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Mario Schabus
University of Melbourne
mario.schabus@unimelb.edu.au

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Abstract

I examine whether directors' superior access to information and resources through their board network improves the quality of firms' planning and forecasting. Managers may benefit from well-connected directors as, even though managers have firm specific knowledge, they may have only limited insight into the decision-making processes of other firms. Employing a first-difference specification, I find that managers of firms with better connected directors can plan more accurately (i.e., realized profits are closer to managers' planned profits). Based on a final sample of 5,576 observations, for U.S.-firms spanning the years 2002 to 2013, I find that a one standard deviation increase in board centrality increases earnings forecast accuracy by around 8 percent. In addition, more central firms make more accurate one-year ahead predictions of sales and capital expenditures. Overall, these firms have smaller positive and negative forecast errors. Cross-sectional analyses indicate that relatively more complex firms (i.e., firms with likely higher advisory needs), and firms with a high proportion of advisory directors benefit from networked directors. The findings suggest that networked directors provide managers with valuable advice. This planning role of directors complements their more extensively studied role in preventing expropriation by managers.

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1. Introduction

Accurate forecasting is a different task for managers compared to external parties such as analysts. While analysts primarily use their knowledge to accurately guess future earnings, managers have to plan business activities properly to make sure that realized earnings from these planned business activities do yield the profit level that managers had initially forecasted. In this process, it can be informative for managers to assess the behavior of other firms. For example, because a firm shares the same input and product markets as its competitors, information about how competitors perceive and react to developments will also be relevant for firm's outlook. Not considering this may lead to misforecasted sales and costs. In this study, I assess whether greater access to information about decision-making, strategies, and operations of other firms, through director networks, helps managers to make better plans and forecasts.[1] Following Larcker, So and Wang (2013) I focus on directors with large corporate networks, who are likely to have this information.

Well-connected directors have access to decision-making, strategies and operations of multiple firms. They can obtain insights into other managers' estimates of, and reactions to, external shocks, and can seek advice from other highly competent and connected directors. These directors have a better general understanding of competitors behavior, and can reinterpret publicly available information released by competitors in a way useful for current firms' management in their planning and forecasting. Managers may also benefit from subordinates' specific knowledge; however, subordinates are unlikely to have high-level understanding of public information and how it relates to the planning process of the focal firm. While prior literature extensively studied the directors' role in preventing rent extraction, we know little about their role in helping managers in planning and forecasting. I study the role of well-networked directors specifically in the context of management earnings forecasts because on average managers benefit from accurate forecasts (Lee et al. 2012; Trueman 1986;

[1]Firms rarely disclose detailed operational and strategic plans but they often provide earnings forecasts. As pointed out in Goodman, Neamtiu, Shroff and White (2013) and Lee, Matsunaga and Park (2012), forecasting earnings accurately requires managers' in-depth knowledge about firms' internal and external information environments, and capabilities in information processing and aggregation. These skills are likely *primarily* beneficial for strategic and operational decision making, as opposed to communication with capital market participants (Goodman et al. 2013).

Williams 1996), and therefore, in this setting, directors' role in advising management may be specifically relevant.[2]

My initial sample contains all U.S.-listed companies covered by BoardEx, spanning the years 2002 to 2013, with management earnings forecast data available in I/B/E/S, and non-missing data on firm fundamentals. To explore the impact of directors' professional board connections, I build a yearly firm-to-firm network, where two firms are connected if, in a given year, they share at least one director. A firm's position within this network can be described in terms of its board centrality: more central firms are linked via interlocking directorates to well-connected other firms. Central firms have relatively more direct and indirect connections, resulting in faster access to other firms in the network. These firms would, therefore, benefit the most from being part of the network. I hypothesize that these firms make better plans and forecasts (i.e., under or over budget less) as reflected by the accuracy of their first annual earnings forecast.

Based on a final sample of 5,567 firm-year observations, I find that an annual change in board centrality is predictive of an annual change in management forecast accuracy. A one standard deviation increase in centrality enhances the accuracy of the first annual management earnings forecast by 8 percent (evaluated at the mean of absolute annual changes in forecast accuracy).[3] I find that the positive network effect stems from reductions in both absolute positive (i.e., realization is higher than forecast) and absolute negative earnings forecast errors. Corroborative evidence shows that firms with networked directors also have more accurate revenue forecasts, and project their one-year ahead capital expenditures better.

Next, I test whether the relation between board centrality and management earnings forecast accuracy may be attributed to a causal link. First, I exploit quasi-exogenous varia-

[2]Managers can reap relatively higher personal benefits from perks, abnormally high compensation packages, or opportunistic capital investments or mergers and acquisitions (M&A). Under specific circumstances managers primary goal when investing or engaging in M&As may be empire-building instead of shareholder-value maximization [e.g., see El-Khatib, Fogel and Jandik (2015), footnote 2]. My findings do not suggest that the relation between more accurate forecasts and well-connected boards is driven by opportunistically or strategically biased forecasts, or earnings management to meet management forecasts.

[3]I compare the magnitude of this network effect to results in other work on management earnings forecast accuracy and corporate directors in Section 4.2.

tion in the network. Following Larcker et al. (2013), I keep the board composition and direct connections of a focal firm stable and examine the relation between a focal firm's earnings forecast accuracy and a change in higher degree connections. For this subsample, any annual change in a focal firm's centrality is likely not endogenous, and therefore represents an external shock to its position in the board-network. I continue to find support for my hypothesis in this subsample. Second, in placebo tests, I assess whether earnings forecast accuracy relates to future board centrality. I do not find significant results, which is not suggestive of reverse causality (i.e., unobserved firm-quality, potentially correlated with accuracy, does not drive centrality). Third, I examine whether a change in board centrality is either solely correlated with accuracy of the subsequent earnings forecast, or if it is also correlated with the accuracy of earnings forecasts of successive one-year and two-year fiscal-years. I do not find support for the latter. This suggests that changes in board centrality have an immediate effect on firms' planning and forecasting.

I apply cross-sectional tests to investigate potential mechanisms through which directors networks can relate to better planning and ultimately to more more accurate earnings forecasts. First, the relation between board centrality and earnings forecast accuracy varies predictably with firm characteristics that likely capture the complexity of planning and forecasting. These results indicate that if a firms' advisory needs are relatively high, directors' connections have a more pronounced impact on the quality of the firms' plans and forecasts. Second, the relation between board centrality and forecast accuracy is higher if a set of measures for directors' advisory efforts (based on board committee structure and co-option) are relatively high. Therefore, directors' connections may matter more for firms' planning and earnings forecasts if directors likely put more effort into advising management.

Finally, I test several further alternative hypotheses and probe the robustness of the main results to various definitions of board centrality and earnings forecast accuracy. Controlling for CEO or CFO fixed effects, director characteristics, and earnings management to increase accuracy, does not alter inferences; neither does employing alternative scalars of forecast accuracy, nor altering the nature of the board centrality variable. The wealth of the results provides me with some confidence that well-networked directors give valuable advice that causes managers to plan better, and hence enables managers to release a more accurate first annual earnings forecast.

My paper adds to existing literature in the following ways; first, I contribute to research on directors' role in advising management. Directors play a role in safeguarding shareholders' assets, however, only recently has more attention been drawn to directors' role in productively supporting managerial decision making (Brickley and Zimmerman 2010; Fama and Jensen 1983; Hermalin and Weisbach 1998; Schwartz-Ziv and Weisbach 2013). Second, this work extends literature on board centrality. Results in Larcker et al. (2013) and Horton, Millo and Serafeim (2012) suggest a positive relation between board centrality and future firm performance but provide little insight into specific channels underlying this relation. More specifically, I follow the call of Adams, Hermalin and Weisbach (2010) to examine the networks of directors with multiple board seats (page 99). Findings in Core, Holthausen and Larcker (1999), Falato, Kadyrzhanova and Lel (2014), Fich and Shivdasani (2006), and Perry and Peyer (2005) suggest that these directors are too distracted and busy to add value to each of their single employers. On the other hand, Fama and Jensen (1983), Ferris, Jagannathan and Pritchard (2003), and Field, Lowry and Mkrtchyan (2013) conclude that directors with multiple board assignments can add value.

Third, the paper adds to work on managers' ability to provide high quality forecasts (Baik et al. 2011; Goodman et al. 2013; Lee et al. 2012; Trueman 1986). Specifically, we know little about how the quality of management forecasts can be affected by individuals with firm-specific and market-wide knowledge (in other words, directors with a large professional network). In a related working paper, Ke, Li and Zhang (2015) find that interlocking directorates with firms in related (i.e., upstream or downstream) industries relate to management forecast accuracy. As further elaborated on in Section 2.3, this work is distinct from Ke et al. (2015) since here the influence of firms' board networks is not restricted to connections into related industries (which can be especially relevant for firms operating in multiple business and geographic segments). Also, examining first-degree connections only provides an incomplete picture of the aggregate network effects (Larcker et al. 2013); even in cases where intra-industry interlocks are prohibited by law, higher degree connections within the same industry are not.

2. Background and Hypothesis

2.1. Planning and Earnings Forecast Accuracy

Managers draw on similar skills when preparing externally disclosed forecasts and steering the fortunes of a firm; for example, information about internal operations, such as cost structure, capacity constraints, margins, and personnel developments, is required to be able to both disclose an accurate earnings forecast and also to optimize operations (Goodman et al. 2013). Similarly, Trueman (1986) concludes that managers aim to signal their type by voluntarily releasing earnings forecasts. Related, Baik et al. (2011) find that management earnings forecast accuracy correlates with various measures of CEO ability, and Goodman et al. (2013) find that it is predictive of more profitable capital investments and M&As. Finally, Lee et al. (2012) show a relation between high forecast errors and CEO turnover, which indicates that directors interpret management forecast accuracy as a signal of CEOs' ability. In order to achieve the profit forecasted at the beginning of the period by the manager, meticulous planning of business activities is required (because, for example, over-, and under-budgeting can be costly (Cassar and Gibson 2008)). In essence, management earnings forecast accuracy should be indicative about how well managers craft strategic and operational plans.[4]

Managers can attempt to collect and interpret all public information relevant to accurately plan and forecast. However as this is costly, managers conductively must seek support by outside parties such as consultants, lower level employees or corporate directors. Directors may be specifically useful because they generally have firm-specific knowledge and a high-level understanding of other firms' behavior in light of unfolding market developments. This enables them to complement the managers' information set, and reinterpret public information in a way useful for a given firms' management to plan and forecast.

[4]Profits disclosed in management forecasts may not reflect the true expected profit because it may be purposefully biased by managers to influence capital market participants. For example, management may communicate bad news to depress prices around stock option award periods (Aboody and Kasznik 2000), or to benefit from insider trading (Rogers and Stocken 2005). Also, firms may issue downward-biased forecasts to walk-down market expectations and increase the probability to beat their own forecast (Cotter, Tuna and Wysocki 2006; Matsumoto 2002). I address alternative explanations in the empirical section.

2.2. Board Networks

Directors with multiple board seats likely have this high-level understanding of competitors' behavior and markets. This is supported by literature on trading strategies linked to well-connected directors. For example, Berkman, Koch and Westerholm (2017) find that directors make above-average profitable trades in stocks of firms to which they are second-degree connected (and thus do not classify as insider). Next, Akbas, Meschke and Wintoki (2016) find that sophisticated traders (short-sellers, institutional investors and option traders) exploit information transmitted by well-connected directors.Also, descriptive evidence suggests that these directors get timely access to knowledge and up-to-date market information, they learn from colleagues about practices on other boards, and they observe adoptions and failures in other firms. Well-connected directors can apply acquired knowledge or expertise in the context of their employer (Carpenter and Westphal 2001; Charan, Carey and Useem 2014), and anecdotally they see board appointments as a way to scan the environment for timely and pertinent information (Useem 1984).[5] Firms seem to value the contacts that well-connected directors bring to management (Mace 1986). For example, following an appointment of a new director, a press release by Eli Lilly notes: "A successful business leader with experience on four continents, Sir Win Bischoff brings to our board his extensive global perspective, network and financial skills... Win will be an invaluable asset in helping us achieve global leadership."[6]

To holistically capture directors' or boardroom connections, I take a bird's-eye view on board-interlocks by drawing conceptually and empirically on network centrality (Borgatti 2005; Jackson 2008). A central firm typically shares directors with several other firms, which are in turn, well-connected to other (well-connected) firms. However, a firm has only limited control over its position in the network because its position depends on the connections of

[5]For example, one executive in Useem (1984) states: "Direct involvement in other companies' affairs replaces an awful lot of reading ... it's a hell of a tool for top management education" (pp. 209-210). Similar, as directors in Lorsch and Young (1990) observe; "serving on a board is a way of seeing how somebody else is doing the same thing you're doing" or "you learn so much about situations that you, in turn, become faced with." (page 27).

[6]"Lilly looks for added global perspective with board additions", Associated Business Wires, June 26, 2000.

other firms in the network.[7] Larcker et al. (2013), and Horton et al. (2012) find that board centrality positively correlates with future firm performance, but there is little systematic evidence about the underlying mechanism. Central firms make similar investment decisions (Fracassi 2016), and have fewer accounting restatements (Omer, Shelley and Tice 2016). To the best of my knowledge, nobody has examined whether central firms plan and forecast better, and through this channel potentially increase firm value.

2.3. Hypothesis Development

Based on evidence from board minutes of Israelian firms Schwartz-Ziv and Weisbach (2013), and interviews with executives and directors of major U.S.-firms Charan et al. (2014), find that directors counsel management on strategic and operational plans and work with executives on capital, and resource allocation decisions.[8] Planning can be facilitated through early identification of industry developments in own and related industries, macroeconomic shocks, or technological innovations and applications. Also experiencing multiple firms' considerations related to these shocks can be valuable. Knowledge about other market participants can alter firms' actions. In particular, links to similar firms may be useful (Haunschild and Beckman 1998), although firms operating in the same industry are in many cases prohibited from sharing directors [under Section 8 of the Clayton Antitrust Act of 1984 (LLP 2010; Ropes and Gray 2011)].[9] Nevertheless, second-degree (that is, indirect) within-industry linkages, as captured by board centrality, are not prohibited and may provide a

[7]One implicit assumption of employing the concept of board centrality is that higher-degree connections matter. That is, besides focal firms' directors, directors of interlocked firms (first-degree connections), and (at least) second-degree connections should matter. Interaction between linked firms in a network is naturally difficult to observe for the researcher; however, board-meetings are observable and interactive events (Schwartz-Ziv and Weisbach 2013). A typical board of a U.S.-listed firm meets seven or eight times a year (Falato et al. 2014; Karamanou and Vafeas 2005) and meetings are distributed evenly throughout the year (Kim 2016). This suggests that formal board meetings may provide a mechanism for the effects of director changes in a higher-degree connected firm.

[8]For example, the former CFO of General Electric points out that during strategy meetings executives and directors discuss their concerns about the assumptions underlying important estimates (e.g., review assumptions about growth rates) (Sherin 2010). Similarly, during the planning process at Johnson & Johnson, the corporate board requests updated budget projections several times a year, suggesting repeated manager-director interaction related to capital budgeting and resource allocation decisions (Simons 2000).

[9]For example, in 2009 FTC investigations lead to the resignations of Google Executive Chairman of the Board Eric Schmidt from the board of Apple and of former Genentech CEO Levinson from the board of Apple and Google.

competitive edge over less-connected competitors.[10]

Firms can also benefit from interlocking directorates with firms in related industries, that is, customer or supplier industries (Dass, Kini, Nanda, Onal and Wang 2014). The accuracy of a sales plan hinges on nuances about expected growth in target industries. Production plans can be refined and capacity updated, if supplier bottlenecks are identified early. Providing corroborating evidence, Ke et al. (2015) find that firms sharing a director with firms in related industries have smaller forecast errors. Also, multiple indirect connections to firms in related industries may increase the reliability of information and estimates.

Also interlocking directorates with firms in unrelated (on a first glance) industries can be advantageous. First, large firms are often conglomerates that operate in multiple industries and countries. They may have interlocking directorates with firms operating in the same geographical areas. Alternatively, single divisions of conglomerates may operate in the same industry as an interlocked firm. In this case, Section 8 of the Clayton Act may not apply, because revenues or profits may not exceed the legally binding threshold.[11] Second, firms can learn from other firms' adoption of particular practices and by adaption of their decision-making processes, which can be applied to multiple domains (e.g., in multiple industries) (Westphal, Seidel and Stewart 2001).[12] Third, directors are keenly aware of their economic environment (Davis 1991), so they may be more likely than executives to recognize macroeconomic developments. While macroeconomic analysts typically employ sophisticated tools to analyze the economy, directors observe other firms' reactions to trends, and are able to interpret information useful for a focal firm, which may provide insights that outside analysts may not have. Given the potential benefits of having well-connected directors, I expect a positive relation between board centrality and the quality of firms' plans and forecasts (as measured by firms' first annual management earnings forecast), which motivates the

[10]If firm A has interlocking directorates with a supplier who is further connected to firm B, another customer that happens to compete in the same industry as firm A, A and B are second-degree connections.

[11]Two firms that have interlocked directorates, but competitive sales of under 3 million or undivided profits of under 30 million are exempted from this regulation (LLP 2010; Ropes and Gray 2011).

[12]Westphal et al. (2001) refer to this as second-order imitation. Contagion studies usually identify the spill over of a specific practice [e.g., related to accounting and disclosure practices and board interlocks see Cai, Dhaliwal, Kim and Pan (2014); Chiu, Teoh and Tian (2012), and Reppenhagen (2010)], which is more likely first-order imitation.

following hypothesis:

H1: Board centrality is positively related to the accuracy of firms' first annual management earnings forecast.

However, firms that are more central in a board network likely have more ”distracted” directors. Research indicates that ”distracted” directors can lead to lower firm performance and firm value, potentially because directors have difficulties focusing on multiple tasks at the same time (Core et al. 1999; Falato et al. 2014; Perry and Peyer 2005). Dedicating less attention to issues and management of a particular firm may inhibit a director's planning role, therefore, board centrality may be unrelated to the accuracy of firms' earnings forecasts.

3. Methodology

3.1. Sample Composition

My starting sample contains all U.S.-listed firms in the BoardEx database for the years 2002 to 2013, including all S&P 1500 firms for each year.[13] Data on annual management earnings forecasts stem from I/B/E/S (excluding the less reliable quarterly reports because they do not have mandatory audits (Goodman et al. 2013)). Forecasts made more than one year in advance (at t-1), made in the fourth quarter of year t, or after the end of the fiscal year t are discarded (Ajinkya, Bhojraj and Sengupta 2005; Gong, Li and Xie 2009). Following Rogers and Van Buskirk (2013), I retain management forecasts bundled with earnings announcements, as this would result in an unnecessary loss of observations. Any forecasts containing missing data on projected earnings or realized earning, and forecasts that are neither point nor range estimates are removed as well. The midpoint of range estimates are assumed to represents management expectations. I conduct my analysis on

[13] I thank Joseph Engelberg for providing the algorithm to match BoardEx data to Compustat, and as discussed in Engelberg, Gao and Parsons (2013). For the firm-years after their sample period, I create a matching algorithm based on CUSIP, company name, and ISIN. Limiting the sample to the years after 2000 has several advantages. First, there are selection issues with both BoardEx data (Engelberg et al. 2013; Fracassi and Tate 2012) and I/B/E/S earnings guidance data (Chuk, Matsumoto and Miller 2013) in earlier time periods. Second, I abstract from the impact of Regulation FD (introduced in 2000), which mandates that all publicly traded companies must disclose material information to all investors at the same time (Hutton, Lee and Shu 2012).

the first annual earnings forecast made after the prior year's fiscal year-end date, which more likely reflects managers belief of the earnings realization (as compared to guidance revisions) which are more likely to be affected by strategic considerations.

I merge management forecast data with director data from BoardEx, and firm data from Compustat, I/B/E/S, and Audit Analytics. Requiring non-missing values for all variables used in the main analysis results in 8,855 unique firm-year observations. However, because I test my hypothesis with an annual change specification, data requirements reduce the final sample size to 5,576 observations.[14] To reduce the impact of outliers I winsorize all continuous variables at the 1st and 99th percentile.

3.2. Construction and Description of the Board Network

To calculate board centrality per firm-year, I first collect data on all director and executive positions reported in the Board-Ex database as of the end of 2013. To minimize the impact of self-reporting bias, I restrict the sample to listed firms in the U.S. I build a network of firms for each calendar year from 2002 to 2013, and I define two firms as being connected in year t_1 if they share at least one executive or director at the beginning of the year, and being unconnected otherwise. This results in an unweighted, symmetric, binary matrix (see example network in Appendix A for details of the network calculation).[15] All isolated nodes (i.e., firms that do not share any director with any other firm) are removed and are thereby not part of the network.

Descriptive statistics of the board network are reported in Table 1. A network component is defined as an entirely connected part of a network, that is, within each component, every node (here firm) can reach every other node. I target firms in the largest component because this allows comparison of board centrality of all firms. However, this constraint should not

[14]The sample size deviates for other tests that require additional or less data. For the first stage test (probability of issuing a management forecast) the sample size is 20,957 because also firms that do not issue forecasts are included. The sample sizes in additional and robustness analyses vary according to the respective data requirements.

[15]In this parsimonious approach I ignore the presence of multiple directors forming an interlock between two firms. I do so to avoid further complicating conceptual assumptions about dynamics in the board network. Nevertheless, I address some. For example, I construct networks weighted by the amount of shared directors, and impose the restriction that director interlocks have to be in place for at least three years (untabulated). Also, in this paper I do not restrict the analysis to professional directors only but allow for executive overlaps to capture the entire firm-network. Note that they occur rarely. Controlling for CEOs' connections does not alter inferences (untabulated).

affect inferences as the percentage of firms in the largest component is around 90 percent of all non-isolated firms (while less than 1 percent of all firms belong to the second largest component). The largest component has on average a mean (median) degree of 5.2 (4), meaning reaching any firm in the board network requires to pass four to five firms (which is commonly referred to as "degrees of separation"). Network statistics are similar to those of Larcker et al. (2013), which serves as validation for the network data.

3.3. Board Centrality

As outlined in more detail in Appendix A, the concept of centrality is multidimensional in that each of the network measures employed (i.e., Degree, Eigenvector, and Closeness) captures different aspects of access to information and resources (Freeman 1979; Jackson 2008).[16] Degree (DEGREE) proxies for the number of direct connections and is used to estimate the number of channels through which the board network can be accessed. It equals the number of board interlocks. Although widely used and advantageous due to its parsimony, the main drawback of Degree is that it only captures firms' local board connections. Eigenvector (EIGENVECTOR) builds on Degree but takes n-degree connections (discounted) into account. The idea is to capture increasing access to the network with more and better connections. Finally, centrality may be represented by firms' Closeness (CLOSENESS). This measure is defined as the inverse of the number of other firms that have to be passed to reach any other firm in the network, and measures how fast a firm can access information and resources.

Even though these dimensions of network centrality are to some extent distinct, it is ex-ante unclear which of the three measures matters most. To address this lack of clarity, I conduct a factor analysis for each firm year, with DEGREE, EIGENVECTOR and CLOSENESS as input factors and define the factor with the largest Eigenvalue (denoted as CENTRALITY) as the main independent variable of interest.[17] The annual Eigenvalue of

[16] A fourth centrality measure frequently used in social network literature is Betweenness, which measures how often a firm falls on the shortest path between other pairs of nodes in the network. I do not include this measure based on conceptual grounds: According to social network theory, Betweenness captures focal firms' ability to withhold or distort information transmission between two other nodes (Freeman 1979), but does not relate to focal firms' ability and speed to access information and resources in the network.

[17] See El-Khatib et al. (2015), Larcker et al. (2013) and Omer et al. (2016) for similar approaches.

this first factor ranges from 2.24 to 2.50 (and is in every year clearly the only factor with an Eigenvalue greater than one). The average factor-loadings of DEGREE, CLOSENESS and EIGENVECTOR are all greater than 0.8 in each year. Due to these relatively high correlations, I both use the largest factor throughout the paper, as well as tabulate the results of the main analysis using each of the individual centrality measures.

3.4. Measuring Management Earnings Forecast Accuracy

Following the discussion in Section 2.1, the quality of firms' planning is measured with the accuracy of firms' one-year ahead first annual management earnings forecasts (MFC_ACC). Similar to Feng, Li and McVay (2009), earnings forecast accuracy is calculated by taking the absolute difference between realized earnings per share and the first annual earnings per share estimate, scaled by assets per share. I multiply this by minus one so that higher values of accuracy correspond to higher values of director connectedness. Following Hutton et al. (2012), the focus is exclusively on firms' first disclosed annual earning forecast in each fiscal year because these less likely capture forecast revisions. I dedicate Section 4.5.5 to alternative measurement approaches.

3.5. Empirical Model and Control Variables

To test my main hypothesis, I use a first difference specification and control for determinants of management forecast accuracy related to firm structure and board structure variables, as well as year fixed effects and Fama-French 17 industry indicators. Unless otherwise specified, this vector of controls, defined in Appendix B, is consistently applied throughout all regression specifications. I test my hypothesis using the following OLS estimation and cluster standard errors by firm and year (where i refers to the firm, j to the industry, and t to the fiscal year):

$$\begin{aligned}\Delta MFC\_ACC_{ijt} = {} & \alpha_1 \Delta CENTRALITY_{ijt} + \alpha_2 \Delta AN\_FC\_DISP_{ijt} + \alpha_3 \Delta BOARD\_SIZE_{ijt} \\ & + \alpha_4 \Delta DISAG_{ijt} + \alpha_5 \Delta EARNINGS\_VOL_{ijt} + \alpha_6 ERR\_ICMWD_{ijt} \\ & + \alpha_7 \Delta LEVERAGE_{ijt} + \alpha_8 \Delta MFC\_HOR_{ijt} + \alpha_9 \Delta PER\_OUT\_DIR_{ijt} \\ & + \alpha_{10} \Delta REL\_IND\_DIR_{ijt} + \alpha_{11} \Delta R\&D_{ijt} + \alpha_{12} \Delta ROA_{ijt} + \alpha_{12} \Delta SIZE_{ijt} \\ & + \gamma_t + \delta_j + \epsilon_{ijt}\end{aligned} \tag{1}$$

Based on my hypothesis, I expect board centrality (ΔCENTRALITY) to be positively related to management forecast accuracy (ΔMFC_ACC). To test whether board centrality has an effect over and above commonly-used board structure variables, I control for board size (ΔBOARD_SIZE), the fraction of outside directors on the board (ΔPER_OUT_DIR), and interlocking directorates to related (i.e., supplier or costumer) industries (ΔREL_IND_DIR)[18] (Ajinkya et al. 2005; Karamanou and Vafeas 2005; Ke et al. 2015). Firms' information environment likely influences the accuracy of management forecasts. Firms' external information environment is measured with earnings volatility (ΔEARNINGS_VOL) and analyst forecast dispersion (ΔAN_FC_DISP) (Waymire 1984). Firms' internal information environment should be captured by an indicator variable taking the value of one if a firm reports recent internal control material weaknesses or accounting restatements due to errors (ERR_ICMWD), and zero otherwise (Gallemore and Labro 2015). Finally, I control for general firm characteristics (ΔROA, ΔLEVERAGE, ΔSIZE, ΔR&D), the number of items a firm forecasts as reported in I/B/E/S (ΔDISAG) (Lansford et al. 2013), and the days between earnings forecast release and earnings realization (ΔMFC_HOR) (e.g., Feng et al. (2009)).

4. Results

4.1. Descriptive Statistics

Univariate statistics are reported in levels of all variables (to facilitate comparability across studies) in Table 2, and Pearson correlations in Table 3. First, unconditional on controlling for determinants of accuracy, more central firms tend to have higher forecast accuracy, independent of whether this is measured by annual changes or levels. In addition, more central firms tend to have larger boards, higher market value and ROA, more debt, less volatile earnings, and spend more on R&D. They also are more likely to have an interlock with a firm operating in a related industry. In untabulated analysis, I find that the correlation between annual change in board centrality and annual changes in any of the control variables is smaller than 0.15. The only exception is annual changes in board size, which is 0.39 (and somewhat by construction) correlated with changes in board centrality. Overall, bivariate results are similar to prior studies on board centrality of U.S. firms (e.g., Fracassi (2016); Larcker et al. (2013)). In Section 4.5.6, I specifically address potential multicollinearity.

[18] To calculate connections to firms in related industries, I collect data from the Input-Output table provided by the Bureau of Economic Analysis, and follow closely the procedure explained in detail in Dass et al. (2014), p. 1,544.

4.2. The Relation between Board Centrality and Management Earnings Forecast Accuracy

The Results in Table 4 indicate that board centrality is consistently positively related to management forecast accuracy. Column (1) provides the results of the main model (as outlined in Section 3.5), columns (3), (5), and (7) present results of each individual centrality measure. Columns (2), (4), (6), and (8) present the same estimations, including the Inverse Mills Ratio as control for the propensity of firms to self-select into issuing a forecast.

Results of a basic multivariate analysis show that ΔCENTRALITY is positively related to management forecast accuracy (coefficient=0.215, $p < 0.01$), which provides initial support for the hypothesis that firms with better-connected directors make more accurate forecasts. The economic significance is non-negligible: A one standard deviation change in ΔCENTRALITY changes ΔMFC_ACC (evaluated at the mean of the absolute annual change in management forecast accuracy) by 8 percent.[19] The marginal effect of each individual centrality measure is similar (i.e., 5 percent, 5 percent, and 9 percent for ΔDEGREE, ΔEIGENVECTOR, and ΔCLOSENESS, respectively), hence I use the factor-centrality measure only for further analyses. The economic significance of board centrality is comparable to other studies on management forecast accuracy and variables related to corporate directors. That is, Ajinkya et al. (2005), and Ke et al. (2015) report that a one standard deviation change in the percentage of outside directors, board size, and interlocked directorates with firms in related industries is associated with a 18 percent, 5 percent, and 9 percent (respectively) change in management earnings forecast accuracy.

As firms self-select into issuing a forecast, I include the Inverse Mills Ratio (estimated by means of a Heckman selection model (Heckman 1979)) as an additional control. According to Ajinkya et al. (2005) and Feng et al. (2009), the number of analysts is associated with the decision to forecast, but not with forecast accuracy. Therefore, I instrument with the number of analysts following a firm during the 30 days before the release of the earnings forecast. I estimate a probit model (with clustered standard errors by firm) with the dependent

[19]Coefficients are multiplied by 100 for presentation. The mean absolute value of ΔMFC_ACC is 0.0087 and one standard deviation of ΔCENTRALITY is 0.307. The magnitude is the result of the following calculation: ((0.215/100)*0.307)/0.0087=0.0759 I evaluate results at the *absolute value* of ΔMFC_ACC, because the mean of ΔMFC_ACC is very close to zero, which renders the economic significance difficult to interpret.

variable being an indicator that equals one if a firm issues a forecast in a given year, and the independent variables number of analysts following, board centrality, and levels of controls also used in the main model (untabulated). The Inverse Mills Ratio (IMR) is constructed by dividing the probability density function by the cumulative distribution.[20] Results of the main estimations including IMR as control are presented in Table 4, columns (2), (4), (6), and (8). The economic significance across all centrality measures decreases by one (i.e., ΔEIGENVECTOR), or two (i.e., ΔCENTRALITY, ΔDEGREE, and ΔCLOSENESS) percentage points. In the next section, I take a first step to investigate causality of the main results and examine signed forecast errors, exploit quasi-exogenous variation in centrality, and probe the suggested timeline of events.

4.3. Identification

First, I analyze the relation between signed forecast errors and board centrality. I rerun model 1 in subsamples of firm-years with positive (i.e., EPS realization equals or is higher than predicted EPS) and negative (i.e., EPS realization is lower than predicted EPS) forecast errors. As reported in Table 5, columns (1) and (2), board centrality is inversely related to annual changes in absolute forecast errors in both subsamples ($p<0.05$). The coefficients for board centrality are not statistically significantly different from each other ($p>0.1$), and the economic magnitudes are 6 percent for the subsample of positive, and 7 percent for the subsample of negative forecast errors. This indicates that in firms where managers over- or under-predict profits, they do so by a smaller amount when their board is composed of well-networked directors. Importantly, the findings of reduced positive forecast errors can not alternatively be explained by well-connected directors simply facilitating firm performance.

Second, I exploit a quasi-exogenous shock to firms' board network to probe the robustness of my main results. Even in the presence of a first-difference specification and a theoret-

[20]Diagnostic tests following Larcker and Rusticus (2010) and Lennox, Francis and Wang (2011) provide confidence in the validity of my estimation. First, the instrument is bivariately significantly correlated with the propensity to forecast but not with the dependent variable of interest. Second, the coefficient for the instrument is significantly positively related to the propensity to forecast (coefficient=0.071, $p<0.05$). Third, including the IMR in the main model does not induce multicollinearity as indicated by variance inflation factors for the IMR of less than 5 in all analyses (Feng et al. 2009). I conduct subsequent tests without controlling for IMR because selection models potentially introduce bias (Larcker and Rusticus 2010; Lennox et al. 2011). Findings are qualitatively similar if I control for IMR throughout the paper.

ically sound vector of controls, endogeneity and correlated omitted variable bias remain a concern. An unobserved component in the regression error term may drive changes in forecast accuracy, and also changes in board composition (and hence alter how central a firm is in the network). Therefore, I rerun the main model for firm-years only in which a focal firm does not experience any director turnover, but still experiences a change in centrality because it moves within the global network (note that this is equivalent to keeping director characteristics fixed). The change in board centrality in these years is entirely driven by director turnover at other firms, which is likely largely unrelated to the focal firm. As reported in column (3) of Table 5, the coefficient for centrality is still positive and (weakly) significant (coefficient=0.099, $p<0.1$). However, even in these cases it may still be that focal firms' board centrality changes endogenously because focal firms' directors selectively take on additional board assignments, which can be related to focal firm-characteristics. To rule out that this drives my findings, I restrict director turnover at the focal firm, as well as at all interlocked firms, to zero. As shown in Table 5 column (4), for this subsample centrality is still (weakly) significantly positive (coefficient=0.773, $p<0.1$).[21] These results suggest that it is unlikely that any firm or director-specific unmeasured component in the error term drives the relation between board centrality and forecast accuracy.

Third, I probe the timing of events, or whether forecast accuracy relates to board centrality measured one year lagged, two years lagged, one year lead, or two years lead. Finding positive coefficients for the lagged centrality measures would suggest that time factors into the materialization of directorial network benefits, while positive coefficients for the lead centrality measures point toward reverse causality. The results in Table 5, column (5) to (8) are not in line with either of these conjectures; all coefficients for centrality are statistically insignificant ($p>0.1$). Taken together, the results discussed in this section and presented in Table 5 increase confidence in a causal interpretation of the main findings.

[21] The weak statistical significance may be explained by low powered tests. The magnitude of the coefficients of centrality tested in the subsamples presented in column (3) and (4) are 2 percent and 10 percent, respectively.

4.4. Cross-sectional Analyses

4.4.1. Firms' Advisory Needs

I conduct a series of cross sectional tests partitioning on firm characteristics that should capture variation in the effectiveness of directors' advice. I partition the sample in subsamples of firms that are more or less likely to be in greater need of, or at least more or less likely to benefit from, directors' network resources.Following prior literature, I operationalize firms' advisory needs by measuring the following aspects of how difficult, complex and hence costly it likely is to forecast accurately: scope of operations, firm maturity, uncertainty related to business operations and the business environment, cost complexity, and the sensitivity to macroeconomic developments.

First, managing a firm that operates in several business segments and internationally is likely more complex (Coles, Daniel and Naveen 2008; Hermalin and Weisbach 1998). Directors' advisory role gains relevance for these firms due to the difficulty for managers to stay well-informed in many diverse product markets and about international developments. I define SCOPE_OPERAT by calculating the Herfndahl-Hirschmann index of revenue concentration, where higher values indicate that a firm has sales from various segments (Jennings, Seo and Tanlu 2015), and I adjust for firms' foreign transactions, which both captures aspects of business complexity (Feng et al. 2009). Second, young firms may benefit more from directors' advice and their networks because they have more growth opportunities and potentially less experienced management (Falato et al. 2014; Larcker et al. 2013). I measure YOUNG_FIRM as the inverse of the number of years since a firm's IPO date (as specified in Compustat).

Third, firms that undergo organizational change face more uncertainty regarding the future benefits of their restructuring or merger and acquisition initiatives, thereby increasing the challenge in planning operations and predicting future earnings (Feng et al. 2009). Directors may add value by providing operational and strategic advice during times managers are challenged by major organizational changes (Schmidt 2015). The variable RESTRUCT or M&A takes the value of one if a firm reported recent restructuring charges or merger or acquisitions. Fourth, forecasting is more difficult in volatile environments, which I measure with the standard deviation of monthly returns over the last year (σ RETURN) (Feng et al.

2009).

Fifth, firms' cost structure can influence the difficulty to predict earnings (Hutton et al. 2012; Jennings et al. 2015). In firms with relatively high fixed and low variable costs, expenses co-move less with sales and thus sales forecasts are less informative about future earnings. In other words, planning of expenses and production becomes more important, which makes (e.g.) assumptions and estimates about inputs in production processes more relevant. Here director networks to supplier industries, may become useful in supporting production planning. I define COST_COMPLEX as the inverse of the last 12 months within-firm correlation between quarterly revenue and expense growth (Jennings et al. 2015), such that higher values indicate relatively more fixed to variable costs. Sixth, if firms earnings are more sensitive to macroeconomic developments I expect well-networked directors to be in a good position to advise due to their knowledge about macroeconomic developments and shocks. Directors may observe other firms' anticipation or reaction to macroeconomic shocks, and may also learn from analysts about macroeconomic developments. I define macroeconomic synchronicity (MACRO_SYNC) as the co-movement of a firm's earnings with macroeconomic indicators (Hutton et al. 2012), where managers of firms with high co-movement may benefit specifically from the knowledge of well-networked directors.[22]

To test whether the relation between board centrality and forecast accuracy varies in a predictable manner with the firm characteristics outlined above, I partition the respective moderator variable in high versus low values based on median splits, conduct subsample tests, and test for significant differences in the coefficient for ΔCENTRALITY between subsamples. I test for significant differences by estimating the basic regression specification on

[22]I measure macroeconomic synchronicity closely following Hutton et al. (2012), pages 1224 - 1226. In short, I calculate the R-square from firm level estimation of the following model over the prior 12 quarters:

$$EARN_{i,t} = \alpha_0 + \alpha_1 FACTOR_t + \epsilon_{i,t},$$

where EARN is income before extraordinary items and FACTOR either the nominal quarterly GDP, energy costs, or the spread between the 30-year mortgage rate and the t-bill rate. High R-square indicates that firms earnings move in cyclical fashion with the overall economy (i.e., GDP), economic indicators like energy costs, or interest rates, respectively. Mean and median values for the R-square variables are similar to Hutton et al. (2012). To build a single variable that captures firms' macroeconomic synchronicity, I run a factor analysis with the three R-square variables as inputs. The first factor has an eigenvalue of 1.49, is the only that is larger than one, and each factor loading is higher than 0.6.

the full sample and add interaction terms of the partitioning variable with ΔCENTRALITY, all control variables and fixed-effects. Consistent with my predictions, and reported in Table 6, I find the relation between board centrality and forecast accuracy to be significantly more pronounced in the subsample of high values for the respective moderator across all six partitioning variables. These findings indicate the usefulness of director networks when profit planning and forecasting are specifically difficult. To the extent that the cross-sectional characteristics capture firms' advisory needs, the results suggest that connectedness of directors matters in situations where directors are more likely to provide business advice.

4.4.2. Advisory Directors

I cross-sectionally examine board characteristics that should capture the extent to which directors advise management. Researchers rarely observe how much time directors spend advising executives, hence measures are mostly derived from observable board characteristics (Brickley and Zimmerman 2010; Schwartz-Ziv and Weisbach 2013). Information-based models of boards (i.e., models of 'friendly' boards) stress that a prerequisite to get effective advice from directors is that managers communicate firm specific information, which directors may combine with their (more general) knowledge (Adams and Ferreira 2007; Adams et al. 2010; Harris and Raviv 2006; Raheja 2005). Based on this, empirical measures on advising intensity are derived from aspects of the relation between managers and directors.[23] Therefore, I measure the extent to which directors advice with proxies related to directors' committee membership (Adams and Ferreira 2007; Faleye, Hoitash and Hoitash 2011, 2013) and board co-option (Coles, Daniel and Naveen 2014).

The audit, compensation, and nominating/governance committees are firms' three principal monitoring committees (Adams and Ferreira 2007; Faleye et al. 2011), whereas investment, strategy, acquisitions, and science/technology committees are commonly classified as advisory committees (Faleye et al. 2013). Directors on advisory committees likely commence their role aiming to facilitate managerial decision making. Also, directors who are not on monitoring committees may be more trusted by management to use firm-specific information

[23] Early studies posit that inside directors rather advise, however, it is not clear why they would not intend to advise management, whether outside board membership measures de-facto independence, and empirical results are largely inconclusive (Adams and Ferreira 2007; Adams 2017; Brickley and Zimmerman 2010).

to consult managers (and therefore will receive more firm-specific information). I classify a director as an advisory director if he serves on no monitoring committee but one advisory committee (if the company has any) (Faleye et al. 2013). I build variables based on the presence (ADV_DIR_INDICATOR) and the percentage (PERC_ADV_DIR) of advisory directors on the board. Next, I calculate the percentage of monitoring-intense directors (MONITORING_INTENSITY), where a director is classified as monitoring intense if he is part of two or more monitoring committees (Faleye et al. 2011). I expect the relation between management earnings forecast accuracy and board centrality to be more pronounced if there are (relatively) more advisory directors on a board, and if monitoring intensity is lower. If true, director networks would be especially beneficial for firms' plans and forecasts if directors are more likely to actively advice.

Co-opted directors are directors who have been appointed after the CEO has assumed office (Coles et al. 2014). Nominations for directorates are controlled by the nominating or governance committee (with likely influence of the CEO). Co-option has been found to be associated with managerial rent-extraction, potentially because the CEO is unlikely to agree on appointing directors who he expects to restrict his decision authority. The CEO may prefer to hire directors who are more likely to share similar beliefs and visions, and to whom these directors may be more beholden (Coles et al. 2014; Fracassi and Tate 2012). Khanna, Kim and Lu (2015) also point out the 'bright side' of co-opted directors; closely knit top executives may expedite decision-making, or may implement decisions more efficiently via effective communication and coordination. Similarly, Clune, Hermanson, Tompkins and Ye (2014) stress the importance of fit of incoming directors with the CEO. Following the intuition that co-opted directors are relatively more effective in advising, I define a variable PERC_CO-OPTED as the fraction of directors appointed contemporaneously or after the CEO (Coles et al. 2014). Next, because PERC_CO-OPTED may capture simply CEO tenure, I orthogonalize it to CEO tenure (RES_PERC_CO-OPTED) (Coles et al. 2014). Finally, I combine proxies for the percentage of advisory directors and co-opted directors and build the variable PERC_CO-OPTED & PER_ADV_DIR, which is high for firm-years of above median values for PERC_CO-OPTED and at the same time above median values for PER_ADV_DIR, low otherwise.

Results, reported in Table 7, indicate that the relation between management earnings forecast accuracy and board centrality is significantly more pronounced if firms have relatively more (fewer) directors on advisory (monitoring) committees and more co-opted directors. To the extent that these board structure variables capture the effort directors put into advising management (or the inclination of management to collaborate with directors) the cross-sectional evidence suggests that director networks can be specifically beneficial for planning and forecasting if directors are likely to focus more on advising.

4.5. Additional Analyses

4.5.1. Accuracy of Revenue and CapEx Forecasts

The analyses throughout the paper focus on the accuracy of earnings forecasts, following the intuition that accounting earnings (as an aggregate measure) reflect the quality of sales and investment plans. That is, most corporate activities affect the income statement either directly (e.g., sales, labor costs or R&D), or indirectly (e.g., asset purchases/disposals and a change in assets' value affect depreciation expenses and impairment charges). Nevertheless, I exploit firms' disclose of other financial items; that is, I examine to accuracy of projections of sales and capital expenditures (CapEx). The quality of firms' sales projections vary with knowledge about actual demand for a focal firm's product. Further, as a firm's planned CapEx outlays follow from expectations about future demand, CapEx will also vary with projected developments in customer industries. Also, to accurately anticipate which capital investments will be worthwhile in the future, managers require knowledge about developments in the firm's supplier industries.

In 54 percent (23 percent) of the sample firm-years, firms disclose annual revenue (CapEx) predictions at the beginning of their fiscal year.[24] Consistent with the definition of earnings forecast accuracy, the accuracy of revenue (CapEx) forecasts is calculated as the absolute difference between the first annual revenue (CapEx) forecast and realized revenue (CapEx) at the end of the year, scaled by total assets. I apply the main model and use the same estimation procedure (see Table 8). Results in Table 8 suggest that board centrality is related to

[24]This is similar to findings in prior studies on disaggragated management earnings forecasts (Lansford et al. 2013) and investment guidance (Biddle et al. 2017; Lu and Tucker 2012), that consider different or partly overlapping time periods. Management forecasts on CapEx have been available in I/B/E/S since 2008.

revenue and CapEx forecast accuracy, however, some coefficients are only weakly significant. The economic effect of director networks on the quality of revenue (CapEx) forecasts is 4 percent (11 percent). Results hold when estimated in subsamples of positive forecast errors, however, only in the subsample of negative CapEx forecast errors. Findings are qualitatively similar if I control for self-selection into issuing a forecast by means including the Inverse Mills Ratio as control variable (untabulated). Overall, firms with networked directors do not only have more accurate earnings forecasts, but also seem to better predict one-year ahead sales, and more accurately estimate their capital expenditures over the upcoming year.

4.5.2. Director Networks and Director Quality

In this analysis, I examine how a set of measures for director quality relates to management forecast accuracy. Results in Section 4.3 suggest that director networks have a significant impact on management earnings forecast accuracy, when holding director quality constant. Following prior studies, I assess director quality along several dimensions; that is, I include controls for director tenure, age, the number of past directorships and industry experience.

I build each director quality variable at the board-level. Director tenure is defined as the average tenure of the board (mean=8.27, median=8.66, std. dev.=3.2), and measures firm-specific knowledge (Brickley and Zimmerman 2010; Kim, Mauldin and Patro 2014). Director age is defined as the average age of the board (mean=61, median=61, std. dev.=3.5), where older directors are supposedly less effective (despite being more experienced) due to the tendency to see directorships as lucrative part-time jobs (Ferris et al. 2003). Directors' past directorships measures general board experience and is the total number of board assignments all current directors had in the past at other firms, divided by board size (mean=15.0, median=2.62, std. dev.=22) (Gray and Nowland 2013). Directors' past industry experience is an indicator variable taking the value of one if a firm has at least one director who worked at another firm in the same industry in the past, as defined by firms' two-digit SIC code (mean=0.21, std. dev.=0.64), and zero otherwise (Faleye, Hoitash and Hoitash 2014).

I rerun the main model controlling for each director quality characteristic at a time, separately for annual changes or levels of the control variables. The magnitude of the effect of board centrality on management forecast accuracy is slightly smaller after controlling for the different measures of director quality but does not vary much, independent of the quality measure included, and the coefficient on centrality is significant on conventional levels (untabulated). These findings do not suggest that director quality and networks are substitutes (i.e., industry experience may not substitute for access to resources and knowledge from current director networks). Also, these results do not indicate that a firm's network position can be explained by any one specific proxy for director quality (that I employ here).[25]

4.5.3. CEO and CFO fixed-effects Analysis

I test whether considering time invariant CEO and CFO characteristics (by controlling for executive and executive-firm fixed effects) in my main analysis affects my inferences regarding board centrality. CEOs and CFOs are the executives who likely have the greatest influence on management forecasts. Brochet, Faurel and McVay (2011) show that CEO and CFO turnover is related to whether firms provide management earnings forecasts, which is to some extent attributable to the specific incoming manager. Baik et al. (2011) find that several characteristics of management forecasts are related to measures of CEO ability, and Lee et al. (2012) show that high forecast errors increase the probability of CEO turnover. Also, CEOs and CFOs can have an extensive network through current board positions on other boards, which may correlate with my independent variable of interest. Generally, executive type can influence a range of firm policies (Bertrand and Schoar 2003). I probe the robustness of my main results to the inclusion of CEO, CEO-firm, CFO, and CFO-firm fixed effects. Results, reported in Table 9, indicate that the coefficient for ΔCENTRALITY gets slightly smaller after controlling for executive or executive-firm effects, however, remains significant different from 0. This analysis does not suggest that executive or executive-firm time invariant effects alter the inferences from the main analysis.

4.5.4. Earnings Management and Earnings Forecast Accuracy

In this subsection, I examine whether firms with well-connected directors engage in earnings management to increase earnings forecast accuracy. Inaccurate forecasts can be costly to firms and management; therefore, I control for whether firms manage earnings to increase

[25] Note that this is not intended to be a detailed examination of the substitutive or complementary nature of director networks and all potentially interesting time-(in)variant director traits, as this is out of the scope of this paper.

forecast accuracy (Kasznik 1999; Lee et al. 2012; Matsumoto 2002).

I address whether earnings management drives my main results in two ways: first, I re-estimate my main model with additional controls for earnings management.[26] I add performance matched discretionary accruals (alternatively performance matched absolute discretionary accruals) (Kothari, Leone and Wasley 2005) as control variables, and find (untabulated) that the coefficient for board centrality is similar compared to the estimation for the main model. Specifically, the coefficient for board centrality is 0.26 (0.27), $p<0.01$, when I add (absolute) discretionary accruals.

Second, I split the full sample into subsamples around the zero forecast-error threshold, and examine whether centrality has a steeper slope in these subsamples. I assume that only firms with prospects to meet their own forecast through the use of accounting discretion will manage earnings, and hence have a forecast error close to zero. I re-examine the main model three times, letting the slope for centrality vary in the following ways: I interact centrality with an indicator variable being one if a firm is in the (1) small-miss sample (has a positive forecast error below the 25th percentile of the positive forecast error subsample), (2) small-beat sample (has a negative forecast error above the 75th percentile of the negative forecast error subsample), (3) or either in the small-miss or small-beat sample. Within these subsamples, firms close to zero forecast errors are assumed to have managed earnings, while the others have not. Earnings management facilitated by director networks will be reflected in a higher coefficient for centrality in these subsamples. In untabulated analyses, I do not find a significantly different coefficient for centrality in the small-miss ($p=0.384$), small-beat ($p=0.606$), or small-miss/small-beat ($p=0.940$) sample. Overall, these findings are not consistent with the conjecture that the relation between forecast accuracy and centrality is driven by an increased propensity to minimize forecast errors through earnings management.

4.5.5. Alternative Measurement Approaches to Earnings Forecast Accuracy

In this subsection, I discuss the robustness of findings to different measurement approaches to earnings forecast accuracy. Throughout the paper I follow the convention that

[26] The standard vector of controls includes already an indicator variable for internal control material weaknesses disclosure or restatements due to errors, which proxies for the susceptibility of the accounting system to misreporting.

midpoints of range forecasts constitute managements earnings expectations (Feng et al. 2009; Karamanou and Vafeas 2005). I address whether midpoints or upper bounds in range estimates represent managers' expectations by examining the actual EPS distribution (Ciconte III, Kirk and Tucker 2014). Of all range estimates in my sample, 44 percent (34 percent) of actual EPS fall above (below) the higher bound (lower bound) estimate, and 10 percent (12 percent) fall between the lower (higher) bound estimate and the midpoint estimate. Due to this relatively normal distribution of estimates around the midpoint (as opposed to the upper bound or lower bound), I interpret the mid-point as managers' expected EPS. However, assuming the upper or lower bound reflects managements' expectations and rerunning the main model provides similar results (untabulated).[27]

Next, I calculate annual earnings forecast accuracy by using different scalars identified in the management forecast literature. I use the following alternative scalars: absolute forecast value, log of total assets, total assets, lagged stock price, standard deviation of EPS, or I do not scale. Subsequently the main model is re-estimated with these alternative measures for earnings forecast accuracy. The coefficient for centrality is significant positive at the 5 percent level in all estimations (untabulated), hence results do not appear sensitive to alternative ways of scaling management earnings forecast accuracy. Specifically, due to the robustness of the findings to the use of the absolute earnings forecast as scalar, it is unlikely that variation in the denominator (i.e., asset per share) drives my results.

4.5.6. Correcting for the Correlation between Board Centrality and further Firm Characteristics

I employ two variants of the main model to address potential multicollinearity concerns that may arise from the correlation of board centrality with firm characteristics (Akbas et al. 2016; Larcker et al. 2013). I first account specifically for the correlation of centrality with firm size (and, secondarily, employ a non-parametric approach to examine my hypothesis). Therefore, similar to Larcker et al. (2013), I construct size-quartiles based on the natural logarithm of total revenues, to account for the tendency of larger firms to have larger and subsequently likely better connected boards. Within each size quartile I construct quartiles

[27] Re-estimating model 1 assuming the upper (lower) bound is the actual expectations provides a coefficient for centrality of 0.19 (0.23), and p-values <0.01.

for centrality and rerun the main model, and substitute centrality with its quartile measure. In this non-parametric approach, finding hypothesized results in an annual change specification implies that changes in board centrality have to be large enough that a firm-year will be classified in a different centrality-quartile; which biases against finding significant results. Untabulated results show a significantly positive coefficient for annual changes in quartile-centrality (coefficient=0.07, $p<0.01$). This implies that board centrality corrected for firm size has a positive effect on accuracy.

In a second approach I control for the correlation between board centrality and several firm characteristics. I orthogonalize centrality to a set of firm characteristics found to be related to board centrality (Akbas et al. 2016; Larcker et al. 2013). I run annual regressions of board centrality on size, firm age, board size, market-to-book, ROA, and changes in ROA, and use the change in the residual value as an alternative centrality measure. The coefficient for changes in residual board centrality is 0.24 ($p<0.01$). Both approaches indicate that the results are not driven by firm characteristics that correlate with a firm's connectedness. Specifically, neither changes nor levels in firm performance affect the relation between annual changes in board centrality and annual changes in management forecast accuracy.

5. Conclusion

In this study, I aim to shed light on whether directors' current professional connections facilitate firms' annual planning and forecasting. While external parties somewhat speculate about firms future earnings, managers have to properly plan to reach the profit level that they initially forecasted. I examine firms' direct as well as indirect board networks, which allows for a wider range of influential connections than only interlocking directorates. I employ a U.S. sample of 5,576 firm-year observations, spanning the years 2002 to 2013. I find that an increase in board centrality relates economically significant to annual changes in earnings forecast accuracy. Magnitudes of the results compare to reported findings of other work on directors and forecast accuracy. I exploit a quasi-exogenous shock and lead/lag specifications to address endogeneity. These results indicate that firms with better connected directors make better earnings forecasts. Findings are corroborated with evidence of better sales and CapEx forecasts. In cross-sectional analyses I find that director networks matter especially if firms' are likely more complex to manage (i.e., advisory needs are high), and have a relatively larger proportion of directors who more likely advice than monitor (as measured by committee memberships and co-option). The results in their entirety suggest that in the context of firms annual planning and forecasting, directors' professional connections facilitate directors' effectiveness in advising management.

This paper points towards one (out of many) mechanism through which well connected directors may support managerial decision making. To the best of my knowledge, it is the first study that suggests that directors' access to multiple firms through their professional network can be beneficial because their connections have the potential to increase the quality of firms' planning and the subsequently disclosed earnings forecast. Further, according to evidence from this study, directors with multiple board interlocks can play an active role in corporate decision-making, as opposed to being too distracted to add value. Finally, this implies that indirect connections should not be ignored to understand directors' role in forecasting. However, it may be difficult to argue that every firm should (or can) strive for a central position in a board network. Building such a network may not always be cost-effective, or even possible. There are costs associated with the search process for new directors, hiring and firing directors, and overly large boards. Further, a firm has limited control over its position in a network. Board centrality is a relational concept, which implies that the position of a firm in the board network is determined by directors of other firms. Additionally, there are contractual impediments to building interlocking directorates.

The study has several limitations. First, even though I employ an extensive research design to facilitate identification and address endogeneity concerns it is difficult to make strong causal claims in social network research. Second, given the costs involved in investigating a global versus a local network, one has to trade-off the costs and benefits of each empirical approach. Third, there may not be satisfactory measures for firms' advisory needs and directors' advisory efforts; to the extent this applies one has to interpret the cross-sectional results in this study with caution. Conditional on these caveats, I believe this work provides a valuable contribution to the literature on board centrality and directors' role in providing decision facilitating information.

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APPENDIX A: Calculation of Centrality Measures and Example Network

Centrality Measures

The main measure employed, CENTRALITY, is the first eigenvalue from a factor analysis with the three input variables Degree, Closeness and Eigenvector (for a detailed discussion see Freeman (1979), Jackson (2008) pp. 37). I first build a symmetric binary matrix (called adjacency matrix), with each row and column representing a different firm in the network. Each entry in the matrix is set to one if two firms share a director in a given year. That is, the network is calculated for each year that belongs to the sample period. Based on this, I calculate centrality measures that are commonly applied in finance and accounting research (El-Khatib et al. 2015; Fracassi 2016; Larcker et al. 2013).

Degree, as the simplest of the four measures, is an ex-post multiplication of the adjacency matrix (A) with the unit vector. The unit vector includes all nodes (=firms) of the network. The result indicates the amount of direct connections of each node. In my setting, Degree equals the amount of firms a given firm is connected to through at least one shared director. Common alternative expressions for the same measure are *number of interlocks* or *interlock centrality* (Davis 1991).

Freeman Closeness measures how easy a node can reach every other node in the network. It is defined as the inverse of the average distance between one node to any other node in the network. The numerator is multiplied by n-1, while the average distance is defined as the average number of steps firm (i) has to take to reach every other firm in the network on the shortest path. Let l(i,j) be the number of links in the shortest path between (i) and (j), then closeness is calculated as

$$\frac{n-1}{\sum_{j\neq i} l(i,j)}$$

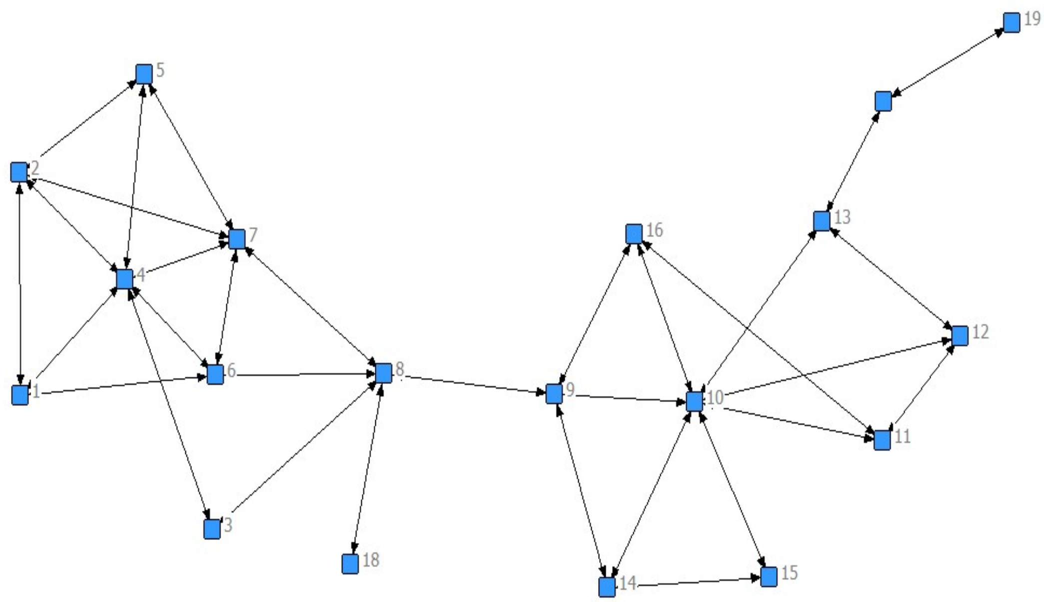
Closeness captures the inverse of the average time it takes a signal, sent by the focal firm, to arrive at any other firm in the network.

Eigenvector considers not only first-degree connections but as well higher-degree connections, accounting therefore for the number of direct and indirect connections of each node. A firm with higher Eigenvector does not necessarily have more direct connections, but the connections the firm has, are well-connected. Because this is a self-referring calculation with x unknown and x equations, it can be solved by calculating an Eigenvector of the adjacency matrix $E_{(A)}$ related to the largest eigenvalue θ. In matrix notation, $\theta E_{(A)} = AE_{(A)}$ gives the Eigenvector $E_{(A)}$. I use a modification to this measure, which is referred to as Katz-Bonacich centrality, because it discounts higher degree connections with a decay parameter. The intuition is that, as connections increase in distance, they are assigned smaller weights, captured by the decay parameter. Further, only board connections up to the sixth degree are factored in the calculation because including more distant connections is not compelling from both an intuitive and theoretical standpoint.

Example Network

The purpose of the example network (presented below) is to exhibit that centrality is a multifaceted concept, i.e., different firms are most central depending on which of the centrality-measures are used. As an example, I focus on nodes with many connections and compare their local and global network position. Node 10 has the highest Degree (7) but low Eigenvector (0.117), while node 4 has the highest Eigenvector (0.465) even though it only has the second highest Degree (6). That indicates that the connections of node 4 are better connected than the connections of node 10, putting node 4 in a more central position in a global network. However, node 4 is less central if only the local network ties are considered. As another example, Closeness captures how fast a firm can reach any other node in the network. According to this criterion node 9 and 8 are the most central ones, but both score relatively low on Degree and Eigenvector.

Graphical presentation of an Example Network: The most central nodes as evaluated on their Degree centrality are 10 and 4. Based on Closeness centrality, the nodes 9 and 8 are most central, and when evaluated on Eigenvector centrality the nodes 4 and 7 are most central.



Example Network: Calculation of Degree centrality, Closeness centrality and Eigenvector centrality

Node	Degree	Closeness	Eigenvector
1	3	0.290	0.286
2	4	0.295	0.360
3	2	0.346	0.181
4	6	0.305	0.465
5	3	0.291	0.304
6	4	0.360	0.355
7	5	0.367	0.429
8	5	0.450	0.283
9	4	0.462	0.133
10	7	0.428	0.117
11	3	0.316	0.060
12	3	0.327	0.054
13	3	0.333	0.044
14	3	0.375	0.072
15	2	0.310	0.046
16	3	0.375	0.075
17	2	0.260	0.011
18	1	0.316	0.069
19	1	0.209	0.003

APPENDIX B: Sample and Variable Description

The main sample consists of all U.S.-listed firms available in BoardEx for the years 2002-2013 with management forecast data available in I/B/E/S, and data for control variables in Compustat, I/B/E/S and Audit Analytics, that are part of the largest component of the board network. The final sample comprises 5,576 observations, spans all industries over the years 2002 to 2013, and is used to test the main hypothesis of this study. The number of observations deviates for other analyses depending on the respective data requirements. Variables are constructed as follows:

CENTRALITY	Largest factor of an annual factor analysis of Closeness, Eigenvector and Degree centrality (Board-Ex)
CLOSENESS	Standardized number of firms that lie on the shortest path between firm (i) and any other firm in the network (Board-Ex)
DEGREE	Standardized number of first-degree links to outside boards (Board-Ex)
EIGENVECTOR	Standardized number of nth-degree links to outside boards (Board-Ex)
MFC_ACC	Absolute difference between the first management EPS forecast for year t issued after the announcement of earnings for year t-1, minus the actual EPS for year t, deflated by total assets per share, and multiplied by (-1) (I/B/E/S)
AN_FC_DISP	Standard deviation of analyst forecasts (I/B/E/S)
BOARD_SIZE	Number of directors on the board (BoardEx)
DISAG	Number of items a firm forecasts (e.g., earnings, revenues, CapEx) (I/B/E/S)
EARNINGS_VOL	Standard deviation of quarterly ROA over the last 20 quarters (Compustat)
ERR_ICMWD	Indicator variable taking the value of 1 if a firm has a restatement due to errors or reports material weaknesses in its internal controls in the current year, and 0 otherwise (Audit Analytics)
IMR	Inverse Mills ratio estimated in a Heckman selection model as in Heckman (1979).
LEVERAGE	Total debt over total assets (Compustat)
MFC_HOR	Days between fiscal year end date and release date of the first annual EPS management forecast (I/B/E/S)
PER_OUT_DIR	Percentage of outside directors on the board (BoardEx)
REL_IND_DIR	Indicator being 1 if a firm has a board interlock with a firm in a related industry, 0 otherwise (BoardEx and Bureau of Economic Analysis), and explained in Dass et al. (2014).
R&D	Research and development expenses deflated by lagged assets (Compustat)
ROA	Net income scaled by lagged total assets (Compustat)
SIZE	Natural logarithm of market value (Compustat)

CAPEX_FC_ACC	Absolute difference between the first management CapEx forecast for year t issued after the announcement of earnings for year t-1, minus actual CapEx for year t, deflated by total assets, and multiplied by (-1) (I/B/E/S)
REV_FC_ACC	Absolute difference between the first management revenue forecast for year t issued after the announcement of earnings for year t-1, minus actual revenues for year t, deflated by total assets, and multiplied by (-1) (I/B/E/S)
COST_COMPLEX	12 quarters rolling window calculation of the correlation between quarterly revenue growth and quarterly expense growth. Inverted, so that high (low) values indicate relatively high fixed (variable) costs (Compustat).
MACRO_SYNC	Variation of earnings with the macroeconomic indicators GDP, energy costs and interest rates, calculated as described in Hutton et al. (2012)
SCOPE_OPERAT	Scope of operations is measured with the Herfindahl-Hirschman index of segment concentration combined with whether a firm has foreign operations (Compustat).
RESTRUCT or M&A	Indicator variable that takes the value 1 if a firm reports recently restructuring charges (Compustat item RCP is non-zero) or mergers or acquisitions (Compustat item AQI is non-zero), 0 otherwise.
σ RETURN	Standard deviation over the the past 12 monthly stock returns (CRSP).
YOUNG_FIRM	Inverse of firm age, as measured by the current fiscal year minus the IPO date (Compustat).
ADV_DIR_INDICATOR	Dummy variables that is 1 if a firm has at least one director who is part of at least one advisory committee, and 0 otherwise (BoardEx).
PERC_ADV_DIR	The percentage of advisory directors (as defined above) on the board (BoardEx).
MONITORING_INTENSITY	The percentage of directors on the board who are members of at least 2 of the 3 principal monitoring (i.e., audit, compensation, and nomination/governance) committees (BoardEx).
PERC_CO-OPTED	The percentage of directors who commence office after or at the same time as the CEO (BoardEx).
RESID_PERC_CO-OPTED	PERC_CO-OPTED orthogonalized to CEO tenure (BoardEx).

Table 1: Description of the Board Network

Network by fiscal year	2002	2003	2004	2005	2006	2007
Number of unique directors	7,465	7,512	7,718	7,884	7,882	7,515
Number of non-isolated firms	5,978	5,912	5,886	5,863	5,754	5,455
Number of firms in largest component	5,450	5,357	5,351	5,394	5,253	4,907
Percentage of firms in largest component	91.1%	90.6%	90.9%	92.0%	91.2%	89.9%
Number of links	15,579	14,850	14,834	15,046	14,493	13,160
Largest component characteristics:						
Average Degree	5.71	5.54	5.54	5.57	5.51	5.36
Median Degree	4	4	4	4	4	4
Average path length	5.48	5.51	5.50	5.47	5.50	5.50
Network by fiscal year	2008	2009	2010	2011	2012	2013
Number of unique directors	7,403	7,198	6,876	6,734	6,704	7,432
Number of non-isolated firms	5,342	5,106	4,843	4,748	4,670	4,879
Number of firms in largest component	4,818	4,575	4,349	4,226	4,142	4,428
Percentage of firms in largest component	90.1%	89.6%	89.7%	89.8%	88.5%	90.4%
Number of links	12,624	11,904	11,178	10,822	10,613	12,089
Largest component characteristics:						
Average Degree	5.24	5.20	5.14	5.12	5.12	5.46
Median Degree	4	4	4	4	4	4
Average path length	5.56	5.50	5.52	5.52	5.58	5.33

Table 1 reports basic network characteristics of firm-to-firm networks for the years 2002 to 2013, where two firms are connected if they share at least one director in a given year. The sample described in Table 1 contains all U.S.-listed firms available in the BoardEx database (S&P 1500+), before requiring non-missing data on other variables used in this study. The largest component comprises the sample used for the analysis in this paper. Therefore, the final sample is a subset of all firm-years that belong to the largest component for which data on other required variables are available. A component is defined as the structure in which every node can reach any other in the component. In Appendix A, I provide an example network and discuss further network characteristics.

Table 2: Summary statistics

Variable	N	Mean	Std. Dev.	P10	P25	P50	P75	P90
MFC_ACC	5,576	-0.012	0.028	-0.024	-0.011	-0.004	-0.002	-0.001
ΔMFC_ACC	5,576	-0.002	0.017	-0.013	-0.004	0	0.003	0.011
CENTRALITY	5,576	0.368	1.021	-0.750	-0.363	0.194	0.865	1.721
ΔCENTRALITY	5,576	0.021	0.307	-0.333	-0.128	0.008	0.174	0.393
ΔDEGREE	5,576	0.024	0.343	-0.343	-0.169	0.009	0.208	0.430
ΔEIGENVECTOR	5,576	0.011	0.286	-0.240	-0.067	0.009	0.093	0.276
ΔCLOSENESS	5,576	0.020	0.341	-0.308	-0.119	0.008	0.146	0.366
AN_FC_DISP	5,576	0.075	0.100	0.000	0.020	0.040	0.080	0.140
BOARD_SIZE	5,576	11.70	5.088	7	8	11	13	18
DISAG	5,576	1.94	1.01	1	1	2	2	5
EARNINGS_VOL	5,576	0.019	0.026	0.003	0.006	0.011	0.021	0.042
ERR_ICMWD	5,576	0.240	0.427	0	0	0	0	1
IMR	5,576	0.394	0.230	0.135	0.214	0.348	0.537	0.714
LEVERAGE	5,576	0.255	0.211	0.000	0.096	0.237	0.364	0.502
MFC_HOR	5,576	247	32	233	242	249	256	289
PER_OUT_DIR	5,576	0.657	0.160	0.444	0.556	0.667	0.778	0.857
REL_IND_DIR	5,576	0.785	0.411	0	1	1	1	1
R&D	5,576	0.029	0.056	0	0	0	0.036	0.092
ROA	5,576	0.062	0.083	0.001	0.030	0.062	0.100	0.142
SIZE	5,576	7.808	1.524	5.897	6.752	7.732	8.852	9.812
ΔCAPEX_FC_ACC	1,290	0	0.013	-0.010	-0.003	0	0.004	0.010
ΔREV_FC_ACC	3,032	-0.002	0.091	-0.087	-0.031	0	0.030	0.078
COST_COMPLEX	5,241	1.586	2.336	1.002	1.009	1.045	1.260	2.028
MACRO_SYNC	5,576	-0.034	0.872	-0.853	-0.693	-0.334	0.380	1.301
SCOPE_OPERAT	4,877	0.343	0.325	0.000	0.001	0.359	0.606	0.741
RESTRUCT or M&A	5,576	0.585	0.492	0	0	1	1	1
σ RETURN	5,576	0.088	0.046	0.040	0.055	0.078	0.109	0.147
YOUNG_FIRM	5,576	0.102	0.075	0.052	0.062	0.076	0.111	0.166
ADV_DIR_INDICATOR	5,576	0.758	0.427	0	1	1	1	1
PERC_ADV_DIR	5,576	0.168	0.165	0	0.037	0.125	0.250	0.400
MONITORING_INTENSITY	5,576	0.417	0.193	0.166	0.272	0.411	0.555	0.666
PERC_CO-OPTED	4,715	0.452	0.242	0.125	0.236	0.437	0.666	0.782
RESID_PERC_CO-OPTED	4,715	-0.029	0.205	-0.273	-0.199	-0.058	0.114	0.263

Table 2 reports descriptive statistics of the variables used in tabulated analyses. The main sample consists of all U.S.-listed firms available in BoardEx from 2002 to 2013 with management forecast data available in I/B/E/S, and data for control variables in Compustat, I/B/E/S and Audit Analytics, which are part of the largest component of the board network. The sample to test the main model comprises 5,576 observations. Appendix B provides variable definitions.

Table 3: Pearson correlations of all variables used in the main analysis, based on the main sample, which comprises all U.S.-listed firms available in BoardEx from 2002 to 2013 with non-missing data on management forecasts and control variables, which are part of the largest component of the board network. P-values are reported in parenthesis. Variable definitions are reported in Appendix B.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1) MFC_ACC	1															
(2) ΔMFC_ACC	0.64	1														
	(0.00)															
(3) CENTRALITY	0.12	0.05	1													
	(0.00)	(0.00)														
(4) ΔCENTRALITY	0.02	0.04	0.15	1												
	(0.11)	(0.01)	(0.00)													
(5) AN_FC_DISP	-0.46	-0.13	-0.03	0.01	1											
	(0.00)	(0.00)	(0.03)	(0.42)												
(6) BOARD_SIZE	0.13	0.04	0.76	0.07	0.04	1										
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)											
(7) DISAG	-0.05	-0.01	-0.04	-0.02	0.02	0.00	1									
	(0.00)	(0.50)	(0.00)	(0.09)	(0.04)	(0.52)										
(8) EARNINGS_VOL	-0.23	-0.05	-0.13	0.01	-0.01	-0.16	-0.01	1								
	(0.00)	(0.00)	(0.00)	(0.54)	(0.33)	(0.00)	(0.69)									
(9) ERR_ICMWD	-0.04	-0.03	-0.02	0.00	0.00	-0.02	0.01	0.03	1							
	(0.00)	(0.02)	(0.16)	(0.89)	(0.77)	(0.06)	(0.12)	(0.01)								
(10) LEVERAGE	0.08	0.04	0.08	-0.01	0.10	0.09	-0.01	-0.08	0.01	1						
	(0.00)	(0.00)	(0.00)	(0.65)	(0.00)	(0.00)	(0.43)	(0.00)	(0.4)							
(11) MFC_HOR	0.00	-0.06	0.19	0.00	0.00	0.17	-0.05	-0.03	-0.02	0.00	1					
	(0.84)	(0.00)	(0.00)	(0.82)	(0.99)	(0.00)	(0.00)	(0.05)	(0.07)	(0.82)						
(12) PER_OUT_DIR	-0.05	-0.02	-0.36	0.00	0.01	-0.56	-0.09	0.00	-0.02	0.00	-0.06	1				
	(0.00)	(0.09)	(0.00)	(0.83)	(0.65	(0.00)	(0.00)	(0.75)	(0.1)	(0.95)	(0.00)					

Continued on next page...

... table 3 continued

(13) REL_IND_DIR	-0.02	-0.01	0.15	0.04	0.03	0.11	-0.01	0.01	0.04	-0.02	0.02	-0.11	1			
	(0.12)	(0.70)	(0.00)	(0.00)	(0.02)	(0.00)	(0.96)	(0.37)	(0.01)	(0.08)	(0.20)	(0.00)				
(14) R&D	-0.16	0.00	0.04	0.01	-0.06	-0.01	-0.01	0.33	-0.01	-0.17	0.00	-0.09	0.04	1		
	(0.00)	(0.88)	(0.00)	(0.36)	(0.00)	(0.62)	(0.25)	(0.00)	(0.62)	(0.00)	(0.96)	(0.00)	(0.00)			
(15) ROA	0.26	0.18	0.07	0.03	-0.07	0.08	-0.03	-0.14	-0.05	-0.11	0.09	-0.09	0.02	-0.19	1	
	(0.00)	(0.00)	(0.00)	(0.03)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.10)	(0.00)		
(16) SIZE	0.24	0.11	0.65	0.02	0.03	0.70	-0.02	-0.23	-0.05	0.13	0.21	-0.36	0.05	-0.05	0.28	1
	(0.00)	(0.00)	(0.00)	(0.09)	(0.02)	(0.00)	(0.04)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	

Table 4: Annual changes in management forecast accuracy as a function of annual changes in centrality and annual changes in controls. Columns (2), (4), (6) and (8) present results of test controlling for self selection into issuing a forecast by means of a Heckman selection model.

DV=ΔMFC_ACC (Predicted sign)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔCENTRALITY	0.215***	0.164***						
(+)	(3.94)	(2.81)						
ΔDEGREE			0.120**	0.079*				
(+)			(2.12)	(1.33)				
ΔEIGENVECTOR					0.166*	0.136*		
(+)					(1.61)	(1.52)		
ΔCLOSENESS							0.217***	0.176***
(+)							(4.15)	(3.24)
IMR		-1.32***		-1.29***		-1.33***		-1.33***
		(-4.84)		(-4.91)		(-4.84)		(-4.81)
ΔAN_FC_DISP	-0.97***	-0.73**	-0.96***	-0.74**	-0.97***	-0.73***	-0.97***	-0.73**
	(-2.71)	(-2.49)	(-2.73)	(-2.53)	(-2.71)	(-2.57)	(-2.69)	(-2.45)
ΔBOARD_SIZE	-0.001	0.008	0.005	0.012	0.008	0.015	0.002	0.008
	(-0.06)	(0.41)	(0.28)	(0.70)	(0.44)	(0.79)	(0.14)	(0.49)
ΔDISAG	-0.055	-0.052	-0.054	-0.052	-0.054	-0.052	-0.056	-0.053
	(-1.47)	(-1.40)	(-1.43)	(-1.39)	(-1.47)	(-1.39)	(-1.50)	(-1.42)
ΔEARNINGS_VOL	-6.52	-5.88	-6.56	-5.86	-6.63	-5.93	-6.41	-5.81
	(-1.16)	(-1.05)	(-1.17)	(-1.04)	(-1.18)	(-1.06)	(-1.15)	(-1.04)
ERR_ICMWD	-0.064	-0.064	-0.063	-0.063	-0.065	-0.064	-0.06	-0.065
	(-1.49)	(-1.55)	(-1.48)	(-1.53)	(-1.51)	(-1.55)	(-1.49)	(-1.45)
ΔLEVERAGE	0.48**	0.40**	0.47**	0.40**	0.48**	0.40**	0.48**	0.39**
	(2.55)	(2.27)	(2.53)	(2.26)	(2.55)	(2.25)	(2.56)	(2.25)
ΔMFC_HOR	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***
	(-7.30)	(-7.34)	(-7.31)	(-7.36)	(-7.25)	(-7.31)	(-7.31)	(-7.34)
ΔPER_OUT_DIR	-1.09***	-1.21***	-1.03***	-1.14***	-1.01**	-1.14***	-1.10***	-1.23***
	(-2.73)	(-3.04)	(-2.60)	(-2.88)	(-2.42)	(-2.79)	(-2.85)	(-3.17)
ΔREL_IND_DIR	0.19*	0.19*	0.19*	0.19*	0.21*	0.19*	0.19*	0.19*
	(1.74)	(1.84)	(1.73)	(1.81)	(1.90)	(1.91)	(1.67)	(1.82)
ΔR&D	0.375	0.627	0.360	0.561	0.410	0.678	0.28	(1.67)
	(0.11)	(0.18)	(0.10)	(0.16)	(0.12)	(0.20)	(0.08)	(0.15)
ΔROA	4.42***	4.18***	4.42***	4.19***	4.41***	4.19***	4.42***	4.18***
	(3.47)	(3.50)	(3.46)	(3.48)	(3.45)	(3.50)	(3.47)	(3.49)
ΔSIZE	0.78***	0.74***	0.78***	0.75***	0.79***	0.74***	0.78***	0.74***
	(8.22)	(8.81)	(8.24)	(8.74)	(8.32)	(8.88)	(8.20)	(8.84)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	5,576	5,576	5,576	5,576	5,576	5,576	5,576	5,576
R-squared	0.115	0.122	0.114	0.121	0.115	0.122	0.115	0.123

Table 4 reports estimates of an OLS regression of the following model:

$$\Delta MFC\_ACC_{ijt} = \alpha_1 \Delta CENTRALITY_{ijt} + \sum \alpha_k \Delta CONTROLS_{ijt} + \gamma_t + \delta_j + \epsilon_{ijt}$$

It estimates an annual change in annual earnings forecast accuracy as a function of an annual change in various centrality measures, a set of control variables, and year and industry effects. Standard errors are clustered by firm and year. Columns (2), (4), (6), and (8) present estimations controlling for self selection into issuing a management forecast in a given year by means of a Heckman selection model. The sample consists of all U.S.-listed firms available in BoardEx from 2002 to 2013 with management forecast data available in I/B/E/S, and data for control variables in Compustat, I/B/E/S and Audit Analytics, which are part of the largest component of the board network. Appendix B provides the variable definitions. t-statistics are reported in parenthesis. ***,**,* corresponds to 1%, 5%, and 10% significance levels (one-tailed when the coefficient sign is predicted, two-tailed otherwise). Due to small values for the dependent variable the coefficients are multiplied by 100 for presentation.

Table 5: Columns (1) to (4) present an estimation of annual changes in management forecast accuracy as a function of annual changes in centrality, estimated in subsamples of firm-years with positive forecast errors, negative forecast errors, no director changes at firm (i), and no director changes at firm$_i$ and firm$_i$'s direct connections, respectively. Columns (5) to (8) present an estimation of annual changes in management forecast accuracy as a function of one year lag, two years lag, one year lead, and two years lead annual changes in centrality, respectively.

DV=ΔMFC_ACC (Predicted sign)	MFC_ERR$^+$	MFC_ERR$^-$	Δ board composition=0	Δ outside directorships=0	full sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔCENTRALITY	0.121***	0.269**	0.099*	0.773*				
(+)	(2.73)	(2.04)	(1.63)	(1.36)				
LAG_ΔCENTRALITY					-0.073			
					(-1.07)			
LAG2_ΔCENTRALITY						0.009		
						(0.09)		
LEAD_ΔCENTRALITY							-0.079	
							(-0.73)	
LEAD2_ΔCENTRALITY								-0.072
								(-0.88)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3,250	2,326	1,500	803	5,092	4,491	4,829	4,141
R-squared	0.061	0.23	0.137	0.108	0.113	0.108	0.121	0.117

Table 5, columns (1) to (4) report estimates of an OLS regression with clustered standard errors by firm and year of the following (i.e., standard) model, where specific subsamples, as defined in the caption, are used:

$$\Delta MFC\_ACC_{ijt} = \alpha_1 \Delta CENTRALITY_{ijt} + \sum \alpha_k \Delta CONTROLS_{ijt} + \gamma_t + \delta_j + \epsilon_{ijt}$$

Table 5, columns (5) to (8) report estimates of an OLS regression with clustered standard errors by firm and year of the following models, where the independent variable ΔCENTRALITY is replaced by one year lag ΔCENTRALITY (column (5)), two year lag ΔCENTRALITY (column (6)), one year lead ΔCENTRALITY (column (7)) and two year lead ΔCENTRALITY (column (8)):

$$\Delta MFC\_ACC_{ijt} = \alpha_1 LAG\_\Delta CENTRALITY_{ijt} + \sum \alpha_k \Delta CONTROLS_{ijt} + \gamma_t + \delta_j + \epsilon_{ijt}$$

$$\Delta MFC\_ACC_{ijt} = \alpha_1 LAG2\_\Delta CENTRALITY_{ijt} + \sum \alpha_k \Delta CONTROLS_{ijt} + \gamma_t + \delta_j + \epsilon_{ijt}$$

$$\Delta MFC\_ACC_{ijt} = \alpha_1 LEAD\_\Delta CENTRALITY_{ijt} + \sum \alpha_k \Delta CONTROLS_{ijt} + \gamma_t + \delta_j + \epsilon_{ijt}$$

$$\Delta MFC\_ACC_{ijt} = \alpha_1 LEAD2\_\Delta CENTRALITY_{ijt} + \sum \alpha_k \Delta CONTROLS_{ijt} + \gamma_t + \delta_j + \epsilon_{ijt}$$

The vector ΔCONTROLS contains the conventional control variables used throughout the paper and defined in Section 3.5 and Appendix B. The sample consists of all U.S.-listed firms available in BoardEx from 2002 to 2013 with management forecast data available in I/B/E/S, and data for control variables in Compustat, I/B/E/S and Audit Analytics, which are part of the largest component of the board network. t-statistics are reported in parentheses. ***,**,* corresponds to 1%, 5%, and 10% significance levels (one-tailed when the coefficient sign is predicted, two-tailed otherwise). The coefficients are multiplied by 100 for presentation.

Table 6: The moderating effect of firms' advisory needs on the relation between annual changes in management forecast accuracy and annual changes in centrality.

DV=ΔMFC_ACC	SCOPE OPERAT		YOUNG FIRM		RESTRUCT or M&A		σ RETURN		COST COMPLEX		MACRO SYNC	
	HIGH	LOW	HIGH	LOW	HIGH	LOW	HIGH	LOW	HIGH	LOW	HIGH	LOW
Predicted sign for	+	/	+	/	+	/	+	/	+	/	+	/
ΔCENTRALITY	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ΔCENTRALITY	0.33***	0.09	0.38***	0.03	0.26***	0.11**	0.34***	0.08	0.37***	0.11	0.38***	0.07
	(4.75)	(0.92)	(3.52)	(0.32)	(3.22)	(2.20)	(3.46)	(1.44)	(3.35)	(1.17)	(3.78)	(0.70)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2,439	2,438	2,758	2,818	3,266	2,310	2,788	2,788	2,621	2,620	2,788	2,788
R-squared	0.158	0.107	0.115	0.129	0.171	0.075	0.139	0.057	0.134	0.177	0.099	0.158
p-val. sign. diff. ΔCENTRALITY	0.039		0.017		0.065		0.008		0.058		0.036	

Table 6 reports estimates of an OLS regression with clustered standard errors by firm and year of the following model (i.e., main model), in subsamples:

$$\Delta MFC\_ACC_{ijt} = \alpha_1 \Delta CENTRALITY_{ijt} + \sum \alpha_k \Delta CONTROLS_{ijt} + \gamma_t + \delta_j + \epsilon_{ijt}$$

In Table 6 results of an analysis of the moderating effect of firms' advisory needs on the relation between board centrality and forecast accuracy are presented. The main model has been re-estimated in subsamples (median splits) of the scope of operations (column (1) and (2)), firm age (column (3) and (4)), restructuring or M&A (column (5) and (6)), standard deviation of returns (column (7) and (8)), cost complexity (column (9) and (10)), and macroeconomic synchronicity (column (11) and (12)). Scope of operations (SCOPE_OPERAT) is measured with a Herfindahl-Hirschman index of segment concentration combined with whether a firm has foreign operations. YOUNG_FIRM is the inverse of firm age, as measured by the current fiscal year minus the IPO date (as specified in Compustat). Restructuring or M&A (RESTRUCT or M&A) is an indicator variable that takes the value 1 if a firm reports recently restructuring charges (Compustat item RCP is non-zero) or mergers or acquisitions (Compustat item AQI is non-zero), 0 otherwise. σ RETURN is the standard deviation over the the past 12 monthly stock returns. Cost complexity (COST COMPLEX) is a moving window calculation of the correlation between quarterly revenue growth and quarterly expense growth over the last 12 quarters. I invert this measure so that high (low) values for the correlations indicate relatively high fixed (variable) costs. Macroeconomic synchronicity (MACRO SYNC) is the degree to which a firm's earnings vary with macroeconomic indicators (e.g., GDP). The vector ΔCONTROLS contains the same control variables that are used throughout the main analysis. The sample consists of all U.S.-listed firms available in BoardEx from 2002 to 2013 with management forecast data available in I/B/E/S, and data for control variables in Compustat, I/B/E/S, Execucomp and Audit Analytics, which are part of the largest component of the board network. Appendix B provides all variable definitions. t-statistics are reported in parentheses. ***,**,* corresponds to 1%, 5%, and 10% significance levels (one-tailed when the coefficient sign is predicted, two-tailed otherwise). The coefficients are multiplied by 100 for presentation. The last row presents p-values of t-tests for significant differences (one-tailed) of the coefficient for ΔCENTRALITY between subsamples of the respective partitioning variable. Therefore, the basic regression specification is re-estimated on the full sample with interaction terms of the respective subsample indicator with ΔCENTRALITY, all control variables and fixed-effects.

Table 7: The moderating effect of firms' advisory directors on the relation between annual changes in management forecast accuracy and annual changes in centrality.

DV=ΔMFC_ACC	ADV DIR INDICATOR		PERC ADV DIR		MONITORING INTENSITY		PERC CO-OPTED		RESID PERC CO-OPTED		PERC CO-OPTED & PERC ADV DIR	
	HIGH	LOW	HIGH	LOW	HIGH	LOW	HIGH	LOW	HIGH	LOW	HIGH	LOW
Predicted sign for	+	/	+	/	/	+	+	/	+	/	+	/
ΔCENTRALITY	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ΔCENTRALITY	0.27***	0.02	0.35***	0.11*	0.10	0.271***	0.30***	0.14*	0.30***	0.11	0.34***	0.16**
	(4.19)	(0.20)	(3.04)	(1.82)	(1.05)	(4.62)	(3.70)	(1.85)	(3.05)	(1.39)	(2.98)	(2.50)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	4,231	1,345	2,637	2,939	2,805	2,771	2,288	2,287	2,288	2,287	1,180	4,396
R-squared	0.102	0.186	0.132	0.110	0.135	0.107	0.126	0.125	0.131	0.143	0.154	0.118
p-val. sign. diff. ΔCENTRALITY	0.039		0.040		0.060		0.054		0.086		0.081	

Table 7 reports estimates of an OLS regression with clustered standard errors by firm and year of the following model (i.e., main model), in subsamples:

$$\Delta MFC\_ACC_{ijt} = \alpha_1 \Delta CENTRALITY_{ijt} + \sum \alpha_k \Delta CONTROLS_{ijt} + \gamma_t + \delta_j + \epsilon_{ijt}$$

In Table 7 results of an analysis of the moderating effect of firms' advisory needs on the relation between board centrality and forecast accuracy are presented. The main model has been re-estimated in subsamples (median splits) of the presence of an advisory director on the board (column (1) and (2)), the percentage of advisory directors (column (3) and (4)), monitoring intensity of the board (column (5) and (6)), the percentage of co-opted directors (column (7) and (8)), the percentage of co-opted directors orthogonalized to CEO tenure (column (9) and (10)), and high percentage of advisory (as in column 3) and co-opted directors (as in column 7) (column (11) and (12)). ADV_DIR_INDICATOR is a dummy variables that takes the value of one if a firm has at least one advisory director, classified based on committee memberships, on its board, 0 otherwise. PER_ADV_DIR is the percentage of advisory directors on the board, classified based on committee memberships. MONITORING_INTENSITY is the percentage of directors on the board that are members of at least two of the three principal monitoring (i.e., audit, compensation, and nomination/governance) committees. PERC_CO-OPTED is the percentage of directors who commence office after or with the CEO. RESID_PERC_CO-OPTED is defined as PERC_CO-OPTED orthogonalized to CEO tenure. The variable captures the fraction of co-opted directors not correlated with CEO tenure. PERC_CO-OPTED & PER_ADV_DIR is high for firm-years of above median values for PERC_CO-OPTED *and* above median values for PER_ADV_DIR, low otherwise. The vector ΔCONTROLS contains the same control variables that are used throughout the main analysis. The sample consists of all U.S.-listed firms available in BoardEx from 2002 to 2013 with management forecast data available in I/B/E/S, and data for control variables in Compustat, I/B/E/S, Execucomp and Audit Analytics, which are part of the largest component of the board network. The smaller amount of observations for the cross sectional tests reported in columns (7) to (12) arise due to missing observations on CEOs and the date they commenced the position as CEO at the respective firm. Appendix B provides all variable definitions. t-statistics are reported in parentheses. ***,**,* corresponds to 1%, 5%, and 10% significance levels (one-tailed when the coefficient sign is predicted, two-tailed otherwise). The coefficients are multiplied by 100 for presentation. The last row presents p-values of t-tests for significant differences (one-tailed) of the coefficient for ΔCENTRALITY between subsamples of the respective partitioning variable. Therefore, the basic regression specification is re-estimated on the full sample with interaction terms of the respective subsample indicator with ΔCENTRALITY, all control variables and fixed-effects.

Table 8: Annual changes in revenue and CapEx forecast accuracy as a function of annual changes in centrality and annual changes in controls.

Predicted sign	DV = ΔREV_FC_ACC Full sample	DV = ΔREV_FC_ACC MFC_ERR^{+}	DV = ΔREV_FC_ACC MFC_ERR^{-}	DV = ΔCAPEX_FC_ACC Full sample	DV = ΔCAPEX_FC_ACC MFC_ERR^{+}	DV = ΔCAPEX_FC_ACC MFC_ERR^{-}
ΔCENTRALITY	0.84*	0.92**	0.49	0.28***	0.36*	0.15*
(+)	(1.33)	(1.92)	(0.42)	(3.13)	(1.54)	(1.39)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	3,032	1,524	1,508	1,290	444	846
R-squared	0.043	0.087	0.093	0.057	0.076	0.100

Table 8 reports estimates of OLS regressions with clustered standard errors by firm and year of the following models:

$$\Delta REV\_FC\_ACC_{ijt} = \alpha_1 \Delta CENTRALITY_{ijt} + \sum \alpha_k \Delta CONTROLS_{ijt} + \gamma_t + \delta_j + \epsilon_{ijt}$$

$$\Delta CAPEX\_FC\_ACC_{ijt} = \alpha_1 \Delta CENTRALITY_{ijt} + \sum \alpha_k \Delta CONTROLS_{ijt} + \gamma_t + \delta_j + \epsilon_{ijt}$$

The equations model an annual change in annual revenue (ΔREV_FC_ACC) and capital expenditure (ΔCAPEX_FC_ACC) forecast accuracy as a function of an annual change in centrality (ΔCENTRALITY) and a set of control variables. The vectors of controls include the same variables as in the main model with the following exceptions: In both models, forecast horizon is calculated with the respective sales or CapEx forecast release date, and in both models the variable analyst earnings forecast dispersion is removed as it is a control variable that specifically relates to earnings forecasts. For the same reason, in the sales-forecast model, the variable volatility of earnings is substituted with volatility of sales. The sample consists of all U.S.-listed firms available in BoardEx from 2002 to 2013 with revenue and CapEx forecast data available in I/B/E/S, and data for control variables in Compustat, I/B/E/S and Audit Analytics, which are part of the largest component of the board network. REV_FC_ACC (CAPEX_FC_ACC) denotes the absolute difference between the first one-year ahead forecasted revenue (CapEx) and realized revenue (CapEx), scaled by total assets. Appendix B provides the remaining variable definitions. t-statistics are reported in parentheses. ***,**,* corresponds to 1%, 5%, and 10% significance levels (one-tailed when the coefficient sign is predicted, two-tailed otherwise). The coefficients are multiplied by 100 for presentation.

Table 9: Presents an estimation of annual changes in management forecast accuracy as a function of annual changes in centrality and controls, and CEO fixed effects (column 2), CEO-firm fixed effects (column 3), CFO fixed effects (column 5), or CFO-firm fixed effects (column 6). The coefficient for ΔCENTRALITY reported in column (1) [4] provides a benchmark for coefficients in columns (2) and (3) [columns (5) and (6)], because the number of observations deviates from the main sample.

DV=ΔMFC_ACC (Predicted sign)	sample identified CEOs (1)	CEO fixed effects (2)	CEO-firm fixed effects (3)	sample identified CFOs (4)	CFO fixed effects (5)	CFO-firm fixed effects (6)
ΔCENTRALITY	0.19***	0.16**	0.15**	0.19**	0.17*	0.16*
(+)	(2.81)	(1.86)	(1.80)	(1.92)	(1.67)	(1.51)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
CEO FE	No	Yes	No	No	No	No
CEO-firm FE	No	No	Yes	No	No	No
CFO FE	No	No	No	No	Yes	No
CFO-firm FE	No	No	No	No	No	Yes
Joint sign CEO or CFO FE or CEO-firm or CFO-firm FE		$p < 0.05$	$p < 0.05$		$p < 0.01$	$p < 0.01$
N	4,766	4,766	4,766	3,378	3,378	3,378
R-squared	0.109	0.374	0.375	0.127	0.457	0.471
Adjusted R-sqrt.	0.102	0.124	0.123	0.117	0.187	0.197

Table 9, reports estimates of an OLS regression of the following (i.e., standard) model, with CEO, CEO-firm, CFO, or CFO-firm effects included:

$$\Delta MFC\_ACC_{ijt} = \alpha_1 \Delta CENTRALITY_{ijt} + \sum \alpha_k \Delta CONTROLS_{ijt} + \gamma_t + \delta_j + \epsilon_{ijt}$$

Standard errors in models reported in columns (1) and (4) are clustered by firm and year, standard errors in the remaining models are not clustered. All results remain qualitatively similar if clustered by firm or year. The vector ΔCONTROLS contains the conventional control variables used throughout the paper and defined in Section 3.5 and Appendix B. The sample consists of all U.S.-listed firms available in BoardEx from 2002 to 2013 with management forecast data available in I/B/E/S, and data for control variables in Compustat, I/B/E/S and Audit Analytics, which are part of the largest component of the board network. t-statistics are reported in parentheses. ***,**,* corresponds to 1%, 5%, and 10% significance levels (one-tailed when the coefficient sign is predicted, two-tailed otherwise). The coefficients are multiplied by 100 for presentation.