CEO Network Centrality and Insider Trading Gains*

Rwan El-Khatib
Zayed University

Dobrina Jandik
University of St. Thomas

Tomas Jandik
University of Arkansas

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Abstract:

Insider trading gains are affected by the position of the chief executive officer (CEO) within the hierarchy of all business executives, as assessed by the CEO's network centrality. CEOs with high centrality are associated with significantly more positive abnormal returns following purchases of their company's stocks, compared to the CEOs with low centrality. High-centrality CEOs earn higher abnormal returns following their share purchases primarily in riskier firms and firms with weak corporate governance. High centrality CEOs also generate more significant personal gains by selling their shares prior to bad news event experienced by their firm. Our findings suggest high network centrality allows CEOs to more efficiently gather information about the value of their company.

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1. Introduction

The purpose of this study is to analyze the link between the personal social networks of Chief Executive Officers (CEOs) and the gains from CEO insider trading activities – purchases and sales of their firms' shares. We build on fast growing research on the importance of social ties – such as shared past employment history, educational overlaps, joint position on boards of charities or social clubs – in finance. Early studies in this area focused mainly on the effect of bilateral ties between two individuals. These personal connections have been found to facilitate transfer of knowledge and/or to allow easier contracting based on familiarity or trust, which leads to improved analyst performance (Cohen, Malloy, and Frazzini, 2010), better investment allocation (Duchin and Sosyura, 2013), higher merger and acquisition synergies (Cai and Sevilir, 2012), lower costs of debt contracting (Engelberg, Gao, and Parsons, 2012) and, ultimately, superior firm performance (Fracassi, 2016). On the other hand, interpersonal ties can worsen corporate governance and monitoring of managers (Hwang and Kim, 2009; Fracassi and Tate, 2012), as well as lead to collusion between contractual parties at the expense of investors (Ishii and Xuan, 2014).

The studies of bilateral ties have two limitations. First, interpersonal ties are not formed frequently.[1] Second, and more importantly, studies of bilateral ties by design cannot capture the concept of social hierarchy (as well as the resulting consequences of differential impact of connections for each of the contractual parties). Consequently, recent papers have instead focused on the effect of the overall position of an individual in the large social network of all business executives. Managers occupying more significant positions in this network are expected to be higher in a social hierarchy, and should be considered more influential and powerful (e.g. Mizruchi and Potts, 1998). Based on ample social science research findings, greater network influence grants individuals easier access to information and allows them to process and transmit information more

[1] The frequency of interpersonal connections is typically below 15% (e.g. Fracassi and Tate, 2012; Cai and Sevilir 2012; Duchin and Sosyura, 2013).

efficiently (Burt, 2010; Jackson, 2010; Newman, 2010). Ultimately, more significant network positions allow managers to generate greater social capital – that is, information and reputational trust one can gain through a social network (Woolcock, 1998).[2]

Finance studies on the topics of overall network connectedness and network hierarchy generally find support for the information advantages enjoyed by better-connected managers by showing that such individuals are associated with more efficient corporate policies. Faleye, Kovacs, and Venkateswaran (2014) show that well-connected CEOs invest more in research and development, and generate more and higher quality patents as a result. Javakhadze, Ferris, and French (2016) document better overall investment efficiency and lower need to rely on internally generated investment funds at firms managed by CEOs with higher network standing. Fogel, Ma, and Morck (2015) show that well-connected external board members are superior monitors. Fogel, Jandik, and McCumber (2016) find that better-connected CFOs are able to negotiate loan contracts with lower loan spreads and fewer covenant restrictions at firms they manage.[3]

Unlike the above papers that examine the link between network positions and better access to information only indirectly (through the impact on corporate policies), this study is the first to directly test the value of information associated with superior network standings – by analyzing the gains associated with insider trades initiated by firm CEOs. Purchases (sales) by insiders have been shown to reveal positive (negative) signals about the future value of the firm (e.g. Seyhun, 1992; Clarke, Dunbar, and Kahle, 2001; Jeng, Metrick, and Zeckhauser 2003). Ravina and Sapienza (2010)

[2] Social capital issues have been extensively studied in social sciences (e.g., Knack and Keefer, 1997; Woolcock, 1998; Portes, 1998; Dasgupta, 2005; Schneider, 2006). The concept of social capital has been associated with transfer of information (Montgomery, 1991; Rauch and Casella, 2003), improved contracting (Kandori, 1992), and risk-taking (Genicot and Ray, 2005; Bloch, Genicot, and Ray, 2008).

[3] On the other hand, El-Khatib, Fogel, and Jandik (2015) show that well-connected bidder CEOs are associated with value reducing acquisitions, because higher positions in social network hierarchy allow CEOs to achieve greater entrenchment, and to pursue deals that enrich managers at the expense of firm investors. Similarly, Jandik, Jandik, and Xu (2016) find that initial public offerings of companies managed by highly-connected CEOs are associated with greater riskiness, higher initial underpricing, and higher likelihood of value transfers away from the initial firm owners.

use the gains from insider trades by independent board members to directly assess their competence to be informed about the firm value. We utilize the same approach to gauge the information content of (legal) insider purchases and sales by highly- versus less-connected CEOs of large US companies from S&P 1500 index.

In contrast to previous studies based on bilateral ties, we strive to capture the CEO's ability to receive and spread information even in the absence of direct links to various counterparties. Following extensive research in graph theory (e.g., Proctor and Loomis, 1951; Sabidussi, 1966; Freeman, 1977; Bonacich, 1972), we argue that network centrality – a set of measures that characterize a position of an individual within a network – captures the concept of network hierarchy and describes the personal ability to gather and process information flows (e.g. Padgett and Ansell, 1993; Jackson, 2010). Relatedly, it should be also less costly and more efficient for others to recognize and comprehend information-related signals sent by individuals who are more central in the network. We utilize two centrality variables frequently employed in social science network studies: degree centrality (the number of ties between the CEO and any other network members), and eigenvector centrality (a variable that assesses the importance of a personal network by giving greater weight to highly-connected people directly tied to the CEO). Ultimately, greater network centrality both facilitates the ability to receive and communicate material information (Burt, 2010; Jackson, 2010; Newman, 2010), and enables reputational effects by sanctioning negative behavior of the highly visible network members, effectively inducing highly-connected individuals to voluntarily disclose truthful information, and to honor both explicit and implicit contractual obligation (Boot et al., 1993; Burt, 2005; Brass and Labianca, 2006). All the above arguments imply that high-centrality CEOs should have advantage gathering and transmitting of information – both material and "soft" – over the less connected counterparts. Consequently, the insider trades initiated by high-centrality CEOs should be have greater consequences for the firm stock value. That is, the post-trade stock

returns following the purchase (sale) of stocks by the firm highly-connected CEO should be significantly more positive (negative) compared to the returns following the transactions by low-centrality CEOs.

Based on the sample of insider transactions of initiated by CEOs of S&P 1500 firms between 2001 and 2014, we find results suggesting that network centrality is associated with insider trading gains. Highly central CEOs (in a vast network of more than 350,000 executives and board members of public and private firms around the world, tracked by BoardEx database) earn significantly higher abnormal returns after open market purchases of shares of their own firms, compared to the transactions by low-centrality CEOs. We further show that the extra abnormal returns generated by well-connected CEOs are the largest in subsamples of firms where information advantages are likely the largest – companies that are riskier or associated with weaker corporate governance (as judged by high levels of E-Index of Bebchuk, Cohen, and Ferrell, 2009).

We do not find consistent outperformance for high centrality CEOs' open market sales. However, based on the results of insider trading literature, insider sales transactions are less likely to be information-driven, as they often are motivated by optimal diversification need or by automatic execution of option grants. In order to identify likely information-driven sales, we follow Ravina and Sapienza (2010) and analyze sale trades shortly preceding "bad news" (a day when a firm experiences a sizable market-adjusted decline in stock price). For this subsample, we again find results consistent with information advantage by well-connected CEOs, as post-sale abnormal returns are significantly more negative for transactions initiated by high-centrality CEOs, compared to those initiated by less-connected CEOs. In addition, high-centrality CEOs sell more often and trade greater volumes of shares prior to the "bad news" event.

We make the following notable contributions: First, we extend the fast-growing literature on the role of social networks in finance. Our paper is the first to uncover the ability of well-connected

CEOs residing in the higher positions within social network hierarchy to receive, process, and transmit valuable information, which ultimately leads to more significant value impact of insider trades by those managers. We extend the work of Ahern (2017) who documents benefits of high centrality for gains from illegal trades and relatively very small fragmented networks of criminal conspirators in each particular legal case. However, our findings consistent with high-centrality CEOs being better informed are documented in the context of legal open market personal trades by those top managers, and within the largest possible social network of all worldwide executives and board members of both public and private companies – about 350,000 individuals in total.[4] The implication of our results is that network centrality of key firm decision makers may have important consequences for company's activities. While abnormal returns following executives' insider trades by design measure the extent of personal gains for those individuals, it is likely that the information advantages of the CEOs achieved through superior network positions may shape CEO decision making, daily firm operations, and ultimately influence overall firm valuation – positively or negatively.

Second, we extend the literature on determinants insider trading gains. We show that CEO personal characteristics, such as individual social capital proxied by network centrality, matter for abnormal returns due to insider trading. Importantly, the network centrality measures we use are objectively quantifiable, and network links based on past shared work or educational experiences are unlikely to be endogenous to the insider trading outcomes we study (and therefore unlikely to suffer from possible reverse causality issues).

The paper proceeds as follows. Section 2 describes our data. Section 3 presents the results. Section 4 concludes.

[4] Individual networks based on BoardEx database contain hundreds of thousands of individuals who are linked through millions of bilateral ties. Calculation of centrality statistics is thus very computer memory-intensive. For example, for the 2013 network, individual eigenvector centrality statistics calculations on a mainframe supercomputer take more than three days to converge.

2. Data

2.1 CEO centrality

We generate our centrality variables utilizing BoardEx database, which contains records on bilateral links (shared work, education, social clubs), and biographical data for board members and firm executives of private and public companies of firms around the world. BoardEx forms separate networks built on connections through employment, education, or social activities for different geographical regions. Since the focus of our study are S&P 1500 companies, we utilize the North American network. Following El-Khatib et al. (2015), we calculate centrality statistics constructed from employment ties in public companies. These connections are likely the most reliable, verifiable, not subject to self-reporting bias, and they most likely identify relationships between individuals who indeed met via a particular link.[5] Our centrality variables are recalculated for each of our sample years, based on annual social networks utilizing all possible connections established prior a particular year. Consistent with previous studies on network centrality in finance, we assume that once established, the link between two individuals lasts until one of the connected people dies. As a result, the annual social networks grow over time. Our largest sample-period network contains 350,471 individuals connected via 13.9 million employment links in 2013.

We utilize two widely used measures of centrality to assess the CEO's position within the network and the ability to efficiently gather and transfer information – degree centrality and eigenvector centrality. Degree centrality is equal to the number of network nodes (board members

[5] In our main analysis, we do not consider connections via shared educational or social activities experiences, as they are likely less reliable indicators of a truly established link between two individuals. The sizes of institutions where two people overlap are usually big, and therefore the chances of two people forming a meaningful connection while overlapping at the same institution are not high. This is true particularly for university overlaps, where BoardEx creates a connection between two people whenever they attended the same institution during overlapping periods regardless of the degree earned or school attended. In unreported robustness analysis, we generate networks built on various different types of links – including educational and social ties. Our results are similar to those presented in the paper.

and executives in case of the BoardEx social network) a particular individual is connected with – thus it is an appropriate measure of the individual's network "size." Eigenvector centrality, in contract, is a recursive measure that enables to estimate the individual's network "quality." A person has a higher eigenvector centrality scores if he/she is connected – both directly and indirectly via other people – to more individuals who themselves are more (eigenvector) central in the network.

We identify CEOs for the S&P 1500 firms through the BoardEx database.[6] In order to compare and rank-order centrality values computed for different years, we generate percentile values for degree and eigenvector centralities in each of the annual networks. The percentile values – from 0 for the lowest centrality to 99 for the highest centrality – reflect the relative rank of an individual in the whole BoardEx network of all board members and executives in a given year, not just the position within our sample of S&P 1500 CEOs. In addition to allowing comparisons of relative positions in networks that monotonously increase in size over time, percentiles facilitate presentation of eigenvector centrality-related results (eigenvector centrality is a dimension-less variable without cardinal number interpretation).

2.2 Insider trading data

We obtain the CEOs insider transaction data for our sample ranging from 2001 up to end of 2014 from Thomson Reuters Insiders Data which contains information that is reported on SEC forms 3,4,5, and 144.[7] The data contains information regarding the type of the transaction, transaction price, transaction date, name of the filer, and the filer's role, etc. We merged this data with the CEO S&P 1500 centrality data using an algorithm that matches on CEO name and we

[6] We also use BoardEx to obtain CEO characteristics including their employment history, age, tenure in position, and tenure in company.

[7] Form 3 contains the initial statement of beneficial ownership for all officers, form 4 presents the change in an insider's ownership position, form 5 contains the annual statement of change in beneficial ownership, and form 144 documents insider's declaration of their intention to sell restricted stock.

manually hand checked the match. Following Ravina and Sapienza (2010), we only focus on open market purchases and sales and we exclude transactions that occur mechanically from option or stock grants. We merged this data with stock return data from CRSP and financial data from COMPUSTAT, to get a final sample of 963 CEOs in 841 companies who conducted 11803 open market purchases, and 1792 CEOs in 1433 companies who conducted 147, 098 open market sales.

[Table 1 about here]

Table 1 presents summary statistics of CEO centralities, firm characteristics, and transaction data for the purchase trades in panel A, and the sale trades in panel B. *Size* is the log of total assets. *Book to Market* is the sum of the market value of common equity and total assets minus the book value of equity over the book value of equity. *Average number of trades* is the average number of trades by a CEO in a given trading day during the sample period. *Average trade size* is the transaction dollar value (or the average dollar value of trades if there was more than one trade in a given trading day).

The number of observations (N) does not reflect the total number of trades as each observation reflects a transaction on a trading date, so if a CEO has more than one purchase trade on the same day it will be reflected as one observation in the panel, thus the number of observations for the purchase trades (panel A) is 4451 with a mean of 2.65 for *Average number of trades* on a trading day. The number of observations for the sale trades (panel B) is 26887 with a mean of 5.47 for the *Average number of trades* on a trading day.

The mean [median] centrality of an S&P 1500 CEO who conduct insider purchases lies in the 68th [69th], and 60th [61st] percentile rank of the network of all US executives and directors, when using degree and eigenvector respectively. In addition, the mean [median] centrality for and S&P 1500 CEO who conduct insider sales lies in the 74th [76th] , and 67th [71st] percentile rank of the network of all US executives and directors, when using degree and eigenvector respectively. Hence, on average, S&P 1500 CEOs who conduct insider transactions have high positions in the central

network of all US executives and directors.

3. CEO Network Centrality and Insider Trading Gains

3.1 Abnormal returns following insider purchases and sales

In order to examine how informed a CEO is based on his centrality, we investigate whether more central CEOs will gain more when trading in their respective companies by employing an OLS regression using standard robust errors as follows:

$$BHAR(180) = \alpha_t + \beta_1 Centrality_{t-1} + \beta_2 Size_{t-1} + \beta_3 Book\ to\ Market_{t-1} + \varepsilon_t \quad (1)$$

The dependent variable is the market - adjusted buy-and-hold return over 180 trading days (BHAR 180) following the trade, and is calculated by subtracting the market return from the firm return, compounding it over time and then averaging within each trader category (Ravina and Sapienza, 2010).[8] On average, the market adjusted returns post insider CEO purchase [sales] trades are 24.48% [-0.09%]. *Centrality* is the natural logarithm of either degree or eigenvector percentile rank (to capture the likely diminishing impact of increasing centrality percentile ranks). All other independent and control variables are as previously defined in section 2 and are lagged one year.

[Table 2 about here]

Results of the estimation of equation (1) on purchase trades are included in panel A of table 2. In columns 1 and 5 we present the results for the basic model that only includes degree and eigenvector as measures of CEO centrality. In columns 2 and 6 we include the full model controlling for *Size* and *Book to Market* and including year effects. In all those 4 models, centrality significantly positively increases CEO insider trading gains (significant at the 1% level). The results are also economically significant, increasing the CEO centrality from the 10th to the 90th percentile rank

[8] In our main analysis, we focus on the 180 trading day horizon, because Rule 16(b) of the Securities and Exchange Act of 1934 requires insiders to return any profits realized from a purchase and sale (or vice versa) executed within a six month period. This makes the 180 trading day horizon particularly suitable to judge gains from insider trading activities. However, in unreported analysis, we repeated our tests utilizing the 90 trading day horizon returns. The results were similar to those reported in this paper.

increases the CEO post purchase trade gains by 20.76% and 9.12% when using degree and eigenvector as the measures of centrality in columns 2 and 6, respectively. Moreover, to focus on the effect of highly central CEOs compared to less central CEOs on insider trading gains, we define centrality in columns 3, 4, 7, and 8 as an indicator that is set to 1 if the CEO has centrality higher than the sample median and zero otherwise. In all those models, centrality remains to be significantly positively related to CEO post trading gains.

Results of the estimation of equation (1) on sale trades are included in panel B of table 2. In 4 out of the 8 models, centrality is significantly negatively associated with the post sale abnormal returns. Results in the subsample of sale trades are not as significant as the purchase trades, but this is consistent with the insider trading literature which documents that insider sale trades are not information driven.

To control for any unobserved time-invariant heterogeneity, we include fixed effects in our equation (1). Results are presented in table 3 with results for purchase trades in panel A and results for sale trades in panel B.

[Table 3 about here]

Table 3 replicates table 2, with degree being used to measure centrality in columns 1 to 4 and eigenvector used to measure centrality in columns 5 to 8. The log transformation for centrality percentile is used in columns 1, 2, 5, and 6. In all those columns, after including fixed effects, using both basic models and after controlling for *Size*, *Book to Market*, and year effects, centrality is significantly positively related with market adjusted returns post purchase trades (in panel A) at the 10% level. In addition, results are economically significant, increasing CEO centrality from the 10th to the 90th percentile rank, increases the CEO post trade gains by 18% and 12% when using degree and eigenvector as measures of centrality in columns 2 and 6, respectively. Furthermore, when using an indicator to identify the highly central CEOs in columns 3, 4, 7, and 8, results become stronger,

with significance raising to 1% level. In all those models, consistent with prior literature, *Size* is negatively significantly related to post trade market adjusted returns, and *Book to Market* is significantly positively related to post trade market adjusted returns.

The results with sale trades (panel B) become less significant after including fixed effects when using degree as a measure of centrality, however when using eigenvector as a measure of centrality, which is the measure that considers the importance of the CEOs links rather than just numbers, the CEO centrality is significantly negatively related to CEO post sale insider trades.

3.2 The effect of governance, firm's risk, and the timing of trade

A CEO could gain more information advantages if he is managing a low governed firm. Hence, to investigate whether the CEO centrality will still impact the CEO insider trade gains after controlling for governance, and to measure the combined effect of having a highly central CEO in a low governed firm , we test the following model that includes fixed effects and time effects:

$$BHAR(180) = \alpha_t + \beta_1 High\ Centrality + \beta_2 High\ Entrenchment + \beta_3 High\ Centrality * High\ Entrenchment + \beta_4 Size_{t-1} + \beta_5 Market\ to\ Book_{t-1} + \varepsilon_t \quad (2)$$

The dependent variable is the market - adjusted buy-and-hold return over 180 trading days (BHAR 180) as defined in tables 2 and 3. *High Centrality* is an indicator that is set to 1 if CEO centrality is higher than the sample median and zero otherwise. *High Entrenchment* is an indicator that is set to 1 if the firm has and E index that is higher than the sample median and zero otherwise. E index is Bebchuk, Cohen, and Ferrell's (2009) entrenchment index. *High Centrality***High Entrenchment* is the interaction of *High Centrality* and *High Entrenchment*. All other variables are as previously defined and are lagged one year.

[Table 4 about here]

Results of the estimation of equation (2) are presented in table 4. This model is only applied on a

subsample of purchase trades during the sample period spanning from 2001 up to 2009 due to the unavailability of E index after that date. Purchase trades are only examined since they are the information driven. *Centrality* is measured by degree in column 1 and by eigenvector in column 2. Even after controlling for governance, *High centrality* is still positively significantly related to CEO insider post purchase gains. *High Entrenchment* is positively significantly related to CEO insider post purchase gains too, suggesting that highly entrenched CEOs will be more profitable in their insider gains compared to less entrenched CEOs. The interaction between *High Centrality* and *High Entrenchment* is significantly positively related to CEO insider post purchase gains showing that high entrenchment (low governance) amplifies the effect of CEO centrality and hence more central CEOs working in low-governed firms will have higher information advantages compared to highly central CEOs who work in better governed firms.

Another possible reason for higher market adjusted returns post CEO insider purchase trades (information driven trades) could be the riskiness of the firm that the CEO is trading in. In our previous equations (1 &2) we partially addressed this concern by controlling for the *Market to Book* ratio. However now we are specifically looking at what will the effect of centrality be on insider post purchase gains in risky versus less risky companies by estimating the following fixed effects model:

$$BHAR(180) = \alpha_t + \beta_1 High\ Centrality + \beta_2 High\ Risk + \beta_3 High\ Centrality * High\ Risk + \beta_4 Size_{t-1} + \varepsilon_t \quad (3)$$

[Table 5 about here]

Results of the estimation of equation (3) are displayed in table 5. *Centrality* is measured by degree in column 1 and by eigenvector in column 2. *High Centrality* is an indicator that is set to 1 if CEO centrality is higher than the sample median and zero otherwise. *High Risk* is an indicator that is set to 1 if the firm has a Tobin's Q ratio that is higher than the sample median and zero otherwise. Tobin's Q ratio is calculated as the sum of the market value of equity (end-of-year price per share multiplied by the number of shares outstanding at year-end), short-term and long-term debt, and the liquidating

value of preferred stock, all divided by the total book value of assets. *High Centrality*High Risk* is the interaction of *High Centrality* and *High Risk*. All other variables are as previously defined. All independent and control variables are lagged one year. All models include year effects.

The results in table 5 suggests that the impact of centrality amplifies in highly risky companies. The interaction of *High Centrality* and *High Risk* is positive and statistically significant at the 1% level when using degree or eigenvector as the measure of centrality.

Finally, to examine the impact of CEO centrality on insider post sale trade gains more precisely, it is necessary to study the sale trades that could be information driven. With that regards, we follow Ravina and Sapienza (2010) by analyzing a subsample of CEO insider sale trades occurring around company's bad news.

[Table 6 about here]

Bad news are identified as trading days when the firm had a price drop greater than 5% after adjustment for market wide price movements. In our sample, 84,688 obs were considered as bad news. We then identified the sales transactions that occurred between 0 and 120 trading days before the bad news (price drop) and studied their market adjusted returns post 180 days. Table 6 presents key statistics regarding the average and median number of trades, market adjusted returns, and trade size .

When only considering sale transactions surrounding bad news, the significant impact of centrality on CEO insider post trade gains is more evident now. Looking at the univariate statistics in table 6, the average [median] market adjusted returns of highly central CEOs post sale trades are -11% [-12.9%] compared to low central CEOs -4.4% [-6%] when using degree as the measure of centrality, and -11.2% [-12.4%] for highly central CEOs while -4.2% [-7.5%] for low central CEOs when eigenvector is used as the measure of centrality. The difference in means [medians] between the market adjusted returns of high and low centrality CEOs is statistically significant at the 1% level

(t test was used for the difference in means and Wilcoxon rank test for the difference in median). Moreover, the difference between average [and median] transaction dollar value of high central versus low central CEOs is significantly different, with high central CEOs trading in larger values [an average difference of $247,733 when using degree and $ 116,803 when using eigenvector).

To further test the effect of CEO centrality on insider post sale transaction gains in a multivariate setting, we employed the following fixed effects model:

$$BHAR(180) = \alpha_t + \beta_1 High\ Centrality + \beta_2 Bad\ News + \beta_3 High\ Centrality * Bad\ News + \beta_4 Size_{t-1} + \beta_5 Book\ to\ Market_{t-1}\ \varepsilon_t \quad (4)$$

[Table 7 about here]

Results of estimating equation (4) are presented in table 7. *Centrality* is measured by degree in column 1 and by eigenvector in column 2. *High Centrality* is an indicator that is set to 1 if CEO centrality is higher than the sample median and zero otherwise. *Bad News* is an indicator that is set to 1 if the sale trade has occurred in a window of 120 trading days prior to the bad news and zero otherwise. Bad news are as previously identified in table 6. *High Centrality*Bad News* is the interaction of *High Centrality* and *Bad News*. All other variables are as previously defined. All control variables are lagged one year. All models include year effects.

The results of table 7 highlight the significant impact of CEO Centrality in information driven sale trades that occur surrounding firms' bad news. *Bad News* is significantly negative at the 1% level showing that the sale trades surrounding bad news had significant negative post trade returns compared to other sale trades. The interaction between *High Centrality* and *Bad News* is also significant and negative illustrating that the high CEO centrality position amplifies the negative post insider sale trades associated with bad news.

4. Conclusion

We show that CEO individual network centrality is a significant determinant of insider trading gains. CEOs with high network centrality earn greater abnormal returns following purchases of their firms' shares compared to CEOs who are not as well-connected. We find similar superior personal gains accrued to high-centrality CEOs in cases of insider sales – particularly orders that precede "bad news" events (days with a substantial market-adjusted drops in firm's equity value). We also show that gains due to superior network positions are particularly important in cases of companies that are riskier or associated with weak corporate governance – that is, firms with presumably substantial information asymmetry problems.

Our findings are consistent with long-standing social science predictions that more central individuals (that is, those in higher positions within the network's hierarchy) have superior access to information, can process and transmit information more efficiently, and/or have greater reputation (causing their activities and signals to have more powerful effects). Ultimately, more important network positions may help managers to gain significant social capital. Unlike previous studies that tested the power of high-centrality finance decision makers indirectly (through impact on corporate and investment policies), our paper is the first to examine the value of information associated with high network positions directly, by analyzing the signals about future company values revealed through voluntary and legal purchase and sales orders of firms' most important insider managers – the CEOs.

References

Bebchuk, L.A., Cohen, A., Ferrell, A., 2009. What matters in corporate governance? Review of Financial Studies 22, 783-827.

Bloch, F., Genicot, G., Ray, D., 2008. Informal insurance in social networks. Journal of Economic Theory 143, 36–58.

Bonacich, P., 1972. Factoring and weighting approaches to status scores and clique identification. Journal of Mathematical Sociology 2, 113-120.

Boot, A. W., Greenbaum, S. I., Thakor, A. V., 1993. Reputation and discretion in financial

contracting. The American Economic Review 1165-1183.

Brass, D.J., Labianca, G., 2006. Exploring the social ledger: negative relationships and negative asymmetry in social networks in organizations. The Academy of Management Review 31 (3), 596-614.

Burt, R. S., 2010. Neighbor networks: Competitive advantage local and personal. Oxford University Press.

Burt, R. S. 2005. Brokerage and closure: An introduction to social capital. Oxford University Press.

Cai, Y., Sevilir, M., 2012. Board connections and M&A transactions. Journal of Financial Economics 103, 327-349.

Clarke, J., Dunbar., C., Kahle, K.M., 2001. Long run performance and insider trading in completed and canceled seasoned equity offerings. Journal of Financial and Quantitative Analysis 36, 415-430.

Cohen, L.H., Malloy, C., Frazzini, A., 2010. Sell-side school ties. The Journal of Finance 65(4) 1409- 1437.

Dasgupta, P., 2005. Economics of social capital. The Economic Record.

Duchin, R., Sosyura, D., 2013. Divisional managers and internal capital markets. The Journal of Finance 68, 387-429.

El-Khatib, R., Fogel, K., Jandik, T., 2015. CEO network centrality and merger performance. Journal of Financial Economics 116 (2), 349-382.

Engelberg, J., Gao, P., Parsons, C., 2012. Friends with money. Journal of Financial Economics 103(1), 169 – 188.

Fracassi, C., 2017. Corporate finance policies and social networks. Management Science, forthcoming.

Fracassi, C., Tate, G., 2012. External networking and internal firm governance. The Journal of Finance 67(1), 153-194.

Freeman, L.C., 1977. Set of measures of centrality based on betweenness. Sociometry 40, 35-41.

Genicot, G., Ray, D., 2005. Informal insurance, enforcement constraints, and group formation in economics: Networks, clubs, and coalitions. Edited by Gabrielle Demange and Myrna Wooders, Cambridge: Cambridge University Press.

Hwang, B.H., Kim, S., 2009. It pays to have friends. Journal of Financial Economics 93, 138-158.

Ishii, J., Xuan, Y., 2014. Acquirer-target social ties and merger outcomes. Journal of Financial Economics 112, 344-363.

Jackson, M.O., 2010. Social and economic networks. Princeton University Press, Princeton, New Jersey.

Jandik, D., Jandik, T., Xu, W., 2016. CEO network centrality and IPO performance. Unpublished working paper.

Jeng, L.A., Metrick, A., Zeckhauser, R., 2003. Estimating the returns to insider trading: A performance evaluation perspective. The Review of Economics and Statistics 85(2), 453-471.

Kandori, M., 1992. Social norms and community enforcement. Review of Economic Studies,59 (1), 63-80.

Knack, S., Keefer, P., 1997. Does social capital have an economic payoff? A cross- country investigation. The Quarterly Journal of Economics 112(4), 1251-1288.

Mizruchi, M.S., Potts, B.B., 1998. Centrality and power revisited: actor success in group decision making. Social Networks 20, 353-387.

Montgomery, J.D., 1991. Social networks and labor-market outcomes: Toward an economic analysis. The American Economic Review 81 (5), 1408-1418.

Newman, M., 2010. Networks: An introduction. Oxford University Press.

Padgett, J.F., Ansell, C.K., 1993. Robust action and the rise of the Medici. The American Journal of Sociology 98 (6), 1259-1319.

Portes A., 1998. Social capital: Its origins and applications in modern sociology. Annual Review of Sociology 24, 1-24.

Proctor, C.H., Loomis, C.P., 1951. Analysis of sociometric data. In: P.W. Holland, and S. Leinhardt, ed.: Research Methods in Social Relations. Dryden Press, New York, pp. 561–586.

Rauch, J., Casella, A., 2001. Overcoming informational barriers to international resource allocation: Prices and group ties. Economic Journal 113, 21-42.

Ravina, E., Sapienza, P., 2010. What do independent directors know? Evidence from their trading. The Review of Financial Studies 23(3), 962-1003.

Sabidussi, G., 1966. Centrality index of a graph. Psychometrika 31, 581-581.

Schneider, J.A., 2006. Social capital and welfare reform: Organizations, congregations, and communities. Columbia University Press.

Seyhun, H.N., 1992. Why does aggregate insider trading predict future stock returns? The Quarterly Journal of Economics 107, 1303-1331.

Woolcock, M., 1998. Social capital and economic development: Toward a theoretical Synthesis and policy framework. Theory and Society 27, 151-208.

Table 1

Summary Statistics of CEO Centralities, Firm Characteristics, and Transaction Data

This table presents the summary statistics of CEO centralities, firm characteristics, and transaction data for the purchase trades in panel A, and the sale trades in panel B. The sample includes insider transactions of S&P 1500 CEOs during the years spanning from 2001 up to end of 2014. Purchase trades and sale trades include open transactions only. *Degree* and *Eigenvector* are measures of CEO centrality as explained in section 2.1. *Degree percentile* is the percentile ranking of the CEO in the social network of all directors and executives of US public companies with respect to the centrality measure *Degree*. *Eigenvector percentile* is the percentile ranking of the CEO in the social network of all directors and executives of US public companies with respect to the centrality measure *Eigenvector*. *Size* is the log of total assets. *Book to Market* is the sum of the market value of common equity and total assets minus the book value of equity over the book value of equity. *Average number of trades* is the average number of trades by a CEO in a given trading day during the sample period as reported by Thomson Reuters. *Average trade size* is the transaction dollar value (or the average dollar value of trades if there was more than one trade in a given trading day) as reported by Thomson Reuters.

Panel A: Purchase Trades

	N	Mean	Std. dev.	P25	Median	P75
Degree	4451	134.69	228.78	32	55	127
Eigenvector	4451	0.000302	0.002567	0.000000284	0.00000148	0.0000334
Degree Percentile	4451	68.29th	18.14	54th	69th	84th
Eigenvector Percentile	4451	60.94th	23.40	39th	61st	81st
Size	4451	7.21	1.55	6.22	7.08	8.09
Book to Market	4451	0.69	1.01	0.30	0.56	0.86
Average number of trades	4451	2.65	5.24	1	1	1
Average trade size	4451	$ 115,065	$ 275,115	$ 10,783	$ 28,500	$ 92,500

Panel B: Sale Trades

	N	Mean	Std. dev.	P25	Median	P75
Degree	26887	189.79	272.52	39	78	196
Eigenvector	26887	0.000476	0.003132	0.000000678	0.00000772	0.000069
Degree Percentile	26887	73.96th	18.12	61th	76th	89th
Eigenvector Percentile	26887	67.90th	23.71	53th	71th	88th
Size	26887	7.38	1.66	6.16	7.20	8.36
Book to Market	26887	0.45	0.30	0.25	0.40	0.59
Average number of trades	26887	5.47	14.99	1	1	2
Average trade size	26887	$ 1,032,374	$ 1,508,946	$ 111,955	$ 388,500	$ 1,177,500

Table 2

CEO Centrality and Market Adjusted Returns Post CEO Trades (OLS Regressions)

This table displays OLS estimates of regressing CEO market adjusted returns post CEO purchases(Panel A) and CEO sales (Panel B) on measures of CEO centrality and control variables. The dependent variable is the market - adjusted buy-and-hold return over 180 trading days (BHAR 180) and is calculated by subtracting the market return from the firm return, compounding it over time and then averaging within each trader category (Ravina and Sapienza, 2010). *Centrality* is measured by the log transformation of degree percentile rank in columns 1 and 2 and the log transformation of eigenvector percentile rank in columns 5 and 6. In columns 3,4,7,and 8 *Centrality* is measured by an indicator that is set to 1 if the CEO centrality is higher than the median centrality in the sample and zero otherwise. *Size* is the log of total assets. *Book to Market* is the sum of the market value of common equity and total assets minus the book value of equity over the book value of equity. Columns 2,4,6, and 8 include year effects. All independent and control variables are lagged one year. Robust standard errors are used.. Heteroskedastic-consistent probability values rejecting the null hypotheses of zero coefficients are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A : Purchase Trades

Dep. Variable : BHAR 180	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Centrality is:		**Degree**				**Eigenvector**		
Centrality	0.2106***	0.2595***	0.1007***	0.1281***	0.1154***	0.1141***	0.1087***	0.1381***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Size		-0.0498***		-0.0483***		-0.0433***		-0.0451***
		(0.000)		(0.000)		(0.000)		(0.000)
Book to Market		0.0712		0.0668		0.0682		0.0686
		(0.163)		(0.183)		(0.178)		(0.177)
Constant	-0.6365***	-0.4947**	0.2114***	0.5489***	-0.2166***	0.0956	0.2033***	0.5120***
	(0.000)	(0.018)	(0.000)	(0.000)	(0.000)	(0.404)	(0.000)	(0.000)
Year Controls		Yes		Yes		Yes		Yes
N	4451	4451	4451	4451	4451	4451	4451	4451
Adjusted R^2	0.55%	6.01%	0.32%	5.73%	0.63%	5.82%	0.40%	5.85%

Panel B: Sale Trades

Dep. Variable : BHAR 180	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Centrality is:		**Degree**				**Eigenvector**		
Centrality	-0.0256***	-0.0033	-0.0073**	0.0042	-0.0203***	-0.0140***	-0.0048	0.0014
	(0.000)	(0.652)	(0.037)	(0.260)	(0.000)	(0.000)	(0.172)	(0.696)
Size		-0.0033***		-0.0094***		-0.0080***		-0.0091***
		(0.000)		(0.000)		(0.000)		(0.000)
Book to Market		-0.0129*		-0.0114*		-0.0158**		-0.0121*
		(0.051)		(0.084)		(0.018)		(0.068)
Constant	0.1311***	0 .1129***	0.0253***	0.1007***	0 .1053***	0.1532***	0.0241***	0 .0997***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year Controls		Yes		Yes		Yes		Yes
N	26887	26887	26887	26887	26887	26887	26887	26887
Adjusted R^2	0.06%	2.74%	0.02%	2.74%	0.12%	2.79%	0.01%	2.74%

Table 3

CEO Centrality and Market Adjusted Returns Post CEO Trades (Fixed Effects)

This table presents estimates of regressing CEO market adjusted returns post CEO purchases(Panel A) and CEO sales (Panel B) on measures of CEO centrality and control variables as in table 2 but after including firm fixed effects. The dependent variable is the market - adjusted buy-and-hold return over 180 trading days (BHAR 180) and is calculated by subtracting the market return from the firm return, compounding it over time and then averaging within each trader category (Ravina and Sapienza, 2010). *Centrality* is measured by the log transformation of degree percentile in columns 1 and 2 and the log transformation of eigenvector percentile in columns 5 and 6. In columns 3,4,7,and 8 *Centrality* is measured by an indicator that is set to 1 if the CEO centrality is higher than the median centrality in the sample and zero otherwise. *Size* is the log of total assets. *Book to Market* is the sum of the market value of common equity and total assets minus the book value of equity over the book value of equity. Columns 2,4,6, and 8 include year effects. All independent and control variables are lagged one year. Robust standard errors are used.. Heteroskedastic-consistent probability values rejecting the null hypotheses of zero coefficients are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A : Purchase Trades

Dep. Variable : BHAR 180	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Centrality is:		Degree				Eigenvector		
Centrality	0.2123*	0.2015*	0.1142***	0.1240***	0.1542*	0.1370*	0.0852***	0.0948***
	(0.075)	(0.096)	(0.000)	(0.000)	(0.060)	(0.094)	(0.007)	(0.003)
Size		-0.1727***		-0.0521***		-0.1707***		-0.0464**
		(0.000)		(0.007)		(0.000)		(0.017)
Book to Market		0.1957***		0.0236**		0.1976***		0.0234**
		(0.000)		(0.011)		(0.000)		(0.013)
Constant	-0.6435	0.4845	0.0742***	0.4284***	-0.3718	0.7645	0.0903***	0.4040***
	(0.198)	(0.416)	(0.000)	(0.002)	(0.257)	(0.102)	(0.000)	(0.004)
Year Controls		Yes		Yes		Yes		Yes
N	4451	4451	4451	4451	4451	4451	4451	4451
F	3.17	18.15	27.99	11.35	3.54	18.15	7.3	9.77
Prob> F	0.075	0.000	0.000	0.000	0.060	0.000	0.007	0.000

Panel B: Sale Trades

Dep. Variable : BHAR 180	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Centrality is:		Degree				Eigenvector		
Centrality	0.0216	0.0243	0.0084	0.0037	-0.0218**	-0.0132	-0.0376***	-0.0300***
	(0.202)	(0.149)	(0.258)	(0.613)	(0.035)	(0.198)	(0.000)	(0.000)
Size		-0.1186***		-0.1186***		-0.1185***		-0.1186***
		(0.000)		(0.000)		(0.000)		(0.000)
Book to Market		0.2124***		0.2129***		0.2133***		0.2133***
		(0.000)		(0.000)		(0.000)		(0.000)
Constant	-0.0706	0.7483***	0.0176***	0.8498***	0.1117***	0.9055***	0.0405***	0.8670***
	(0.330)	(0.000)	(0.000)	(0.000)	(0.009)	(0.000)	(0.000)	(0.000)
Year Controls		Yes		Yes		Yes		Yes
N	26887	26887	26887	26887	26887	26887	26887	26887
F	1.63	81.84	1.28	81.72	4.45	81.81	19.23	82.53
Prob> F	0.202	0.000	0.2578	0.000	0.0349	0.000	0.000	0.000

Table 4

CEO Centrality and Market Adjusted Returns Post CEO Purchase Trades in High vs. Low Governed Firms

This table presents the results of a fixed effects model that estimates the impact of CEO Centrality on CEO market adjusted returns in high versus low governed firms. Only purchase trades are included. The dependent variable is the market - adjusted buy-and-hold return over 180 trading days (BHAR 180) as defined in table 2. *Centrality* is measured by degree in column 1 and by eigenvector in column 2. *High Centrality* is an indicator that is set to 1 if CEO centrality is higher than the sample median and zero otherwise. *High Entrenchment* is an indicator that is set to 1 if the firm has and E index that is higher than the sample median and zero otherwise. E index is Bebchuk, Cohen, and Ferrell's (2009) entrenchment index. *High Centrality*High Entrenchment* is the interaction of *High Centrality* and *High Entrenchment*. All other variables are as previously defined. All independent and control variables are lagged one year. All models include year effects. Robust standard errors are used. Heteroskedastic-consistent probability values rejecting the null hypotheses of zero coefficients are reported in parentheses. ***, and ** denote statistical significance at the 1% and 5% levels, respectively.

Dep. Variable: BHAR 180	**(1)**	**(2)**
Centrality is:	**Degree**	**Eigenvector**
High Centrality	0.1880**	0.2792***
	(0.027)	(0.004)
High Entrenchment	0.2981***	0.2488**
	(0.003)	(0.015)
High Centrality * High Entrenchment	0.2492**	0.4055***
	(0.033)	(0.002)
Size	-0.1555***	-0.1519***
	(0.006)	(0.007)
Book to Market	-0.0086	-0.0078
	(0.761)	(0.782)
Constant	1.2931***	1.2099***
	(0.002)	(0.003)
Year Controls	Yes	Yes
N	3278	3278
F	13.15	13.69
Prob > F	0.000	0.000

Table 5

CEO Centrality and Market Adjusted Returns Post CEO Purchase Trades in High vs. Low Risk Firms

This table presents the results of a fixed effects model that estimates the impact of CEO Centrality on CEO market adjusted returns in high versus low risk firms. Only purchase trades are included. The dependent variable is the market - adjusted buy-and-hold return over 180 trading days (BHAR 180) as defined in table 2. *Centrality* is measured by degree in column 1 and by eigenvector in column 2. *High Centrality* is an indicator that is set to 1 if CEO centrality is higher than the sample median and zero otherwise. *High Risk* is an indicator that is set to 1 if the firm has a Tobin's Q ratio that is higher than the sample median and zero otherwise. Tobin's Q ratio is calculated as the sum of the market value of equity (end-of-year price per share multiplied by the number of shares outstanding at year-end), short-term and long-term debt, and the liquidating value of preferred stock, all divided by the total book value of assets. *High Centrality*High Risk* is the interaction of *High Centrality* and *High Risk*. All other variables are as previously defined. All independent and control variables are lagged one year. All models include year effects. Robust standard errors are used. Heteroskedastic-consistent probability values rejecting the null hypotheses of zero coefficients are reported in parentheses. *** denote statistical significance at the 1% levels, respectively.

Dep. Variable: BHAR 180	**(1)**	**(2)**
Centrality is:	**Degree**	**Eigenvector**
High Centrality	0.0471	0.0058
	(0.535)	(0.947)
High Risk	-0.2574***	-0.2522***
	(0.000)	(0.000)
High Centrality * High Risk	0.3463***	0.3001***
	(0.000)	(0.001)
Size	-0.1704***	-0.1778***
	(0.000)	(0.000)
Constant	1.5035***	1.5746***
	(0.000)	(0.000)
Year Controls	Yes	Yes
N	4451	4451
F	14.3	13.66
Prob > F	0.000	0.000

Table 6

CEO Sale Trades Surrounding Bad News

Bad news are identified as trading days when the firm had a price drop greater than 5% after adjustment for market wide price movements. Following Ravina and Sapienza (2010), we then keep the sales transactions that occur between 0 and 120 trading days before the bad news (price drop). Market adjusted returns are as explained in table 2. *Trade size* is the total dollar value of the transaction. This table displays the statistics (average and median) broken down by the *High Centrality* subsample (CEOs with centrality higher than the sample median), the *Low Centrality* subsample (CEOs with centrality lower than the sample median), and then the difference between *High Centrality* and *Low Centrality*. ***, ** denotes that the statistical difference in means (or medians) is significantly different at the 1%, and 5% levels, respectively (using the T-test for difference in means and the Wilcoxon rank test for difference in medians).

	Degree			**Eigenvector**		
	High Centrality	Low Centrality	Diff	High Centrality	Low Centrality	Diff
Average number of trades (by piece of bad news)	6.308	5.542	0.766	5.974	5.769	0.205
Median number of trades (by piece of bad news)	1	1	0	1	1	0
Average market adjusted return (180 days)	-0.110	-0.044	-0.066***	-0.112	-0.042	-0.070***
Median market adjusted return (180 days)	-0.129	-0.060	-0.069***	-0.124	-0.075	-0.049***
Average trade size	1,193,026	945,293	247,733**	1,114,227	997,424	116,803**
Median trade size	480,000	282,980	197,020***	428,100	311,500	116,600**

Table 7

CEO Centrality and Market Adjusted Returns of CEO Sale Trades Surrounding Bad News

This table presents the results of a fixed effects model that estimates the impact of CEO Centrality on CEO market adjusted returns in sale trades that occur surrounding bad news. Only sale trades are included. The dependent variable is the market - adjusted buy-and-hold return over 180 trading days (BHAR 180) as defined in table 2. *Centrality* is measured by degree in column 1 and by eigenvector in column 2. *High Centrality* is an indicator that is set to 1 if CEO centrality is higher than the sample median and zero otherwise. *Bad News* is an indicator that is set to 1 if the sale trade has occurred in a window of 120 trading days prior to the bad news and zero otherwise. Bad news are as previously identified in table 6. *High Centrality*Bad News* is the interaction of *High Centrality* and *Bad News*. All other variables are as previously defined. All control variables are lagged one year. All models include year effects. Robust standard errors are used. Heteroskedastic-consistent probability values rejecting the null hypotheses of zero coefficients are reported in parentheses. *** denote statistical significance at the 1% levels, respectively.

Dep. Variable: BHAR 180	**(1)**	**(2)**
Centrality is:	**Degree**	**Eigenvector**
High Centrality	0.0062	-0.0288***
	(0395)	(0.001)
Bad News	-0.0406***	-0.0530***
	(0.000)	(0.000)
High Centrality * Bad News	-0.0807***	-0.0495***
	(0.000)	(0.004)
Size	-0.1195***	-0.1194***
	(0.000)	(0.000)
Book to Market	0.2136***	0.2141***
	(0.000)	(0.000)
Constant	0.8613***	0.8779***
	(0.000)	(0.000)
Year Controls	Yes	Yes
N	26887	26887
F	78.46	78.4
Prob > F	0.000	0.000