Do director networks improve managerial learning from stock prices?*

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Abstract: We find that the sensitivity of investment to noise in stock prices is smaller for firms with more connected boards, consistent with connected directors possessing information that can help managers filter out the noise in prices. This effect is more pronounced for firms with stronger corporate governance and less entrenched managers. We further find that boards with more industry and executive connections are more effective in preventing managerial mislearning from prices. Taken together, our findings identify director networks as a mechanism through which managers can more effectively learn from financial markets.

Keywords: Director networks; feedback effects; learning from prices; corporate investment.

JEL Classification: G3, G14, L14.

1. Introduction

Stock prices can improve managerial decisions to the extent that they reveal fundamental information that is not already possessed by the manager (Bond, Edmans, and Goldstein, 2012; Edmans, Jayaraman, and Schneemeier, 2017). Separating the fundamental component of prices from transient shocks that emanate from noise trading or investors' liquidity needs, however, is difficult for any decision maker. Therefore, it is possible that stock prices could provide faulty signals to managers and misguide their decisions (Morck, Shleifer, and Vishny, 1990; Dessaint, Foucault, Frésard, and Matray, 2016). In this paper, we examine whether director networks serve as a mechanism for information production that can help managers filter out the noise from fundamentals in prices, thereby improving managerial learning from financial markets.

Like financial markets, director networks serve as a conduit of information exchange and managers may access a wealth of information from the network through their boards' connections—connections that directors have formed through previous and current employers, educational institutions attended, military service, as well as civic services like non-profit boards and club memberships. Indeed, prior studies show that latest business practices, innovations, and information useful to investors can flow through director networks (e.g., Useem, 1984; Haunschild and Beckman, 1998; Akbas, Meschke, and Wintoki, 2016). Directors possess valuable non-public information that confirms or complements the information in stock prices (e.g., information on industry trends, changes in the regulatory landscape, potential entrants into product markets, or market conditions). Thus, more connected boards likely have a greater information advantage, which can help managers better gauge the precision of price signals and understand whether changes in stock prices are due to fundamentals or noise. Director networks may therefore represent an important source of external information that helps managers more effectively use the information in prices in their investment decisions.

However, the literature on director networks has also identified various detrimental effects of having a well-connected board, which may hinder the ability of the board to fully exploit its information advantage. First, well-connected directors are highly sought after, serve on multiple boards, and tend to be busy (Fich and Shivdasani, 2006; Stein and Zhao, 2016; Ferris, Jayaraman, and Liao, 2017). Hence, connected directors may be less concerned about their reputation and devote less time and effort to their monitoring and advising roles, limiting their ability to utilize and share their knowledge in understanding the firm's business strategy and value. Moreover, prior research finds that director interlocks may spread not only good practices, but also bad practices such as the adoption of poison pills (Davis, 1991; Benton, 2016), option backdating (Bizjak, Lemmon, and Whitby, 2009), and earnings management (Chiu, Teoh, and Tian, 2013). Lastly, information transmitted through director networks may be incorrect and misguide managers (Larcker So, and Wang, 2013). Therefore, whether connected directors help prevent managerial mislearning from stock prices is ultimately an empirical question.

We address the above question by studying the effect of board connections on investment sensitivity to noise in stock prices using a panel of U.S. firms over the period 2000-2012.[1] We use the number of director connections to capture board connectedness (e.g., Larcker et al., 2013; Akbas et. al., 2016) and a Q-theory of investment framework to capture the extent of managerial (mis)learning from stock prices (e.g., Chen, Goldstein, and Jiang, 2007; Foucault and Frésard, 2014). We follow Dessaint et al. (2016) and decompose stock prices into a non-fundamental component (noise) and its orthogonal component using mutual fund redemptions as an exogenous

[1] Our sample ends in 2012, when our access to the board connection data (from BoardEx) ends.

negative non-fundamental shock to stock prices.[2] This approach allows us to directly examine the role of director networks in curbing the real effects of faulty price signals, i.e., how board connections affect managers' reliance on the noise component of stock prices when making investment decisions.[3]

Consistent with Dessaint et al. (2016), we find that firm investment responds significantly to the non-fundamental component of its own stock prices. Specifically, a one standard deviation decrease in the non-fundamental component of stock prices corresponds to a 2.5% drop in investment for the average firm in our sample. More importantly, we find that the sensitivity of investment to the noise in prices is significantly lower for well-connected firms, while the sensitivity to the orthogonal component does not vary with board connectedness.[4] In particular, for a one standard deviation drop in the non-fundamental component of the firm's stock price, the investment cut goes from 4.6% for firms in the lowest decile of board connectedness to 0.05% for firms in the highest decile of board connectedness, representing an economically significant difference. These results are consistent with our main hypothesis—connected boards help managers filter out the noise in stock prices and reduce the extent to which financial markets act as a faulty informant.

[2] As in Edmans, Goldstein, and Jiang (2012) and Dessaint et al. (2016), we use mutual fund hypothetical sales instead of actual sales of the firm's stock to capture negative non-fundamental shocks to stock prices because actual sales may reflect fund managers' private information about fundamentals. We find that stock prices drop sharply following these shocks and take more than a year to recover. See Section 3.2.2 and Appendix B for a detailed discussion of this approach.

[3] To address the concerns related to correlated information channels, prior research (e.g., Chen et al., 2007; Zuo 2016) performs cross-sectional analyses and examines whether investment-to-price sensitivity varies in ways that are consistent with managerial learning. Foucault and Frésard (2014) mitigate this concern by examining how firm investment responds to peer firms' stock prices because managers are less likely to have access to the private information in peers' stock prices than to the private information in their own firm's stock prices.

[4] The orthogonal component reflects information already possessed by the manager, other fundamental information, and noise not captured by hypothetical mutual fund sales.

Our finding that director connections are associated with a reduced investment-to-noise sensitivity is subject to several alternative explanations. First, a non-fundamental drop in a firm's stock price may increase its cost of capital (e.g., Baker, Stein, and Wurgler, 2003) and lead to an investment cut. If well-connected firms have easier access to external capital and enjoy lower cost of financing (Engelberg, Gao, and Parsons, 2012; Chuluun, Prevost, and Puthenpurackal, 2014), the cost of capital effect of the negative price shock may be muted for these firms, resulting in a reduced investment-to-noise sensitivity that is unrelated to director connections enhancing managerial learning from prices. We address this financing cost argument in three ways. First, we perform the same analysis using peer firms' stock prices instead of the firm's own stock price. A non-fundamental shock to peers' stock prices is less likely to have a direct effect on the firm's cost of financing. Hence, firm investment is less likely to respond to the noise in peers' stock prices for reasons other than managerial learning. We find that firm investment responds significantly not only to the noise in its own stock price, but also to the noise in peers' stock prices, consistent with Dessaint et al. (2016). More importantly, the sensitivity of investment to the noise in peers' stock prices is significantly lower for well-connected firms. Second, using several cost of debt and cost of equity capital measures, we directly test whether mutual fund hypothetical sales are associated with an increase in the firm's cost of capital but do not find affirmative evidence. Third, we repeat our main analysis controlling for measures of cost of capital and find qualitatively similar results. Together, these findings suggest that the financing cost argument does not explain the negative association between board connectedness and the investment-to-noise sensitivity.[5]

[5] We should note that although it is important that we show our results are consistent with managers mislearning from stock prices, the focus of the study, unlike Dessaint et al. (2016), is not on providing evidence of mislearning from prices, but rather, the effect of board connections on managers' use of faulty signals in prices. Conceptually, given the role of boards of directors, it is more likely that firm connections would have a first order effect on managers' learning from their own firm's stock price than their peers' stock prices. We therefore focus our analyses on whether director networks prevent mislearning from a firm's own stock price.

A second alternative explanation for our results is that well-connected boards may be busy boards who provide ineffective monitoring. Hence, well-connected firms may face greater agency problems, producing "lazy" or entrenched managers, who are more likely to ignore valuable information channels, including stock prices, in their investment decisions. Therefore, it is possible that the lower investment-to-noise sensitivity for firms with well-connected boards merely reflects managers of connected firms ignoring stock prices altogether in their investment decisions. Our finding of a significant reduction in the sensitivity of investment to noise, and not to the orthogonal component, however, is inconsistent with the "lazy or entrenched manager hypothesis" because while an informed manager would ignore only the noise component in price, a lazy or entrenched manager would ignore both components of price. Further, using the *G-Index* from Gompers, Ishii, and Metrick (2003) and the *E-Index* from Bebchuk, Cohen, and Ferrell (2009) to proxy for the strength of corporate governance and the degree of managerial entrenchment, respectively, we find that the negative relation between board connectedness and investment-to-noise sensitivity is more pronounced for firms with stronger corporate governance and lower managerial entrenchment. These findings, again, are inconsistent with the lazy or entrenched manager hypothesis. Rather, these results suggest that the information channel from director networks is most beneficial when firms have a governance structure that is conducive to learning and when managers are more likely to listen to their board of directors, lending additional support to our hypothesis.

We next perform several cross-sectional analyses to shed light on the types of board connections that would matter more in preventing mislearning from prices. First, industry knowledge is useful in understanding the triggers of price movements, and hence boards with more connections to directors in the same industry likely obtain more private information on industry trends that can help managers filter out faulty price signals. Consistent with our conjecture, we find that the negative relation between board connectedness and investment-to-noise sensitivity is stronger in firms with a larger proportion of board connections to directors who serve at industry peers' boards. Second, we find that boards are more effective in curbing managerial mislearning from stock prices when executive directors, who ultimately make the investment decisions, are more connected compared to non-executive directors. These findings suggest that while director networks serve as an important channel through which managers can better learn from financial markets, connections are not homogenous—selecting directors with certain types of connections can have significant real effects.

Our paper makes several contributions to the literature. First, it complements the growing body of research on the feedback effects of financial markets by identifying director networks as a mechanism through which managers can improve their learning from stock prices. Our evidence suggests that director networks fulfil an information discovery function that increases the quality of managers' private information, which complements the market information and is crucial for managers in understanding whether changes in prices are due to fundamentals (Bond, Goldstein, and Prescott, 2009).[6] Our findings also underscore the importance of accounting for the effects of other information channels as we advance our understanding of how financial markets affect real decisions.

Second, we add to the corporate governance literature by highlighting the information production role of corporate boards through director connections. In particular, recent research shows that board connections have a positive effect on firm value (Larcker et al., 2013); however, the channel through which these connections create value is less clear. Our findings suggest that

[6] While Bond et al. (2009)'s model focuses on how an agent's sources of information can affect his ability to understand the implications of his own corrective actions on price, the spirit of the model can be extended to our context, i.e., to understanding the non-fundamental component in price.

director connections may enhance firm value by providing managers with the information required to filter out the noise from fundamentals in prices, thereby preventing faulty price signals from affecting investment decisions. Further, we add to the rich literature on the consequences of weak corporate governance (e.g., Core, Holthausen, and Larcker, 1999; Bertrand and Mullainathan, 2001; Masulis, Wang, and Xie, 2007) by uncovering a lesser known negative effect of managerial entrenchment on the firm—entrenched managers fail to exploit the informational benefits of having a well-connected board in interpreting stock price signals.

Third, our study complements the nascent research on the effects of non-fundamental price shocks on real decisions (e.g., Morck et al., 1990; Dessaint et al., 2016; Heater, Liu, and Matthies, 2017). In particular, we identify a mechanism that can mitigate the negative effects of faulty price signals in the context of investment decisions. To the extent that the effect of non-fundamental price shocks on a firm's investment feedbacks on the firm's stock prices, the effect can be amplified and spread through the economy. Our findings suggest that director networks can have significant real effects by curbing the ripple effect of non-fundamental price shocks.

The rest of the paper is organized as follows. Section 2 provides a brief review of related literature. Section 3 describes our sample, variables, and research design. Section 4 presents our main empirical results and alternative explanations. Section 5 provides additional cross-sectional analyses. Section 6 concludes.

2. Related Literature

2.1 The feedback effect of stock prices

By aggregating relevant pieces of information dispersed among investors, prices can coordinate the separate actions of different agents. This argument, which dates back to Hayek (1945), has led to a flurry of research, both theoretical and empirical, examining whether managers learn from financial markets (see Bond et al. (2012) for a review of this literature).[7] The managerial learning hypothesis does not imply that managers are less informed about the prospects of their own firms than investors; rather, it merely presumes that prices may contain information that managers do not have (Dow and Gorton, 1997; Subrahmanyam and Titman, 1999; Ozdenoren and Yuan, 2008).

A growing body of research provides empirical evidence consistent with the managerial learning hypothesis. Chen et al. (2007) are among the first to show that the sensitivity of investment to price (Tobin's Q) is stronger when prices contain more private information. Foucault and Frésard (2012) find a higher investment-to-price sensitivity for cross-listed firms, suggesting that managers learn more from prices that are more informative. Further, Foucault and Frésard (2014) develop a model to show how peers' stock prices may complement a firm's own price in its investment decisions and show empirically that firms can learn from the stock prices of their industry peers. Collectively, this stream of research, along with others such as Bakke and Whited (2010), Edmans et al. (2012), and Loureiro and Taboada (2015), establishes the existence of a feedback effect from financial markets to real economic decisions.

The extent to which prices reveal information that is useful to decision makers, a notion that Bond et al. (2012) term revelatory price efficiency, is what makes financial markets valuable for real decisions. Exploiting the enforcement of insider trading laws across a number of countries as an exogenous shock to the source of information in stock prices, Edmans et al. (2017) find that only outsider information—i.e., information new to managers—is important for obtaining revelatory price efficiency. However, separating the revelatory component of prices from transient

[7] Prior research suggests that market prices do not only affect managers' decisions, they can reveal information to other agents, such as directors and regulators, making decisions in various other contexts. For example, Roll (1984) shows that citrus futures markets improve weather forecasting above and beyond traditional meteorological forecasts. Wolfers and Zitzewitz (2004) find that market-generated forecasts outperform those from the polls.

shocks stemming from noise trading or investors' liquidity needs is difficult. Morck et al. (1990) argue that the information that managers glean from stock prices may not be correct about future fundamentals, i.e., stock prices may provide faulty signals to managers. Using hypothetical mutual fund sales as a transient non-fundamental shock to stock prices, Dessaint et al. (2016) show that firms reduce their investment in response to a decline in the noise component of their own stock prices as well as those of their product market peers, suggesting that managers fail to filter out the noise from stock prices when making investment decisions.

We extend this work by examining whether director connections represent a valuable information source that complements the information from financial markets. Specifically, we argue that managers' access to the information from their boards' director networks is important for the effective use of the information in stock prices. This argument is consistent with the insight from Bond et al. (2009) that a decision maker's direct sources of information are crucial in his understanding of the fundamental signal in price.[8] Our study seeks to expand our understanding of *how* managers can more effectively learn from stock prices as well as what firms can do to promote more effective managerial learning from financial markets (e.g., by forming connections with certain types of directors or those who have certain types of connections).

2.2. Director networks

A growing body of literature in accounting and finance examines the role of social networks in the flow of information as well as in attaining various economic outcomes. For example, Cohen, Frazzini, and Malloy (2008) show that educational networks improve

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[8] Specifically, Bond et al. (2009) show, in a rational expectations model of market-based corrective actions, that the extent to which an agent (e.g., director, regulator, manager, or activist) can extract information from prices depends on his direct sources of information, which affect his ability to understand whether changes in prices are due to fundamentals or expectations about his own actions. We extend this insight and argue that an agent's (in our context, the manager's) sources of information can affect his ability to filter out the noise in prices, and thereby improve his learning from financial markets.

information transmission from board members to portfolio managers, resulting in better portfolio performance. Hwang and Kim (2009) demonstrate that CEOs who are socially connected to their firms' directors enjoy higher compensation. Similarly, Engelberg, Gao, and Parsons (2013) show that outside connections increase compensation at the margin. Moreover, Engelberg et al. (2012) find that firms with social connections to banks enjoy lower interest rates and superior stock market performance, suggesting that social networks facilitate either better information flow or more effective monitoring.

More related to our work is the literature that examines network connections formed among board members across firms, i.e. director networks. Earlier studies show that director networks have important consequences: they impact firm decisions such as adopting poison pills (Davis, 1991), switching stock exchanges (Rao, Davis, and Ward, 2000), and engaging in acquisitions (Beckman and Haunschild, 2002). A related strand of literature finds that board interlocks are associated with value-enhancing corporate practices, such as business innovations (Haunschild, 1993) and alliance formation (Gulati and Westphal, 1999). Brown and Drake (2014) find that firms linked to other low-tax firms enjoy lower cash effective tax rates themselves. On the other hand, prior literature also finds that board interlocks are associated with value-reducing activities. Bizjak et al. (2009) demonstrate that board interlocks are associated with the spread of stock option backdating. Similarly, Chiu et al. (2013) show that a firm is more likely to manage earnings when another firm with which it shares a director is managing earnings. Collectively, these studies suggest that board connections matter, but their net economic impact is not clear.

Recent studies rely on measures from social network theory that consider the entire network, rather than only board interlocks, to examine the effect of information transfer between directors. Larcker et al. (2013), focusing on the net economic impact of director connections on firm value, show that better-connected firms earn significantly higher risk-adjusted stock returns and operating profits. Akbas et al. (2016) provide evidence that sophisticated investors like short sellers, option traders, and financial institutions are more informed when trading stocks of companies with more connected board members.

Our paper extends this literature by documenting that director networks are a valuable information channel that can improve the quality of managers' information and thereby facilitate more effective managerial learning from financial markets. Specifically, the information accessed through director connections can help managers avoid using faulty signals in prices when they make corporate investment decisions. Our findings highlight the importance of director networks in both financial markets and the real economy.

3. Sample Selection, Research Design, and Descriptive Statistics

3.1. Sample

Our sample consists of an unbalanced panel of BoardEx firms over the period from 2000 to 2012. We require firms in the BoardEx sample to have financial data from Compustat and price and return data from the Center for Research in Security Prices (CRSP). We exclude firms in the financial industries (SIC code 6000–6999) and utility industries (SIC code 4900–4949). Following Chen et al. (2007), we exclude firm-year observations with less than $10 million book value of equity or with less than 30 days of trading activity in a given year. We also exclude firms with fiscal year end stock prices below $1. We obtain analyst data from I/B/E/S and institutional ownership data from Thomson Reuters CDA/Spectrum Institutional Holdings database. Further, we obtain mutual fund data from the CRSP Survivorship Bias Free Mutual Fund Database and Thomson Financial CDA/Spectrum holdings database. The final sample used in our analyses includes 14,109 firm-year observations for 1,492 unique firms.

3.2. Research design

3.2.1. General framework

We explore the effect of board connectedness on managerial learning from stock prices using a Q-theory model of corporate investment as a general framework, which has been used extensively in the literature on financial feedback from financial markets (e.g. Chen et al., 2007; Foucault and Frésard 2014; Dessaint et al., 2016). Specifically, we estimate the following panel regression:

$$\begin{aligned} CAPX_{it+1} = \quad & \gamma_t + \delta_i + \beta_1 x Q_{it} + \beta_2 x CONNECT_{it+1} + \beta_3 x CONNECT_{it+1} x Q_{it} \\ & + \beta_4 CF_{it} + \beta_5 Ln(SALE_{it}) + \beta_6 FRET_{it} + \beta_7 SIZE_{it} + \beta_8 INV_{AT\,it} + \varepsilon_{it}, \end{aligned} \quad (1)$$

where $CAPX_{i,t+1}$ is defined as capital expenditures in year $t+1$ scaled by total assets at the end of year t (AT_{it}).[9] Q_{it} is (normalized) price and is measured as the market value of equity (price times shares outstanding from CRSP) plus book value of assets minus the book value of equity, scaled by book assets, all measured at the end of year t. γ_t, and δ_i represent year and firm fixed effects, respectively.

CONNECT is our measure of board connectedness and constructed using director level information from the BoardEx database. This database provides information on first-degree links for all directors in the BoardEx universe and includes connections through universities attended, current and previous employers, military service as well as civic institutions such as non-profit boards, charities, and clubs. We aggregate the number of connections of all directors on the board for each firm-year. To ensure that our results are not driven by firm characteristics that might affect both the extent of board connectedness and managerial learning from stock prices, following Akbas et al. (2016), we regress the natural logarithm of the total number of connections on the

[9] Our results are qualitatively similar when we use *CAPXRND*, defined as capital expenditures plus R&D expenses divided by *AT*, as our investment measure.

natural logarithm of board size, firm size, analyst following, institutional ownership, and firm age and use the residuals from this regression as our connectedness measure.[10]

To capture the well-known sensitivity of investment to cash flows, we include CF_{it}, calculated as net income before extraordinary items plus depreciation and amortization expenses plus R&D expenses, scaled by total assets. We also include $Ln(SALE_{it})$, defined as the natural logarithm of reported sales revenue in year t scaled by beginning of the year total assets. $FRET_{it}$ is value-weighted market adjusted three-year cumulative forward return. We include future returns because prior literature (e.g. Baker et al., 2003; Chen et al., 2007) suggests that firms invest more when their stocks are overvalued (i.e., when expected future returns are lower). $SIZE_{it}$ is measured as decile ranked market value of equity at the end of year t. Consistent with Chen et al. (2007), we control for INV_AT_{it}, defined as $1/AT_{it}$, since both the dependent variable (INV_{it+1}) and Q_{it} are scaled by assets at the end of year t, AT_{it}. All continuous variables are winsorized at the top and bottom 1% levels and standardized (except where the variable is on a logarithmic scale) to have mean zero and standard deviation of one in order to ease their interpretations.

3.2.2. Identifying noise in stock prices

Following Dessaint et al. (2016), we decompose the annual stock price (*Tobin's Q*) of each firm into a non-fundamental component (noise) and its orthogonal component using mutual fund redemptions as a shock to stock prices. Sales of stocks by mutual funds experiencing large outflows of capital create a negative price pressure on stocks liquidated by these funds (Coval and Stafford, 2007). Forced sales by mutual funds are primarily due to investor redemptions and are unlikely to reflect fund managers' private information about firm fundamentals; however, if fund managers choose to liquidate stocks for which they have negative information, forced sales might be

[10] Our inferences remain the same when we use the natural logarithm of total board connections as our connectedness measure.

correlated with fundamentals. Therefore, we follow Edmans et al. (2012) and Dessaint et al. (2016) and use mutual fund hypothetical, rather than actual, sales in a given year as our measure of observable (ex-post to the econometrician) non-fundamental shocks to prices.

This approach has two attractive features. First, a fundamental challenge that the managerial learning literature faces is that evidence of a positive association between investment and stock prices does not necessarily imply a causal relation and the presence of learning—a positive association can arise from managers and investors having correlated information channels or from reverse causality. However, as Dessaint et al. (2016) note, a positive association between investment and the noise component of stock prices offers strong evidence of managerial (mis)learning from stock prices as there is no obvious reason why this association should be different from zero. Second, this approach allows a direct examination of the effect of director networks on the faulty informant channel, i.e., how board connections affect managers' reliance on the noise component of stock prices when making investment decisions

We obtain information on fund returns, total net assets, and investment objectives from the CRSP Survivorship Bias Free Mutual Fund Database and stockholdings from the Thomson Financial CDA/Spectrum holdings database. We use open-end domestic equity mutual funds, for which the holdings data are most complete and reliable (Kacperczyk, Sialm, and Zheng, 2008) and eliminate funds that specialize in a single industry (Edmans et al., 2012). We then measure mutual fund hypothetical sales following the three-step procedure proposed by Edmans et al. (2012).[11]

Intuitively, for each stock i in year t, we measure mutual fund hypothetical sales, $MFHS_{it}$, as the annual sum of quarterly hypothetical stock sales due to large outflows experienced by all U.S. mutual funds holding stock i (i.e., larger than 5% of their assets) scaled by total quarterly

[11] See Appendix B for technical details on how $MFHS_{it}$ is calculated.

CRSP dollar trading volume on stock *i*. By construction, $MFHS_{it}$ takes only negative values and the smaller $MFHS_{it}$ is, the larger are hypothetical sales of stock *i* in year *t*.

To provide perspective on the effect of hypothetical mutual fund sales on stock prices, in Figure 1, we plot the cumulative average abnormal returns relative to CRSP equal-weighted index returns from four quarters before to six quarters after the event quarter. We define the event quarter as a firm-quarter in which *MFHS* falls below the 10[th] percentile of its sample distribution. The figure suggests that there is no significant decline in stock prices before the event quarter; however, starting with the event quarter, stock prices decline sharply and it takes around six calendar quarters for prices to revert to their pre-event levels.[12] Thus, mechanical mutual fund forced sales do not appear to be driven by firm fundamentals as they have a temporary effect on stock prices.

Following Dessaint et al. (2016), we decompose stock prices into a non-fundamental and its orthogonal component via the following model:

$$Q_{it} = \lambda_i + \delta_t + \phi MFHS_{it} + \upsilon_{it}, \tag{2}$$

where λ_i and δ_t are firm and year fixed effects, respectively. Coefficients from Equation (2) are not tabulated for brevity.[13] We refer to $MFHS_{it}$ as the non-fundamental (noise) component of price and the estimated residuals, $Q^*_{it} = \hat{\upsilon}_{it}$, as the orthogonal component. Finally, in order to examine the effect of board connectedness on the sensitivity of investment to the non-fundamental and orthogonal components, we estimate the following panel regression:

$$\begin{aligned} INV_{it+1} = \quad & \gamma_t + \delta_i + \beta_1 x MFHS_{i,t} + \beta_2 x Q^*_{i,t} + \ \beta_3 x CONNECT_{it+1} x MFHS_{it} \\ & +\beta_4 x CONNECT_{it+1} x Q^*_{i,t} + \beta_5 x CONNECT_{it+1} \\ & +\beta_6 CF_{it} + \beta_7 SALE_{it} + \beta_8 SIZE_{it} + \beta_9 RET_{it} + \beta_{10} INV\_AT_{it} + \varepsilon_{it+1}. \end{aligned} \tag{3}$$

[12] The duration over which stock prices recover after the shock is slightly shorter in our sample period than that in prior studies (about 6 quarters for our sample vs. 8 quarters in Edmans et al. (2012) and Dessaint et al. (2016)), which is likely driven by our BoardEx sample including larger firms on average.

[13] Consistent with Dessaint et al. (2016), we find that Q_{it} is significantly positively correlated with $MFHS_{it}$. For our sample period (2000-2012), ϕ is equal to 2.56 (*t*-statistic=6.5). For the 1996 to 2011 period, Dessaint et al. (2016) report a coefficient of 2.59 on peer firms' *MFHS* when they regress the equal weighted average of peer firms' *Q* on the average *MFHS* of peer firms. When we estimate the same regression with peer firms' *Q* and *MFHS*, the coefficient on peer firms' *MFHS* is 2.21.

Dessaint et al. (2016) report a significantly positive investment-to-noise sensitivity; therefore, we conjecture that if board connections enable managers to filter out the noise in stock prices, then the coefficient on $CONNECT_{it+1}xMFHS_{it}$ should be negative (i.e., $\beta_3 < 0$).[14]

3.2.3. Descriptive statistics

Table 1, Panel A reports summary statistics for the variables used in our empirical analyses. Summary statistics on the book value of assets, *AT*, and firm size, *SIZE*, suggest that our sample firms are on average large in comparison to those in the CRSP-COMPUSTAT universe, which is due to BoardEx including mainly large firms.

Summary statistics on *Q, CF, and CAPX* are comparable to those reported by Chen et al. (2007). The mean (median) number of connections aggregated at the board level is 3,856 (3,181) and exhibits substantial variation ranging from 726 connections at the 5th percentile to 9,343 connections at the 95th percentile. The average board in our sample includes 9 members (including executive and non-executive directors). Finally, peer firms have similar characteristics (*Q*, *CF*, and *SIZE*) on average to sample firms.

Panel B of Table 1 reports Pearson and Spearman correlations among the variables we use in our analyses. Correlations that are significant at the 1% level are in bold. *TOTAL BOARD CONNECTIONS* is significantly positively correlated with firm size, total assets, board size, analyst following, institutional ownership, and firm age. *CONNECT*, however, is by construction not correlated with any of these variables. Consistent with the prior literature, *CAPX* is positively correlated with Q_i and Q_{-i} as well as their non-fundamental and orthogonal components.

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[14] We do not provide formal hypotheses regarding how board connectedness affects the sensitivity of investment to the orthogonal component, $Q^*_{i,t}$, because, although it is a less noisy predictor of firm fundamentals than *Q* itself , the orthogonal component contains information already held by managers, predictive information not possessed by the manager, and additional noise not captured by *MFHS*.

4. Empirical Results

4.1. Main findings

Table 2, Panel A reports coefficient estimates for Equation (1). In column (1) we report the results when measures of board connectedness and their interactions with Q are not included in the regression. Consistent with prior literature, we find that investment is highly significantly associated with Q—a one standard deviation increase in Q_t is associated with roughly a 9% increase in $CAPX_{t+1}$.[15] $SALE_t$ and CF_t are also significantly positively associated with $CAPX_{t+1}$, as documented in Fazzari, Hubbard, and Petersen (1988) and Chen et al. (2007). Moreover, we find that the coefficient on *FRET* is significantly negative, consistent with the idea that firms over-invest when expected future returns are low (Loughran and Ritter, 1995; Baker and Wurgler, 2002; Baker et al., 2003; Chen et al., 2007).

In column (2) we examine whether the faulty information channel results of Dessaint e al. (2016) hold in our sample. Specifically, in column (2) we estimate the regression model of column (1) with Q decomposed into a noise component, *MFHS,* and its orthogonal component, Q^*. The faulty informant channel predicts a positive coefficient on *MFHS.* The results in column (2) confirm this prediction. Consistent with Dessaint et al. (2016) we find that investment responds significantly to both components, with the sensitivity of investment to Q^* twice as large as that to *MFHS*. The marginal effects of the two components are also comparable to those calculated by Dessaint et al. (2016) – one standard deviation increase in Q^* is associated with a 5.8% (0.00323/0.56) increase in investment while a one standard deviation decrease in $MFHS_t$ is associated with a 2.5% (0.0014/0.56) decrease in investment.

[15] All continuous variables are standardized to have a mean zero and variance one. From column (1), the coefficient on Q is 0.501, suggesting that a one standard deviation increase in Q is associated with a 0.005 increase in $CAPX_{t+1}$ (in the regression, $CAPX_{t+1}$ is multiplied by 100). This corresponds to an 8.95% (0.005/0.560) increase in $CAPX_{t+1}$, evaluated relative to the sample average of $CAPX_{t+1}$.

In columns (3)-(6), we examine the effect of connectedness on the sensitivity of investment to *Q*, Q^*, and *MFHS*. In columns (3) and (4) we use the continuous version of residual connectedness and in columns (5) and (6) we use the decile ranked residual connectedness. For completeness, we include the results from estimating the regression model of column (2) modified to include the interaction of the measure of board connectedness with *Q*. The coefficient on the interaction term *CONNECTxQ* is negative and significant at the 1% level in both columns. We then test our main hypothesis in columns (4) and (6) and examine whether the reduced investment sensitivity to *Q* is primarily driven by a reduced investment sensitivity to the noise component. Specifically, in columns (4) and (6), we interact *CONNECT* with both *MFHS* and Q^*. The coefficient on *CONNECTxMFHS* is significantly negative while the coefficient on $CONNECTxQ^*$ is insignificant in both columns.

The effect of board connectedness on the investment-to-noise sensitivity is economically significant—for a one standard deviation drop in the non-fundamental component of the firm's stock prices, the investment cut goes from 4.6% for firms in the lowest decile of board connectedness to 0.05% for firms in the highest decile of board connectedness. These results are consistent with our main hypothesis: board connections provide managers with information that enables them to better understand the triggers of stock price fluctuations and filter out noise from stock prices, thereby facilitate a more effective use of stock prices as an information signal about firm fundamentals.

4.2. Alternative explanation: financing channel

As noted by Dessaint et al. (2016), a potential concern about drawing inferences from the sensitivity of a firm's investment to the noise component of its own stock prices is that this sensitivity may be driven by non-fundamental shocks affecting the firm's cost of capital (Fisher and Merton, 1984; Baker et al., 2003). Moreover, well-connected firms have been shown to have easier access to external capital and enjoy lower cost of financing (Engelberg et al., 2012; Chuluun et al., 2014), which may reduce the effect of negative non-fundamental shocks on firm investment.

We perform three additional analyses to rule out the above financing cost explanation. First, we examine the effect of board connectedness on the sensitivity of investment to the noise in peer firms' stock prices because non-fundamental shocks to peers' stock prices are less likely to have a direct effect on the firm's cost of financing. Hence, firm investment is less likely to respond to the noise in peers' stock prices for reasons other than managerial learning. Second, we directly test whether the non-fundamental component of a firm's stock prices is inversely related to firm-level measures cost of capital. Third, we repeat our main analysis controlling for measures of cost of capital. We discuss these analyses in the following two subsections.

4.2.1. Board connectedness and investment sensitivity to noise in peer firms' stock prices

To examine the effect of board connectedness on the sensitivity of investment to the noise in peer firms' stock prices, we estimate the following panel regression:

$$\begin{aligned} INV_{it+1} = {} & \gamma_t + \delta_i + \beta_1 xMFHS_{i,t} + \beta_2 xMFHS_{-i,t} + \beta_3 xQ^*_{i,t} + \beta_4 xQ^*_{-i,t} \\ & + \beta_5 xCONNECT_{it+1} xMFHS_{i,t} + \beta_6 xCONNECT_{it+1} xMFHS_{-it} \\ & + \beta_7 xCONNECT_{it+1} xQ^*_{i,t} + \beta_8 xCONNECT_{it+1} xQ^*_{-i,t} + \beta_9 xCONNECT_{it+1} \\ & + \beta_{10} CF_{it} + \beta_{11} SALE_{it} + \beta_{12} RET_{it} + \beta_{13} SIZE_{it} + \beta_{14} INV\_AT_{it} \\ & + \beta_{15} CF_{-it} + \beta_{16} SIZE_{-it} + \varepsilon_{it+1}, \end{aligned} \quad (4)$$

where subscript *i* denotes the focal firm and -*i* denotes the median firm across the portfolio of product market peers.[16] We follow the approach delineated in Section 3.2.2 to decompose peer firm's stock prices into a noise component and its orthogonal component. Following Foucault and Frésard (2014), we determine peer firms for a given firm-year using the Text-based Network Industry Classification (TNIC) developed by Hoberg and Phillips (2016), wherein firms are

[16] We find similar results when we use the equally weighted mean across the portfolio of product market peers.

matched to peers in each year based on product similarities computed from product descriptions reported in their 10-Ks. γ_t and δ_i represent year and firm fixed effects, respectively. Focal firm controls include *CF, SALE, FRET, SIZE,* and *INV_AT*. Consistent with Dessaint et al. (2016), we also control for peer firm's cash flows (CF_{-it}) and size ($SIZE_{-it}$).

Table 3 reports the results from estimating Equation (4). In column (1), we estimate a version of Equation (4), where Q_i and Q_{-i} are both included in their raw form (i.e., before decomposition). We conduct this test to verify that Foucault and Frésard's (2014) result that firm i's investment responds both to its own stock prices as well as its peers' stock prices holds in our sample. The results suggest that this is indeed the case: the coefficients on both Q_i and Q_{-i} are significantly positive and the coefficient on Q_i is more than twice as large as that on Q_{-i}.

In column (2), we decompose both Q_i and Q_{-i} into their noise and orthogonal components and include them in the regression simultaneously. Consistent with Dessaint et al. (2016), firm investment responds significantly to the noise components of its own prices as well as those of its peers. In particular, even after controlling for the noise and orthogonal components of stock prices for both the focal firm and its peers as well as other known determinants of investment, investment decreases significantly in response to transient shocks to peer firms' stock prices induced by mutual fund redemptions.

For completeness, in columns (3) and (5) we interact board connectedness with both Q_i and Q_{-i}. The coefficients on both interaction terms are negative and significant, which is consistent with the results in columns (3) and (5) in Table 2. In columns (4) and (6), Table 3, we interact residual connectedness with the noise and orthogonal components of both the focal firm's and peer firms' prices. The coefficients on $CONNECTxMFHS_i$ and $CONNECTxMFHS_{-i}$ are both negative and statistically significant while the coefficients on both $CONNECTxQ_i$ and $CONNECTxQ_{-i}$ are insignificant. In columns (5) and (6), we find a similar pattern when we use decile ranked residual connectedness. These results suggest that board connections provide managers with information that enables them to better understand the causes of stock price fluctuations and filter out noise from stock prices.[17]

4.2.2. Non-fundamental shocks to stock prices and cost of capital

In this subsection we examine whether non-fundamental shocks to stock prices are negatively associated with measures of cost of capital and financing constraints. Dessaint et al. (2016) show that the sensitivity of a firm's cost of financing to the non-fundamental component of its peers' stock prices is either insignificant or significantly positive; however, these results may not extend to the non-fundamental shocks to a firm's own stock prices. Since we focus on the sensitivity of investment to a firm's own stock prices in our context, we first explore the association between various firm-level measures of cost of capital and financing constraints and non-fundamental shocks stemming from mutual fund redemptions to ensure that our results are not driven by the financing channel. We estimate the following panel regression:

$$\begin{aligned} COC_{it} = \quad & \gamma_t + \delta_i + \beta_1 xMFHS_{i,t} + \beta_2 xQ^*_{i,t} + \beta_3 CF_{it} + \beta_4 Ln(SALE_{it}) \\ & + \beta_5 SIZE_{it} + \beta_6 RET_{it} + \beta_7 INV\_AT_{it} + \varepsilon_{it}, \end{aligned} \tag{5}$$

where COC_{it} denotes measures of cost of capital and financing constraints. We use two sets of *COC* measures – one related to debt financing and the other related to equity financing. For debt financing, we use 1) *Debt Spread*, defined as the firm-level all-in-drawn spread on new debt issues, obtained from Dealscan, as a proxy for the cost of debt,[18] and 2) *Debt Constr.*, a textual-based

[17] For brevity, in subsequent sections of the paper, we report results using only the decile ranked residual connectedness. Our results are qualitatively similar when we use the continuous version of residual connectedness.

[18] If a firm has more than one new loan facility in a year, we compute the firm-level all-in-drawn spread as the weighted-average of loan facility spreads, with weights equal to the loan amounts.

measure from Hoberg and Maksimovic (2015), to capture the degree of debt-market constraints.[19] For equity financing, we use 1) *Cost of Equity*, the implied cost of equity measure developed by Gebhardt, Lee, and Swaminathan (2001), computed using the cross-sectional earnings prediction model of Hou, Van Dijk, and Zhang (2012), as a proxy for the ex-ante cost of equity,[20] and 2) *Equity Constr.*, a textual-based measure from Hoberg and Maksimovic (2015), to capture the degree of equity-market constraints. γ_t and δ_i denote year and firm fixed effects, respectively. The financing cost argument predicts a negative coefficient on *MFHS (i.e.,* $\beta_1 < 0$ *).*

The results from estimating Equation (5) are reported in Panel A of Table 4. *MFHS* has an insignificant coefficient for all measures of cost of capital or financing constraints. This suggests that a firm's cost of capital and financing constraints are insensitive to the non-fundamental shock to its own stock prices, which is inconsistent with the financing cost argument.[21]

Lastly, to directly examine whether our main findings are driven by the financing cost channel, in Panel B of Table 4, we estimate Equation (3) controlling for measures of debt and equity financing costs. In columns (1) and (2), we control for debt financing costs and equity financing costs, respectively, and in column (3) we control for both. We continue to find a significantly negative coefficient on *CONNECTxMFHS* in all three specifications and the coefficient on *CONNECTxQ** remains insignificant, suggesting that our findings in Table 2 are unlikely driven by the financing cost channel.

[19] *Debt Constr.* and *Equity Constr.* are constructed using textual analysis of the Management's Discussion and Analysis (MD&A) section of firms' annual reports. Conceptually, firms with higher scores on *Debt Constr.* (*Equity Constr.*) are at higher risk of delaying their investments due to liquidity issues and are more likely to issue debt (equity). We thank Jerry Hoberg and Max Maksimovic for sharing their data online.

[20] We follow Hou et al. (2012) and Green, Jame, Markov, and Subasi (2014) in computing the implied cost of equity measure.

[21] To examine whether the effect of non-fundamental shocks on firms' financing costs increases with board connectedness, we modify these regressions by including *CONNECT* and its corresponding interactions with *MFHS* and *Q**. In untabulated results we find an insignificant coefficient on *CONNECT*MFHS*.

4.3. Alternative explanation: managerial entrenchment

Well-connected directors are highly sought after, serve on multiple boards, and tend to be busy, which reduces their effectiveness as advisors or monitors (Fich and Shivdasani, 2006; Stein and Zhao, 2016; Ferris et al. 2017). Ineffective board monitoring may, in turn, lead to higher managerial entrenchment. Hence, well-connected firms may face greater agency problems, producing "lazy" or entrenched managers, who are more likely to ignore valuable information channels, including stock prices, in their investment decisions. Thus, the lower sensitivity of investment to the noise in stock prices may simply be a manifestation of managers ignoring stock prices in their investment decisions when their boards members are more connected.

We first note that according to the entrenched manager argument, board connections should reduce the sensitivity of investment to both the noise in stock prices and its orthogonal component. That is, managers of firms with well-connected boards would ignore stock prices altogether including the noise and its orthogonal component. However, in line with an informed manager argument, we find that board connections only affect the sensitivity of investment to the noise component, suggesting that our findings cannot be explained by this alternative argument.

Second, we explicitly address the issue of whether our results are driven by the managerial entrenchment argument using the *G-Index* from Gompers et al. (2003) and the *E-Index* from Bebchuk et al. (2009) to proxy for the strength of corporate governance and the degree of managerial entrenchment, respectively. Lower values of these two indices imply stronger corporate governance and lower managerial entrenchment. The correlations between board connectedness and the *G-Index* and *E-Index* are small (Pearson correlations: 0.03 and 0.06, respectively) suggesting that our results are unlikely to be driven by highly connected firms having weaker corporate governance or higher managerial entrenchment. Nevertheless, we estimate

Equation (3) by partitioning our sample based on *G-Index* and *E-Index* and examine the effect of board connectedness on the investment-to-noise sensitivity within each subsample.

Table 5 reports the results. Columns (1) and (2) report the results when the sample is partitioned into two groups based on the median *G-Index* while Columns (3) and (4) report the results when the sample is partitioned into two groups based on the median *E-Index*.[22] The results in Table 5 suggest that the negative relation between board connectedness and the investment-to-noise sensitivity that we documented above is driven by firms with stronger corporate governance (Low *G-Index*) or lower managerial entrenchment (Low *E-Index*). This finding provides further support to our conjecture that connected boards help managers filter out the noise from stock prices since firms with better governance and low managerial entrenchment are more likely to have an environment where managers listen to their board members.

5. Additional Analyses: Types of Connections

The results we have reported thus far are consistent with director connections helping managers filter out the noise from stock prices and facilitating more effective managerial learning from financial markets. By construction, our measure of board connectedness includes all types of connections between directors formed through current and previous employers, educational institutions attended, military service, as well as civic services like non-profit boards and club memberships and may be too broad for the specific channel that we are hypothesizing. In order to gain additional insight into the types of connections that facilitate better managerial learning from stock prices, in this section we explore the effect of three types of connections on the effectiveness

[22] Both *G-Index* and *E-index* assume integer values such that the former varies between 2 and 17 and the latter between 0 and 6. While it is possible to partition our sample mechanically into terciles with comparable numbers of observations based on the *G-Index*, this is not possible with the *E-index* due to the span of the data. In particular, forcing the sample into terciles based on the *E-index* would result in a skewed and uneven sample size. Therefore, we partition the sample into two instead of three subsamples based on the median value of the *E-Index*, which yields two groups with comparable numbers of observations.

with which board connectedness helps managers filter out noise from prices: industry connections, executive director connections, and business connections (i.e., connections formed through prior shared work experience).

5.1.Industry connections

Connections to directors serving on the boards of firms in the same industry likely provide more information for understanding the causes of price movements within that industry. We therefore conjecture that industry connections enable boards to better interpret information accessed through director networks. Thus, when a firm has more connections from the same industry, the effect of overall board connectedness on helping managers filter out the noise from stock prices should be more pronounced. To test this conjecture, we partition our sample into two groups based on the median *Industry Connections*. We calculate the number of industry connections as follows: if two directors who serve in the same year on the boards of two firms that are in the same Hoberg–Philips industry have overlapped with each other in the past (university, private/public firm, military etc.), we count that connection as one in the industry connectedness measure. Compared to the aggregate board connections that has an average of 3,856, the average number of industry connections is small with a mean of 15.[23]

Columns (1) and (2) in Table 6 report results from Equation (3) estimated within each group of *Industry Connections.* The coefficient on *CONNECTxMFHS* is negative and (marginally) significant (coeff=-0.370, *t*-stat=-1.92) for high *Industry Connections* and not different from zero for low *Industry Connections*. Moreover, the coefficients on *CONNECTxMFHS* are significantly different across the *Low* and *High* groups at the 10% level. These results are consistent with

[23] The number of industry connections is small because for any given firm *i* in year *t*, it counts only firm *i*'s Hoberg-Philips industry peers where at least one director on firm *i's* board is connected to any director on the industry peer's board.

industry connections increasing the effectiveness of board connectedness at helping managers filter out the noise from stock prices.

5.2. Executive director connections

The average board in our sample has nine board members, two of whom are classified by BoardEx as executive and the other seven non-executive. Since executive directors ultimately make the investment decisions, their connections could matter more than those of non-executive directors in filtering out the noise from stock prices. To explore whether this is the case, we estimate Equation (3) separately for the subsample with *Executive Connections* above and below the sample median.

Columns (3) and (4) in Table (6) report the results. The coefficient on *CONNECTxMFHS* is significantly negative (-0.56, *t*-stat=-3.82) for the *High* Executive Connections subsample and is not different from zero for the *Low* Executive Connections subsample. Further, the coefficients on *CONNECTxMFHS* is significantly different across the two subsamples. Overall, the results imply that boards are more effective in curbing managerial mislearning from stock prices when executive directors, who ultimately make the investment decisions, are more connected compared to non-executive directors.

5.3. Business connections

The information shared across boardroom networks likely depends on the environment where these networks were formed. Connections formed while working at the same private or public firm may weigh more than those formed at universities, military, social organizations and government in improving managerial learning from stock prices. For example, directors connected through employment in public firms are arguably more likely to share experiences about secondary markets than directors connected through social organizations. In order to explore whether connections formed through shared work experience improve managerial learning from stock prices more than other types of connections, we estimate Equation (3) separately for the subsample with *Business Connections*—the total number of board connections formed during past concurrent employment at a private or public firm—above and below the sample median.

The results are reported in Columns (5) and (6) of Table 6. The coefficient on *CONNECTxMFHS* is (marginally) significantly negative for both groups of *Business Connections* and the coefficients on *CONNECTxMFHS* are not statistically different from each other across the two groups. Thus, business connections formed through shared past employment do not appear to have an effect incremental to other connections (e.g., social, educational, military etc.) in curbing managerial reliance on noise in stock prices.

6. Conclusion

Recent research finds that managers use the information contained in stock prices when making investment decisions, suggesting that financial markets have a feedback effect on the real economy. However, while stock prices aggregate information from a diverse set of traders and speculators, they may contain noise and, therefore, provide faulty signals to managers. It is through this faulty informant channel—managers using faulty signals in prices in their investment—that non-fundamental shocks to stock prices can have detrimental real effects (Morck et al., 1990; Dessaint et al., 2016). In this paper, we examine whether a specific information channel, director networks, can help managers filter out the noise in prices and, thereby, facilitate more effective learning from financial markets.

We find that the sensitivity of investment to the noise component of stock prices, either the firm's own or its peers' stock prices, is significantly lower for well-connected firms. This effect is more pronounced for firms with stronger corporate governance and less entrenched managers, suggesting that the information transmitted through board connections improves managerial learning from financial markets the most when firms have a governance structure that is conducive to learning and when managers are more likely to listen to their boards of directors. We further show that director connections are not homogenous—connections that come with stronger industry knowledge and connections that are "closer" to top management are more effective in preventing managers from relying on the faulty signals from stock prices in their investment decisions. These findings provide a first step towards improving our understanding of board and director network characteristics that are conducive to more efficient learning from financial markets.

Our results add to the growing literature on the feedback effects of financial markets by identifying an important information channel through which managers can learn to unlearn from the faulty signals in prices. Dessaint et al. (2016) are the first to provide empirical evidence on the faulty informant hypothesis originally proposed by Morck et al. (1990) as a channel through which non-fundamental shocks could influence the real economy. Their study offers an intriguing view—non-fundamental shocks to a firm's stock prices can affect both its own investment as well as that of its peers, and these effects may feedback on the stock prices of these firms, amplifying the real effects of the initial shocks. In this vein, non-fundamental shocks at the micro level can ripple through the economy via the faulty informant channel and have significant real effects at the aggregate level. Our study identifies a specific channel that can mitigate mislearning from faulty signals in stock prices and hence curb this ripple effect.

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Appendix A: Variable Definitions

Variable	Definition
CONNECT	Residuals from regressing the natural logarithm of total board connections on the natural logarithm of firm size, board size, firm age, analyst following, and institutional ownership with firm and year fixed effects.
CAPX	Capital expenditures scaled by beginning-of-year assets.
Q	The market value of equity plus book value of assets minus book value of equity, scaled by book value of assets.
MFHS	Mutual fund hypothetical stock sales due to large outflows (i.e., larger than 5% of their assets) experienced by U.S. mutual funds holding the stock (See Appendix B for details on how *MFHS* was constructed).
Q^*	The residual obtained from regressing *Q* on *MFHS* with firm and year fixed effects.
CF	Net income before extraordinary items plus depreciation and amortization expenses plus R&D expenses, total assets at the beginning of the year.
SALE	Total sale revenue scaled by total assets at the beginning of the year.
FRET	The value-weighted market-adjusted three-year cumulative forward return.
SIZE	Market value of equity, price times shares outstanding from CRSP, decile ranked and adjusted to have values between 0 and 1
INV_AT	Inverse of total assets, *1/AT*.
ANAFOLLOW	Number of analysts covering the firm (Source: I/B/E/S).
FIRMAGE	Total number of years since the firm's initial public offering date.
IO	Sum of the holdings of all 13f institutions for each stock in each calendar quarter, averaged over the year, divided by the number of shares outstanding obtained from CRSP.

Continued on the next page.

Appendix A Cont'd.

Variable	**Definition**
Debt Spread	Firm-level all-in-drawn spread on new debt issues, from Dealscan.
Debt Constr.	Score of debt-market constraints from Hoberg and Maksimovic (2015), constructed using textual analysis of the Management's Discussion and Analysis (MD&A) section of firms' annual reports.
Cost of Equity	Implied cost of equity, developed by Gebhardt et al. (2001), computed using cross-sectional earnings prediction model of Hou et al. (2012).
Equity Constr.	Score of equity-market constraints from Hoberg and Maksimovic (2015), constructed using textual analysis of the Management's Discussion and Analysis (MD&A) section of firms' annual reports.
G-Index	A summary measure of corporate governance based on 24 firm-specific provisions, developed by Gompers et al. (2003).
E-Index	A summary measure of managerial entrenchment based on 6 firm-specific provisions, developed by Bebchuk et al. (2009).
Industry Connections	The number of connections with directors who currently serve on boards of other firms in the same industry, based on the Text-Based Network Industry Classification (TNIC) developed by Hoberg and Phillips (2016).
Executive Connections	The number of connections by executive members of the board.
Business Connections	The number of connections formed through prior employment at a private or public firm.

Appendix B: Mutual Fund Hypothetical Sales (MFHS)

In this appendix, we provide details on how $MFHS_{i,t}$, mutual fund hypothetical sales for each stock *i* in year *t*, is constructed. We follow the three-step procedure proposed by Edmans et al. (2012) and subsequently used by Dessaint et al. (2016).

Step 1: Quarterly mutual fund flows

For each domestic equity mutual fund in the CRSP mutual funds database that is not concentrated in a particular industry, we obtain monthly Total Net Assets (*TNA*) and net returns (including dividends and capital gains and excluding expenses) for each share class in the fund's portfolio. We first calculate the total raw return for each share class in the fund's portfolio by adding back the expense rate to the net return in that share class. We then calculate the monthly weighted average fund return, $Return_{f,m,t}$, which is the return of all share classes in the fund's portfolio, weighted by each share class's beginning of the month *TNA*. Next, for each fund *f* in quarter *q* of year *t*, we calculate the quarterly fund returns, $Return_{f,q,t}$, by compounding the monthly weighted fund returns in quarter *q*. Finally, we calculate the net flow experienced by fund *f*, in quarter *q* of year *t* as:

$$Flow_{f,q,t} = \frac{TNA_{f,q,t} - TNA_{f,q-1,t} x(1+Return_{f,q,t})}{TNA_{f,q-1,t}},$$

where $TNA_{f,q,t}$ denotes total net assets (across all share classes) held by mutual fund *f* at the end of quarter *q* of year *t*.

Step 2: Dollar value of firm-level quarter-end mutual fund holdings

Using quarterly mutual fund holdings data from the CDA Spectrum/Thomson database, we calculate the dollar value of stock *i* shares held by mutual fund *f* at the end of quarter *q* as:

$$SHARES_{i,f,q,t} x PRC_{i,q,t},$$

where $SHARES_{i,f,q,t}$ denotes the number of shares of stock *i* held by mutual fund *f* at the end of quarter *q* of year *t;* and, $PRC_{i,q,t}$ denotes the price per share of stock *i* at the end of quarter *q*.

Step 3: Mutual fund hypothetical sales ($MFHS_{i,t}$)

For all mutual funds where $Flow_{f,q,t} \leq -0.05$, we first calculate the dollar value of mutual fund hypothetical sales in stock *i* in quarter *q* of year *t* as follows:

$$MFHS_{i,q,t}^{dollar} = \sum_f (Flow_{f,q,t}\ x\ SHARES_{i,f,q-1,t} x PRC_{i,q-1,t}).$$

$MFHS_{i,q,t}^{dollar}$ is the total dollar value of hypothetical sales in stock *i* in quarter *q* of year *t* across all mutual funds experiencing an outflow larger than or equal to 5% of total net assets. The price impact of mutual fund outflows depends on stock liquidity. Therefore, we divide $MFHS_{i,q,t}^{dollar}$ by the total CRSP dollar volume of trading in stock *i* in quarter *q* of year *t*. Taking the sum across the four quarters of year *t*, $MFHS_{i,t}$ is calculated as:

$$MFHS_{i,t} = \sum_{q=1}^{q=4} \frac{\sum_f \left(Flow_{f,q,t} x SHARES_{f,i,q,t} x PRC_{i,q,t}\right)}{VOL_{i,q,t}}$$

Figure 1. The Effect of Hypothetical Mutual Fund Sales on Stock Returns

This figure plots quarterly cumulative average abnormal returns relative to CRSP equal-weighted index returns (*CAAR*) for stocks around calendar quarters in which *MFHS* falls below the 10^{th} percentile of its sample distribution.

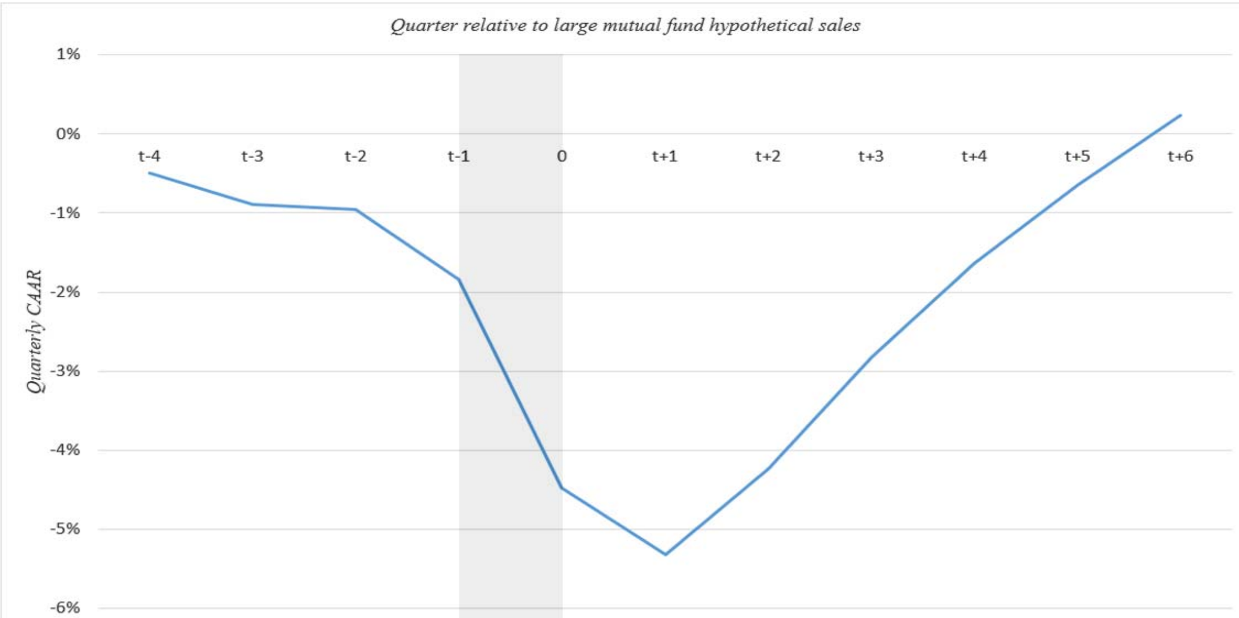

Table 1: Descriptive statistics

This table presents descriptive statistics on the variables used in the analyses. The main sample includes 1,492 unique firms and 14,109 firm-year observations between 2000 and 2012. Corporate governance metrics are available for 11,052 firm-year observations. Panel A presents the summary statistics and Panel B presents the Pearson correlations. In Panel B correlations in bold are significant at the 1% level. Peers are determined using TNIC industries developed by Hoberg and Phillips (2016). Variable definitions are provided in Appendix A.

Panel A: Summary statistics

	N	**Mean**	**Std.Dev**	**5th Pctl**	**25th Pctl**	**Median**	**75th Pctl**	**95th Pctl**
Firm Characteristics								
CAPX	14,109	0.056	0.057	0.007	0.020	0.038	0.069	0.178
Q	14,109	1.834	1.003	0.954	1.245	1.529	2.015	3.902
MFHS	14,109	-0.019	0.018	-0.053	-0.023	-0.014	-0.009	-0.002
SIZE ($MIL)	14,109	4,465	9,389	141	525	1,341	3,750	19,090
AT ($MIL)	14,109	4,572	8,722	156	547	1,440	3,984	21,946
SALE ($MIL)	14,109	1.200	0.833	0.288	0.621	1.004	1.517	2.931
CF	14,109	0.129	0.111	-0.024	0.068	0.116	0.181	0.328
FRET	14,109	0.201	0.886	-0.849	-0.324	0.048	0.483	1.770
FIRMAGE(Years)	14,109	24	19.098	4	10	17	35	68
ANAFOLLOW	14,109	6	5.310	0	2	5	9	16
IO(%)	14,109	66.96	30.20	0.00	54.16	76.32	89.49	100
Peer Firm Characteristics								
Q_{-i}	14,109	1.602	0.521	1.055	1.247	1.462	1.789	2.810
$MFHS_{-i}$	14,109	-0.013	0.009	-0.030	-0.017	-0.011	-0.006	-0.002
$SIZE_{-i}$	14,109	1,023	1,209	113	315	620	1,236	3,190
CF_{-i}	14,109	0.104	0.056	0.009	0.071	0.105	0.134	0.200
Board Characteristics								
Total Board Connections	14,109	3,856	2,801	726	1,858	3,181	5,118	9,343
Board Size	14,109	9	2.329	6	7	9	11	13
CONNECT	14,109	0.000	0.595	-1.063	-0.323	0.081	0.396	0.832
G-Index	11,052	9	2.605	5	7	9	11	13
E-Index	11,052	2	1.260	0	1	2	3	4
Business Connections	14,109	2,347	1,897	311	989	1,891	3,145	5,946
Executive Connections	14,064	1,468	1,541	77	435	1,003	1,961	4,431
Industry Connections	14,109	15	22	0	1	6	19	60

Table 1 Cont'd.

Panel B: Pearson (below the diagonal) and Spearman (above the diagonal) correlations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(8)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(1) CONNECT		**-0.21**	0.02	-0.02	**0.16**	**-0.12**	-0.02	**-0.06**	**-0.04**	**-0.03**	**-0.02**	0.01	**-0.02**	0.02	0.02	**0.05**	**0.68**	**-0.03**
(2) CAPX	**-0.21**		**0.14**	**0.07**	**-0.13**	**0.11**	**0.30**	**0.15**	**0.03**	**0.17**	**0.10**	**0.03**	**0.19**	**-0.03**	**0.05**	**0.05**	**-0.05**	**0.10**
(3) Q_i	0.02	**0.11**		**0.06**	**0.03**	**0.06**	**0.56**	**0.10**	**-0.06**	**0.23**	**-0.15**	**-0.14**	**0.22**	**0.08**	**-0.06**	**-0.06**	**0.03**	**-0.11**
(4) MFHS	0.01	**0.08**	**0.08**		-0.01	**0.14**	0.01	-0.01	**-0.05**	-0.00	0.01	**-0.09**	**0.13**	**-0.17**	**-0.03**	**-0.03**	**-0.03**	-0.02
(5) Q_{-i}	**0.13**	**-0.10**	-0.00	0.01		**0.16**	**0.13**	**-0.13**	**-0.11**	**-0.03**	**-0.16**	**-0.12**	-0.01	**0.07**	**-0.03**	**0.03**	**0.04**	**-0.12**
(6) $MFHS_{-i}$	**-0.10**	**0.15**	**0.09**	**0.09**	**0.19**		**0.11**	**-0.10**	-0.01	**-0.08**	**-0.17**	**-0.23**	**0.07**	**-0.15**	**-0.08**	**-0.03**	**-0.19**	**-0.15**
(7) CF	**-0.03**	**0.27**	**0.44**	**0.05**	**0.11**	**0.11**		**0.24**	0.01	**0.23**	**-0.13**	**-0.07**	**0.19**	**0.12**	**-0.06**	**-0.04**	0.00	**-0.11**
(8) SALE	**-0.09**	**0.06**	**0.06**	0.00	**-0.17**	**-0.06**	**0.15**		**0.07**	**-0.08**	**-0.14**	**-0.04**	**-0.06**	**0.06**	0.02	-0.00	**-0.09**	-0.01
(9) FRET	**-0.04**	0.01	**-0.08**	-0.02	**-0.07**	**0.02**	**-0.03**	**0.07**		-0.02	**0.04**	**0.03**	**-0.07**	**-0.04**	**0.07**	**0.06**	-0.01	**0.06**
(10) SIZE	-0.00	**0.11**	**0.19**	**0.09**	**-0.03**	**-0.05**	**0.23**	**-0.06**	**-0.15**		**0.81**	**0.32**	**0.52**	**0.16**	**0.15**	**0.03**	**0.54**	**0.47**
(11) AT	0.00	**0.04**	**-0.17**	**0.07**	**-0.19**	**-0.13**	**-0.10**	**-0.11**	**-0.05**	**0.82**		**0.41**	**0.38**	**0.08**	**0.19**	**0.05**	**0.56**	**0.60**
(12) FIRMAGE	-0.00	**-0.04**	**-0.12**	**-0.06**	**-0.13**	**-0.21**	**-0.07**	**-0.06**	**-0.05**	**0.31**	**0.40**		-0.01	-0.01	**0.32**	**0.10**	**0.27**	**0.39**
(13) ANAFOLLOW	0.00	**0.18**	**0.19**	**0.17**	-0.01	**0.10**	**0.17**	**-0.03**	**-0.09**	**0.47**	**0.34**	-0.02		**0.17**	-0.01	-0.02	**0.29**	**0.15**
(14) IO	0.00	0.01	**0.05**	**-0.09**	0.00	**-0.12**	**0.11**	0.01	**-0.06**	**0.18**	**0.10**	**0.08**	**0.15**		-0.02	**0.07**	**0.14**	**-0.05**
(15) G-Index	**0.04**	-0.00	**-0.08**	0.00	**-0.03**	**-0.07**	**-0.07**	0.01	**0.03**	**0.13**	**0.17**	**0.31**	-0.00	**0.03**		**0.71**	**0.19**	**0.29**
(16) E-Index	**0.06**	**0.03**	**-0.09**	-0.00	**0.03**	-0.02	**-0.06**	-0.01	**0.04**	-0.00	0.02	**0.09**	-0.00	**0.08**	**0.72**		**0.12**	**0.15**
(17) Total Conn.	**0.75**	**-0.11**	0.01	**0.05**	**0.03**	**-0.15**	-0.00	**-0.10**	**-0.08**	**0.54**	**0.55**	**0.24**	**0.27**	**0.16**	**0.19**	**0.12**		**0.58**
(18) Board Size	-0.00	0.01	**-0.12**	0.02	**-0.12**	**-0.13**	**-0.10**	-0.02	-0.01	**0.48**	**0.60**	**0.37**	**0.13**	0.01	**0.28**	**0.15**	**0.58**	

Table 2: Board connectedness and sensitivity of investment to noise in stock prices

This table reports coefficient estimates from Equation (3). The dependent variable is the investment of firm *i* in year *t+1*, defined as capital expenditures (*CAPX*) divided by beginning of the year assets. *CONNECT* is residual from regressing the natural logarithm of total board connections on the natural logarithm of firm size, board size, firm age, analyst following, and institutional ownership with firm and year fixes effects. $MFHS_{it}$, is the annual sum of quarterly hypothetical stock sales due to large outflows experienced by all U.S. mutual funds holding stock *i* (i.e., larger than 5% of their assets) scaled by total quarterly CRSP dollar trading volume on stock *i*. Q^* is defined as the residual obtained from regressing Q_t on $MFHS_t$ with firm and year fixed effects. All other variables are defined in Appendix A. The sample includes 1,492 unique firms and 14,109 firm-year observations between 2000 and 2012. The *t*-statistics, reported in parentheses, are based on robust standard errors clustered by firm. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable:			*CAPX*			
			Continuous CONNECT		*Decile Ranked CONNECT*	
	(1)	(2)	(3)	(4)	(5)	(6)
Q	0.501***		0.496***		0.810***	
	(7.46)		(7.38)		(6.20)	
MFHS		0.140***		0.133***		0.289***
		(3.67)		(3.48)		(4.15)
Q^*		0.323***		0.320***		0.361***
		(7.32)		(7.31)		(3.89)
CONNECTxQ			-0.165***		-0.565***	
			(-3.14)		(-2.89)	
CONNECTxMFHS				-0.075***		-0.286***
				(-2.65)		(-2.78)
CONNECTxQ^*				-0.032		-0.075
				(-0.83)		(-0.52)
CONNECT			-0.097	-0.099	-0.562*	-0.574*
			(-0.98)	(-0.99)	(-1.78)	(-1.81)
CF	0.507***	0.504***	0.506***	0.499***	0.501***	0.495***
	(5.78)	(5.74)	(5.69)	(5.65)	(5.67)	(5.63)
SALE	1.726***	1.732***	1.718***	1.728***	1.720***	1.731***
	(10.14)	(10.17)	(10.04)	(10.11)	(10.04)	(10.12)
FRET	-0.249***	-0.244***	-0.242***	-0.238***	-0.237***	-0.234***
	(-5.32)	(-5.20)	(-5.20)	(-5.10)	(-5.11)	(-5.01)
SIZE	0.543***	0.546***	0.535***	0.530***	0.527***	0.519***
	(4.05)	(4.07)	(3.97)	(3.94)	(3.93)	(3.89)
INV_AT	-0.117	-0.113	-0.105	-0.104	-0.102	-0.102
	(-1.37)	(-1.32)	(-1.22)	(-1.21)	(-1.18)	(-1.18)
Intercept	7.820***	7.614***	7.793***	7.549***	8.073***	7.836***
	(46.71)	(44.47)	(43.66)	(41.44)	(39.12)	(37.39)
Observations	14,109	14,109	14,109	14,109	14,109	14,109
Adjusted R^2	69.16%	69.19%	69.22%	69.21%	69.23%	69.22%

Table 3: Board connectedness and sensitivity of investment to noise in peers' stock prices

This table reports coefficient estimates from Equation (3) modified to include the noise in the median peer firm's stock prices ($MFHS_{-i}$) and its orthogonal component (Q_{-i}). The dependent variable is the investment of firm *i* in year *t+1*, defined as capital expenditures (*CAPX*) divided by beginning of the year assets. *CONNECT* is the residual from regressing the natural logarithm of total board connections on the natural logarithm of firm size, board size, firm age, analyst following, and institutional ownership with firm and year fixes effects. $MFHS_{it}$, is the annual sum of quarterly hypothetical stock sales due to large outflows experienced by all U.S. mutual funds holding stock *i* (i.e., larger than 5% of their assets) scaled by total quarterly CRSP dollar trading volume on stock *i*. Q^* is defined as the residual obtained from regressing Q_t on $MFHS_t$ with firm and year fixed effects. All other variables are defined in Appendix A. The sample includes 1,492 unique firms and 14,109 firm-year observations between 2000 and 2012. The *t*-statistics, reported in parentheses, are based on robust standard errors clustered by firm. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable:			*CAPX*			
			Continuous CONNECT		*Decile Ranked CONNECT*	
	(1)	(2)	(3)	(4)	(5)	(6)
Q_i	0.569***		0.557***		0.912***	
	(8.34)		(8.12)		(6.94)	
Q_{-i}	0.206***		0.197***		0.470***	
	(3.18)		(3.02)		(3.92)	
$MFHS_i$		0.141***		0.135***		0.294***
		(3.71)		(3.54)		(4.22)
$MFHS_{-i}$		0.253***		0.255***		0.500***
		(5.51)		(5.56)		(5.74)
Q^*_i		0.375***		0.375***		0.430***
		(8.33)		(8.33)		(4.43)
Q^*_{-i}		0.114***		0.115***		0.136
		(3.01)		(3.00)		(1.64)
$CONNECTxQ_i$			-0.189***		-0.641***	
			(-3.72)		(-3.33)	
$CONNECTxQ_{-i}$			-0.124***		-0.499***	
			(-2.60)		(-3.02)	
CONNECTxMFHSi				-0.076***		-0.290***
				(-2.65)		(-2.83)
$CONNECTxMFHS_{-i}$				-0.100***		-0.443***
				(-2.98)		(-3.78)
$CONNECTxQ^*_i$				-0.03		-0.099
				(-0.79)		(-0.67)
$CONNECTxQ^*_{-i}$				0.008		-0.035
				(0.21)		(-0.29)
CONNECT			-0.113	-0.082	-0.546*	-0.551*
			(-1.14)	(-0.84)	(-1.72)	(-1.75)

Continued on the next page.

Table 3 Cont'd.

			Continuous CONNECT		Decile Ranked CONNECT	
	(1)	(2)	(3)	(4)	(5)	(6)
CF_i	0.516***	0.501***	0.513***	0.492***	0.511***	0.487***
	(5.89)	(5.74)	(5.82)	(5.63)	(5.83)	(5.61)
$SALE_i$	1.751***	1.745***	1.740***	1.740***	1.737***	1.739***
	(10.26)	(10.25)	(10.15)	(10.19)	(10.13)	(10.18)
$FRET_i$	-0.240***	-0.232***	-0.232***	-0.230***	-0.229***	-0.226***
	(-5.11)	(-4.95)	(-4.99)	(-4.93)	(-4.92)	(-4.85)
$SIZE_i$	0.497***	0.464***	0.485***	0.442***	0.479***	0.426***
	(3.71)	(3.50)	(3.61)	(3.32)	(3.59)	(3.22)
INV_AT_i	-0.117	-0.112	-0.105	-0.103	-0.102	-0.099
	(-1.37)	(-1.31)	(-1.22)	(-1.20)	(-1.19)	(-1.15)
CF_{-i}	-0.128**	-0.113**	-0.122**	-0.121**	-0.124**	-0.125**
	(-2.31)	(-2.04)	(-2.20)	(-2.19)	(-2.23)	(-2.26)
$SIZE_{-i}$	0.090***	0.090***	0.085**	0.090**	0.083**	0.088**
	(2.59)	(2.59)	(2.44)	(2.58)	(2.39)	(2.52)
Intercept	7.874***	7.689***	7.879***	7.658***	8.158***	7.937***
	(46.48)	(44.81)	(43.15)	(41.25)	(39.27)	(37.72)
Observations	14,109	14,109	14,109	14,109	14,109	14,109
Adjusted R^2	69.21%	69.32%	69.30%	69.36%	69.31%	69.39%

Table 4: Alternative explanation: noise in stock prices and cost of capital

Panel A reports coefficient estimates from Equation (3), where CAPX is replaced with a measure of cost of capital. The dependent variable in Column (1) is *Debt Spread*, defined as the firm-level all-in-drawn spread on new debt issues; in column (2), *Debt Constr.*, the text-based measure of debt-market constraints from Hoberg and Maksimovic (2015); in column (3), *Cost of Equity*, the implied cost of equity measure proposed by Gebhardt, Lee, and Swaminathan, 2001; in column (4), *Equity Constr.*, the text-based measure of debt-market constraints from Hoberg and Maksimovic (2015). Panel B reports coefficient estimates from Equation (3) modified to include cost of capital measures as controls. *CONNECT* is decile ranked residual from regressing the natural logarithm of total board connections on the natural logarithm of firm size, board size, firm age, analyst following, and institutional ownership with firm and year fixes effects. $MFHS_{it}$, is the annual sum of quarterly hypothetical stock sales due to large outflows experienced by all U.S. mutual funds holding stock *i* (i.e., larger than 5% of their assets) scaled by total quarterly CRSP dollar trading volume on stock *i*. Q^* is defined as the residual obtained from regressing Q_t on $MFHS_t$ with firm and year fixed effects. All other variables are defined in Appendix A. The sample includes 1,492 unique firms and 14,109 firm-year observations between 2000 and 2012. The *t*-statistics, reported in parentheses, are based on robust standard errors clustered by firm. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: The impact of non-fundamental shocks to stock prices on cost of capital

	Debt Financing		***Equity Financing***	
Dependent Variable:	*Debt Spread*	*Debt Constr.*	*Cost of Equity*	*Equity Constr.*
	(1)	(2)	(3)	(4)
MFHS	0.019	0.00	-0.036	-0.001
	(1.25)	(0.59)	(-1.61)	(-1.13)
Q^*	-0.044**	0.00	-0.152***	0.001
	(-2.55)	(-0.62)	(-7.60)	(1.07)
CF	-0.108***	-0.003***	0.803***	-0.001
	(-2.79)	(-3.61)	(12.27)	(-0.68)
SALE	-0.021	0.007***	-0.681***	-0.003
	(-0.36)	(3.92)	(-7.00)	(-0.99)
FRET	0.115***	0.002***	-0.845***	-0.003***
	(6.98)	(2.59)	(-9.49)	(-3.63)
SIZE	-0.01	0.001	0.540***	-0.003
	(-0.30)	(0.39)	(15.10)	(-1.00)
INV_AT	0.122**	-0.001	-0.173***	0.000
	(2.47)	(-1.53)	(-3.51)	(-0.37)
Intercept	1.178***	0.003	6.454***	-0.019***
	(26.53)	(1.20)	(69.92)	(-6.55)
Observations	5,214	11,552	13,195	11,552
Adjusted R^2	67.25%	45.50%	24.33%	58.38%

Table 4 Cont'd.

Panel B: Controlling for the financing channel

	Dependent Variable: CAPX		
	Controlling for:		
	Debt Financing	***Equity Financing***	***Both***
	(1)	(2)	(3)
MFHS	0.449***	0.229***	0.431***
	(3.18)	(2.80)	(2.99)
CONNECTxMFHS	-0.553***	-0.291**	-0.519**
	(-2.72)	(-2.48)	(-2.52)
Q^*	0.432*	0.434***	0.415*
	(1.77)	(3.88)	(1.68)
CONNECT xQ^*	-0.105	-0.188	-0.126
	(-0.28)	(-1.14)	(-0.34)
CONNECT	-0.579	-0.365	-0.515
	(-0.99)	(-1.00)	(-0.85)
CF	0.958***	0.673***	1.179***
	(4.55)	(6.23)	(4.91)
SALE	1.782***	1.735***	1.685***
	(5.91)	(8.43)	(5.24)
FRET	0.301	0.418**	0.16
	(1.37)	(2.40)	(0.73)
SIZE	-0.279***	-0.214***	-0.237**
	(-3.04)	(-3.75)	(-2.39)
INV_AT	-0.409	-0.214**	-0.459
	(-1.36)	(-2.02)	(-1.47)
DEBT SPREAD	-0.043		-0.033
	(-0.38)		(-0.28)
DEBT CONSTR.	-0.063		0.478
	(-0.04)		(0.30)
COST OF EQUITY		-0.088***	-0.111**
		(-3.50)	(-2.29)
EQUITY CONSTR.		0.067	1.339
		(0.08)	(1.01)
Intercept	7.775***	8.454***	8.604***
	(18.10)	(26.30)	(14.62)
Observations	4,153	10,817	3,934
Adjusted R^2	74.27%	70.06%	74.27%

Table 5: Alternative explanation: corporate governance and managerial entrenchment

This table reports results from estimating Equation (3) for subsamples created based on median *G-index* (Columns 1 and 2) and *E-index* (Columns 3 and 4). The dependent variable is the investment of firm *i* in year *t+1*, defined as capital expenditures (*CAPX*) divided by beginning of the year assets. *CONNECT* is decile ranked residuals from regressing the natural logarithm of total board connections on the natural logarithm of firm size, board size, firm age, analyst following, and institutional ownership with firm and year fixes effects. $MFHS_{it}$, is the annual sum of quarterly hypothetical stock sales due to large outflows experienced by all U.S. mutual funds holding stock *i* (i.e., larger than 5% of their assets) scaled by total quarterly CRSP dollar trading volume on stock *i*. Q^* is defined as the residual obtained from regressing Q_t on $MFHS_t$ with firm and year fixed effects. All other variables are defined in Appendix A. The sample includes 1,492 unique firms and 14,109 firm-year observations between 2000 and 2012. The *t*-statistics, reported in parentheses, are based on robust standard errors clustered by firm. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	G-Index		*E-Index*	
	Low	*High*	*Low*	*High*
	(1)	(2)	(3)	(4)
MFHS	0.414***	0.241*	0.415***	0.173
	(3.74)	(1.94)	(4.03)	(1.52)
CONNECTxMFHS	-0.501***	-0.150	-0.494***	-0.122
	(-2.88)	(-0.88)	(-3.24)	(-0.75)
Q^*	0.477***	0.686***	0.301***	0.628***
	(3.63)	(3.37)	(2.84)	(3.15)
CONNECTxQ^*	-0.247	-0.386	-0.085	-0.458*
	(-1.08)	(-1.34)	(-0.46)	(-1.72)
CONNECT	-0.599	-0.047	-0.167	-0.088
	(-1.10)	(-0.09)	(-0.31)	(-0.17)
CF	0.779***	0.579***	0.711***	0.670***
	(5.77)	(3.81)	(5.62)	(4.63)
SALE	1.681***	1.814***	1.796***	1.487***
	(7.50)	(5.83)	(7.77)	(5.52)
FRET	-0.122	-0.300***	-0.11	-0.286***
	(-1.60)	(-3.88)	(-1.63)	(-4.29)
SIZE	0.476***	0.429**	0.424**	0.672***
	(2.71)	(2.13)	(2.40)	(3.01)
INV_AT	0.114	0.287	0.016	-0.260*
	(0.76)	(1.02)	(0.19)	(-1.75)
Intercept	7.466***	7.158***	7.139***	7.107***
	(22.53)	(21.10)	(23.1)	(19.82)
Observations	6,103	4,949	6,169	4,883
Adjusted R^2	71.74%	71.55%	71.25%	72.17%
CONNECTxMFHSi: High-Low		0.351		0.372*
(p-value)		(0.392)		(0.066)

Table 6: Cross-sectional tests: types of director connections

This table reports results from estimating Equation (3) for subsamples created based on median *Industry Connections* (Columns 1 and 2), *Executive Connections* (Columns 3 and 4), and *Business Connections* (Columns 5 and 6). The dependent variable is the investment of firm *i* in year *t+1*, defined as capital expenditures (*CAPX*) divided by beginning of the year assets. *CONNECT* is decile ranked residuals from regressing the natural logarithm of total board connections on the natural logarithm of firm size, board size, firm age, analyst following, and institutional ownership with firm and year fixes effects. $MFHS_{it}$, is the annual sum of quarterly hypothetical stock sales due to large outflows experienced by all U.S. mutual funds holding stock *i* (i.e., larger than 5% of their assets) scaled by total quarterly CRSP dollar trading volume on stock *i*. Q^* is defined as the residual obtained from regressing Q_t on $MFHS_t$ with firm and year fixed effects. All other variables are defined in Appendix A. The sample includes 1,492 unique firms and 14,109 firm-year observations between 2000 and 2012. The *t*-statistics, reported in parentheses, are based on robust standard errors clustered by firm. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Industry Connections		***Executive Connections***		***Business Connections***	
	Low	*High*	*Low*	*High*	*Low*	*High*
	(1)	(2)	(3)	(4)	(5)	(6)
MFHS	0.215***	0.338**	0.125	0.525***	0.232***	0.427***
	(2.84)	(2.25)	(1.46)	(4.51)	(2.89)	(2.66)
CONNECTxMFHS	-0.123	-0.370*	0.016	-0.560***	-0.291*	-0.346*
	(-0.92)	(-1.92)	(0.11)	(-3.82)	(-1.93)	(-1.92)
Q^*	0.468***	0.280**	0.316**	0.272*	0.272**	0.374
	(3.73)	(1.97)	(2.47)	(1.67)	(2.37)	(1.59)
CONNECTxQ^*	-0.149	-0.054	0.114	-0.034	0.159	-0.090
	(-0.65)	(-0.28)	(0.49)	(-0.15)	(0.61)	(-0.30)
CONNECT	0.498	-1.398***	-0.736	-0.751*	0.953	-0.313
	(1.07)	(-3.00)	(-1.51)	(-1.74)	(1.51)	(-0.74)
CF	0.600***	0.423***	0.670***	0.344***	0.714***	0.217**
	(4.46)	(4.09)	(4.35)	(3.26)	(4.75)	(2.16)
SALE	1.887***	1.639***	1.595***	2.016***	1.794***	1.752***
	(7.94)	(6.71)	(6.07)	(9.21)	(6.62)	(8.24)
FRET	-0.243***	-0.156**	-0.274***	-0.183***	-0.299***	-0.117**
	(-3.96)	(-2.34)	(-3.60)	(-3.10)	(-4.20)	(-2.01)
SIZE	0.270	0.728***	0.427**	0.615***	0.603***	0.339***
	(1.41)	(3.46)	(2.04)	(3.10)	(2.66)	(2.82)
INV_AT	-0.169	-0.021	-0.143	-0.042	-0.136	-0.194*
	(-1.03)	(-0.26)	(-0.91)	(-0.50)	(-0.91)	(-1.95)
Intercept	6.728***	8.903***	8.036***	7.708***	7.811***	7.177***
	(28.06)	(23.21)	(29.43)	(21.53)	(32.90)	(15.68)
Observations	7,055	7,054	7,055	7,054	7,055	7,054
Adjusted R^2	69.14%	71.38%	70.94%	70.13%	73.03%	65.81%
CONNECTxMFHSi		-0.247*		-0.576***		-0.055
High-Low (p-value)		(0.09)		(0.00)		(0.37)