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

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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.

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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 leveraging a policy reform as a natural experiment to assess whether exogenous changes in the network structure affect firms' market valuations. 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]

The main identification challenge lies in the fact that the network structure is endogenous and that one needs to isolate network effects from a number of confounding factors, stemming either from omitted industry characteristics or the endogenous matching between firms and directors. For example, better-connected directors may connect with better firms, have an informational advantage, or simply be more experienced and talented. These issues fall in the category of the so-called *reflection problem*.[2]

Our main contribution therefore lies in exploiting changes in firms' network centrality

1 See Drexler and Schoar (2014) or Mariolis (1975) on interlocking boardrooms as channels for soft information and Larcker et al. (2013) on the value benefits of centrality in the boardroom networks associated with information shared via the network. See also Hansen (1999) for information diffusion in the context of innovation processes.

2 For a more general discussion of associated issues by e.g. Manski (1993), Kline and Tamer (2020), Graham and De Paula (2020), and Gabaix and Koijen (2020).

arising from a reform banning interlocking directorships for financial and insurance firms to identify the advantages of being more *central* in the boardroom network. Specifically, we leverage a ban on interlocking directorships between competing financial firms enacted in Italy in December 2011. Even though the ban was directed at banks and insurance companies, it affected the entire corporate network, with analysts characterizing it as "one of the biggest shake-ups in Italian corporate life since the Second World War."[3]

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 shows that multiple board appointments of directors may diminish directors' ability to monitor effectively (e.g. Falato et al., 2014) or disseminate bad managerial practices (e.g. Bizjak et al., 2009), others find that board networks have information sharing benefits with net positive effects on value (Larcker et al., 2013), similarly to other types of personal linkages, such as those arising from common educational experiences (e.g. Cohen et al., 2010).[4] In addition, our study focuses on broader measures of network centrality that are able to capture both direct and indirect connections, rather than on the role of mere bilateral connections.

After presenting our quasi-experimental evidence on the role of centrality in the boardroom network, we examine the potential economic channels driving our results and find evidence consistent with network centrality reducing asymmetric information. Conversely, we find no evidence of positive 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, by providing causal evidence that director's compensation is positively affected by firm centrality, in line with theories of rent sharing.

To measure the impact of exogenous changes in the network structure on firm valuation,

3 See "Italian companies are forced into board shake-ups," The Financial Times, April 25, 2012.

4 Past empirical work has examined the link between board connections and several corporate outcomes, such as innovation activities (Chang and Wu, 2021), M&A 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).

we estimate the reaction of stock prices to changes in firms' network centrality in the days surrounding the surprise announcement of the policy regulating interlocking directorships, in December 2011. We use hand-collected data on the board composition of publicly listed firms to construct the boardroom network and compute changes in four measures of network centrality.[5] 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 see our network centrality measure as a parsimonious representation of the process underlying information diffusion[6]; 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.

First we document that the ban has a significant and long-lasting impact on the structure of the firm network, as affected firms were unable to fully recover their central position after the reform. This is not surprising, given that these industries have historically had a pervasive role in the boardrooms of the private sector.[7] Then we regress in our baseline specification 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 92 basis point increase in stock returns. This result is robust to using different time windows for the measurement of stock return responses, 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 and similarly placebo tests based on networks with randomly generated links (Bramoullé et al., 2009) suggest

5 As we discuss in detail in Section 2.2, the measures are degree, Katz centrality, betweenness, and closeness, as in Hochberg et al. (2007), El-Khatib et al. (2015), and Fracassi (2017).

6 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.

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

that our evidence is not spurious. 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.

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 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 find 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 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 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 bargaining models with assortative matching (along the lines of Gabaix and Landier, 2008) or competition for talents (see, e.g., Terviö, 2008) predict that firms' surplus should be shared between shareholders and executives and shocks to firm value due to changes in the network structure would spill over to executives' pay. We hand-collect data on compensation for over 12,500 directors and 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 the compensation of board members. 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.

Related Literature. Our work is related to the literature that examines the effects of board characteristics, and especially board networks, on firm outcomes. Previous work has typically focused either on the role of bilateral connections between firms through directors or managers (Engelberg et al., 2012, 2013) or on centrality in the firm network (e.g. Larcker et al., 2013; Hochberg et al., 2007). This paper adds in particular to the latter by exploiting a novel quasi-experimental setting to isolate exogenous variation in network centrality by exploiting an exogenous regulatory shock, which affects the network structure but is

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

unlikely to directly affect other board characteristics. Other papers instead measure the influence of networks through social, educational, or professional ties predating the outcomes being studied (Cohen et al., 2008, 2010; Fracassi and Tate, 2012; Kuhnen, 2009; Engelberg et al., 2012, 2013; Kramarz and Thesmar, 2013) to address the risk that confounding factors affect both network structure and current firm performance. Alternatively, they consider changes in the network or bilateral ties arising from the appointment of existing board members on other boards (Larcker et al., 2013; Burt et al., 2019) or variation in board composition due to unexpected deaths of directors (Bakke et al., 2020; Falato et al., 2014). An additional advantage of our setting, is therefore that firms were not allowed to reestablish their ties by hiring other directors, resulting in permanent changes to network centrality.

Besides, most other papers examine the role of bilateral, and often personal, connections between individuals whereas causal evidence on the effects of boardroom ties, and in particular firm-level centrality, is less common and more mixed. While managers' connections, and thus centrality, may increase information access, they may at the same time increase their power and influence, undermining corporate governance.[9] Our setting addresses endogeneity concerns common in the previous literature and help resolve ambiguity about previous findings.

Our paper emphasizes the role of boardroom networks in facilitating information diffusion. Specifically, we test whether network centrality facilitates learning by managers or reduces asymmetric information, and find strong evidence for the latter channel. Other settings in which the role of information diffusion appears important are venture capital (Hochberg et al., 2007), borrowing (Engelberg et al., 2012), monitoring (Fogel et al., 2021), mutual fund investments (Cohen et al., 2008), analyst recommendations (Cohen et al., 2010), hedge fund activism (He and Li, 2022), and R&D (Faleye et al., 2014). Our paper is also related to the literature on the impact of social ties between transaction parties

9 See, in different contexts, Fracassi and Tate (2012); Kuhnen (2009); Fogel et al. (2021); El-Khatib et al. (2015); Güner et al. (2008); Butler and Gurun (2012).

(see Banerjee and Munshi, 2004, and Bandiera et al., 2009) stressing the role of networks in mitigating information asymmetries in contractual relationships.

The evidence on the complementarity with the input-output network contributes to the growing body of work on the role of directors shared between upstream and downstream firms (see, e.g., Dass et al., 2013). Similarly boardroom connections may potentially help absorb idiosyncratic shocks in input–output networks (see Gabaix, 2011; Carvalho and Gabaix, 2013, among others) or may substitute for cross-ownership links.[10]

Finally, our paper sheds light on an important aspect of CEO compensation.[11] 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 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

10 See Azar et al., 2018, and, for a different perspective, Lewellen and Lowry, 2021.

11 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).

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.[12] Thus, we expect the exogenous change in the network structure to have a significant impact on firms' market valuation.

Our data include 260 publicly listed companies with non-missing stock return data. Most of them 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.[13] 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.[14] Second, the law imposed a ban on interlocks among competing

12 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)

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

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

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 (an administrative unit comparable to a US county). This contrasts with to 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.[15] 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 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.[16] 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 financial sector, and involved a total of 26 companies.[17] 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

15 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).

16 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 4). See also Appendix C for an example of how the actual Italian boardroom network was affected by the reform.

17 The affected companies account for 23% of the market capitalization and 76% of the total assets of our sample of firms.

was highly heterogeneous across firms. For example, Mediobanca, an investment bank that 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 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,[18] whereas no article on the topic of interlocking directors appeared in the year leading up to the decree.[19] 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

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

19 Note that, while the decree was passed into law on Tuesday, December 6, details on the austerity measures that were part of 'Save Italy' decree became known during the previous weekend and were discussed in newspaper articles. Importantly, the interlocking board member regulation that we are exploiting was absent from these discussions before our event date and only appeared in the news on the 7th of December, making the event unexpected.

measures. The most relevant ones, at least for their potential impact on firms' valuation, 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 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. For this reason, all 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 contains other, less relevant 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.

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 D.

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.[20]

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 C shows an extract of the *actual* network and of the impact of the reform). Figure 2 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 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

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

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 2, 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.[21] 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. We show in Section 3.4 that results are robust to the use of alternative approaches to predict directors' choices and, thus, the network configuration.

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 24 resignations that explicitly refer to the ban as the reason. 19 correspond to events correctly predicted by our procedure, whereas 5 resignations were wrongly predicted (i.e., we predicted that a director would resign from "Company A" but she chose to resign from "Company B"). Figure 3 plots buy-and-hold returns in a $(-5, +5)$-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 are very similar to those of the companies that the director leaves. Hence, as expected, investors do not appear "surprised" by the director's choice.[22] 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:

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

21 *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.

22 We do not report corresponding results for directors whose resignation we fail to predict correctly, as we have press release dates in only five instances.

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 statistics 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 A.6. We relegate additional details on the data cleaning process to Appendix E.

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:

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

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 6.05. 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, omitting the coefficient corresponding to the last pre-reform year, 2011. The dependent variable is, again, *centrality.* Figure 4 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:

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

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 E 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 Log(total assets), and ROA, defined as income divided by lagged total assets.[23] We use these controls as they are non-missing for the entire sample, but results remain robust when including additional controls or no controls

23 Throughout the paper, the centrality measures and the control variables are winsorized at the 1%-level. Table A.2 reports additional robustness tests for different levels of winsorization of ΔCentrality.

at all (see Section 3.4). X also includes industry dummies, defined using the Fama-French 17 industry classification.[24] 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 ΔBetweenness, 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 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 92 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 $\tau = -5, ..., +5$ as the dependent variable. Figure 5 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.

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

3.4 Robustness Tests

This section presents several robustness checks.

Alternative Windows, Risk Adjustments, and Controls. 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 ΔCentrality is unaffected.[25]

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 generated 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 our baseline regression in column 8.[26] 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, although insignificant, suggesting that investors may reward smaller boards (Jenter et al., 2019, Yermack, 1996). Moreover, and mechanically, the number of affected directors is negatively related to the expected change in centrality, given that a firm with several shared directors is more likely to lose ties and, thus, centrality.

25 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, 2022). 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.

26 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).

As a result, the inclusion of this control variables results in an *increase* in the coefficient on ΔCentrality, which rises to 1.54. Hence, if anything,the coefficient found in the baseline tests may be a *conservative* estimate of the true effect of network centrality.[27]

Firms may be connected by social ties, besides board interlocks (Engelberg et al., 2013), and be therefore unaffected by changes in their boardroom network centrality if they are already central in the *social* network. Even though the reform effectively prevents previously interlocked companies in the financial industry from recovering the lost links through new hires, existing social connections or the hiring of new directors might restore the information flow lost because of the ban on interlocks. Further, Fogel et al. (2021) document the importance of independent, socially well-connected directors for firm valuation. Thus, in column 11 we control for the change in firms' centrality computed 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.[28] 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 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.

27 Furthermore, results are robust to controlling for board size. We additionally check that results are not driven by the number of independent or executive directors affected by the law (see among others Nguyen and Nielsen, 2010, on the importance of independent directors). To this end we hand-collect data on independence and executive status of affected directors from annual reports and corporate governance reports. Director independence is reported following either the definition from the Consolidated Finance Act (*Testo Unico della Finanza* Section 147-ter) or from the Code of Conduct (*Indipendente da Codice*) and we classify a director as independent if she is independent according to either status. If not reported we assume Presidents/CEO/COO to be executives and further classify executives as not independent unless otherwise reported. Results remain very similar and are available upon request.

28 We consider all ties that existed before June 2011 and June 2012, respectively, and match directors across datasets using first and last names. We obtain the social network of 1190 unique directors in 2011 and , which create links between 159 companies with links both in 2011 and 2012, ultimately resulting in a smaller sample.

The role of the banking sector. Previous research documents the important role of bilateral ties between non-financial firms and their banks in reducing the cost of debt (Engelberg et al., 2012; Karolyi, 2018). Given that the ban on interlocks affects firms in the financial industry, a concern is that firms losing centrality are simply losing ties, direct or indirect, with banks. In this case, the change in market value would simply reflect variation in access to potential lenders. In Appendix A we show that, after controlling for the expected change in *distance* from firms in the financial industry, results remain robust (see Appendix-Table A.1).

Alternative definitions of the predicted change in network centrality. As discussed in Section 2.3, to construct the predicted change in network centrality we need to establish a "decision rule" to predict which seat directors affected by the ban will keep. A potential concern is that results are sensitive to the particular choice made. In Table 5, we show that results are qualitatively similar, although with varying levels of precision, if we take a more agnostic stance.

In column 1, we simulate the post-ban network by simply removing the directors creating the interlock. As shown in Panel B, re-estimating Equation (2) based on this alternative predicted change in centrality the statistical power falls as the t-statistic decreases to 4.86, relative to 6.50 in our baseline results (Table 2). Given that ΔCentrality has less predictive power for the realized network, it is also a less strong predictor than the abnormal return; the coefficient obtained after regressing cumulative abnormal returns on the predicted change in centrality remains positive and large (equal to 0.53), although insignificant. In column 2, we simulate the effect of the reform by simply removing only links between firms in the financial industry while preserving any links to other firms. In column 3, we *randomly* remove a director from one of the interlocked boards. We repeat this exercise 5000 times to obtain a distribution of estimated coefficients and report the average estimate.[29] In both columns 2 and 3, results remain comparable to those obtained in the baseline analysis of Table 3.

A placebo test. One of the main challenges of this analysis is due to the endogeneity of network formation, which may in turn be related to changes in the economic environment. For example, more central firms may be more likely to lose centrality and, at the same time, to be affected by other provisions of the reform package. We address this concern using a Placebo test based on randomly generated networks to simulate and estimate the effects of the reform, where positive significant effects would indicate that our effects spuriously reflect the underlying correlation of the true network with firms' exposure to other parts of the reform (Bramoullé et al., 2009). The placebo network preserves the degree distribution of the pre-ban network before the reform but generates links between firms at random; i.e., we fix how many connections a firm has, but vary who they are connected with.[30] We then simulate the potential consequences of the reform in this setting by removing all the links between firms in the financial industry and compute the predicted change in centrality as before. Based on 5000 draws of the network, we re-estimate our main specification for each network and obtain a distribution of estimated coefficients. Average coefficients together with the 2.5^{th} and 97.5^{th} percentiles in square parentheses are displayed in column 4 of Table 5.[31] As expected, in this case coefficients are close to zero and insignificant.

In sum, our key results appear robust to a number of variations over our baseline empirical model. Next, we examine the economic channels underlying this evidence

29 In square brackets we report instead the 2.5^{th} and 97.5^{th} percentiles of the distribution of estimated coefficients. The full distribution is displayed in Figure A.2a.

30 The random links are generated from a so-called configuration model. For more details, see Newman (2018)

31 The entire distribution is shown in Figure A.2b. Note also that this approach does not allow us to test how well the predicted change can forecasts actual changes in the network after the ban as the network would be regenerated randomly at each point in time.

starting with the information channel and then moving to test complementarities with other types of connections between firms.

3.5 The Asymmetric Information 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 this section, we focus on the first channel and explore the heterogeneity in the reaction of firms' valuation in response to the announcement. Specifically, we differentiate firms according to various proxies for the degree of information asymmetry between firms 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 (IVOL), analyst coverage, and the dispersion of analyst earnings forecasts to test for differences in the effect of the policy announcement across firms.

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 (Schutte and Unlu, 2009; Hong et al., 2000). 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). It is constructed as the standard deviation of net income forecasts for 2010, standardized by the book value of assets.[32] Analyst coverage and forecast dispersion data are from IBES.

We re-estimate the baseline specification of equation (3), but now interact the predicted change in centrality Δ with a dummy variable that takes the value one if the value of each of the three measures described above is greater than the sample median. Table 6 shows the results. The effect of changes in network centrality on stock returns appears to be stronger in firms with high idiosyncratic volatility, low analyst coverage, and high dispersion of analyst forecasts. In columns 1 and 3, the estimated coefficient of the interaction terms between ΔCentrality and either the high IVOL or high forecast dispersion dummies are 1.39 and 2.28, respectively, both significant at the 1% level. The interaction term between ΔCentrality and the high analyst coverage dummy is negative as expected (-0.61), but is imprecisely estimated.[33] Taken together, these results imply that firms whose market valuation is less uncertain or for which there is ample and precise external reporting appear to benefit less from boardroom connections.

Next, we explore the heterogeneity in the response of firms' stock market valuation to their position in the input-output and ownership network in order to further corroborate the evidence on the role of the information diffusion channel. Firms that are central in the

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

33 Note that here we additionally include the log of market capitalization and its interaction with ΔCentrality to control for the positive correlation between firm size and analyst coverage (Hong et al., 2000).

input-output network are more exposed to value chain shocks and thus may have more uncertain asset valuation and benefit more from information dissemination.[34] Moreover, 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.

Information can also disseminate via cross-ownership of firms. Owning shares allows investors to gather information about the firm through screening and monitoring, thereby reducing the need for other forms of information transmission. Consequently, if the information channel is driving our results, firms that are more central in the ownership network should be less dependent on a central position in the boardroom network and hence display lower sensitivities to changes in their boardroom centrality.

We proxy for firms' position in the input-output network by using input-output data for the year 2010, aggregated to 62 NACE industries, provided by the Italian National Institute of Statistics (ISTAT).[35] We compute *input-output centrality* at the industry-level as the Katz centrality[36] of the resulting weighted directed input-output network,[37] and proxy for firms' centrality in the input-output network using the industry's centrality in which a given firm operates. Data on the ownership of Italian firms is instead collected from mandatory filings with CONSOB and manually matched to our board data. Our

34 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. More generally, 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).

35 See Appendix E.3 for further details.

36 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.

37 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, 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.

sample of shareholders includes Italian and foreign companies, as well as individuals and asset management firms reported as owners. We compute the Katz centrality for an undirected, weighted network where edges connecting two firms are weighted using the respective ownership stake.[38]

The results displayed in column 4 of Table 6 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, the interaction term between the ΔCentrality and the high input-output network centrality dummy, is 1.16 and significant at the 10% level. 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.

In contrast, estimates in column 5 indicate that firms benefit more from a central position in the boardroom network when they are less central in the ownership network. The coefficient on the relevant interaction term is -1.20, significant at the 5% level. Hence, because cross-ownership helps reduce information asymmetry (Brooks et al., 2018) and serves as an important coordination device (Azar et al., 2018), firms that cannot take advantage of these linkages benefit more from the information flows channeled through the boardroom. In other words, the two networks substitute each other.

3.6 The Learning Channel

In Table 7 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 straightforward. First, we hypothesize that young firms might 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 add

38 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.

to the baseline specification a dummy that takes on the value one if firms' age is above the sample median, as well as its interaction with ΔCentrality in our baseline specification.[39] As shown in column 1, we do not find evidence of a differential response of stock prices for firms of different 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 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, Table 7 additionally includes interactions with proxies aimed at capturing investment opportunities, namely dummies for high sales growth and Tobin's Q. Again, there does not appear to be a differential response related to growth prospects. The coefficients on the interaction terms are imprecisely estimated and are actually negative.

Thus, we find no evidence of a learning channel through board connections. If anything, more established and mature firms appear to exhibit a stronger response to changes in network centrality.

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.[40] This also

39 We also considered firms' research and development expenditures as a candidate measure of uncertainty in the business environment, but unfortunately have this information for only 30% of the firms in our sample.

40 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

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:

$$\log(Compensation_{i,j,t}) = \lambda \times Centrality_{i,t} + \eta_{ij} + \delta_t + \varepsilon_{i,j,t} \tag{4}$$

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. In our preferred tests we do not include other control variables because they could be endogenous but, as Appendix-Table A.4 shows, results remain similar if we control for size, profitability, and Tobin's Q.

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 $Centrality$. This strategy is motivated by the evidence presented in Section 3.2, where we show that the reform has a meaningful effect on realized network centrality after the reform. 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 12,694 directors, whose compensation is hand-collected from mandatory filings with CONSOB obtained either from corporate websites or from the

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.

website of the Italian stock exchange.[41] 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 E. Summary statistics on total compensation are in Panel B of Table 1.

4.2 Network Centrality and Compensation

Panel A of Table 8 presents estimates of the coefficient λ from equation (4).[42] Column 1 shows that a one-standard deviation increase in network centrality is associated with a 6.6% 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 11.7% pay raise (column 2). This estimate is statistically significant at the 5% level. The F-statistic is equal to 47.07, 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 0.11 for the OLS and IV

41 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.

42 Table A.3 reports results of the corresponding reduced-form regressions.

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 8 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 0.49. 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 (0.43 and 0.53, 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 Conclusion

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, there is no evidence that younger firms and companies characterized by lower investment opportunities, which may benefit from learning from others by sharing directors or executives, exhibit exhibit a more pronounced reaction relative 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.

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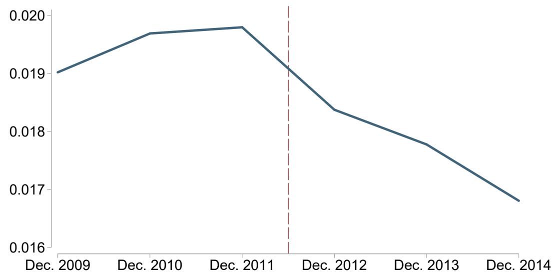
6 Figures and Tables

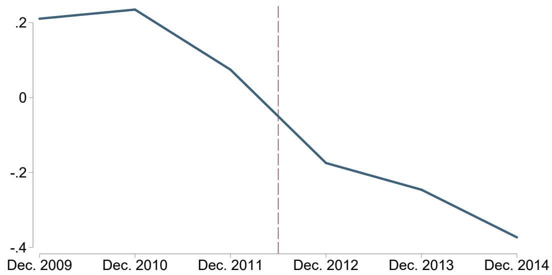
Figure 1
Properties of the Boardroom Network

Panel (a) of Figure 1 plots 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. Panels (b) through (f) plot cross-sectional averages of the corresponding centrality measures for each year. The horizontal dashed lines correspond to June 2012.

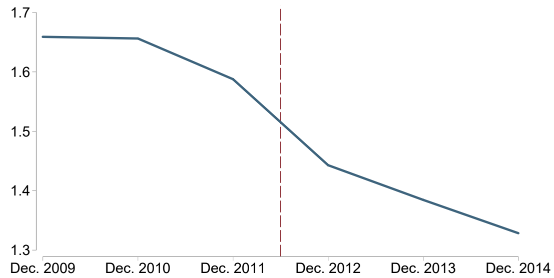
(a) Graph Density



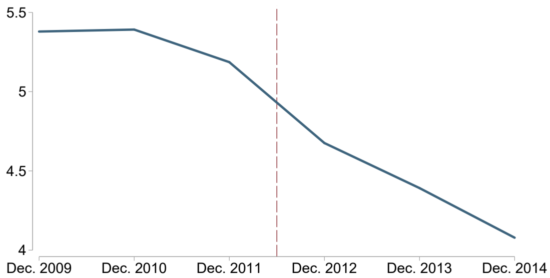
(b) Centrality



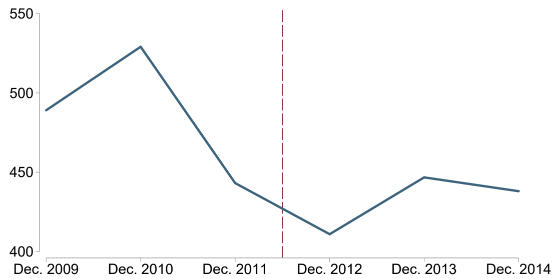
(c) Katz



(d) Degree



(e) Betweeness



(f) Closeness

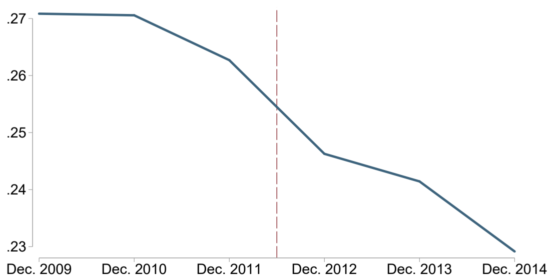


Figure 2
Fictional Corporate Network and Potential Effect of Regulation

Figure 2 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 between Bank A and Bank B. The size of the nodes is proportional to the principal component of the four network measures (Degree, Katz, Closeness, Betweeness) as used in the main analysis.

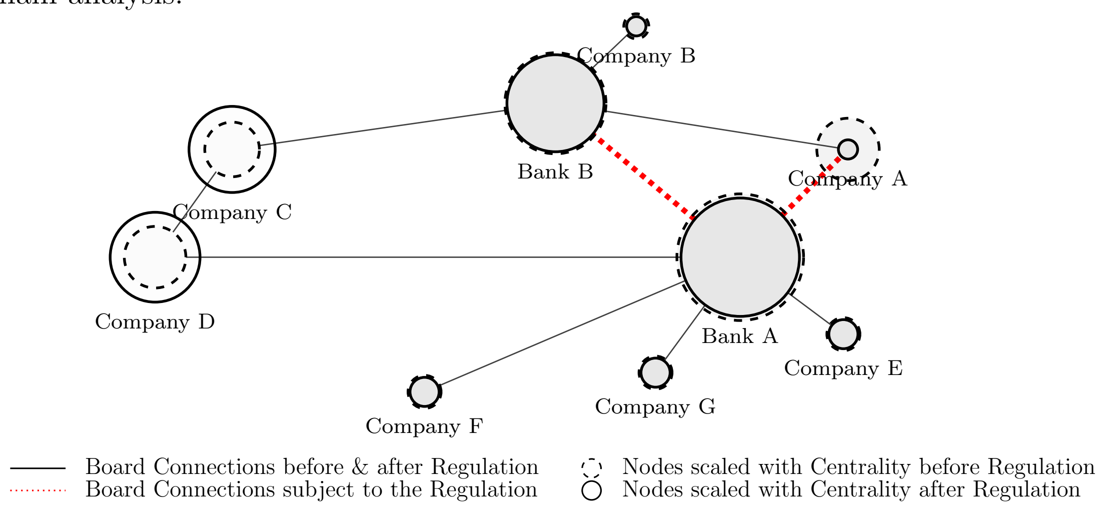


Figure 3
Buy-and-Hold Abnormal Returns around Actual Resignation Dates

Figure 3 shows average buy-and-hold abnormal returns adjusted using the market model around the actual announcement of resignations of interlocked directors. Announcement dates are collected from companies' press releases. The figure plots average buy-and-hold returns around the dates of resignations that we correctly predicted based solely on the information available when the reform was announced (see Section 2.3 for details). Due to delistings, we use data on 24 events. The average buy-and-hold return for companies that are never affected by the reform are plotted as black dashed line. For companies from which board a given director eventually did and did not resign are plotted in blue solid and red solid lines, respectively.

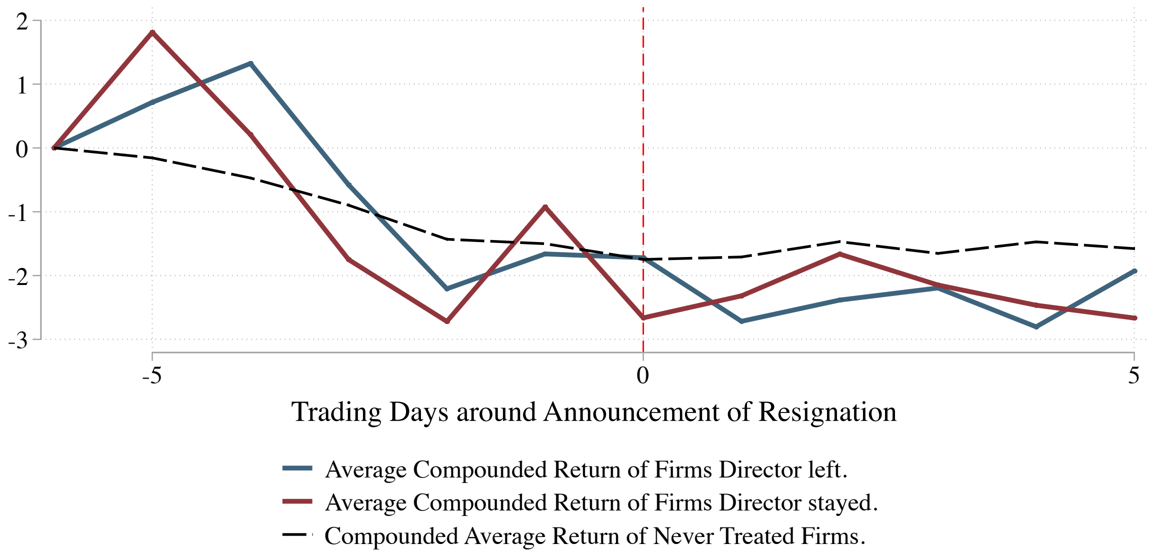


Figure 4
Event Study: Network Centrality

Figure 4 shows coefficients from regressing Centrality on year dummies multiplied by the predicted change in Centrality, Δ, as well as year and firm fixed effects. The coefficients β_t associated with the year dummies interacted with Δ are plotted together with 95% confidence intervals based on robust standard errors. The coefficient corresponding to the reform year, 2011, is normalized to zero.

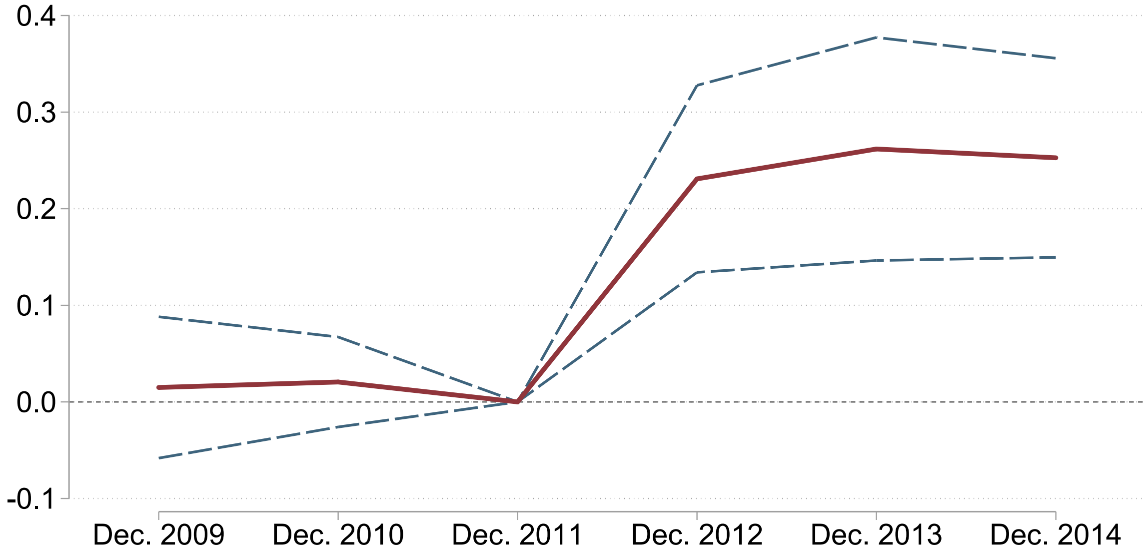


Figure 5
Event Study: Buy-and-Hold Abnormal Returns

Figure 5 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.

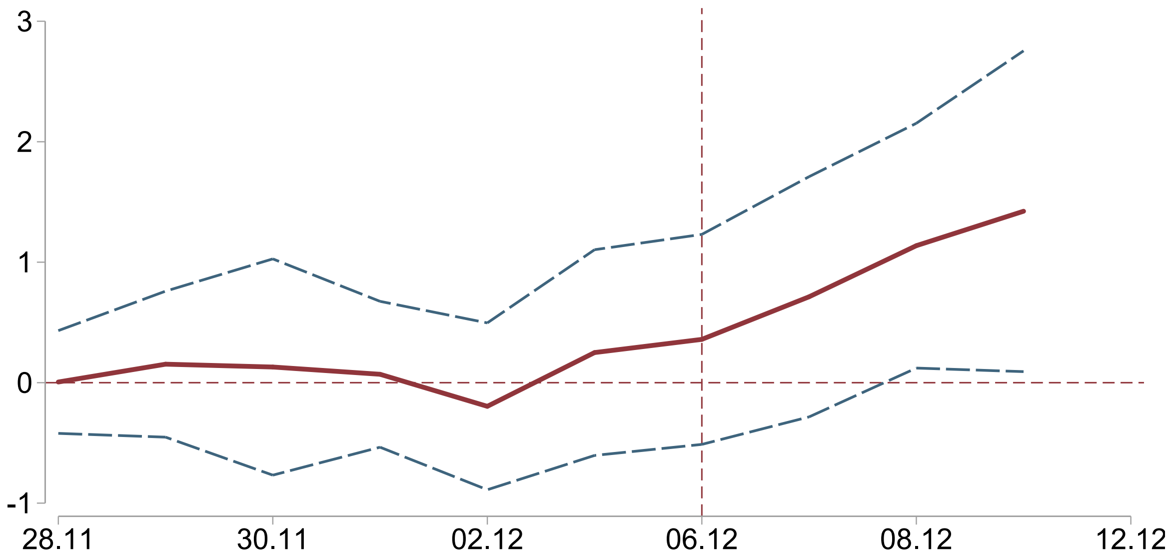


Table 1
Summary Statistics

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 regressions. ΔCentrality is the predicted change in network centrality, where Centrality is the first principal component of degree, Katz Centrality, closeness and betweeness (see Appendix D 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. Number of affected directors is the number of directors at a given firm creating an interlock. Social network centrality is the firm's centrality in the network created by social ties between their board members. 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. Analysts' coverage is the number of analysts covering the firm in the previous calendar year. 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 from 2009 to 2014. Data on total compensation is reported in tens of thousands (see Appendix E for additional details on the data collection).

Panel A. Stock Return Regressions

	Obs.	Mean	Median	St. Dev.	1^{st} P.	99^{st} P.
ΔCentrality	260	−0.25	−0.12	0.43	−2.81	0.07
ΔKatz	260	−0.12	−0.02	0.23	−1.19	0.00
ΔDegree	260	−0.33	0.00	1.08	−7.00	0.00
ΔCloseness	260	−0.01	−0.00	0.02	−0.10	0.00
ΔBetweenness	260	6.22	0.00	220.58	−1,099.22	472.60
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
Number of Affected Directors	260	0.24	0.00	1.03	0.00	5.00
Social Network Centrality	201	−0.01	−0.18	1.93	−3.35	4.33
Idiosyncratic Volatility	260	0.02	0.02	0.01	0.01	0.06
Analysts' Coverage	260	4.80	1.00	7.18	0.00	33.00
St. Dev. of Analysts' Forecasts	124	0.00	0.00	0.01	0.00	0.04
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
Age	257	52.02	37.00	52.71	3.00	186.00
Sales Growth	204	0.08	0.07	0.72	−1.23	1.07

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)	12,694	268.35	63.00	980.84	3.00	2,859.30
Total Compensation (Firm Level)	1,328	236.08	149.66	308.60	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. Robust standard errors 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^{***}	0.241^{***}	0.136^{**}	0.033	0.236^{***}
	(0.049)	(0.043)	(0.067)	(0.023)	(0.039)
Observations	1,514	1,514	1,514	1,514	1,514
R^2	0.903	0.885	0.751	0.798	0.875
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. ΔCentrality, 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(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. Robust standard errors 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)
ΔKatz	1.142***				
	(0.386)				
ΔDegree		0.739*			
		(0.428)			
ΔBetweenness			0.185		
			(0.411)		
ΔCloseness				0.760**	
				(0.296)	
ΔCentrality					0.916**
					(0.408)
log(Total Assets)	-0.373	-0.719	-1.075**	-0.872*	-0.628
	(0.522)	(0.490)	(0.489)	(0.463)	(0.497)
ROA	-0.917	-0.914	-0.867	-0.859	-0.916
	(0.624)	(0.629)	(0.627)	(0.623)	(0.627)
Observations	260	260	260	260	260
R^2	0.150	0.141	0.134	0.143	0.145
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), and in column 4, where they are risk-adjusted using the Fama French three-factor model. The vector of control variables includes size, defined as log(total assets), and ROA, defined as net income divided by lagged total assets. Column 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, measured in 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 the change in firms' centrality in the social network computed as the change of the first principal component of the four centrality measures obtained from directors' social networks in 2012 and 2011, respectively. Each regression includes industry fixed effects, following the Fama-French 17-industry classification. Robust standard errors are displayed in parentheses. ***, **, and * indicate statistically different from zero at the 1%, 5%, and 10% level of significance, respectively.

Varying:	Time Window		Risk Adjustment		Controls and Sample						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
ΔCentrality	1.041**	1.250**	0.913**	0.925**	1.246***	0.919**	0.887**	0.985**	0.772**	1.538***	1.241***
	(0.476)	(0.550)	(0.404)	(0.415)	(0.423)	(0.444)	(0.407)	(0.405)	(0.356)	(0.573)	(0.455)
log(Total Assets)	-1.877**	-1.721*	-0.517	-0.594		0.941	-0.619	-0.407	-0.287	-0.706	0.315
	(0.773)	(0.924)	(0.496)	(0.495)		(0.869)	(0.502)	(0.531)	(0.361)	(0.489)	(0.643)
ROA	-1.422	-1.804	-0.952	-0.865		-0.471	-0.934	-0.819	-0.708	-0.890	-1.808
	(0.959)	(1.232)	(0.626)	(0.626)		(0.605)	(0.620)	(0.731)	(0.455)	(0.635)	(1.377)
Tobin's Q						0.343					
						(0.436)					
log(Market Cap.)						-2.090**					
						(1.038)					
Sovereign Yield Exposure							-0.160				
							(0.440)				
# Aff. Directors										0.820	
										(0.656)	
ΔSocial Network Centrality											-0.457
											(0.356)
Observations	260	260	260	260	260	254	260	225	247	260	159
R^2	0.147	0.148	0.144	0.142	0.118	0.168	0.145	0.127	0.170	0.148	0.272
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
Alternative Definitions of Predicted Change in Network Centrality and Placebo Test

Table 5 tests the robustness of the main results to alternative specifications of the predicted change in network centrality (ΔCentrality) and randomly generated placebo networks. Panel A reports coefficients from a regression of cumulative abnormal returns on ΔCentrality, computed as the predicted change in the first principal component of the four centrality measures. In column 1 the predicted change is derived from a simulated network obtained by deletion of affected directors and in column 2 by deletion of links between firms in the financial industry. The results in column 3 are based on the predicted change in network centrality derived from the random resignation of affected directors based on 5,000 random draws. Results in column 4 are based on 5,000 randomly generated networks constructed from a configuration model. In Panel A coefficients are obtained from a regression of cumulative abnormal returns on the predicted change in network centrality. 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(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. Robust standard errors are displayed in parentheses and 95% confidence intervals in square brackets. Panel B tests the predictive power of Δ, the predicted change in network centrality induced by the reform, in explaining the future evolution of the network. Coefficients are estimated by regressing Centrality on ΔCentrality times a post-reform dummy, computed as described Each regression includes firm and year fixed effects. Standard errors, clustered at the firm level, are displayed in parentheses, and 95% confidence intervals in square parentheses. ***, **, and * indicate statistically different from zero at the 1%, 5%, and 10% level of significance, respectively.

	Director Deletion	Link Deletion	Random Resignations	Placebo Network
	Panel A. Stock Returns			
	(1)	(2)	(3)	(4)
ΔCentrality	0.527	0.658*	0.753***	0.135
	(0.347)	(0.380)	[0.362,1.092]	[-0.747,0.887]
Industry FE	X	X	X	X
Controls	X	X	X	X
	Panel B. Network Centrality			
	(1)	(2)	(3)	(4)
ΔCentrality$\times\mathbb{1}(t >$ Dec. 2011$)$	0.219***	0.240***	0.231***	-
	(0.045)	(0.033)	[0.208,0.252]	(-)
T-Statistic	4.86	7.29	5.69	-
Firm FE	X	X	X	X
Time FE	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 interacted with firm characteristics. Cumulative abnormal returns are calculated over a three-day window surrounding the announcement date and are risk-adjusted using the market model. Firm characteristics are IVOL (column 1), analysts' coverage (columns 2), standard deviation of earnings forecasts (columns 3), centrality in the input-output network (columns 4) and centrality in the cross-ownership network (columns 5). Idiosyncratic volatility (IVOL) is estimated by regressing, for each firm, the 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. Analysts' coverage is the number of analysts covering the firm in the previous calendar year. Standard deviation of forecasts is the standard deviation of analysts' net income forecasts in the previous calendar year divided by total assets. Input-output network centrality is the Katz centrality in the input-output network, where weights are the input flows from sector i to j relative to sector j's input demand, while ownership network centrality is the Katz centrality in the cross-ownership network, where weights correspond to the respective ownership stake. Each firm variable is included as a dummy variable that takes on the value one if a measure is above the respective sample median. Each regression includes industry fixed effects, following the Fama-French 17-industry classification, and the vector of control variables includes size, defined as log(total assets), and ROA, defined as net income divided by lagged total assets. Column 2 additionally includes the log of market capitalization and its interaction with ΔCentrality (not shown). Robust standard errors are displayed in parentheses. ***, **, and * indicate statistically different from zero at the 1%, 5%, and 10% level of significance, respectively.

	(1)	(2)	(3)	(4)	(5)
ΔCentrality	0.449	2.438***	0.535	0.351	1.606***
	(0.329)	(0.729)	(0.600)	(0.468)	(0.408)
High IVOL	2.021**				
	(0.888)				
High IVOL × ΔCentrality	1.387***				
	(0.470)				
High Analysts' Coverage		-0.347			
		(1.020)			
High Analysts' Coverage × ΔCentrality		-0.611			
		(0.537)			
High St. Dev. Forecasts			0.530		
			(1.170)		
High St. Dev. Forecasts × ΔCentrality			2.275***		
			(0.802)		
High IO Network Centrality				1.929	
				(1.390)	
High IO Network Centrality × ΔCentrality				1.156*	
				(0.622)	
High Ownership Network Centrality					-0.448
					(0.843)
High Ownership Network Centrality × ΔCentrality					-1.203**
					(0.469)
Observations	260	254	124	260	260
R^2	0.168	0.177	0.220	0.161	0.153
Industry FE	X	X	X	X	X
Controls	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 interacted with firm characteristics. Cumulative abnormal returns are calculated over a three-day window surrounding the announcement date and are risk-adjusted using the market model. Firm characteristics are firm age (column 1), sales growth (column 2), and Tobin's Q (column 3). 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 net income divided by lagged total assets. Each firm variable is included as a dummy variable that takes on the value one if a measure is above the respective sample median. Each regression includes industry fixed effects, following the Fama-French 17-industry classification. Robust standard errors are displayed in parentheses. ***, **, and * indicate statistically different from zero at the 1%, 5%, and 10% level of significance, respectively.

	(1)	(2)	(3)
ΔCentrality	0.700	1.566*	1.169**
	(0.658)	(0.817)	(0.515)
High Age	-0.829		
	(0.821)		
High Age × ΔCentrality	-0.024		
	(0.676)		
High Sales Growth		0.168	
		(0.846)	
High Sales Growth × ΔCentrality		-2.735*	
		(1.637)	
High Tobin's Q			-2.175**
			(0.900)
High Tobin's Q × ΔCentrality			-0.872
			(0.570)
Observations	257	204	254
R^2	0.149	0.123	0.164
Industry FE	X	X	X
Controls	X	X	X

Table 8
Executives' and Directors' Compensation

Table 8 shows coefficients from regressions of log(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(total compensation) and standard errors are clustered at the firm level. All the regressions include year fixed effects, together with director-year or firm fixed effects in Panels A and B, respectively. ***, **, and * indicate statistically different from zero at the 1%, 5%, and 10% level of significance, respectively.

Panel A. Director-Level Regressions

	All		High-Rank		Low-Rank	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Centrality	0.066***	0.117**	0.030	0.167	0.093***	0.108**
	(0.024)	(0.051)	(0.042)	(0.139)	(0.026)	(0.046)
Observations	12,694	12,694	3,191	3,191	9,340	9,340
R^2	0.915	0.001	0.892	-0.007	0.898	0.004
F-Stat		47.067		31.148		46.107
Director-Firm FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X

Panel B. Firm-Level Regressions

	All		High-Rank		Low-Rank	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Centrality	0.041	0.486**	0.145**	0.429**	0.050	0.526***
	(0.050)	(0.209)	(0.058)	(0.188)	(0.050)	(0.184)
Observations	1,328	1,328	1,317	1,317	1,325	1,325
R^2	0.839	-0.204	0.803	-0.027	0.838	-0.198
F-Stat		37.656		38.087		37.666
Firm FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X

Appendix

This appendix presents additional results, details, and definitions omitted from the main text for brevity. Appendix A presents additional robustness checks to account for how the role of board connections to banks may affect the interpretation of the results. Appendix B presents additional results and robustness checks. Figure A.1 displays the full distribution of coefficients obtained from simulating 5000 random resignations in Panel (a) and the full distribution of coefficient obtained from the Placebo exercise in Panel (b). (See Section 3.4 for details.) Table A.2 replicates the baseline empirical analysis without adopting any correction for outliers, or by winsorizing ΔCentrality at the 1%, 2.5%, and 5% level. Table A.3 presents reduced-form results for the executives' and directors' compensation regressions. Table A.4 replicates the baseline analysis on executives' and directors' compensation but includes, as control variables, the logarithm of total assets, ROA, and Tobin's Q. Appendix C presents an example from the actual network of Italian listed firms. Appendix D gives formal definitions of the centrality measures used in the main text. Appendix E has details regarding the data collection and the calculation of option values. Appendix F describes the procedure for the risk adjustment of stock returns. Appendix G has definitions for all the variables used in the empirical analysis.

A Bilateral Connections

This section explores the possibility that the effects we find in our baseline analysis are due to the reform affecting primarily the formation of bilateral connections, in particular with firms in the financial industry. This is motivated by findings in, among others, Engelberg et al. (2012) or Karolyi (2018), who show that existing bilateral ties between non-financial firms and their banks can reduce their cost of debt. To test this explanation, we analyze the firm network of shared directors just before the reform to compute the distance between any two firms as the smallest number of edges from one node, i.e., firm, to another. We account for firms that are not part of the largest connected component by top-coding the distance at ten step such that also unconnected firms (infinitely many steps apart) are assigned a distance of ten. We see this a reasonable upper bound, given that only two firms are connected but more than 10 steps apart.

Based on these measures, we compute for each firm the average distance to: (i) other firms belonging to the banking sector, as defined according to the 49-industry Fama-French classification, (ii) firms belonging to the financial industry as defined according to the 17-industry Fama-French classification, or (ii) firms directly affected by the reform. Similarly, we recompute all three measures based on the simulated effect of the reform on the firm network, as described in the main text. Finally, analogously to the main analysis, we isolate exogenous changes in the distance between firms by defining ΔDistance as the difference between the distance computed from the simulated network and the actual pre-ban network (see Section 2.3). Table A.1 displays the effect of the predicted changes in bilateral connections with the financial sector.

In columns 1, 3, and 5, we find that an increase in the distance between a firm and a financial firm, ΔDistance, has a negative effect on stock returns. This effect is relatively large but imprecisely estimated and is further reduced once we include in the regressions also ΔCentrality, our key measure (in columns 2, 4, and 6). The latter retains its predictive power for stock returns, aside from a slight loss in statistical precision.

Table A.1
Bilateral Connections

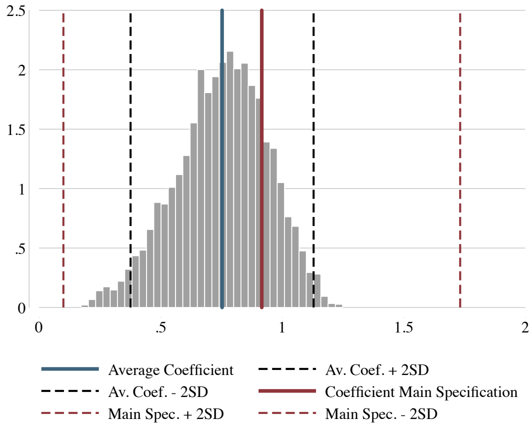
Table A.1 shows coefficients from a regression of cumulative abnormal returns on the predicted change in network centrality. Cumulative abnormal returns, risk-adjusted using the market model, are calculated over a three-day window surrounding the announcement date. Distance is computed as the average path length between firms, i.e., as the smallest number of edges from one firm to another based on the boardroom network just before the reform. The predicted change in distance, ΔDistance, is the difference between the average distance computed from the simulated effect of the reform on the network and the actual network. Results for the average change in the distance to a bank as defined in the 49-industry Fama-French classification is in columns 1 and 2, to firms belonging to the financial industry as defined in the 17-industry Fama-French classification in columns 4 and 5 and to firms directly affected by the reform in columns 5 and 6. Each regression includes a vector of control variables controlling for size, defined as log(total assets), and ROA, defined as net income divided by lagged total asset and industry fixed effects, following the Fama-French 17-industry classification. Robust standard errors are displayed in parentheses. ***, **, and * indicate statistically different from zero at the 1%, 5%, and 10% level of significance, respectively.

	Banks		Financial Industry		Affected	
	(1)	(2)	(3)	(4)	(5)	(6)
ΔCentrality		0.814*		0.796*		0.756*
		(0.425)		(0.444)		(0.431)
Δ Distance	-0.570	-0.389	-0.571*	-0.343	-0.702*	-0.498
	(0.396)	(0.407)	(0.336)	(0.355)	(0.360)	(0.375)
Observations	260	260	260	260	260	260
R^2	0.139	0.147	0.139	0.147	0.142	0.148
Industry FE	X	X	X	X	X	X
Controls	X	X	X	X	X	X

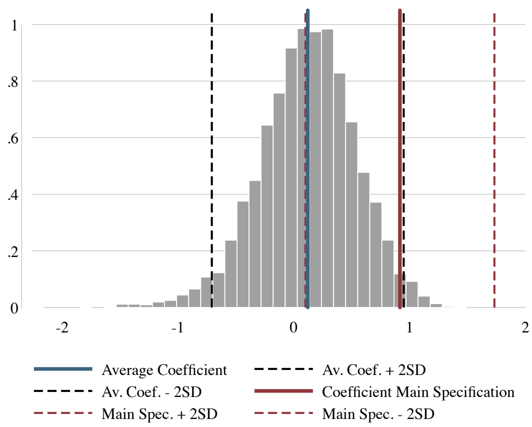
B Additional Results

Figure A.1
Random Resignations and Placebo Networks

Panel (a) Figure A.1 of plots the distribution of coefficients obtained from 5,000 simulations removing directors from their board seats at random to resolve any interlocks between firms in the financial industry that are banned by the reform. Panel (b) plots the distribution of coefficients obtained from 5000 randomly generated networks from a configuration model. For each draw (in both panels), coefficients are obtained from a regression of cumulative abnormal returns on the predicted changes in centrality, ΔCentrality, computed as the predicted change in the first principal component of the four network 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(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.



(a) Estimated Coefficients - Random Resignations



(b) Estimated Coefficients - Placebo Networks

Table A.2
Outliers in the Independent Variable

Table A.2 shows coefficients from a regression of cumulative abnormal returns on the predicted change in network centrality, ΔCentrality. Cumulative abnormal returns are calculated over a three-day window surrounding the announcement date and are risk-adjusted using the market model. ΔCentrality is included unwinsorized in column 1 and winsorized at the 1% (column 2), 2.5% (column 3) and 5% level (column 4).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. Robust standard errors are displayed in parentheses. ***, **, and * indicate statistically different from zero at the 1%, 5%, and 10% level of significance, respectively.

	None	1%	2.5%	5%
	(1)	(2)	(3)	(4)
ΔCentrality	1.872*	0.916**	0.880**	0.759*
	(0.997)	(0.408)	(0.418)	(0.392)
Observations	260	260	260	260
R^2	0.143	0.145	0.143	0.141
Industry FE	X	X	X	X
Controls	X	X	X	X

Table A.3
Compensation — Reduced Form-Results

Table A.3 shows coefficients from reduced-form regressions corresponding to results in Table 8 obtained from regressions of log(total compensation) on the instrument defined as the predicted change in network centrality multiplied by the post-reform dummy. In columns 1, 2 and 3 the unit of observation is a director-year and in columns 4, 5 and 6 the dependent variable is the average of log(total compensation). Network centrality is derived from the firm-level network. Column 1 and 3 uses data on all board members, while columns 2 and 4 include only high-ranked directors (CEO, President and Vice-President), and columns 3 and 6 include the remaining directors. Standard errors are double-clustered at the firm and director level (columns 1,2, and 3) or at the firm level (columns 4,5, and 6) and displayed in parentheses. ***, **, and * indicate statistically different from zero at the 1%, 5%, and 10% level of significance, respectively.

	Director-Firm Level			Firm Level		
	All	High-Rank	Low-Rank	All	High-Rank	Low-Rank
	(1)	(2)	(3)	(4)	(5)	(6)
ΔCentrality$\times$	0.034**	0.047	0.030**	0.144**	0.129**	0.157***
$\mathbb{1}(t >$ Dec. 2011$)$	(0.015)	(0.036)	(0.015)	(0.060)	(0.058)	(0.052)
Observations	12,694	3,191	9,340	1,328	1,317	1,325
R^2	0.915	0.892	0.898	0.844	0.803	0.843
Director-Firm FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X

Table A.4
Compensation with Firm-Level Controls

Table A.4 shows coefficients from regressions of log(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. All regressions include lagged values of firm size, measured as the log of total assets, profitability, measured as the return on assets, and Tobin's Q. 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(total compensation) and standard errors are clustered at the firm level. All the regressions include year fixed effects, together with director-year or firm fixed effects in Panels A and B, respectively. ***, **, and * indicate statistically different from zero at the 1%, 5%, and 10% level of significance, respectively.

Panel A. Director-Level Regressions

	All		High-Rank		Low-Rank	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Centrality	0.066***	0.098*	0.040	0.141	0.090***	0.097**
	(0.025)	(0.050)	(0.043)	(0.133)	(0.027)	(0.046)
log(Total Assets)	0.159	0.153	0.346*	0.332	0.049	0.047
	(0.174)	(0.175)	(0.194)	(0.203)	(0.182)	(0.182)
ROA	0.001	0.001	0.024	0.026	-0.002	-0.002
	(0.022)	(0.022)	(0.028)	(0.028)	(0.020)	(0.020)
Tobin's Q	-0.011	-0.010	-0.012	-0.008	-0.019	-0.019
	(0.020)	(0.021)	(0.027)	(0.027)	(0.021)	(0.021)
Observations	12,224	12,224	3,091	3,091	8,979	8,979
R^2	0.916	0.002	0.892	0.002	0.898	0.005
F-Stat		50.387		33.493		49.289
Director-Firm FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X

...*Table A.4 continued from previous page*

Panel B. Firm-Level Regressions						
	All		High-Rank		Low-Rank	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Centrality	0.061	0.422**	0.160***	0.381**	0.071	0.467***
	(0.050)	(0.190)	(0.058)	(0.174)	(0.049)	(0.166)
log(Total Assets)	0.105	0.025	0.134	0.084	0.115	0.027
	(0.134)	(0.161)	(0.207)	(0.221)	(0.149)	(0.176)
ROA	-0.006	-0.006	0.029	0.029	-0.005	-0.004
	(0.031)	(0.032)	(0.031)	(0.030)	(0.032)	(0.032)
Tobin's Q	-0.024	-0.006	-0.029	-0.018	-0.016	0.003
	(0.028)	(0.032)	(0.038)	(0.039)	(0.030)	(0.034)
Observations	1,272	1,272	1,263	1,263	1,269	1,269
R^2	0.852	-0.146	0.802	-0.007	0.852	-0.149
F-Stat		45.847		45.941		45.859
Firm FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X

C Example of the Actual Italian Boardroom Network

Figure A.3 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 the 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 A.5 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 A.3

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

Figure A.3 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.

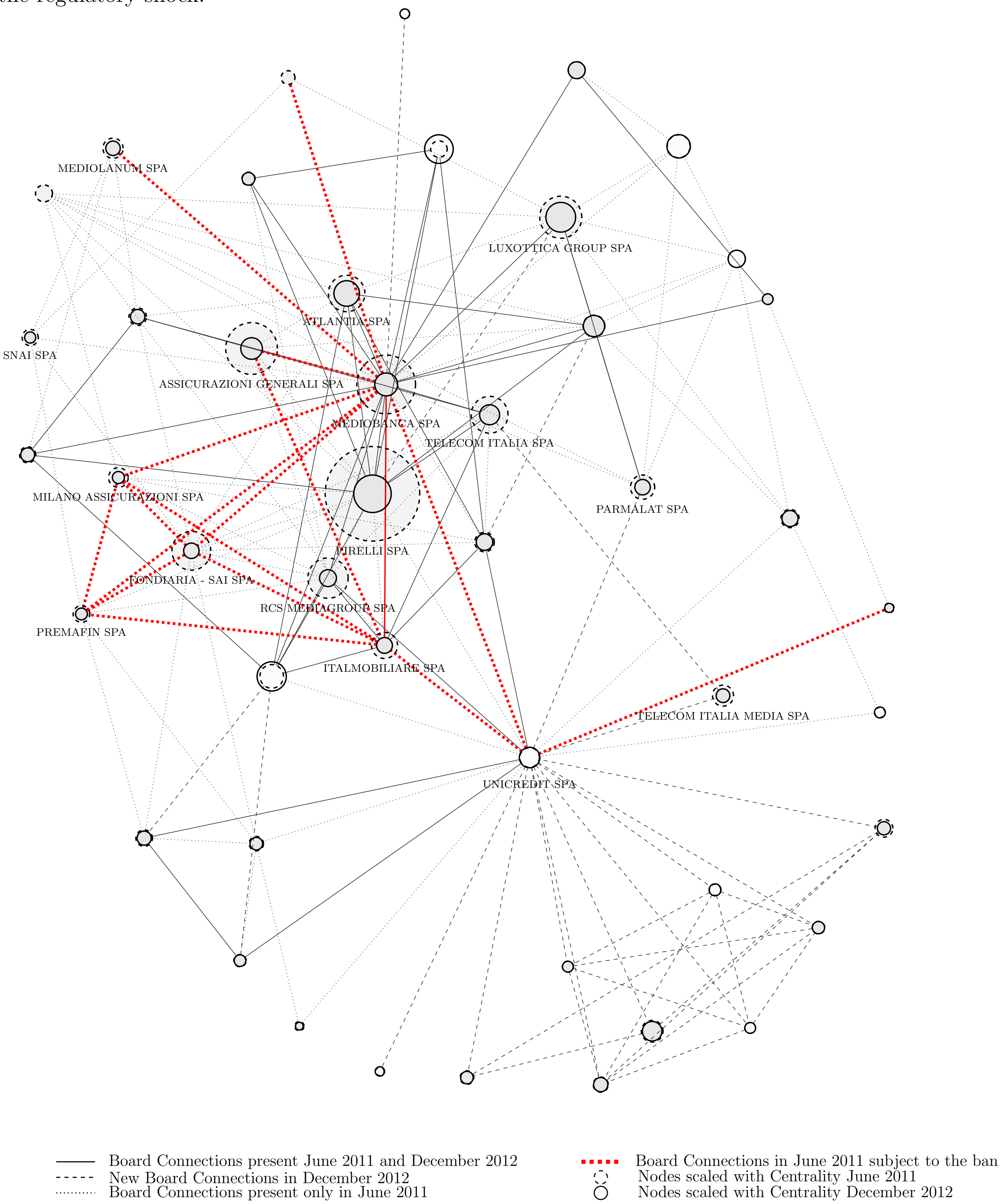


Table A.5
Changes in Centrality for Network Example

Table A.5 shows values of centrality as used in the main analysis for firms in the network of the first-degree neighbours of Mediobanca Spa and Unicredit Spa (displayed in Figure A.3) 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)
MEDIOBANCA SPA	Banks, Insurance, Finance	8.437	3.728
PIRELLI SPA	Other	10.820	6.191
FONDIARIA - SAI SPA	Banks, Insurance, Finance	6.372	1.761
ASSICURAZIONI GENERALI SPA	Banks, Insurance, Finance	7.811	3.437
RCS MEDIAGROUP SPA	Other	6.557	2.221
TELECOM ITALIA SPA	Other	6.105	3.053
ITALMOBILIARE SPA	Construction	4.384	1.863
MILANO ASSICURAZIONI SPA	Banks, Insurance, Finance	2.973	0.509
PARMALAT SPA	Food	4.015	1.765
TELECOM ITALIA MEDIA SPA	Other	3.305	1.154
⋮	⋮	⋮	⋮
INDESIT COMPANY SPA	Consumer Durables	2.296	2.310
VIANINI LAVORI SPA	Construction	–0.063	–0.024
INTERPUMP GROUP SPA	Machinery& Business Equipment	3.722	3.843
EL EN SPA	Other	–0.749	–0.583
CEMENTIR HOLDING SPA	Construction	0.232	0.468
UNICREDIT SPA	Banks, Insurance, Finance	2.950	3.187
ASTALDI SPA	Construction	–0.268	0.024
VALSOIA SPA	Food	–1.223	–0.733
ITALCEMENTI SPA	Construction	3.877	4.950
PRELIOS SPA	Banks, Insurance, Finance	2.095	4.842

D Definition of Centrality Measures

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

Degree centrality is formally defined as:

$$d_i = \sum_{j \neq i} a_{ij}, \tag{5}$$

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:

$$k_i = \alpha \sum_j a_{ij} k_j + \beta \tag{6}$$

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:

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

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:

$$b_i = \sum_{s,t} n^i_{s,t}, \tag{8}$$

where $n^i_{s,t}$ 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.

E Data Collection

E.1 Board-Level 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.

E.2 Compensation Data Collection

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.

E.3 Input-Output Data

We match our sample of firms to NACE codes provided by ISTAT using official crosswalks available from Eurostat's RAMON database to Compustat's NAICS codes 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.

F Risk-Adjusted Returns

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`) and estimate the following equation:

$$R_{it} - R_f = \alpha_i + \beta_{i,m}\left(R_{m,t} - R_f\right) + \beta_{i,SMB} SMB_t + \beta_{i,HML} HML_t + \epsilon_{it}, \tag{9}$$

where R_f is the risk-free rate, $R_{m,t}$ is the market return, SMB and HML measure the excess returns of small caps over big caps and of value stocks over growth stocks respectively. The loadings on the market, size, and value factors are estimated, for each stock, over a $(-300, +46)$-day window. Fama-French adjusted returns are obtained from estimating Equation (9), and market-adjusted returns in the main text are obtained from estimating Equation (9) excluding the size and value factors.

G Variables Definitions

Table A.6
Variables Definitions

Variable	Definition	Source
Total Assets	Total Assets (*at*)	Compustat Global
ROA	Income Before Extraordinary Items (*ib*) divided by lagged total Assets (*at)*	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 (*at*) plus Market Value of Equity minus Common Value of Equity (*ceq*) all divided by Total Assets	Compustat Global & Datastream
Sales Growth	Log growth rate of Sales (*sale*); 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
Analyst Coverage	The number of analysts covering the firm in 2010	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	Online sources (esp. corporate websites, Wikipedia)
IO Network Centrality	Katz Centrality computed from Italian Input-Output Network	ISTAT
Ownership Network Centrality	Katz Centrality computed from data on ownership stakes in listed Italian companies	CONSOB
Centrality Social Network	First principal component of Katz centraliy, degree, closeness and betweeness computed based on directors' social & professional networks	BoardEX
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 (*compensi fissi*) + bonus payments (*bonus*) + non-monetary benefits (*benefici non-monetari*) + other compensation (*altri compensi*) + value of stock and option grants	Borsa Italiana & Company Reports