Executive Networks and Price Efficiency

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JEL classifications: G14, G40

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This study documents that executive networks are relevant to the price discovery process. Stocks of firms led by executives with large, influential, and dense networks are more quickly and accurately priced compared to firms led by less connected executives. Both the relative size of executive networks and the spatial representations of the networks afford efficiencies in pricing. We present evidence that separates these results into executive reputational and information channel effects. The results are robust to various model specifications, controls, and alternate explanations, with magnitudes that are economically meaningful.

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Introduction

There is general agreement among academics, regulators, politicians, and practitioners that the informational efficiency of stock prices is a far-reaching public good.[1] Theoretical literature on large information networks amongst traders argues that when information is exogenous, communication amongst market participants causes more information to be impounded into market prices, thus improving market efficiency (Colla and Mele, 2009; Ozsoylev and Walden, 2011; Bing and Han, 2013). A young but growing empirical literature explores the relationship between social networks and market outcomes, providing evidence that information diffuses through a network of market participants. Participant networks are shown to affect trading profits (Ozsoylev et al., 2014; Akbas et al., 2016), the level of informed trading (Akbas et al., 2016), the cost of equity (Ferris et al., 2017), the level and cost of debt (Engelberg et al., 2012; Fogel et al., 2018; Karolyi, 2018), and stock liquidity (Egginton and McCumber, 2018). Theory and empirical evidence to date strongly suggest that networks are also relevant to the price discovery process. However, trading networks are largely unobservable, and thus work to date attempts to actualize networks either by implication, e.g. "similar trading activities" (Ozsoylev et al., 2014) or educational overlap (Engelberg et al., 2012), by the history of executive appointments (e.g. El-Khatib et al., 2015; Fogel et al., 2018; Egginton and McCumber, 2018), or within a small experimental setting (Halim, Riyanto, and Roy, 2019). Halim et al. (2019) find that information exchange amongst traders in a small experimental setting increases trading volume and enhances the ability of prices to reflect aggregate information, though the authors do not find that price informativeness improves. Whether these findings may be generalized to a large, active market is

[1] See, for example, Dow and Gorton (1997), Goldstein and Guembel (2008), Boehmer and Wu (2013), among others.

an open question. We therefore take a meaningfully different approach than previous studies in our examination of network dynamics and price informativeness. In this article we measure the ability of secondary market participants to obtain information from corporate executives. This may happen directly via intentional disclosure e.g. analyst call, Bloomberg interview, etc. or indirectly via "bits and pieces" per Akbas et al. (2016). Executives who are more "visible" to market participants are more likely to communicate, intentionally or unintentionally, not only information directly relevant to expected share prices, but also small details, opinions, body language, interpretations of current events, regulation, legislation, and so on that may provide some insight as to the trajectory of the firm's share price.

To quantify the effect of executive networks on the informational efficiency of the market we measure the size, quality, and density of contemporaneous executive networks. We focus on current, dynamic, networks as opposed to past professional relationships given the intuition that current (contemporaneous) networks of professional ties are more relevant to immediate information acquisition and price discovery. While previous relationships and shared backgrounds have been shown to decrease information asymmetries between contracting parties as in Engleberg et al. (2012) and Fogel et al. (2018), we focus on verified concurrent relationships to illustrate the overall informational environment around executives. Market participants and executives are not directly contracting, and thus the network structure around executives is intuitively more relevant to the information environment for market participants. We construct annual networks of all North American executive and non-executive directors serving on the boards of public, private, for-profit, not-for-profit, and quasi-governmental entities. From these, we calculate several measures of executive network centrality that capture the import of executive network size and power, spatial representations of the networks around the executives, as well as the common component and orthogonal representations of executive networks. From these, we focus on the networks circumambient to chief executive officers (CEOs) and chief financial officers (CFOs) of publicly traded firms. The concurrent networks are dynamic and broadly heterogeneous.

Following Hasbrouck (1993) and Boehmer and Kelley (2009) we construct two measures of high-frequency price efficiency, and also estimate Hou and Moskowtiz's (2005) low-frequency measure of pricing delay. The high-frequency measures are meant to capture the efficiency of transaction prices, while the low-frequency measure estimates the speed with which public information is incorporated into stock prices. We then examine whether, and the extent to which, the size and spatial position of executive networks aids in the speed and accuracy of information diffusion to the market.

Our results strongly suggest that executive networks improve the informational efficiency of stock prices. Executive network centrality is shown to improve the intra-day efficiency of stock prices, as the deviations from a random walk are smaller for firms whose executives are more central in the network. Further, network centrality is associated with shorter delays in the incorporation of public information into stock prices. With the exception of the high-frequency pricing error of Hasbrouck (1993), CFO networks appear to be as relevant as CEO networks in promoting pricing efficiency. This is intuitive, as both the CEO and the CFO are market-facing executives and those responsible for firm financial disclosure and, ultimately, the share price. The results are robust to the inclusion of various controls and executive, firm, industry, and time effects. Endogeneity and reverse causality, always a concern in finance studies, are partially or wholly mitigated by design. Professional appointments to boards predate measurements of price efficiency by years or decades, while reverse causality is difficult to argue given it relies upon feedback from stock price efficiency to professional appointments.[2] Omitted variables is a possibility, thus we control for unobserved colinear variables via multiple fixed effects and additional tests discussed in section 4. The effects of networks on price discovery are economically meaningful. Importantly, network effects are multi-dimensional in that pricing efficiency is shown to be improved not only by the size and influence of an executive's immediate network, but also by the spatial position of the executive relative to other executives, e.g. the density of the network surrounding the CEO or CFO.

Our finding that the size and shape of an executive's network is positively associated with price efficiency provides empirical evidence that social networks impound information into stock prices and further expands the growing literature relating networks and market outcomes. More broadly, we build upon the literature on behavioral finance by documenting that the personal characteristics of executives are relevant to firm and market outcomes.

The rest of the article proceeds as follows. Section 1 describes the construction of the executive networks and centrality variables and provides details as to the specific measures used in this study. Section 2 discusses the market data and construction of the high and low-frequency measures of pricing efficiency. Section 3 discusses the final sample and reports summary statistics. Section 4 reports our main results, and section 5 concludes.

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[2] It is difficult to argue that smaller pricing deviations from a random walk and/or more rapid incorporation of public information into stock prices leads to more executive board appointments, from which networks and centrality measures are derived.

1. Empirical representation of executive networks

Empirical derivation of executive networks begins with raw data from BoardEx of executive board and non-board appointments. Appointments include managerial positions, e.g. CEO, CFO, senior manager, chief accounting officer, and executive and non-executive board positions at North American corporate and non-corporate entities. In network terminology, an individual is a *node* and connections between nodes are *links* or *edges*. For our purposes, executives are nodes and the relationships between executives are edges. We examine edges annually. For example, in 2012 the CFO at company XYZ is directly connected to all other XYZ senior executives. If she sits on the board of XYZ, she is directly connected to executive and non-executive board members of XYZ. If she also has a non-executive appointment on the board of ABC, she is connected to the executive and non-executive directors of ABC. If she subsequently leaves the board of ABC in 2013, she is no longer directly connected to the directors of ABC.

The sum of the number of direct connections is one's *degree* centrality; it is a measure of the size of one's immediate network. A conceptually and computationally simple extension of degree centrality is *eigenvector* centrality, wherein each node's connections are weighted by their respective degree centralities. Eigenvector centrality is thus a measure of both the size and reach of the node's network; eigenvector centrality is greater when a node is connected to many people who in turn also have many connections.

To measure the spatial position of each node in the network we calculate *closeness* centralities, meant to capture the properties of the network circumambient to each executive. Closeness centrality is a measure of the density of one's network in that it is the inverse of the number of "steps" it takes for an executive to reach all other executives in the network. In common parlance, it is the "six degrees of separation" phenomenon. Higher closeness centrality implies “closer,” denser networks that potentially afford more rapid information diffusion around more central nodes.

Current centrality measures are dynamic, as managerial and board appointments change over time. We calculate the four measure of executive network centrality annually.[3] To foster intuition, we normalize each measure by placing each node in percentile “buckets” in each variable each year, such that an executive whose classness centrality is in the 83rd percentile is between other nodes more often than 82 percent of all other executives that year. Since centrality measures are correlated, as, for example, an executive with a large network (degree) is also more likely to be connected to executives whom also have large networks (eigenvector), we also calculate the first principal component of the four centrality measures, which we deem simply *Centrality*.

[Figure 1 about here]

Figure 1 is a visualization of the 2014 network of 11,029 CEOs of publicly traded companies with headquarters in the United States. The CEOs are directly concurrently connected to 124,586 managers and non-CEO executives at their companies and the companies they serve in non-executive board roles. There are 680,526 direct connections between CEOs and other executives that year. The visualization renders executives as black dots; the size of the dots varies by degree centrality such that larger nodes have more direct connections. Lines between executives are relationships between them, e.g. the two executives sit on the same board at the same time. The colors in figure 1 represent the states in which the companies are headquartered.

[3] Calculation of network centrality measures is time and computationally intensive. The network is comprised of close to one million unique executives and the hundreds of millions of relationships between them. The edge list between executives for any given year is several gigabytes in size, and a single centrality measure for a single year takes many weeks to calculate on a dedicated super computer.

Purple lines represent boards of companies headquartered in California (18.39% of observations), green lines are New York companies (16.97%), burnt orange are Texas companies (7.07%), and other colors represent Massachusetts, Illinois, Pennsylvania, New Jersey, and the other states.

[Figure 2 about here]

Figure 2 is a close up of the top central region of figure 1, zooming in on a portion of the “cloud” of relationships in the California-dominant region. One can easily see individual nodes in the close up, and clusters of nodes where the density of the immediate networks around executives is greater.[4] Nodes and the sizes of the nodes are as above, but the colors of the relationships are now attributable to industry. For example, green lines are software and computer services firms (11.4% of observations). Red lines are electrical equipment firms (4.34%), orange lines are business services firms (4.39%), and specialty and other finance firms are light blue (7.08%). Figures 1 and 2 are meant to develop intuition with regard to information flows through and around executives. If information diffuses through a network of market participants, one may better visualize how traders may directly receive or indirectly gather information from and around more central nodes.

2. Measuring price efficiency

In this study, we calculate several measures documented in extant literature that capture the incorporation of information into stock prices at different time frequencies. Our primary high

[4] To visualize the network we use a “force atlas” algorithm that maximizes both the density within a cluster and distance between nodes that are farther away.

frequency measure of stock price efficiency is based on Hasbrouck (1993). Hasbrouck (1993) decomposes stock prices (p_t) into a random walk component (m_t) and a stationary component (s_t) where t indicates the time of the trade.

$$p_t = m_t + s_t$$

The random walk component is presumed to be the efficient price, while the stationary component captures implied market frictions. Hasbrouck (1993) suggests that because s_t has an expected value of zero, the standard deviation of the stationary component σ_s, measures the magnitude of the pricing error and is an inverse measure of price efficiency.

To calculate a pricing error measure, we follow Hasbrouck (1993), Boehmer and Kelley, 2009, and Boehmer and Wu (2013) and estimate the following vector autoregression (VAR) with five lags:

$$r_t = a_1 r_{t-1} + a_2 r_{t-2} + a_3 r_{t-3} + a_4 r_{t-4} + a_5 r_{t-5} + b_1 x_{t-1} + b_1 x_{t-1} + b_1 x_{t-1} + b_2 x_{t-2} + b_3 x_{t-3} + b_4 x_{t-4} + b_5 x_{5-1} + \mu_{1,t},$$

$$x_t = c_1 r_{t-1} + c_2 r_{t-2} + c_3 r_{t-3} + c_4 r_{t-4} + c_5 r_{t-5} + d_1 x_{t-1} + d_1 x_{t-1} + d_1 x_{t-1} + d_2 x_{t-2} + d_3 x_{t-3} + d_4 x_{t-4} + d_5 x_{5-1} + \mu_{2,t}, \quad (1)$$

where r_t is the difference in log prices, x_t is a vector of three trade variables, including a trade sign indicator, signed trading volume, and signed squared trading volume, and $\mu_{1,t}$ and $\mu_{2,t}$are disturbance terms. The vector moving average (VMA) representation of the VAR expressed in terms of disturbance is

$$r_t = a_0^* \mu_{1,t} + a_1^* \mu_{1,t-1} + a_2^* \mu_{1,t-2} + a_3^* \mu_{1,t-3} + a_4^* \mu_{1,t-4} + a_5^* \mu_{1,t-5} + b_0^* \mu_{2,t} + b_1^* \mu_{2,t-1} + b_2^* \mu_{2,t-2} + b_3^* \mu_{2,t-3} + b_4^* \mu_{2,t-4} + b_5^* \mu_{2,t-5},$$

$x_t = c_0^* \mu_{1,t} + c_1^* \mu_{1,t-1} + c_2^* \mu_{1,t-2} + c_3^* \mu_{1,t-3} + c_4^* \mu_{1,t-4} + c_5^* \mu_{1,t-5} + d_0^* \mu_{2,t} + d_1^* \mu_{2,t-1} + d_2^* \mu_{2,t-2} + d_3^* \mu_{2,t-3} + d_4^* \mu_{2,t-4} + d_5^* \mu_{2,t-5},$ (2)

We use the return equation of (2), calculating the variance of the pricing error as

$$\sigma_s^2 = \sum_{j=0}^{5} [\alpha_j \beta_j] Cov(\mu) \begin{bmatrix} \alpha_j \\ \beta_j \end{bmatrix} \tag{3}$$

where $\alpha_j = -\sum_{i=j+1}^{5} a_i^*$, $\beta_j = -\sum_{i=j+1}^{5} b_i^*$, $Cov(\mu)$ is the disturbance term covariance matrix.

We estimate σ_s daily for each sample stock. To allow for comparisons of price efficiency across stocks, we scale $\sigma_s$by the standard deviation of log price, σ_p (Boehmer and Wu, 2013). We then average σ_s/σ_p over each sample year.

As an alternate high frequency efficiency measure, we also estimate the absolute value of 30-minute midpoint return autocorrelations, |AR30|, per Boehmer and Kelley (2009). If prices follow a random walk, then |AR30| is expected to be zero. Deviations of |AR30| from zero implies inefficiency. |AR30| is estimated daily for each sample stock and averaged over each year.

To observe stock price efficiency over a longer time horizon we also estimate the Hou and Moskowitz (2005) price delay measure to estimate stock price efficiency. To estimate *Delay* we utilize the following

$$r_{i,t} = \alpha_i + \beta_i R_{m,t} + \sum_{n=1}^{4} \delta_i R_{m,t-n} + \epsilon_{i,t} \tag{4}$$

where $r_{i,t}$, is the return of stock *i* at day *t*, and $R_{m,t}$ is the CRSP value-weight market return. The equation is estimated for n = 4 (unconstrained model) and where n = 0 (constrained model). From each equation (4), we capture the R^2 from the estimation. *Delay* is then calculated using equation (5).

$$Delay = 1 - \frac{R^2_{constrained}}{R^2_{unconstrained}} \tag{5}$$

3. Sample description

The sample period encompasses 2009 – 2017 for all U.S. firms with stock price data in the CRSP and TAQ databases and with CEOs and CFOs for which we have centrality data. Table 1 reports summary statistics of efficiency measures and executive centralities. Panel A of table 1 report summary statics for our three price efficiency measures σ_s/σ_p, , |AR30|, and *Delay*. As stock liquidity has been shown to impact price efficiency (Boehmer and Kelley, 2009), we include control variables that measure variation in liquidity in our empirical test. Summary statics for control variables are reported in Panel A of Table 1. *VWAP* is the daily volume-weighted average price. *Size* is the market capitalization of equity. *Volume* is the daily trading volume. *RES* is the daily trade-weighted relative effective spread. |*OIB*| is the absolute value of the difference between buyer-initiated trades seller-initiated trade standardized by volume.

[Table 1]

Panels B and C of table 1 report mean, median, and standard deviations of CEO and CFO percentile centrality measures, respectively. The dynamic nature of current appointments, and therefore network centrality, is clearly visible as there is considerable heterogeneity even among top executives of publicly traded firms. For example, at the mean (median), CEOs are in the 64th (67th) percentile in eigenvector centrality while CFOs are in the 59rd (60th) percentile. The standard deviation of eigenvector centrality across the sample period is 21 and 20 percentiles, for CEOs and CFOs respectively.

4. Empirical results

Price Efficiency and CEO Networks

To study the relation between CEO network centrality and price efficiency we estimate the following model:

$$Eff_{t,i} = \beta_0 + \beta_1 Central_{t,i} + \sum_{j=1}^{j} \delta_j X_{j,i,t} + \epsilon_{i,t}, \qquad (6)$$

where $Eff_{t,i}$ measures of relative price efficiency, $Central$ measures of firm CEO centrality, and $X_j$is a vector of j control variables.

$Eff_{t,i}$ is one of three measures of price efficiency:σ_s/σ_p, |AR30|, or $Delay$ for stock i in year *t*. $\sigma_s/\sigma_p$is the standard deviation of the estimated price stationary component (σ_s) based on Hasbrouck (1993), scaled by the standard deviation of log prices σ_p. $\sigma_s/\sigma_p$is estimated daily and then averaged over each sample year. |AR30| absolute value of 30-minute midpoint return autocorrelations. |AR30| is also estimated daily and then averaged over each year. $Delay$ is he Hou and Moskowitz (2005) price delay measure estimated weekly and then averaged over each sample year.

$Central$ is one of four measures of firm CEO network centrality: *Degree*, *Eigen*, *Closeness*, or *Centrality*. *Degree*, *Eigen*, and *Closeness* centralities were previously described in section 1. *Centrality* is the first principal component of *Degree*, *Eigen*, and *Closeness* centralities. We estimate *Centrality* using Principal Component Analysis (PCA) on the four measures of centrality. As all four measures of centrality are correlated, estimating *Centrality* using PCA allows us to observe the joint impact the four types CEO centrality has on price efficiency.

Table 2 reports results for our estimation of equation 6. Panel A of Table 2 reports results using σ_s/σ_p as the dependent variable. To control for unobserved heterogeneity of executives, we include a director-level fixed effect in the model. The coefficient on *Centrality* is negative and significant. The negative coefficient on *Centrality* suggests that there is an inverse relationship between a CEO's network centrality and price inefficiency. All other measures of centrality, *Degree*, *Eigen*, and *Closeness,* also have negative coefficient although only *Degree* is statically significant. The negative coefficients on the four centrality measures are also consistent with higher CEO centrality improving stock price efficiency.

Panel B of Table 2 reports results when |AR30| as the dependent variable. Again, we observe a negative coefficient on *Centrality*. *Degree*, *Eigen,* and *Closeness* also are negatively related to |AR30|. Thus, when measuring price efficiency by looking at the 30-minute autocorrelation of returns, greater CEO centrality is associated with faster price discovery.

Taken together the results reported in table 2 are consistent with CEO centrality improving stock price efficiency. Table 2 results also suggest not only the size of a CEO's immediate network but also the spatial position of a firm's CEO relative to other executives improves efficiency and the speed of price discovery.

Consistent with prior literature (see Boehmer and Wu, 2012), most of the coefficient on the five control variables have expected sign although the significance level varies. In the |AR30| regression, larger *RES* is associated with greater quote-midpoint autocorrelation. The positive relation between RES and |AR30| is consistent with higher transaction cost preventing price discovery from occurring quickly.

[Table 2]

Both σ_s/σ_p and |AR30| are calculated using intraday data. These high-frequency measures typically capture short term deviations in prices from intrinsic values. Next, we examine the impact CEO centrality has on longer-term price efficiency. *Delay,* which is based on Hou and Moskowitz (2005), is a measure of stock price efficiency estimated at a weekly frequency. Table 3 reports model 6 regression results when using *Delay* as the dependent variable.

Consistent with σ_s/σ_p and |AR30|, the coefficient on *Centrality* is negative and significant when price efficiency is measured using *Delay.* The coefficients on *Degree, and Eigen* are also negative. These results are consistent with greater CEO centrality decreasing the time it takes for information to be incorporated into prices, thus improving stock price efficiency.

[Table 3]

Price Efficiency and Orthongal CEO Centrality

In order to determine whether the spatial position of the executive in the network also informs price discovery we orthogonalize the centrality measures such that each variable is comprised of only the element of centrality that is unique to each measure. Table 4 reports results of our base regressions of high and low frequency efficiency proxies against orthogonal representations of centrality. We report that while the size of the CEO's network, as measured by degree, displays the most significance in all models, closeness centrality (loosely, the density of the network around a CEO) is negatively significant at better than the 5% level when measuring high-frequency efficiency using |AR30|, and eigenvector centrality (the connectedness of the CEO's connections) is negatively significant at better than the 5% level in determining low frequency efficiency. These results strongly suggest that the size of the executive's network and her spatial position amongst all other executives contribute to price discovery.

[Table 4]

Price Efficiency and CFO Centrality

Next, we explore if a CFO's network position is related to stock price efficiency. To do this, we re-estimate equation 6, replacing CEO measures of centrality with centrality levels for firm CFOs. As the Sarbanes-Oxley Act of 2002 increased the public responsibility of CFOs to be equal to that of CEOs with regard to reporting accountability there has been increased attention paid to the ability of CFOs to meaningfully affect firm policies and financials.[5] Further, Graham, Harvey, and Rajgopal (2005) report that CFOs volunteer information to market participants to decrease information asymmetries between the firm and investors, primarily due to reputational and career concerns. It follows that whether CFOs voluntarily disclose information or that market participants are better able to gather public or soft information from more connected CFOs, the network centrality of CFOs may also be relevant to the price discovery mechanism.

Table 5 reports regression results of CFO centrality on high frequency measures σ_s/σ_p, |AR30|, and table 6 reports results of centrality on low-frequency $Delay$. Both tables report that the coefficients on all control variables are consistent with CEO regression results reported in previous tables.

[Table 5]

[5] See, for example, Geiger and North (2006), Jiang, Petroni, and Wang (2010), and Chava and Purnanandam (2010).

With regard to high frequency measures of efficiency, results are mixed. When measured by |AR30|, CFO centrality is negative and significant at better than the 1% level in all model specifications. However, the economic importance of CFO centrality appears to be less than that of CEOs. When measuring efficiency via σ_s/σ_p, CFO centrality appears largely insignificant. Table 6 reports that when measuring price efficiency using the *Delay* low frequency measure, CFO centrality is again highly statistically but marginally economically significant.

[Table 6]

Price Efficiency and Independent Chairman Centrality

Finally, we examine if non-executive chair of the board of directors' centrality is related to price efficiency. We present orthogonalized results of our high and low frequency efficiency proxies against orthogonal representations of centrality in Table 7. We do not find evidence that non-executive chair centrality is related to any of our price efficiency proxies. The absence of evidence of a relation between non-executive chair centrality price efficiency makes intuitive sense in that non-exec chairman, while important with regard to monitoring and advising, do not have the same day-to-day understanding of firm trivia and are not necessarily public facing.

[Table 7]

Separating network effects: diffusion speed vs. information value

While we argue in the introduction that endogeneity and reverse causality are partially mitigated by design, we acknowledge that omitted variables remain a possibility. The first line of defense with regard to omitted variables is the use of fixed effects in the tests. Results presented in the tables include firm and time fixed effects. We also employ executive fixed effects, interactions between effects, e.g. industry-time, executive-time, etc. and our results hold. We further sought to identity observable personal characteristics of executives that are correlated with our network measures but not correlated with price efficiency. Investigations of professional networks are also studies of reputation, social capital, and trust outcomes, since presumedly one does not get a board appointment without relevant knowledge, experience, and reputation. We have educational information, employment histories, and other relevant information on North American executives, and therefore are able to isolate results due to reputational effects (trust, experience, knowledge, fame) from those due to information flows (diffusion speed).

We first find the first principal component of degree, eigenvector, and closeness centralities. We then regress the principal component on observable characteristics of executives. Specifically, we capture experience as the difference between the observation year and the year of a first executive appointment, the total number of boards served to date, whether the executive graduated from an elite institution of higher learning, whether they have professional certifications, e.g. CFA, CPA, JD, MD, PhD, and the number of industry recognitions or meaningful awards won.[6] The residuals of this first stage regression comprise that element of centrality that is not attributable to social capital, trust, reputation, experience, or knowledge. We call this residual "information channel" centrality, and revisit our main tests substituting information channel centrality for centrality.

[Table 8]

Interestingly, we see that both information channel centrality and reputation effects matter with regard to price efficiency. The speed of information diffusion is relevant to high

[6] "Elite" and "Award" are necessarily subjective measures. With regard to education, we rely upon an overlap of several global rankings to identify the top 50 institutions in each year to decide that the University of Pennsylvania is "elite" whilst Colorado College is not. Similarly, we consider an award "meaningful" if it has both size and scope, for example, being named the *Institutional Investor* "America's Best CFO" is meaningful (Award = 1) while a local "citizen of the year" award is not.

frequency errors, while the value of information is more relevant to slower measures of efficiency. Table 8 reports that information centrality is statistically significant and economically meaningful in lessening high frequency pricing errors but is insignificant when measuring efficiency with slower measures. These results help one to interpret previous results. Revisiting table 4, we report that orthogonal measures of centrality differently affect price discovery. It is interesting to note that degree and eigenvector centralities, which by definition heavily depend upon experience, tenure, knowledge, and reputation in their construction, improve efficiencies for slower-moving measures of efficiency, where market participants are more likely to weigh or value information by the reputation of the source. Closeness, on the other hand, which is a measure of the density of the network around any given executive, is uniquely important with regard to the fastest measure of efficiency, where the speed of diffusion is likely driving results.

5. Conclusion

In this study we examine the effective a firm's executive network dynamics have on price informativeness. We measure the ability of secondary market participants to directly or indirectly obtain information from corporate executives to quantify the effect of executive networks on the informational efficiency of the market. Following Hasbrouck (1993) and Boehmer and Kelley (2009) we construct two measures of high-frequency price efficiency. We also estimate Hou and Moskowtiz's (2005) low-frequency measure of pricing delay. We then examine whether the size and spatial position of executive networks aids in the speed and accuracy of information diffusion to market stock prices.

For both measures of high-frequency price efficiency and the Hou and Moskowtiz's low-frequency price delay, firm's with executives that have higher levels of network centrality experience greater market efficiency. The positive correlation between market efficiency and executive network centrality results is robust to a variety of model specifications. Our results strongly suggest that executive networks improve the informational efficiency of stock prices. More broadly, our results build upon the literature on behavioral finance by documenting that the personal characteristics of executives are relevant to firm and market outcomes.

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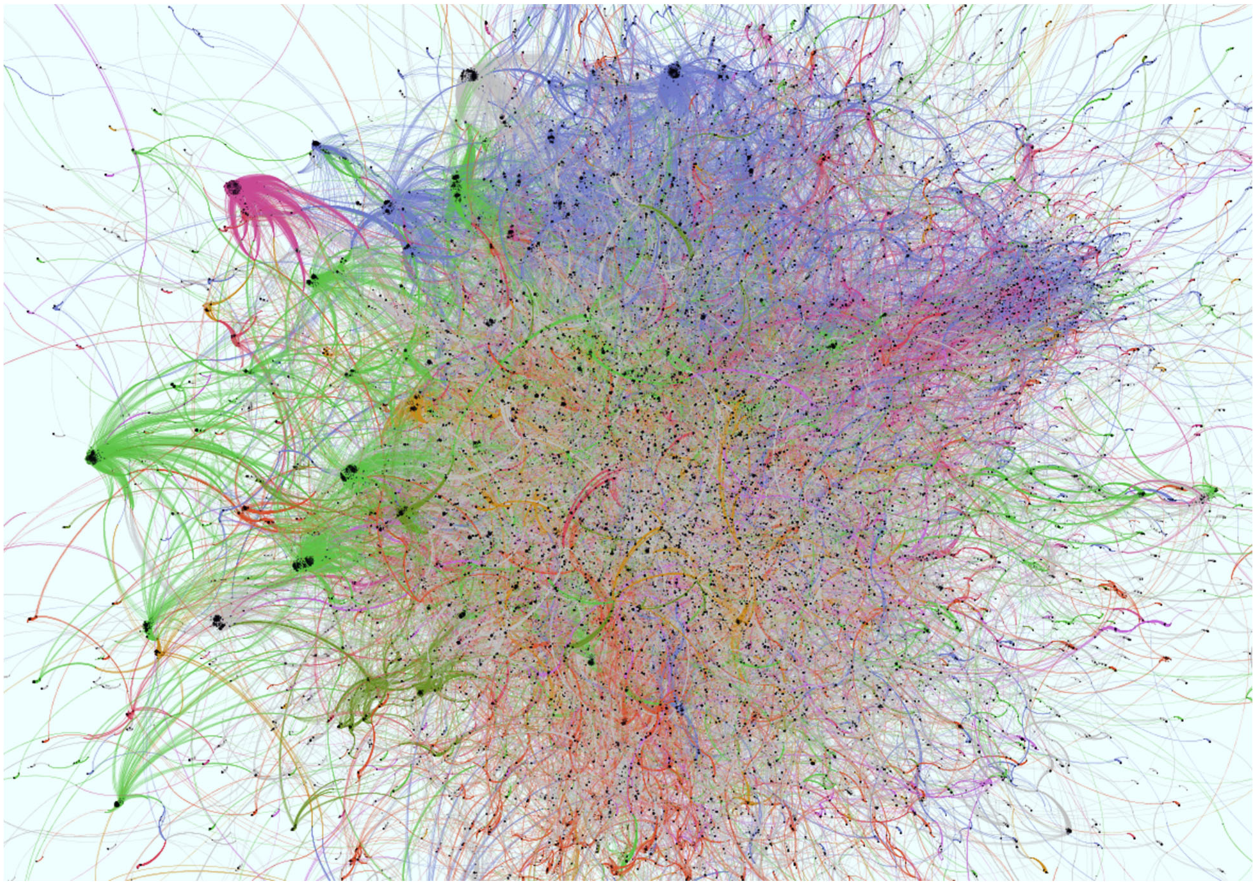
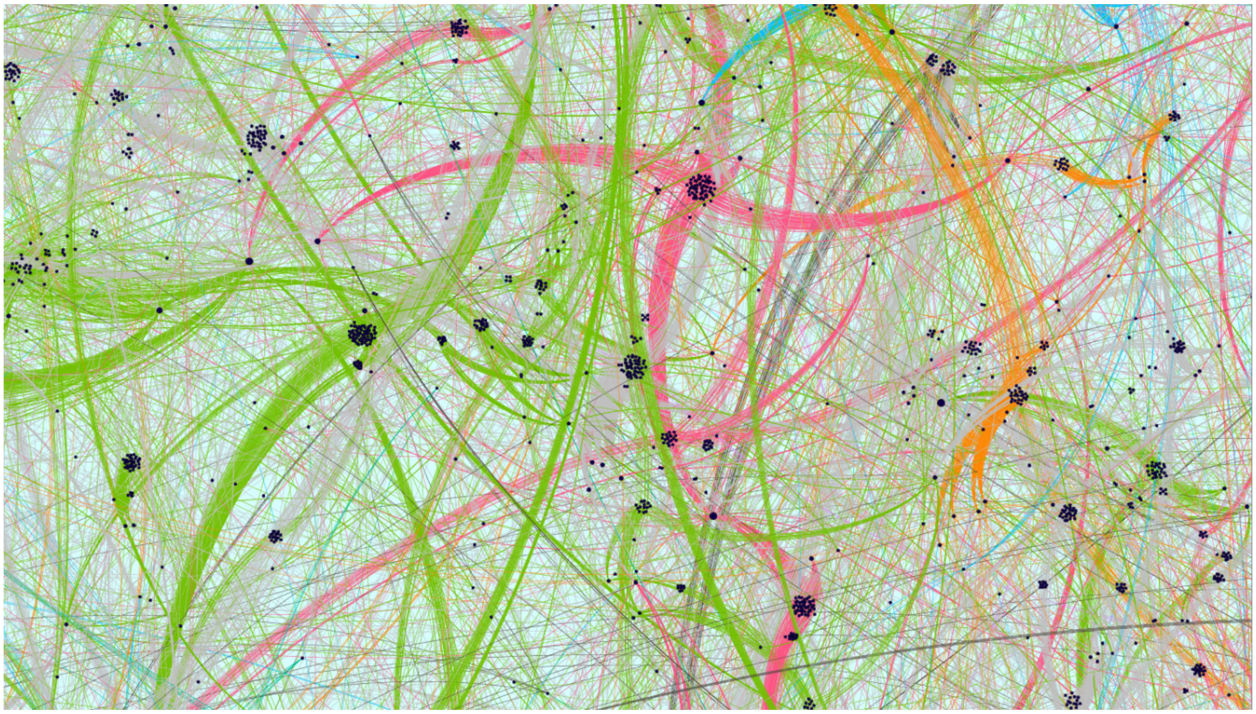
Figure 1: 2014 network of CEOs of U.S. public firms



This figure is a visualization of the 2014 network of 11,029 CEOs of public companies headquartered in the United States. They are connected, via board appointments, to 124,586 non-CEO executives. There are 680,526 connections between them. Black dots are executive and non-executive directors (nodes), the size of which are scaled by degree centrality. Larger dots are more connected executives. Lines between nodes are connections (edges); colors represent the states in which the firms are headquartered. Purple lines represent California boards (18.39% of observations), green lines are New York boards (16.97%), burnt orange are Texas boards (7.07%), and other prominent colors represent Massachusetts, Illinois, Pennsylvania, New Jersey, Georgia, Virginia, and others.

Figure 2: Close up of the 2014 network of CEOs of U.S. public firms



This figure is a visualization a portion of the 2014 network of 11,029 CEOs of public companies headquartered in the United States. They are connected, via board appointments, to 124,586 non-CEO executives. There are 680,526 connections between them. Black dots are executive and non-executive directors (nodes), the size of which are scaled by degree centrality. Larger dots are more connected executives. Clusters of dots are "hubs" of densely clustered people and the relationships between them. Lines between nodes are connections (edges); colors represent the primary industries of their firms. In this region of the network, the highest representations of sectors include software and computer services in green (11.4% of all observations), electronic equipment in red (4.34% of all observations), business services in orange (4.39%), and specialty and other finance in light blue (7.08%).

Table 1 Summary Statistics

This table reports summary statistics for sample stocks. σ_s/σ_p is the pricing error biased on Hasbrouck (1993). σ_s/σ_p is the standard deviation of intra-day prices. |AR30| is the absolute value 30-minute of midpoint return autocorrelations. *Delay* is the price efficiency measure as defined in Hou and Moskowitz (2005). *VWAP* is the daily volume-weighted average price. *Size* is the market capitalization of equity. *Volume* is the daily trading volume. *RES* is the daily value weighted relative effective spread. $|OIB|$ is the absolute value of the difference between buyer-initiated trades seller-initiated trade standardized by volume. All variables except centrality variable are averaged over each sample year. Each centrality measure is expressed as a percentage of the maximum centrality of all individuals in the U.S. network of executives in the BoardEx database from 2009-2017.

Panel A: Full Sample

Variable	**Mean**	**Median**	**Std. Dev.**
σ_s/σ_p	0.1133	0.0617	0.1649
|AR30|	5.8708	5.6632	2.5762
Delay	10.0202	9.8098	1.6635
LnVWAP	13.3599	13.4863	2.3002
LnSize	12.5388	12.4939	1.6586
LnVolume	3.0162	0.0144	56.2834
RES	0.2324	0.1612	0.1812
|OIB|	0.0363	0.0081	0.0901
Panel B: CEO Centrality			
Degree	70	71	17
Eigenvector	64	67	21
Closeness	64	64	24
Panel C: CFO Centrality			
Degree	65	64	15
Eigenvector	59	60	20
Closeness	56	56	21

Table 2 High Frequency Price Efficiency and CEO Network Centrality
The table presents regression results relating CEO network centrality to various measure of price efficiency. σ_s/σ_p is the pricing error biased on Hasbrouck (1993). σ_s/σ_p is the standard deviation of intra-day prices. |AR30| is the absolute value 30-minute of midpoint return autocorrelations. *Delay* is the price efficiency measure as defined in Hou and Moskowitz (2005). *Centrality* is the first principal component of *Degree*, *Eigen*, and *Closeness* centralities. *VWAP* is the daily volume-weighted average price. *Size* is the market capitalization of equity. *Volume* is the daily trading volume. *RES* is the daily value weighted relative effective spread. $|OIB|$ is the absolute value of the difference between buyer-initiated trades seller-initiated trade standardized by volume. All variables except centrality variable are averaged over each sample year. Each centrality measure is expressed as a percentage of the maximum centrality of all individuals in the U.S. network of executives in the BoardEx database from 2009-2017

Panel A: Dependent Variable = σ(s)/σ(p)

	(1)	(2)	(3)	(4)
Centrality	-0.0047**			
	(-2.243)			
Degree		-0.0002		
		(-1.184)		
Eigen			-0.0001	
			(-0.827)	
Closeness				-0.0002
				(-1.256)
LnVWAP	0.0089**	0.0084**	0.0084**	0.0084**
	(2.510)	(2.359)	(2.357)	(2.358)
LnSize	-0.0039	-0.0042	-0.0043	-0.0041
	(-1.092)	(-1.171)	(-1.188)	(-1.141)
LnVolume	-0.0437***	-0.0432***	-0.0433***	-0.0433***
	(-12.259)	(-12.107)	(-12.153)	(-12.161)
RES	-0.0000	-0.0000	-0.0000	-0.0000
	(-0.082)	(-0.093)	(-0.092)	(-0.093)
|OIB|	-0.0812***	-0.0860***	-0.0855***	-0.0855***
	(-7.590)	(-8.038)	(-7.990)	(-8.031)
Constant	0.6436***	0.6652***	0.6581***	0.6562***
	(12.818)	(12.998)	(13.031)	(12.812)
FE	Yes	Yes	Yes	Yes
Adj. R^2	0.46	0.46	0.46	0.46

Panel B: Dependent Variable = |AR30|

	(1)	(2)	(3)	(4)
Centrality	-0.0039***			
	(-3.426)			
Degree		-0.0005***		
		(-4.416)		
Eigen			-0.0002***	

			(-2.597)	
Closness				-0.0002**
				(-2.235)
LnVWAP	0.0089**	-0.0018	-0.0018	-0.0016
	(2.510)	(-0.965)	(-0.949)	(-0.848)
LnSize	-0.0039	0.0014	0.0013	0.0010
	(-1.092)	(0.753)	(0.666)	(0.511)
LnVolume	-0.0437***	0.0182***	0.0179***	0.0177***
	(-12.259)	(9.749)	(9.599)	(9.451)
RES	-0.0000	0.0001***	0.0001***	0.0001***
	(-0.082)	(2.698)	(2.700)	(2.761)
|OIB|	-0.0812***	0.2714***	0.2727***	0.2748***
	(-7.590)	(48.651)	(48.824)	(49.572)
Constant	-0.2549***	-0.2234***	-0.2390***	-0.2496***
	(-9.675)	(-8.323)	(-9.018)	(-9.266)
FE	Yes	Yes	Yes	Yes
Adj. R^2	0.52	0.52	0.52	0.52

Table 3 Low Frequency Price Efficiency and CEO Network Centrality
The table presents regression results relating CEO network centrality to price delay. σ_s/σ_p is the pricing error biased on Hasbrouck (1993). σ_s/σ_p is the standard deviation of intra-day prices. |AR30| is the absolute value 30-minute of midpoint return autocorrelations. *Delay* is the price efficiency measure as defined in Hou and Moskowitz (2005). *Centrality* is the first principal component of *Degree*, *Eigen*, and *Closeness* centralities. *VWAP* is the daily volume-weighted average price. *Size* is the market capitalization of equity. *Volume* is the daily trading volume. *RES* is the daily value weighted relative effective spread. $|OIB|$ is the absolute value of the difference between buyer-initiated trades seller-initiated trade standardized by volume. All variables except centrality variable are averaged over each sample year. Each centrality measure is expressed as a percentage of the maximum centrality of all individuals in the U.S. network of executives in the BoardEx database from 2009-2017.

Dependent Variable = Delay				
	(1)	**(2)**	**(3)**	**(4)**
Centrality	-0.0972***			
	(-3.771)			
Degree		-0.0145***		
		(-5.927)		
Eigen			-0.0057***	
			(-3.251)	
Closeness				-0.0017
				(-0.927)
LnVWAP	-0.0708*	-0.0712*	-0.0667	-0.0676
	(-1.713)	(-1.720)	(-1.612)	(-1.634)
LnSize	-0.2065***	-0.2077***	-0.2147***	-0.2103***
	(-4.749)	(-4.777)	(-4.933)	(-4.832)
LnVolume	-0.1763***	-0.1776***	-0.1841***	-0.1809***
	(-4.141)	(-4.170)	(-4.320)	(-4.248)
RES	-0.0001	-0.0001	-0.0001	-0.0001
	(-0.128)	(-0.127)	(-0.085)	(-0.109)
|OIB|	3.1811***	3.1880***	3.2459***	3.2345***
	(25.634)	(25.667)	(26.377)	(26.180)
Constant	10.8253***	11.7859***	11.2222***	10.9984***
	(17.276)	(18.345)	(17.712)	(17.354)
FE	Yes	Yes	Yes	Yes
Adj. R^2	0.74	0.74	0.74	0.74

Table 4 Price Efficiency and CEO Network Centrality Orthogonalized
The table presents regression results relating orthogonalized CEO network centrality to various measure of price efficiency. σ_s/σ_p is the pricing error biased on Hasbrouck (1993). σ_s/σ_p is the standard deviation of intra-day prices. |AR30| is the absolute value 30-minute of midpoint return autocorrelations. *Delay* is the price efficiency measure as defined in Hou and Moskowitz (2005). *VWAP* is the daily volume-weighted average price. *Size* is the market capitalization of equity. *Volume* is the daily trading volume. *RES* is the daily value weighted relative effective spread. $|OIB|$ is the absolute value of the difference between buyer-initiated trades seller-initiated trade standardized by volume. All variables except centrality variable are averaged over each sample year. Each centrality measure is expressed as a percentage of the maximum centrality of all individuals in the U.S. network of executives in the BoardEx database from 2009-2017.

Dependent Variable	**σ(s)/σ(p)** **(1)**	**|AR30|** **(2)**	**Delay** **(3)**
Degree	-0.0041	-0.0055***	-0.2313***
	(-1.486)	(-4.074)	(-7.644)
Eigen	-0.0001	-0.0012	-0.0866***
	(-0.056)	(-1.042)	(-3.332)
Closeness	-0.0079***	-0.0050***	-0.0730*
	(-3.530)	(-2.584)	(-1.693)
LnVWAP	0.0104***	-0.0018	-0.0769*
	(2.889)	(-0.980)	(-1.867)
LnSize	-0.0020	0.0013	-0.2151***
	(-0.560)	(0.668)	(-4.966)
LnVolume	-0.0446***	0.0183***	-0.1576***
	(-12.481)	(9.817)	(-3.711)
RES	-0.0000	0.0001***	-0.0001
	(-0.058)	(2.696)	(-0.130)
|OIB|	-0.0686***	0.2707***	3.0926***
	(-5.994)	(48.296)	(24.886)
Constant	0.6128***	-0.2563***	10.7834***
	(11.975)	(-9.730)	(17.274)
FE	Yes	Yes	Yes
Adj. R^2	0.46	0.52	0.75

Table 5 High Frequency Price Efficiency and CFO Network Centrality
The table presents regression results relating CFO network centrality to various measure of price efficiency. σ_s/σ_p is the pricing error biased on Hasbrouck (1993). σ_s/σ_p is the standard deviation of intra-day prices. |AR30| is the absolute value 30-minute of midpoint return autocorrelations. *Delay* is the price efficiency measure as defined in Hou and Moskowitz (2005). *Centrality* is the first principal component of *Degree*, *Eigen*, and *Closeness* centralities. *VWAP* is the daily volume-weighted average price. *Size* is the market capitalization of equity. *Volume* is the daily trading volume. *RES* is the daily value weighted relative effective spread. $|OIB|$ is the absolute value of the difference between buyer-initiated trades seller-initiated trade standardized by volume. All variables except centrality variable are averaged over each sample year. Each centrality measure is expressed as a percentage of the maximum centrality of all individuals in the U.S. network of executives in the BoardEx database from 2009-2017.

Panel A: Dependent Variable = σ(s)/σ(p)

	(1)	(2)	(3)	(4)
Centrality	-0.0001			
	(-0.042)			
Degree		0.0001		
		(0.289)		
Eigen			0.0003*	
			(1.897)	
Closeness				0.0002
				(1.126)
LnVWAP				
	0.0070*	0.0070*	0.0071*	0.0071*
LnSize	(1.784)	(1.783)	(1.805)	(1.801)
	-0.0146***	-0.0146***	-0.0147***	-0.0148***
LnVolume	(-3.423)	(-3.427)	(-3.436)	(-3.454)
	-0.0434***	-0.0434***	-0.0434***	-0.0433***
RES	(-10.342)	(-10.343)	(-10.350)	(-10.330)
	-0.0002	-0.0002	-0.0002	-0.0002
|OIB|	(-1.305)	(-1.292)	(-1.255)	(-1.259)
	-0.0765***	-0.0759***	-0.0732***	-0.0750***
Constant	(-6.397)	(-6.280)	(-6.071)	(-6.243)
	-0.0765***	0.7958***	0.7811***	-0.0750***
FE	Yes	Yes	Yes	Yes
Adj. R^2	(-6.397)	(11.953)	(12.016)	(-6.243)

Panel B: Dependent Variable = |AR30|

	(1)	(2)	(3)	(4)
Centrality	-0.0073***			
	(-5.875)			
Degree		-0.0010***		

		(-6.744)		
Eigen			-0.0004***	
			(-4.299)	
Closeness				-0.0004***
				(-3.851)
LnVWAP	-0.0074***	-0.0074***	-0.0076***	-0.0076***
	(-3.504)	(-3.500)	(-3.564)	(-3.578)
LnSize	0.0062***	0.0060***	0.0062***	0.0064***
	(2.669)	(2.594)	(2.667)	(2.738)
LnVolume	0.0062***	0.0060***	0.0062***	0.0064***
	(2.669)	(2.594)	(2.667)	(2.738)
RES	0.0227***	0.0227***	0.0228***	0.0226***
	(9.897)	(9.934)	(9.923)	(9.867)
|OIB|	-0.0001	-0.0001	-0.0001	-0.0001
	(-1.348)	(-1.379)	(-1.227)	(-1.267)
Constant	-0.3199***	-0.2557***	-0.2966***	-0.2955***
	(-9.120)	(-7.032)	(-8.337)	(-8.266)
FE	Yes	Yes	Yes	Yes
Adj. R^2	0.58	0.58	0.58	0.58

Table 6 Low Frequency Price Efficiency and CFO Network Centrality
The table presents regression results relating CEO network centrality to price delay. σ_s/σ_p is the pricing error biased on Hasbrouck (1993). σ_s/σ_p is the standard deviation of intra-day prices. |AR30| is the absolute value 30-minute of midpoint return autocorrelations. *Delay* is the price efficiency measure as defined in Hou and Moskowitz (2005). *Centrality* is the first principal component of *Degree*, *Eigen*, and *Closeness* centralities. *VWAP* is the daily volume-weighted average price. *Size* is the market capitalization of equity. *Volume* is the daily trading volume. *RES* is the daily value weighted relative effective spread. $|OIB|$ is the absolute value of the difference between buyer-initiated trades seller-initiated trade standardized by volume. All variables except centrality variable are averaged over each sample year. Each centrality measure is expressed as a percentage of the maximum centrality of all individuals in the U.S. network of executives in the BoardEx database from 2009-2017.

Dependent Variable = Delay				
	(1)	**(2)**	**(3)**	**(4)**
Centrality	-0.1678***			
	(-6.398)			
Degree		-0.0290***		
		(-9.532)		
Eigen			-0.0083***	
			(-4.350)	
Between				
Closeness				-0.0074***
				(-3.073)
LnVWAP	-0.1591***	-0.1561***	-0.1582***	-0.1582***
	(-3.573)	(-3.525)	(-3.555)	(-3.548)
LnSize	-0.0782	-0.0926*	-0.0819*	-0.0820*
	(-1.582)	(-1.882)	(-1.657)	(-1.656)
LnVolume	-0.1360***	-0.1328***	-0.1350***	-0.1353***
	(-2.803)	(-2.752)	(-2.784)	(-2.786)
RES	0.0026	0.0025	0.0026	0.0027
	(1.518)	(1.468)	(1.502)	(1.611)
|OIB|	2.9450***	2.7641***	2.9081***	2.9888***
	(21.609)	(20.215)	(21.275)	(22.048)
Constant	9.5881***	11.6008***	10.0656***	9.9627***
	(12.713)	(14.829)	(13.156)	(12.963)
FE	Yes	Yes	Yes	Yes
Adj. R^2	0.79	0.79	0.78	0.78

Table 7 Price Efficiency and Non-Executive Chair Network Centrality Orthogonalized

The table presents regression results relating orthogonalized Non-Executive Chair network centrality to various measure of price efficiency. σ_s/σ_p is the pricing error biased on Hasbrouck (1993). σ_s/σ_p is the standard deviation of intra-day prices. |AR30| is the absolute value 30-minute of midpoint return autocorrelations. *Delay* is the price efficiency measure as defined in Hou and Moskowitz (2005). *VWAP* is the daily volume-weighted average price. *Size* is the market capitalization of equity. *Volume* is the daily trading volume. *RES* is the daily value weighted relative effective spread. $|OIB|$ is the absolute value of the difference between buyer-initiated trades seller-initiated trade standardized by volume. All variables except centrality variable are averaged over each sample year. Each centrality measure is expressed as a percentage of the maximum centrality of all individuals in the U.S. network of executives in the BoardEx database from 2009-2017.

Dependent Variable	**σ(s)/σ(p)**	**|AR30|**	**Delay**
	(1)	**(2)**	**(3)**
Degree	-0.0020	-0.0033	0.0235
	(-0.140)	(-0.272)	(0.113)
Eigen	-0.0001	-0.0040	0.0857
	(-0.008)	(-0.899)	(0.579)
Closeness	0.0304	0.0104*	-0.0143
	(1.062)	(1.955)	(-0.034)
LnVWAP	0.0164	-0.0040	-0.6524***
	(1.020)	(-0.899)	(-2.864)
LnSize	-0.0148	0.0064	0.4634*
	(-0.894)	(0.705)	(1.871)
LnVolume	-0.0569***	0.0244**	0.3645
	(-3.235)	(2.541)	(1.425)
RES	0.0000	0.0004	0.0051
	(0.009)	(1.240)	(0.718)
|OIB|	-0.0907*	0.2085***	2.9342***
	(-1.804)	(7.441)	(4.017)
Constant	0.8658***	-0.3227**	1.7431
	(3.506)	(-2.315)	(0.482)
FE	Yes	Yes	Yes
Adj. R^2	0.61	0.59	0.78

Table 8 Information Centrality

The table presents regression results relating information share centrality. σ_s/σ_p is the pricing error biased on Hasbrouck (1993). σ_s/σ_p is the standard deviation of intra-day prices. |AR30| is the absolute value 30-minute of midpoint return autocorrelations. *Delay* is the price efficiency measure as defined in Hou and Moskowitz (2005). *VWAP* is the daily volume-weighted average price. *Size* is the market capitalization of equity. *Volume* is the daily trading volume. *RES* is the daily value weighted relative effective spread. $|OIB|$ is the absolute value of the difference between buyer-initiated trades seller-initiated trade standardized by volume. All variables except centrality variable are averaged over each sample year. Each centrality measure is expressed as a percentage of the maximum centrality of all individuals in the U.S. network of executives in the BoardEx database from 2009-2017.

Dependent Variable	**σ(s)/σ(p)** **(1)**	**|AR30|** **(2)**	**Delay** **(3)**
Information Centrality	-0.0045**	-0.0001	-0.0015
	(-2.273)	(-0.080)	(-0.072)
LnVWAP	0.0082**	0.0057***	-0.1298***
	(2.213)	(3.246)	(-2.986)
LnSize	-0.0064*	-0.0095***	-0.3394***
	(-1.685)	(-5.146)	(-7.372)
LnVolume	-0.0456***	0.0046**	-0.1891***
	(-12.280)	(2.551)	(-4.231)
RES	-0.0000	0.0000	-0.0007
	(-0.096)	(1.267)	(-0.821)
|OIB|	-0.0784***	-0.0830***	1.2188***
	(-7.149)	(-9.007)	(5.472)
Constant	0.7091***	0.0422	13.4541***
	(13.297)	(1.633)	(20.430)
FE	Yes	Yes	Yes
Adj. R^2	0.46	0.62	0.76