CEO Network Size and Earnings Management

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ABSTRACT This study examines whether a CEO's social network influences the firm's form of earnings management. Using the number of social connections to outside executives and directors to measure network size, we find that CEO network size correlates negatively with accrual earnings management (*AEM*) but positively with real activities management (*RAM*), especially when the network reflects influential connections. Additional evidence suggests that while a large network may aggravate the CEO's reputation loss from *AEM*, it mitigates the CEO's labor market costs associated with *RAM*, resulting in high levels of earnings management that degrade the firm's long-term performance. Overall, we conclude that CEO social networks generate costs and benefits that induce executives to engage in distinctly different forms of earnings management.

KEY WORDS: Social networks, CEO network size, Earnings management, Real activities management, Accrual earnings management

JEL CLASSIFICATION: G30, L14, M41.

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1. Introduction

A substantial literature examines firms' corporate disclosure and financial reporting policies (Healy and Palepu, 2001; Beyer, Cohen, Lys, and Walther, 2010). This literature, however, provides at best an incomplete picture of the determinants of those policies because it does not consider the social network of the executive who develops and implements them. This absence is noteworthy as a growing number of studies in corporate finance documents that executives' social network can significantly influence firms' financial policies, on executive compensation

(Engelberg, Gao, and Parsons, 2013), board monitoring (Fracassi and Tate, 2012), acquisition activity (El-Khatib, Fogel, and Jandik, 2015), and capital investment (Fracassi, 2016). Social structure can also enhance firm value (Larcker, So, and Wang, 2013). These financial policies link tightly with firms' disclosure and reporting policies, including an executive's use of earnings management to misrepresent performance. We contribute to the literature by examining the relation between a CEO's social network and his or her choice of the two main forms of earnings management – accrual earnings management (*AEM*) and real activities management (*RAM*). In the first case, managers strive to achieve a short-run earnings target by choosing accounting accruals to misrepresent earnings (*AEM*). In the second case, managers change the firm's operations to report earnings based on departures from normal operating activities as if they were normal (*RAM*).

First, we rely on the social science literature to define a CEO's social network as a web of connections developed from past service of the CEO in executive, director, and similar senior positions at other firms, alumni educational network associations, and social clubs (Brass and Burkhardt, 1992; Haunschild, 1993; Mizruchi, 1996; Mizruchi and Potts, 1998; Reagans and McEvily, 2003; Granovetter, 2005; Inkpen and Tsang, 2005). Building on this literature, we posit that as a CEO's network grows in size, it produces net benefits for the CEO that can change decision-making. These benefits emanate from two types of channels: (i) information-sharing and communication channels, which improve CEO decision making, and (ii) non-information-sharing channels, which extract private advantages from the network in such forms as trust building, reputational and regulatory protection, entrenchment and mobility in the labor market, and imitation in policy making, among others.

These channels could be especially relevant in a CEO's decision to manage earnings, by reducing the detection likelihood and the net cost of detected earnings management and by increasing the net benefit of undetected earnings management. The first channel allows the CEO to acquire information from the network to choose a form and level of earnings management that minimizes costs (e.g., from implementation, regulatory, and reputational factors). The second channel may be further advantageous when the earnings management remains undetected, where the benefits could include increased CEO compensation (Engelberg *et al*., 2013), more outside options in the labor market (Liu, 2014), and enhanced reputation from successfully delivering "superior" earnings to the market.

Importantly, the private benefits from the CEO's network may or may not translate into better earnings management decisions for the firm. On the one hand, a large network can augment CEO reputation loss from detected wrongdoings, which helps discipline the CEO to act on behalf of all shareholders. On the other hand, well-connected CEOs are better insulated from internal monitoring and external scrutiny and may suffer less from labor market consequences, which could induce them to engage in activities that hurt the firm in the long run.

We then examine whether well-connected CEOs choose one form of earnings management over another. *AEM*, which window-dresses earnings with accruals, can increase the probability of the firm violating GAAP. This could result in Securities and Exchange Commission (SEC) scrutiny and class action or enforcement litigation (e.g., Karpoff, Lee, and Martin, 2008a; DuCharme, Malatesta, and Sefcik, 2004; Gong, Louis, and Sun, 2008; Zang, 2012). These negative consequences are often high-profile and unambiguous. Also, survey results show that CFOs and CEOs perceive *AEM* as more ethically questionable than other forms of earnings management (Coram, Frederickson, and Pinnuck, 2016). Given this evidence, we predict that well-connected CEOs, with more to lose, will strive to protect their reputation and preserve their other positions in the labor market by reducing large (detectable) accruals. In contrast, *RAM* may permit CEOs to achieve short-term earnings targets without significantly increasing the regulatory and reputational costs, as detection, liability, and investor losses from *RAM* litigation can be difficult to establish.

Even if *RAM* eventually leads to performance-induced CEO turnover, it could be less costly to the CEO's reputation than a litigation-related departure resulting from alleged or proven cases of wrongdoing from *AEM*. Given the less explicit nature of *RAM*, well-connected CEOs could utilize their social networks to justify dubious activities, entrench themselves in the current firm, and, in the event of forced turnover, obtain subsequent positions elsewhere.[1] Thus, we predict that well-connected CEOs faced with these lower costs will use *RAM* adjustments to meet short-term targets and achieve private gains. There is anecdotal evidence consistent with these predictions. General Electric's (GE) legendary and well-connected CEO Jack Welch is well known to have used *RAM* to manage earnings by engaging in certain merger and acquisition activities.[2,] In contrast, Jeffrey Immelt, the successor chairman at GE, with relatively fewer connections in his social and professional web (according to our sample 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.[3]

This study is the first to examine whether the size of a CEO's social network, as reflected in the number of social connections to outside executives and directors, relates to the CEOs' use of *RAM* versus *AEM* to manufacture earnings.[4] Specifically, we address the following core research question: Do firms with well-connected CEOs rely more on *RAM* versus *AEM* to bolster earnings primarily to achieve short-run targets? We then delve deeper into this question by examining whether the relation between CEO network size and *RAM* or *AEM* differs predictably for sub-samples of influential persons who share more information and when the manufactured earnings impose different reputational costs on the CEO. We also consider whether CEO network size affects the future operating performance of the firm and the post turnover employment prospects of the CEO, conditional on the CEO's choice of earnings management form.[5]

Answers to these questions are important because the presence of executive-level social networks may shed light on why CEOs insist on managing earnings (Graham, Harvey, and Rajgopal, 2005). CEOs invariably believe this activity benefits the firm as well as themselves, despite increased scrutiny by analysts, investors, regulators, and Congress, and the imposition of substantial costs in the managerial labor market (Karpoff *et al.*, 2008b). The presence of strong social networks may also help explain why managers prefer one form of earnings management to another. This study, thus, contributes to knowledge about earnings management in corporate social structures.

We first construct the CEO social network for a sample of U.S. firms covering 1999–2014 by extracting those CEOs' professional, educational, and social connections from the BoardEx database. As detailed in Section 4, we construct a direct measure of CEO connectedness, calculated as the sum of direct connections to outside executives or directors linked to the CEO through his or her past or current business relationships, affiliations with charitable or volunteer organizations, boards on which he or she serves or has served, and past tertiary schools attended. We also use alternative network measures of connectedness to check the results. Second, we follow the prior literature (Roychowdhury, 2006; Cohen, Dey, and Lys, 2008) and measure *RAM* as the abnormal level of operating cash flows, production costs, or discretionary expenditures. We also follow an extensive literature on *AEM*, which uses discretionary accruals to proxy for accrual-generated earnings changes. We measure all variables at the firm/CEO level as of year *t* and analyze a maximum sample of 25,283 firm-years and 4,362 unique firms. We acknowledge that these proxies represent noisy estimates of the earnings manufactured by the CEO to meet or beat an earnings target.

We document two key results. We first find a significantly *positive* relation between CEO network size and *RAM*. This result confirms our social theory that larger CEO networks enable the

CEO to increase *RAM* by reducing the expected net cost of the *RAM* activity, either by lowering detection probability, increasing acceptability, or by reducing the regulatory, reputational, and labor market costs of the activity upon detection. At least in the short term, the choice of *RAM* can thus be firm-wise desirable, to the extent that the net benefits from the larger CEO network exceed the costs. In the long term, however, the CEO's preference for *RAM* could be a symptom of misaligned incentives. Despite research showing that the use of *RAM* to achieve short-term earnings targets imposes capital costs (Kim and Sohn 2013) and may worsen future firm performance (Leggett, Parsons, and Reitenga, 2009), a well-connected CEO who is able to justify these activities and seek post turnover employment may have less concern for these longer-term costs to the firm.

Second, we find a significantly *negative* relation between CEO network size and accrual earnings management (*AEM*). Why do we observe different effects of network size on *RAM* versus *AEM* given that larger networks should be beneficial to the CEO and the firm? The answer lies in the relative net cost of *AEM* versus *RAM*, which prior research (Section 2) shows is greater for the former. With larger *AEM*, monitoring by audit committees and independent accountants increases detection probability. Moreover, as the research shows, the costs to the firm (e.g., loss of market value) and the CEO (e.g., ouster, loss of reputation, reduction in severance pay) can be substantial. Well-connected CEOs could be especially concerned about the loss of reputation and outside directorships. This should steer them away from *AEM*.

We further find that the effect of network size on earnings management is less substantial at the left tail of the *AEM* or *RAM* distribution, namely, when the amounts of manufactured earnings are smaller. With smaller *AEM*, the probability and cost of detection declines. Smaller *AEM* can also be explained by judgment within GAAP (and the Supreme Court rule in the Dura decision (Dura Pharmaceuticals, Inc. v. Broudo, 544 U.S. 336 2005), which allows for reasonable, i.e., more-likely-than-not, explanations of GAAP choice as a defense against plaintiffs' allegations). Similarly, with smaller *RAM*, the probability of performance-induced CEO turnover and the relevance of post-turnover employment prospects are lower. Thus, the positive (negative) effect of CEO network size on the choice of *RAM* (*AEM)* becomes less important with lower levels of earnings management.

Next, we show a stronger positive (negative) relation between *RAM* (*AEM*) and network size when the CEO's network allows for greater information sharing proxied by the number of connections to persons of influence. Whereas, for *AEM*, such persons could aggravate potential reputation and litigation loss, those same persons could enhance the CEO's ability to reduce the expected cost of *RAM*. We use three proxies to represent networks with persons of high and low influence. Specifically, we find a stronger positive (negative) relation between *RAM* (*AEM*) and network size for (i) BoardEx's classification of executive director versus supervisorial director, (ii) when the connections involve S&P 500 firms, and (iii) when the network involves current versus non-current directorships. Taken together, these results further support our social theory of earnings management, in that a larger and more influential CEO network implies a decrease in the net costs of *RAM* and an increase of the net costs of *AEM*.

We also examine how CEO network size conditions the relation between earnings management and future firm performance. Using return on assets and operating cash flows as performance measures, we find that *RAM* associates negatively with the future performance of the firm when the CEO network is large but not when the CEO network is small. Thus, while CEOs with larger networks associate with larger *RAM* adjustments, these adjustments also presage poor future firm performance, possibly because the *RAM* adjustments can only occur by shifting cash flows from one period to the next, which can be firm-wise undesirable. The use of *AEM* in larger networks, by comparison, has less impact on future operating returns and does not shift cash flows.

We contend that the future performance associated with *AEM* is not significantly different for large and small networks because the potential reputation loss from higher *AEM* serves to offset any private benefits from the network from the CEO's self-interested behavior.

Our interpretation of the key result that CEOs with large networks favor *RAM* versus *AEM* also relies on the assumption that well-connected CEOs have advantages in the executive labor market in that they can use their social network to resist ouster or find another job. The private costs of the less conspicuous form of earnings management, *RAM*, are lower. We directly test this network effect on the likelihood of the CEO getting an outside position after forced turnover. Consistent with Liu (2014), we find that, conditional on CEO turnover, large networks generally increase the departed CEO's chance of outside employment. However, we do not find that the use of *RAM* versus *AEM* changes the positive relation between network size and the CEO's employment prospects following turnover.

We further subject our results to possible confounding factors. Smaller *AEM* or larger *RAM* could occur if more able CEOs are well connected CEOs. If CEO network size simply reflects ability, then we can infer little about the effect of network size on *RAM* or *AEM*. However, our main results are qualitatively identical after controlling for CEO ability as per the Demerijian, Lev, and McVay (2012) measure. We also state an alternative specification of the network size-earnings management relation to address another potential endogeneity. One issue is that whereas CEO network size influences the conduct of *RAM* or *AEM* (our main contention), those activities could simultaneously prompt CEOs to build stronger networks to maximize the net benefit of *RAM* or to minimize the net cost of *AEM* at least in the short term. We use a two-stage instrumental variable (IV) approach to check for this endogeneity. The use of this alternative econometric specification suggests that the negative association between *AEM* and CEO network size is susceptible to reverse causality. In other words, a low level *AEM* could both influence and result from CEO network size. However, the positive effect of CEO network on *RAM* is robust to the IV approach, confirming our result that well-connected CEOs engage in *RAM* to garner short-term benefits that could be harmful to the firm in the long run.

Finally, we corroborate our results using alternative proxies to quantify the CEO's network size. These other measures include the number of direct and indirect links between the CEO and other individuals as well as measures of the "significance" of the CEO's network (i.e., the closeness of the CEO's path to other individuals, the frequency with which the CEO lies on the closest path between two individuals, and the relevance of the individuals connected to the CEO). The majority of these alternative network measures explains *RAM* and *AEM* in the same way.

Our paper proceeds as follows. 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

We combine two strands of literature to develop our hypotheses. We first rely on the social science literature to define a CEO's social network as the number of ties the CEO has to other CEOs and senior executives through shared educational and work experiences.[6] This literature suggests that well-connected CEOs have two key traits: (i) better access to relevant information internal and external to the firm and (ii) higher status and greater economic and political power (Brass and Burkhardt, 1992; Haunschild, 1993; Mizruchi, 1996; Mizruchi and Potts, 1998; Reagans and McEvily, 2003; Granovetter, 2005; Inkpen and Tsang, 2005). Assuming appropriate incentive alignment, these traits can be beneficial to a CEO and the firm through advantages in the labor, product, and corporate control markets. Shared information, for example, allows network members to improve and establish acceptable and beneficial practices by relying on the information of others (Glaeser, Kalla, Scheinkman, and Shleifer, 1992; Jaffe, Trajtenberg, and Henderson, 1993).[7] In actions to manage earnings, we assume that the network accrues value to the CEO and, potentially, to the firm through the accomplishments and efforts of the CEO.

A growing literature on the effects of social networks on corporate financial policies supports this assumption. Key studies have examined the effects of CEO networks on the following financial policies: compensation (Coles, Daniel, and Naveen, 2008; Hwang and Kim, 2009; Engelberg *et al*., 2013), executive employment options in the labor market (Liu, 2014), stock options backdating (Bizjak, Lemmon, and Whitby, 2009), corporate innovation (Faleye, Kovacs, and Venkateswaran, 2014), board monitoring (Fracassi and Tate, 2012; Fracassi, 2016), acquisition activity (Haunschild, 1993; El-Khatib, Fogel, and Jandik, 2015), tax rates (Brown and Drake, 2014), private equity transactions (Stuart and Yim, 2010), and future performance (Horton, Millo, and Serafeim, 2012; Larcker, So, and Wang, 2015). None of this prior work, however, relates to relations between CEO network size and the form and scale of earnings management, with the possible exceptions of Chiu, Teoh, and, Tian (2013) and Kedia, Koh, and Rajgopal (2015), who show that the presence of a network induces the earnings management practices of one firm to spread to others. Notably absent from this literature is whether the strength or size of an executive social network might affect the form and scale of earnings management. This is important as the social aspects of network size may shed light on why certain earnings management practices endure despite assertions that they should not (Bruns and Merchant, 1990).[8]

The second literature studies the effects of and motivations for real activities earnings management (*RAM*) and accrual earnings management (*AEM*). *RAM* creates earnings by changing the timing or structuring of operating, investing, or financing transactions. The changes usually involve intentionally non-disclosed departures from normal business activities. Such changes can also have adverse cash flow consequences in the long run. Examples include overproduction to decrease cost of goods sold and research and development expenditure reduction to boost current earnings. In contrast, managers achieve *AEM* by the intentional choice of accounting accruals to misrepresent earnings. For example, increasing the estimated useful life for depreciation and underestimating doubtful debts increases net earnings with no change in the underlying transactions or pretax cash flows. Both manufacture additional earnings, and much evidence indicates that both are used to meet or beat a management or analyst earnings target when unmanaged earnings may fall short.[9]

Importantly, and a factor motivating this study, even though both forms of earnings management permit CEOs to achieve short-term earnings targets, the probability of detection and the costs incurred given detection can differ substantially. With *AEM*, larger accruals increase the probability of an alleged GAAP violation (Sun and Liu, 2016). *AEM* can also destroy firm value through short trading in anticipation of its detection (Griffin, 2003). Moreover, any disclosure that alleges *AEM* can increase the chances of regulatory enforcement and class action litigation with costly consequences (Bruns and Merchant, 1990; DuCharme *et al.*, 2004; Gong *et al.*, 2008; Zang, 2012). Detected *AEM* can also impose steep reputational costs on CEOs as a loss of value of firm stock and stock options or loss of future job opportunities due to forced turnover (Karpoff, 2008b). CEOs wanting to protect their larger social network may have much to lose if their friends and colleagues in the network perceive (and investigations conclude) their *AEM* practices as wrong and possibly unlawful. Accordingly, to avoid these costs, we predict that well-connected CEOs' conduct of *AEM* relates to smaller accrual adjustments. By manufacturing smaller earnings changes with *AEM*, the expected cost of *AEM* detection drops, and the CEO's reputation and availability of outside options in the labor market from the network remain relatively unaffected. A smaller *AEM* adjustment could also be firm-wise desirable if the expected benefits to the firm of having a larger and untarnished CEO network are at least equal to the expected cost of a small *AEM* adjustment.

Most studies, however, simply deem an equivalent dollar of *RAM* versus *AEM* adjustment as the lower-cost alternative. *RAM* permits CEOs to achieve short-term earnings targets without tarnishing the CEOs' reputation. Also, detection probability is small, and loss exposure from regulatory oversight and litigation can be difficult to establish given that courts accept reasonable explanations of *RAM* practices unrelated to the intentional manufacturing of earnings to meet or beat a target (Dura Pharmaceuticals, Inc. v. Broudo, 544 U.S. 336 2005). However, *RAM* can potentially destroy firm value in the long run, because it involves a departure from the planned use of cash. So why do studies conclude that most managers favor *RAM* over *AEM* to manufacture earnings to meet or beat an earnings target?[10] Three factors may drive this choice. First, compared to *AEM*, *RAM* has lower detection probability and lower cost in terms of its effects on regulatory enforcement, market discipline, and CEOs' current and future job prospects and reputation. Second, it can be difficult to separate a change in real activity intended to manage earnings from one that represents good decision-making. Third, most managers believe (and auditors indirectly confirm this by lack of qualification) that all but the most egregious *RAM* adjustments do not require disclosure as a change in GAAP or a change in accounting estimate. Perhaps for these reasons, survey data (Graham *et al.*, 2005) indicate that managers prefer *RAM* to *AEM* as the less costly way to achieve an earnings target to satisfy investors' demands for short-term share price performance.[11]

Yet *RAM* may still impose significant net costs on the firm in the longer term from the inefficient use of cash if managers forgo positive net present value projects in favor of managing earnings to meet or beat an earnings target. This analysis, however, excludes consideration of the CEO's social network in the decision to use *RAM*. This overlooked ingredient is important and relevant, as the larger the CEO network, the larger the potential benefits of *RAM* for the CEO and the firm. The CEO acquires information from the network to identify, evaluate, and implement a form and level of *RAM* that minimizes the cost of earnings management (e.g., implementation costs, and detection and penalization costs) and maximizes the benefit of earnings management (e.g., solidifying political and economic status and promoting reputation by delivering "superior" earnings to the market). Additionally, CEOs with large networks may use their entrenchment status to insulate themselves from internal monitoring by the board and from external scrutiny in the corporate control and executive labor markets. More strongly networked CEOs may, thus, be able to make earnings management decisions with inefficient cash flows to meet or beat earnings benchmarks. Prior studies illustrate that beating earnings forecasts associates positively with contemporaneous stock returns (Bhojraj, Hribar, Picconi, and McInnis, 2009), and that several positive surprises in a row can produce a valuation premium (Bartov, Givoly, and Hayn, 2002; Kasznik and McNichols, 2002). If those benefits exceed the costs of the *RAM* activity, then this implies that we should observe that higher *RAM* adjustments associate with larger CEO networks. Accordingly, we predict a positive relation between earnings from *RAM* adjustments and CEO network size and a negative relation between *AEM* adjustments and CEO network size. We state our first hypothesis as follows.

H1: Firms' adjustments from *RAM* (*AEM*) increase (decrease) in CEO network size.

We also conduct tests of whether *H1* holds for specific sub-samples, namely, for influential connections when information sharing is higher, when the manufactured earnings impose different net costs on the CEO, and for different degrees of incentive alignment between the firm and the CEO. We state three proxies for connections to persons of influence, namely, whether BoardEx uses a classification of executive director versus supervisorial director, whether the connections involve large firms, and whether the information sharing relates to current or past directorships. The connection to an executive director should facilitate information sharing because executive directors have greater direct knowledge, status, and power to influence corporate decision-making.

Also, the effects of information sharing from influential connections should be stronger for ties to large firms and when the CEO has more current versus past director positions through the influence of CEO reputation. Since greater information sharing in the network benefits the CEO, we expect that the relations in *H1* will strengthen compared with networks with less information sharing. In addition, when a CEO has more current outside director positions, questions on accounting issues from *AEM* could jeopardize his or her reputation. Aware of this potential threat to reputation, the CEO is likely to choose the less costly of *RAM* over *AEM* to meet or beat the earnings target. We state our second hypothesis as follows.

> *H2*: The positive (negative) relation between CEO network size and *RAM* (*AEM*) strengthens for networks with persons of influence.

We next examine whether the relations in *H1* vary for differences in incentive alignment between the firm and the CEO. We use the CEO's percentage of common shares owned as the proxy and expect that with less alignment from lower common share ownership in the firm the CEO will take more aggressive *RAM* and *AEM* actions to manage earnings. We state our third hypothesis as follows.

> *H3*: The positive (negative) relation between CEO network size and *RAM* (*AEM*) strengthens for CEOs with a lower percentage of common share ownership.

While beating earnings forecasts associates positively with contemporaneous stock returns (Bhojraj *et al.*, 2009), and several positive surprises in a row can produce a valuation premium (Bartov *et al*., 2002; Kasznik and McNichols, 2002), this trend should eventually reverse unless offset by better underlying performance. Several studies support this view, finding that firms that persistently manage earnings do worse in the long term than those that do not (and that may also have missed their earnings targets). However, because the future costs of earnings management to the CEO and firm can increase more for *AEM* versus *RAM*, a priori, we expect future returns and operating cash flows to suffer less for *RAM*, despite the view that *RAM* can aggravate the inefficient use of cash. The evidence, however, is mixed on this point. Gunny (2010) finds that firms conducting *RAM* have better future operating performance than those that do not. However, Taylor and Xu (2010) find that *RAM* firms do not differ in future operating performance compared to non-*RAM* firms; and Leggett *et al.* (2009) find that *RAM* firms have worse future operating performance. These studies, however, do not investigate whether network size might affect future operating performance. This is important because, as we have already argued, CEO network size should be more beneficial for CEOs and firms conducting *RAM* versus *AEM*. We address the relation between earnings management, future operating performance, and CEO network size by testing the following hypothesis.

> *H4*: The strength of the relation between future operating performance and earnings adjustments from *RAM* (*AEM*) increases with the size of the CEO's network.

A strong network can protect a CEO in the executive labor market. Higher status and political power not only provide job security, but also confer higher compensation on the networked CEO at both appointment and in later salary negotiations. A well-connected CEO will also be more likely to implement projects with less board oversight and discipline if the project fails. In addition, a well-connected CEO will face a more favorable job market in the event of forced turnover. For example, Liu (2014) documents higher CEO turnover in large networks, presumably because well-connected CEOs can find similar jobs and better compensation regardless of the reason for separation. Well-connected CEOs may also receive similar job benefits in the market corporate control. For example, while El-Khatib *et al.* (2015) find that well-connected bidder CEOs are more likely to be dismissed after value-destroying mergers and acquisitions, they also find that such CEOs are more likely to secure an equivalent job after the separation compared with less-connected CEOs.

The effects of *RAM* and *AEM* on CEOs' current and future employment may, however, differ due to the different costs and risks associated with *RAM* and *AEM*. When the detection costs of earnings management are low (i.e., with *RAM*), network size should be beneficial to a CEO's career. The probability of a departed CEO obtaining a future job and network size should, thus, have a positive relation. In contrast, when earnings management detection costs are high (i.e., with *AEM*), network size could hurt the CEO if the stronger network imposes higher job market costs on the departing CEO. Those costs can be considerable when formal securities law violations are filed (Karpoff *et al.*, 2008b).[12] CEO post-turnover employment and network size should then relate less positively for *AEM*. Well-connected CEOs who balance the risks and benefits of *RAM* and *AEM* to meet an earnings target may, therefore, perceive *RAM* as less costly and risky because the adverse effects of *RAM* on their career are relatively marginal. Our final hypothesis tests whether network size moderates the impact of earnings management on CEO post-turnover employment. We state this hypothesis as follows.

> *H5*: The positive relation between CEO post-turnover employment and network size differs for *RAM* versus *AEM*.

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. BoardEx reports generated in November 2015 provide a summary of board composition and/or senior management team by year for 12,972 companies in North America. The summary report dates range from January 1999 to November 2015. 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 firm-level financial and accounting information from Standard & Poor's Compustat North America database and then merge BoardEx data with Compustat 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 extract CUSIP from ISIN and match it to the Compustat header CUSIP. We are able to find the GVKEY for 7,433 quoted firms in BoardEx through matching to CUSIP. 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 are able to find the GVKEY for an additional 1,007 BoardEx quoted firms under this procedure. In total, we find the GVKEY for 8,440 out of 8,558 (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 CRSP/Compustat Merged (CCM) dataset, we merge BoardEx board composition data and Compustat fundamentals data with CRSP stock return data. To identify a unique CRSP security identifier (PERMNO) for each firm-year observation, we ensure 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 sample distribution by fiscal year and industry classification and shows a broad sample of unregulated, non-financial firms, covering approximately 66 and 74 percent of CRSP stocks at the beginning and end of the sample period, respectively. 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 (15.29%), electronic equipment (9.41%), and pharmaceutical products (5.88%), each of the other 39 industries represents less than five percent of the sample. The larger coverage of firms in BoardEx database is constrained by the requirement for earnings management measures computed from Compustat data. However, it is important to note that the connections forming a

CEO's network derive from links established in all organizations as reported in BoardEx biographical histories and are not limited to only the sample firms.

4. Research design

CEO network size measure

We measure CEO network size by counting the number of executives or directors on the annual network with whom the CEO has connections. We define a CEO network connection at *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 prior to 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 BoardEx education file. Following Cohen, Frazzini, and Malloy (2008), we clean the BoardEx 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) PhD, (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, with the exception of 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: $NETWORK\_TOT_{i,t} = \Sigma Network\_Employment_{i,t} + \Sigma Network\_Education_{i,t} + \Sigma Network\_Activities_{i,t}$, where *Network_Employment* sums the CEO's employment connections, *Network_Education* sums the CEO's education connections, and *Network_Activities* sums the CEO's other-activity connections.[13]

Table 2 shows summary statistics for the network size variable (in thousands). The average CEO in our sample has 147.4 connections with a standard deviation of 209.2 connections and a median CEO in our sample has 61 connections. Similar to Fracassi and Tate (2012) and Engelberg *et al.* (2013), our data are skewed to the right.[14]

Real activities management (RAM) measure

Following Roychowdhury (2006) and Cohen *et al.* (2008), we measure *RAM* as the abnormal level of operating cash flow, production cost, and R&D expenditure. First, for every firm-year, abnormal operating cash flow equals actual cash flow from operations (*CFO*) less the normal *CFO* as defined by Eq. (1) below.

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

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

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

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. The abnormal production cost is the difference between actual production cost and 'normal' production cost. Third, abnormal discretionary expenditure equals actual discretionary expenditure less normal R&D, as defined by Eq. (3) below.

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

where actual $DISEXP_{it}$= discretionary expenses in year *t* for firm *i* calculated as the sum of research and development, advertising, and sales, general, and administrative expenses. Following Cohen *et al.* (2008), we combine the three abnormal *RAM* measures to capture the effects of real activities management as a single measure, defined in Appendix A as RAM_{it} = CF_RAM_{it} – $PROD\_RAM_{it}$ + $DISEXP\_RAM_{it}$ and then multiply RAM_{it} by minus one so that a higher value represents more *RAM* by using these three activities.

Accrual-based earnings management (AEM) measure

We use discretionary accruals to proxy for *AEM*, where discretionary accruals equal firms' actual accruals (net income less cash flow from operations) less the normal level of accruals. We estimate the latter using the following modified Jones (1991) model, as defined by Eq. (4) below.

$$TA_{it}/AT_{it-1} = \alpha_0 + \alpha_1 \left(1/AT_{it-1}\right) + \alpha_2 \left((\Delta REV_{it} - \Delta REC_{it})/AT_{it-1}\right) + \alpha_3 \left(PPE_{it}/AT_{it-1}\right) + \alpha_3 \left(IBXI_{it-1}/AT_{it-1}\right) + \varepsilon_{it}, \quad (4)$$

where: TA_{it}= total accruals for a firm *i* in year *t*, ΔREV_{it}= change in net revenues 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 A_{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 in Eq. (4) as the proxy for accrual-based earnings management, that is, $AEM_{it} = TA_{it}/AT_{it}$ – est. (TA_{it}/AT_{it}).

Table 2 shows the summary statistics for *RAM* and *AEM*. The average firm has *RAM* of -2.71 percent of total assets with a median level of 2.73 percent. The average firm has *AEM* as 0.20 percent of total assets with a median level of 1.4 percent. Thus, on balance, the majority of sample firm-years has mildly positive measures of earnings management, meaning that reported earnings are more likely than not to be higher due to earnings management than would be considered normal based on the estimation models. While these variables are skewed to the left, note that the approximately equivalent Q1 and Q3 quartiles for *RAM* and *AEM* suggest a broadly symmetric distribution around the median values for both variables. Table 3 also shows a low positive correlation between *RAM* and *AEM*, suggesting that they represent different dimensions of earnings management.

Regression models

We first regress *RAM* and *AEM* on *NETWORK_TOT* and controls to capture the effect of CEO network size on real activities management, Eq. (5) and accrual earnings management, Eq. (6). All variables are measured on a firm-year basis. The equations are:

$$RAM_t = \beta_1 NETWORK\_TOT_t + \beta_2 RAM_t + \beta_3 SIZE_t + \beta_4 BTM_t + \beta_5 ROA_t + \beta_6 LEV_t + \beta_7 EVOL_t + \beta_8 CFVOL_t + \beta_9 CYCLE_t + \beta_{10} SALESGROWTH_t + \beta_{11} AGE_t + \beta_{12} TENURE_t + \beta_{13} BIG4_t + \varepsilon_t\,, \quad (5)$$

$$AEM_t = \beta_1 NETWORK\_TOT_t + \beta_2 RAM_t + \beta_3 SIZE_t + \beta_4 BTM_t + \beta_5 ROA_t + \beta_6 LEV_t + \beta_7 EVOL_t + \beta_8 CFVOL_t + \beta_9 CYCLE_t + \beta_{10} SALESGROWTH_t + \beta_{11} AGE_t + \beta_{12} TENURE_t + \beta_{13} BIG4_t + \varepsilon_t. \quad (6)$$

We measure the variable of interest, *NETWORK_TOT*, as the summation of the CEO's employment, education, and other activity connections. Eq. (5) and Eq. (6) also include controls to isolate the CEO network effect from other firm-level factors. We also add the other form of earnings management as a control variable, so that the coefficients for *NETWORK_TOT* capture the response of *RAM* or *AEM* to network size incremental to the ability of *RAM* to explain *AEM* and vice versa. 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*) (Kothari *et al.*, 2005; Roychowdhury, 2006; Cohen *et al.*, 2008). We also control for earnings volatility (*EVOL*) and cash flow volatility (*CFVOL*), as some firms may manage volatile performance. To control for the cost of earnings management, we include *SALESGROWTH* and *BIG4* (Zang, 2012, Chan *et al.*, 2015). We also include the CEO's age (*CEO_AGE*) and the number of years that the CEO has held the position (*CEO_TENURE*) to control for CEO characteristics (Yun, 2014; Ali and Zhang, 2015). In addition, 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 different years).

5. Results

Main results

Table 4 summarizes the main results. Regarding the *RAM* regressions (Eq. 5) in columns 1–4, the significant contributors are *BTM*, *LEV*, *CFVOL,* and *SALESGROWTH* (other than *NETWORK_TOT*). Thus, the typical *RAM* firm has lower sales growth and higher debt, and lower market value relative to book value. Column 4 also shows that a CEO with shorter tenure may be prone to higher *RAM*. We observe positive but insignificant coefficients for *AEM*. Thus, the directional effect of *AEM* on *RAM* is minor. The main variable of interest, however, is *NETWORK_TOT*, which shows a significantly positive coefficient ($p<0.01$) in all four regressions.[15] Thus, the amount of *RAM*-managed earnings increases with the size of the CEO network. This result suggests that larger CEO networks, at least from the CEO's perspective, reduce the expected net cost of *RAM*, either by lowering detection probability or by reducing the regulatory, reputational, and labor market costs conditional on future detection. Columns 5–8 of Table 4 show the results of estimating Eq. (6). While some of the control variables have the same sign as Eq. (5) (e.g., *ROA*, *LEV*, *SALESGROWTH*), others are not significant or have the opposite sign. For example, larger firms (*SIZE*) associate more with *AEM*, whereas smaller firms associate more with *RAM*, and *RAM* contributes significantly ($p<0.01$) to *AEM* (columns 5–8) as shown by the significantly positive coefficients for *RAM* (columns 5–8). Thus, the common factors (other than the effects of network size) that drive decisions to use *RAM* or *AEM* weight differently across the two forms of earnings management.

The most interesting aspect of columns 5–8 of Table 4, however, is the reversal of sign of the coefficient for *NETWORK_TOT*, which shows that the level of discretionary accruals from *AEM* adjustments *decreases* with the size of the CEO network. Put differently, CEOs with large networks are less likely to use *AEM* to increase earnings. Why do we observe the different effects of network size on *RAM* and *AEM* given that larger networks should be beneficial to the firm and the CEO? The answer lies in the nature of the net costs associated with *AEM* versus *RAM*. With *AEM*, detection probability is higher and once executed the reputation cost of ex post detection is substantial for both the firm and the CEO. For example, who would want to hire a CEO terminated from that position for cause and accused of bolstering earnings by violating GAAP by the SEC or by shareholders in class action litigation? With more personal social capital at stake, well-connected CEOs become especially wary of the reputation costs. A key benefit to firms with larger CEO networks is, thus, the avoidance of the cost of detected positive *AEM*.

Large versus small amount of manufactured earnings

Our main findings show that large CEO network increases *AEM* and reduces *RAM*. We suggest the reason for the opposite network effects on the two forms of earnings management is because the network aggravates the reputation costs associated with *AEM* and alleviates the future career concerns associated with *RAM*. If this is the case, the effect of network size on the choice of earnings management form should be most pronounced when the amount of manufactured earnings is sufficiently large for any potential litigation or forced turnover to materialize. To test this idea, we partition the sample based on high versus low *RAM* and high versus low *AEM*.

Table 5 shows the sub-sample regression results. The signs of the coefficients for *NETWORK_TOT* in all four regressions are consistent with our main findings, that is, positive for the *RAM* regressions and negative for the *AEM* regressions. However, when the amount of manufactured earnings is small, the coefficients for *NETWORK_TOT* become insignificant in both the *AEM* and *RAM* regressions (see columns 1 and 3). The differences in the magnitude of coefficients between low versus high *RAM* and low versus high *AEM* are also significant ($p<0.01$). This result supports the view that at the left tail of the *AEM* or *RAM* distribution, the expected reputation costs and labor market costs are less substantial and, therefore, network size plays a lesser role in the CEO's choice of earnings management.

Connections to executive versus supervisorial directors

If the benefits from a large CEO network derive from information sharing, then we should observe stronger results for networks whose information sharing relates to the CEO's connections with more influential persons, such as other CEOs or similar insider executives versus those in networks in lesser positions or capacities. There is also a flipside that CEOs who benefit from greater information sharing from their networks face steeper costs and risks to their reputation in the event of earnings management activities linked to their CEO position. On the one hand, well-connected CEOs may utilize influential connections to justify high *RAM* as a low cost, acceptable activity and evade reputation or labor market costs. On the other hand, engaging in higher *AEM*, which is perceived as clear wrongdoing, unacceptable activity, may tarnish their reputation more when they are connected to persons with high versus low influence. We use BoardEx's classification of ED (executive directors) and SD (supervisorial directors) to make this distinction, implicitly assuming that a connection linked to an SD director at another firm would entail less information sharing than a connection to an ED director at another firm. Several prior studies show differences in results consistent with this or a similar dichotomy (Adams and Ferreira, 2007; Ravina and Sapienza, 2010; Engelberg *et al.*, 2012).

Table 6 summarizes the results of estimating Eq. (5) and Eq. (6) including ED (the number of connections to executive directors), SD (the number of connections to supervisorial directors), and ED-SD as additional regressor variables. We include the same control variables as in column 5 (*RAM*) and column 8 (*AEM*) of Table 4. First, consistent with Table 4, we observe similar significant and insignificant coefficients for the control variables. Of main interest in Table 6, however, is that the coefficients for *ED*, *SD*, and *ED-SD* confirm that *NETWORK_TOT* for the *ED* group is more positive for *RAM* and more negative for *AEM*. Moreover, the coefficient for the difference in network size, *ED-SD*, is significantly positive (p<0.01) for *RAM* (column 2) and significantly negative (p<0.01) for *AEM* (column 4). Thus, as expected, these results confirm the notion that CEO networks with greater information sharing through connections to persons of influence not only associate with increased adjustments from the use of *RAM* but, also, with decreased adjustments from *AEM*.

Connections to large versus small firms

Another proxy for the relative importance of connections is based on firm size. A connection linked to persons working at large firms channels more important information, represents higher social status, and expands the CEO's outside employment option. To address whether the effect of CEO network size on earnings management differs cross-sectionally for connections to large versus small firms, we measure network size for CEO connections involving S&P 500 firms versus others.[16] Table 7 summarizes the results of estimating Eq. (5) and Eq. (6) including *S&P 500*, *Other* (the number of connections to non-S&P 500 firms), and *S&P 500-Other* as additional regressor variables. The results show that the magnitudes of network effect on *RAM* and *AEM* are both larger if we measure the connections to S&P 500 firms than other firms. The results for *RAM* show a positive coefficient (p<0.05) for *S&P 500-Other*. However, the coefficient for *S&P 500-Other* for *AEM* while negative is not significant at conventional levels. These results, thus, confirm

H2 for *RAM* only, that is, while CEO networks with connections to large firms imply an increase the net benefits of *RAM*, they have no appreciable effect on the net costs of *AEM*.

Connections through current versus past directorships

A third proxy for the relative importance of connections identifies whether the relationship is ongoing. A CEO currently serving on other corporate boards could access more up-to-date information and connect to persons with actual influence. This may afford more advantages for the CEO to justify RAM or seek future outside employment. In addition to reflecting information sharing, counting the number of current versus past directorship ties in a CEO's network may proxy for reputation. When a CEO has many outside director positions, a class action complaint or an enforcement action on accounting issues by the SEC can jeopardize the CEO's reputation. Aware of the potential for loss of such social capital from detection, the CEO is likely to choose the less costly of *RAM* over *AEM* to meet or beat the earnings target. In Table 8, we test this idea by re-estimating Eq. (5) and Eq. (6) including network variables that reflect the number of (a) current directorship ties and (b) the number of current and past directorship ties. As expected, the coefficient for *NETWORK_CURR* is positive for *RAM* ($p<0.05$) and negative for *AEM* (but not significant). However, the coefficients for *NETWORK_CURRPAST*, while still positive ($p<0.10$) and negative ($p<0.05$) for *RAM* and *AEM*, respectively, diminish in magnitude for this measure. These results suggest that connections established through current outside directorships have more effect on *RAM* than those established through past directorships, perhaps due to access through the network to more relevant information and informed individuals. The effect of current directorship on *AEM* is not statistically significant, suggesting no differential reputation effect based on connections established through current and past directorships. This result, thus, offers partial evidence favoring the prediction in H2 that the positive (negative) relation between CEO network size and *RAM* (*AEM*) strengthens for networks with greater CEO information sharing (and with greater benefit (or potential for loss) through the effects of *RAM* (*AEM*) on CEO reputation).

Managerial ownership

We next test whether CEO ownership helps explain the relation between CEO network size and *RAM* or *AEM*. Given that high CEO ownership better aligns the interests of the CEO and the other shareholders, high ownership should also better align the benefits of the CEO's network with those of the shareholders. In contrast, if the interests do not align well (e.g., the CEO has low ownership), the CEO would be more likely to extract benefits from the shareholders. In particular, we might observe a stronger relation between *NETWORK_TOT* and *RAM* when the CEO has low ownership and a large CEO network because the cost of *RAM* to the CEO is low (relative to the non-use of earnings management or the use of *AEM*), even though the real cost to the firm is high. This is what we find. In Table 9, the coefficient for *NETWORK_TOT* for low CEO ownership is significantly ($p<0.01$) greater than the *NETWORK_TOT* coefficient for high CEO ownership, which is significantly negative. This supports H3 for *RAM*. The results also show no significant difference in the network effects on *AEM* for lower versus high ownership. This is consistent with the idea that the expected costs associated with *AEM* are high for both the firm and the CEO with reputational concerns. The coefficients for *NETWORK_TOT* are insignificant in the *AEM* regressions using both ownership subsamples. The results in Table 9, however, are based on smaller samples (5,989 observations versus 25,283 in Tables 4 and 5), which could affect the power of the tests.

Future operating performance

Much has been said about the relation between contemporaneous earnings management and future firm performance, but with mixed results showing that *RAM* or *AEM* varies with future performance (Leggett *et al.*, 2009; Gunny, 2010; Taylor and Xu, 2010). This prior work does not, however, control for CEO network effects. This is important because CEOs with stronger networks, who also have more options in the executive labor market, may face more reputational loss from the cost of detected *AEM* or the inefficient use of cash with *RAM*. Both factors could cause lower future operating performance for more-connected compared to less-connected CEOs.

We measure future performance as return on assets (*ROA*) or operating cash flow (*CFO*) in years *t+2* and *t+3*, relative to earnings management measurement year *t*, where *ROA* equals net income before extraordinary items divided by the prior year's total assets. Table 10 presents the results of regressing *ROA* for year *t+3* on firm size (*SIZE*), book-to-market ratio (*BTM*), leverage (*LEV*), stock return (*RET*), and insolvency risk (*ZScore*).[17] We expect significantly positive coefficients for all variables except *BTM*, which should relate negatively to future return performance, as high *BTM* suggests low growth opportunities. Panel A summarizes the results for *RAM* for large and small CEO networks. The panel shows that higher *RAM* associates with lower future performance for large CEO networks but not for small CEO networks. The negative difference in the *RAM* coefficients for large versus small networks is also significant across the two comparisons ($p<0.01$). The same results hold for future performance specified as *CFO* for *t+2* (not tabulated) and *t+3*, suggesting that simple expense shifting is not the primary driver of this result. Hence, on average, the larger the CEO network, the more likely that *RAM* relates negatively to future earnings or cash flows. These results support *H4* – that the relation between *RAM* and future firm performance strengthens negatively for larger networks. These results also coincide with the earlier tables showing that CEOs with larger networks employ larger *RAM* adjustments, which potentially involve the inefficient use of cash in the long term. These larger *RAM* adjustments by well-connected CEOs may thus be precursors of worse future performance.

Panel B of Table 10 summarizes the results for *AEM* for large and small CEO networks. Here we find that network size does not explain the difference in future returns and operating cash flows, as none of the differences in the *AEM* coefficients for large versus small networks is significant. This suggests no support for *H4* for *AEM*. Thus, with larger networks, higher *RAM* strongly associates with worse future performance. With larger networks, higher *AEM*, however, does not associate with worse future performance, arguably because *AEM* does not involve the shifting of cash from one period to the next, which could decrease firm value.

CEO post-turnover employment

As we reasoned earlier, CEOs with large networks have advantages in the labor market in that they can use their entrenchment to avoid discipline or dismissal and, if dismissed, they can use the labor market to find another CEO-equivalent job regardless of the reason for separation and its possible effects on their reputation (Liu, 2014; El-Khatib *et al.*, 2015). A well-connected CEO may, therefore, perceive that the expected net benefits of detectable earnings management outweigh the net costs of detected earnings management because of the marginal adverse effects of detection on the CEO's career. To investigate the role of CEO turnover, we first examine whether CEO turnover increases or decreases in network size (*NETWORK_TOT*) after controlling for other variables to explain turnover. From our data set, we identify 782 firm-year observations of the CEO finding at least one new (outside) position within the next five years following the year of network measurement (*Post Position*). For those observations, *Post Position* = 1. If no new position occurs in the next five years, *Post Position* = 0. We then test whether the ability of *NETWORK_TOT* to explain *Post Position* differs for sub-samples of high versus low *RAM* or high versus low *AEM*. We also test in a separate regression whether the difference in the ability of *NETWORK_TOT* to explain *Post Position* differs for sub-samples of high minus low *RAM* or high minus low *AEM*.

We show the results in Table 11. First, column 1 shows a significantly positive coefficient ($p<0.01$) for *NETWORK_TOT*, indicating that CEOs with larger networks are more likely to obtain post-turnover employment. Thus, on balance, stronger networks associate with a higher likelihood that the CEO finds a new (outside) position in the next five years.[18] Columns 3 and 5 also show that increased likelihood of obtaining a subsequent position associates with higher *RAM* ($p<.05$) or *AEM* ($p<.05$), that is, misrepresentations of earnings exceeding what would otherwise have been reported. However, our tests of differences in the *NETWORK_TOT* coefficient for high minus low *RAM* or high minus low *AEM* indicate that the differences are not significant. Thus, in terms of new positions for the CEO, we find no evidence that higher relative to lower *RAM* or *AEM* makes a difference. These results, thus, do not support *H5*. In contrast, as one might expect, CEOs with superior performance (*INDJ_ROE*), higher age (*CEOAGE*), longer tenure with the firm (*CEOTENURE*), and in a chairman position (*CEO_DUAL*) all suggest significantly lower likelihoods of CEO turnover in the next five years.

Additional tests

Effects of CEO ability

We examine here the possibility that CEOs with larger networks are more able managers and, potentially, whether that ability explains why they have larger networks. To conduct this test, we assign to each CEO observation a measure of managerial ability for the same firm-year. We use the measure of managerial ability developed by Demerjian, Lev, and McVay (2012) as our proxy.[19] Table 12 summarizes the results of estimating Eq. (5) and Eq. (6), including *ABILITY* as an additional regressor variable. For both regressions, we continue to show significantly positive and negative ($p<0.01$) *NETWORK_TOT* coefficients for *RAM* and *AEM*, respectively. Thus, the main results in Table 4 hold after controlling for managerial ability and the other control variables. Of interest, however, is that for *RAM* the coefficient for *ABILITY* is insignificant (column 1), whereas we observe a significantly positive coefficient ($p<0.01$) for *ABILITY* in the *AEM* regression (column 2). In other words, more able CEOs appear more likely to manufacture higher earnings through positive accruals than less able CEOs, even though with larger networks our results suggest that CEOs are less likely to generate higher earnings through positive accruals. Thus, we document the interesting finding that while CEOs with large networks may curtail their use of positive *AEM* (negative coefficient for *NETWORK_TOT*), CEOs with higher ability may still manufacture earnings using *AEM* rather than *RAM* to achieve the same result (positive coefficient for *ABILITY*).[20]

Endogeneity

Another consideration is the direction of causation. While we have specified models with CEO network size as a determinant of *RAM* or *AEM*, the expectation of those activities could prompt a CEO to build stronger networks to maximize the net benefits of *RAM* or minimize the net cost of *AEM*, at least for the intended duration of the CEO's current employment. Also, a CEO could be hired to improve accounting and reporting quality, and any subsequent improvement in quality (e.g., from a reduction in *RAM* or *AEM*) could induce an increase in network size. However, network size does not necessarily arise from preferred outcomes for the CEO. Many factors determine CEO network size, only some of which are influenced by the CEO's choices. For example, a CEO can choose to become involved in a social organization or serve as an outside board member for a public company. But CEOs may have little control over whether other graduates from their alma mater become executive officers. Similarly, while the board may consider the CEO's network in appointing the CEO, it is unclear whether this is a first-order effect. A CEO's network is also likely to change over time for reasons over which the board has no control.

We use a two-stage instrumental variables approach to check for the effects of endogeneity, where at the first stage we choose an instrument that relates positively to the underlying explanatory variable (representing the CEO network size at firm *i* in year *t*) but unrelated to the residuals in the second-stage equation (i.e., unexplained *RAM* or *AEM*). As the instrument, we choose the average network size for the *other* firms in the dataset in the same industry (based on the Fama-French 48 industry classification) of firm *i* in year *t.* Table 13a presents the two-stage regressions for *RAM*, where the second-stage includes predicted *NETWORK_TOT* as the regressor estimated from the first-stage equation. We show a positive and significant coefficient ($p<0.01$) for *NETWORK_TOT*, similar to the main results (Table 4). The control variable coefficients are similar also. Table 13b shows the results for *AEM* as the dependent variable. Unlike the significantly negative coefficient for *NETWORK_TOT* in Table 4, the second-stage coefficient for *NETWORK_TOT* is not significant. This result suggests that *AEM* represents one source of variation in *NETWORK_TOT*, consistent with an endogenous relation between *AEM* and *NETWORK_TOT*, i.e., for *AEM* that the coefficient for *NETWORK_TOT* reflects causation in both directions.

Alternative network measures

Following the literature (e.g., Engelberg *et al*., 2013; Javakhadze, Ferris, and French, 2016), our main analysis uses the number of direct connections to measure a CEO's network size. In graph theory, this is referred to as the *degree* centrality measure. This measure is also straightforward to interpret. However, there are more sophisticated centrality measures that capture (i) how frequently the CEO lies on the shortest path between two other individuals in the network (*betweenness*), (ii) indirect as well as direct connections (*closeness*), (iii) how central the individuals connected to the CEO are (*eigenvector*), and (iv) the number of first-degree connections in the network (*rdegree*).[21] We use these centrality measures as alternative proxies for CEO network size. Table 14 shows that our main findings are robust to most of these alternatives.

6. Conclusion

This study is the first to investigate how executives' social structure relates to their use of real activities management (*RAM*) and accrual earnings management (*AEM*). We theorize that social structure influences the impact of earnings management by moderating the net costs and benefits of those practices to the CEO. These can differ depending on the form and extent of the earnings management practice. Tests confirm our social theory of earnings management. Specifically, we find a positive relation between network size and *RAM* and a negative relation between network size and *AEM*. These relations differ in sign because network size interacts with the CEO's choice of earnings management practice. For *RAM*, social structure confers net benefits on the CEO and the firm, arguably making the activity firm-wise efficient in the short term, even for larger *RAM* adjustments. In the longer term, however, larger *RAM* adjustments by well-connected CEOs associate with worse future performance. But well-connected CEOs with strong outside employment options may not care about the possibility of worse future performance from *RAM* potentially from the inefficient use of cash. This result may explain the widespread and seemingly acceptable use of *RAM* in practice. In contrast, social structure imposes net costs on the CEO and the firm from the use of *AEM*. These costs can be substantial when the egregious use of *AEM* invites a high probability of detection. Our results suggest a more constrained use of *AEM* for CEOs with large networks.

Thus, we learn from this study that large CEO social networks can generate costs and benefits that induce executives to engage in distinctly different forms of earnings management. Our tests further indicate that these opposing earnings management relations are accentuated in settings of greater information sharing, which is one of the key traits of a strong executive social network.

Notes

[1] The interpersonal ties of a stronger CEO network also suggest that different managers will more likely adopt acceptable and common earnings management policies that reap similar net effects on themselves and the firm, for example, promote and adopt *RAM* as the more advantageous form of earnings management.

[2] "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 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).

[3] "General Electric agreed to pay a $50 million fine to the Securities and Exchange Commission, ending an investigation into accounting shenanigans that severely tarnished the company's reputation and helped set the stage for last year's collapse in its stock price. Like a professional baseball player revealed to have been dabbling in steroids, GE prolonged a nearly decade-long record of meeting or exceeding analyst expectations by resorting to tricks including "selling" locomotives to financial institutions in transactions that looked a lot like loans, and fiddling with the accounting for interest-rate hedges. … In the filing in federal court in Connecticut, the SEC detailed several methods GE used to inflate revenue and earnings and dampen volatility in its reported results.…The company ultimately deviated from accounting rules to avoid reporting a $200 million pre-tax hit to earnings and continue reporting profits that met analysts' expectations. The company fessed up in 2007, correcting earnings for 2001 through 2005." (Dan Fisher, *Forbes*, August 4, 2009).

[4] We are not the first, though, to identify network effects as potentially important for firms' disclosure decisions. See, e.g., Gibbins, Richardson, and Waterhouse (1990, 138).

[5] Throughout this paper, we assume that earnings management actions ultimately reside with the CEO. For recent evidence of CEO marital status on earnings management, see Hilary, Huang, and Xu (2016). However, we also acknowledge that other senior executives such as the CFO may influence these actions. For example, despite the lower seniority of the CFO, Jiang, Petroni, and Wang (2010) find that the CFO has a stronger influence than the CEO on earnings management incentives.

[6] For example, if at time t CEO_a at firm i and CEO_b at firm j are Stanford MBAs and both previously worked at Apple Computer and Facebook, and CEO_c at firm k has a Harvard MBA and also previously worked at Apple, then CEO_a and CEO_b would each have three connections in their social networks (Stanford, Apple, and Facebook), whereas CEO_c would have two connections (to CEO_a and CEO_b through the Apple tie).

[7] CEO networks also flourish as business organizations that actively promote membership based on information sharing, where CEO members can share ideas, best practices, experiences, and advice in a confidential and conflict-of-interest free environment (e.g., https://www.chiefexecutivenetwork.com/, http://g100.com/).

[8] See, also, SEC Chairman Harold Leavitt's notable "numbers game" speech on accounting gimmicks, available at https://www.sec.gov/news/speech/speecharchive/1998/spch220.txt.

[9] Key topics examined include (i) why and when some firms are more likely to engage in one form or the other (or both) (Ewert and Wagenhofer, 2005; Roychowdhury, 2006; Cohen, Dey, and Lys, 2008; Badertscher, 2011; Zang, 2012; Chan, Chen, Chen, and Yu, 2015), (ii) whether equity incentives matter (Cheng and Warfield, 2005; Bergstresser and Philippon, 2006; Armstrong,

Jagolinzer, and Larcker, 2010), and (iii) the effects of detected *AEM* or *RAM* on performance (Cohen and Zarowin, 2010; Gunny, 2010), capital costs (Francis, LaFond, Olsson, and Schipper, 2005; Aboody, Hughes, and Liu, 2005; Kim and Sohn, 2013), and firm value (Bartov, Givoly, and Hayn, 2002; Kasnik and McNichols, 2002; Skinner and Sloan, 2002; Myers, Myers, and Skinner, 2007; Chi and Gupta, 2009). Forms of earnings management around different events and in different settings have also been explored. Examples include (i) share offerings (Teoh, Welch, and Wong, 1998; Kothari, Mizik, and Roychowdhury, 2015), (ii) regulatory changes (Cohen, Dey, and Lys, 2008), (iii) management turnover (Wells, 2002; Guan, Wright, and Leikam, 2005; Desai, Hogan, Wilkins, 2006; Hazarika, Karpoff, and Nahata, 2012), (iv) restatements (Ettredge, Scholz, Smith, and Sun, 2010), and (v) litigation events (Dechow, Sloan, and Sweeney, 1996; DuCharme *et al.*, 2004). See, also Healy and Wahlen (1999) and Xu, Taylor, and Dugan (2007), respectively, for reviews of the earlier *AEM* and *RAM* literature.

[10] Several prior studies show that firms or managers prefer the use of *RAM* to *AEM* to achieve short-term earnings targets (Merchant and Rockness, 1994; Cohen *et al.*, 2008; Cohen and Zarowin, 2010; Badertscher, 2011; Zang, 2012; Irani and Oesch, 2016).

[11] Consistent with this survey, Roychowdhury (2006) documents that managers avoid reporting annual losses or missing analyst forecasts by manipulating sales, reducing discretionary expenditures, and overproducing inventory to decrease the cost of goods sold, all of which are deviations from otherwise optimal operational decisions, with the intention of biasing earnings upward. Consistent with these predictions, researchers document that variations in R&D expenditures and asset sales link to firms meeting and/or beating earnings benchmarks. For example, Bartov (1993) finds that firms with negative earnings changes report higher profits from asset sales, suggesting that the profits are used to blunt bad earnings news. Dechow and Sloan (1991) find that executives near the end of their tenure reduce R&D expenditures to increase short-term earnings. In related studies, Baber and Fairfield (1991) and Bushee (1998) report evidence consistent with firms reducing R&D expenditures to meet earnings benchmarks such as positive earnings or positive earnings changes.

[12] For managers with securities law violations, Karpoff (2008b) documents that 93.4% lose their jobs. Smaller percentages face sanctions (barred from future employment as an officer or director of a public firm) and some face criminal prosecution, penalties, and jail time. Not all violations studied by Karpoff *et al.* (2008b), however, relate to earnings management activities that violate GAAP.

[13] Our measure of network, based on the sum of a CEO's direct connections, is often referred to as a "direct" measure of network connectedness. Other measures of connectedness represent the "*Betweenness*", "*Closeness*", "*Eigenvector*", and "*rDegree*" dimensions of network connections. For completeness, we report the results of estimating Eq. (5) and Eq. (6) for each of these other measures. Table 14 reports the results.

[14] As a robustness check, we employ the natural logarithm of CEO network size as the dependent variable and report that the results are qualitatively the same as those reported in Table 4.

[15] We also obtain similar significant results ($p<0.01$) when we scale *NETWORK_TOT* by total network size for each year.

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

[17] We exclude t+1 as future performance to avoid the predictably negative relation between current accruals and next year's net income. Table 10 also excludes the results for t+2, as they are qualitatively the same as those for t+3.

[18] While we do not track the new job of the dismissed CEO, studies suggest that CEOs with stronger networks tend to find an equivalent replacement job (Liu, 2014), consistent with strong networks minimizing the cost of dismissal.

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

[20] To the extent that CEO network size associates positively with CEO reputation, this result is consistent with Francis, Huang, Rajgopal, and Zang (2008), who find that reputable CEOs manage earnings using *AEM* more than non-reputable CEOs. In contrast, Demerjian, Lev, Lewis, and McVay (2013) find that higher-ability managers engage less in *AEM*. However, Demerjian *et al.* (2013) do not control for network size, which associates negatively with *AEM* (column 2 of Table 12). Once we control for network size (*NETWORK_TOT*), higher ability managers use *AEM* more that low-ability CEOs, consistent with Francis *et al.* (2008). That is, the coefficient for *ABILITY* for *AEM* is significantly positive ($p<0.01$) in column 2 of Table 12.

[21] Liu (2014) shows the details of these definitions.

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Appendix A. Variable Definitions

Key Variables:		
AEM	=	Accrual based earnings management measure, firm's discretionary accrual.
CF_RAM	=	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.
DISEXP_RAM	=	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_RAM	=	Abnormal production cost, 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 production cost.
RAM	=	Total amount of real transactions management, computed as the sum of *CFRAM*, *PRODRAM* and *DISEXPRAM*, as defined by Cohen *et al.* (2008).
Control 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.
EVOL	=	Standard deviation of return on asset for five years
EVOL	=	Standard deviation of ROA for five years.
INDADJ_ROE	=	Firm’s return on equity minus industry return on equity. Industry ROE is calculated as the mean ROE of firms in the same industry (based on 2-digit SIC code) for the same period.
Inst_Ownership	=	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.
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	=	Firm’s return on Asset, measured as income before extraordinary items divided by total assets.
SALESGROWTH	=	One-year sales growth ratio.
SIZE	=	Natural log of market value.

Table 1. Sample distribution

Panel A. Sample distribution by fiscal year

Fiscal Year	Frequency	Percent
1999	67	0.27
2000	668	2.64
2001	829	3.28
2002	883	3.49
2003	1,755	6.94
2004	1,950	7.71
2005	2,012	7.96
2006	1,965	7.77
2007	1,855	7.34
2008	1,864	7.37
2009	1,754	6.94
2010	1,745	6.9
2011	2,031	8.03
2012	2,029	8.03
2013	2,071	8.19
2014	1,805	7.14
Total	25,283	100.00

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

Industry	Frequency	Percent	Industry	Frequency	Percent
Agriculture	64	0.25	Machinery	1,074	4.25
Aircraft	169	0.67	Measuring Equipment	744	2.94
Almost Nothing	131	0.52	Medical Equipment	1,201	4.75
Apparel	390	1.54	Industrial Metal Min..	271	1.07
Automobiles and Trucks	450	1.78	Personal Services	251	0.99
Beer & Liquor	109	0.43	Petroleum and Natural Gas	1,971	7.8
Business Services	3,866	15.29	Pharmaceutical Products	1,487	5.88
Business Supplies	320	1.27	Precious Metals	254	1
Candy & Soda	98	0.39	Printing and Publishing	214	0.85
Chemicals	751	2.97	Recreation	230	0.91
Coal	132	0.52	Restaurants, Hotels, Motels	472	1.87
Computers	1,173	4.64	Retail	1,761	6.97
Construction	361	1.43	Rubber and Plastic Products	195	0.77
Construction Materials	678	2.68	Railroad Equipment	75	0.3
Consumer Goods	499	1.97	Shipping Containers	84	0.33
Defense	86	0.34	Steel Works Etc	420	1.66
Electrical Equipment	573	2.27	Textiles	84	0.33
Electronic Equipment	2,379	9.41	Trading	292	1.15
Entertainment	406	1.61	Transportation	60	0.24
Fabricated Products	59	0.23	Wholesale	447	1.77
Food Products	518	2.05			
Healthcare	484	1.91	Total	25,283	100

Table 2. Descriptive statistics

	Mean	S.D.	Q1	Median	Q3
NETWORK_TOT	0.1474	0.2092	0.0110	0.0610	0.1980
RAM	-0.0271	1.9904	-0.2500	0.0273	0.2944
AEM	0.0002	0.0899	-0.0228	0.0014	0.0267
SIZE	6.1890	2.1052	4.8149	6.2433	7.5484
BTM	0.5317	0.5162	0.2437	0.4354	0.7156
ROA	-0.0828	2.8960	-0.0337	0.0359	0.0799
LEV	0.1725	0.3628	0.0000	0.1028	0.2631
EVOL	0.1538	2.4288	0.0158	0.0367	0.0951
CFVOL	0.0827	0.9008	0.0213	0.0407	0.0758
BIG4	0.7453	0.4357	0.0000	1.0000	1.0000
CYCLE	-0.0339	4.7002	0.0232	0.0638	0.1145
SALEGROWTH	0.0042	0.1402	-0.0002	0.0008	0.0023
CEO_AGE	4.0191	0.1491	3.9318	4.0254	4.1271
CEO_TENURE	1.5195	0.8135	0.8755	1.5041	2.0919

This table reports descriptive statistics on real activities management (*RAM*), accrual-based earnings management (*AEM*), CEO network size (*NETWORK_TOT*), and firms' characteristics for the sample. The sample comprises 25,283 firm-years from 4,362 firms. Appendix A defines the variables.

Table 3. Pearson/Spearman correlation matrix among selected variables

		(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*
1.	*RAM*	1.000	0.042	-0.011	-0.062	0.224	-0.163	0.124	-0.073	-0.081
		0.00	0.00	0.08	0.00	0.00	0.00	0.00	0.00	0.00
2.	*AEM*	0.028	1.000	-0.022	0.014	-0.017	0.073	0.012	-0.016	-0.012
		0.00	0.00	0.00	0.03	0.01	0.00	0.05	0.01	0.06
3.	*NETWORK_TOT*	0.001	-0.003	1.000	0.397	-0.094	0.050	0.137	-0.100	-0.173
		0.82	0.61	0.00	0.00	0.00	0.00	0.00	0.00	0.00
4.	*SIZE*	-0.014	0.025	0.386	1.000	-0.268	0.444	0.237	-0.404	-0.401
		0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
5.	*BTM*	0.056	0.008	-0.084	-0.242	1.000	-0.186	-0.042	-0.084	-0.104
		0.00	0.22	0.00	0.00	0.00	0.00	0.00	0.00	0.00
6.	*ROA*	0.018	0.101	-0.001	0.093	0.054	1.000	-0.067	-0.412	-0.228
		0.00	0.00	0.87	0.00	0.00	0.00	0.00	0.00	0.00
7.	*LEV*	0.026	0.044	0.048	0.025	-0.153	-0.072	1.000	-0.169	-0.236
		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
8.	*EVOL*	-0.048	0.006	0.003	-0.084	-0.061	-0.684	0.167	1.000	0.542
		0.00	0.37	0.62	0.00	0.00	0.00	0.00	0.00	0.00
9.	*CFVOL*	-0.064	0.079	-0.020	-0.069	-0.040	-0.098	0.015	0.674	1.000
		0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00

This table reports the correlation coefficients among selected variables. Pearson correlation coefficients are shown in the lower triangle, while Spearman rank correlations appear above the diagonal. Appendix A defines the variables.

Table 4. Effect of CEO network on accrual and real activities management

Dep Variable =			*RAM*				*AEM*	
NETWORK_TOT	0.0652	0.0603	0.0536	0.0440	-0.0062	-0.0064	-0.0080	-0.0080
	(3.60)***	(4.53)***	(3.01)***	(3.61)***	(-3.79)***	(-3.82)***	(-3.92)***	(-4.03)***
AEM		0.6622	0.6238	0.6150				
		(1.56)	(1.42)	(1.40)				
RAM						0.0013	0.0012	0.0012
						(2.47)**	(2.47)**	(2.48)**
SIZE	-0.0089	-0.0107	-0.0141	-0.0140	0.0012	0.0013	0.0013	0.0013
	(-1.08)	(-1.24)	(-1.35)	(-1.34)	(1.95)*	(2.00)**	(1.86)*	(1.83)*
BTM	0.2177	0.2145	0.2084	0.2007	0.0030	0.0031	0.0038	0.0037
	(3.38)***	(3.75)***	(3.91)***	(4.09)***	(0.79)	(0.82)	(0.98)	(0.95)
ROA	0.0037	0.0008	0.0020	0.0014	0.0054	0.0054	0.0054	0.0054
	(0.27)	(0.05)	(0.12)	(0.09)	(1.91)*	(1.89)*	(1.89)*	(1.88)*
LEV	0.2071	0.1945	0.1763	0.1757	0.0104	0.0104	0.0113	0.0113
	(6.17)***	(4.89)***	(4.53)***	(4.60)***	(1.71)*	(1.70)*	(1.89)*	(1.90)*
EVOL	-0.0087	-0.0104	-0.0082	-0.0086	0.0037	0.0037	0.0037	0.0037
	(-0.77)	(-0.91)	(-0.62)	(-0.64)	(1.53)	(1.53)	(1.51)	(1.50)
CFVOL	-0.1188	-0.1224	-0.1242	-0.1228	0.0028	0.0031	0.0031	0.0031
	(-2.51)**	(-2.74)***	(-2.73)***	(-2.63)***	(0.70)	(0.77)	(0.78)	(0.78)
CYCLE	0.0052	0.0051	0.0050	0.0052	-0.0004	-0.0004	-0.0004	-0.0004
	(0.82)	(0.86)	(0.81)	(0.85)	(-0.52)	(-0.53)	(-0.55)	(-0.55)
SALESGROWTH	-0.1989	-0.1821	-0.1757	-0.1744	-0.0291	-0.0288	-0.0290	-0.0290
	(-2.94)***	(-2.80)***	(-2.78)***	(-2.92)***	(-0.66)	(-0.65)	(-0.65)	(-0.65)
CEO_AGE				0.4925				0.0063
				(1.77)*				(0.86)
CEO_TENURE				-0.0197				0.0005
				(-3.03)***				(0.47)
BIG4					0.0003	-0.0003	-0.0004	-0.0001
					(0.19)	(-0.25)	(-0.31)	(-0.12)
Industry Fixed Effect	No	No	Yes	Yes	No	No	Yes	Yes
Year Fixed Effect	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Observations	25,283	25,283	25,283	25,283	25,283	25,283	25,283	25,283
Adjusted R^2	0.0084	0.0115	0.0145	0.0156	0.0252	0.0272	0.0326	0.0156

This table reports the results of an OLS regression examining the effect of CEO network size on *RAM* and *AEM*. This table presents the OLS regression coefficients and two-sided *t*-values for the maximum samples of 25,283 firm-years. We regress the firm's *RAM* and *EAM* measures on CEO Network size and other control variables. 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.

Table 5. Effect of CEO network on accrual and real activities management, conditional on level of earnings management

Level of earnings management =	*Low*	*High*	*Low*	*High*
Dependent variable =	*RAM*	*RAM*	*AEM*	*AEM*
NETWORK_TOT	0.0085	0.0292	-0.0013	-0.0147
	(0.2177)	(3.7534)***	(-1.6163)	(-3.8564)***
Difference [High – Low]		0.0207		-0.0134
		(3.12)***		(-2.43)***
AEM	-1.5193	0.6336		
	(-0.9045)	(1.3497)		
RAM			-0.0001	0.0020
			(-2.4567)**	(2.5414)**
SIZE	-0.0099	-0.0194	0.0001	0.0027
	(-0.6449)	(-2.8082)***	(1.4509)	(1.8319)*
BTM	0.1839	0.2055	0.0001	0.0055
	(5.1352)***	(2.7666)***	(0.3716)	(0.8368)
ROA	-0.2170	0.0085	0.0005	0.0054
	(-2.2647)**	(0.5127)	(1.3536)	(1.9289)*
LEV	0.3051	0.1328	0.0001	0.0137
	(6.0692)***	(2.8350)***	(0.2318)	(2.0088)**
EVOL	-0.3144	0.0042	0.0001	0.0037
	(-1.3257)	(0.3555)	(0.3279)	(1.8022)*
CFVOL	-0.6989	-0.1440	0.0029	0.0032
	(-2.7284)***	(-2.8283)***	(1.1773)	(1.0250)
CYCLE	0.0092	-0.0019	-0.0000	-0.0008
	(1.4807)	(-0.3279)	(-2.5324)**	(-0.5493)
SALESGROWTH	0.0279	-0.2735	0.0002	-0.0436
	(1.5157)	(-2.3955)**	(1.5452)	(-0.5999)
CEO_AGE	0.5966	0.3824	0.0015	0.0111
	(1.4434)	(2.4501)**	(2.3463)**	(0.8263)
CEO_TENURE	-0.0136	-0.0314	0.0001	0.0011
	(-0.8673)	(-2.0327)**	(0.8732)	(0.5154)
BIG4			-0.0002	-0.0001
			(-0.5902)	(-0.0552)
Industry Fixed Effect	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Observations	12,642	12,641	12,642	12,641
Adjusted R^2	0.0312	0.0134	0.0126	0.0385

This table reports the result for an OLS regression, examining the effect of CEO network size on *RAM* and *AEM* conditional on the size of the firm (S&P 500 firm versus other). This table presents the OLS regression coefficients for samples of 18,479 firm-years. *, **, *** denote significance at the 0.10, 0.05, and 0.01 level, respectively, all two-tailed. Appendix A defines the variables.

Table 6. Effect of CEO network on accrual and real activities management: Network with insiders

Dependent variable =	*RAM*	*RAM*	*AEM*	*AEM*
Insiders (*ED*)	0.2285		-0.0580	
	(5.71)***		(-4.43)***	
Outsiders (*SD*)		0.0723		-0.0101
		(2.88)***		(-4.42)***
Difference [ED – SD]		0.1562		-0.0479
		(3.31)***		(-3.61)***
AEM	0.6149	0.6160		
	(1.41)	(1.41)		
RAM			0.0012	0.0012
			(2.48)**	(2.49)**
SIZE	-0.0140	-0.0152	0.0014	0.0014
	(-1.26)	(-1.46)	(1.99)**	(1.94)*
BTM	0.2007	0.2001	0.0038	0.0038
	(4.06)***	(4.19)***	(0.96)	(0.96)
ROA	0.0015	0.0015	0.0053	0.0054
	(0.09)	(0.09)	(1.88)*	(1.88)*
LEV	0.1756	0.1750	0.0114	0.0114
	(4.60)***	(4.60)***	(1.92)*	(1.90)*
EVOL	-0.0085	-0.0087	0.0036	0.0037
	(-0.63)	(-0.64)	(1.48)	(1.50)
CFVOL	-0.1230	-0.1227	0.0032	0.0031
	(-2.64)***	(-2.63)***	(0.79)	(0.78)
CYCLE	0.0052	0.0052	-0.0004	-0.0004
	(0.85)	(0.85)	(-0.55)	(-0.55)
SALESGROWTH	-0.1746	-0.1744	-0.0289	-0.0290
	(-2.92)***	(-2.92)***	(-0.65)	(-0.65)
CEO_AGE	0.4919	0.4920	0.0066	0.0063
	(1.77)*	(1.78)*	(0.90)	(0.87)
CEO_TENURE	-0.0200	-0.0194	0.0006	0.0005
	(-3.02)***	(-2.99)***	(0.50)	(0.46)
BIG4			-0.0002	-0.0001
			(-0.15)	(-0.10)
Industry Fixed Effect	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Observations	25,283	25,283	25,283	25,283
Adjusted R^2	0.0156	0.0156	0.0327	0.0327

This table reports the results of an OLS regression examining the effect of CEO network size on *RAM* and *AEM* conditional on networks with insiders (ED) and outsiders (SD). This table presents the OLS regression coefficients for samples of 25,283 firm-years. 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.

Table 7. Effect of CEO network on accrual and real activities management: Larger firms

Dependent variable =	*RAM*	*RAM*	*AEM*	*AEM*
S&P 500	0.1861		-0.0221	
	(5.03)***		(-4.06)***	
Other		0.0668		-0.0124
		(2.06)**		(-3.63)***
Difference		*0.1193*		*-0.0097*
[S&P 500–Other]		*(2.42)***		*(-1.51)*
AEM	0.6167	0.6151		
	(1.41)	(1.40)		
RAM			0.0012	0.0012
			(2.48)**	(2.48)**
SIZE	-0.0164	-0.0140	0.0015	0.0013
	(-1.52)	(-1.34)	(1.95)*	(1.86)*
BTM	0.2001	0.2005	0.0038	0.0037
	(4.07)***	(4.10)***	(0.96)	(0.96)
ROA	0.0016	0.0014	0.0053	0.0054
	(0.10)	(0.09)	(1.87)*	(1.88)*
LEV	0.1747	0.1756	0.0114	0.0114
	(4.58)***	(4.60)***	(1.91)*	(1.90)*
EVOL	-0.0086	-0.0086	0.0036	0.0037
	(-0.63)	(-0.64)	(1.49)	(1.50)
CFVOL	-0.1230	-0.1227	0.0032	0.0031
	(-2.64)***	(-2.63)***	(0.79)	(0.78)
CYCLE	0.0052	0.0052	-0.0004	-0.0004
	(0.85)	(0.84)	(-0.55)	(-0.55)
SALESGROWTH	-0.1744	-0.1745	-0.0290	-0.0289
	(-2.92)***	(-2.92)***	(-0.65)	(-0.65)
CEO_AGE	0.4885	0.4936	0.0066	0.0061
	(1.76)*	(1.78)*	(0.91)	(0.84)
CEO_TENURE	-0.0193	-0.0198	0.0005	0.0005
	(-2.91)***	(-3.05)***	(0.47)	(0.48)
BIG4			-0.0004	-0.0000
			(-0.31)	(-0.01)
Industry Fixed Effect	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Observations	18,479	18,479	18,479	18,479
Adjusted R^2	0.00923	0.00918	0.0103	0.0103

This table reports the results of an OLS regression examining the effect of CEO network size on *RAM* and *AEM* conditional on the size of the firm (S&P 500 firm versus other). This table presents the OLS regression coefficients for samples of 18,479 firm-years. 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.

Table 8. Effect of CEO network on accrual and real activities management: Number of directorships

Dependent variable =	*RAM*	*AEM*	*RAM*	*AEM*
NETWORK_CURR	39.3740	-1.5041		
	(2.13)**	(-1.61)		
NETWORK_CURRPAST			15.5291	-0.8830
			(1.77)*	(-2.12)**
AEM	0.6172		0.6169	
	(1.41)		(1.41)	
RAM		0.0012		0.0012
		(2.48)**		(2.47)**
SIZE	-0.0165	0.0011	-0.0150	0.0011
	(-1.59)	(1.52)	(-1.52)	(1.60)
BTM	0.1977	0.0037	0.1990	0.0037
	(4.01)***	(0.95)	(4.05)***	(0.95)
ROA	0.0015	0.0054	0.0016	0.0054
	(0.09)	(1.88)*	(0.10)	(1.88)*
LEV	0.1744	0.0112	0.1733	0.0113
	(4.54)***	(1.88)*	(4.57)***	(1.89)*
EVOL	-0.0083	0.0036	-0.0081	0.0036
	(-0.60)	(1.48)	(-0.60)	(1.47)
CFVOL	-0.1235	0.0032	-0.1237	0.0032
	(-2.64)***	(0.79)	(-2.66)***	(0.80)
CYCLE	0.0051	-0.0004	0.0051	-0.0004
	(0.83)	(-0.54)	(0.83)	(-0.54)
SALESGROWTH	-0.1733	-0.0290	-0.1735	-0.0290
	(-2.88)***	(-0.65)	(-2.88)***	(-0.65)
CEO_AGE	0.4706	0.0069	0.4619	0.0078
	(1.68)*	(0.95)	(1.61)	(1.11)
CEO_TENURE	-0.0212	0.0007	-0.0195	0.0006
	(-3.34)***	(0.60)	(-2.86)***	(0.53)
BIG4		-0.0000		-0.0000
		(-0.03)		(-0.01)
Industry Fixed Effect	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Observations	25,283	25,283	25,283	25,283
Adjusted R^2	0.0158	0.0325	0.0157	0.0326

This table reports the results of an OLS regression examining the effect of CEO network size on *RAM* and *AEM* conditional on the number of current or past directorships. This table presents the OLS regression coefficients for samples of 25,283 firm-years. 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.

Table 9. Effect of CEO network on earnings management:
Conditioning on managerial ownership

Managerial ownership	*Lower Ownership*	*Higher Ownership*	*Lower Ownership*	*Higher Ownership*
Dependent variable =	*RAM*	*RAM*	*AEM*	*AEM*
NETWORK_TOT	0.1656	-0.4419	-0.0006	-0.0008
	(2.22)**	(-1.67)*	(-0.26)	(-0.10)
Difference		*0.6075*		*0.0002*
		(2.21)**		(0.02)
AEM	0.5234	0.7363		
	(1.95)*	(1.31)		
RAM			0.0009	0.0011
			(1.76)*	(3.29)***
SIZE	-0.0186	-0.0067	-0.0017	0.0016
	(-1.57)	(-0.34)	(-2.06)**	(1.61)
BTM	0.2213	0.3286	-0.0001	0.0017
	(4.30)***	(4.45)***	(-0.01)	(0.38)
ROA	-0.3092	0.1350	0.0465	-0.0109
	(-1.82)*	(0.80)	(1.04)	(-1.26)
LEV	0.0230	0.4049	0.0052	-0.0015
	(0.29)	(1.93)*	(0.33)	(-0.13)
EVOL	-0.1207	0.6802	-0.0063	-0.0212
	(-0.58)	(1.67)*	(-0.75)	(-0.95)
CFVOL	-0.8461	0.3487	-0.0309	0.0561
	(-1.67)*	(0.48)	(-0.55)	(1.42)
CYCLE	-0.0026	0.0380	-0.0000	0.0005
	(-3.64)***	(1.74)*	(-1.51)	(1.06)
SALESGROWTH	-10.1269	-0.3159	0.3436	-0.3643
	(-0.85)	(-1.19)	(1.85)*	(-1.10)
CEO_AGE	0.6586	0.4608	0.0109	-0.0110
	(1.73)*	(2.58)**	(1.09)	(-1.93)*
CEO_TENURE	-0.0454	0.0448	-0.0020	0.0005
	(-1.08)	(1.65)*	(-1.85)*	(0.38)
Big4			-0.0075	0.0028
			(-1.79)*	(0.92)
Industry Fixed Effect	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Observations	5,989	5,989	5,989	5,989
Adjusted R^2	0.0450	0.0325	0.0517	0.138

This table reports the results of an OLS regression examining the effect of CEO network size on *RAM* and *AEM* conditional on the degree of the CEO's ownership of the firm. This table presents the OLS regression coefficients for samples of 5,989 firm-years. 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.

Table 10. Effect of earnings management on future operating performance:
Conditioning on network size

Panel A: *RAM*

Network size	*Small*	*Large*	*Small*	*Large*
Dep Variable =	*ROA t+3*	*ROA t+3*	*CFO t+3*	*CFO t+3*
RAM	0.0028	-0.0608	0.0019	-0.0077
	(0.93)	(-2.63)***	(0.57)	(-4.08)***
Difference	-0.0636		-0.0096	
	(-2.73)***		(-2.47)**	
SIZE	0.0218	0.0279	0.0154	0.0191
	(4.74)***	(5.33)***	(4.20)***	(5.22)***
BTM	-0.0030	0.0089	-0.0113	-0.0162
	(-0.24)	(0.77)	(-1.55)	(-2.27)**
LEV	0.0734	0.0647	0.0809	0.0231
	(1.60)	(1.85)*	(2.17)**	(2.12)**
RET	0.0315	0.0399	0.0180	0.0174
	(4.41)***	(2.07)**	(3.62)***	(2.57)**
ZScore	0.0374	0.0206	0.0273	0.0118
	(4.48)***	(2.80)***	(3.75)***	(4.69)***
Industry Fixed Effect	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Observations	7,964	7,829	7,912	7,794
Adjusted R^2	0.156	0.0827	0.137	0.231

Panel B: *AEM*

Network size	*Small*	*Large*	*Small*	*Large*
Dep Variable =	*ROA t+3*	*ROA t+3*	*CFO t+3*	*CFO t+3*
AEM	0.1140	-1.5405	0.1947	-0.1602
	(0.67)	(-1.28)	(0.86)	(-4.39)***
Difference	-1.6545		-0.3549	
	(-1.36)		(-1.55)	
SIZE	0.0219	0.0279	0.0157	0.0191
	(4.84)***	(4.92)***	(4.44)***	(5.24)***
BTM	-0.0017	-0.0173	-0.0099	-0.0194
	(-0.13)	(-2.31)**	(-1.34)	(-2.68)***
LEV	0.0739	0.0595	0.0804	0.0223
	(1.59)	(1.31)	(2.11)**	(1.95)*
RET	0.0315	0.0380	0.0182	0.0172
	(4.41)***	(2.11)**	(3.58)***	(2.61)***
ZScore	0.0372	0.0214	0.0270	0.0119
	(4.51)***	(2.76)***	(3.80)***	(4.61)***
Industry Fixed Effect	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Observations	7,964	7,829	7,912	7,794
Adjusted R^2	0.156	0.0581	0.139	0.224

This table reports the results of OLS regressions examining the effect of *RAM* and *AEM* on future operating performance, split by CEO Network Size. 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.

Table 11. CEO positions in the subsequent five years:
Conditioning on high or low *RAM* or *AEM*

	All	*Low RAM*	*High RAM*	*Low AEM*	*High AEM*
Dep.Variable	*Post Position*	*Post Position*	*Post Position*	*Post Position*	*Post Position*
NETWORK_TOT	1.6066	1.2862	1.7106	1.4853	1.8482
	(3.37)***	(1.61)	(2.57)**	(2.09)**	(2.15)**
DIFF		0.4244		0.3629	
		(0.41)		(0.33)	
LNSALE	-0.0845	-0.1107	-0.0308	-0.0494	-0.0479
	(-1.07)	(-0.84)	(-0.24)	(-0.37)	(-0.38)
INDADJ_ROE	-0.0901	-0.0802	-0.2261	-0.1165	0.0376
	(-2.89)***	(-2.32)**	(-1.18)	(-3.34)***	(0.28)
EVOL	-0.0831	0.5341	-0.2863	0.1201	-0.9166
	(-0.16)	(0.64)	(-0.36)	(0.18)	(-0.59)
CEOAGE	-5.9528	-4.9071	-7.3997	-7.2581	-6.7198
	(-6.84)***	(-3.68)***	(-4.96)***	(-4.94)***	(-4.07)***
CEOTENTURE	-0.0426	-0.0242	-0.0639	0.0078	-0.1357
	(-1.89)*	(-0.67)	(-1.78)*	(0.25)	(-3.55)***
CEO_DUAL	-0.7003	-0.5955	-0.8527	-0.6159	-0.6072
	(-3.41)***	(-1.69)*	(-2.68)***	(-1.85)*	(-1.60)
Analyst_Error	-0.2445	-1.8494	0.1712	-0.1119	-0.0566
	(-1.04)	(-2.62)***	(0.52)	(-0.52)	(-0.12)
Inst_Ownership	-0.1099	0.3837	-0.4939	-0.9835	0.9536
	(-0.24)	(0.53)	(-0.76)	(-1.44)	(1.28)
RET	-0.2339	-0.5690	-0.0682	-0.0771	-0.2777
	(-1.35)	(-1.45)	(-0.24)	(-0.25)	(-0.62)
RETVOL	0.0691	2.6527	-2.6539	-0.2400	3.9008
	(0.04)	(1.10)	(-0.77)	(-0.07)	(1.21)
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes
Observations	782	336	331	337	308
Pseudo R^2	0.2107	0.2474	0.2658	0.2646	0.2834

This table reports the results of a logit regression that regresses *Post Position* on *NETWORK_TOT* and control variables. *Post Position* is a dummy variable equal to one if the CEO finds a new position in the five years subsequent to *NETWORK_TOT* measurement year *t*, otherwise zero. 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.

Table 12. Effect of CEO network on real and accrual earnings management: CEO ability

Dep Variable =	*RAM*	*AEM*
NETWORK_TOT	0.1101	-0.0080
	(2.59)***	(-2.70)***
ABILITY	-0.0564	0.0093
	(-0.19)	(7.600)***
AEM	1.1889	
	(2.33)**	
RAM		0.0016
		(2.25)**
SIZE	-0.0164	-0.0001
	(-0.84)	(-0.15)
BTM	0.2346	-0.0005
	(3.67)***	(-0.14)
ROA	0.0533	0.0106
	(0.85)	(2.37)**
LEV	0.2330	0.0084
	(3.10)***	(1.04)
EVOL	0.1232	0.0191
	(1.02)	(2.28)**
CFVOL	-0.3513	-0.0226
	(-2.25)**	(-1.59)
CYCLE	0.0083	0.0002
	(2.05)**	(0.52)
SALESGROWTH	-0.1149	-0.0629
	(-1.25)	(-0.75)
CEO_AGE	0.5118	0.0126
	(1.56)	(1.73)*
CEO_TENURE	-0.0246	-0.0001
	(-4.14)***	(-0.10)
BIG4		0.0013
		(0.93)
Industry Fixed Effect	Yes	Yes
Year Fixed Effect	Yes	Yes
Observations	18,571	18,571
Adjusted R^2	0.0155	0.0371

This table reports the result of an OLS regression examining the effect of CEO network size on *RAM* and *AEM*. This table presents the OLS regression coefficients and two-sided t-values for the maximum samples of 18,571 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.

Table 13a. Two-stage least squares using instrumental variables: *RAM*

	1^{st} *Stage Dep= NETWORK_TOT*	2^{nd} *Stage Dep= RAM*	*Table 4 Column 4*
NETWORK_TOT		0.0513	0.0440
		(2.63)***	(3.61)***
IND_NETWORK	0.8917		
	(19.94)***		
AEM	-0.0365	0.6318	0.6150
	(-2.75)***	(1.93)*	(1.40)
SIZE	0.0415	-0.0336	-0.0140
	(68.37)***	(-2.89)***	(-1.34)
BTM	0.0172	0.1932	0.2007
	(6.79)***	(7.73)***	(4.09)***
ROA	-0.0014	0.0020	0.0014
	(-1.76)*	(0.08)	(0.09)
LEV	0.0256	0.1638	0.1757
	(7.31)***	(4.10)***	(4.60)***
EVOL	0.0021	-0.0097	-0.0086
	(1.64)	(-0.35)	(-0.64)
CFVOL	-0.0029	-0.1213	-0.1228
	(-1.17)	(-2.05)**	(-2.63)***
CYCLE	-0.0003	0.0053	0.0052
	(-1.24)	(0.74)	(0.85)
SALEGROWTH	-0.0006	-0.1745	-0.1744
	(-0.07)	(-1.99)**	(-2.92)***
CEO_AGE	0.0378	0.4734	0.4925
	(4.46)***	(4.97)***	(1.77)*
CEO_TENURE	-0.0135	-0.0134	-0.0197
	(-8.86)***	(-0.83)	(-3.03)***
Industry Fixed Effect	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes
Observations	25,283	25,283	25,283
Adjusted R^2	0.2072	0.0163	0.0145
Partial F-Statistic	F = 106.73 (P-value < 0.0001)		
Weak Identification Test	Cragg-Donald Wald F = 397.76		
	Stock-Yogo C.V.: 10% Max IV size 16.38		
	Stock-Yogo C.V.: 15% Max IV size 8.96		
Endogeneity Test	Chi-sq = 6.17 (p = 0.01)		

This table presents the results of a two-stage regression using the industry average CEO total network size as the instrumental variable. In the first-stage regression the dependent variable is the CEO's network size. In the second-stage regression *RAM* is the dependent variable and the predicted value of CEO network size is the test variable. Appendix A defines the variables..

Table 13b. Two-stage least squares using instrumental variables: *AEM*

	1st Stage Dep= NETWORK_TOT	*2nd Stage Dep = AEM*	*Table 4 Column 8*
NETWORK_TOT		0.0094	-0.0080
		(0.34)	(-4.03)***
IND_NETWORK	0.8912		
	(19.93)***		
RAM	0.0003	0.0012	0.0012
	(0.47)	(1.93)*	(2.48)**
SIZE	0.0416	0.0006	0.0013
	(58.36)***	(0.44)	(1.83)*
BTM	0.0170	0.0034	0.0037
	(6.70)***	(1.43)	(0.95)
ROA	-0.0016	0.0054	0.0054
	(-2.02)**	(1.38)	(1.88)*
LEV	0.0252	0.0109	0.0113
	(7.18)***	(1.65)*	(1.90)*
EVOL	0.0019	0.0036	0.0037
	(1.54)	(1.41)	(1.50)
CFVOL	-0.0030	0.0032	0.0031
	(-1.20)	(0.81)	(0.78)
CYCLE	-0.0003	-0.0004	-0.0004
	(-1.18)	(-0.61)	(-0.55)
SALESGROWTH	0.0005	-0.0290	-0.0290
	(0.06)	(-0.71)	(-0.65)
CEO_AGE	0.0372	0.0056	0.0063
	(4.39)***	(1.10)	(0.86)
CEO_TENURE	-0.0135	0.0008	0.0005
	(-8.87)***	(0.77)	(0.47)
Big4	-0.0008	-0.0001	-0.0001
	(-0.23)	(-0.06)	(-0.12)
Industry Fixed Effect	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes
Observations	25,238	25,238	25,238
Adjusted R^2	0.2069	0.0340	0.0156
Partial F-Statistic	F = 106.63 (P-value < 0.0001)		
Weak Identification Test	Cragg-Donald Wald F = 397.05		
	Stock-Yogo C.V.: 10% Max IV size 16.38		
	Stock-Yogo C.V.: 15% Max IV size 8.96		
Endogeneity Test	Chi-sq = 0.41 (p = 0.52)		

This table presents the results of a two-stage regression using the industry average CEO total network size as the instrumental variable. In the first-stage regression the dependent variable is the CEO's network size. In the second-stage regression *AEM* is the dependent variable and the predicted value of CEO network size is the test variable. Appendix A defines the variables.

Table 14. Effect of CEO network on *RAM* and *AEM* with other measures of CEO network centrality

Dependent variable =	*RAM*	*RAM*	*RAM*	*RAM*	*AEM*	*AEM*	*AEM*	*AEM*
Betweenness	0.1465				-0.0042			
	(4.9081)***				(-2.5414)**			
Closeness		0.4970				-0.0249		
		(1.7255)*				(-1.1040)		
Eigenvector			-0.0133				-0.0083	
			(-0.1955)				(-1.1101)	
rDegree				8.5721				-0.8532
				(1.9393)*				(-4.4009)***
AEM	0.6144	0.6149	0.6133	0.6157				
	(1.4036)	(1.4027)	(1.4020)	(1.4047)				
RAM					0.0012	0.0012	0.0012	0.0012
					(2.4768)**	(2.4859)**	(2.4741)**	(2.4872)**
SIZE	-0.0135	-0.0155	-0.0121	-0.0143	0.0010	0.0011	0.0010	0.0012
	(-1.2831)	(-1.5712)	(-1.1755)	(-1.4833)	(1.4235)	(1.7879)*	(1.4280)	(1.6662)*
BTM	0.2006	0.2003	0.2014	0.2005	0.0036	0.0036	0.0036	0.0037
	(4.0600)***	(4.0955)***	(4.0752)***	(4.0985)***	(0.9208)	(0.9358)	(0.9198)	(0.9375)
ROA	0.0014	0.0014	0.0014	0.0014	0.0054	0.0054	0.0054	0.0054
	(0.0878)	(0.0874)	(0.0835)	(0.0878)	(1.8884)*	(1.8884)*	(1.8886)*	(1.8858)*
LEV	0.1761	0.1743	0.1768	0.1756	0.0112	0.0113	0.0111	0.0113
	(4.5573)***	(4.5392)***	(4.5698)***	(4.5814)***	(1.8449)*	(1.8779)*	(1.8435)*	(1.8701)*
EVOL	-0.0086	-0.0086	-0.0085	-0.0087	0.0036	0.0037	0.0036	0.0037
	(-0.6345)	(-0.6314)	(-0.6328)	(-0.6357)	(1.4888)	(1.4917)	(1.4889)	(1.4951)
CFVOL	-0.1229	-0.1223	-0.1229	-0.1227	0.0032	0.0031	0.0032	0.0031
	(-2.6492)***	(-2.6140)***	(-2.6407)***	(-2.6257)***	(0.7891)	(0.7831)	(0.7866)	(0.7844)
CYCLE	0.0052	0.0052	0.0052	0.0052	-0.0004	-0.0004	-0.0004	-0.0004
	(0.8426)	(0.8498)	(0.8428)	(0.8425)	(-0.5453)	(-0.5460)	(-0.5452)	(-0.5444)
SALESGROWTH	-0.1744	-0.1734	-0.1745	-0.1743	-0.0290	-0.0290	-0.0290	-0.0290
	(-2.9185)***	(-2.8590)***	(-2.9151)***	(-2.9146)***	(-0.6503)	(-0.6509)	(-0.6506)	(-0.6502)
CEO_AGE	0.4860	0.4928	0.4944	0.4921	0.0062	0.0061	0.0060	0.0062
	(1.7466)*	(1.7820)*	(1.7747)*	(1.7758)*	(0.8416)	(0.8284)	(0.8149)	(0.8494)
CEO_TENURE	-0.0197	-0.0173	-0.0204	-0.0187	0.0006	0.0005	0.0006	0.0005
	(-2.9126)***	(-2.3375)**	(-2.8688)***	(-2.6669)***	(0.5581)	(0.4113)	(0.5279)	(0.4304)
BIG4					-0.0002	0.0000	-0.0002	-0.0002
					(-0.1383)	(0.0337)	(-0.1511)	(-0.1699)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. obs.	25,283	25,283	25,283	25,283	25,283	25,283	25,283	25,283
Adjusted R^2	0.0156	0.0156	0.0156	0.0156	0.0324	0.0324	0.0324	0.0326

This table reports the results of an OLS regression examining the effect of CEO network size on *RAM* and *AEM* conditional on the size of the firm (S&P 500 firm versus other). This table presents the OLS regression coefficients for samples of 25,283 firm-years. *, **, *** denote significance at the 0.10, 0.05, and 0.01 level, respectively, all two-tailed. *Betweenness* = how frequently the CEO lies on the shortest path between two other individuals in the network; *Closeness* = the number of indirect as well as direct connections; *Eigenvector* = how central are the individuals connected to the CEO; *rDegree* = the number of first-degree connections in the network. See Liu (2014) for further details of these definitions. Appendix A defines the remaining variables.