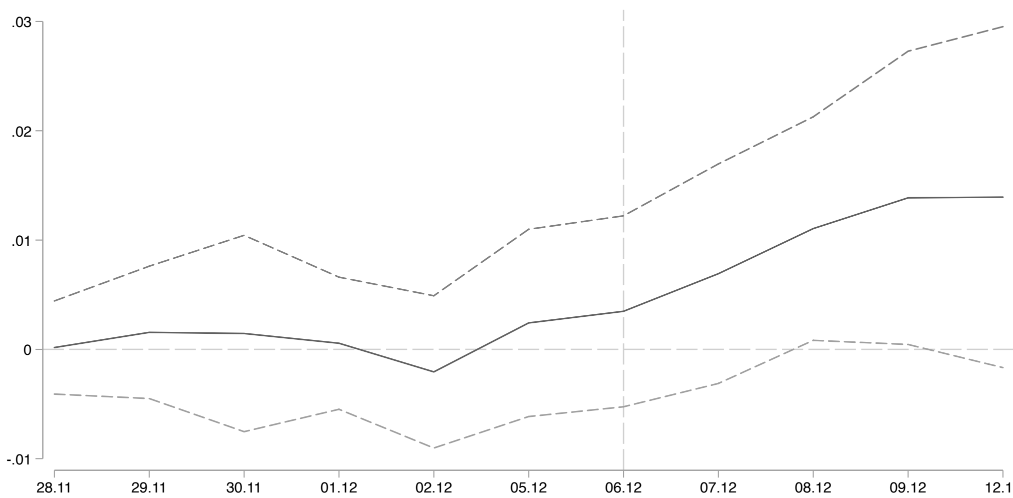


Figure 3
Event Study: Buy-and-Hold Abnormal Returns

Figure 3 shows coefficients from regressing compounded abnormal returns using the market model for risk adjustment on the predicted change in Centrality Δ. The coefficients β_j associated with the cross-sectional regression of returns compounded from $t-5$ to $t=j$ on Δ are plotted together with 95% confidence intervals.



8. Tables

Table 1
Fictional Corporate Network and Potential Effect of Regulation

Table 1 shows values for the four different network measures used in the main analysis before and after the simulated effect of the reform based on the fictional network example illustrated in Figure 2. We use degree centrality, Katz centrality, closeness, and betweenness as defined in Section 3.2. Density is the number of observed links normalized by the total number of all possible links in a given year.

	Before				After			
	Degree	Katz	Betweeness	Closeness	Degree	Katz	Betweeness	Closeness
Bank A	5.00	1.65	13.00	0.86	3.00	1.35	11.00	0.62
Bank B	4.00	1.54	8.50	0.79	3.00	1.35	11.00	0.62
Comp A	2.00	1.32	0.00	0.64	1.00	1.14	0.00	0.43
Comp B	1.00	1.15	0.00	0.50	1.00	1.14	0.00	0.43
Comp C	2.00	1.29	1.50	0.62	2.00	1.26	12.00	0.60
Comp D	2.00	1.28	1.00	0.60	2.00	1.26	12.00	0.60
Comp F	1.00	1.16	0.00	0.52	1.00	1.14	0.00	0.43
Comp G	1.00	1.16	0.00	0.52	1.00	1.14	0.00	0.43
Density	0.31				0.25			

Table 2
Predicted and Actual Changes in Network Centrality

Table 2 shows results from testing the predictive power of Δ, the predicted change in the board network induced by the reform. Coefficients are estimated by regressing the instrument (Δ multiplied by a post-reform dummy) on each of the different network measures. Each regression includes firm and year fixed-effects. Standard errors, clustered at the firm level, are displayed in parentheses. ***, **, and * indicate statistically different from zero at the 1%, 5%, and 10% level of significance, respectively.

	Centrality	Degree	Katz	Betweenness	Closeness
	(1)	(2)	(3)	(4)	(5)
$\Delta \times \mathbb{1}(t > \text{Dec. } 2011)$	0.238^{***}	0.241^{***}	0.535^{***}	0.134^{**}	0.034
	(0.039)	(0.043)	(0.049)	(0.067)	(0.023)
Observations	1,514	1,514	1,514	1,514	1,514
R^2	0.875	0.885	0.903	0.751	0.798
Firm FE	X	X	X	X	X
Time FE	X	X	X	X	X

Table 3
Baseline

Table 3 shows estimated coefficients from a regression of cumulative abnormal returns on the predicted change in network centrality. Cumulative abnormal returns are calculated over a one-day window surrounding the announcement date. Daily abnormal returns are either raw (obtained by subtracting the risk-free rate) or risk-adjusted, using either the market model (column 2) or the Fama French three-factor model (column 3). The vector of control variables includes size, defined as log(total assets), and ROA, defined as net income divided by lagged total assets. Each regression includes industry-fixed effects, following the Fama-French 17-industry classification. Standard errors, clustered at the firm level, are displayed in parentheses. ***, **, and * indicate statistically different from zero at the 1%, 5%, and 10% level of significance, respectively.

Risk Adjustment:	Raw	Market Model	Fama-French
	(1)	(2)	(3)
ΔCentrality	0.899**	0.903**	0.911**
	(0.404)	(0.408)	(0.415)
Observations	260	260	260
R^2	0.144	0.144	0.141
Industry FE	X	X	X
Controls	X	X	X

Table 4
Robustness

Table 4 shows coefficients from a regression of cumulative abnormal returns on the predicted change in network centrality. Cumulative abnormal returns are calculated over a three-day window surrounding the announcement date, except in columns 2 and 3, where we use a 5- and 7-day window, respectively. Abnormal returns are risk-adjusted using the market model. The vector of control variables includes size, defined as log(total assets), and ROA, defined as net income divided by lagged total assets. Column 8 is estimated without any controls, while column 9 additionally includes log of market capitalization and Tobin's Q. Column 4 - 7 shows results of regressing cumulative abnormal returns on predicted changes in four centrality measures: Katz centrality (column 4), Betweenness Centrality (column 5), Degree Centrality (column 6), Closeness Centrality (column 7). Each regression includes industry-fixed effects, following the Fama-French 17-industry classification. Standard errors, clustered at the firm level, are displayed in parentheses. ***, **, and * indicate statistically different from zero at the 1%, 5%, and 10% level of significance, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ΔCentrality	0.903**	1.018**	1.193**					1.237***	0.898**
	(0.408)	(0.473)	(0.547)					(0.420)	(0.443)
ΔKatz				1.139***					
				(0.385)					
ΔBetweenness					0.173				
					(0.413)				
ΔDegree						0.739*			
						(0.428)			
ΔCloseness							0.798***		
							(0.293)		
Observations	260	260	260	260	260	260	260	260	254
R^2	0.144	0.147	0.147	0.150	0.134	0.141	0.144	0.118	0.167
Industry FE	X	X	X	X	X	X	X	X	X
Window	-1,+1	-2,+2	-3,+3	-1,+1	-1,+1	-1,+1	-1,+1	-1,+1	-1,+1
Controls	X	X	X	X	X	X	X	None	All

Table 5
Information Transmission

Table 5 shows coefficients from a regression of cumulative abnormal returns on the predicted change in network centrality. Cumulative abnormal returns are calculated over a three-day window surrounding the announcement date and are risk-adjusted using the market model. Firms are sorted according to three variables: IVOL (columns 1 and 2), residual analysts' coverage (columns 3 and 4), and standard deviation of earnings forecasts (columns 5 and 6). Firms belong to the "Low" or "High" subsample if each measure is below or above the sample median. Idiosyncratic volatility (IVOL) is estimated by regressing, for each firm, daily excess stock return on the daily equity premium over the 12 months that predate the announcement and computing the standard deviation of the residuals. Residual analysts' coverage is the residual of a regression of the logarithm of 1 plus the number of analysts covering the firm in the previous calendar year on log market capitalization and its squared value. Standard deviation of forecasts is the standard deviation of analysts' net income forecasts in the previous calender year normalized by total assets. The vector of control variables includes size, defined as log(total assets), and ROA, defined as net income divided by lagged total assets. Each regression includes industry-fixed effects, following the Fama-French 17-industry classification. Standard errors, clustered at the firm level, are displayed in parentheses. ***, **, and * indicate statistically different from zero at the 1%, 5%, and 10% level of significance, respectively.

Sorting by:	IVOL		Residual Analysts' Coverage		St. Dev. Forecast	
	Low	High	Low	High	Low	High
ΔCentrality	0.682*	1.494**	1.236**	0.732	0.846	2.161**
	(0.387)	(0.638)	(0.567)	(0.603)	(0.598)	(0.912)
Observations	129	131	127	127	62	62
R^2	0.252	0.230	0.127	0.198	0.287	0.356
Industry FE	X	X	X	X	X	X
Controls	X	X	X	X	X	X

Table 6
Network Complementarities — Input-Ouput Network

Table 6 shows coefficients from a regression of cumulative abnormal returns on the predicted change in network centrality. Cumulative abnormal returns are calculated over a three-day window surrounding the announcement date and are risk-adjusted using the market model. Firms are sorted according to their centrality in the unweighted input-output network (columns 1 and 2) or weighted input-output network (columns 3 and 4). Firms belong to the "Low" or "High" subsample if each measure is below or above the sample median. The vector of control variables includes size, defined as log(total assets), and ROA, defined as net income divided by lagged total assets. Each regression includes industry-fixed effects, following the Fama-French 17-industry classification. Standard errors, clustered at the firm level, are displayed in parentheses. ***, **, and * indicate statistically different from zero at the 1%, 5%, and 10% level of significance, respectively.

Sorting by:	Unweighted IO Network		Weighted IO Network	
	Low	High	Low	High
ΔCentrality	0.122	1.660***	1.041**	1.772**
	(0.529)	(0.508)	(0.466)	(0.884)
Observations	154	106	130	130
R^2	0.103	0.265	0.396	0.270
Industry FE	X	X	X	X
Controls	X	X	X	X

Table 7
Network Complementarities — Ownership Network

Table 5 shows coefficients from a regression of cumulative abnormal returns on the predicted change in network centrality. Cumulative abnormal returns are calculated over a three-day window surrounding the announcement date and are risk-adjusted using the market model. Firms are sorted according to their centrality in the weighted (column 1 and 2) or unweighted cross-ownership network, where two firms are connected if the ownership exceed 1% (column 3 and 4) or 2% (column 5 and 6). Firms belong to the "Low" or "High" subsample if each measure is below or above the sample median. The vector of control variables includes size, defined as log(total assets), and ROA, defined as net income divided by lagged total assets. Each regression includes industry-fixed effects, following the Fama-French 17-industry classification. Standard errors, clustered at the firm level, are displayed in parentheses. ***, **, and * indicate statistically different from zero at the 1%, 5%, and 10% level of significance, respectively.

Sorting by:	Weighted Own. Network		Unweighted Own. Network (1%)		Unweighted Own. Network (2%)	
	Low	High	Low	High	Low	High
ΔCentrality	1.432**	0.553	1.443***	0.753	1.749***	0.580
	(0.561)	(0.466)	(0.509)	(0.457)	(0.426)	(0.409)
Observations	130	130	130	130	130	130
R^2	0.314	0.072	0.174	0.172	0.192	0.162
Industry FE	X	X	X	X	X	X
Controls	X	X	X	X	X	X

Table 8
Profitability and Growth Opportunities

Table 8 shows coefficients from a regression of cumulative abnormal returns on the predicted change in network centrality. Cumulative abnormal returns are calculated over a three-day window surrounding the announcement date and are risk-adjusted using the market model. Firms are sorted according to three variables: ROA (columns 1 and 2), sales growth (columns 3 and 4), and Tobin's Q (columns 5 and 6). Firms belong to the "Low" or "High" sample sample if each measure is below or above the median. ROA is defined as net income divided by lagged total assets. Sales growth is defined as the growth rate of firm revenues. Tobin's Q is defined as total assets plus market value of equity minus common value of equity all divided by total assets. The vector of control variables includes size, defined as log(total assets), and ROA, defined as return divided by lagged total assets. Each regression includes industry-fixed effects, following the Fama-French 17-industry classification. Standard errors, clustered at the firm level, are displayed in parentheses. ***, **, and * indicate statistically different from zero at the 1%, 5%, and 10% level of significance, respectively.

Sorting by:	ROA		Sales Growth		Tobin's Q	
	Low	High	Low	High	Low	High
ΔCentrality	1.396***	-0.136	1.902**	-1.660	1.365**	-0.013
	(0.511)	(0.393)	(0.824)	(1.650)	(0.587)	(0.422)
Observations	130	130	102	102	127	127
R^2	0.212	0.107	0.178	0.222	0.259	0.103
Industry FE	X	X	X	X	X	X
Controls	X	X	X	X	X	X

Table 9
Return Co-Movement and Firm Connections

Table 9 shows regressions testing the effect of firm connections on the co-movement of returns. Coefficients in column 1 and 2 are estimated from a regression of firm's yearly beta on centrality. In column 2 we instrument centrality by the predicted change in the network multiplied by the post-reform dummy. In columns 3 through 6, the dependent variable is the annual correlation of raw (colunm 3 and 4) and abnormal (column 5 and 6) stock returns between each possible firm pair, where we include only one observation per firm-pair and year. Coefficients are estimated from a regression of the pairwise correlation on board proximity defined as the negative of the shortest path between the firm pair across the boardroom network. In column 4 and 6 we instrument board proximity by the predicted change in the shortest path multiplied by the post-reform dummy. Standard errors are clustered at the firm-pair level. ***, **, and * indicate statistically different from zero at the 1%, 5%, and 10% level of significance, respectively.

	Beta		Correlation			
			Raw Returns		Abnormal Returns	
	OLS	IV	OLS	IV	OLS	IV
Centrality	-0.005	-0.165**				
	(0.015)	(0.065)				
Board Proximity			0.001***	-0.013**	0.000	-0.012***
			(0.000)	(0.006)	(0.000)	(0.004)
Observations	1,456	1,456	110,365	110,365	110,365	110,365
F-Stat		41.747		215.153		215.153
Firm FE	X	X				
Firm-Pair FE			X	X	X	X
Year FE	X	X	X	X	X	X

Table 10
Directors' Compensation

Table 10 shows regressions testing the effect of centrality on total compensation. Coefficients are estimated from a regression of log(total compensation) on centrality, where centrality is instrumented by the predicted change in the network multiplied by the post-reform dummy. Data on compensation is hand-collected from mandatory filings and annual financial reports. In columns 1 through 3 the unit of observation is a director-year, whereas network centrality is derived from the firm-level network. Column 1 uses data on all board members, column 2 includes only high-ranked directors (CEO, President and Vice-President), and column 3 includes the remaining directors. Standard errors are twoway-clustered at the firm and director level and displayed in parentheses. Column 4-6 repeats the analysis at the firm-level, where the dependent variable is the average of log(total compensation) and standard errors are clustered at the firm level. ***, **, and * indicate statistically different from zero at the 1%, 5%, and 10% level of significance, respectively.

Unit of Observation:	Director			Firm		
Directors:	All	High Rank	Low Rank	All	High Rank	Low Rank
Centrality	0.120**	0.176	0.109**	0.333**	0.321**	0.408***
	(0.049)	(0.133)	(0.046)	(0.148)	(0.159)	(0.156)
Observations	12,622	3,175	9,287	1,323	1,312	1,320
R^2	0.000	-0.009	0.004	-0.118	-0.012	-0.140
F-Stat	47.160	31.899	46.195	25.336	25.615	25.344
Director-Firm FE	X	X	X			
Firm FE				X	X	X
Year FE	X	X	X	X	X	X

Table 11
Peer-Effects and Compensation

Table 9 shows regressions testing peer-effect of firm connections on compensation. Coefficients are estimated from a regression of the similarity of log(compensation) at the firm level on board proximity, where board proximity is instrumented by the predicted change in proximity multiplied by the post-reform dummy. Similarity is defined in Equation (9) and board proximity is the negative of the shortest path between firm pairs. Data on compensation is hand-collected from mandatory filings and annual financial reports. Column 1 and 3 uses the raw absolute differences in log(compensation) for a given firm pair while the similarity of compensation in column 2 and 4 are based on residuals from regressing log(compensation) on year and firm fixed effects. In column 2 and 4 firm-pairs where both firms belong to the same industry following the Fama-French 17 industry classification are excluded. Regression include firm-pair and year fixed effects. Standard errors are clustered at the firm-pair level. ***, **, and * indicate statistically different from zero at the 1%, 5%, and 10% level of significance, respectively.

	Pair-Distance Metric			
Board Proximity	0.108***	0.083***	0.118***	0.086***
	(0.018)	(0.013)	(0.022)	(0.017)
Observations	91,945	91,945	78,517	78,517
F-Stat	213.472	213.472	142.487	142.487
First-Stage Residuals		X		X
Exclude Same Industry			X	X
Firm-Pair FE	X	X	X	X
Year FE	X	X	X	X

A. Definition of Centrality Measures

The board data represents a bi-partite (firm - director) graph $\mathcal{G}$ with corresponding adjacency matrix B. We obtain the firm network $\mathcal{F}$ and director network $\mathcal{D}$ as the unweighted graphs from the respective one-mode projections of B ($B'B$ and BB').

Degree centrality is formally defined as:

$$d_i = \sum_{j \neq i} a_{ij} \tag{10}$$

Katz Centrality is defined as:

$$k_i = \alpha \sum_{j} a_{ij} k_j + \beta \tag{11}$$

The first term is exactly the definition of "Eigenvector centrality" while the second term is the constant centrality assigned to any vertex. The parameter α governs the contribution of each term to the overall centrality; i.e. for $\alpha = 0$ each firm would have the same centrality β. Throughout our analysis we chose $\alpha = 0.05$, but results are similar for different α. Technically, there is an upper limit on α for K to converge. With respect to this bound we choose a fairly conservative value that ensure consistency and convergence across time.

Closeness centrality is defined, following Newman (2018), as the harmonic mean distance between firms:

$$c_i = \frac{1}{n-1} \sum_{j \neq i} \frac{1}{d_{ij}}, \tag{12}$$

where d_{ij} This definition has two convenient properties: firstly, for unconnected firms $d_{ij} = \infty$ and hence the corresponding term in the sum is zero and simply drops out. Secondly, firms that are close to firm i are naturally given more weight reflecting that once a firm is far away in the network it matters less how far away it is exactly.

Betweenness centrality is defined as:

$$b_i = \sum_{s,t} n^i_{s,t}. \tag{13}$$

B. Data Collection

Data on board members and compensation are hand-collected from mandatory annual filings with the Italian Companies and Exchange Commission (CONSOB), the Italian stock exchange (Borsa Italiana) and firms' annual reports. Data on board members (names and role) and firm names are reported bi-annually and are available from CONSOB. Reports were first cleaned and name spelling harmonized across reporting years. Company names have been hand-matched to Compustat and Datastream firm-identifiers to obtain data on daily stock returns and annual firm-level data. For any inconsistencies we cross-referenced the hand-collected board composition and financial data from Compustat with data from annual reports to ensure proper matching.

Data on compensation of all board members (executives and directors) was hand-collected from mandatory annual *Relazioni sulla Remunerazione* filed with the Italian stock exchange. These filings are only available starting in 2011. For the remaining years we hand-collected compensation data from annual reports. While coverage starting in 2011 is universal for all listed companies, there are a few companies where we were unable to recover annual reports or compensation information for 2009 or 2010.

The contents of the reports are similar to DEF 14A filings of US companies. They contain data on fixed compensation (*compensi fissi*), bonus payments (*bonus*), non-monetary benefits (*benefici non-monetari*) and other compensation (*altri compensi*). Reporting is not consistent across firms and differences in categorization were harmonized so that differently reported compensation components were assigned to one of the broader categories above.

Stock and option grants are recorded separately. We collected (if available) the number of stocks or options, grant date, grant date share price, and, specifically for option grants, the strike price and expiration date. We calculate the value of the option grants using the

Black-Scholes formula, following the methodology and conventions used by Execucomp in order to estimate option values. Unless otherwise reported we assume the strike price to equal the grant date stock price. As a risk-free rate we use the interest rates paid on a 7-year German government bond.

We estimates the stock variance using 60-month return data. If the price series are shorter than 12 months, we use the sample average standard error. We obtain estimates for the dividend yield by averaging dividend yields over a three-year period. Both variance and dividend yield are winsorized at the 5% level.

To calculate the time to expiration, we assume the options are granted on 1st July if the grant date is not reported. We follow Execucomp's convention and use 70% of the option term calculated from grant-date and term data given that executives rarely wait until the expiration date to exercise their options. For the companies who do not provide any information on neither grant and expiration dates we assume the time to expiration to be 7 years.

C. Variable Definition

Table A1
Variable Definition

Variable	Definition	Source
Total Assets	Total Assets (*at*)	Compustat Global
ROA	Income Before Extraordinary Items (*ib*) divided by lagged total Assets (*at)*; all 2010	Compustat Global
Market Value of Equity	Stock price multiplied by Common Shares Outstanding both at end-of-fiscal-year month; all 2010	Compustat Global & Datastream
Tobin's Q	Total Assets (*at*) plus Market Value of Equity minus Common Value of Equity (*ceq*) all divided by Total Assets; all 2010	Compustat Global & Datastream
Sales Growth	Log growth rate of Sales (*sale*); all 2010	Compustat Global
IVOL	Residual standard deviation of regression of daily excess stock return on the equity premium over the from December 2010 to November 2011	Compustat Global
Residual Analyst's Coverage	Residual of regression of logarithm of 1 plus the number of analysts covering the firm in 2010 on the logarithm of total market capitalization and its squared value	IBES
Standard Deviation of Earnings Forecasts	Standard deviation of last analysts' consensus net income forecast preceding the end of the firm fiscal year 2010 divided by total assets	IBES
Total Compensation	Fixed compensation (*compensi fissi*) + bonus payments (*bonus*) + non-monetary benefits (*benefici non-monetari*) + other compensation (*altri compensi*) + value of stock and option grants	Borsa Italiana