Journal of Corporate Finance 68 (2021) 101920

Contents lists available at ScienceDirect

Journal of Corporate Finance

journal homepage: www.elsevier.com/locate/jcorpfin

The dark side of CEO social capital: Evidence from real earnings management and future operating performance

Paul A. Griffin [a,*], Hyun A. Hong [b], Yun Liu [c], Ji Woo Ryou [d]

[a] Graduate School of Management, University of California, Davis, CA 95616, United States of America
[b] Anderson Graduate School of Management, University of California, Riverside, CA 92521, United States of America
[c] Keck Graduate Institute, Claremont Colleges, Claremont, CA 91711, United States of America
[d] John Chambers College of Business and Economics, West Virginia University, Morgantown, WV 26507, United States of America

ARTICLE INFO

Keywords:
Network size
CEO social capital
Real earnings management
Future operating performance

ABSTRACT

We examine the role of CEO social capital as an important driver of the widespread practice of real earnings management (*REM*). Using the number of social connections to outside executives and directors to measure CEO social capital, we first find that well-connected CEOs associate with higher levels and volatilities of *REM*. The positive relation between *REM* and CEO network size is stronger when the CEO connects with more informed and influential persons, and when a more severe misalignment of interests can occur. Second, we find a contagion of *REM* among well-connected CEOs in an industry. Third, the level of *REM* induced by a large CEO social network associates negatively with future operating performance. This result is consistent with social capital circulating *REM*-related information *ex-ante* and increasing the power and influence for the CEO to deviate from optimal operating policies *ex-post*. Social capital shields the well-connected executive in the takeover and labor markets despite possible suboptimal future operating performance. While the prior literature finds that CEO social capital reduces accrual earnings management, our findings suggest a dark side of CEO social capital: it induces excessive levels and volatilities of *REM* costly to the firm in the long run while imposing relatively low personal risk on the top executive.

1. Introduction

We examine whether executives' social capital affects firms' real earnings management (*REM*), a practice whereby a manager purposely alters the firm's cash flow to report earnings based on departures from the timing or structuring of normal or optimal operations. Considering the pervasive and popular use of *REM*, especially after the Sarbanes-Oxley Act (Gilliam et al., 2015; Koh et al., 2008; Brown and Caylor, 2005; Larcker et al., 2013), a significant body of literature has examined what drives *REM* practices and their operating consequences (e.g., Barton and Simko, 2002; Demski et al., 2004; Ewert and Wagenhofer, 2005; Zang, 2012). However, extant studies overlook an important human factor underlying a decision to engage in *REM*, the social capital of the executive who develops and implements the financial reporting practices. We contribute to the literature by being the first to examine the impact on *REM* practices of CEO social capital and its role as an important channel through which *REM* affects future firm operating performance.

* Corresponding author.
E-mail addresses: pagriffin@ucdavis.edu (P.A. Griffin), hyunh@ucr.edu (H.A. Hong), yun_liu@kgi.edu (Y. Liu), jiwoo.ryou@mail.wvu.edu (J.W. Ryou).

https://doi.org/10.1016/j.jcorpfin.2021.101920
Received 17 September 2020; Received in revised form 17 February 2021; Accepted 23 February 2021
Available online 1 March 2021
0929-1199/

Prior research has developed the causes and consequences of *REM* in a dichotomous manner. On the one hand, a firm manager could use *REM* to signal firm quality and managerial competence by meeting or beating a market expectation, and provide financial benefits to the firm (Gunny, 2010). On the other hand, *REM* could be driven by managerial opportunism to inflate or smooth earnings. This opportunistic earnings management strategy could boost stock price in the short term and increase the manager's job security or compensation to the detriment of firm value in the long run (Bens et al., 2002). The former and the latter strands of literature find a positive and negative relation between *REM* and firm future operating performance, respectively. We contend that the extant literature provides at best an incomplete picture of firms' *REM* practices by not considering the social capital of the CEO. CEO social capital can influence both the informational and opportunistic incentives of engaging in *REM*. Our study on how CEO social networks shape *REM* practices, thus, may shed new light on the determinants of *REM*. Our investigation may also clarify the mixed findings regarding *REM* and firm future performance. A growing number of studies in corporate finance documents that executives' social capital significantly alters firms' operating, investing, and financial policies (e.g., El-Khatib et al., 2015; Faleye et al., 2014; Fracassi, 2016; Shue, 2013). These policies link tightly with firms' *REM* strategies, including executives' use of R&D expenditures and production decisions to influence market or contractual outcomes and, thus, firms' operating performance in the long-term (Dechow and Sloan, 1991).

The social science literature has long established the two channels of social connections, such as the information-sharing and communication and the power and influence channels (Brass and Burkhardt, 1992; Burt, 2000; Coleman, 1988; Granovetter, 2005; Haunschild, 1993; Inkpen and Tsang, 2005; Mizruchi, 1996; Mizruchi and Potts, 1998; Reagans and McEvily, 2003). With respect to the information-sharing channel, CEO social connections may serve as less costly venues to convey information and to signal firm quality or managerial trust and competency. Engelberg et al. (2012) document similar benefits of CEO social capital. Informal ties between a borrower and a lender that facilitate communication could lead to larger loans, lower interest rates, and less restrictive covenants. The information and reputation benefits of CEO social capital are, thus, likely manifested in a wide variety of corporate outcomes and business activities potentially with less cost to the executive than *REM*.[1] Similarly, one reason why a CEO may rationally engage in *REM* is to smooth reported earnings and lower creditors' perception of the variance of the firm's underlying economic activities. The managed earnings could, in turn, improve firm value by reducing the cost of debt and avoiding a debt covenant violation (Bartov, 1993; Trueman and Titman, 1988). To the extent that network information-sharing and communication is a less costly way to achieve the firm's objectives (e.g., avoid a debt covenant violation, reduce the cost of debt) than deviating from normal or optimal operating policies, CEO social capital could *reduce* the need for a CEO to use *REM* to inform stakeholders or to build trust and credibility with stakeholders.

Social capital, however, can also induce a CEO to engage in rent-extraction through *REM* rather than other earnings management techniques, such as accrual-based earnings management (*AEM*). We contend that an opportunistic manager's choice of an earnings management practice depends on its costs and benefits to the individual. There is likely to be increased pressure to deliver performance and meet the market's expectation when CEO social capital increases. Compared to *AEM* that can induce a violation of GAAP, SEC litigation, and adverse media coverage, *REM* adjustments are less detectable and less scrutinized (Cohen et al., 2008a; Cohen and Zarowin, 2010). CEOs with large social capital are also more in the limelight, under more public monitoring, and risk a bigger reputation loss for detected misconduct. Thus, with increased pressure to meet the market's expectation and greater reputation concerns, well-connected CEOs could prefer using *REM*.

The power and influence channel of an extensive network could further empower CEOs' position to deviate from normal or optimal operating policies and thus "enable" the design and execution of *REM* in two ways. First, this channel could elicit support from the board to use *REM* by deviating from normal or optimal operating policies. Second, this channel could provide takeover and labor market insurance for a CEO in the event of separation resulting from poor performance. While the executive survey conducted by Graham et al. (2005) shows that *REM* is a CEO's favorable earnings management technique to achieve a short-term target, the disadvantage of *REM* is that it involves altering actual business decisions that could negatively affect long-term performance and firm value. The poor long-term performance imposes personal costs of *REM* on a CEO, which come mostly from disciplinary measures. These costs may not be obvious in the short-run. Studies of CEO social capital also show that large networks associate with risk-taking (Faleye et al., 2014; Fang et al., 2019; Ferris et al., 2017). These studies suggest that social ties can minimize the personal consequences of failed risky strategies by protecting CEOs against job losses or improving the chances of re-employment post CEO turnover. With mitigated career concerns, the personal benefits extracted from bolstering short-term performance are likely to outweigh the personal costs borne by a well-connected CEO from poor long-term performance associated with *REM*. In other words, the choice of *REM*, though potentially costly to the firm, involves low personal risk and cost to a well-connected CEO. Such a person may gain power and influence from the attention given to abnormally high levels of earnings (Koester et al., 2016) while enjoying job protection in the takeover and labor markets (e.g., Bebchuk et al., 2011; El-Khatib et al., 2015; Hwang and Kim, 2009).

In sum, because well-connected CEOs can use the information-sharing and communication features of their social capital for the benefit of stakeholders and the firm, there may be little reason for an executive to use *REM* to manage earnings. *REM* often involves an inefficient use of corporate resources to generate the earnings adjustment. Under this scenario, we predict a negative relation between CEO social capital and the level and volatility of *REM*. However, for well-connected CEOs more concerned with their private benefits at the expense of stakeholders, we predict that CEOs with larger social capital will instigate larger *REM* adjustments to manage earnings than CEOs with smaller social capital. Under this alternative scenario, we predict a positive relation between CEO social capital and the

[1] For example, Ke et al. (2019) find that social connections within the executive team associate with higher management forecast accuracy. Larcker et al. (2013) find that firms with connected boards earn superior stock returns, which they attribute to greater information access. Hochberg et al. (2007) find that venture capital network improves investment performance.

level and volatility of *REM*. Which of these two *REM* scenarios associates with large CEO social capital is unresolved. It is also unsettled whether CEOs with larger social capital compared to CEOs with smaller social capital instigate larger *REM* adjustments that generate better or worse operating performance in the long run. We provide empirical evidence on how these *REM* scenarios relate to CEOs with substantial social capital.

We use CEO network size to proxy for CEO social capital and measure CEO network size for a sample of U.S. firms by summing for each firm-year the CEO's professional, educational, and social connections to other CEOs and directors identified in the BoardEx dataset (Engelberg et al., 2013). We then follow the earnings management literature and use the individual measures of an abnormal level of operating cash flow, production cost, and discretionary expenditure and a combined measure to proxy for *REM* for each firm-year. We analyze 24,549 firm-years and 4362 unique firms over 1999–2014.

We document the following key findings. First, we find a positive relation between CEO network size and the level of *REM* (for the individual and combined measures of *REM*). This persists after we control for the level of *AEM* and when we use alternative CEO network size and *REM* measures, different periods, and a two-stage instrumental-variable approach. We further find that CEO network size relates positively to the volatility of *REM*. This finding further supports the view that a CEO's social capital increases the executive's incentive to design and execute *REM*.

Second, we find a stronger positive relation between CEO network size and the level of *REM* for networks that are more informative or influential, consistent with the channels of information-sharing and power and influence through which social networks could affect *REM*. We also find evidence of a contagion effect, that is, the level of *REM* of the focal firm associates positively with the average level of *REM* of connected firms. This supports the idea that CEOs share information about *REM* practices through their social connections.

Third, we find that high levels of *REM* presage poorer future return on assets and lower operating cash flows when the CEO network is large. By contrast, we do not find a negative association between *REM* and future operating performance when the CEO network is small. Thus, while engaging in *REM* per se may not be value-decreasing for all firms, our findings suggest that larger networks embolden the CEO to deviate from optimal operational decision-making if the costs exceed the benefits to the firm. As such, the CEO's preference for *REM* could be a symptom of misaligned interests leading to poor operating performance in the long-term. Consistent with this interpretation, we find that the positive relation between CEO network size and the level of *REM* and the negative relation between future operating performance and the level of *REM* concentrates in the sub-sample with low CEO share ownership. This is where the misalignment of interests is most severe.

Fourth, we document that CEO network size relates negatively to the level of *AEM* and the possibility of a future restatement, corroborating the findings in Bhandari et al. (2018). In addition, the positive effect we document for *REM* and the negative effect for *AEM* are not driven by different samples or methodology. As such, we contend that social network size plays a unique role in explaining CEOs' use of *REM* as opposed to *AEM* as an earnings management practice. It is important to note that we control for the level of *AEM* throughout our analysis of *REM*. So, the relation between *REM* and CEO network size goes beyond what a substitutional relation between *AEM* and *REM* might explain. Therefore, our paper offers a more complete portrayal of the association between CEO network size and earnings management and challenges the view that CEO social connections necessarily improve financial reporting quality by reducing *AEM* practices.

Our paper contributes to the literature in several directions. The first relates to the determinants and consequences of *REM*. Studies show that managers facing stricter regulation of their accounting practices are more likely to use *REM* to achieve an earnings target.[2] We identify CEO network size as a key factor influencing the personal costs and benefits of alternative earnings management strategies to the executive. CEO network size has significant impacts on the level, volatility, and propagation of *REM* practices. Our results also shed light on the effect of *REM* on firms' future operating performance in the long run. Existing studies provide mixed evidence on whether *REM* increases or decreases future operating performance (Gunny, 2010; Leggett et al., 2009; Taylor and Xu, 2010). Our study indicates that CEO social capital is a factor that helps reconcile this mixed evidence: a negative relation between *REM* and future operating performance appears only when *REM* adjustments and CEO network size are large.

Second, our study complements a nascent body of literature on how CEO social networks shape firms' reporting policies. Ke et al. (2019) focus on the social connections among executives within the same firm and find that the internal network improves management forecast accuracy. By contrast, we look at the external network of a CEO (i.e., involving ties to people outside of the firm) and document its impact on *REM*. Using a similar network construct, Bhandari et al. (2018) find that CEOs with larger networks have lower discretionary accruals, suggesting that well-connected CEOs improve earnings reporting quality due to reputation concerns. However, this is an incomplete assessment of the relation between CEO network size and earnings management because it does not consider the network's effect on *REM*. Prior studies indicate that managers trade off *AEM* and *REM* (Zang, 2012). *REM* may be a preferred form of earnings management for well-connected CEOs because of its lower detection cost. Therefore, a focus on only the network effects of *AEM* understates the total earnings management activities of well-connected executives. This paper adds to the literature by demonstrating that well-connected CEOs are more aggressive in *REM*.

Third, our paper relates to the studies showing that executive social capital increases CEOs' tendency to take risk in operations (Faleye et al., 2014; Fang et al., 2019; Ferris et al., 2017), of which a *REM* strategy could be a symptom. In our empirical analysis, we include several measures of corporate risk-taking as control variables. Thus, our evidence of a relation between CEO social capital and

[2] *REM*, for example, more frequently occurs after the introduction of the Sarbanes-Oxley Act (SOX) of 2002, which was intended to limit questionable accounting practices (Cohen, Dey, and Lys 2008; Gilliam et al., 2015; Koh et al., 2008; Brown and Caylor, 2005) and strengthen auditing standards (Cohen and Zarowin, 2010; Zang, 2012). The use of *REM* also tends to be limited by the presence of institutional investors and analysts, who may discipline managers for questionable forms of the GAAP practice (Bushee, 1998).

the level and volatility of *REM* is incremental to those variables.

More broadly, we contribute to the corporate finance literature on executives' social capital and firms' operating, investing, and financial policies. Many of the studies in this literature highlight the information channel through which social capital improves firm value (e.g., Larcker et al., 2013). Fewer studies recognize the value-destroying aspects of social capital due to weakened external monitoring and labor market insurance (e.g., El-Khatib et al., 2015). We provide new evidence of this darker side of CEO social capital from a financial reporting perspective by showing that the power and influence and labor market insurance conferred on well-connected managers make them more likely to resort to earnings management practices that alter operations and that ultimately degrade firm performance in the long run.[3]

Section 2 develops the hypotheses. Section 3 describes the sample and data. Section 4 outlines the research design. Section 5 presents the results, and Section 6 concludes.

2. Hypothesis development

The earnings management literature suggests both value-enhancing and self-serving reasons for managers to intervene in the financial reporting process. Motivated by the social science literature, we argue that network connections play a role in encouraging both types of *REM*.

On the positive side, smoothing reported income and meeting benchmarks through *REM* can overcome information asymmetry, enhance the firm's credibility, signal firm quality, and convey managerial competence to the capital market and suppliers and customers (Bartov et al., 2002; Chaney and Lewis, 1995; Sankar and Subramanyam, 2001; Tucker and Zarowin, 2006). Social networks can confer similar benefits through enhanced information-sharing. Well-connected CEOs can acquire, transmit, and certify business-relevant information through their social networks, which is likely to be more efficient and less expensive than resorting to altering real business transactions. Shared information from the CEO social network may allow executives to respond more efficiently to future shocks to their operating environments such as changes in market environments, competitors' market entrance, macroeconomic shocks, shifts in legislation, and cost structures. Therefore, large networks could enable managers to exploit information shared through their social web, optimize firm operating policies, and achieve capital market benefits, while avoiding high levels of *REM*. In this situation, we predict that CEOs with large networks will engage in low levels of *REM* (or perhaps not at all) after weighing the costs and benefits of using this method. In related research, Ke et al. (2019) show that CEOs with social connections to other top executives in the same firm produce more accurate management guidance forecasts.[4] However, we also note that social network members may also share dysfunctional information. *AEM* practices, for example, are shared among interlocked board members (Chiu et al., 2013). Controversial firm practices such as option backdating, adoption of poison pills, and golden parachutes can propagate through social connections (Bizjak et al., 2009; Davis, 1991; Davis and Greve, 1997).

On the negative side, *REM* practices could be a symptom of a rent-extraction behavior that reduces firm value. Compared to *AEM* practices that may reap similar personal benefits, *REM* can be less detectable and not raise the same level of scrutiny about appropriate GAAP. While questionable accounting practices and policies are subject to auditor review and litigation risk, there is a subtle

[3] A criticism of the view that well-connected CEOs could use *REM* (or other low-personal cost practices to adjust GAAP earnings such as through the use of non-GAAP adjustments) to maintain or increase their reputation and build trust within the social network is that such a strategy to bolster or smooth earnings that hurts performance in the long-term may not be sustainable in an equilibrium setting. While ours is not a theoretical paper on the persistence of *REM* in equilibrium, much evidence exists that *REM* practices have endured over time and that the mechanisms and norms (e.g., regulations, the courts, accounting standards, whistler-blower laws, the media, and investor arbitrage strategies) that would discipline or eliminate the use of *REM* or other low-personal cost practices to adjust GAAP earnings have failed to do so. The evidence further suggests that the level of positive earnings management adjustments may have increased over time (Bradshaw and Sloan, 2002). Two recent papers conceive that the solution to this puzzle may lie in "limited attention theory". Hirshleifer and Teoh (2003) theorize that a manager's use of non-GAAP adjustments (of which *REM* is an example) can occur in equilibrium, in part because the effort of an analyst or investor to pay more attention is costly. Koester et al. (2016) attribute the popularity and persistence of extreme positive earnings surprises (which can result from the use of *REM* and other non-GAAP adjustments) to analysts' and investors' inattention to earnings numbers. Managers exploit this inattention by generating earnings numbers designed to increase their attention (i.e., by changing the cost calculus of analysts or investors to pay more attention). Well-connected managers–better informed because of their larger networks–would naturally be able to exploit this inattention better than less well-connected managers. Koester et al. (2016) also find that the attention-seeking outcomes of extreme positive earnings surprises are successful in the long-term. There may be other ways to conceptualize the persistence of *REM* practices in an equilibrium setting such as those that involve assumptions about managers' and analysts' horizons and career incentives, but we leave this challenge to future work.

[4] See Glaeser et al. (1992) and Jaffe et al. (1993). CEO networks also flourish as business organizations that actively promote membership based on information-sharing, where CEO members can share ideas, best practices, and experiences in a confidential and conflict-of-interest free environment (www.chiefexecutivenetwork.com).

distinction between operating efficiently or optimally and real earnings management, which results from managerial decisions that are inefficient or suboptimal for firm value. To protect or enhance their reputation or increase their power and influence, well-connected CEOs may favor the lower cost and scrutiny of *REM* more than less-connected CEOs. By contrast, a large adjustment to earnings from *AEM* could be costly to firm stakeholders and managers if its detection raises questions about a possible violation of GAAP. Once detected, *AEM* can also induce significant harm to well-connected CEOs' reputation and destroy their social capital. Thus, we expect well-connected CEOs to steer away from *AEM* and compensate for a lower level of *AEM* with a higher level of *REM* to meet or beat the market expectation.[5] In this situation, we predict that CEOs with large networks will engage in higher levels of *REM* after weighing the costs and benefits of using this method to protect or enhance their reputation.

The disadvantage of *REM* is that it involves abnormal or suboptimal decision-making, which can hurt firm value. Because of their cash flow consequences, abnormal or suboptimal operating policies may aggravate future operating performance (Cohen and Zarowin, 2010). However, with large social networks, executives could weather out the disciplinary consequences of poor performance. They could also insulate themselves from monitoring by the board and others in the executive labor market (Bebchuk et al., 2011; Fracassi and Tate, 2012; Hwang and Kim, 2009; Masulis et al., 2007). Hwang and Kim (2009) find that firms with board members socially independent of the CEO compensate the CEO less and exhibit stronger pay-performance and turnover-performance sensitivity. Fracassi and Tate (2012) show that better-connected CEOs tend to appoint directors with ties to the CEO, which weakens board monitoring and creates more value-reducing acquisitions. More recently, (Sandvik, 2020) extends this result, finding that the monitoring effectiveness of directors is weakest when their board position occurs after the CEO's appointment.

A CEO with a large network could also compromise the disciplinary role of the takeover market (El-Khatib et al., 2015; Mitchell and Lehn, 1990). A large social network may provide additional insurance to CEOs in the executive job market. For example, Liu (2014) finds that well-connected CEOs are quicker to land an executive job.[6] As anecdotal evidence of the power and influence from a large network, we note that Jack Welch, General Electric's well-connected, legendary former CEO is commonly known to have met or exceeded earnings benchmarks using *REM* based on mergers and acquisitions accounting as well as strategically-timed asset sales to financial institutions.[7] Given the two scenarios, we state our first hypothesis as:

H1. A firm's earnings adjustments from *REM* vary positively in CEO network size versus the alternative that a firm's earnings adjustments from *REM* do not vary positively in CEO network size.

To improve identification that *REM* relates causally to network size, we test cross-sectionally whether certain CEO networks associate with a higher level of *REM* than others. In particular, we conduct tests of whether *H1* holds when the network includes more connections to people of power and influence and those who are also likely to share higher-quality information in the network. Below, we discuss two proxies for these factors, whether (i) BoardEx uses the classification of an executive director or non-executive director and (ii) the network connections involve CEOs at large firms.

First, executive directors participate in daily corporate operations and have greater direct knowledge, reputation, and power to influence decision-making. Connections to executive directors should, thus, provide a given CEO with power and influence as well as better information. By contrast, theoretical models describe non-executive directors (such as outside directors) as advisors who rely on executive directors to provide proprietary information to them (Adams and Ferreira, 2007). Thus, their information quality is lower than that of executive directors (Ravina and Sapienza, 2010). Second, ties to larger firms are more likely to deliver competitive advantage and reputation to a focal CEO compared to ties to CEOs at smaller firms. Firms with a higher market share are also a better source of high-quality information as well as an attractive coalition. Conversely, a firm's size may be merely an outcome of past successful business policies and strategies and information that allow for market penetration. Overall, though, the effects of deriving power and influence from large social networks and their insurance benefits in the labor and takeover markets should be stronger for CEOs with more powerful and influential connections. Our second hypothesis is:

H2. The positive relation between CEO network size and REM strengthens for networks with CEOs with power and influence.

We further consider whether firms that manage earnings with REM fare better or worse in the future than those that do not (and

[5] *AEM* detection, moreover, can significantly affect firm stakeholders if it results in a Securities and Exchange Commission (SEC) inquiry, a restatement, or securities litigation (Bruns and Merchant, 1990; DuCharme et al., 2004; Gong et al., 2008; Graham et al., 2005; Zang, 2012). For example, DuCharme et al. (2004) show that abnormal accruals are highest for firms with seasoned equity offerings (SEO) that are subsequently sued. Settlement amounts are also positively related to the levels of abnormal accruals. Gong et al. (2008) show a positive association between stock-for-stock acquirers' pre-merger abnormal accruals and post-merger announcement lawsuits. CEOs with a large network could find litigation resulting from accrual manipulation particularly costly because the litigation and penalization tarnish well-networked CEOs' reputation, jeopardizing their outside options in the executive labor market. Also, *AEM* is constrained by outside monitoring and GAAP rules, making it harder to convince auditors of managers' earnings management choices (Zang, 2012).

[6] Less effective monitoring from social ties can also impact corporate operating activities. Ishii and Xuan (2014) find that social ties between bidders and targets lead to firm value losses, potentially because social conformity weakens critical analysis and due diligence. Chikh and Filbien (2011) show that well-connected CEOs continue to support acquisitions even if the market reacts negatively upon announcement.

[7] "Jack Welch was known for his fondness of business acquisitions. 'Accretive' means that a merger per se can instantly push up E.P.S. if, percentage-wise, the earnings added to the acquirer's books are larger than the additional stock the acquiring firm must issue as part of the merger (if any). This trick works even if subsequently slower growth in the acquired firm's earnings drags down the overall growth of the E.P.S. of the combined entities. Remarkably, most financial analysts in the 1990s fell for this trick and bid up its P/E ratio even higher." (Uwe Reinhardt, *New York Times*, February 13, 2009).

Table 1
Sample distribution.

Panel A. Sample distribution by fiscal year.

Fiscal year	Frequency	Percent
2000	30	0.12
2001	665	2.75
2002	873	3.60
2003	903	3.73
2004	1651	6.82
2005	1989	8.21
2006	2030	8.38
2007	1899	7.84
2008	1995	8.24
2009	1839	7.59
2010	1821	7.52
2011	2133	8.81
2012	2129	8.79
2013	2111	8.71
2014	2156	8.90
Total	24,224	100.00

Panel B. Sample distribution by Fama-French 48 industry classification.

Industry	Frequency	Percent	Industry	Frequency	Percent
Agriculture	51	0.21	Healthcare	461	1.90
Aircraft	157	0.65	Machinery	987	4.07
Apparel	362	1.49	Measuring and Control Equipment	674	2.78
Automobiles and Trucks	397	1.64	Medical Equipment	1083	4.47
Beer & Liquor	110	0.45	Non-Metallic and Industrial Metal Min.	251	1.04
Business Services	3443	14.21	Others	114	0.47
Business Supplies	302	1.25	Personal Services	227	0.94
Candy & Soda	93	0.38	Petroleum and Natural Gas	1714	7.08
Chemicals	677	2.79	Pharmaceutical Products	1340	5.53
Coal	101	0.42	Precious Metals	281	1.16
Communication	813	3.36	Printing and Publishing	206	0.85
Computers	1063	4.39	Recreation	219	0.90
Construction	219	0.90	Restaraunts, Hotels, Motels	400	1.65
Construction Materials	630	2.60	Retail	1537	6.34
Consumer Goods	434	1.79	Rubber and Plastic Products	179	0.74
Defense	79	0.33	Shipbuilding, Railroad Equipment	50	0.21
Electrical Equipment	540	2.23	Shipping Containers	78	0.32
Electronic Equipment	2186	9.02	Steel Works Etc	387	1.60
Entertainment	348	1.44	Textiles	77	0.32
Fabricated Products	56	0.23	Transportation	450	1.86
Food Products	473	1.95	Wholesale	975	4.02
			Total	24,224	100.00

may also have missed their earnings targets). Firms that engage in *REM* may do worse because the outcomes to generate the earnings adjustments arise from the inefficient use of cash. The evidence on this point is mixed. Gunny (2010) finds that firms conducting *REM* to meet or just beat an earnings benchmark have better future operating performance; Taylor and Xu (2010) find that *REM* firms do not differ in future operating performance compared to non-*REM* firms, and Leggett et al. (2009) find that *REM* firms have worse future operating performance.

These studies, however, do not investigate whether CEO network size conditions the relation between *REM* and future operating performance. For one, using shared information as well as power and influence channels, well-connected CEOs may exploit *REM* to achieve personal gains at the expense of firm value. In that case, we predict a negative association between *REM* and future firm performance for CEOs with larger social networks.[8] Alternatively, well-connected CEOs may use *REM* to motivate firm performance, signal firm value, and build a reputation (Bartov et al., 2002; Burgstahler and Dichev, 1997; Subramanyam, 1996). This second view suggests that CEOs extract relevant information through their information channels to further optimize their decisions on *REM*. Social networks are especially important in facilitating the exchange of information when there is a lack of general knowledge about the practice in question. To the extent that *REM* is less visible and involves higher complexity and uncertainty (e.g., it needs to be done early in an accounting period before the fiscal year-end, making it difficult to predict a precise earnings effect) to achieve the desired level of managed earnings, knowledge spillover of such practices within their social networks could allow CEOs to engage in levels of *REM* that improve firm future operating performance. Under this scenario, we expect a positive correlation between *REM* and future firm performance for CEOs with large social networks. Given the two scenarios, we test the following non-directional hypothesis.

H3. The relation between future operating performance and a firm's earnings adjustments from *REM* is conditional on CEO network size.

3. Sample and data

We start with the BoardEx database (http://corp.boardex.com/data/), which contains biographical information on the senior executives and board members of public and private firms. A November 2015 BoardEx report provides a summary of board composition and senior management team by year (from January 1999 to November 2015) for 12,972 companies in North America. For each director or executive, BoardEx compiles a full historical profile containing the past employment history, current employment, board memberships, educational background, and social activities such as memberships in social and charitable organizations. BoardEx states that they gather and verify information from multiple reliable sources and build profiles as complete as disclosure allows.

We next extract annual firm-level financial and accounting information from Standard & Poor's Compustat North America and then merge BoardEx with the Compustat data by linking the BoardEx firm identifier (CompanyID) to the Compustat identifier (GVKEY). BoardEx provides the International Securities Identification Number (ISIN) for firms with stock quotes. We then extract CUSIP from ISIN and match it to the GVKEY Compustat header. We can find the GVKEY for 7433 quoted firms in BoardEx through this matching process. For the BoardEx firms without ISIN, we use a Levenshtein algorithm (http://www.keldysh.ru/departments/dpt_10/lev.html) to aid in approximate name matching and verify the matched pairs manually. We can find the GVKEY for an additional 1007 BoardEx quoted firms under this procedure. In total, we find the GVKEY for 8440 out of 8558 (98.6%) quoted U. S. firms covered by BoardEx. The remaining 118 firms are either too small or too new for Compustat coverage. We obtain stock return information from the Center for Research in Security Prices (CRSP). Using the link history table of the CRSP/Compustat Merged (CCM) dataset, we merge BoardEx and Compustat fundamentals data with CRSP stock return data. To identify a unique CRSP security identifier (PERMNO) for each firm-year observation, we ensure that the fiscal year-end date is within the effective link dates and choose the link with the CCM primary security marker and primary link type marker.

Table 1 summarizes the 24,224-observation sample by fiscal year and industry and shows a broad sample of unregulated, non-financial firms, covering approximately 66% and 74% of CRSP stocks at the beginning and end of the sample period, respectively.[9] Differences in accounting and reporting and industry regulation oblige us to exclude firms in the financial (SIC 6000–7000) and the utility industries (SIC 4400–5000). While the most represented industries are business services (14.21%), electronic equipment (9.02%), and petroleum and natural gas (7.08%), each of the other 39 industries represents less than 7% of the sample. The larger coverage of firms in BoardEx is constrained by the requirement for earnings management measures computed from Compustat data. Note, also, that the connections forming a CEO's network derive from links among all organizations in BoardEx biographical histories, not just among the sample firms.

4. Research design

4.1. CEO network size

We measure CEO network size annually as the number of executives or directors in the network with whom the CEO has a connection. We define a CEO network connection at year *t* as one established between a CEO and another individual if they link on one or more of employment, education, or other activities (e.g., social club) during or before year *t*. Two individuals are connected via employment if their careers overlap with the same employer in the same year. We exclude any connections the CEO has with other individuals currently employed at the same firm.

Individuals are connected via education if they have graduated within a year from the same university and have the same degree type. Education overlaps are identified based on the BoardEx education file. Following Cohen et al. (2008b), we clean the BoardEx

[8] We also refine this prediction by examining whether the negative association between *REM* and future firm performance for CEOs with larger social networks is attenuated when the CEO holds larger ownership in the firm, which should better align the CEO's personal interests with outside shareholders.

[9] To arrive at our sample of 24,224 firm-years, we start with 187,737 after matching BoardEx to Compustat from 2000 to 2014. We drop 67,667 firm-years with less than $1 million or missing sales or total assets, 67,356 firm-years without data to calculate *REM* or *AEM*, 26,689 without data to calculate *NETWORK_TOT*, and 1801 with missing control variables or in the Finance and Utilities industries.

Table 2
Descriptive statistics.

Variable	N	Mean	Std. dev.	25%-tile	Median	75%-tile
NETWORK_TOT	24,224	0.1415	0.1919	0.0110	0.0590	0.1930
NETWORK_TOT based on executive director networks (*ED*)	24,224	0.0250	0.0338	0.0030	0.0110	0.0320
NETWORK_TOT based on non-executive director networks (*NED*)	24,224	0.1518	0.1766	0.0300	0.0810	0.2060
S&P 500	24,224	0.0582	0.0866	0.0030	0.0220	0.0750
OTHER	24,224	0.1186	0.1302	0.0280	0.0690	0.1600
CF_REM	24,224	0.0049	0.7668	−0.2337	0.0302	0.2848
DISEXP_REM	24,224	−0.0112	0.2858	−0.1200	−0.0321	0.0481
PROD_REM	24,224	0.0003	0.2296	−0.1150	−0.0027	0.1039
REM	24,224	0.0255	0.6024	−0.1037	0.0440	0.2103
AEM	24,224	0.0010	0.0552	−0.0218	0.0015	0.0258
SIZE	24,224	6.2242	2.1014	4.8226	6.2892	7.6235
BTM	24,224	0.5436	0.6021	0.2531	0.4492	0.7392
ROA	24,224	−0.0257	0.2924	−0.0324	0.0361	0.0782
LEV	24,224	0.1707	0.2511	0.0000	0.1074	0.2629
EVOL	24,224	0.0816	0.1283	0.0150	0.0349	0.0894
CFVOL	24,224	0.0595	0.0658	0.0205	0.0388	0.0714
CYCLE	24,224	0.0624	0.1161	0.0233	0.0622	0.1110
SALES_GROWTH	24,224	0.0015	0.0083	−0.0002	0.0008	0.0020
MKT_SHARE	24,224	0.0635	0.0535	0.0326	0.0425	0.0782
ZSCORE	24,224	0.7952	3.6771	0.4859	1.5973	2.5158
NOA	24,224	0.6225	0.4848	0.0000	1.0000	1.0000
INSTOWN	24,224	0.5470	0.4191	0.0594	0.6069	0.9128
BIG4	24,224	0.7471	0.4347	0.0000	1.0000	1.0000
CEO_AGE	24,224	4.0148	0.1463	3.9120	4.0254	4.1109
CEO_TENURE	24,224	1.5187	0.8072	0.8755	1.5041	2.0919

This table summarizes the sample descriptive statistics. The sample comprises 24,224 firm-years with BoardEx and other data over 1999–2015, representing 4226 different firms. Appendix A defines the variables.

education file in two ways. First, for universities with multiple Institute IDs, we aggregate them into a single Institute ID. For example, BoardEx assigns "Stanford University" ID # 743905436, "Stanford University, Graduate School of Business" ID # 8034910975, "Stanford University School of Law" ID # 9164011235, and "Stanford Medical School" ID # 5881139024. We merge all of these into the "Stanford University" ID. Universities with an unspecified campus are assumed to be the flagship campus. Second, BoardEx does not list a unique ID for degree type, only a description of the executive's "qualification." We map each of the degree descriptions into (i) undergraduate, (ii) masters, (iii) MBA, (iv) Ph.D., (v) law, (vi) medical, and (vii) other education. We drop professional certificates such as CFA or CPA designations.

Two individuals are connected via other social activities if they both have active roles in the same professional/non-profit association or social club. Following Engelberg et al. (2013), we require that both individuals' roles exceed mere membership except for social clubs. We do not require the roles to overlap in time, however, because most have missing start and end dates for social activities.

Our measure of network size for firm i's CEO sums these direct connections for each year t as follows: $NETWORK\_TOT_{i,t} = \Sigma Network\_Employment_{i,t} + \Sigma Network\_Education_{i,t} + \Sigma Network\_Activity_{i,t}$ where *Network_Employment* sums the CEO's employment connections, *Network_Education* sums the CEO's education connections, and *Network_Activity* sums the CEO's other-activity connections.[10] Table 2 shows summary statistics for network size (*NETWORK_TOT*) (in thousands). The average CEO in our sample has 141.5 connections with a standard deviation of 191.9 connections and a median CEO in our sample has 59 connections. Similar to Fracassi and Tate (2012) and Engelberg et al. (2013), these data skew to the right.[11]

4.2. Real earnings management

Following prior work (Cohen et al., 2008a; Roychowdhury, 2006), we measure *REM* by combining estimates of the abnormal level of operating cash flow, production cost, and R&D expenditure, thus creating a comprehensive proxy for *REM*. First, for each firm-year (i,t), abnormal operating cash flow (*CF_REM*) equals actual cash flow from operations (*CFO*) less normal *CFO* defined by Eq. (1) below.

$$CFO_{it}/AT_{it-1} = \alpha_0 + \alpha_1\left(1/AT_{it-1}\right) + \beta_1\left(S_{it}/AT_{it-1}\right) + \beta_2\left(\Delta S_{it}/AT_{it-1}\right) + \varepsilon_{it} \tag{1}$$

[10] Our measure of network size, based on the sum of a CEO's direct connections, is often referred to as the "*Absolute Degree*" measure of network connectedness. Other measures of connectedness represent the "*Betweenness*", "*Closeness*", "*Eigenvector*", and "*Relative Degree*" dimensions of network connections. For completeness, we report the results of estimating Eq. (4) for each of these other measures. Table A of the on-line supplement reports the results.

[11] As a robustness check, we specify the natural logarithm of CEO network size as the experimental variable and find results qualitatively the same as those reported in Table 3.

where CFO_{it}= operating cash flow in year *t* of firm *i*, AT_{it-1}= lagged total assets, S_{it}= Net sales in year *t* of firm *i*, and ΔS_{it}= change in net sales from the prior year.

Second, abnormal production cost (*PROD_REM*) equals actual production cost less normal production cost defined by Eq. (2) below as a linear function of the cost of goods sold and the change in inventory.

$$PROD_{it}/AT_{it-1} = \alpha_0 + \alpha_1\left(1/AT_{it-1}\right) + \beta_1\left(S_{it}/AT_{it-1}\right) + \beta_2\left(\Delta S_{it}/AT_{it-1}\right) + \beta_3\left(\Delta S_{it-1}/AT_{it-1}\right) + \varepsilon_{it} \tag{2}$$

where $PROD_{it} = COGS_{it} + \Delta INV_{it}$, $COGS_{it}$ = cost of goods sold in year *t* of firm *i*, ΔINV_{it}= change in inventory in year *t* of firm *i*, and the other variables are defined as before. Abnormal production cost is the difference between actual production cost and normal production cost.

Third, abnormal discretionary expenditure (*DISEXP_REM*) equals actual discretionary expenditure less normal R&D defined by Eq. (3) below.

$$DISEXP_{it}/AT_{it-1} = \alpha_0 + \alpha_1\left(1/AT_{it-1}\right) + \beta\left(S_{it-1}/AT_{it-1}\right) + \varepsilon_{it} \tag{3}$$

where actual $DISEXP_{it}$= discretionary expenses for firm-year *i,t* calculated as the sum of research and development, advertising, and sales, general, and administrative expenses.

To capture the effects of real earnings management as a single measure, we define REM_{it} = (CF_REM_{it} – $PROD\_REM_{it}$ + $DISEXP\_REM_{it}$)*(−1). We multiply the summation by minus one so that a higher value represents additional *REM* earnings from these activities. The literature shows that this *REM* proxy associates with financial reporting behavior in a wide range of settings.[12] The use of an *REM* proxy also avoids a look-ahead selection bias. This can occur when a researcher uses an ex-post variable (e.g., an SEC enforcement action, a restatement, a securities class action lawsuit) to infer earlier financial reporting behavior.[13]

4.3. Descriptive statistics

Table 2 lists the descriptive statistics. The average firm reflects a combined *REM* adjustment of 2.55% of total assets with a median level of 4.40%. Thus, on balance, more firm-years have positive measures of our proxy for *REM* earnings management, that is, reported earnings are more-likely-than-not higher due to *REM*. While *REM* is left-skewed, we also observe approximately equivalent Q1 and Q3 quartiles relative to the median value, suggesting a broadly symmetric distribution around that value. The negative of the Eq. (2) and Eq. (3) components of *REM* are also left-skewed similarly. Of the three components of *REM*, the largest portion relates to discretionary adjustments as per Eq. (3). The other variables in Table 2 describe the variables in the regressions of *REM* on network size and control variables. Most reflect distributions similar to those that describe any large and diversified sample of listed U.S. firms. For example, 74.71% are audited by a Big 4 accounting firm, a large majority reflects positive past sales growth (*SALES_GROWTH*) and future growth opportunities (*BTM*), and the log of market capitalization (*SIZE*) is reasonably symmetric around the mean of 6.2242 (or $505 million). We also calculate a proxy for *AEM* based on the modified Jones (1991) model.[14] Mean *AEM* for the sample is close to zero and mostly ranges within −2.18 (Q1) and 2.58 (Q3) percent of total assets for the sample firms.

4.4. Regression models

To capture the effect of CEO network size on real earnings management, we regress measures of *REM* on $NETWORK\_TOT_{t-1}$ and controls, shown below as Eq. (4). To increase the likelihood that CEO social capital influences *REM* and not vice-versa, we lag

[12] Representative studies include (i) why and when some firms are more likely to engage in earnings management (Badertscher, 2011; Chan et al., 2015; Cohen et al., 2008a; Ewert and Wagenhofer, 2005; Roychowdhury, 2006; Zang, 2012), (ii) whether equity incentives matter (Armstrong et al., 2010; Bergstresser and Philippon, 2006; Cheng and Warfield, 2005), and (iii) the effects of detected earnings management on performance (Cohen and Zarowin, 2010; Gunny, 2010), capital costs (Aboody et al., 2005; Francis et al., 2004; Kim and Sohn, 2013), debt covenants (DeFond and Jiambalvo, 1994), and firm value (Bartov et al., 2002; Kasznik and McNichols, 2002; Myers et al., 2007). Forms of earnings management around different events and in different settings have also been explored. Examples include (i) share offerings (Kothari et al., 2005; Teoh et al., 1998), (ii) regulatory changes (Cohen et al., 2008a), (iii) management turnover (Desai et al., 2006; Guan et al., 2005; Hazarika et al., 2012; Wells, 2002), (iv) restatements (Ettredge et al., 2010; Richardson et al., 2002), (v) litigation events (Dechow et al., 1996; DuCharme et al., 2004), and (vi) bad debts (McNichols and Wilson, 1988). See Xu et al. (2007) for a review of the pre-2007 *REM* literature.

[13] Nonetheless, we test our results using a restatement sample to provide a more complete picture of the effect of CEO network size on earnings management (Section 5.4.1). We acknowledge that these proxies represent noisy estimates of the earnings adjustment by a CEO or other senior officer to meet a benchmark.

[14] We define *AEM* as follows. $TA_{it}/AT_{it-1} = \alpha_0 + \alpha_1\left(1/AT_{it-1}\right) + \alpha_2\left((\Delta REV_{it} - \Delta REC_{it})/AT_{it-1}\right) + \alpha_3\left(PPE_{it}/AT_{it-1}\right) + \alpha_3\left(IBXI_{it-1}/AT_{it-1}\right) + \varepsilon_{it}$,

where: TA_{it}= total accruals for a firm *i* in year *t*, ΔREV_{it}= change in net revenue in year *t-1* to *t*, ΔREC_{it}= change in net receivables, PPE_{it}= gross property, plant, and equipment, $IBXI_{it-1}$= income before extraordinary items at year *t-1*, and AT_{it-1}= lagged total assets. We estimate the above regression cross-sectionally for all industry-years with at least 15 observations. We then define the estimated residuals as the proxy for accrual-based earnings management, that is, $AEM_{it} = TA_{it}/AT_{it-1}$ – estimated (TA_{it}/AT_{it-1}).

Table 3
CEO network size and *REM*: OLS and two-stage least squares regressions.

Dependent variable =	*CF_REM*	*PROD_REM*	*DISEXP_REM*	*REM*	*REM*	*NETWORK_TOT*	*REM*
Regression =	*OLS*					*First and second stage least squares*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$NETWORK\_TOT_{t-1}$	0.0237**	0.0182**	0.0465**	0.0749***	0.0655***		0.5916***
	(2.16)	(2.37)	(2.03)	(4.63)	(4.10)		(2.77)
Controls:							
AEM	0.1557***	0.112***	−0.0029	0.3064*	0.302*	−0.0361**	0.4306***
	(3.00)	(4.83)	(−0.02)	(1.75)	(1.75)	(−2.02)	(3.59)
SIZE	−0.0056	−0.0121***	−0.0099**	−0.023***	−0.0233***	0.0488***	−0.0405***
	(−1.41)	(−12.65)	(−2.40)	(−8.46)	(−7.64)	(10.95)	(−3.48)
BTM	0.0265***	0.0558***	0.0372***	0.1218***	0.1204***	0.0258***	0.1282***
	(3.07)	(9.23)	(2.68)	(4.82)	(4.89)	(5.34)	(8.87)
ROA	−0.1628***	−0.1599***	0.0515	−0.3241***	−0.3237***	−0.0599***	−0.5991***
	(−8.97)	(−11.50)	(1.21)	(−11.19)	(−11.46)	(−10.07)	(−9.36)
LEV	0.0137	0.0877***	0.1433***	0.2603***	0.2565***	0.0475***	0.2971***
	(0.81)	(10.28)	(3.94)	(5.53)	(5.67)	(2.66)	(6.82)
EVOL	−0.083**	−0.0835***	−0.1079	−0.3084***	−0.3029***	0.0029	−0.3815***
	(−2.56)	(−6.09)	(−1.29)	(−4.48)	(−4.25)	(0.15)	(−4.13)
CFVOL	0.1986***	−0.114***	−0.802***	−0.779**	−0.7783**	−0.1172***	−0.5705***
	(2.68)	(−3.27)	(−4.69)	(−2.51)	(−2.52)	(−2.88)	(−3.40)
CYCLE	0.0178	−0.0208	0.195***	0.2213	0.2049	−0.0008	0.0029
	(0.26)	(−0.97)	(2.86)	(1.23)	(1.16)	(−0.65)	(0.77)
SALES_GROWTH	−0.1006	−0.022	−3.0671*	−3.7301**	−3.6343**	−0.6585***	−2.3472**
	(−0.24)	(−0.18)	(−1.85)	(−2.08)	(−2.05)	(−3.79)	(−2.13)
MKT_SHARE	0.2718***	−0.0817**	−0.7102***	−0.5275***	−0.5507***	−0.0363	−0.2932
	(2.63)	(−2.17)	(−2.90)	(−3.11)	(−3.15)	(−0.53)	(−1.45)
ZSCORE	−0.0103***	0.0062***	0.0151***	0.0105**	0.0103**	−0.0026***	0.0155***
	(−3.60)	(6.82)	(3.95)	(2.37)	(2.40)	(−4.96)	(3.98)
NOA	−0.005	0.0536***	0.078***	0.1277***	0.1278***	−0.0349***	0.1469***
	(−0.52)	(18.33)	(6.89)	(4.56)	(4.57)	(−3.53)	(7.06)
INSTOWN	−0.0099***	−0.0157***	−0.0187***	−0.0495***	−0.0476***	−0.0158*	−0.0477**
	(−4.62)	(−6.33)	(−3.35)	(−5.32)	(−5.44)	(−1.84)	(−2.49)
CEO_AGE	−0.0265	0.0854***	0.1961***		0.2282***	0.046***	0.2031***
	(−0.85)	(7.27)	(2.86)		(3.54)	(2.80)	(3.68)
CEO_TENURE	−0.0046***	−0.0102***	−0.0093**		−0.0223***	−0.0107***	−0.0133
	(−2.61)	(−6.90)	(−2.11)		(−4.35)	(−2.81)	(−1.45)
Instrumental variables:							
DIR_SUPPLY100						0.886***	
						(13.06)	
IND_NETWORK						0.0306**	
						(2.22)	
Partial F-Statistic						55.95	(<0.0001)
Under-identification test (Chi square)						86.82	(<0.0001)
Weak Identification Test (Cragg Donald Wald F)						143.94	(<0.0001)
Endogeneity Test (Chi square)						11.262	(<0.01)
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	24,224	24,224	24,224	24,224	24,224	20,013	20,013
Adjusted R^2	0.169	0.0814	0.0791	0.0559	0.0576	0.221	0.0669

This table reports the results of regressing *REM* on CEO network size for year *t*-1. Columns 1–5 report the results of an OLS regression examining the effect of CEO network size on the three components and a combined proxy for *REM*. Columns 6–7 present the results of a two-stage regression using the executive/directors within 100 miles geographically and the industry average CEO total network size as the instrumental variables. In the first-stage regression, the dependent variable is the CEO's network size. In the second-stage regression *REM* is the dependent variable and the predicted value of CEO network size is the test variable. We report *t*-statistics in parentheses with standard errors clustered by industry and year. *, **, *** denote significance at the 0.10, 0.05, and 0.01 level, respectively, all two-tailed. Appendix A defines the variables.

NETWORK_TOT by one year.[15] We measure all other variables for the same year as *REM*. The equation is:

$$REM_t = \alpha + \beta_1 NETWORK\_TOT_{t-1} + \beta_2 AEM + \beta_3 SIZE + \beta_4 BTM + \beta_5 ROA + \beta_6 LEV + \beta_7 EVOL + \beta_8 CFVOL + \beta_9 CYCLE + \beta_{10} SALES\_GROWTH + \beta_{11} MKT\_SHARE + \beta_{12} ZSCORE + \beta_{13} NOA + \beta_{14} INSTOWN + \beta_{15} CEO\_AGE + \beta_{16} CEO\_TENURE + \varepsilon_t \quad (4)$$

We estimate the variable of interest, *NETWORK_TOT*, as the summation of the CEO's employment, education, and other activity connections. Eq. (4) also includes controls to isolate the CEO network effects from other firm- and manager-related characteristics. We

[15] In later analysis, we also examine the potential for *REM* to influence *NETWORK_TOT*.

also add *AEM* as a control, so that the coefficients for *NETWORK_TOT* capture the response of *REM* to network size incremental to the ability of *AEM* to explain *REM*. To control for scale effects and profitability, we include firm size (*SIZE*), return on assets (*ROA*), financial leverage (*LEV*), and book-to-market ratio (*BTM*) (Cohen et al., 2008a; Kothari et al., 2005; Roychowdhury, 2006). We also control for earnings volatility (*EVOL*) and cash flow volatility (*CFVOL*), as some firms may manage volatile performance. To control for the cost associated with real earnings management, we include sales growth ratio (*SALES_GROWTH*), market share (*MKT_SHARE*), and financial health (*ZSCORE*) (Chan et al., 2015; Zang, 2012). We also include institutional ownership percentage (*INSTOWN*) as a control because firms with lower institutional holdings may be more inclined to cater to retail investors with less awareness of the mechanics of *REM*. In addition, we include CEO age (*CEO_AGE*) and the number of years that the CEO has held the position (*CEO_TENURE*) to control for CEO characteristics (Ali and Zhang, 2015; Liu, 2014). Lastly, we include year- and industry-fixed effects and report *t*-statistics with standard errors adjusted for clustering by industry (since firms in the same industry share common factors) and year (since the same CEO may enter in multiple years).

5. Results

We present our results in four sections. Section 5.1 examines Eq. (4), which regresses the level of *REM* on lagged CEO network size and control variables (*H1*). We also address endogeneity based on a two-stage model. Section 5.2 examines whether the network relation in Eq. (4) is especially strong when the connections are informative or influential (*H2*). Section 5.3 examines the possibility that CEO networks have a darker side by testing hypotheses about the relation between *REM* and the firm's future operating performance conditional on network size (*H3*). Section 5.4 examines whether the network effect on *REM* differs from earnings management measures based on restatements and accruals.

5.1. CEO network size and the level of REM

5.1.1. Baseline result

Columns 1–5 of Table 3 report the main finding of regressing *REM* on lagged network size and control variables based on ordinary least squares (OLS) regression. (We discuss columns 6–7 in subsection 5.1.2.) The variable of interest in Table 3 is $NETWORK\_TOT_{t-1}$, which shows a significantly positive coefficient (at least $p < 0.10$) across all proxies for *REM* (i.e., Eq. (1), Eq. (2), Eq. (3), and the combined measure of *REM*) and controls.[16] Thus, the level of *REM* to increase earnings varies positively in CEO network size. This supports *H1*. As the underlying mechanism for this result, we contend that larger CEO networks encourage larger *REM*, at least from the CEO's perspective, because the larger network lowers the net cost of the activity to the CEO, either through channels that share information (by lowering detection probability or regulatory and labor market costs conditional on detection) or through power and influence channels that enhance reputation (e.g., by delivering superior earnings to the market). Based on the *REM* coefficients in columns 4 and 5 of Table 3, assuming a relevant range of linearity, this suggests that an increase of 1000 social connections increases the average level of *REM* by 6.55% to 7.49%. Given that the sample's average network size is 141.5 connections and the standard deviation is 191.5 connections, this implies that a shift from the mean to one standard deviation above the mean of CEO network size generates a 1.254 (0.0655*0.1915)% to 1.434 (0.0749*0.1915)% increase in *REM*. While these percentage increases seem small, recall that *REM* sums amounts scaled by lagged total assets, so that a more appropriate comparison of the economic impact of the *NETWORK_TOT* coefficients relates to *ROA,* which has an interquartile range of 11.06 (0.0782 + 0.0324)% and a standard deviation of 29.24%.

We also observe that several of the control variables, namely, *AEM*, *SIZE, BTM*, *LEV*, *EVOL*, *CFVOL*, *ZSCORE*, and *NOA* significantly explain *REM.* For example, the negative coefficients for *SIZE*, *EVOL*, and *CFVOL* suggest that *REM* is not an activity that varies positively in measures of firm risk. *REM*, however, relates positively to *BTM*, indicating potentially that firms with lower future growth prospects associate with higher levels of *REM* (Cheng et al., 2016). Table 3 also indicates that older CEOs (*CEO_AGE*) and newer CEOs (*CEO_TENURE*) have higher *REM*. In short, absent network effects, firms using higher levels of *REM* are smaller (*SIZE*), less risky (lower *EVOL* and *CFVOL*), more leveraged (higher *LEV*), and have lower future growth opportunities (*BTM*). The positive and significant coefficients on *AEM* also indicate that firms use the two different earnings management practices–*REM* and *AEM*–in a complementary way.

5.1.2. Endogeneity and related issues

While we have specified models with CEO network size as an exogenous determinant of *REM*, the positive association between CEO network size and the level of *REM* could be subject to endogeneity and selection bias. We remedy this as follows. We first consider whether an improvement in accounting performance from *REM* could boost the CEO's visibility and induce an increase in network size. As a simple way to alleviate this potential for reverse causality, we lag *NETWORK_TOT* by one year and find a similar positive relation between unlagged CEO network size and *REM*. Further, we use an instrumental variable for CEO network size, *DIR_SUPPLY100*, which is the number of executives and directors at other firms in the same industry (based on two-digit SIC codes) within 100 miles of the firm's headquarters. We contend that the geographical proximity to other executives is likely to associate positively with the connectedness of the CEO but is unlikely to result from a higher level of *REM.* While the *REM* conducted by CEOs could induce better

[16] We also obtain similar significant results ($p < 0.01$) when we scale *NETWORK_TOT* by total network size for each year, indicating that our results are robust to alternative econometric methods and year effects.

short-term performance and enhance their visibility and connectedness, *REM* is unlikely to attract other executives to relocate to the same area.

This instrumental variable approach also helps address selection bias, that is, the expectation that beneficial *REM* could prompt a CEO to intentionally build stronger networks to maximize the benefits. For example, CEOs who contemplate using *REM* could choose to become involved in a social organization or serve as an outside board member for a public company. The instrumental variable based on geographic location is immune to this alternative interpretation because CEOs may have little control over where the firm is located. Even if they do, they are unlikely to relocate to a firm just to conduct a certain accounting practice.

A more general endogeneity issue relates to omitted variables. Perhaps network size is correlated with some unobservable CEO characteristic that causes a high level of *REM*. A suitable instrument in our context would be a variable that affects the CEO network (relevance condition) and affects *REM* only through its effect on the CEO network (exclusion condition). Geographic distance has been shown to affect accounting practices through social networks in prior research. For example, Choi et al. (2012) suggest that geographic proximity between auditors and firms enhances audit quality because they may "have informal interactions in business or social settings, allowing for more information to be passed between individuals." Similarly, we contend that CEOs close to many other executives and directors are more likely to have a large network, and hence better information and power and influence to conduct *REM*. The instrument meets the exclusion condition to the extent there is no other reasonable channel linking the location of the firm's headquarters to the use of *REM*.[17]

To strengthen our prediction that *NETWORK_TOT* relates to *DIR_SUPPLY100* incremental to industry effects, we also include average network size for the *other* firms in the dataset in the same industry of firm *i* in year *t* (*IND_NETWORK*) as an additional instrumental variable. We estimate the following equation.

$$NETWORK\_TOT_t = \beta_1 DIR\_SUPPLY100 + \beta_2 IND\_NETWORK + \beta_3 AEM + \beta_4 SIZE + \beta_5 BTM + \beta_6 ROA + \beta_7 LEV + \beta_8 EVOL + \beta_9 CFVOL + \beta_{10} CYCLE + \beta_{11} SALES\_GROWTH + \beta_{12} MKT\_SHARE + \beta_{13} ZSCORE + \beta_{14} NOA + \beta_{15} INSTOWN + \beta_{16} CEO\_AGE + \beta_{17} CEO\_TENURE + \varepsilon_t \quad (5)$$

Columns 6 and 7 of Table 3 present the findings of a two-stage least squares model using the instrumental variables, where the second-stage includes predicted *NETWORK_TOT* from the first-stage. We observe that the first-stage coefficients for *DIR_SUPPLY100* and *IND_NETWORK* are positive and significant, indicating that these two instrumental variables are a significant source of exogenous variation in *NETWORK_TOT* (meets the relevance condition). The Cragg-Donald Wald F and the Hausman (1978) endogeneity test provide further validation of the instrumental variables. The second-stage coefficient for *NETWORK_TOT* is positive and significant, supporting our baseline result that CEO network size increases the level of *REM*.

A specific omitted variable issue is that CEO network size could relate to managerial ability, so that more skillful CEOs conduct more *REM*. To address this, we assign to each CEO observation a measure of managerial ability for the same firm-year. We use a proxy for managerial ability (Demerjian et al., 2012).[18] We then estimate Eq. (4), including *ABILITY* as an additional control variable. We continue to find a significantly positive coefficient for *NETWORK_TOT,* so that the main result in Table 3 holds after controlling for managerial ability.

Another concern is that the observations surrounding CEO transitions are particularly prone to simultaneity problems because both *REM* and CEO network size can change for various reasons during this time. A CEO could be hired to improve accounting and reporting quality. In particular, "big bath" earnings adjustments could be made to make the new CEO look good. Henry and Schmitt (2001) show that firms are exposed to downside risk by taking a big bath. Yet a clear upside arises from recording a large and extreme loss, which reduces future periods of the burden and paves the way for a newly-appointed CEO to meet or beat an earnings benchmark in the future. Further, a board could consider network size in selecting a new CEO and appoint a better-networked candidate. These changes may lead to a spurious correlation between *REM* and CEO network size. Therefore, as an additional test, we exclude those firm-year observations with a CEO change in the year of the change or one year later (*TENURE* = 0 or 1 year). Our findings in Table 3 remain similar after making this adjustment.

5.1.3. Other robustness tests

First, we consider alternative measures of CEO network size. Eq. (4) uses the number of direct connections to measure network size, which is a measure of absolute degree centrality in graph theory. While it has been used in the literature for ease of interpretation (Engelberg et al., 2013; Javakhadze et al., 2016), other centrality measures may capture further aspects of connectedness. We consider four additional centrality measures as alternatives, reflecting: (i) how frequently the CEO lies on the shortest path between pairs of other individuals in the network (*betweenness*), (ii) the average degree of separation between the CEO and others in the network (*closeness*), (iii) how well connected are those individuals who are in the CEO's network (*eigenvector*), and (iv) the number of first-degree connections in the network relative to total network degree (*relative degree*).[19] Online Supplement A indicates that our findings in Table 3 are robust to most of these alternatives. Second, we consider concerns that BoardEx individual educational backgrounds and other activities are self-reported and contain incomplete information. In an alternative specification, we use *Network_Employment*

[17] Knyazeva et al. (2013) use the number of directors within 100 miles as an instrumental variable for board independence. They argue that proximity to larger pools of local director talent leads to more independent boards without directly influencing firm performance.

[18] Available at http://faculty.washington.edu/pdemerj/data.html.

[19] These measures are popular in the sociology literature and have been used in recent finance literature (Liu, 2014; Hochberg et al., 2007; Renneboog and Zhao, 2011). Appendix A of Liu (2014) states the mathematical definitions of the centrality measures used in this study.

Table 4
CEO network size and *REM*: Network characteristics.

Dependent variable =	*REM*	*REM*	*REM*	*REM*	*REM*
	(1)	(2)	(3)	(4)	(5)
NETWORK_TOT for executive directors (*ED*) $_{t-1}$	0.3407*** (3.94)				
NETWORK_TOT for non-executive (*NED*) $_{t-1}$		0.0821*** (4.90)			
S&P 500			0.2578*** (5.11)		
Other				0.0726*** (2.95)	
NETWORK_TOT					0.0468** (2.09)
CONNECTED_REM (the *REM* of other firms)					0.2328*** (4.78)
Difference (*ED* – *NED*)	0.2586*** (2.98)		0.1852*** (5.24)		
Difference (*S&P 500* – *Other*)	0.3407*** (3.94)				
Firm Controls	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes
Observations	24,224	24,224	24,224	24,224	16,097
Adjusted R^2	0.0576	0.0577	0.0579	0.0575	0.113

This table reports the results of OLS regressions examining the effect of CEO network characteristics on *REM* for samples of a max. of 24,224 firm-years. The first two columns (1 and 2) are based on networks with executive (ED) versus non-executive (NED) directors. The next two columns (3 and 4) are based on the size of the firm (*S&P 500* versus *Other)*. The last column (5) controls for the prior three-year average level of *REM* by the other firms in the CEO's network in the same 48 Fama-French industry category. We report *t*-statistics in parentheses with standard errors clustered by firm. *, **, *** denote significance at the 0.10, 0.05, and 0.01 level, respectively, all two-tailed. Appendix A defines the variables.

connections only since CEO employment histories are the most accurate and complete. Our results are robust to this alternative network measure. Third, we use two additional measures of *REM*. Gunny (2010) suggests abnormal R&D expense and abnormal gain from asset sales as measures of *REM*. We find our results hold using these two alternative *REM* measures, that is, abnormal R&D expense and abnormal gain from asset sales also increase in CEO network size.

Fourth, we consider a possible spurious relation between network size and *REM* that could arise if the level of *REM* and executive network size follow a similar time trend. To control for this possibility, we estimate Eq. (4) as a time-series regression for each firm over the sample years 1999–2014. We then test whether the mean of the cross-sectional distribution of the *NETWORK_TOT* coefficients from the firm-level regressions is positive for *REM*. We find that the mean coefficient under this time-series approach for *NETWORK_TOT* is significantly positive, which is the same result as in Table 3. The findings in Table 3 also hold for subsamples split into pre- and post-2002 Sarbanes-Oxley Act observations.

Fifth, we conduct the following test to examine the issue of whether our results are primarily driven by between- or within-firm variation in *NETWORK_TOT*. We first split the sample into those firms for which the percentage increase in *NETWORK_TOT* from 2000 (or the first year of a firm in the dataset)–2007 to 2008–2014 is above or below the median increase. Second, we re-estimate Eq. (4) as per cols. 4 and 5 of Table 3 for each subsample. In an untabulated analysis, we find that the regressions for firms with an increase in *NETWORK_TOT* versus no increase in *NETWORK_TOT* have higher significance levels for the *NETWORK_TOT* coefficient and higher adjusted R^2s, but the differences are not significant at $p < 0.05$. Hence, it is mainly between-firm variation that drives our results.

5.2. *Influential or informative connections*

If larger CEO networks increase *REM* through information or power and influence channels, which is our main hypothesis, this also implies that the positive effect of network size on *REM* should strengthen when the connections are more influential or informative. We consider three proxies, namely, CEO connections to executive versus non-executive directors (Section 5.2.1), CEO connections to people in large versus small firms (Section 5.2.2), and CEO connections to firms with higher use of *REM* (Section 5.2.3). The findings summarized below indicate the cross-sectional patterns are consistent with this implication.

5.2.1. *Connections to executive vs. non-executive directors*

If the benefits of a large CEO network derive from shared information, then we should observe stronger results for networks whose information-sharing relates to CEO connections with more influential people such as other CEOs or similar insider executives. There is a potential flip side, though, in that CEOs who benefit from greater information-sharing from their networks could face steeper costs and risks to their reputation in the event of detected *REM* linked to their CEO position. However, *REM* has a low detection risk compared to an equal adjustment from *AEM* or related practices (Cohen and Zarowin, 2010). We use BoardEx's classification of *ED* (executive director) and *NED* (non-executive director) and contend that a CEO's link to a *NED* at another firm offers less ability to share information or enhance reputation than a link to an *ED* at another firm. Compared to non-executive directors, executive directors engage in firm business operations daily, thus having access to firm proprietary information. They also exert power and influence in the selection process of executive and non-executive members and mergers and acquisitions, thus influencing the labor market and takeover market. Prior studies show differences in findings consistent with this dichotomy (Adams and Ferreira, 2007; Engelberg et al., 2012; Ravina and Sapienza, 2010).

We test this idea by re-estimating Eq. (4) separately for *NETWORK_TOT* for *ED* and *NETWORK_TOT* for *NED* as the network size variables. Table 4 indicates the findings. Columns 1 and 2 of Table 4 confirm that the *NETWORK_TOT* coefficient for *ED* is more positive than for *NED*. Moreover, the difference between the coefficients (column 1), *ED-NED*, is significantly positive ($p < 0.01$). These findings confirm that CEO networks with more information-sharing and more ties to people of power and influence associate with higher levels of *REM* (supports *H*2).

5.2.2. Connections to large vs. small firms

Connections to people at large firms potentially provide access to more economically-significant information and may generate higher influence and expand outside employment options. If the underlying channel of network-induced *REM* is driven by information or influence, we should expect a larger effect from the connections to large firms. To test this hypothesis, we measure network size for CEO connections involving S&P 500 firms versus others.[20] Columns 3 and 4 of Table 4 present the findings of re-estimating Eq. (4) with the number of connections to 500 firms (*S&P 500*) and the number of connections to non-S&P 500 firms (*Other*). The results show that the magnitude of the network effect on *REM* is larger for connections to S&P 500 firms versus connections to other firms. The difference in the two coefficients is significant at $p < 0.01$ (column 3). These results indicate that the network benefits of *REM* are higher for CEOs with network connections to large firms (supports *H2*).

5.2.3. The use of REM by connected firms

Assuming CEOs' decision-making process is influenced by information percolating through their social connections, the use of *REM* in connected firms will be especially relevant in affecting the level of *REM* in the firm managed by the CEO. We, therefore, measure the average level of *REM* over the prior three-years by managers and directors at the *other* firms in the CEO's network in the same 48 Fama-French industry (*CONNECTED_REM*). Column 5 of Table 4 indicates that the coefficient for *CONNECTED_REM* is significantly positive ($p < 0.01$). Thus, *REM* not only associates with the overall size of the CEO's network (*NETWORK_TOT*) but, also, with the level of *REM* used by *other* firms in the same industry in the CEO's network (*CONNECTED_REM*). This is additional evidence of a more direct information channel of the network linking the CEO to the use of *REM*. This is also consistent with a contagion effect of earnings management (Chiu et al., 2013), wherein extreme earnings management in one firm spreads to other firms through shared directors.[21]

5.3. Network-induced REM and future operating performance

5.3.1. REM and future operating performance conditional on network size

While a large network reduces the personal costs for the CEO to engage in a higher level of *REM*, this behavior may not necessarily benefit the firm, as the prior literature on the relation between *REM* and future operating performance shows mixed results (Gunny, 2010; Leggett et al., 2009; Taylor and Xu, 2010). This prior research does not, however, consider the role of CEO network size as an underlying channel. CEOs with large networks could have higher personal benefits and lower personal costs from *REM* because information from their network enables them to select a form of *REM* with low detectability. CEOs with large networks may also be less concerned because their network shields them from takeover and forced separation if their choice of *REM* leads to poor performance. Therefore, we conjecture that the level of *REM* chosen by well-connected CEOs would go beyond what is optimal for the firm. To test this hypothesis, we measure future operating performance as return on assets (*ROA*) or operating cash flow (*CFO*) in a future year relative to earnings management measurement in year *t*, where *ROA* equals net income before extraordinary items divided by the prior year's total assets.[22]

Panel A of Table 5 reports the results of estimating the effects of *REM* on future operating performance, split on small and large CEO network size (the sample median of *NETWORK_TOT* each year). We regress *ROA* or *CFO* for year $t + 3$ on firm size (*SIZE*), book-to-market ratio (*BTM*), leverage (*LEV*), stock return (*RET*), insolvency risk (*ZSCORE*) for subsamples of firms with small and large CEO networks (the results for $t + 1$ and $t + 2$ are similar). We expect that *REM* conducted by CEOs with large networks will have a more negative effect on future firm performance. For the control variables, we expect significantly positive coefficients for all variables except *BTM*, which should relate negatively to future return performance, as lower *BTM* suggests higher future growth opportunities.

Panel A of Table 5 indicates that higher *REM* associates with a lower future operating performance for firms with large CEO networks. Moreover, the differences in the *REM* coefficients for small and large networks in columns 1 and 2 are negative and significant for the two comparisons ($p < 0.05$ for ROA_{t+3} and $p < 0.05$ for CFO_{t+3}). We also show this in pooled regressions with an

[20] Note that the CEO need not necessarily have a CEO position with an S&P 500 firm in year *t*. Rather, it is simply that the measurement of CEO network size captures ties to persons in other S&P 500 firms only.

[21] While it is not a point-to-point connection, our test of *CONNECTED_REM* uses the average level of *REM* by other firms whose managers are in the same industry as the focal firm. The other firms are simply a subset of all the firms represented in the CEO's network.

[22] We exclude $t + 1$ to avoid the predictably negative relation between current accruals and next year's net income. Table 8 also excludes the results for $t + 2$, as they are qualitatively the same as those for $t + 3$.

Table 5
REM and future operating performance.

Panel A: Conditional on CEO network size

Dependent variable =	*ROA t + 3*	*ROA t + 3*	*ROA t + 3*	*CFO t + 3*	*CFO t + 3*	*CFO t + 3*
NETWORK_TOT	*Small*	*Large*	*Full sample*	*Small*	*Large*	*Full sample*
	(1)	(2)	(3)	(4)	(5)	(6)
REM	0.0007	−0.0022**	0.001	−0.0007	−0.0028***	0.0005
	(0.60)	(−2.27)	(1.35)	(−0.90)	(−3.84)	(0.72)
DIFF (Large – Small)	−0.0029**			−0.0021**		
	(−2.18)			(−2.12)		
SIZE	0.017***	0.0208***	0.0182***	0.0126***	0.0149***	0.0146***
	(13.35)	(16.19)	(23.66)	(16.22)	(19.65)	(24.86)
BTM	−0.0214***	−0.0117**	−0.0203***	−0.0223***	−0.0195***	−0.0182***
	(−4.44)	(−2.52)	(−7.45)	(−9.06)	(−7.03)	(−9.90)
LEV	0.0144	0.0344**	0.0086	−0.0018	0.0166*	0.0138**
	(1.24)	(2.40)	(1.16)	(−0.26)	(1.89)	(2.24)
RET	0.0005**	0.0014***	0.001***	−0.0001	0.0011***	0.0004***
	(2.03)	(4.27)	(5.35)	(−0.62)	(5.45)	(2.73)
ZSCORE	0.02***	0.0228***	0.0176***	0.0105***	0.0162***	0.015***
	(18.23)	(12.90)	(24.56)	(22.66)	(15.92)	(25.28)
NETWORK_TOT			−0.008*			−0.0136***
			(−1.72)			(−3.85)
*REM*NETWORK_TOT*			−0.0358***			−0.0707***
			(−3.40)			(−8.37)
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8107	8123	16,230	8053	8088	16,141
Adjusted R^2	0.3552	0.2657	0.327	0.3658	0.346	0.381

Panel B: Conditional on CEO ownership

Dependent variable =	*ROA t + 3*	*ROA t + 3*	*ROA t + 3*	*CFO t + 3*	*CFO t + 3*	*CFO t + 3*
Ownership	*Low Ownership*	*High ownership*	*Full sample*	*Low Ownership*	*High ownership*	*Full sample*
	(1)	(2)	(3)	(4)	(5)	(6)
REM	0.0054	0.0004	0.001	0.0038	−0.0021*	0.0005
	(1.06)	(0.45)	(1.35)	(1.02)	(−1.71)	(0.72)
NETWORK_TOT	−0.012	0.015	−0.008*	−0.0249**	0.0085	−0.0136***
	(−0.71)	(1.48)	(−1.72)	(−2.55)	(0.94)	(−3.85)
*REM*NETWORK_TOT*	−0.0886**	−0.0158	−0.0358***	−0.129***	0.0018	−0.0707***
	(−2.19)	(−1.06)	(−3.40)	(−4.02)	(0.22)	(−8.37)
DIFF (Low – High)	−0.0728**			−0.1308***		
	(−1.96)			(−4.47)		
SIZE	0.0209***	0.0143***	0.0182***	0.0167***	0.0143***	0.0146***
	(6.11)	(11.50)	(23.66)	(7.29)	(12.53)	(24.86)
BTM	−0.0108	−0.0158***	−0.0203***	−0.012*	−0.0151***	−0.0182***
	(−0.87)	(−3.65)	(−7.45)	(−1.79)	(−3.79)	(−9.90)
LEV	0.0625**	0.0185*	0.0086	0.0455***	0.0373***	0.0138**
	(2.16)	(1.70)	(1.16)	(2.99)	(3.57)	(2.24)
RET	0.0001	0.0014***	0.001***	−0.001	0.0007***	0.0004***
	(0.10)	(5.79)	(5.35)	(−1.38)	(3.10)	(2.73)
ZSCORE	0.0267***	0.0189***	0.0176***	0.0178***	0.0192***	0.015***
	(10.43)	(20.96)	(24.56)	(12.20)	(16.92)	(25.28)
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6767	6454	16,230	6767	6454	16,141
Adjusted R^2	0.2362	0.3132	0.327	0.2921	0.3103	0.381

This table reports the results of OLS regressions examining the effect of *REM* on future operating performance, split on network size (Panel A) and CEO ownership (Panel B). We split at the sample median of *NETWORK_TOT* and *Ownership* each year. We report *t*-statistics in parentheses with standard errors clustered by firm. *, **, *** denote significance at the 0.10, 0.05, and 0.01 level, respectively, all two-tailed. Appendix A defines the variables.

interaction term, that is, the coefficients in columns 3 and 6 for *REM*NETWORK_TOT* are significantly negative ($p < 0.01$). Hence, our findings indicate that although *REM* per se may not be detrimental to the average firm, the higher level of *REM* induced by a large CEO network associates negatively with future operating return (*ROA*) and cash flow (*CFO*). These results, thus, support *H3*–that the relation between *REM* and future firm performance is conditional on CEO network size.

Panel B of Table 5 refines *H3* by examining whether the negative association between *REM* and future firm performance for large networks in Panel A is aggravated when the CEO holds smaller ownership in the firm. We split the sample at the sample median of

Table 6
CEO network size and the volatility of REM.

Dependent variable =	*Vol. of REM*	*Vol. of REM*
$NETWORK\_TOT_{t-1}$	0.089***	0.0899***
	(2.70)	(2.66)
AEM	−0.1474	−0.1464
	(−1.43)	(−1.42)
SIZE	−0.0137**	−0.0136**
	(−2.38)	(−2.48)
BTM	0.0069	0.0074
	(0.43)	(0.47)
ROA	0.0093	0.0095
	(0.24)	(0.25)
LEV	−0.1595***	−0.1588***
	(−4.62)	(−4.67)
EVOL	0.5607***	0.5589***
	(7.92)	(7.82)
CFVOL	1.3804***	1.3824***
	(4.63)	(4.64)
CYCLE	−0.2877**	−0.2817*
	(−2.29)	(−2.15)
SALES_GROWTH	0.3744	0.3479
	(0.60)	(0.56)
MKT_SHARE	−2.0676***	−2.0623***
	(−3.38)	(−3.39)
ZSCORE	0.0072	0.0073
	(1.41)	(1.43)
NOA	0.0759***	0.0757***
	(4.08)	(4.09)
INSTOWN	−0.0925***	−0.0932***
	(−4.46)	(−4.50)
CEO_AGE		−0.0624
		(−0.90)
CEO_TENURE		0.0045
		(0.74)
Industry Fixed Effect	Yes	Yes
Year Fixed Effect	Yes	Yes
Observations	17,509	17,509
Pseudo R^2	0.440	0.440

This table reports the results of examining the effect of CEO network size on the volatility of *REM*. The columns present the OLS regression coefficients and two-sided *t*-values for a sample of 17,509 firm-years. We report *t*-statistics in parentheses with standard errors clustered by industry and year. *, **, *** denote significance at the 0.10, 0.05, and 0.01 level, respectively, all two-tailed. Appendix A defines the variables.

Ownership each year. The coefficients for *DIFF* are significantly negative (at least $p < 0.05$). Thus, the negative coefficients for *DIFF* in columns 1 and 4 of Panel B support the idea that the relation between *REM* and future operating performance is more negative when CEO ownership is low. This is consistent with the presence of agency costs from misaligned equity incentives. For completeness, columns 3 and 6 of Panel B repeat the regression results for columns 3 and 6 of Panel A.

5.3.2. *The volatility of REM by connected firms*

We examine the relation between CEO social network size and the volatility of *REM*. CEO network size could affect the volatility of *REM* in two contrasting ways. On the one hand, to the extent that CEO social capital delivers information to help improve firm operating performance, well-connected CEOs could exploit this information and smooth their *REM*. A smoother *REM* adjustment may signal to shareholders a higher value of their operating strategies. On the other hand, CEO social capital may confer power and influence. Moreover, power and influence may allow well-connected CEOs to circumvent internal and external monitoring to protect their deviation from optimal operating strategies and performance, allowing them to pursue a higher level of *REM*. Thus, they can entertain the capital market benefits of meeting or beating the market expectation through *REM* (Bartov et al., 2002). This pursuance of *REM*, however, may inevitably lead to an increase in the volatility of *REM*. The higher volatility of *REM* could be symptomatic of a well-connected CEO undertaking suboptimal operating policies, which could then signify lower future operating performance to shareholders.

To test these two opposing views of CEO network size on *REM* volatility, we employ an eight-year rolling window to compute the

Table 7
Future operating performance, *REM*, and earnings benchmarks conditional on network size.

Dependent variable =	*CFO t + 1*	*CFO t + 1*	*CFO t + 1*	*ROA t + 1*	*ROA t + 1*	*ROA t + 1*
		NETWORK_TOT			*NETWORK_TOT*	
	Full sample	*Bottom Tercile*	*Top tercile*	*Full sample*	*Bottom tercile*	*Top tercile*
	(1)	(2)	(3)	(4)	(5)	(6)
BEAT	−0.008**	−0.0232***	−0.0183***	0.0018	0.0265***	−0.015
	(−2.43)	(−4.11)	(−4.47)	(0.27)	(3.97)	(−1.13)
JUSTMISS	−0.0094*	−0.0022	−0.0196***	−0.0157**	−0.0034	−0.0231*
	(−1.92)	(−0.17)	(−3.16)	(−2.51)	(−1.61)	(−1.84)
BENCH	−0.0042	0.006	−0.0229***	−0.0051	0.0114	−0.0142
	(−0.74)	(0.62)	(−4.16)	(−0.68)	(1.24)	(−1.63)
REM	−0.0121***	−0.0009	−0.0103***	0.0003	0.002	−0.0047
	(−4.80)	(−0.23)	(−3.70)	(0.09)	(0.54)	(−0.88)
*BENCH*REM*	0	−0.0229	0.0221**	0.0121***	0.0009	0.0179**
	(0.09)	(−1.43)	(2.06)	(4.88)	(0.15)	(1.96)
DIFF (Top-Bottom)		0.045**			0.017*	
		2.43)			1.76)	
ROA	0.3665***	0.4247***	0.3894***	0.5045***	0.3822***	0.541***
	(9.74)	(13.16)	(16.92)	(9.53)	(7.69)	(6.73)
SIZE	0.0079***	0.0083***	0.0057***	0.0059***	0.0037***	0.0076***
	(5.80)	(6.41)	(8.63)	(7.16)	(3.14)	(5.03)
BTM	−0.0088*	−0.0076	−0.021***	−0.0255***	−0.0266***	−0.0221*
	(−1.95)	(−1.31)	(−6.00)	(−3.91)	(−4.59)	(−1.82)
RET	−0.0009	0.0012	−0.0037	0.0082***	0.0082***	0.0084*
	(−0.77)	(0.34)	(−1.59)	(3.50)	(2.65)	(1.73)
ZSCORE	0.0133***	0.0136***	0.0121***	0.0157***	0.0159***	0.0177***
	(6.04)	(7.18)	(10.88)	(6.01)	(7.15)	(4.07)
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,253	5778	5744	17,253	5778	5744
Adjusted R^2	0.523	0.638	0.5075	0.482	0.498	0.410

This table extends the model in Gunny (2010) by showing that the relation between *REM* and CFO_{t+1} (columns 1–3) and ROA_{t+1} (columns 4–6) when *REM* is used to just meet a benchmark varies conditional on CEO network size. To establish variation in CEO network size, we split *NETWORK_TOT* into terciles each year. We then regress *CFO/ROA* on *BENCH*, *REM*, *BENCH*REM*, and other variables separately for the *Top* and *Bottom* tercile samples. A positive coefficient for *BENCH*REM* indicates that *REM* is positive when the firm's earnings number just meets the benchmark. We then test whether the coefficient for *BENCH*REM* differs for large (in the top tercile) and small networks (in the bottom tercile) and report this as *DIFF*(*Top-Bottom*). We report *t*-statistics in parentheses with standard errors clustered by firm. *, **, *** denote significance at the 0.10, 0.05, and 0.01 level, respectively, all two-tailed. Appendix A defines the variables.

standard deviation of *REM*.[23] We then regress *REM* volatility on CEO network size and the other control variables as in Eq. (4). Table 6 shows two key results. First, we observe that *REM* volatility relates positively to the risk measures of *EVOL* and *CFVOL* and negatively with firm *SIZE* (also a risk measure), Second, after controlling for these factors, Table 6 indicates that CEO network size relates positively to *REM* volatility ($p < 0.01$). This supports the view that the positive relation between CEO network size and *REM* also generates a positive relation between CEO network size and *REM* volatility incremental to firm-level risk and other factors.

5.3.3. *REM to just meet an earnings benchmark*

Gunny (2010) suggests that *REM* in a particular setting may be beneficial to the firm by providing evidence that firms using *REM* to just meet an earnings benchmark have better future operating performance than those not using *REM* to just meet the benchmark, that is, using *REM* to beat the benchmark by a larger amount or using *REM* for other reasons. We test whether the negative effect on operating performance that we find (Table 5) is mitigated for well-connected CEOs engaging in this type of *REM*. Following the method in Gunny (2010), we identify firms that undertake *REM* to just meet zero earnings or beat last year's earnings as those firm-years with net income or change in net income divided by total assets ≤0.01(*BENCH*). We next regress CFO_{t+1} or ROA_{t+1} on *REM* with an interaction variable for *BENCH*REM*. Table 7 shows significantly negative coefficients for the overall effect of *REM* on CFO_{t+1} (also shown in Table 5) but insignificant coefficients for the overall effect of *REM* on ROA_{t+1}. Thus, we corroborate Gunny (2010) that firms using *REM* to just beat the benchmark have better future operating performance when measured as CFO_{t+1} but not when measured as ROA_{t+1}.

We then partition the sample into CEO network size terciles, splitting *NETWORK_TOT* into terciles each year. For this analysis, we address a potential endogeneity concern of CEO network size, by employing entropy-balanced matching to pair the top- and bottom-tercile firms. Entropy-balanced matching in our case reweights the observations of the bottom-tercile sample such that the moments of

[23] The choice of eight years, while arbitrary, trades off the need for a lower variance firm-level estimate of *REM* volatility against the need for sufficient sample size for the regression. We find similar results, though, with shorter and longer periods of a rolling window.

Table 8
REM and CEO network size conditional on CEO share ownership.

Dependent variable =	*REM*	*REM*	*REM*
CEO share ownership	*Full sample*	*Low ownership*	*High ownership*
	(1)	(2)	(3)
NETWORK_TOT$_{t-1}$	0.1086	0.1218**	−0.1122
	(1.55)	(1.97)	(−1.41)
Ownership	0.0798***		
	(3.01)		
*NETWORK_TOT*Ownership*	−3.0754***		
	(−3.01)		
DIFF (Low - High)		−0.234**	
		(−2.47)	
AEM	0.3863**	0.7905***	0.2680
	(2.27)	(3.57)	(1.32)
SIZE	−0.0311***	−0.0276***	−0.033***
	(−2.64)	(−2.99)	(−3.34)
BTM	0.1244***	0.1059***	0.122***
	(5.99)	(5.36)	(6.82)
ROA	−0.5238***	−0.4437***	−0.4429***
	(−7.82)	(−6.92)	(−6.52)
LEV	0.3191***	0.1144	0.4597***
	(4.52)	(1.50)	(6.80)
EVOL	−0.6589***	−0.4273***	−0.3891**
	(−4.36)	(−3.52)	(−2.43)
CFVOL	−0.2402	−0.081	−0.5692**
	(−0.77)	(−0.36)	(−2.10)
CYCLE	0.2461**	0.1328	0.0867
	(1.97)	(1.12)	(0.71)
SALES_GROWTH	−3.312	−1.9899	−7.568***
	(−1.44)	(−1.39)	(−2.63)
MKT_SHARE	−0.4518**	0.2525	0.1676
	(−2.03)	(0.48)	(0.79)
ZSCORE	0.0153**	0.0257***	0.0202***
	(2.26)	(5.18)	(3.17)
NOA	0.1827***	0.0591*	0.1903***
	(4.95)	(1.90)	(6.34)
INSTOWN	−0.0888***	−0.0467	−0.0863**
	(−2.79)	(−1.63)	(−2.37)
CEO_AGE	0.1907**	0.1756**	0.1350*
	(2.09)	(2.02)	(1.71)
CEO_TENURE	0.0044	−0.002	−0.018
	(0.23)	(−0.11)	(−1.33)
Industry Fixed Effect	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes
Observations	11,332	5666	5666
Adjusted R^2	0.0765	0.1313	0.0837

This table reports the results of OLS regressions examining the effect of CEO network size on *REM* conditional on the degree of CEO ownership in the firm. *Ownership* is the percentage of shares held by the CEO at year *t*. *Lower/Higher Ownership* is a dummy variable split at the median value of *Ownership* each year. We report *t*-statistics in parentheses with standard errors clustered by firm. *, **, *** denote significance at the 0.10, 0.05, and 0.01 level, respectively, all two-tailed. Appendix A defines the variables.

the distributions of the matching variables for the reweighted bottom-tercile sample are similar to the moments of the distributions of these variables for the top-tercile sample (Hainmueller, 2012; McMullin and Schonberger, 2020). Columns 3 and 6 of Table 7 indicate that the coefficients for *BENCH*REM (*the incremental effect of *REM* on *CFO/ROA* to meet the benchmark) are significantly positive for firms with large CEO networks (*Top Tercile*) but not for firms with small CEO networks (*Bottom Tercile*). The latter have insignificant coefficients for *BENCH*REM* (columns 2 and 5). The significantly positive coefficients for *DIFF* indicate that the *Top Tercile* coefficient is significantly greater than the *Bottom Tercile* coefficient. Thus, we extend Gunny (2010) by showing that the positive coefficient for *BENCH*REM* concentrates in the sample where CEO network size is large. In other words, the overall negative effect of *REM* on future operating performance (Table 5) is attenuated when well-connected (*Top Tercile*) CEOs undertake *REM* to just meet an earnings benchmark (Table 7).

5.3.4. Reining in network-induced REM with CEO share ownership

Given our finding in Table 5 that higher *REM* associates with a lower future operating performance for firms with large CEO networks, the potential gains from this earnings management practice accrue personally to the CEO rather than the firm. As such, higher levels of *REM* related to large CEO networks may be considered as an agency problem. If the CEO and shareholder interests do not align well (e.g., the CEO has low ownership), the CEO might act more opportunistically. Because the personal cost of *REM* to the

Table 9
CEO network size and restatements.

Dependent variable =	*Restatement*	*Restatement*
$NETWORK\_TOT_{t-1}$	−0.4001***	−0.3951**
	(−2.59)	(−2.50)
AEM_{t-1}	−0.666	−0.7015
	(−1.36)	(−1.38)
AEM_{t-2}	0.8569***	0.8075***
	(3.55)	(3.54)
SIZE	−0.0211	−0.0153
	(−0.66)	(−0.46)
BTM	0.0677	0.0635
	(1.42)	(1.27)
ROA	0.0597	0.0505
	(0.29)	(0.25)
LEV	0.2131	0.198
	(1.58)	(1.45)
EVOL	−0.1029	−0.0268
	(−0.21)	(−0.05)
CFVOL	−0.5119	−0.453
	(−0.61)	(−0.53)
CYCLE	0.103	0.0818
	(0.77)	(0.74)
SALESGROWTH	−1.8362	−1.6746
	(−0.31)	(−0.28)
MKT_SHARE	−0.0267	−0.0335
	(−0.06)	(−0.07)
ZSCORE	0.0061	0.0032
	(0.37)	(0.19)
NOA	−0.1773***	−0.188***
	(−3.07)	(−3.10)
INSTOWN	−0.0498	−0.0389
	(−0.63)	(−0.46)
BIG4	0.1591*	0.1747*
	(1.87)	(1.89)
CEO_AGE		0.5225**
		(1.99)
CEO_TENURE		0.0711**
		(2.08)
Industry Fixed Effect	Yes	Yes
Year Fixed Effect	Yes	Yes
Observations	10,409	10,409
Pseudo R^2	0.035	0.036

This table reports the results of regressing *Restatement* on CEO network size. *Restatement* equals one for the restatement-year of firm-years with a restatement in the Audit Analytics dataset categories of financial fraud, errors, and regulatory investigation (www.auditanalytics.com) and zero otherwise. The columns present the logistic regression coefficients for a sample of 10,409 firm-years. We report *t*-statistics in parentheses with standard errors clustered by industry and year. *, **, *** denote significance at the 0.10, 0.05, and 0.01 level, respectively, all two-tailed. Appendix A defines the variables.

CEO is low even though the cost to firm value could be high, we should observe a stronger positive relation between *NETWORK_TOT* and *REM* when a well-connected CEO has *low* share ownership. We define *Ownership* as the percentage of shares held by the CEO at year *t*. Table 8 summarizes the results. The coefficient for *NETWORK_TOT*Ownership* is significantly negative (column 1), and the positive coefficient for *NETWORK_TOT* for low CEO ownership (column 2) is significantly greater than the *NETWORK_TOT* coefficient for high ownership (column 3), which is significantly negative.[24] Thus, we find that network-induced *REM* resides more with CEOs that have lower share ownership in the firm.

5.4. CEO network size and other types of earnings management

We argue that the low detectability and cash flow consequences of *REM* can make it more preferable for CEOs with large networks

[24] The negative relation between *REM* and future operating performance for well-connected CEOs (Panel A of Table 5) is also more negative for CEOs with lower ownership in the firm (Panel B of Table 5). Also, to address a potential endogeneity concern of CEO ownership percentage, we employ an entropy-balanced matching approach to pair firms with low- versus high-CEO ownership (Hainmueller, 2012; McMullin and Schonberger, 2020).

Table 10
CEO network size and *AEM*.

Dependent variable =	*AEM*	*AEM*	*AEM small*	*AEM large*
			Level of earnings management	
	(1)	(2)	(3)	(4)
NETWORK_TOT$_{t-1}$	−0.0032**	−0.0032**	−0.0015*	−0.0157***
	(−2.05)	(−1.96)	(−1.95)	(−4.27)
DIFF (Large – Small)			−0.0142***	
			(−3.81)	
REM	0.0014	0.0014	−0.0001	0.0026***
	(1.50)	(1.50)	(−0.65)	(2.74)
SIZE	−0.0005	−0.0005	0.0001	−0.0007
	(−1.24)	(−1.25)	(1.06)	(−1.11)
BTM	−0.0007	−0.0007	0.0002	−0.0019
	(−0.42)	(−0.42)	(0.68)	(−1.24)
ROA	0.0169***	0.0169***	0.0015	0.0212***
	(3.59)	(3.58)	(1.51)	(4.09)
LEV	0.01***	0.01***	−0.0005	0.0144***
	(5.08)	(5.04)	(−0.80)	(4.10)
EVOL	0.0077	0.008	0.0002	0.0118
	(1.37)	(1.41)	(0.11)	(1.32)
CFVOL	0.0024	0.0025	0.0064*	−0.0081
	(0.35)	(0.37)	(1.92)	(−0.51)
CYCLE	0.0152**	0.0149**	0.002	0.0236***
	(2.19)	(2.16)	(1.27)	(2.93)
SALES_GROWTH	0.1079	0.1097	0.0504***	0.1456
	(1.14)	(1.17)	(3.10)	(1.11)
MKT_SHARE	0.0038	0.0037	0.0039	0.0316
	(0.27)	(0.26)	(0.46)	(0.80)
ZSCORE	−0.0001	−0.0001	0	−0.0001
	(−0.50)	(−0.55)	(−0.56)	(−0.36)
NOA	0.0053***	0.0053***	0.0002	0.01***
	(3.76)	(3.73)	(0.54)	(5.17)
INSTOWN	−0.0044***	−0.0044***	−0.0006	−0.0083***
	(−3.95)	(−3.94)	(−1.60)	(−4.37)
BIG4	0.0008	0.0009	−0.0003	0.002
	(0.66)	(0.72)	(−0.69)	(1.03)
CEO_AGE		0.0029	0.0022**	0.0032
		(0.72)	(2.08)	(0.63)
CEO_TENURE		0.0001	0.0002	0.0001
		(0.27)	(0.81)	(0.12)
Industry Fixed Effect	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Observations	24,224	24,224	12,112	12,112
Adjusted R^2	0.0323	0.0323	0.0156	0.0484

This table reports the results of examining the effect of CEO network size on *AEM*. Columns 1 and 2 report the results of an OLS regression examining the effect of CEO network size for t-1 on *REM*. These columns present the OLS regression coefficients and two-sided *t*-values for the maximum samples of 24,224 firm-years. Columns 3 and 4 present the results of examining the effect of CEO network size on *AEM* after splitting our sample into 12,112 *Large* and 12,112 *Small* group observations of *AEM*, split at the sample median each year of *AEM*. We report *t*-statistics in parentheses with standard errors clustered by industry and year. *, **, *** denote significance at the 0.10, 0.05, and 0.01 level, respectively, all two-tailed. Appendix A defines the variables.

due to lower personal costs and risk. We broaden our inquiry by examining whether the effect of CEO network size varies for other proxies for earnings management that CEOs might consider as alternatives. As detailed below, network size varies negatively with restatements (Table 9) and a proxy for *AEM* (Table 10). These tests distinguish *REM* from other arguably riskier means to manage earnings, where a large network could have the opposite effects on the earnings management practice.

5.4.1. Restatements

We consider a restatement as evidence of a material accounting irregularity (that more-likely-than-not reflects *AEM*) in an earlier period. Restatements also associate with poorer future job prospects for terminated CEOs (Desai et al., 2006). To estimate the relation between restatements and network size, we re-estimate Eq. (4) as a logistic regression by replacing the dependent variable *REM* with

Restatement, set equal to one for the fiscal year of a restatement (the first year of misreporting if the restatement involved multiple years) as indicated in the Audit Analytics restatement dataset and zero otherwise. For this variable, we use the Audit Analytics restatement categories of financial fraud, errors, and regulatory investigation (www.auditanalytics.com). Because *AEM* has been linked to a future restatement (Ettredge et al., 2010; Richardson et al., 2002), we lag *AEM* as a control variable by one year in Eq. (4). We expect CEOs with larger networks to refrain from this detected form of irregularity, as a restatement represents a material correction to a firm's earnings and shareholders' equity. The findings in Table 9 confirm this expectation and show significantly negative coefficients ($p < 0.05$) for *NETWORK_TOT* for both specifications of Eq. (4) estimated as a logistic regression with *Restatement* as the dependent variable. Thus, *Restatement*, which represents the outcome of an accounting irregularity (e.g., a GAAP violation) in a prior period, associates negatively with CEO network size.

5.4.2. Accrual earnings management

While *AEM* may not always be opportunistic or intentional, a large discretionary accrual could constitute a departure from GAAP, potentially reportable by the auditor.[25] This could result in additional outside scrutiny, a restatement, an Securities and Exchange Commission (SEC) investigation, or class action or enforcement litigation (Dechow et al., 2012; Dechow et al., 1995; Dechow et al., 1996; DuCharme et al., 2004; Gong et al., 2008; Karpoff et al., 2008; Richardson et al., 2002; Zang, 2012). Also, survey results show that CEOs perceive *AEM* as more ethically questionable and riskier than other forms of earnings management (Coram et al., 2016). Given this evidence, we predict that well-connected CEOs with more social capital to lose will reflect lower levels of *AEM*. Supporting this argument, Table 10 indicates that when *AEM* is regressed onto *NETWORK_TOT* and controls, the coefficient for *NETWORK_TOT* is negative and significant (at least $p < 0.10$). This result implies that greater CEO network size amplifies the regulatory and reputational costs of *AEM*, limiting the size of the *AEM* adjustment. It is also consistent with Bhandari et al. (2018), who report a negative relation between the level of *AEM* and CEO network size.

Further, we predict that the effect of CEO network size on *AEM* should be stronger at the right tail of the *AEM* distribution, suggesting that a higher level of *AEM* generates an expectation of the risk of higher legal and reputational costs. By contrast, the use of a lower level of *AEM* could be warranted based on judgment within accounting choice under the Supreme Court ruling in the Tellabs decision (Tellabs, Inc. v. Makor Issues & Rights, Ltd., No. 06–484, 437 F. 3d 588), which allows for reasonable, i.e., more-likely-than-not, explanations of accounting choice as a defense against plaintiffs' allegations. The cost and litigation risk associated with a lower level of *AEM* could, therefore, be lower than for a higher level of *AEM*. Supporting this argument, columns 3 and 4 of Table 10 show that when we split our sample on *Large AEM* and *Small AEM* and run the regression of *AEM* onto *NETWORK_TOT* and controls, the coefficient of *NETWORK_TOT* is more negative and significant for the *Large AEM* subgroup ($p < 0.01$).[26]

6. Conclusion

Based on established proxies for real earnings management (*REM*), and after employing a wide array of controls for other possible factors, we find a positive relation between CEO network size and the level and volatility of *REM*. We theorize that this positive relation occurs because the information-sharing and power and influence channels from a large CEO social network enable the use of *REM* to confer net personal benefits on the connected executive. This may even make the practice firm-wise desirable in the short-term because the firm reports a superior trend of earnings, beats earnings benchmarks, and may reduce information asymmetry, all of which can increase firm value. In the long-term, however, we show that large *REM* adjustments by well-connected CEOs associate with worse future firm performance, even in the absence of detection. But with takeover and labor market insurance, a well-connected CEO may not care about the possibility of worse future firm performance from the consequences of departures from normal or optimal operations from the use of *REM*. These CEO network benefits may also explain the pervasive and successful use of *REM* in practice. To our knowledge, we are the first to show that larger CEO networks associate with higher levels of *REM*. Those higher earnings adjustments, however, can degrade firm performance in the longer term. Thus, when a large CEO network amplifies the power and influence of the top executive, our study indicates that such CEO networks have a darker side regarding future firm performance.

Acknowledgements

For their helpful comments, the authors thank attendees at the 2017 New Zealand Finance Colloquium; Linda Harold, Rosiland Whiting, David Lont, Dyna Seng, Mariela Carvajal, and others at the University of Otago; research seminar participants at the University of Waterloo; Brad Barber, Hollis Skaife, and others at UC Davis; discussants at the 2017 Western Regional Meetings of the American Accounting Association; the 2017 National Meetings of the American Accounting Association (Sangwan Kim); and HARC 2020 (Sebastian Tideman).

[25] Jeffrey Immelt, the successor chairman at GE, with fewer social connections than its former legendary CEO, Jack Welch (according to our data set), was reported to have engaged in *AEM*. As a result, he incurred substantial reputational and regulatory costs, including a $50 million fine paid to the SEC.

[26] To address a potential endogeneity concern of *AEM*, we employ an entropy-balanced matching approach to pair firms with low- versus high-levels of *AEM* (Hainmueller, 2012; McMullin and Schonberger, 2020).

Appendix A. Variable definitions

Earnings management and network variables:		
AEM	=	Accrual based earnings management measure, firm's current discretionary accrual.
CF_REM	=	Abnormal cash flow from operations, measured as the deviations from the predicted values of the corresponding industry-year regression and then multiply −1. High value represents more abnormal level of operating cash flow.
Connected_REM	=	The average *REM* in the prior three years of other firms in the same Fama-French industry category.
DISEXP_REM	=	Abnormal discretionary expenses, measured as the deviations from the predicted values of the corresponding industry-year regression and then multiply −1. High value represents more abnormal level of discretionary expenses.
Network_Education	=	Summation (in thousand) of the CEO's educational ties. An educational tie occurs if the CEO went to the same university at the same time with another executive or director.
Network_Employment	=	Summation (in thousand) of the CEO's employment ties. An employment tie occurs if the CEO currently or historically overlapped with another executive or director
Network_OtherActivity	=	Summation (in thousand) of the CEO's other activity ties. Another activity tie occurs if the CEO participated in a same organization (e.g., charity or recreational club) at the same time as another executive or director.
NETWORK_TOT	=	Summation (in thousands) of *Network_Employment, Network_Education*, and *Network_OtherActivity*.
PROD_REM	=	Abnormal production cost, measured as the deviations from the predicted values of the corresponding industry-year regression. High value represents more abnormal level of production cost.
REM	=	Total amount of real transactions management, computed as the sum of *CF_REM*, *PROD_REM* and *DISEXP_REM*, as defined by Cohen et al. (2008b).
Other Variables:		
Analyst_Error	=	Analyst forecast error that is measured as the difference between actual earnings per share.
BIG4	=	1 if the firm is audited by a Big 4 CPA firm, and 0 otherwise.
BTM	=	Book to market ratio.
CEO_AGE	=	Natural log of one plus CEO's age at the fiscal year t.
CEO_DUAL	=	1 if the CEO has the dual positions of chairman at the beginning of the fiscal year containing quarter t-1, and 0 otherwise
CEO_TENURE	=	Number of years that the CEO has held the position of chief executive officer as of the beginning of the fiscal year
CFVOL	=	Standard deviation of operating cash flow on asset for five years.
CYCLE	=	Thousand days receivable plus the days inventory less the days payable.
DIR_SUPPLY100	=	Number of directors in the same industry (based on 2-digit SIC code) within 100 miles of the firm's headquarters.
EVOL	=	Standard deviation of ROA for five years.
IND_NETWORK	=	Average network size for the *other* firms in the dataset in the same industry (based on the Fama-French 48 industry classification).
INDADJ_ROE	=	Firm's return on equity minus industry ROE. Industry ROE is calculated as the mean ROE of firms in the same industry (based on 2-digit SIC code) for the same period.
INSTOWN	=	Percentage of outstanding shares owned by institutions.
LEV	=	Firm's leverage ratio, measured as long-term liabilities divided by total assets.
LNSALE	=	Natural log of sales at year t.
MKT_SHARE	=	Herfindahl index using two-digit SIC-codes
NOA	=	1 if the net operating assets (i.e., shareholders' equity less cash and marketable securities and plus total debt) at the beginning of the year divided by lagged sales is above the median of the corresponding industry-year, and 0 otherwise.
Ownership	=	Percentage of common shares in firm held by the CEO at year t.
Post_Position	=	1 if the departed CEO has a new full-time position in another organization within two years of turnover, and 0 otherwise.
RET	=	Firm's raw return for the fiscal year t.
RETVOL	=	Standard deviation of monthly raw stock returns for five years.
ROA	=	Income before extraordinary items divided by total assets.
SALES_GROWTH	=	One-year sales growth ratio.
SIZE	=	Natural log of market value.
ZSCORE	=	Altman's *Z*-score (Altman 1968, 2000)

Appendix B. Supplementary table

A supplementary table to this article can be found online at https://doi.org/10.1016/j.jcorpfin.2021.101920.

References

Aboody, D., Hughes, J., Liu, J., 2005. Earnings quality, insider trading, and cost of capital. J. Account. Res. 43 (5), 651–673.
Adams, R.B., Ferreira, D., 2007. A theory of friendly boards. J. Financ. 62 (1), 217–250.
Ali, A., Zhang, W., 2015. CEO tenure and earnings management. J. Account. Econ. 59 (1), 60–79.
Armstrong, C.S., Jagolinzer, A.D., Larcker, D.F., 2010. Chief executive officer equity incentives and accounting irregularities. J. Account. Res. 48 (2), 225–271.
Badertscher, B.A., 2011. Overvaluation and the choice of alternative earnings management mechanisms. Account. Rev. 86 (5), 1491–1518.
Barton, J., Simko, P.J., 2002. The balance sheet as an earnings management constraint. Account. Rev. 77, 1–27.
Bartov, Eli, 1993. The timing of asset sales and earnings manipulation. The Accounting Review 68 (4), 840–855. https://www.jstor.org/stable/248507.
Bartov, E., Givoly, D., Hayn, C., 2002. The rewards to meeting or beating earnings expectations. J. Account. Econ. 33 (2), 173–204.
Bebchuk, L.A., Cremers, K.J.M., Peyer, U.C., 2011. The CEO pay slice. J. Financ. Econ. 102 (1), 199–221.
Bens, D.A., Nagar, V., Wong, M.H.F., 2002. Real investment implications of employee stock option exercises. J. Account. Res. 40 (2), 359–393.
Bergstresser, D., Philippon, T., 2006. CEO incentives and earnings management. J. Financ. Econ. 80 (3), 511–529.
Bhandari, A., Mammadov, B., Shelton, A., Thevenot, M., 2018. It is not only what you know, it is also who you know: CEO network connections and financial reporting quality. Audit. J. Pract. Theory 37 (2), 27–50.
Bizjak, J., Lemmon, M., Whitby, R., 2009. Option backdating and board interlocks. Rev. Financ. Stud. 22 (11), 4821–4847.

Bradshaw, M.T., Sloan, R.G., 2002. GAAP versus the street: an empirical assessment of two alternative definitions of earnings. J. Account. Res. 40 (1), 41–66.
Brass, D.J., Burkhardt, M.E., 1992. Networks and organizations: structure, form, and action. In: Centrality and Power in Organizations. In N. Nohria & R. Eccles (Eds.).
Brown, L.D., Caylor, M.L., 2005. A temporal analysis of quarterly earnings thresholds: propensities and valuation consequences. Account. Rev. 80 (2), 423.
Bruns, W.J., Merchant, K.A., 1990. The dangerous morality of managing earnings. Manag. Account. 72 (2), 22–25.
Burgstahler, D., Dichev, I., 1997. Earnings management to avoid earnings decreases and losses. J. Account. Econ. 24 (1), 99–126.
Burt, R.S., 2000. In: Sutton, R., Staw, B. (Eds.), The Network Structure of Social Capital. JAI Press, Greenwich CT.
Bushee, B.J., 1998. The influence of institutional investors on myopic R&D investment behavior. Account. Rev. 73 (3), 305–333.
Chan, L.H., Chen, K.C.W., Chen, T.Y., Yu, Y., 2015. Substitution between real and accruals-based earnings management after voluntary adoption of compensation clawback provisions. Account. Rev. 90 (1), 147–174.
Chaney, P.K., Lewis, C.M., 1995. Earnings management and firm valuation under asymmetric information. J. Corp. Finan. 1 (3), 319–345.
Cheng, Q., Warfield, T.D., 2005. Equity incentives and earnings management. Account. Rev. 80 (2), 441–476.
Cheng, Q., Lee, J., Shevlin, T., 2016. Internal governance and real earnings management. Account. Rev. 91 (4), 1051–1085.
Chikh, S., Filbien, J.-Y., 2011. Acquisitions and CEO power: evidence from French networks. J. Corp. Finan. 17 (5), 1221–1236.
Chiu, P.C., Teoh, S.H., Tian, F., 2013. Board interlocks and earnings management contagion. Account. Rev. 88 (3), 915–944.
Choi, J.-H., Kim, J.-B., Qiu, A.A., Zang, Y., 2012. Geographic proximity between auditor and client: how does it impact audit quality? Audit. J. Pract. Theory 31 (2), 43–72.
Cohen, D.A., Zarowin, P., 2010. Accrual-based and real earnings management activities around seasoned equity offerings. J. Account. Econ. 50 (1), 2–19.
Cohen, D.A., Dey, A., Lys, T.Z., 2008a. Real and accrual-based earnings management in the pre-and post-Sarbanes-Oxley periods. Account. Rev. 83 (3), 757–787.
Cohen, L., Frazzini, A., Malloy, C., 2008b. The small world of investing: board connections and mutual fund returns. J. Polit. Econ. 116 (5), 951–979.
Coleman, J.S., 1988. Social capital in the creation of human capital. Am. J. Sociol. 94 (Supplement), 95–120.
Coram, P., F. J, Pinnuck, M., 2016. Earnings management: the role of economics and ethics on managers' decision making. In: Working Paper. https://doi.org/10.2139/ssrn.2868350. Avaiable at.
Davis, G.F., 1991. Agents without principles? The spread of the poison pill through the intercorporate network. Adm. Sci. Q. 36 (4), 583–613.
Davis, G.F., Greve, H.R., 1997. Corporate elite networks and governance changes in the 1980s. Am. J. Sociol. 103 (1), 1–37.
Dechow, P.M., Sloan, R.G., 1991. Executive incentives and the horizon problem. J. Account. Econ. 14 (1), 51–89.
Dechow, P.M., Sloan, R.G., Sweeney, A.P., 1995. Detecting earnings management. Account. Rev. 70 (2), 193–225.
Dechow, P.M., Sloan, R.G., Sweeney, A.P., 1996. Causes and consequences of earnings manipulation: an analysis of firms subject to enforcement actions by the SEC. Contemp. Account. Res. 13 (1), 1–36.
Dechow, P.M., Hutton, A.P., Kim, J.H., Sloan, R.G., 2012. Detecting earnings management: a new approach. J. Account. Res. 50 (2), 275–334.
DeFond, M.L., Jiambalvo, J., 1994. Debt covenant violation and manipulation of accruals. J. Account. Econ. 17 (1), 145–176.
Demerjian, P., Lev, B., McVay, S., 2012. Quantifying managerial ability: a new measure and validity tests. Manag. Sci. 58 (7), 1229–1248.
Demski, J.S., Frimor, H., Sappington, D.E.M., 2004. Efficient manipulation in a repeated setting. J. Account. Res. 42 (1), 31–49.
Desai, H., Hogan, C.E., Wilkins, M.S., 2006. The reputational penalty for aggressive accounting: earnings restatements and management turnover. Account. Rev. 81 (1), 83–112.
DuCharme, L.L., Malatesta, P.H., Sefcik, S.E., 2004. Earnings management, stock issues, and shareholder lawsuits. J. Financ. Econ. 71 (1), 27–49.
El-Khatib, R., Fogel, K., Jandik, T., 2015. CEO network centrality and merger performance. J. Financ. Econ. 116 (2), 349–382.
Engelberg, J., Gao, P., Parsons, C.A., 2012. Friends with money. J. Financ. Econ. 103 (1), 169–188.
Engelberg, J., Gao, P., Parsons, C.A., 2013. The price of a CEO's rolodex. Rev. Financ. Stud. 26 (1), 79–114.
Ettredge, M., Scholz, S., Smith, K.R., Sun, L., 2010. How do restatements begin? Evidence of earnings management preceding restated financial reports. J. Bus. Financ. Acc. 37 (3–4), 332–355.
Ewert, R., Wagenhofer, A., 2005. Economic effects of tightening accounting standards to restrict earnings management. Account. Rev. 80 (4), 1101–1124.
Faleye, O., Kovacs, T., Venkateswaran, A., 2014. Do better-connected CEOs innovate more? J. Financ. Quant. Anal. 49 (5–6), 1201–1225.
Fang, Y., Hasan, I., Wang, H., 2019. Do social networks encourage risk-taking?. In: Evidence from bank CEOs, DJB Discussion Paper 1902, Stuart School of Business. Apriil 25.
Ferris, S.P., Javakhadze, D., Rajkovic, T., 2017. CEO social capital, risk-taking and corporate policies. J. Corp. Finan. 47, 46–71.
Fracassi, C., 2016. Corporate Finance Policies and Social Networks. Management Science. Forthcoming.
Fracassi, C., Tate, G., 2012. External networking and internal firm governance. J. Financ. 67 (1), 153–194.
Francis, J., LaFond, R., Per, M.O., Schipper, K., 2004. Costs of equity and earnings attributes. Account. Rev. 79 (4), 967–1010.
Gilliam, T.A., Heflin, F., Paterson, J.S., 2015. Evidence that the zero-earnings discontinuity has disappeared. J. Account. Econ. 60 (1), 117–132.
Glaeser, E.L., Kallal, H.D., Scheinkman, J., Shleifer, A., 1992. Growth in cities. J. Polit. Econ. 100 (6), 1126–1152.
Gong, G., Louis, H., Sun, A.X., 2008. Earnings management, lawsuits, and stock-for-stock acquirers' market performance. J. Account. Econ. 46 (1), 62–77.
Graham, J.R., Harvey, C.R., Rajgopal, S., 2005. The economic implications of corporate financial reporting. J. Account. Econ. 40 (1–3), 3–73.
Granovetter, M., 2005. The impact of social structure on economic outcomes. J. Econ. Perspect. 19 (1), 33–50.
Guan, L., Wright, C.J., Leikam, S.L., 2005. Earnings management and forced CEO dismissal. Adv. Account. 21, 61–81.
Gunny, K.A., 2010. The relation between earnings management using real activities manipulation and future performance: evidence from meeting earnings benchmarks. Contemp. Account. Res. 27 (3), 855–888.
Hainmueller, J., 2012. Entropy balancing for causal effects: a multivariate reweighting method to produce balanced samples in observational studies. Polit. Anal. 20 (1), 25–46.
Haunschild, P.R., 1993. Interorganizational imitation: the impact of interlocks on corporate acquisition activity. Adm. Sci. Q. 38 (4), 564–592.
Hausman, J.A., 1978. Specification tests in econometrics. Econometrica 46 (6), 1251–1271.
Hazarika, S., Karpoff, J.M., Nahata, R., 2012. Internal corporate governance, CEO turnover, and earnings management. J. Financ. Econ. 104 (1), 44–69.
Henry, D., Schmitt, C., 2001. The numbers game. Business Week 3732, 100–107.
Hirshleifer, D., Teoh, S.H., 2003. Limited attention, information disclosure, and financial reporting. J. Account. Econ. 36 (1), 337–386.
Hochberg, Y.V., Ljungqvist, A., Lu, Y., 2007. Whom you know matters: venture capital networks and investment performance. J. Financ. 62 (1), 251–301.
Hwang, B.-H., Kim, S., 2009. It pays to have friends. J. Financ. Econ. 93 (1), 138–158.
Inkpen, A.C., Tsang, E.W.K., 2005. Social capital, networks, and knowledge transfer. Acad. Manag. Rev. 30 (1), 146–165.
Ishii, J., Xuan, Y., 2014. Acquirer-target social ties and merger outcomes. J. Financ. Econ. 112 (3), 344–363.
Jaffe, A.B., Trajtenberg, M., Henderson, R., 1993. Geographic localization of knowledge spillovers as evidenced by patent citations. Q. J. Econ. 108 (3), 577–598.
Javakhadze, D., Ferris, S.P., French, D.W., 2016. Social capital, investments, and external financing. J. Corp. Finan. 37, 38–55.
Jones, J.J., 1991. Earnings management during import relief investigations. J. Account. Res. 193–228.
Karpoff, J.M., Lee, D.S., Martin, G.S., 2008. The cost to firms of cooking the books. J. Financ. Quant. Anal. 43 (3), 581–611.
Kasznik, R., McNichols, M.F., 2002. Does meeting earnings expectations matter? Evidence from analyst forecast revisions and share prices. J. Account. Res. 40 (3), 727–759.
Ke, R., Li, M., Ling, Z., Zhang, Y., 2019. Social connections within executive teams and management forecasts. Manag. Sci. 65 (1), 439–457.
Kim, J.-B., Sohn, B.C., 2013. Real earnings management and cost of capital. J. Account. Public Policy 32 (6), 518–543.
Knyazeva, A., Knyazeva, D., Masulis, R., 2013. The supply of corporate directors and board independence. Rev. Financ. Stud. 26 (6), 1561–1605.
Koester, A., Lundholm, R., Soliman, M., 2016. Attracting attention in a limited attention world: exploring the causes and consequences of extreme positive earnings surprises. Manag. Sci. 62 (10), 2871–2896.

Koh, K., Matsumoto, D.A., Rajgopal, S., 2008. Meeting or beating analyst expectations in the post-scandals world: changes in stock market rewards and managerial actions. Contemp. Account. Res. 25 (4), 1067–1098.
Kothari, S.P., Leone, A.J., Wasley, C.E., 2005. Performance matched discretionary accrual measures. J. Account. Econ. 39 (1), 163–197.
Larcker, D.F., So, E.C., Wang, C.C., 2013. Boardroom centrality and firm performance. J. Account. Econ. 55 (2), 225–250.
Leggett, D., Parsons, L.M., Reitenga, A.L., 2009. Real earnings Management and Subsequent Operating Performance. Available at SSRN 1466411.
Liu, Y., 2014. Outside options and CEO turnover: the network effect. J. Corp. Finan. 28, 201–217.
Masulis, R.W., Wang, C., Xie, F.E.I., 2007. Corporate governance and acquirer returns. J. Financ. 62 (4), 1851–1889.
McMullin, Jeff, Schonberger, Bryce, 2020. Entropy-balanced accruals. Review of Accounting Studies 25, 84–119. https://doi.org/10.1007/s11142-019-09525-9.
McNichols, M., Wilson, G.P., 1988. Evidence of earnings management from the provision for bad debts. J. Account. Res. 26, 1–31.
Mitchell, M.L., Lehn, K., 1990. Do bad bidders become good targets? J. Appl. Corp. Finance 3 (2), 60–69.
Mizruchi, M.S., 1996. What do interlocks do? An analysis, critique, and assessment of research on interlocking directorates. Annu. Rev. Sociol. 22, 271–298.
Mizruchi, M.S., Potts, B.B., 1998. Centrality and power revisited: actor success in group decision making. Soc. Networks 20 (4), 353–387.
Myers, J.N., Myers, L.A., Skinner, D.J., 2007. Earnings momentum and earnings management. J. Acc. Audit. Financ. 22 (2), 249–284.
Ravina, E., Sapienza, P., 2010. What do independent directors know? Evidence from their trading. Rev. Financ. Stud. 23 (3), 962–1003.
Reagans, R., McEvily, B., 2003. Network structure and knowledge transfer: the effects of cohesion and range. Adm. Sci. Q. 48 (2), 240–267.
Renneboog, L., Zhao, Y., 2011. Us knows us in the UK: on director networks and CEO compensation. J. Corp. Finan. 17 (4), 1132–1157.
Richardson, S.A., Tuna, A., Wu, M., 2002. Predicting Earnings Management: The Case of Earnings Restatements. Available at SSRN 338681.
Roychowdhury, S., 2006. Earnings management through real activities manipulation. J. Account. Econ. 42 (3), 335–370.
Sandvik, Jason, 2020. Board monitoring, director connections, and credit quality. Journal of Corporate Finance 65. https://doi.org/10.1016/j.jcorpfin.2020.101726.
Sankar, M.R., Subramanyam, K.R., 2001. Reporting discretion and private information communication through earnings. J. Account. Res. 39 (2), 365–386.
Shue, K., 2013. Executive networks and firm policies: evidence from the random assignment of MBA peers. Rev. Financ. Stud. 26 (6), 1401–1442.
Subramanyam, K.R., 1996. The pricing of discretionary accruals. J. Account. Econ. 22 (1), 249–281.
Taylor, G.K., Xu, R.Z., 2010. Consequences of real earnings management on subsequent operating performance. Res. Account. Regul. 22 (2), 128–132.
Teoh, S.H., Welch, I., Wong, T.J., 1998. Earnings management and the long-run market performance of initial public offerings. J. Financ. 53 (6), 1935–1974.
Trueman, Brett, Titman, Sheridan, 1988. An explanation for accounting income smoothing. Journal of Accounting Research 26, 127–139. https://doi.org/10.2307/2491184.
Tucker, J.W., Zarowin, P.A., 2006. Does income smoothing improve earnings informativeness? Account. Rev. 81 (1), 251–270.
Wells, P., 2002. Earnings management surrounding CEO changes. Account. Finance 42 (2), 169–193.
Xu, R.Z., Taylor, G.K., Dugan, M.T., 2007. Review of real earnings management literature. J. Account. Lit. 26, 195.
Zang, A.Y., 2012. Evidence on the trade-off between real activities manipulation and accrual-based earnings management. Account. Rev. 87 (2), 675–703.