

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

Ester Faia [†]
Goethe University Frankfurt, and CEPR

Maximilian Mayer [‡]
Goethe University, Frankfurt

Vincenzo Pezone [§]
Tilburg University

October 2021

Abstract

We present causal evidence on the effect of boardroom networks on firm value and compensation policies. We exploit a ban on interlocking directorates of Italian financial and insurance companies as exogenous variation and show that firms that lose centrality in the network experience negative abnormal returns around the announcement date. The key driver of our results is the role of boardroom connections in reducing asymmetric information. The complementarities with the input-output and cross-ownership networks are consistent with this channel. Using hand-collected data, we also show that network centrality has a positive effect on directors' compensation, providing evidence of rent sharing.

Keywords: Firm Networks, Natural Experiment, Executives' Compensation, Interlocking Directorates.

JEL Code: D57, G14, G32, L14.

* We would like to thank Lauren Cohen, Cesare Fracassi, Xavier Gabaix, Theresa Kuchler, Jeremy Stein, Ferdinand von Siemens, and seminar participants at the American Finance Association, European Economic Association, and Goethe University for useful comments. We gratefully acknowledge financial support from the Fritz Thyssen Foundation (Project 10.17.2.025WW) and SAFE. These institutions played no role during the conduct of the study. We would also like to thank Vincenzo Morello, Lu Jialei and Yiran Wei for helpful research assistance.

[†] faia@wiwi.uni-frankfurt.de

[‡] Maximilian.Mayer@hof.uni-frankfurt.de

[§] Corresponding author. v.pezone@tilburguniversity.edu. Address: Department of Finance, Tilburg University, 5000 LE Tilburg, The Netherlands

1 Introduction

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

This paper examines the role of inter-firm networks arising from shared (interlocking) directorships. A long tradition in sociology (Scott, 1991) epitomizes them as the distinguishing feature of the elite social networks of capitalism, whose primary motivation is to benefit from information synergies. Our paper exploits a policy reform as a natural experiment to assess whether exogenous changes in the network structure affect firms' market valuations. Network ties among firms foster information diffusion, which in turn affects firm valuation either by reducing information asymmetries or by affecting learning and the pace of innovation.¹ Network structure is itself endogenous, however, and can be confounded by other firm characteristics.² Our main contribution lies in exploiting changes in firms' network centrality arising from a ban of interlocking directorships for financial and insurance firms to identify the advantages of being more *central* in the boardroom network. In addition, we examine several potential informational channels underlying our results by exploiting the heterogeneity of the results across firm characteristics.

Our estimates reveal that firms' stock market valuations and executive compensation increase if a firm becomes more central after the reform, thereby resolving the ambiguity of results from the previous literature. While past empirical work has shown that

1 See Drexler and Schoar (2014) or Mariolis (1975) on interlocking boardrooms as channels for soft information. See also Hansen (1999) for information diffusion in the context of innovation processes.

2 See Manski (1993), Kline and Tamer (2020), Graham and De Paula (2020), and Gabaix and Koijen (2020).

multiple board appointments may diminish directors' ability to monitor effectively, others have found that the resulting board interlock networks have information sharing benefits, similarly to other types of personal linkages, such as those arising from common educational experiences (Cohen et al., 2010).³

Relative to these studies, which have noted the endogenous nature of network formation and have attempted to control for potential confounding factors, our analysis provides quasi-experimental evidence. Further tests on the heterogeneity in firm and network characteristics are consistent with network centrality reducing asymmetric information. Conversely, we do not find evidence of effects of board centrality due to *learning* by better connected directors.

Finally, our analysis sheds light on the role of board connections for CEO compensation as well. We find an increase in compensation of directors of firms gaining centrality after the ban, which provides evidence in favor of theories of rent sharing.

To measure the impact of exogenous changes in the network structure on the valuation of firms, we estimate the reaction of stock returns to changes in firms' network centrality around the announcement of a policy regulating interlocking directorships in December 2011. We use hand-collected data on the board composition of listed firms to construct the boardroom network and compute changes in four measures of network centrality (degree, Katz centrality, betweenness, and closeness).⁴ We show baseline results using all four measures; however, given that they are strongly correlated, the majority of the paper focuses on a synthetic centrality proxy given by their first principal component. We find that the ban has a significant and long-lasting impact on the structure of the firm network. Even though the ban was directed at banks and insurance companies, it affected the

3 Past empirical work has examined the link between board connections and several corporate outcomes, such as merger and acquisition decisions (Cai and Sevilir, 2012), cost of debt (Chuluun et al., 2014), stock returns (Larcker et al., 2013), and firm value (Omer et al., 2014).

4 Hochberg et al. (2007), Larcker et al. (2005), El-Khatib et al. (2015), and Fracassi (2017) consider the same four measures.

entire corporate network, with analysts characterizing it as “one of the biggest shake-ups in Italian corporate life since the Second World war.”⁵ This is not surprising, given that these industries have historically had a pervasive role in the boardrooms of the private sector.⁶

In our baseline specification we regress the three-day return, centered around the policy announcement date, on the predicted change in firms’ network centrality that can be attributed to the reform. A one standard deviation increase in centrality induces a 90 basis point increase in stock returns. This result is robust to the use of different time windows for the measurement of stock return responses, as well as the inclusion of different sets of controls or the exclusion of outliers. We also rule out that other parts of the larger reform package drive our findings by controlling for firms’ exposure to sovereign risk premia or by excluding firms operating in industries that could be affected by other provisions adopted at the same time. Finally, results remain robust when controlling for the number of affected firms and directors, thereby ruling out that our estimates spuriously reflect the response to expected changes in the board composition. We see our network centrality measure as a parsimonious representation of the process underlying information diffusion;⁷ however, results are similar when we use simpler centrality measures, such as degree (i.e., the simple count of firm connections), which are arguably easier for investors to compute.

We also run our tests separately for firms *directly* affected by the ban, i.e., those firms in the finance and insurance sector that had an interlock prior to the ban, and for those that did not. We find qualitatively similar results in either subsample, although generally statistically stronger in the former group of firms. This is consistent with the fact that investors react to changes in expected centrality. Indeed, mechanically, the ban has a lower explanatory power for the subsequent change in the boardroom network once we

5 See “Italian companies are forced into board shake-ups,” *The Financial Times*, April 25, 2012.

6 See Mariolis (1975) on the role of banks in the network of interlocking directors.

7 For instance, Banerjee et al. (2019) use a model and randomized trial experiments in Indian villages to show that central individuals in communities can be identified by the random process of gossip.

exclude directly affected firms. Remarkably, we still uncover a strong market reaction to the expected change in Katz centrality, which is precisely the measure more strongly influenced by the ban in firms only indirectly affected by the reform.

Next, we investigate the economic forces driving our results. The information diffusion channel has traditionally been considered the main economic motive behind board interlocks. Broadly, it can take two forms. First, better connected directors can help improve information provision to outsiders, by mitigating asymmetric information and improving contractual conditions, the more so if other sources of information are scant. Second, a firm focal in the network can gather information and learn from outsiders. Thus, network centrality can enhance directors' ability to monitor, take strategic decisions, or innovate.

To test for the first channel, we sort firms according to standard proxies for the degree of information asymmetry between the firm and outside investors, namely idiosyncratic volatility, analyst coverage, and volatility of earnings forecasts. Our results show that firms for which external information is likely to be less precise (and are thus characterized by higher valuation uncertainty and higher disagreement among investors) benefit more from boardroom centrality. Thus, implicit boardroom ties appear to provide signals to market participants or outsiders, facilitate enforcement, and lubricate contractual relationships (see Greif, 1993). To test for the "learning" channel, we hypothesize that young and growth firms are those that could benefit the most from information acquisition. However, we do not find evidence consistent with this channel: older firms and those with worse growth prospects appear, if anything, to be *more* sensitive to changes in network centrality.

Additional evidence of the information diffusion channel arises from potential complementarities with other forms of economic relationships. Firms are also connected along the value chain in customer-supplier relationships and can be partially owned by common shareholders. Information can therefore spill over into, and complement, other economic linkages. For instance, a reduction in asymmetric information can help improve

contractual relationships within the input-output network. To assess the importance of these complementarities, we consider the interactions between the boardroom network and either the input-output or cross-ownership networks. We find that firms operating in industries that are more central in the input-output network benefit more from boardroom centrality. Sharing information in the boardroom helps firms to convey information about them. This builds trust, thereby facilitating additional contractual relationships, such as supply contracts, and helps absorb the impact of shocks along the supply chain. Conversely, firms with lower cross-ownership centrality benefit the most from boardroom connections, consistent with the idea that cross-ownership can serve as an important device for information diffusion.⁸

Finally, we assess the impact of changes in network centrality on directors' compensation. A number of theoretical models predict that firm surplus should be shared between shareholders and executives. Rent sharing theories include standard bargaining models with assortative matching (along the lines of Gabaix and Landier, 2008) or competition for talents (see, e.g., Terviö, 2008). In these settings, a shock to firm value would spill over to executives' pay; thus, their compensation should also be affected by changes in the network structure. We hand-collect data on compensation for over 13,000 directors and top executives and adopt an instrumental variable strategy that exploits the reform to generate exogenous variation in network centrality. We find a large and significant effect of centrality on CEO compensation. While these results indirectly reinforce the evidence that exogenous changes in network structure affect firms' overall surplus, they also provide novel insights into the broader literature on executive compensation.

In sum, our paper provides novel causal evidence on the importance of director networks for transmitting potentially valuable information. Hiring well-connected directors can be

⁸ See also Azar et al. (2018), who show that cross-ownership can act as a coordination device.

a fruitful investment that improves information transmission and, as a result, provides them with the ability to demand a higher compensation.

Related Literature. Our work is related to the literature that examines the effects of board characteristics, and especially board networks, on firm outcomes. Most papers measure the influence of networks through social, educational, or professional ties predating the outcomes being studied (Cohen et al., 2008, 2010; Kuhnen, 2009; Engelberg et al., 2012, 2013; Kramarz and Thesmar, 2013) to mitigate the concerns of confounding factors contemporaneously affecting network structure and current firm performance. Other authors consider changes in network centrality arising from the appointment of existing board members on other boards (Larcker et al., 2013; Hann et al., 2019; Burt et al., 2019). Our paper proposes a novel approach by exploiting an exogenous regulatory shock, which affects the network structure but is unlikely to directly affect other board characteristics. Besides, most other papers examine the role of bilateral, and often personal, connections between individuals (see, e.g., Cohen et al., 2008; Engelberg et al., 2012; Fracassi and Tate, 2012; Shue, 2013; Fracassi, 2017) whereas causal evidence on the effects of boardroom connections through interlocking directorates is rare.

Our paper also contributes to the research on information diffusion in networks. While there is considerable literature on this topic, our evidence is more directly related to empirical studies of the role of information on corporate decisions. More central firms 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 is mixed for mergers and acquisitions (El-Khatib et al., 2015; Chikh and Filbien, 2011; Stuart and Yim, 2010). Similarly, firm ties create positive peer-effect spillovers on managerial decisions (Shue,

2013), investment (Bernard et al., 2020), or corporate governance practices (Foroughi et al., 2021). 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), or option backdating (Bizjak et al., 2009). Hence, whether boardroom connections, and network centrality in particular, reduce or increase firm value is unclear *ex ante*. Our empirical design can help address endogeneity concerns common in the previous literature and help resolve previous ambivalence in its conclusions.

Our paper is also related to the literature on the impact of social ties between transaction parties (see Banerjee and Munshi, 2004, and Bandiera et al., 2009). This literature also stresses the role of networks in lessening informational asymmetries in contractual relationships.

Our results on the complementarity (or substitutability) with other economic networks contribute to the understanding of the economic mechanism as well. The evidence on information diffusion from the firm to outsiders, as well as the complementarity with the input-output relationships, contribute to the growing body of work on the importance of directors shared between upstream and downstream firms (see, e.g., Dass et al., 2013). Moreover, boardroom connections may potentially help absorb idiosyncratic shocks in input-output networks (see Gabaix, 2011; Carvalho and Gabaix, 2013, among others) or may be a substitute for linkages arising from cross-ownership (see Azar et al., 2018, and, for a different perspective, Lewellen and Lowry, 2021).

Finally, our paper sheds light on an important aspect of CEO compensation.⁹ Various reasons have been suggested for the wide heterogeneity in compensation practices, ranging from luck to poaching or assortative matching. Our paper shows that board connections can also contribute to such heterogeneity. Rent sharing can therefore explain why knowledge

⁹ See Bertrand and Mullainathan (2001), Brick et al. (2006), Garicano and Rossi-Hansberg (2006), Gabaix and Landier (2008), Hwang and Kim (2009) or Engelberg et al. (2013).

economies shifting to industrial systems with a tail of superstar firms (Autor et al., 2020) may exhibit a significant increase in executive compensation.

2 Institutional Setting and Network Centrality

2.1 The Ban on Interlocking Directorates

In December 2011, the Italian government presented a reform package commonly known as the “Save Italy” decree. The decree was adopted due to a precipitous increase in sovereign spreads. The most important element of the package was a general restructuring of government spending, with a reform of the pension and social contribution system (including an increase of the retirement age) and tax increases on residential properties.

The decree also included some minor pro-growth measures, such as the liberalization of opening hours and the sale of certain medications outside of pharmacies. Crucial in this respect was the ban on directorships creating interlocks between large financial and insurance companies. Interlocks act primarily as communication channels, which enable knowledge to be shared through directors who have access to inside information for multiple companies. Hence, the underlying rationale of the ban was that previously connected firms, possibly representing “crony capitalism,” could have exploited an informational advantage to the detriment of business dynamism.¹⁰ Thus, we expect the exogenous change in the network structure to have a significant impact on firms’ market valuation.

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.¹¹

¹⁰ Anecdotal evidence suggest that this was also prime minister Mario Monti’s reasoning. He argued that the so-called *salotto buono* (“fancy parlour”) had “at times prevented the process of creative destruction [and] protected what already exists” (See “Italy aims to break up clubby bank boards,” Reuters, March 5, 2012)

¹¹ For brevity we will refer to members of the audit committee as directors as well.

As a result of this law, several directors had to leave some of their posts: in our sample, we observe 29 directors creating an interlock that are employed at the firms affected by the ban. The regulation was binding, as its impact could not be overcome by a mere reshuffling of board members. The deadline for a decision on which position to leave or keep was set as 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 shock particularly well-suited as a natural experiment. Although the reform targeted the finance and insurance sectors, it proved to be quite effective in dispersing the overall boardroom network of listed firms for two reasons. First, the finance and insurance industries have historically had a central role in the network of firms, with the same directors often being in boardrooms of both banks and other firms.¹² Second, the law imposed a ban on interlocks among competing companies where the definition of the latter was strict and unambiguous, with no scope for interpretation or dispensing. It indeed established that the ban applied to all pairs of banks or insurance companies as long as they had even a single branch in the same province. This contrasts with similar legislation adopted in other countries, such as the Clayton Act in the United States, which has rarely been enforced due to a lack of a well-defined classification of the relevant markets.¹³ Given the nationwide presence of the banks and insurance companies in our sample of large, listed firms, the law had, *de facto*, an impact on all firms in these industries as long as they shared at least one director.

Figure 1 illustrates the effects of the ban on interlocking directorships for the network of Italian companies at large. Panel A 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

¹² The centrality of banks in the boardroom network is not uncommon in other countries as well (see Uzzi and Lancaster, 2003).

¹³ For example, Apple and Google were able to share 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).

for the sample period 2009-2014. It shows that network density, if anything, slightly increased in the years leading up to the ban. This trend starts reverting precisely after the 2011 reform.¹⁴ The other panels of Figure 1 show the trend in the sample averages of the centrality measures on which this empirical analysis focuses (Katz, degree, betweenness, closeness, and their first principal component, labeled *centrality*). All these proxies exhibit a decline after the ban. The ban severed 25 ties between listed companies in the insurance and finance sector, and involved a total of 26 companies (for 23 of which we have stock return and accounting data). To get a sense of the impact of the ban on the corporate network, we estimate that 5% of all the ties observed in our sample are severed due to the reform. The effect of the regulation was highly heterogeneous across firms. For example, Mediobanca, an investment bank which had historically been a key player in both the Italian industrial sector since the post World War II reconstruction, lost five ties. Intesa San Paolo and Unicredit, the two largest Italian banks, lost two connections each. In the insurance sector, the most affected was its largest company, Generali, which lost five ties. In some cases, the regulation had a particularly disruptive impact: Milano Assicurazioni, a mid-sized insurance company, lost four ties and, as a result, six independent directors and three statutory auditors (including the chairmen of both bodies) chose to resign. The impact was therefore significant.

For our design to qualify as a quasi-experimental setting, the introduction of the law must be largely unexpected. The time elapsed between announcement and implementation left little to no room for firms to attempt to neutralize the effect of the reform by, e.g., increasing the board size or changing its statutes. Investors learned about the content of the decree, and the provision on interlocking directorates, only when the decree was presented to the parliament on December 6, and it took effect immediately. The provision

¹⁴ The fact that the graph density keeps dropping even after the reform is due to changes in the composition of listed firms, the number of which decreased over our sample period, from 290 in 2008 to 242 in 2014. As Section 3.2 shows, once we examine the impact of the reform on network centrality by controlling for firm fixed effects, we uncover a much sharper effect (see Figure 5). See also Appendix A.1 for an example of how the actual Italian boardroom network was affected by the reform.

was arguably unexpected as the press did not cover the issue 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 7,¹⁵ whereas no article on the topic appeared in the year leading up to the decree. All the other major newspapers also covered the ban extensively on the same day, listing the affected directors and making predictions regarding the boards from which they were likely to step down.

A potential concern may be the relevance of other confounding factors stemming from the comprehensive nature of the reform which, as discussed above, included several other measures. The most relevant ones, at least for their potential impact on firms’ values, are those geared towards addressing Italy’s debt sustainability. While the restructuring of government spending could have had an impact on the overall economy, equally affecting the the valuations of all firms, it may have had a differential impact on banks holding different portfolios of sovereign bonds or companies that might be especially exposed to shocks to the Italian economy. To address this concern, all of our tests control for industry fixed effects to address the concern that any other part of the larger reform package might have disproportionately affected certain sectors of the economy. As an additional robustness check, we control for the correlation between firms’ stock returns and sovereign yields to proxy for the underlying exposure of firms’ bond portfolios to sovereign bond yields (see Section 3.4).

Finally, the law contained other, less relevant liberalization measures, such as the liberalization of opening hours in the retail sector. These measures are unlikely to bear any meaningful connection to the industrial system of large listed companies. As we show in Section 3.4, results are similar once we exclude firms from the most affected industries.

¹⁵ See “Le regole di Monti sui pluri-banchieri”, *Sole 24 Ore*, December 7, 2011.

2.2 Network Centrality Measures

We capture firms' position in the network structure through several centrality measures, which we present in detail in this section. We also describe our dataset and the economic rationale behind the centrality measures.

Information on the boardroom network is extracted from the website of the *Italian Companies and Exchange Commission* (CONSOB), which reports information on the board composition of Italian listed companies bi-annually. We collect name and position of each board member and manually match firm names to Compustat Global to obtain financial data.

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 boardroom networks. Moreover, unlike members in common clubs, shared directors are guaranteed to interact on economically relevant topics during mandatory meetings. Hence, the boardroom connections seem of first-order relevance for information diffusion.

Network centrality is a multi-dimensional object that encompasses direct and indirect forms of interactions through which information can spread (Fracassi, 2017). Following previous work (e.g., Hochberg et al., 2007; Larcker et al., 2013), we use four centrality statistics, each capturing different nuances of the network configuration. We present formal definitions of the measures in Appendix A.2.

Degree centrality is the simplest measure of a firm's network position and counts the number of direct ties, which in our case is the number of shared directors. Other more complex measures have the advantage of capturing both direct and indirect percolation of information across firms. *Katz centrality*, unlike degree, also weights the directly and

indirectly connected firms by their relative importance in the network. By accounting for the respective centrality of connected firms, this measure can better quantify the quality of the information flows (Fracassi, 2017).

The extent of indirect information diffusion is captured by *closeness centrality*, which is given by the inverse average shortest path between a given firm and any other firm in the network. Intuitively, this measure is large when only few shared directors are needed for the information flow to reach any other firm in the network. The last metric considered is *betweenness centrality*, which measures the frequency with which a given firm lies on the shortest path between two other firms in the network. The directors of firms with high betweenness centrality can pass information from otherwise unconnected parts of the network, thereby capturing their influence on information transmission.

The four centrality measures are highly correlated. For this reason, our main results are based on their first principal component, henceforth labeled *centrality* for simplicity. We find that *centrality* explains 82% of the total variance, suggesting that it does capture a substantial fraction of the variation in the four proxies.¹⁶

Illustrative Example. Before moving to the empirical design it is useful to visually gauge the potential impact of the reform on the network structure. To fix ideas we present an illustrative example. (Appendix A.1 shows an extract of the *actual* network and the impact of the reform.) Figure 3 shows the potential impact of the reform in a stylized network with just two banks and six firms. Circles represent the firms (nodes), lines between nodes (edges) refer to shared directors, and the size of a node is proportional to the *centrality* of the corresponding firm. Enforcement of the regulatory shock results in a ban of the link between Bank A and Bank B. The director shared between these banks is

¹⁶ See also El-Khatib et al. (2015) or Larcker et al. (2013) for similar techniques to reduce dimensionality in the context of corporate networks.

also on the board of Company A. In this example this director leaves the board of Bank A, which then loses ties to both Bank B and Company A.

The shock significantly changes the centrality of each node and the overall density of the network (actual numbers are not shown for brevity). The dashed and solid outlines of each node reflect the centrality of firms before and after the shock, respectively. The change in the size of the nodes shows that banks A and B lose centrality, whereas companies C and D now acquire a pivotal role in diffusing information from all the nodes connected to A and B. Without the ties of either bank with companies C and D, information transmission between the periphery clusters connected to either Bank A or Bank B would be inhibited. As a result, companies C and D have substantially higher centrality after the shock. This example shows how breaking a tie between two firms can have effects on the network at large. Importantly, while the centrality of the firms *directly* affected generally decreases, firms only *indirectly* affected can become either more (companies C and D) or less (companies E, F, and G) central following the reform, suggesting that the ban can have highly heterogeneous effects across firms.

2.3 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 valuation. To identify changes in the network structure that are effectively forecastable by investors, we use only information available to investors at the time of the policy announcement. The underlying working hypothesis is that network centrality is a summary statistics for the process of information diffusion among investors.

We first predict the post-reform network by simulating the change starting from the initial network (June 2011) based on foreseeable choices of interlocked directors regarding which post they will keep after the ban. While investors can predict which ties will be

severed by the law, they cannot know with certainty which seat an affected director will decide to ultimately keep. Going back to the simple example in Figure 3, the post-reform network is going to have a different configuration depending on whether the director shared between the two banks decides to keep her seat at Bank A or Bank B. As this choice is known only ex post, assuming that investors know with certainty the directors' decision already at the time of the announcement would introduce forward-looking bias into our measure. (Remember that directors have time until April 27, 2012 to make their choice, i.e., over four months after the announcement of the ban.)

We develop a simple “decision rule” to predict directors' decision. First, we assume that if a director has a high-ranking position, such as CEO, president, vice president, or general director (in that order) in a company, and that of director or member of the auditing committee in another firm, she will choose to retain the former position.¹⁷ Second, we assume that directors will prefer to retain the role of member of the board of directors to a seat in the auditing committee. Finally, to break the remaining ties, we exploit our hand-collected data on directors' compensation and assume that directors will keep the seat in the company where they earned more in 2010, the latest fiscal year prior to the ban. This simple algorithm correctly predicts 68% of the resignations.

To test whether our algorithm adequately captures investors' expectations, we manually search for companies' official press releases mentioning directors' resignations. We were able to find press releases for 25 resignations that explicitly refer to the ban as the reason. 19 correspond to events correctly predicted by our procedure, whereas 6 resignations were wrongly predicted (i.e., we predicted that a director would resign from “Company A” but she chose to resign from “Company B”). Panel A of Figure 4 plots buy-and-hold returns in a $(-10, +10)$ -day window surrounding the press release for correctly predicted resignations. We find that the stock returns of the companies where the shared director keeps the seat

¹⁷ *Direttore generale* is a role that only exists in a few firms. Effectively equivalent to a Chief Operating Officer, in Italy it is typically the most important executive in the C-suite after the CEO.

are very similar to those of the companies that the director leaves. Hence, investors do not appear “surprised” by the director’s choice. Conversely, in cases that we mispredicted, the stock returns surrounding the press release diverge markedly. Interestingly, firms whose director resigns perform *better* than those ultimately chosen by the shared director, possibly because smaller boards are perceived as more effective (Jenter et al., 2019, Yermack, 1996). Overall, this descriptive evidence suggests that our procedure does a good job at capturing investors’ expectations.

Next, we construct a simulated network based on the predicted director resignations due to the reform, and compute the predicted change in centrality Δ as follows:

$$\Delta \equiv \overline{Centrality}_{i,06/2011} - Centrality_{i,06/2011} \quad (1)$$

where $\overline{Centrality}$ and $Centrality$ are the simulated and actual network centralities, respectively, of firm i before the reform. Intuitively, Δ is a proxy for the change in network centrality that can be attributed solely to the reform, and is the key variable of interest in our empirical analysis.

3 Network Centrality and Firm Value

Our baseline econometric specification estimates the impact of the predicted change in centrality on firm stock returns around the announcement date of the reform. We start by briefly presenting our data sources and then move to discuss the main results.

3.1 Data Sources and Descriptive Statistics

We use company names to match hand-collected data on board composition, obtained from the CONSOB website, with Compustat Global and manually check every match.

Compustat Global provides data on daily stock prices as well as firm-level financial variables for all companies listed on the Milan Stock Exchange. Data on firms' market capitalization are from Datastream, whereas analyst coverage and earnings forecasts are obtained from IBES.

Panel A of Table 1 reports summary statistics for the firm-level variables used in the event study regressions. Panel B reports summary statistic for the panel regressions on compensation (see Section 4). The sample includes 260 listed companies that were traded at the time of the announcement of the reform. *Centrality* is defined as the principal component of the four centrality measures, degree, Katz centrality, betweenness, and closeness. Unsurprisingly, the predicted change in all the four measures, as well as *centrality*, is on average negative (-0.27), but some companies in the right tail of the distribution are also predicted to gain centrality.

We use size and profitability as the main control variables. We define firm size as the logarithm of total assets. Profitability is given by return-on-assets (ROA), defined as net income divided by lagged total assets. In some tests we also include market capitalization (defined as total number of shares outstanding times share price at the end of the fiscal year), Tobin's Q (given by total assets plus market capitalization minus common value of equity, all divided by total assets). We postpone the definition of additional variables employed in the empirical analysis to the following sections.

Control variables are measured at the end of 2010. Definitions of all the variables are in Appendix-Table A2. We relegate additional details on the data cleaning process to Appendix A.3.

3.2 Impact of the Reform on Network Centrality

The first step of our analysis consists of testing whether the reform had a significant impact on the network configuration. We estimate the following equation:

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

where y is one of the network centrality measures described in Section 2.2 and $Post$ is a dummy equal to 1 after December 2011, and zero otherwise. η and δ are firm and year fixed effects, respectively, and ε is the error term. Δ is the predicted change in firm i 's network centrality, described in Section 2.3. For ease of interpretation, Δ is demeaned and divided by its sample standard deviation throughout the paper. The model is estimated over the 12/2009–12/2014 period, and the sample includes all the firms that have at least one observation before and one after the reform.

Table 2 reports coefficient estimates for β . Columns 1 to 4 show results for each of the four centrality measures individually. Estimated coefficients are all large and significant, except for closeness. In column 5 the dependent variable is the first principal component of the four centrality measures, *centrality*: the estimated coefficient is large and significant, with a t -statistic of 6.50. Results lend clear support to a significant impact of the reform.

To verify that the positive association is not driven by pre-existing trends in the network configuration we also conduct an event study analysis by replacing $\Delta \times Post$ with a vector of interactions between Δ and time dummies, and omitting the coefficient corresponding to the last pre-reform year, 2011. The dependent variable is, again, *centrality*. Figure 5 shows that coefficients are small and insignificant for the years 2009 and 2010, whereas they increase significantly in the post-reform years, 2012 through 2014. There is therefore no evidence of a pre-trend for the changes in network composition. Moreover, there is no

apparent reversion after the reform. This suggests that the firms that had their ties to other firms severed were unable to recover their centrality.

3.3 Baseline Results

We estimate the following equation:

$$CAR_i = \beta \times \Delta_i + \gamma X_i + \varepsilon_i \quad (3)$$

where CAR is the cumulative abnormal return of firm i over a three-day window surrounding the announcement date. Daily abnormal returns are adjusted using the market model (see Appendix A.3 for details). β is our main coefficient of interest. It captures the impact of the predicted change in the centrality measures Δ described in Section 2.3. The vector of controls X includes size, defined as $\text{Log}(\text{total assets})$, and ROA, defined as income divided by lagged total assets. We use these controls as they are non-missing for the entire sample, but results remain robust when including additional controls or no controls at all (see Section 3.4). X also includes industry dummies, defined using the Fama-French 17 industry classification.¹⁸ ε is an error term. Table 3 presents the main results.

In columns 1 through 4 we regress the cumulative abnormal return on each of the four key centrality measures (demeaned and standardized). In three out of four cases (Katz, degree, and closeness) the coefficients estimated are positive and at least marginally statistically significant. The economic magnitudes are also large, with coefficients ranging between 0.74 and 1.14. The only exception is the coefficient on $\Delta\text{Betweenness}$, in column 3, which is smaller and imprecise. Nevertheless, the fact that all the four coefficients are positive and relatively large suggests that investors do not just react to the change of a single centrality measure. Given this evidence, we re-estimate equation (3) by using

¹⁸ Using the 12, 30, 38, or 49 industry classifications produces similar results.

the expected change in *centrality*, defined as the first principal component of the four main centrality measures (as in Section 2.3), as a key variable of interest. We find that a one-standard deviation change in predicted centrality induces a 90 basis points increase in stock returns. The coefficient is statistically significant at the 5% level (t -statistic= 2.25). For brevity the remainder of the analysis will largely focus on this centrality proxy, as it appears to capture a substantial amount of variation common to the four underlying centrality measures.

To verify that pre-existing trends in stock returns do not affect the results, and to verify their persistence, we re-estimate equation (3) using the buy-and-hold return between $t - 5$ and $t + \tau$, with $\tau = -5, \dots, +5$ as the dependent variable. Figure 6 shows that the estimated coefficients, plotted alongside the 95% confidence intervals, are close to 0 for the days before the reform and increase only after its announcement. Results, therefore do not seem to be driven by any pre-trend and appear to be persistent.

3.4 Robustness Tests

This section further probes the robustness of our results in Tables 4 and 5. The specifications in columns 1 and 2 of Table 4 employ five-day and seven-day windows around the announcement date, respectively. The coefficients remain positive and significant, suggesting that our results are not sensitive to the specific time window.

To verify that the results are not driven by firms' loading on common risk factors, column 3 and 4 show results when the dependent variable is the cumulative three-day return, either raw (i.e., net of the risk-free rate) or adjusted using the Fama-French factors. Results are statistically robust and the coefficients are very similar to those obtained using the market model (column 5 of Table 3).

In column 5, which excludes all of the controls except the industry dummies, the point estimate of the key coefficient of interest grows to 1.25 and is significant at the 1% level. In

column 6 we expand the set of controls by including standard predictors of stock returns, beyond ROA and size, such as the logarithm of market capitalization and Tobin's Q. We lose 6 observations in this specification due to missing values of the control variables. The coefficient of interest is still significant and similar to the baseline estimate. Besides, only the coefficient on the logarithm of market capitalization is significant, and negative.

As explained in Section 2.1, the interlocking ban was part of a larger reform targeted at improving debt sustainability. One concern could be the possibility that firms' market reaction could be driven by their different exposure to government bond yields, which may in turn have been affected by other provisions of the reform package. To address this concern, we follow Acharya and Steffen (2015) and construct a proxy for the firm's exposure to sovereign bond yields, given by the correlation of the firm's risk-adjusted stock returns with the daily yield spread between the 10-year Italian and German sovereign bonds, estimated over the quarter prior to the announcement of the reform. This variable is included in the specification presented in column 7, and its coefficient is negative as expected, although insignificant. More importantly, the coefficient on Δ Centrality is unaffected.¹⁹

Another provision of the decree that could potentially affect market outcomes is the liberalization of opening hours (See Section 2.1). Firms in the retail sector may have benefited from this additional business opportunity. Alternatively, to the extent that it generates an increase in competition, it may have reduced rents for some of the sector's most dominant firms. Rather than taking a stand on either possibility, we drop the 35 firms in our sample belonging to industries most likely to be affected and re-estimate

¹⁹ Although not part of the "Save Italy" decree, a similar concern might arise from the introduction of board gender quotas with the "Legge Golfo-Mosca" in June 2011 and its staggered implementation beginning in 2012 (Maida and Weber, 2019). Controlling for the share of female directors on the board has, however, no effect on the estimated coefficient on the predicted change in centrality. Results are available upon request.

our baseline regression in column 8.²⁰ We find that the effect of the expected change in network centrality remains statistically significant and is, if anything, slightly larger.

Given our relatively small sample, an additional concern could be that a few extreme observations are driving the results. To check for the influence of outliers, in column 9 we re-estimate the baseline equation after truncating the sample at the 2.5% and 97.5% percentiles of abnormal returns. Results are qualitatively similar, and remain statistically significant.

Column 10 includes as a control variable the number of directors affected by the reform, that is, that are sitting in multiple boards of insurance or finance companies. The coefficient on this variable is positive and statistically significant. This result is not surprising in light of the evidence discussed in Section 2.3 (see Figure 4). Investors appear to reward firms with smaller boards; hence, the prospect that some directors may step down is interpreted as boosting firm value. Interestingly, the key coefficient of interest rises substantially, both in size and statistical significance (1.27, t -statistic= 3.22). To interpret this result, notice that Δ Centrality and the number of affected directors are negatively correlated (correlation coefficient= -0.85). This is mechanical, given that a firm with several shared directors is more likely to lose ties and, thus, centrality. The positive effect that losing some directors has on firm valuation partially counteracts the negative effect due to the loss in network centrality, which reduces the size of the coefficient on Δ Centrality when the former effect is not accounted for. Hence, the coefficient found in the baseline tests is likely to be a *conservative* estimate of the true effect of network centrality.

Firms may be connected by social ties, besides board interlocks (Engelberg et al., 2013), and be unaffected by changes in their boardroom network centrality if they are already central in the *social* network. Thus, in column 11 we control for firms' centrality computed

²⁰ We exclude firms with Fama-French industry codes 4 (textiles, apparel, and footwear), 5 (consumer durables), 7 (drugs, soap, perfumes, and tobacco), and 15 (retail stores).

from the social networks of their directors. BoardEx provides data on social ties between directors due to previous employment in the same company, joint membership in clubs or charities, government positions, or shared educational institutions.²¹ Using these links, we compute our four centrality measures and define “social network centrality” as the first principal component of these four measures. Results in column 11 of Table 4 show that the coefficient on the predicted change in boardroom centrality remains significant and is virtually unchanged compared to the baseline estimate even when we control for firms’ centrality in the social network.

In Panel A of Table 5 we test whether results differ between the 26 firms that were directly affected by the ban (i.e., that had to sever a tie with another firm) and those that, despite not being required to change their board composition, experienced an *indirect* change in centrality, due to the changes in the boardroom network. The effect of the ban on firms’ network centrality is likely to differ between these two groups of firms. Thus, we report separately for the two subsamples regression results along the lines of those discussed in Section 3.2, where we examine whether our predicted change in network centrality has explanatory power for the realized post-ban network centrality. We expect the effect of the ban to be weaker for firms that are only indirectly affected by it.

In columns 1 and 2 of Table 5, Panel A, we find that the predicted change in Katz centrality has a substantial effect on the abnormal returns of both directly and indirectly affected firms. We estimate coefficients equal to 1.26 and 1.48, respectively, both significant at the 1% level. In addition, we estimate significant coefficients for Δ Degree and Δ Betweenness, but only for the subsample of directly affected firms. (Note that Δ Degree is mechanically equal to zero for indirectly affected firms, given that it is defined simply as the count of ties severed by the ban.)

²¹ We consider all ties that existed before June 2011 and match directors across datasets using first and last names. We obtain the social network of 1,077 unique directors, which create links between 201 companies, ultimately resulting in a smaller sample.

Columns 1 through 8 of Panel B of Table 5 show that the predicted change in network centrality appears to have a significant explanatory power for realized centrality for Katz (for both groups of firms), degree, and betweenness (only for directly affected firms). Remarkably, these are precisely the cases in which we uncover a significant effect on stock returns. This provides an important validation of our proposed mechanism: Stock returns react to expected changes in measures of network centrality only when restricting the analysis to the measures that are significantly affected by the ban.

For completeness, columns 9 and 10 of Panel B focus on *centrality*, the first principal component of the four measures. We find statistically coefficients in both subgroups, however with a t -statistic much higher in the subsample of directly affected firms (4.09 as opposed to 2.16), which is not surprising given that the predictive power of Δ Centrality in the not directly affected firms loads uniquely on the Katz centrality measure. As a result, the effect of Δ Centrality on market valuation is imprecise, although relatively large in magnitude (see column 10 of Panel A). Conversely, in column 9, the expected change in network centrality retains a strong explanatory power in the subsample of directly affected firms (coefficient equal to 1.53 and significant at the 5% level).

Overall, our key results appear robust to a number of variations over our baseline empirical model. Next, we examine the economic channels underlying this evidence starting with the information channel and then moving to test complementarities with other types of connections between firms.

3.5 The Information Diffusion Channel

Interlocks act as communication channels by transmitting inside information across boards. Scott (1990) was among the first to examine networks via board interlocks, arguing that

the main incentive for their formation lies in the benefits and spillovers from information sharing.

There are two types of information flows that may benefit the firm. Information can flow *from* a focal firm to market participants and other potential contractors. This is valuable since it reduces information asymmetry between the firm and outsiders, lowering contracting costs with capital providers, customers, and suppliers. Alternatively, information can flow *towards* the firm. In this case, well connected directors may learn about market trends, best practices in governance, or strategic conditions from directors and executives sitting on other boards. In what follows, we test the two channels by exploiting heterogeneity in firm characteristics.

The Asymmetric Information Channel. To identify the first channel, we sort firms according to proxies for the degree of information asymmetry between the firm and outside investors – i.e., frictions that prevent others from learning about the firm. Our hypothesis is that firms more likely to be affected by information asymmetry should benefit the most by an increase in network centrality if information is indeed transmitted via shared directors. We use idiosyncratic volatility, analyst coverage, and the dispersion of analyst earnings forecasts as sorting variables.

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) and extracting the residuals' standard deviation. Idiosyncratic volatility has been widely employed in the literature as a proxy for valuation uncertainty (Kumar, 2009). Similarly, analyst coverage is a proxy for access to reporting by sophisticated external observers. Given its strong positive correlation with firm size (Hong et al., 2000), we first regress one plus the logarithm of the number of analysts making an earnings forecast on the logarithm of total market capitalization and its squared value. Firms are then sorted according to

the estimated residual. Finally, we use the dispersion of analyst earnings forecasts as a measure of disagreement about firms' market valuation, as it captures 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.²²

The baseline specification of equation (3) is now re-estimated separately for firms that are above or below the sample median of each of the above measures. Table 6 shows the results. The effect of changes in network centrality on stock returns is driven by 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, 1.17, and 2.29, respectively, and are all significant at the 5% level. In the other subsamples, the effect of network centrality remains positive but the coefficient is smaller and insignificant at conventional levels. Hence, firms whose market valuation are less uncertain or for which there is ample and precise external reporting appear to benefit less from boardroom connections.²³

The Learning Channel. In Table 6 we examine the alternative type of information diffusion channel that may benefit the firm, i.e., the learning channel. Finding appropriate proxies for the "steepness" in the learning curve is not a straightforward task. We hypothesize that younger firms should benefit more from such learning, as they face a more uncertain and less known business environment. We hand-collect information on each firm's year of establishment and, in columns 1 and 2, sort firms depending on their age.

Firms with ample investment opportunities, i.e., growth firms, can also take advantage of information provided by outsiders to screen and select the best projects. Such benefits

²² Since about half of the firms have no coverage, estimates are based on a smaller sample of 124 observations.

²³ Given the relatively small sample size, the differences in the coefficients are, although economically large, generally not statistically significant.

are likely to be lower in more mature, “value” firms, which will not be required to adapt to sudden technological innovations or demand shocks. To this end, we sort firms according to proxies aimed at capturing investment opportunities, namely sales growth (in columns 3 and 4) and Tobin’s Q (in columns 5 and 6). Table 7 shows that the firms that benefit from boardroom connections tend to be older (column 2) and characterized by lower sales growth and Tobin’s Q (columns 3 and 5). In all of these cases, the coefficient of interest is large and (at least marginally) statistically significant. Conversely, changes in network centrality do not appear to affect market valuations in younger and faster growing firms. Thus, we find no evidence of a learning channel through board connections. If anything, more established and mature firms appear to drive the results. While an in-depth investigation of this finding is beyond the scope of the paper, this result does lend some support to the idea that board connections may favor the survival of old and established firms, possibly despite their lack of encouraging prospects. This is, indeed, the “crony capitalism” hypothesis, which was arguably the reason for the ban (see Section 2.1).

3.6 Complementarities with Input-Output and Ownership

Networks

Boardroom networks are one of many ways in which firms are connected. Alternatives include input-output production networks and cross-ownership connections. Different types of economic relationships may either complement or substitute for the others, and those complementarities also contribute to identifying the information channel. Firms that are more central in either network may be differentially affected by changes in their centrality in the boardroom network, depending on whether there is substitutability or complementarity. To test this hypothesis, we sort firms according to centrality measures in the input-output or the ownership networks and compare the effect of Δ on market

valuations. The goal is to test whether the impact of the change in boardroom centrality is stronger for firms that are more or less central in other networks.

Input-output networks have recently attracted a considerable amount of attention also for the study of the systemic propagation of firms' shocks (see, e.g., Carvalho and Gabaix, 2013). Firms that are more central in the input-output network are more susceptible to shocks, regardless of whether those are upstream technology shocks or downstream demand shocks (see Barrot and Sauvagnat, 2016; Gabaix, 2011).

The input-output network ranking helps us identify the type of information diffusion in two ways. First, firms more exposed to value chain shocks may have more uncertain asset valuation and thus may benefit more from information dissemination.²⁴ Second, contractual links on intermediate goods are most likely to take place through long-term relationships, which require knowledge and trust in sub-contractors. Sharing information in the boardroom can help build trust and lubricate the formation of other contractual linkages, such as customer-supplier relationships.

Input-output data for the year 2010, aggregated to 62 NACE industries, are provided by the Italian National Institute of Statistics (ISTAT). We match our sample of firms to these NACE codes using official crosswalks available from Eurostat's RAMON database to Compustat's NAICS codes.²⁵

Next, we compute *input-output centrality* at the industry-level for a weighted directed input-output network, where the weight attached to the edge connecting two industries i and j is the input flow from sector i to j relative to sector j 's input demand (Carvalho,

24 For instance, Dass et al. (2013) shows 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.

25 The Reference And Management Of Nomenclatures (RAMON) database is available at <https://ec.europa.eu/eurostat/ramon>. The matching is based on 6-digit NAICS codes. Shorter NAICS codes are imputed only if they map uniquely into a NACE category. Wherever this is not possible, we use the NACE code provided by AMADEUS. If a 6-digit NAICS code maps into more than one of the NACE codes, firms' network centrality is computed as the average of the corresponding NACE industry centrality. Home production is excluded.

2014). “Directed” means that links are not bi-directional; instead, they capture the flow of inputs from industry i to j and vice versa. In terms of the adjacency matrix, entries (i, j) and (j, i) now differ. We compute Katz centrality of the resulting network,²⁶ and sort firms according to whether they operate in an industry that is below or above the sample median of input-output centrality. The specification in equation (3) is then re-estimated in these two subsamples.

The results displayed in Table 8 show that a change in boardroom centrality has a greater impact on stock returns when firms operate in more central, downstream industries. The coefficient of interest is equal to 1.60 while the coefficient drops to 0.22 in industries that are less central.²⁷ Thus, investors deem a firm that is more central in the boardroom network as better able to isolate itself from shocks originating in upstream industries, or better able to exploit contractual relations.

Information diffusion through cross-ownership is another important dimension, but has generally received less attention in the literature. Here, the reasoning is reversed compared to the contractual networks case. Owning shares allows investors to gather information about the firm through screening and monitoring, thereby reducing the need for other forms of transmission. Data on 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. Katz centrality is computed for an undirected, weighted network²⁸ where edges connecting two firms are weighted using the respective ownership stake. The baseline specification is estimated for two subsamples of firms — those either above or below the median ownership centrality. The results in Table 8 indicate that

²⁶ See also Carvalho (2014) for a structural interpretation of Katz centrality in the context of input-output networks and Richmond (2019) for an application to global trade networks.

²⁷ We obtain similar results when computing centrality in a unweighted, directed network where two industries i and j are connected if i 's output exceeds 1% of j 's input demand.

²⁸ Past literature on cross-ownership has considered also directed networks in the context of corporate control (Glattfelder and Battiston, 2009). This is, however, a less relevant aspect for our analysis.

firms benefit more from a central position in the boardroom network when they are less central in the ownership network. The coefficient on Δ is a significant 1.21 for firms characterized by low ownership centrality, and 0.68 (insignificant) for firms with high ownership centrality. Cross-ownership helps reduce information asymmetry (Brooks et al., 2018) and serves 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; i.e., the two networks substitute each other.

4 Director Compensation

The main channel through which boardroom centrality can affect directors' compensation is via rent sharing. Rent sharing theories include standard bargaining models with assortative matching along the lines of Gabaix and Landier (2008) or competition for talents (see, e.g. Terviö, 2008, 2009). The value generated by a rise in boardroom centrality is then shared between shareholders and firm employees, including directors.²⁹ This also improves their bargaining position vis-à-vis shareholders (Liu, 2014). Below, we test whether directors of firms subject to an increase in centrality due to the reform experience an increase in their compensation.

4.1 Empirical Design and Data

The baseline specification now reads as follows:

$$\log(\text{Compensation}_{i,j,t}) = \lambda \times \text{Centrality}_{i,t} + \eta_{ij} + \delta_t + \varepsilon_{i,j,t} \quad (4)$$

²⁹ Engelberg et al. (2013) also study the role of CEOs bilateral connections for their compensation. The main advantage of our analysis is the quasi-experimental setting. Moreover, our centrality measure captures both direct and indirect ties. Sitting on multiple boards allows directors to improve their outside options and to climb the ladder by leveraging those connections.

where the dependent variable is the logarithm of the total compensation of director j , employed at firm i in year t . η and δ are director-firm and year fixed effects, respectively, and ε is an error term. To account for two potential layers of autocorrelation, standard errors are double-clustered at the director and firm level .

We estimate equation (4) using both OLS and an instrumental variable approach. In the latter case, we use the predicted change in network centrality induced by the reform, Δ , interacted with a “Post Reform” dummy, as an instrument for *Centrality*. The IV strategy should deliver consistent estimates of the true effect of network centrality on directors’ compensation, β . Comparison with the OLS estimates indicates the extent of the endogeneity of network formation.

The final sample includes 13,066 directors, whose compensation is hand-collected from mandatory filings with CONSOB obtained either from corporate websites or from the website of the Italian stock exchange.³⁰ Like the DEF14A filings in the US, reports contain data on fixed compensation, bonus payments, non-monetary benefits, and “other components.” Summary statistics are provided in Table 1. We also hand-collect information on stock and option grants, which are reported separately. We evaluate options using the Black and Scholes formula, the inputs of which are computed using the standard “Execucomp” methodology. Further details on this procedure, as well as on the data collection, are provided in Appendix A.3. Summary statistics on total compensation are in Panel B of Table 1.

30 Our main sources are the so-called “compensation reports” (*Relazioni sulla Remunerazione*), which became mandatory in 2011. Information on compensation for the years 2009-2010 is collected from firms’ annual reports. While coverage is nearly universal for all listed companies starting in 2011, some companies’ annual reports are missing in 2009 and 2010.

4.2 Network Centrality and Compensation

Panel A of Table 9 presents estimates of the coefficient λ from equation (4). Column 1 shows that a one-standard deviation increase in network centrality is associated with a 6.4% increase in compensation. Column 2 addresses the issue of endogeneity by using an IV strategy, and shows that the effect is on the same order of magnitude, although the coefficient increases in size: A one-standard deviation increase in centrality leads to an 11.2% pay raise (column 2). This estimate is statistically significant at the 5% level. The F -statistic is equal to 52.8, suggesting that the instrument is strong. Thus, we do not detect strong evidence of a positive correlation between network centrality and directors' abilities, which would arguably cause an *upward* bias of the OLS estimates.

In columns 4 through 6 we distinguish between high-ranking directors, e.g., CEO, chairman, and vice-chairman (Volpin, 2002) and low-ranking directors. The results are not clear cut. The coefficient λ is significant only for the sample that includes low-ranking directors (columns 5 and 6), with estimates equal to 0.09 and 0.10 for the OLS and IV regressions, respectively. The wedge between OLS and IV estimates is larger when we restrict the attention to high-ranking directors (0.03 versus 0.17) but the coefficient is not significant in either case, possibly due to the smaller sample size.

In Panel B of Table 9 we collapse the dataset at the firm-year level, using the average compensation for the firm board of directors as dependent variable. An advantage of this approach is that every firm is now weighted equally, regardless of the number of its directors. Moreover, this specification controls for attrition due to directors' turnover.

In this specification the OLS estimate of the key coefficient of interest becomes insignificant; yet, the IV estimate remains large and significant (see column 2); it is also substantially larger than its counterpart from Panel A, and equal to 0.47. Interestingly, while OLS estimates are significant only for high-ranking executives, their IV counterparts are significant both for high and low-ranking executives, with coefficients comparable in

magnitude (0.44 and 0.50, respectively). These results suggest that the effect of board ties on compensation may be valuable not only for CEOs, on whom most of the literature focuses (see for example Engelberg et al., 2013), but for all the board directors and members of the C-suite.

5 Conclusions

This paper presents causal evidence regarding the effects of firms' centrality in the network of shared directors on firm value and compensation policies. To this end, we leverage a change in the Italian corporate governance legislation that eliminates interlocking directorships between banks and insurance companies. As the reform was arguably unexpected, it is an ideal quasi-experimental setting.

First, we verify that the reform had a meaningful impact on network connections and then document that firms losing centrality due to the reform experience negative abnormal returns around the announcement date. This effect is robust to the use of alternative risk adjustments for stock returns, when controlling for different firm-level observables, adopting different sample restrictions, or when using several measures for network centrality. Furthermore, firms becoming more central pay their executives and directors significantly more, suggesting that the increase in firm surplus is shared with top employees.

The value-enhancing effects of network centrality appears to be due to information spillovers. While information diffusion in the form of learning does not appear to explain our results, we do find robust evidence that connections help reduce asymmetric information. The stock market reaction is especially strong for firms with high idiosyncratic risk, low analyst coverage, and high disagreement among analysts, all proxies for the degree of asymmetric information. On the contrary, younger firms and companies characterized by

lower investment opportunities, which may benefit from learning from others by sharing directors or executives, exhibit no market reaction, as opposed to more mature firms.

Interesting positive complementarities emerge between boardroom networks and input-output networks, whereas the cross-ownership links can act as a substitute for directors' ties. Hence, our results have broader implications for other research areas, such as the study of production networks and firms' competitive advantages.

References

- Acharya, V. and Steffen, S. (2015). The “Greatest” Carry Trade Ever? Understanding Eurozone Bank Risks. *Journal of Financial Economics*, 115(2):215–236.
- Adams, R. B., Hermalin, B. E., and Weisbach, M. S. (2010). The Role of Boards of Directors in Corporate Governance: A Conceptual Framework and Survey. *Journal of Economic Literature*, 48(1):58–107.
- Autor, D., Dorn, D., Katz, L. F., Patterson, C., and Van Reenen, J. (2020). The Fall of the Labor Share and The Rise of Superstar Firms. *The Quarterly Journal of Economics*, 135(2):645–709.
- Azar, J., Tecu, I., and Schmalz, M. (2018). Anticompetitive Effects of Common Ownership. *Journal of Finance*, 73(4):1513–1565.
- Bandiera, O., Barankay, I., and Rasul, I. (2009). Social Connections and Incentives in the Workplace: Evidence from Personnel Data. *Econometrica*, 77(4):1047–1094.
- Banerjee, A., Chandrasekhar, A. G., Duflo, E., and Jackson, M. O. (2019). Using Gossips to Spread Information: Theory and Evidence from Two Randomized Controlled Trials. *The Review of Economic Studies*, 86(6):2453–2490.
- Banerjee, A. and Munshi, K. (2004). How Efficiently is Capital Allocated? Evidence from the Knitted Garment Industry in Tirupur. *The Review of Economic Studies*, 71(1):19–42.
- Barrot, J.-N. and Sauvagnat, J. (2016). Input Specificity and the Propagation of Idiosyncratic Shocks in Production Networks. *The Quarterly Journal of Economics*, 131(3):1543–1592.
- Bernard, D., Blackburne, T., and Thornock, J. (2020). Information Flows Among Rivals and Corporate Investment. *Journal of Financial Economics*, 136(3):760–779.
- Bertrand, M. and Mullainathan, S. (2001). Are CEOs Rewarded for Luck? The Ones Without Principals Are. *Quarterly Journal of Economics*, 116(3):901–932.
- Bizjak, J., Lemmon, M., and Whitby, R. (2009). Option Backdating and Board Interlocks. *Review of Financial Studies*, 22(11):4821–4847.
- Brick, I. E., Palmon, O., and Wald, J. K. (2006). CEO Compensation, Director Compensation, and Firm Performance: Evidence of Cronyism? *Journal of Corporate Finance*, 12(3):403–423.
- Brooks, C., Chen, Z., and Zeng, Y. (2018). Institutional Cross-Ownership and Corporate Strategy: The Case of Mergers and Acquisitions. *Journal of Corporate Finance*, 48(C):187–216.
- Burt, A., Hrdlicka, C., and Harford, J. (2019). How Much Do Directors Influence Firm Value? *The Review of Financial Studies*, 33(4):1818–1847.
- Butler, A. W. and Gurun, U. G. (2012). Educational Networks, Mutual Fund Voting Patterns, and CEO Compensation. *Review of Financial Studies*, 25(8):2533–2562.
- Cai, Y. and Sevilir, M. (2012). Board Connections and M&A Transactions. *Journal of Financial Economics*, 103(2):327–349.

- Carvalho, V. and Gabaix, X. (2013). The Great Diversification and its Undoing. *American Economic Review*, 103(5):1697–1727.
- Carvalho, V. M. (2014). From Micro to Macro via Production Networks. *Journal of Economic Perspectives*, 28(4):23–48.
- Chikh, S. and Filbien, J. Y. (2011). Acquisitions and CEO Power: Evidence from French Networks. *Journal of Corporate Finance*, 17(5):1221–1236.
- Chuluun, T., Prevost, A., and Puthenpurackal, J. (2014). Board Ties and the Cost of Corporate Debt. *Financial Management*, 43(3):533–568.
- Cohen, L., Frazzini, A., and Malloy, C. (2008). The Small World of Investing: Board Connections and Mutual Fund Returns. *Journal of Political Economy*, 116(5):951–979.
- Cohen, L., Frazzini, A., and Malloy, C. (2010). Sell-Side School Ties. *Journal of Finance*, 65(4):1409–1437.
- Dass, N., Kini, O., Nanda, V., Onal, B., and Wang, J. (2013). Board Expertise: Do Directors from Related Industries Help Bridge the Information Gap? *The Review of Financial Studies*, 27(5):1533–1592.
- Drexler, A. and Schoar, A. (2014). Do Relationships Matter? Evidence from Loan Officer Turnover. *Management Science*, 60(11):2722–2736.
- El-Khatib, R., Fogel, K., and Jandik, T. (2015). CEO Network Centrality and Merger Performance. *Journal of Financial Economics*, 116(2):349–382.
- Engelberg, J., Gao, P., and Parsons, C. A. (2012). Friends with Money. *Journal of Financial Economics*, 103:169–188.
- Engelberg, J., Gao, P., and Parsons, C. A. (2013). The Price of a CEO’s Rolodex. *Review of Financial Studies*, 26(1):79–114.
- Faleye, O., Kovacs, T., and Venkateswaran, A. (2014). Do Better-Connected CEOs Innovate More? *The Journal of Financial and Quantitative Analysis*, 49(5):1201–1225.
- Foroughi, P., Marcus, A., Nguyen, V., and Tehranian, H. (2021). Peer Effects in Corporate Governance Practices: Evidence from Universal Demand Laws. *The Review of Financial Studies*.
- Fracassi, C. (2017). Corporate Finance Policies and Social Networks. *Management Science*, 63(8):2420–2438.
- Fracassi, C. and Tate, G. (2012). External Networking and Internal Firm Governance. *Journal of Finance*, 67(1):153–194.
- Gabaix, X. (2011). The Granular Origins of Aggregate Fluctuations. *Econometrica*, 79(3):733–772.

- Gabaix, X. and Koijen, R. S. (2020). Granular Instrumental Variables. *NBER Working Paper*, (28204).
- Gabaix, X. and Landier, A. (2008). Why Has CEO Pay Increased So Much? *Quarterly Journal of Economics*, 123(1):49–100.
- Garicano, L. and Rossi-Hansberg, E. (2006). Organization and Inequality in a Knowledge Economy. *The Quarterly Journal of Economics*, 121(4):1383–1435.
- Glattfelder, J. B. and Battiston, S. (2009). Backbone of Complex Networks of Corporations: The Flow of Control. *Physical Review E*, 80(3):036104.
- Graham, B. and De Paula, A. (2020). *The Econometric Analysis of Network Data*. Academic Press.
- Greif, A. (1993). Contract Enforceability and Economic Institutions in Early Trade: the Maghribi Traders’ Coalition. *American Economic Review*, 83(3):525–548.
- Güner, B. A., Malmendier, U., and Tate, G. (2008). Financial Expertise of Directors. *Journal of Financial Economics*, 88(2):323–354.
- Hann, R. N., Subasi, M., and Zheng, Y. (2019). Director Networks, Information Environment, and Corporate Investment. *Working Paper*.
- Hansen, M. T. (1999). The Search-Transfer Problem: The Role of Weak Ties in Sharing Knowledge Across Organization Subunits. *Administrative Science Quarterly*, 44(1):82–111.
- Hirshleifer, D., Hsu, P.-H., and Li, D. (2013). Innovative Efficiency and Stock Returns. *Journal of Financial Economics*, 107(3):632–654.
- Hochberg, Y. V., Ljungqvist, A., and Lu, Y. (2007). Whom You Know Matters: Venture Capital Networks and Investment Performance. *Journal of Finance*, 62(1):251–301.
- Hong, H., Lim, T., and Stein, J. C. (2000). Bad News Travels Slowly: Size, Analyst Coverage, and the Profitability of Momentum Strategies. *The Journal of Finance*, 55(1):265–295.
- Hwang, B. H. and Kim, S. (2009). It Pays to Have Friends. *Journal of Financial Economics*, 93(1):138–158.
- Jenter, D., Schmid, T., and Urban, D. (2019). Does Board Size Matter? *Working Paper*.
- Johnson, T. C. (2004). Forecast Dispersion and the Cross Section of Expected Returns. *The Journal of Finance*, 59(5):1957–1978.
- Kline, B. and Tamer, E. (2020). Econometric Analysis of Models with Social Interactions. In *The Econometric Analysis of Network Data*, pages 149–181. Elsevier.
- Kramarz, F. and Thesmar, D. (2013). Social Networks in the Boardroom. *Journal of the European Economic Association*, 11(4):780–807.

- Kuhnen, C. M. (2009). Business Networks, Corporate Governance, and Contracting in the Mutual Fund Industry. *Journal of Finance*, 64(5):2185–2220.
- Kumar, A. (2009). Hard-to-Value Stocks, Behavioral Biases, and Informed Trading. *Journal of Financial and Quantitative Analysis*, 44(6):1375–1401.
- Larcker, D. F., Richardson, S. A., and Tuna, A. I. (2005). How Important is Corporate Governance? *SSRN Electronic Journal*.
- Larcker, D. F., So, E. C., and Wang, C. C. (2013). Boardroom Centrality and Firm Performance. *Journal of Accounting and Economics*, 55(2-3):225–250.
- Lewellen, K. and Lowry, M. (2021). Does Common Ownership Really Increase Firm Coordination? *Journal of Financial Economics*.
- Liu, Y. (2014). Outside Options and CEO Turnover: The Network Effect. *Journal of Corporate Finance*, 28:201–217.
- Maida, A. and Weber, A. (2019). Female leadership and gender gap within firms: Evidence from an italian board reform. *Industrial and Labor Relations Review*, page 0019793920961995.
- Manski, C. F. (1993). Identification of Endogenous Social Effects: The Reflection Problem. *The Review of Economic Studies*, 60(3):531–542.
- Mariolis, P. (1975). Interlocking Directorates and Control of Corporations: The Theory of Bank Control. *Social Science Quarterly*, pages 425–439.
- Newman, M. (2018). *Networks*. Oxford University Press.
- Omer, T. C., Shelley, M. K., and Tice, F. M. (2014). Do Well-Connected Directors Affect Firm Value? *Journal of Applied Finance (Formerly Financial Practice and Education)*, 24(2):17–32.
- Richmond, R. J. (2019). Trade Network Centrality and Currency Risk Premia. *The Journal of Finance*, 74(3):1315–1361.
- Scott, J. (1990). *The Sociology of Elites*. Edward Elgar Publishing.
- Scott, J. (1991). Networks of Corporate Power: A Comparative Assessment. *Annual Review of Sociology*, 17(1):181–203.
- Shue, K. (2013). Executive Networks and Firm Policies: Evidence from the Random Assignment of MBA Peers. *Review of Financial Studies*, 26(6):1401–1442.
- Stuart, T. E. and Yim, S. (2010). Board Interlocks and the Propensity to be Targeted in Private Equity Transactions. *Journal of Financial Economics*, 97(1):174–189.
- Terviö, M. (2008). The Difference that CEOs Make: An Assignment Model Approach. *American Economic Review*, 98(3):642–68.
- Terviö, M. (2009). Superstars and Mediocrities: Market Failure in the Discovery of Talent. *The Review of Economic Studies*, 76(2):829–850.

- Uzzi, B. and Lancaster, R. (2003). Relational Embeddedness and Learning: The Case of Bank Loan Managers and their Clients. *Management Science*, 49(4):383–399.
- Volpin, P. F. (2002). Governance with Poor Investor Protection: Evidence from Top Executive Turnover in Italy. *Journal of Financial Economics*, 64:257–61–90.
- Yermack, D. (1996). Higher Market Valuation of Companies with a Small Board of Directors. *Journal of Financial Economics*, 40(2):185–211.

6 Figures

Figure 1
Properties of the Boardroom Network

Figure 1 plots descriptive statistics of the boardroom network before and after the reform. Panel (a) displays the annual “graph density” of the firm network where density is defined as the number of observed links normalized by the total number of all possible links in a given year. The remaining panels plot the cross-sectional average of the corresponding centrality measure for each year; horizontal dashed lines corresponds to June 2012.

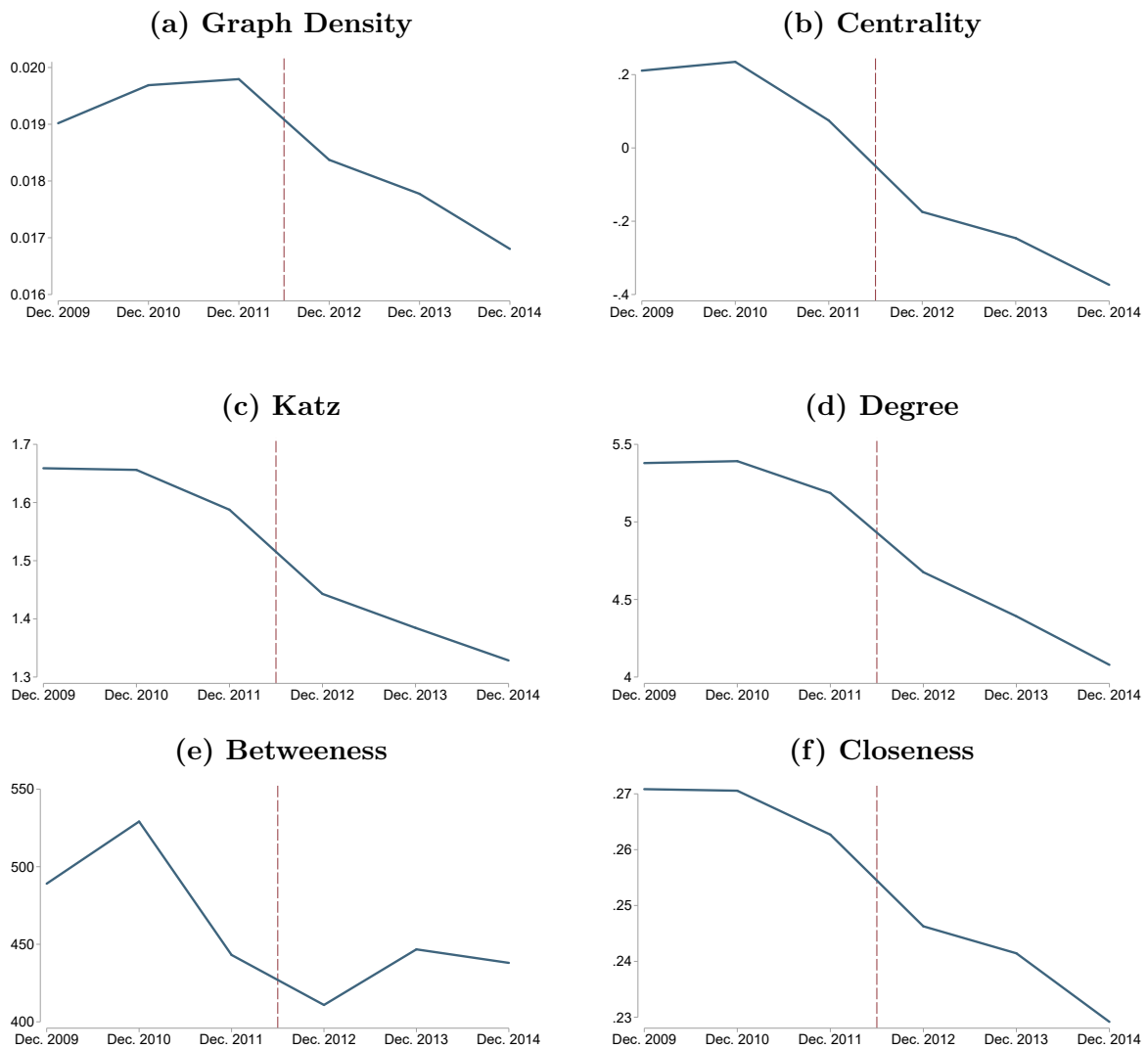


Figure 3

Fictional Corporate Network and Potential Effect of Regulation

Figure 3 shows an illustrative example of a network structure before and after the regulatory shock. Bank A, Bank B, and Company A initially share a director that, after the shock, steps down from Bank A, therefore breaking the tie between Company A and Bank A, as well as Bank A and B. The size of the nodes, shown before and after the shock, is proportional to the principal component of the four network measures (Degree, Katz, Closeness, Betweenness) as used in the main analysis.

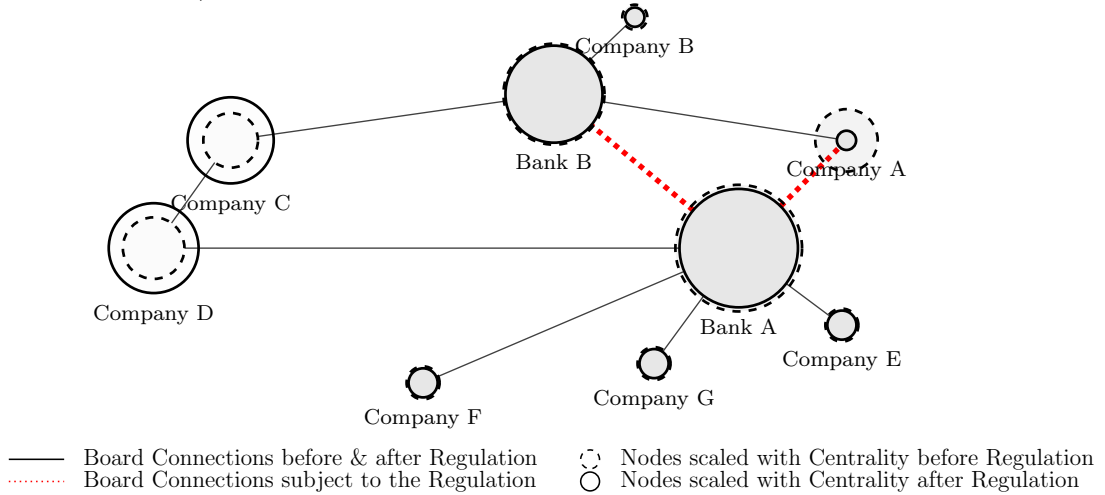


Figure 4

Buy-and-Hold Abnormal Returns around Actual Resignation Dates

Figure 4 shows average compounded abnormal returns using the market model for risk adjustment around the actual announcement of resignations of interlocking directors. Announcement dates are collected from companies' press releases. The left (right) panel plots average compounded returns around the dates of resignations that we correctly (incorrectly) predict with information available when the reform was announced (see Section 2.3 for details). Due to delistings, we use data on 24 events, which include 5 wrong predictions. Each panel plots the average compounded return for companies that are never affected by the reform (black dashed) and for companies from which board a given director eventually did (blue dashed) and did not (red solid) resign.

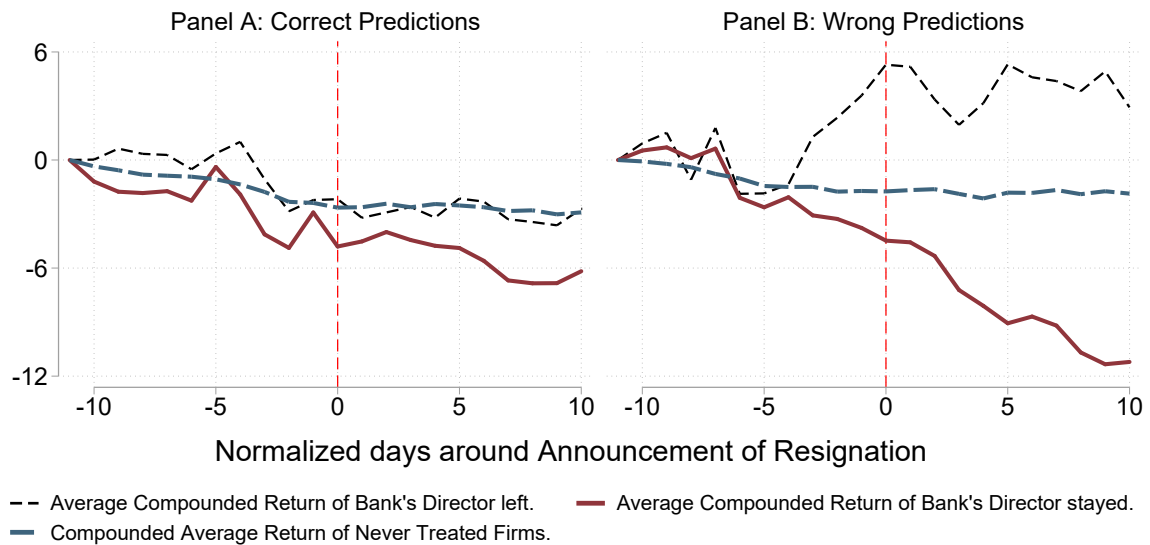


Figure 5
Event Study: Network Centrality

Figure 5 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 with the year dummies interacted with Δ are plotted together with the 95% confidence intervals. Standard errors are clustered at the firm level. The coefficient corresponding to the reform year, 2011, is normalized to zero.

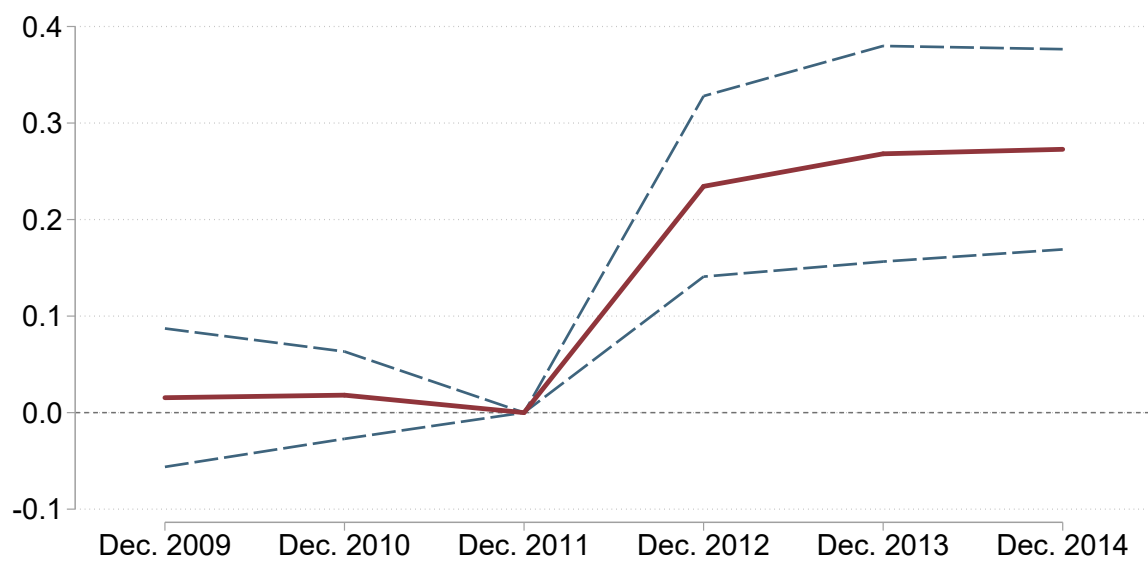
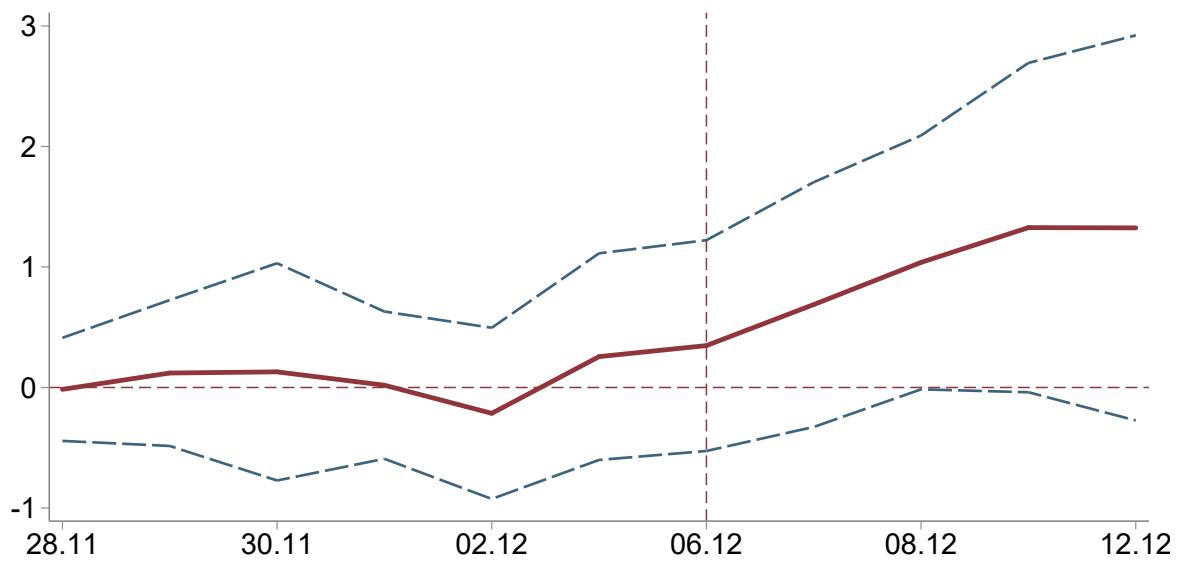


Figure 6

Event Study: Buy-and-Hold Abnormal Returns

Figure 6 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 for a $(-5, +5)$ window. All the regressions include industry fixed effects.



7 Tables

Table 1
Summary Statistics

Table 1 presents descriptive statistics for the main variables used in the paper; Panel A shows summary statistics for variables used in the event studies and Panel B variables used in the compensation panel regressions. Δ Centrality is the predicted change in network centrality, where Centrality is the first principal component of degree, Katz Centrality, closeness and betweenness (see Appendix A.2 for definitions). ROA is defined as net income divided by lagged total assets, Tobins' Q is defined as total assets plus market value of equity minus common value of equity, all divided by total assets. Both variables are measured at the end of 2010. The sovereign yield exposure is the correlation of the daily yield spread between 10-year Italian and German government bonds and the firm's daily return in the third quarter of 2011. Idiosyncratic volatility is estimated by regressing, for each firm, daily excess stock returns 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 calendar year normalized by total assets. Age is defined as the number of years since the firm's establishment. Centrality in the input-output network is defined as the industry's Katz centrality in the weighted input-output network in which a firm operates. Centrality in the ownership network is the Katz centrality in the weighted cross-ownership network. In Panel B, centrality is defined as the first principal component of the other four centrality measures computed annually from 2009 to 2014. Data on total compensation is reported in tens of thousands (see Appendix A.3 for additional details on the data collection).

Panel A. Stock Return Regressions

	Obs.	Mean	Median	St. Dev.	1 st P.	99 st P.
Δ Centrality	260	-0.27	-0.12	0.44	-2.91	0.05
Δ Katz	260	-0.12	-0.02	0.23	-1.19	0.00
Δ Degree	260	-0.33	0.00	1.08	-7.00	0.00
Δ Closeness	260	-0.01	-0.00	0.02	-0.09	0.00
Δ Betweenness	260	5.92	0.00	230.23	-1,164.37	511.05
CAR (3 day window)	260	1.73	0.44	6.81	-11.71	31.62
ROA	260	-0.00	0.01	0.10	-0.49	0.18
log(Total Assets)	260	6.56	6.00	2.23	2.69	12.95
Tobin's Q	254	1.20	1.01	0.67	0.45	4.30
log(Market Capit.)	254	5.06	5.01	2.30	-2.14	10.23
Sovereign Yield Exposure	260	-2.28	-2.10	11.59	-33.48	22.75
Idiosyncratic Volatility	260	0.02	0.02	0.01	0.01	0.06
Residual Analysts' Coverage	254	0.00	-0.00	0.79	-2.12	1.99
St. Dev. of Analysts' Forecasts	124	1.50	1.50	0.50	1.00	2.00
Age	257	52.02	37.00	52.71	3.00	186.00
Centrality IO Network	260	1.65	1.66	0.12	1.42	1.85
Centrality Ownership Network	260	1.45	1.43	0.26	1.00	2.26

Panel B. Compensation Regressions

	Obs.	Mean	Median	St. Dev.	1 st P.	99 st P.
Centrality	1,514	0.00	-0.17	1.00	-1.19	3.57
Total Compensation (Director Level)	13,864	251.15	60.00	801.42	3.00	2,786.00
Total Compensation (Firm Level)	1,335	230.80	148.50	270.79	9.65	1,110.27

Table 2
Predicted and Actual Changes in Network Centrality

Table 2 tests the predictive power of Δ , the predicted change in network centrality induced by the reform. Coefficients are estimated by regressing each of the different network measures (indicated at the top of each column) on Δ times a post-reform dummy. 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.

	Katz	Degree	Betweenness	Closeness	Centrality
	(1)	(2)	(3)	(4)	(5)
$\Delta \times \mathbb{1}(t > \text{Dec 2011})$	0.535*** (0.049)	0.241*** (0.043)	0.134** (0.067)	0.034 (0.023)	0.247*** (0.038)
Observations	1,514	1,514	1,514	1,514	1,514
R ²	0.902	0.885	0.751	0.798	0.876
Firm FE	X	X	X	X	X
Time FE	X	X	X	X	X

Table 3
Baseline Results

Table 3 shows coefficients from a regression of cumulative abnormal returns on the predicted changes in four centrality measures: Katz Centrality, degree, betweenness and closeness. Δ Centrality, in column 5, is computed as the predicted change in the first principal component of the other four centrality measures. Cumulative abnormal returns are calculated over a three-day window around the announcement date and abnormal returns are risk-adjusted using the market model. The vector of control variables includes size, defined as $\log(\text{total assets})$, 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.

	3-day Cumulative Abnormal Return				
	(1)	(2)	(3)	(4)	(5)
Δ Katz	1.138*** (0.385)				
Δ Degree		0.739* (0.428)			
Δ Betweenness			0.172 (0.413)		
Δ Closeness				0.762** (0.294)	
Δ Centrality					0.904** (0.404)
$\log(\text{Total Assets})$	-0.377 (0.522)	-0.719 (0.490)	-1.076** (0.490)	-0.872* (0.463)	-0.624 (0.515)
ROA	-0.918 (0.624)	-0.914 (0.629)	-0.866 (0.626)	-0.857 (0.622)	-0.908 (0.627)
Observations	260	260	260	260	260
R ²	0.150	0.141	0.134	0.143	0.144
Industry FE	X	X	X	X	X
Window	-1,+1	-1,+1	-1,+1	-1,+1	-1,+1
Controls	X	X	X	X	X

Table 4

Robustness Tests: Alternative Windows, Risk Adjustments, and Controls

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 1 and 2, where we use 5- and 7-day windows, respectively. Abnormal returns are risk-adjusted using the market model except in column 3 where returns are raw (obtained by subtracting the risk-free rate) or risk-adjusted using the Fama French three-factor model (column 4). The vector of control variables includes size, defined as $\log(\text{total assets})$, and ROA, defined as net income divided by lagged total assets. Column 5 is estimated without any controls, whereas column 6 additionally includes the logarithm of market capitalization and Tobin's Q. Column 7 controls for the correlation of daily stock returns and the yield spread between 10-year Italian and German government bonds over the third quarter of 2011. Column 8 drops all observations from affected industries (Fama French 17-industry class 4, 5, 7, and 15). In column 9 the sample of abnormal returns is truncated at 2.5% and 97.5% tails. Column 10 includes controls for the number of directors at a given firm that created an interlock (“# Aff. Directors”). Column 11 controls for firms' centrality in the social network computed as the first principal component of the four centrality measures obtained from directors' social networks. 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.

	<i>Varying:</i> Time Window		Risk Adjustment		Controls and Sample						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Δ Centrality	0.985** (0.472)	1.144** (0.542)	0.898** (0.400)	0.911** (0.412)	1.250*** (0.410)	0.888** (0.437)	0.874** (0.402)	0.963** (0.403)	0.779** (0.358)	1.622*** (0.504)	1.068** (0.423)
log(Total Assets)	-1.895** (0.806)	-1.764* (0.967)	-0.515 (0.514)	-0.591 (0.513)		0.928 (0.862)	-0.616 (0.520)	-0.408 (0.553)	-0.273 (0.381)	-0.634 (0.513)	-0.356 (0.730)
ROA	-1.410 (0.956)	-1.787 (1.228)	-0.943 (0.625)	-0.857 (0.626)		-0.465 (0.605)	-0.925 (0.620)	-0.810 (0.731)	-0.700 (0.456)	-0.884 (0.633)	-1.162 (1.189)
Tobin's Q						0.354 (0.439)					
log(Market Cap.)						-2.079** (1.033)					
Sovereign Yield Exposure							-0.157 (0.439)				
# Aff. Directors										0.893** (0.426)	
Social Network Centrality											0.053 (0.262)
Observations	260	260	260	260	260	254	260	225	247	260	201
R ²	0.147	0.146	0.144	0.141	0.119	0.167	0.145	0.126	0.171	0.150	0.173
Industry FE	X	X	X	X	X	X	X	X	X	X	X
Window	-2,+2	-3,+3	-1,+1	-1,+1	-1,+1	-1,+1	-1,+1	-1,+1	-1,+1	-1,+1	-1,+1
Controls	X	X	X	X	None	All	X	X	X	X	X
Risk Adjustment	MM	MM	Raw	FF	MM	MM	MM	MM	MM	MM	MM
Sample	All	All	All	All	All	All	All	w/o Aff.	No Outlier	All	All

Table 5
Baseline Effect for Affected and Non-Affected Firms

Columns 1 through 8 of Panel A of Table 5 show coefficients from a regression of cumulative abnormal returns on the predicted changes in four centrality measures: Katz Centrality, degree, betweenness and closeness. Δ Centrality, in column 9 and 10, is computed as the predicted change in the first principal component of the other four centrality measures. Cumulative abnormal returns are calculated over a three-day window surrounding the announcement date and risk-adjusted using the market model. The vector of control variables includes size, defined as $\log(\text{total assets})$, and ROA, defined as net income divided by lagged total assets. Each regression includes industry-fixed effects, following the Fama-French 17-industry classification. Panel B shows results from testing the predictive power of the predicted change of each centrality measure Δ used in Panel A. Coefficients are estimated by regressing each of the different network measures on Δ times a post-reform dummy. Each regression includes firm and year fixed-effects. Standard errors in both Panels are clustered at the firm level. ***, **, and * indicate statistically different from zero at the 1%, 5%, and 10% level of significance, respectively.

Panel A: Baseline Effects for Affected and Non-Affected Companies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Δ Katz	1.260** (0.527)	1.479** (0.588)								
Δ Degree			1.394** (0.539)	- (-)						
Δ Betweenness					1.200** (0.476)	-1.085 (0.771)				
Δ Closeness							0.818* (0.431)	0.511 (0.622)		
Δ Centrality									1.530** (0.560)	0.864 (0.822)
Observations	26	234	26	-	26	234	26	234	26	234
R ²	0.264	0.159	0.351	-	0.355	0.153	0.206	0.148	0.396	0.148
Industry FE	X	X	X	X	X	X	X	X	X	X
Controls	X	X	X	X	X	X	X	X	X	X
Affected	Y	N	Y	N	Y	N	Y	N	Y	N

Panel B: Predicted and Actual Changes in Network Centrality

	Katz		Degree		Betweenness		Closeness		Centrality	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\Delta \times \mathbf{1}(t > \text{Dec } 2011)$	0.462*** (0.065)	0.724*** (0.087)	0.233*** (0.060)	- (-)	0.231*** (0.073)	-0.088 (0.097)	-0.012 (0.029)	0.054 (0.060)	0.225*** (0.055)	0.360** (0.167)
Observations	150	1,364	150	-	150	1,364	150	1,364	150	1,364
R ²	0.932	0.893	0.900	-	0.807	0.737	0.814	0.788	0.898	0.865
Firm FE	X	X	X	X	X	X	X	X	X	X
Time FE	X	X	X	X	X	X	X	X	X	X

Table 6
Information Transmission

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 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 calendar year divided 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.

<i>Sorting by:</i>	IVOL		Residual Analysts' Coverage		St. Dev. Forecast	
	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Centrality	0.716* (0.386)	1.489** (0.653)	1.167** (0.568)	0.787 (0.591)	0.828 (0.597)	2.291** (0.920)
Observations	130	130	127	127	62	62
R ²	0.254	0.228	0.125	0.200	0.284	0.358
Industry FE	X	X	X	X	X	X
Controls	X	X	X	X	X	X

Table 7
Firm Age and Growth Opportunities

Table 7 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: Firm Age (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 if each measure is below or above the median. Age is defined as the number of years since the firm's establishment. 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.

<i>Sorting by:</i>	Age		Sales Growth		Tobin's Q	
	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Centrality	-0.047 (0.864)	0.876* (0.491)	1.962** (0.827)	-0.922 (1.227)	1.393** (0.599)	-0.016 (0.428)
Observations	129	128	102	102	127	127
R ²	0.185	0.222	0.180	0.220	0.259	0.103
Industry FE	X	X	X	X	X	X
Controls	X	X	X	X	X	X

Table 8**Network Complementarities – Input-Output & Ownership Networks**

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 their centrality in the weighted input-output network, where weights are the input flow from sector i to j relative to sector j 's input demand. In columns 3 and 4 firms are sorted according to their centrality in the weighted cross-ownership network, where weights correspond to the respective ownership stake. 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 $\log(\text{total assets})$, 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.

<i>Sorting by:</i>	IO Network		Ownership Network	
	Low	High	Low	High
	(1)	(2)	(3)	(4)
$\Delta\text{Centrality}$	0.218 (0.529)	1.603*** (0.516)	1.205** (0.575)	0.682 (0.475)
Observations	154	106	130	130
R ²	0.103	0.262	0.300	0.120
Industry FE	X	X	X	X
Controls	X	X	X	X

Table 9
Compensation

Table 9 shows coefficients from regressions of $\log(\text{total compensation})$ on centrality. In Panel A the unit of observation is a director-year. Network centrality is derived from the firm-level network. Columns 1 and 2 use data on all board members, columns 3 and 4 includes only high-ranked directors (CEO, President and Vice-President), and columns 5 and 6 includes the remaining directors. Coefficients in columns 1, 3, and 5 are estimated using OLS, whereas coefficients in columns 2, 4, and 6 are estimates using 2SLS, where centrality is instrumented by the predicted change in network centrality multiplied by the post-reform dummy. Standard errors are double-clustered at the firm and director level and displayed in parentheses. Panel B repeats the analysis at the firm-level, where the dependent variable is the average of $\log(\text{total compensation})$ 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.

Panel A: Director-Level						
	All		High-Rank		Low-Rank	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Centrality	0.064*** (0.023)	0.112** (0.048)	0.027 (0.041)	0.173 (0.136)	0.091*** (0.025)	0.099** (0.045)
Observations	12,689	12,689	3,191	3,191	9,336	9,336
R ²	0.915	0.001	0.892	-0.009	0.898	0.004
F-Stat		52.838		35.306		51.946
Director-Firm FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Panel B: Firm-Level						
	All		High-Rank		Low-Rank	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Centrality	0.041 (0.049)	0.472** (0.197)	0.147*** (0.056)	0.436** (0.176)	0.049 (0.049)	0.501*** (0.172)
Observations	1,327	1,327	1,316	1,316	1,324	1,324
R ²	0.840	-0.199	0.805	-0.030	0.839	-0.186
F-Stat		42.518		43.030		42.530
Firm FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X

Appendix

This appendix presents additional details and definitions omitted from the main text for brevity. Appendix A.1 presents an example from an actual network of Italian listed firms. Appendix A.2 gives formal definitions of the centrality measures used in the main text. Appendix A.3 has details regarding the data collection and the calculation of option values. Appendix A.4 has definitions for all the variables used in the empirical analysis.

A.1 Example of the Actual Italian Boardroom

Network

Figure A1 plots part of the actual network before and after the reform. For exposition we focus on the partial network of first-degree neighbors of Mediobanca and Unicredit; i.e., any node (and their edges) not directly connected to either bank is not displayed.

The size of nodes is proportional to companies' *centrality* in June 2011 (dashed outline) and December 2012 (solid outline) *Centrality* is defined as in the main text (see Section 2.2). The solid edges connect firms sharing a director both in June 2011 and in December 2012, whereas dashed and dotted edges connect firms that shared at least one director in December 2012 or June 2011 respectively. Red dashed edges denote interlocks between banks and insurance companies that were affected by the regulatory shock. Table A1 contains actual centrality values for a sample of 20 firms from the first-degree network with the largest and smallest change in centrality.

The network has two main large components, one around Mediobanca and one around Unicredit. Both companies, which were directly affected by the law, were initially very central, and the reform had an extensive impact on the overall network structure. The large decrease in *centrality* of firms that were more central in the network and were

connected directly to affected banks is apparent, as the lost connection inhibits the flow between the hubs connected to either one of the banks. Unicredit and Mediobanca had initially an important role in connecting these two hubs, which was lost in part, in favor of other less central companies (located on the left and right of Unicredit).

Figure A1

Network of First-Degree Neighbors of Mediobanca Spa & Unicredit Spa

Figure A1 plots the network of first-degree neighbors of Mediobanca Spa and Unicredit Spa. The size of each node is proportional to the company's centrality in June 2011 (dashed) and December 2012 (solid). Solid edges connect firms sharing a director both in June 2011 and December 2012, whereas dashed and dotted edges connect firms that shared at least one director only in December 2012 or June 2011, respectively. Red edges denote interlocks between banks and insurance companies that were affected by the regulatory shock.

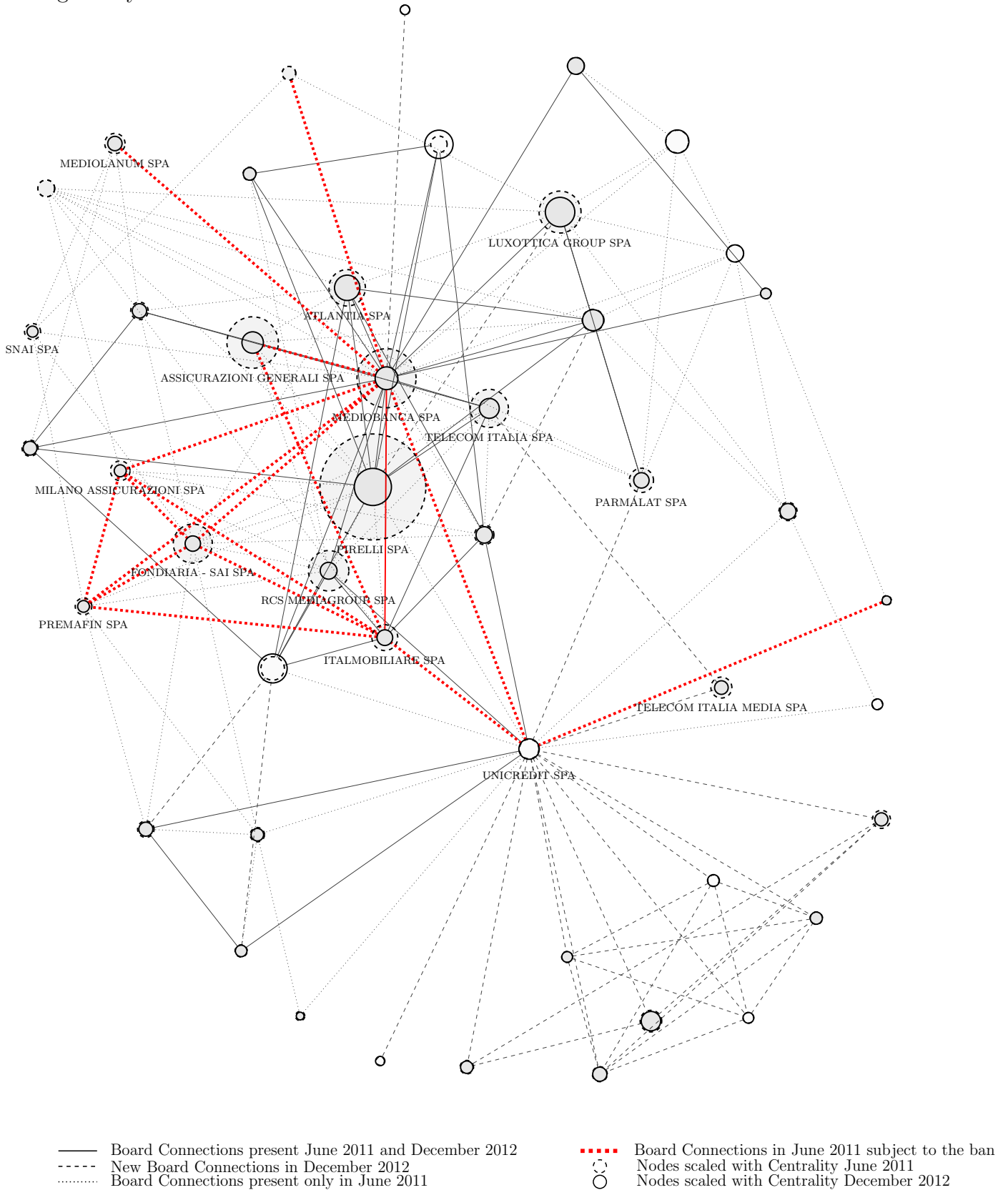


Table A1**Changes in Centrality for Network Example**

Table A1 tabulates values of centrality as used in the main analysis for firms in network of the first-degree neighbours of Mediobanca Spa and Unicredit Spa (displayed in Figure A1) with the ten highest decreases and increases in centrality between June 2011 and December 2012. Industry definitions follow the Fama-French 17-industry classification.

Company Name	Industry	Centrality June 2011	Centrality June 2012
	(1)	(2)	(3)
PIRELLI SPA	Other	11.420	6.175
MEDIOBANCA SPA	Banks, Insurance, Finance	8.497	3.720
FONDIARIA - SAI SPA	Banks, Insurance, Finance	6.429	1.758
RCS MEDIAGROUP SPA	Other	6.604	2.218
ASSICURAZIONI GENERALI SPA	Banks, Insurance, Finance	7.813	3.432
TELECOM ITALIA SPA	Other	6.315	3.045
ITALMOBILIARE SPA	Construction	4.370	1.863
MILANO ASSICURAZIONI SPA	Banks, Insurance, Finance	2.986	0.512
PARMALAT SPA	Food	4.043	1.765
TELECOM ITALIA MEDIA SPA	Other	3.323	1.153
⋮	⋮	⋮	⋮
INDESIT COMPANY SPA	Consumer Durables	2.304	2.313
VIANINI LAVORI SPA	Construction	-0.070	-0.020
INTERPUMP GROUP SPA	Machinery & Business Equipment	3.703	3.831
EL EN SPA	Other	-0.752	-0.582
UNICREDIT SPA	Banks, Insurance, Finance	2.959	3.180
CEMENTIR HOLDING SPA	Construction	0.229	0.472
ASTALDI SPA	Construction	-0.275	0.026
VALSOIA SPA	Food	-1.226	-0.731
ITALCEMENTI SPA	Construction	3.884	4.939
PRELIOS SPA	Banks, Insurance, Finance	2.103	4.824

A.2 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:

$$d_i = \sum_{j \neq i} a_{ij}, \quad (5)$$

where a_{ij} is an element of the adjacency matrix that takes the value 1 if there is an edge between nodes (i.e., firms) i and j and zero otherwise.

Katz Centrality is defined as:

$$k_i = \alpha \sum_j a_{ij} k_j + \beta \quad (6)$$

The first term is exactly the definition of “Eigenvector centrality,” whereas 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 use a value $\alpha = 0.05$, but results are similar for different values of 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 ensures consistency and convergence across time.

Contrary to eigenvector centrality, this measure does not exclude firms located in unconnected components. For these, eigenvector centrality is 0, leading to instability with respect to small changes in board composition over time. The relative centrality of firms that are only indirectly connected to most central firms is tuned by the attenuation

factor, α , which goes from 0 to an upper bound such that Katz centrality coincides with eigenvector centrality.

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

$$c_i = \frac{1}{n-1} \sum_{j \neq i} \frac{1}{d_{ij}}, \quad (7)$$

where d_{ij} is the distance between nodes i and j and n is the total number of nodes in the network. The distance between two nodes is the number of edges in a shortest path connecting them. This definition has two convenient properties. First, for unconnected firms $d_{ij} = \infty$, and hence the corresponding term in the sum is zero and simply drops out. Second, firms that are close to firm i are naturally given a higher weight, reflecting the fact that once a firm is far away in the network it matters less how far away it exactly is.

Betweenness centrality is defined as:

$$b_i = \sum_{s,t} n_{s,t}^i, \quad (8)$$

where $n_{s,t}^i$ takes on the value 1 if the node i lies on the shortest path between any other nodes s and t . Betweenness is then computed as the sum over all pairs of nodes s and t in the network.

A.3 Data Collection

We hand-collect data on board members and compensation 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 roles) and firm names are reported biannually and are available on the CONSOB website.

We harmonize name spellings across reporting years and hand-match company names to Compustat and Datastream to obtain data on daily stock returns and other firm-level variables. We cross-reference the hand-collected information on board composition and the financial data from Compustat with the data from annual reports to ensure proper matching.

We hand-collect data on compensation of all the board members (executives and directors) 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-collect compensation data from annual reports. While coverage starting in 2011 is universal for all listed companies, for some companies we are unable to recover annual reports or compensation information for the years 2009 and 2010.

These 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 components (*altri compensi*). Reporting is not consistent across firms and differences in categorization were harmonized so that different components of total compensation were assigned to one of these broader categories.

Stock and option grants are recorded separately. We hand-collect the number of stocks and options, grant dates, share prices at the grant dates, and, specifically for option grants, the strike prices and expiration dates. We compute the value of option grants using the Black-Scholes formula, following the methodology and conventions used by Execucomp. Unless otherwise reported, we assume that the strike price is equal to the grant date stock price. We use the interest rate paid on a 7-year German government bond as risk-free return.

We estimate the variance of the stock return using 60-month return data. If the price series are shorter than 12 months, we use the sample average variance. We estimate 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 that options are granted on July 1 if the grant date is not reported. Following the Execucomp's convention, we assume that an executive will exercise her option 70% of the way into its nominal term, given that executives rarely wait until the expiration date to exercise their options. For the companies that do not provide any information on grant and expiration dates, time to expiration is assumed to be 7 years.

The loadings on the market, size, and value factors are estimated, for each stock, over a $(-300, 46)$ -day window. We obtain excess returns and Fama-French factors for Europe from Kenneth French's website (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html).

A.4 Variables Definitions

Table A2
Variables Definitions

Variable	Definition	Source
Total Assets	Total Assets (<i>at</i>)	Compustat Global
ROA	Income Before Extraordinary Items (<i>ib</i>) divided by lagged total Assets (<i>at</i>)	Compustat Global
Market Value of Equity	Stock price multiplied by Common Shares Outstanding both at end-of-fiscal-year month	Compustat Global & Datastream
Tobin's Q	Total Assets (<i>at</i>) plus Market Value of Equity minus Common Value of Equity (<i>ceq</i>) all divided by Total Assets	Compustat Global & Datastream
Sales Growth	Log growth rate of Sales (<i>sale</i>); all 2010	Compustat Global
IVOL	Standard deviation of the residuals obtained from regressing the daily excess stock return on the equity premium over the 12 months from December 2010 to November 2011	Compustat Global
Residual Analyst Coverage	Residual of a regression of the 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 the latest analysts' consensus net income forecast preceding the end of the firm fiscal year 2010 divided by total assets	IBES
Firm Age	Time elapsed since foundation of the firm	Manual search from internet sources, such as Wikipedia and corporate websites
Katz Centrality IO Network	Katz Centrality computed from Italian Input-Output Network	ISTAT
Katz Centrality Ownership Network	Katz Centrality computed from data on ownership stakes in listed Italian companies	CONSOB
Sovereign Yield Exposure	Correlation of the daily yield spread between 10 year Italian and German government bonds and firms' daily returns (risk adjusted using the market model) in the third quarter of 2011	Refinitiv Eikon
Total Compensation	Fixed compensation (<i>compensi fissi</i>) + bonus payments (<i>bonus</i>) + non-monetary benefits (<i>benefici non-monetari</i>) + other compensation (<i>altri compensi</i>) + value of stock and option grants	Borsa Italiana