Stock Price Informativeness and CEO Social Capital

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Abstract:

We investigate the association between CEOs' social capital and stock price informativeness in a sample of US firms. We find strong evidence of a negative association, indicating that less private information is incorporated into stock prices for firms with CEOs that are more connected. Results are consistent across five different proxies for stock price informativeness and hold after accounting for endogeneity. There is evidence the negative association stems from outside investors becoming discouraged from collecting and acting on information about more connected companies. Characteristics of CEOs network in terms of nationality and gender diversity also have a negative impact on stock price informativeness while professional and educational differences among members have a positive one instead. Overall, results suggest that private information existing in networks may result in markets that are less informationally efficient.

Keywords: *stock price, informativeness, connections, social capital, CEO*
JEL classification: *G14*

1. Introduction

Researchers have long been interested in the determinants of the rate of private information incorporation into stock prices, or stock price informativeness (French and Roll, 1986; Roll, 1988). Prices reflect both private and public information (e.g., Piotroski and Roulstone, 2004; Hou and Moskowtiz, 2005), but private information is incorporated into prices only to the extent that investors use resources to obtain and trade on that information (Grossman and Stiglitz, 1980). More informative prices improve the quality of the price discovery process, making capital allocation more efficient (Morck et al., 2013). However, the determinants of stock price informativeness are still not well understood.

At the same time, a growing body of research explores the role of social networks in the transfer of private information (Cohen, Frazzini, and Malloy, 2008; Cai, Walking, and Yang, 2015). Cheong et al. (2021) investigate the impact of university alumni reunions on stock options trading. They find that hedge fund managers that know companies' directors involved in the process of M&A tend to increase their holdings of call options in the target firm before the official announcement. Moreover, Shue (2013) argues that the effect on investments and acquisitions is more pronounced if the reunion happened recently because relationships among network members should remain current.

Prior research has focused on determinants of stock prices informativeness associated with insider trading, institutional ownership, or voluntary disclosures. However, no attention has been paid to the general association between CEO connections and the degree of information incorporation into stock prices. In this paper, we investigate the association between stock price informativeness and social capital in the US stock market.

Extant literature shows that social capital affects corporate policy through the following channels: trust, discipline, influence, and information transmission (Ferris et al., 2019). We are particularly interested in the last channel and whether the information flowing in CEO networks can have a significant impact on the stock price informativeness of the company. Specifically, we

ask whether the private information contained in a firm's social capital, measured by CEO's connections, makes prices more or less informative.

Cohen and Prusak (2001) argue that the information transmitted through social networks is firm-specific in nature due to the higher level of trust present among similar members of the network. Moreover, Kandori (1992) mentions that there is always a possibility of exclusion for dishonesty that also disciplines participants. Therefore, we hypothesize a positive association between CEO's social capital and stock price informativeness. On the other hand, while increased connectedness can reduce financial constraints (Grossman and Hart, 1986), information asymmetry, and agency problems (Javakhadze et al., 2016), it can also make the company less susceptible to firm-specific shocks, thereby decreasing informativeness (Faccio et al., 2021). Additionally, the existence of social networks and the corresponding exclusive channels of information transmission may discourage outside investors from gathering and analyzing information about the company (Manove, 1989).

We empirically investigate the association between stock price informativeness and social capital while using five proxies for stock price informativeness: synchronicity (Morck et al., 2000), crash frequency (Jin and Myers, 2006), price delay (Hou and Moskowitz, 2005), C2 coefficient (Llorente et al., 2002), and the probability of informed trading PIN (Easley, 1996).

In a sample of US firms during the period 1995-2020, we find there is a negative association between CEO connectedness and stock price informativeness. Endogeneity is a concern, because it is possible that companies with low stock price informativeness prefer to hire better-connected CEOs; however, the results are more pronounced after accounting for this possible endogeneity problem with the help of IV regression. Specifically, they are stronger after using the instrumental variable of local social organizations. The results are robust and confirmed by taking into account alternative measure of CEO connectedness (degree centrality) as well including only companies that have at least 5 years of data, utilizing another industry classification

(GICS) and running a placebo test. Therefore, we report that less private information is incorporated into stock prices for firms with CEOs that are more connected.

In subsequent analyses, we investigate possible explanations for the observed negative association between CEO social capital and stock price informativeness. We report that companies with more information asymmetry exhibit a stronger negative association between stock price informativeness and CEO connectedness, which is consistent with two possible explanations. First, that investors perceive more connected firms as being less exposed to firm-specific shocks because of the benefits of the network, such as alleviating information asymmetry problems or financial constraints. Second, that investors are discouraged from doing research and trading on more connected firms. Inconsistent with the first possible explanation, we uncover that the negative relation is stronger for firms with CEOs of a shorter tenure and for firms with lower level of financial constraints. Furthermore, we also find stronger (more negative) results for US states with low social capital and for the post-Sarbanes-Oxley Act (SOX) implementation. Overall, the results suggest that outside investors become discouraged from collecting, doing research, and trading on information about more connected companies, which leads to a decrease in stock price informativeness.

Previous literature also underlines not only the importance of the network size but also its characteristics, especially diversity of members who comprise such network (Fang et al., 2018). We investigate four types of diversity including gender, nationality as well as educational and professional. The findings show that networks with greater gender and nationality diversity tend to negatively impact stock price informativeness on their own right. While members considered to be more diverse from professional and educational points of view have a positive relation with informativeness instead.

We contribute to the growing body of research on CEO social capital and extend the literature on market efficiency and informativeness in several ways. First, we uncover a new

determinant of stock price informativeness, which is important for efficient capital allocation in the economy Second, we provide evidence on the impact of information transmission in networks for price discovery; prior literature mostly focuses on its impact on corporate policies. Third, we find that variety of diversity characteristics of CEO network impacts stock price informativeness differently. Finally, we report evidence consistent with the notion that social capital impacts stock price informativeness because outside investors prefer to focus their information-collection, research, and trading efforts on less connected firms.

2. Literature review

2.1. Information transmission

Interest in the role of financial markets in the process of information production goes back to Schumpeter (1912). An important breakthrough is associated with Roll (1988) who uncovers that public information is responsible for only a fraction of a stock price movement; most variation is due to the incorporation of firm-specific information. Such information remains significant after accounting for the general economic environment and industry-specific data that are widely available to the market. More firm-specific information included in prices makes them more informative.

In general, a company's information environment is concerned with the availability of "relevant, reliable information about the periodic performance, financial position, investment opportunities, governance, value, and risk" (Bushman and Smith, 2003). Moreover, such information is transmitted through the following main channels: insider trading and institutional investors' ownership as well as analysts and firm's disclosure policies. However, we note that another possible channel is social networks, which have been relatively unexplored.

First of all, Cohen et al. (2012) argue that despite the reasons for which insiders actually trade and the fact that they also receive stocks through non-market transactions such as compensation, they still have access to much more private information compared to the rest of the

market. It makes them especially important for information transmission. Chen, Goldstein, and Jiang (2007) also mention that informed traders affect the information environment of the company through increased trading activities. On the other hand, Nuno et al. (2009) note that insider trading can eliminate the motivation for outside investors to collect firm-specific information.

Second, Piotroski and Roulstone (2004) find that institutional investors can influence the amount of firm-specific information contained in stock prices as well. Moreover, the authors show that stock price informativeness is improved with the help of those investors as they mostly trade on firm-specific data. Healy et al. (1999) note that institutional investors' monitoring motivates managers to disclose more information about the firm. Hou and Moskowitz (2005) uncover that higher institutional ownership is associated with less price delay and increased informativeness. Moreover, Zhang et al. (2013) find that firms with lower levels of institutional holdings tend to experience longer price delays before available information will be reflected in stock prices. On the other hand, concentrated ownership when institutional investors accumulate too much power can lead to information asymmetries (Leuz et al., 2009).

Third, security analysts make information about the companies available to the market and are also important for stock price informativeness. Li et al. (2014) mention that analysts provide firm-specific information to investors and their recommendations have value for decision-makers. On the other hand, Piotroski and Roulstone (2004) and Farooq et al. (2014) empirically show that analysts produce market and not firm-specific information. Informativeness decreases and synchronicity increases with more extensive analyst coverage both in the US and internationally. Chen, Goldstein, and Jiang (2007) also find that better analyst coverage doesn't improve the informativeness of equity prices containing less firm-specific data due to the noise investors attracted to such stocks. Moreover, Givoly and Lakonishok (1979) point out that analysts can have interests that are different from those of investors. Cheong et al. (2016) show that analysts tend to overrepresent industry information because they often analyze many companies from the same

field simultaneously. Moreover, Banerjee (2017) shows that due to competition and the possibility of correlation with other analysts' opinions, many of them prefer not to base their forecasts on truly private information. In the case of a trade-off between private information inclusion and the goal to differentiate themselves from all other analysts, they usually select the latter. Moreover, analysts can be exposed to different conflicts of interest if their employer has connections with the researched company. For example, it can prevent analysts from publishing their true opinions about the firm's perspectives (Malmendier and Shanthikumar, 2014). When private information is not available, investors rely more on data provided to the market through analysts. Such behavior according to Veldkamp (2006) can increase co-movement in stock prices and decrease their informativeness.

Finally, a high level of corporate governance is usually associated with more information available about the firm that helps to improve the accuracy of the market participants' forecasts. Herawaty and Solihah (2019) also mention that this happens through the lower frequency of earnings manipulation. Previous literature separates mandatory and voluntary disclosures by the firm, however, both types are important information transmission vehicles.

Accounting information in the form of mandatory disclosures helps to identify better investments, makes managers more disciplined, and leads to a decrease in information asymmetries between insiders and other investors. For example, in Beyer et al. (2010) accounting information help owners of the capital better evaluate potential returns and monitor such funds' usage. Callen et al. (2013) show that it's hard for investors to use data if the companies have low-quality accounting information. That's why new information about the firm is being incorporated longer into such stock prices. Hou and Moskowitz (2005) argue that there is a negative relation between the quality of accounting information and price delay. Accounting standards (Fields, Lys, and Vincent, 2001) and audit quality (Adams et al., 2018) influence the information environment of the company as well. Haggard et al. (2008) find that companies with high-quality disclosure policies provide more firm-specific information to investors. They also find a negative connection

between increased disclosure of the company and its stocks' synchronicity. Gelb and Zarowin (2002) also reach the same conclusion and Jin and Myers (2006) confirm those findings in an international setting. Moreover, Grossman and Stiglitz (1980) argue that a high-quality disclosure policy helps to reduce the cost of information and more effectively transmit information to outside investors. Durnev, Morck, and Yeung (2004) also note that a lower cost of information is associated with lower co-movement in stock prices.

While most researchers pay attention to information extracted from financial statements, Bens (2002) also show the importance of voluntary disclosures. The author finds that an increased amount of voluntarily disclosed information leads to better monitoring from the shareholders' side. For example, Bowen et al. (2002) mention an important role of earnings conference calls and how they impact the accuracy of analysts' forecasts pointing to the complementary nature of mandatory and voluntary sources of information. On the other hand, Bhattacharya (2016) shows that market participants can decide to postpone trading if the company is more transparent and instead wait and collect even more information. Banerjee, Davis, and Gondhi (2018) also find that increased transparency changes incentives for market participants to trade and lead to a lower stock price informativeness as a result. Han et al. (2016) uncover a negative effect of higher transparency on stock price efficiency as well.

There is no one opinion on how insiders, institutional investors as well as analysts, and disclosure policies influence stock price informativeness. For example, the market usually perceives analysts as participants with superior knowledge about the company but instead, they can produce a lot of general information. Moreover, insiders can incorporate more firm-specific data into stock prices or just discourage outside investors. Institutional investors also positively impact stock price informativeness but only until their ownership becomes too concentrated. Finally, disclosure policies while being an important instrument of providing more information to the market can also make investors postpone trading.

2.2. Social capital

Social capital was introduced by Hanifan (1916) who discussed rural school communities. In this work, social capital is defined as "fellowship, mutual sympathy, and social intercourse among a group of individuals". Bankston and Zhou (2002) also mention the importance of Durkheimian normative sociology and the impact that it had on the development of today's multidisciplinary theories. Moreover, Watson and Papamarcos (2002) note that psychological contract theory played an important role in the development of social capital understanding as well.

Previous works in the field usually distinguish between cognitive and structural approaches to social capital. Pierre Bourdieu's work (1986) is associated with the structural theory. He pays attention to the individual aspect of social capital, the concept of power, and structural obstacles preventing everyone from equal access to resources. The author also argues that the privileged part of society prospers through connections with other powerful participants.

Coleman (1988) introduces a cognitive theory of social capital. The author applies principles of economics to the concept of social capital. The rational theory, which introduces the utility-maximization goal of the participants, describes the main idea of this concept. People in the social network act independently to reach their own goals. Compared to the previous theory, social capital is not attributed only to some parts of society and is a public good.

Putnam (1993, 1995, 2000) made the topic of social capital especially popular among researchers. In Putnam's theory, social capital is not only an individual's feature but rather a population's characteristic. Widely applied "Putnam instrument" is a simpler version of the "civicness" index that contains such measures as membership in different groups, trust in people and institutions, and reciprocity traditions.

The development of a network approach to the structural theory of social capital, which we follow, began with the work of Granovetter (1973) and received additional perspective with the

publications of Burt (1992), Woolcock (1998), and Lin (2001). The advantage of the network approach is that connections between participants are easily observed. Woolcock (1998) defines a social network as the aggregation of relationships that a person has at his or her disposal. The author published a series of works in 1998, 2001, 2002 and is associated with a multilevel model of social capital. There are three different types of social capital according to Woolcock: bonding social capital representing connections between family members or neighbors; bridging social capital including ties between people that aren't close friends and colleagues; linking social capital is about distant connections between community members and outsiders.

Akcomak (2009) mentions an increased interest in the topic of social capital with 60% of the papers in the field published during the last 5 years. Still, the lack of conceptualization is present in the field. For example, Fukuyama (1995) argues that trust and social capital are indeed the same while other authors posit trust as a source for social capital. Coleman (1988), on the other hand, interprets trust as one of the forms that social capital can have.

2.3. Information transmission within networks

Burt (2000) mentions that a network is an information channel that is needed to transfer what has already been created by its participants. Because such communications take time, the information will diffuse gradually and not all the participants will be aware of it instantly. Members with more connections have a chance to receive such data earlier compared to others. Acemoglu et al. (2015) also show that connected individuals tend to distribute more information on which other members can act.

The network approach also argues that social capital is a specific resource available only through connections formed between participants. That fact makes it not just an abstract idea but a measurable variable.

The most direct measure of connectedness is the number of ties between the members of the network, and we utilize it in this work. Centrality is another popular measure of social capital

used in the literature. Freeman (1979) introduces three centrality measures being closeness, betweenness, and degree[1]. The degree centrality (DC) is the most standard alternative for direct number of connections mentioned above (Landherr et al., 2010).

There are two different outlooks on connectedness and whether it's good or bad for the company. Horton, Millo, and Serafeim (2012) find that improved connectedness positively influences firm performance and helps to restrain top managers from opportunistic behavior. Not only the company's performance in terms of stock returns and ROA improves, but more growth opportunities emerge through enhanced information exchange as well (Larcker et al., 2013). In more connected companies, innovations in both products and management compensation are more frequent (Haunschild and Beckman, 1998). The capital structure of the entity is also impacted by the fact of how information flows inside the networks (Fogel, Jandik, and McCumber, 2018). Moreover, Cohen, Frazzini, and Malloy (2008) investigate the information advantage of portfolio managers through educational ties with corporate board members. The authors show that such managers tend to invest more heavily in stocks of firms where they have connections and gain on average 7.8% more in terms of returns due to their superior information received through such networks, especially around corporate announcements. Akbas et al. (2016) also show that sophisticated market participants benefit from trading firms with more connected directors.

However, not only private information flows inside such networks; public information is transmitted as well. Participants don't usually pass all available information to other members as mentioned by Hagenbach et al. (2010). The authors uncover a trade-off between the personal advantage of more centralized agents and their willingness to distribute private information through the network. Agents with private information may choose not to communicate it due to the conflict of interests or even based on the size of the network and preferences of its members.

[1] Closeness centrality (CC) introduces the idea that nodes closer to each other can transmit information through the network more effectively (Beauchamp, 1965). Betweenness centrality (BC) represents control over information that the node in the network can acquire if it's located on the path between other participants as in Freeman (1977).

For example, El-Khatib, Fogel, and Jandik (2015) show that increased social capital can lead to mergers and acquisitions of lower quality. Shao (2011) also uncovers that more connected CEOs usually enjoy a higher level of compensation that is not always to the shareholders' benefit. Thus, information transmission in the network doesn't by itself mean that the stock price of the company will become more informative.

My main focus is information present in CEOs' social networks formed through connections. According to Ferris et al. (2019), connections with other companies' management are formed through three main channels: employment history, education, and other activities such as membership in non-profit, professional or voluntary associations that we will explore below.

2.3.1. Connections through education

Education is an important basis for network formation and subsequent information flow among its participants. Hasan et al. (2017) and Cai et al. (2016) identify such network participants if they graduate from the same school or were awarded the same degree such as an MBA or JD in the same year or no more than one year apart. The last condition is especially important according to Fracassi (2017) because in this case graduates are more likely to know each other during their school years. Bachelor's degree is not counted towards education connections because there are more students attending universities at this level. Moreover, communications between them don't usually last after graduation.

Cohen et al. (2008) show that people tend to select educational programs that correspond with their overall interests. This fact makes the gathering of participants with similar backgrounds and goals in one place more likely. Moreover, due to the mentioned mutual interests, such relationships usually do not end after graduation according to Fischer et al. (1977) and McPherson et al. (2001). Education-based relationships are more homophilous (Flap and Kalmijn, 2001) and future communication between participants is more effective (Bhowmik et al., 1971). It's also

important that education-based ties are not endogenous as they were formed long before important information about the company started to flow in the networks.

Donations to educational institutions are the second highest in the US after religious organizations and are estimated at 15% of all the donations made in a single year. Such behavior is reinforced through sports and alumni associations that help to prolong communication not only with the place but also with people that person associates it with.

Cohen et al. (2010) show that information sharing based on a similar educational background is pronounced among corporate and mutual fund managers. Educational ties also play an important role in the informational advantage of analysts connected with corporate officers. Cohen, Frazzini, and Malloy (2008) find that analysts issue better recommendations compared to their less connected colleagues. First of all, they have easier access to private conference calls conducted by the firm's officers. Secondly, previous experience during school years can help analysts to better assess their managerial qualities. We investigate whether such connections but formed among future CEOs can play an important role in his or her company's stock price informativeness.

2.3.2. Workplace connections

Hasan et al. (2017) mention that individuals have work-based ties if they were employed in the same company and less than five years passed from that event. The time factor is important because people communicate with their former co-workers for some time after they go their separate ways but usually not longer than 5 years. On the other hand, Cai et al. (2016) don't use the time frame restrictions and acknowledge ties' existence if participants partially overlapped while working at the company which we follow in this study.

Still, all authors emphasize the importance of frequent face-to-face communications between co-workers in network formation. For example, stock picking is usually discussed among colleagues when they meet personally (Guiso and Jappelli, 2005). Bikhchandani et al. (1992) also

mention that co-workers often start to imitate the trading decisions of their colleagues. It can happen either due to the results demonstrated by such investors or by acquiring important diversification principles in the process of communication. Huberman (2001) also finds that investors don't simply prefer local stocks but concentrate on the companies from their respective industry or place of employment even more. However, information circulating in the workplace could be rumors that create more noise than truly important data (March, 1991; Beshears et al., 2011).

2.3.3. Connections through social clubs

Cai et al. (2016) and Hasan et al. (2017) mention that important connections are only established between officers and not general members of professional, non-profit or other social organizations, such as a country club or charity. The ranking positions of participants ensure that they are often engaged in the activities of the organization that increases the probability of developing lasting connections and further information sharing.

2.4. Informativeness measures

Markets in which information is incorporated into prices faster are considered to be more efficient. That's why researchers would like to better understand what factors influence stock price informativeness.

Extant research has used different proxies for stock price informativeness: synchronicity (Morck et al., 2000), crash frequency (Jin and Myers, 2006), and price delay (Hou and Moskowitz, 2005) as well as C2 coefficient (Llorente et al., 2002), PIN (Easley, 1996). We discuss all five proxies and use them in the empirical part because they capture informativeness from different perspectives (Jacobs, 2016). Moreover, Ben-Nasr et al. (2014) also argue the importance of using different stock price informativeness measures to obtain consistent results.

2.4.1. Synchronicity

The word synchronicity is derived from two Latin words and means simultaneousness or coincidence in time. While the first usage of this term is dated back to 1920 and the work of Carl Jung in psychology, to financial and accounting literature it was introduced by Roll in 1988.

The simplest way to measure synchronicity involves counting the number of stocks which prices are growing together and those that go in another direction during the specified time frame. But the most common measure was introduced by Morck, Yeung, and Yu (2000) who calculate the stocks' co-movements with the help of the market model and R^2. This measure has become so popular that in many studies R^2 and synchronicity are used as substitutes.

Most of the authors report a negative connection between synchronicity and stock price informativeness. If stock price co-movement is low, they become more informative for investors according to Li et al. (2004). Co-movement is also reduced when additional sources of information about the stocks are available (Veldkamp, 2006). Haggard et al. (2008) show that more information about the company received from its voluntary disclosure leads to lower synchronicity as well. Finally, Morck et al. (2000) also mention that firm-specific information leads to a decrease in synchronicity measure.

2.4.2. Crash frequency

Crash risk is characterized as a negative skewness in stock returns distribution (Chen et al., 2001; Kim et al., 2014). In other words, when stocks experience extreme negative returns (Callen and Fang, 2015), the probability of a crash is higher. The literature follows Jin and Myers (2006) who argue that the main reason for potential crashes is information asymmetry between insiders and external shareholders. Kothari et al. (2009) mention that in such an asymmetric information environment, it's easier for the management of the company to mask bad news from the rest of the market. Nevertheless, Habib et al. (2018) show that it's hard to withhold bad news from the market for a long period of time and the crash can happen later when it all comes out at once.

Jin and Myers (2006) also uncover that stocks with a lack of transparency, or so-called "opaque" securities, tend to crash more often due to the fact that insiders absorb more negative news than they can bear. They also argue that insiders are better off when other investors think that the cash flows of the company are lower than they actually are. But insiders can't report bad news all the time even if they want to because negative information is credible only if it has a cost. That's why for insiders there is always a dilemma between a potential increase in profit and the cost of translating negative news to the market. Easley and O'Hara (2002) also mention that informed traders use private information to make optimal decisions while others, due to its absence, demand higher returns leading to a decrease in the firm's value.

There are three main proxies for the crash frequency (Jin and Myers, 2006). Chen, Hong, and Stein (2001) introduce crash as the ratio of residual returns' third moment to the third degree of its standard deviation. The next measure of a crash helps to distinguish between the severity of such events as well. But the most popular and the one that we will utilize in this study is based on the stock return comparison with its mean value.

2.4.3. Price Delay

Hong and Stein (1999) propose a theory connected with the gradual diffusion of information into stock prices. Later Hou and Moskowitz (2005) introduce a new proxy for stock price informativeness based on that theory – price delay. It helps to distinguish between the roles that current and previous market returns play in stock prices. The authors also mention that it's connected with frictions in the capital markets.

Compared to other proxies, price delay represents a lower-frequency measure of public information incorporation into stock prices. Chordia, Roll, and Subrahmanyam (2005) and Boehmer and Kelley (2009) mention that stock price informativeness is especially important during the trading day, but Dechow et al. (2001) find that longer periods should be accounted for

as well. Dong et al. (2016) also uncover that stock price delay is a good alternative for a more traditional R^2.

Higher values of all three proxies mentioned above being synchronicity, crash frequency, and price delay correspond with lower informativeness. Below we will add two more proxies - Llorente and PIN measures that have a different relation with informativeness.

2.4.4. Llorente

Llorente et al. (2002) introduce another proxy for stock price informativeness while analyzing the role of asymmetric information on the trading volume-return relation. The authors note that volume is closely related to the participants' motivation for trading, as it can be connected with rebalancing/hedging operations or with speculation. Speculative stocks usually demonstrate positive return autocorrelation while a negative one is found for other securities.

Llorente et al. (2002) also distinguish between stock dynamics generated by those different types of trading. Hedging leads to price returns of an opposite sign by attracting investors with different positions and generating little information about future payoffs. In other words, price decrease today leads to better returns' expectations during the next period or reverse relation. On the other hand, speculative trading incorporates more firm-specific information and is a better predictor of future payoffs. After private news becomes public, insiders' forecasts turn into reality which means that those stocks' returns will continue.

Wang (1994) argues that stocks are traded by both insiders and uninformed investors and that future return reversals will depend on the prevailing force behind the trading volume. Nevertheless, the proxy introduced by Llorente shows the amount of private information contained in stock prices and it has a positive relation with stock price informativeness.

2.4.5. PIN

Easley et al. (1996) propose another proxy for stock price informativeness, PIN, connected to abnormal trading in stocks. The authors distinguish between informed and uninformed trades. The former ones are triggered by new private information while the latter connected with traders' liquidity needs. PIN is calculated as the ratio of informed trades to total ones and captures imbalances in bid-ask orders. PIN is lower for high-volume stocks and those that enjoy extended analytical coverage (Easley et al., 1998). In such stocks informed trading is more than offset by uninformed participants.

On the other hand, PIN is higher for companies of lower sizes and otherwise poorly recognized by investors (Aslan et al., 2011). Less active stocks can be much easier influenced by informed investors. When trading happens in such illiquid equities, it's usually an informed one executed at the market makers' expense that can explain larger spreads. Moreover, Chordia and Swaminathan (2004) argue that informed traders concentrate on stocks about which they have private information. Such investors help stock prices adjust to market news faster compared to equity largely ignored by them that enjoy less informativeness. The PIN measure, similar to the Llorente one, has a positive connection with stock price informativeness.

3. Hypotheses

Networks are usually formed among people with some similarities that help to build trust among participants (Smith et al., 2014). Such trust leads to sharing of high-quality firm-specific information (Daniel, Schwier, and McCalla, 2003; Cohen and Prusak, 2001). Moreover, network participants are more likely to share firm-specific information with others if they expect the same in return due to reciprocity considerations (Molm, 2003) or if they are afraid to be excluded for dishonesty (Kandori, 1992). Transaction costs are also lower among participants of such networks due to the smaller barriers for information to flow from one node of the network to another. That's

why larger CEO networks can lead to a greater amount of private data available about the company and improved informativeness.

On the other hand, social capital reduces financial constraints (Grossman and Hart, 1986), information asymmetry and agency problems (Javakhadze et al., 2016) as well as provides support for network participants (Genicot and Ray, 2005) but at the same time firms with high social capital become less affected by firm-specific shocks (Faccio et al., 2021, Hong et al, 2017) precisely because of the positive effects mentioned above. Furthermore, Manove (1989) mentions that investors outside such networks can react to the exclusive nature of information and decide to stop gathering and analyzing private information to trade on. In other words, insiders of such networks can increase the cost of collecting information by others and decrease overall informativeness. More information available to network members with its increased size doesn't necessarily mean that firm-specific data will be communicated because the lower transaction costs in such networks can lead to cheap, low-quality market information circulating between the members (Beshears et al., 2011). Some members can also mislead others by starting rumors containing incorrect or just general market information instead of sharing important data about the company (Hagenbach, 2011).

Based on the existing literature, CEO conectedness can have a positive or negative association with stock price informativeness.

H_{1a}: CEO connectedness is positively associated with stock price informativeness.

H_{1b}: CEO connectedness is negatively associated with stock price informativeness.

The hypotheses below help to understand why there is a particular association between CEO social capital and stock price informativeness. Information asymmetry, financial constraints, CEO personal, and the company's geographical characteristics, as well as external events, influence the information environment and can potentially moderate the impact of CEO connectedness on stock price informativeness.

High information asymmetry can lead to increased market risks for outside investors according to Jin and Myers (2006) and make them less willing to do research on the company. Moreover, because social capital reduces agency problems (Javakhadze et al, 2016) more pronounced in such an environment, it can also make firms much less responsive to firm-specific shocks (Hong et al., 2017).

Low level of information asymmetry is associated with better disclosure policy and monitoring activities (Lang and Lundholm, 1993). It can also help to lower the cost of data collection (Veldkamp, 2006) stimulating outside investors to use more resources to acquire firm-specific information and act on it.

The following hypothesis is emerging from the literature mentioned above.

H2: *the association between CEO connectedness and stock price informativeness is less positive/more negative for companies with high information asymmetry.*

Next, Alm et al. (2019) mention that financially constrained firms tend to manipulate data more which negatively impacts stock price informativeness. At the same time, social capital alleviate financial constraints that the company has (Grossman and Hart, 1986) and can make it less responsive to shocks (Faccio et al., 2021). On the other hand, if the firm is not financially constrained it has a lot of different sources of financing and is more attractive to analysts. Piotroski and Roulstone (2004), however, mention that analysts tend to report more market than firm-specific information which could also lead to a decrease in informativeness even if the firm is not financially constrained.

H3a: *the association between CEO connectedness and stock price informativeness is more negative for companies with high level of financial constraints.*

H3b: *the association between CEO connectedness and stock price informativeness is more negative for companies with low level of financial constraints.*

Tran et al. (2020) argue that CEO tenure can be an important factor in managerial ties formation as well. We analyze how tenure influences the relation between social capital and informativeness. First of all, CEOs can receive less reliable data from the network because the reciprocity motive of information sharing (Molm, 2003) is weak considering their short tenure. And other network members may not be willing to share important firm-specific data with new managers creating more noise. On the other hand, CEOs with greater experiences at the same firm tend to accumulate more firm-specific knowledge on their own (Chen et al., 2014) without the help of other network participants. Moreover, Genicot and Ray (2005) show that social capital provides support for network participants which can play a more pronounced role in this case taking into account that managers know each other longer. Such support coming from social networks can make stock price less responsive to shocks (Hong et al., 2017) and negatively impact informativeness.

That's why we investigate the following hypothesis based on the past research on the topic.

H_{4a}: *the association between CEO connectedness and stock price informativeness is more negative for companies with short-tenured CEOs.*

H_{4b}: *the association between CEO connectedness and stock price informativeness is more negative for companies with long-tenured CEOs.*

In this study we investigate social capital only in the US but the differences between states still play an important role in its impact on stock price informativeness. Lee (2018) produces a report in which a new state-level index of social capital is presented. It includes seven components from family and community health coefficients to more general indicators. Such an index captures the overall conditions in which information is transmitted. The author finds that only 12 states enjoy the highest social capital: Wyoming, Utah, Nebraska, Colorado, North Dakota, South Dakota, Iowa, Wisconsin, Maine, New Hampshire, Vermont, and Minnesota.

In the states with low social capital, outside investors are more likely to perceive network members as insiders, can become discouraged and do not spend resources to collect private information about the company (Burt, 2001). On the other hand, Guiso et al. (2009) argue that increased trust has a positive impact on stock market participation and also decreases transaction costs (Beshears et al, 2011). Such a positive impact of social capital can lead to lower responsiveness of the company to external shocks (Faccio et al., 2021). The following hypotheses will be investigated based on the findings above.

H_{5a}: the association between CEO connectedness and stock price informativeness is more negative for companies working in states with low social capital.

H_{5b}: the association between CEO connectedness and stock price informativeness is more negative for companies working in states with high social capital.

We also investigate the role of the Sarbanes-Oxley Act's (SOX) implementation and its impact on the relation between social capital and stock price informativeness. Enron scandal and other similar corporate fraud incidents became the starting point for the future SOX federal law that was finalized in 2002. Its main goal is to improve standards of internal control and external audit in the US. At the same time, Mason et al. (2020) argue that the company's management while trying to improve reporting, in fact, starts to manipulate data even more. For example, accrual practices deteriorated after SOX. Moreover, they uncover that managerial decisions become less connected with future company's ROA making them less informative as well.

In pre-SOX period there was a lower level of mandatory data disclosure (Gordon et al., 2006) and social capital while alleviating agency problems (Javakhadze et al., 2016) more pronounced in such environment at the same time leads to firms becoming less responsive to shocks (Hong et al, 2017). On the other hand, after SOX implementation, reputation concerns, taking into account scandals of the past, make participants more cautious and share less firm-

specific information. Other investors become more discouraged to collect and act upon private information as well (Brochet, 2009).

H_{6a}: *the association between CEO connectedness and stock price informativeness is more negative in a pre-SOX period.*

H_{6b}: *the association between CEO connectedness and stock price informativeness is more negative in a post-SOX period.*

But it's important to investigate not only the number of connections itself but also characteristics of the CEO networks. Next, we investigate how diversity and homophily of network members can impact stock price informativeness as well. The term "homophily" means "love of the same" and helps to explain why similar people tend to communicate and bond.

Investigation in sociodemographic factors began with Lazarsfeld and Merton (1954) and was later continued by Smith et al. (2014) who find that social connections are usually formed between similar participants rather than those who don't have anything in common. The authors show that people with similar gender, age as well as race are more likely to form networks. Moreover, Guiso et al. (2009) also uncover that trust is usually much higher between people that have some similarities in terms of language and history of their respective countries. Homophily of network members is especially important when the conflict of interests is present or the environment is not perfect for information sharing.

Very differently from what has been shown above in terms of similarities between network participants, Hagenbach and Koessler (2010) show how their differences can be beneficial for information transmission. Fang et al. (2012), as well as Janis (1982), also mentions the importance of diversity among network participants that help to decrease possible groupthink, provide a wider range of opinions that together lead to a higher quality of available information.

Based on the mixed results in the previous literature, the following hypotheses are investigated about four characteristics of diversity: gender and nationality as well as professional

and educational diversity among the members of CEO networks.

H_{7a}: Diversity of CEO network participants is positively associated with stock price informativeness.

H7b: Diversity of CEO network participants is negatively associated with stock price informativeness.

4. Methodology

4.1. Data

We obtain information about stock price, the number of shares traded and outstanding, from the Center for Research in Security Prices (CRSP) daily stock returns file. We gather annual accounting fundamentals from the Compustat database. Connectedness measure is calculated based on BoardEx data. Information about analysts and their respective coverage is obtained from the Institutional Brokers' Estimate System (IBES). Institutional ownership, as well as insider trading volume, are extracted from Thomson Reuters.

The sample period includes the years from 1995 through 2020. Regulated industries with SIC codes of 4900-4999 and 6000-6999, in which other factors beyond the scope of this study can play an important role in stock price informativeness, have been excluded. Moreover, only companies with non-zero ISIN from BoardEx are considered as well. Similar to Chen (2001), we also exclude REITs, closed-end funds, ADRs, and stocks with type codes other than 10 or 11, which are common stocks according to the CRSP classification. In total, the sample includes around 90,000 firm-year observations.

4.2. Informativeness proxies

We utilize five different proxies for the dependent variable of informativeness that have been proposed in the previous literature: synchronicity, crash, price delay, the measure introduced by Llorente et al. (2002), and PIN. It should be mentioned that they have a different connection

with stock price informativeness that is important for the empirical part of this work. The most popular proxy is represented by synchronicity measure and according to the classical view, there is an inverse connection with stock price informativeness. A higher value of the crash measure is associated with lower stock price informativeness as well. Price delay introduced by Hou and Moskowitz (2005) is also inversely related to stock price informativeness. On the other hand, two proxies, *Llorente* and *PIN*, have a positive connection with stock price informativeness. Both are positively related to informativeness because they measure firm-specific information contained in stock prices (Llorente et al., 2002; Easley et al., 1996).

First of all, synchronicity (*SYNCHRO*) measure, the most standard informativeness proxy, is calculated by regressing weekly firm's returns on the current and lagged value-weighted market (mret) and industry returns (indret).

$$ret_{i,t} = \alpha + \beta_1 mret_{i,t} + \beta_2 mret_{i,t-1} + \beta_3 indret_{i,t} + \beta_4 indret_{i,t-1} + \varepsilon_{i,t} \quad (1)$$

The value of R^2, from the regression above, is then utilized according to Piotroski and Roulstone (2004) to measure synchronicity in the following way:

$$SYNCHRO = log\ (R^2 / 1\text{-}R^2) \quad (2)$$

Secondly, *CRASH* measure of stock price informativeness is a frequency with which outliers of a large magnitude are detected in the company's returns. It's calculated as the difference between negative and positive return outliers that are respectively lower or higher by 2.576 standard deviations compared to the mean. A larger degree of this measure means a higher crash frequency.

The third measure introduced by Hou and Moskowitz (2005) is price delay (*PRICEDELAY*). Two market models should be estimated to receive R^2 measures from each regression. In the first one, the company's stock returns are regressed only on the contemporaneous market returns to calculate the restricted version of R^2. In the second model, both current and

historical market returns are utilized to measure unrestricted R^2. If previous market information is more important for current stock returns, then the measure of price delay will be larger. On the other hand, if the information is incorporated in stock prices relatively fast, the price delay measure will be small due to the higher value of restricted R^2 in the numerator.

$$Delay_{i,t} = 1 - \frac{R^2_{[\delta_{(1;n)}=0]}}{R^2} \tag{3}$$

The next proxy (*LLORENTE*) introduced by Llorente et al. (2002) measures the amount of private information contained in the share prices instead of a market-wide one. The main focus of this measure is the coefficient of C2 from the following regression:

$$R_{i,t+1} = C0_i + C1_i * R_{i,t} + C2_i * R_{i,t} * V_{i,t} + E_{i,t+1} \tag{4}$$

This equation represents the relation among current return ($R_{i,t}$), volume ($V_{i,t}$), and future return ($R_{i,t+1}$). Trading volume $V_{i,t}$ is modified according to the following formula to account for the possibility of zero trading volume days:

$$V_{i,t}=log\ (turnover_t + 0.00000255) \tag{5}$$

Finally, *PIN* measure introduced by Easley et al. (1996, 2002) uses market microstructure model in the following way:

$$PIN = \frac{\alpha\mu}{\alpha\mu + 2\varepsilon}, \tag{6}$$

where α represents the information event's probability and μ captures informed trade arrival while ε is the rate of uninformed buy and sell orders. The numerator captures the arrival rate for orders based on private information while the denominator captures all orders in their entirety. As the result, the coefficient above represents the probability of information-based trading in individual stocks.

4.3. Independent variables

The main independent variable, the size of CEO network (*LOGNETWORKSIZE*), is the number of direct ties between the CEO of the firm and other companies' CEOs. Following Fang et al. (2018) the variable is calculated as:

LOGNETWORKSIZE = ln (number of all connections) (7)

As an alternative measure of CEO connectedness, centrality degree is also used that includes the number of direct ties of CEO normalized by the maximum possible degrees of the network in the sample (Scott, 2017). Both variables include connections based on CEOs' educational background, previous workplace and social organizations' memberships.

4.4. Regression model

The regression model used to test hypotheses 1-7 is represented by the following equation:

$$Informativeness_{i,t} = \beta_0 + \beta_1 Lognetworksize_{i,t} + \beta_2 Controls_{i,t} + \varepsilon_{i,t} \quad (8)$$

We utilize linear model because we don't find squared term of CEO connections to be significant as in Fang et al. (2018).

Five proxies of stock price informativeness mentioned above are used as the main dependent variables while *LOGNETWORKSIZE* is utilized as the main explanatory one. We also add the following controls shown by the previous literature to be important for informativeness:

- The market value of equity (*LOGMVE*) to control for the company's size. Roll (1988) shows that it's an important determinant of R^2 because larger companies are usually better diversified. Additionally, larger companies are also more attractive to investors and enjoy higher media coverage (Piotroski and Roulstone, 2004).
- Tobin's Q (*Q*) as a proxy for the firm's growth opportunities.
- The standard deviation of ROA measure (*STDROA*) accounting for returns' variability (Haggard et al., 2008).

- Industry structure is also important for stock price informativeness. For example, if the industry is more concentrated, the information about each firm becomes more important to the market as a whole (Haggard et al., 2008). That's why the concentration of the firms in the industry measured by the Herfindahl index (*LOGHHI*) is also added.
- Analysts (*ANALYSTS*) influence the amount of available firm-specific information by issuing recommendations, revisions, or forecasts about the company's future earnings (Piotroski and Roulstone, 2004; Tetlock, 2010).
- Insider trading (*LOGINSIDE*) as the absolute value of the difference between insiders' buys and sells (Piotroski and Roulstone, 2004)
- Institutional ownership (*LOGINST*) as the number of shares held by institutions (Piotroski and Roulstone, 2004)
- Quality of disclosure (*DISCLOSURE*) and reporting provided by the firm as proxied by accruals (Mouselli et al., 2012)
- Turnover (*TURNOVER*) which is defined as the total number of shares traded during the period divided by shares outstanding (Hou and Mosckowitz, 2005).
- Past returns (*PREVRET*) should also be added as its one of the predictors of the future outcome for the company as well (Harvey et al., 2000).

MVE, *HHI*, *INST*, and *INSIDE* are utilized in the log format according to Haggard et al. (2008) and Piotroski and Roulstone (2004). Following Haggard et al. (2008), we also control for year fixed effects and industry fixed effects using a two-digit Standard Industrial Classification code (SIC2).

We use the following measures of diversity introduced by Fang et al. (2018) while investigating how such characteristics of CEO network can additionally impact stock price informativeness:

- Gender diversity (*GENDERDIVERSITY*). Ratio of female CEOs in the network.

- Nationality diversity (*NATDIVERSITY*). Number of non-American CEOs compared to the total number of members in network.
- Professional diversity (*POSDIVERSITY*). In this case network is larger as we include not only CEOs into consideration. Ratios of CEO, CFO, all other directors, and board are all utilized to calculate this measure as follows: 1 – (CEO ratio^2 + CFO ratio^2 + Other directors ratio^2 + Board of directors ratio^2).
- Educational diversity (*EDUCDIVERSITY*). Three educational backgrounds of network members are taken into account: 1 − (PhD ratio^2 + Master's ratio^2 + Bachelor's ratio^2).

To conduct split-sample analysis we utilize the following two proxies for the firm's information asymmetry: analyst coverage, and bid-ask spread. Brown and Hillegeist (2007) argue that analysts base their forecasts mostly on the information provided by the companies themselves. They also mention that analysts are indeed outsiders and do not have the same access to the firm-specific information as management of the firm. Instead, they analyze industry and market-level information. Higher analyst coverage is associated with more information asymmetry. Next, Venkatesh et al. (1986) mention that dealers tend to widen the spread when there is an increased chance of losses to insiders and more information asymmetry is present in the market in order to preserve their revenue. Wider spread is also associated with higher information asymmetry. Moreover, we use a firm's size as a proxy for financial constraints. Hovakimian and Titman (2006) mention that larger companies have lower transaction costs, they are also more diversified and it's easier for them to obtain external financing. As such larger company's size is associated with lower financial constraints.

5. Results

5.1. Main results

Table 1 provides the summary statistics for the five informativeness proxies, the modified measure of connectedness (*LOGNETWORKSIZE*), and the control variables winsorized at 1% and

99% level. The variables exhibit descriptive statistics similar to those in Haggard et al. (2008) and Piotroski and Roulstone (2004).

Tables 2-6 in this section follow the same structure. In the first column, we include only the main independent variable of interest – *LOGNETWORKSIZE*. Next, in column (2) we add year and industry fixed effects. In column (3), we add controls following Piotroski and Roulstone (2004) while in column (4) we also include liquidity control variables. Columns (5)-(6) account for all controls, year or industry fixed effects respectively, while the last column (7) contains both fixed effects.

Table 2 reports results using *SYNCHRO* as the measure of stock price informativeness. In the univariate specification (1), the *LOGNETWORKSIZE* coefficient estimate is negative (-0.4187) and significant at the 1% level. Specifications (2), (3), (4), and (6) with -0.4490, -0.0709, -0.0836, and -0.1182 also show a negative association between connectedness and synchronicity while (5) with included year fixed effects does not (0.0937). Moreover, when we account for all controls and both year and industry fixed effects in specification (7), there is also evidence of a positive association between CEO connectedness and synchronicity. The coefficient of *LOGNETWORKSIZE* in this case becomes 0.0486 significant at 1% level. Specification (7) can explain 60.1% of variation in stock price synchronicity compared to just 9.4% in (1). The higher connectedness of the firm's CEO is associated with higher synchronicity or, in other words, a decrease in stock price informativeness and less firm-specific information incorporates into them.

In Table 3, we utilize *CRASH* as the proxy for informativeness. In specification (1) when *LOGNETWORKSIZE* is the only independent variable and in (2) when we add both fixed effects, coefficients are positive and equal to 0.1517 and 0.1927 significant at 1% level. A similar result is also found in specification (5) being 0.0866 when all controls are also added into consideration and year fixed effects are included. On the other hand, when year fixed effects are not utilized in (3), (4), and (6), the coefficient of *LOGNETWORKSIZE* becomes negative -0.2557, -0.2294, and

-0.2931. Finally, in specification (7) with all controls and fixed effects, a positive relation between *LOGNETWORKSIZE* and *CRASH* is also uncovered though it's not significant (0.0331). Thus, crash frequency is higher and stock price informativeness is lower with more connections enjoyed by the CEO. In other words, there is less private information incorporated into stock prices of the companies with more connected CEO.

In Table 4 *PRICEDELAY* is the proxy for stock price informativeness. Specifications (1), (3), and (6) show a negative relation between social capital and price delay proxy with coefficients of -0.0045, -0.0070, and -0.0054 significant at 1% level while in specification (4) coefficient of -0.0038 is significant at 5%. In (2), (5), and (7), the estimated coefficients of -0.0007, -0.0014, and -0.0029, are, on the other hand, insignificant after adding year fixed effects and other controls into consideration. At least there is no increase in firm-specific information incorporated into stock prices with larger CEO social capital as well.

In Table 5, we use *LLORENTE* measure of stock price informativeness. All specifications find a negative association between *LOGNETWORKSIZE* and the dependent variable but with different levels of significance. For example, specifications (1), (6), and (7) show coefficients significant at 5% level. Then (4) and (5) demonstrate significance at 10% level. Finally, specifications (2) and (3) have the following coefficients of -0.0266 and -0.0472 significant at 1%. Such findings show that the amount of private information incorporated into stock prices doesn't increase with larger CEO social capital.

In Table 6, we use *PIN* as the proxy for stock price informativeness. All specifications show consistency in terms of the negative sign for the *LOGNETWORKSIZE* variable. In (1) coefficient equals -0.0132 and in specification (2) it is -0.0156, both significant at the 1% level. Specifications (6) and (7) find -0.0025 and -0.0029 significant at 5% level. All others (3)-(5) produce insignificant coefficients of *LOGNETWORKSIZE*. As *PIN* stands for the probability of

informed trading in stocks, its decreasing value shows that more CEO connections lead to a lower amount of private information incorporated into their prices.

5.2. Endogeneity tests

It is possible that companies with lower stock price informativeness prefer to hire better-connected CEOs. To address this endogeneity issue, in this section we utilize instrumental variable regression. As an instrument, we use the number of local social organizations in the area where each company is located. Information about such organizations is obtained from Northeast Regional Center for Rural Development (Ferris et al., 2017). The number of local social organizations is likely to influence CEO's social capital but there is no reason to believe that such measure can directly impact a firm's stock price informativeness. Endogeneity and instrument's relevance are confirmed by Durbin-Wu-Hausman and Stock and Yogo (2005) tests. They indicate that endogeneity exists in all regression specifications, except for the one in which *PIN* is utilized as the main dependent variable, and that the selected instrument is strong.

Based on the IV regressions in Table 7, the increase in connectedness leads to a significant increase in synchronicity, crash, and price delay measures while decreasing Llorente proxy. The coefficient of *LOGNETWORKSIZE* is 0.1174 and significant at 10% level when we use *SYNCHRO* proxy. In *CRASH* and *PRICEDELAY* specifications, *LOGNETWORKSIZE* variable has coefficients of 1.0741 and 0.0480 respectively both significant at 1% level. Similar magnitude but a different sign of coefficient -0.3578 in *LLORENTE* specification is consistent with previous models due to this proxy's positive relation with informativeness. Overall, these results confirm hypothesis H_{1b} and are even stronger than those mentioned in Tables 2-6. They indicate that increased CEO connectedness is indeed associated with lower stock price informativeness and less private information incorporation.

Ferris et al. (2017) argue that potential endogeneity from reverse causality is not an issue in this setting. The authors mention that the social capital of managers is usually formed long

before the informativeness of stock prices is analyzed. For example, educational ties are formed as far as decades ago when the CEO wasn't at his or her respective position at all. In this study, we include only year and industry fixed effects because according to Faleye et al. (2014), both firm and CEO fixed effects will distort results due to a relatively short period of analysis.

5.3. Diversity analysis

In this section we present results about diversity characteristics of CEO network and their impact on stock price informativeness.

First of all, in Table 8 *GENDERDIVERSITY* coefficient of 0.1138 is highly significant at 1% level in *PRICEDELAY* specification as well as positive but a little less significant for *SYNCHRO* specification with 0.2536 significant at 10%. Both of them show that diversity in terms of gender among participants of CEO network is negatively associated with stock price informativeness.

Next, in Table 9 we also show that *NATDIVERSITY* coefficient is negative -0.7185 and highly significant at 1% in *LLORENTE* specification which shows that increased diversity in CEO network in terms of nationality is also negatively related to stock price informativeness.

In Table 10 we investigate the impact of diverse previous experience of network participants on stock price informativeness and find that it's a positive one as shown in specifications (3) and (5) with *POSDIVERSITY* coefficient equals to -0.0420 and 0.1227. The presence of corporate executives other than CEOs in the network has a positive impact on stock price informativeness in this case.

Finally, educational diversity among CEO network members as shown in Table 11 also positively influences stock price informativeness. In specification (3) *EDUCDIVERSITY* coefficient is significant at 1% level and equals to -0.0980 while in specification (4) where *LLORENTE* utilized as main dependent variable it has a value of 0.8689 also highly significant.

5.4. Robustness checks

First of all, we change the main independent variable from *LOGNETWORKSIZE* to degree centrality (*DCENTRALITY)* to investigate whether the results are different while utilizing alternative measure of CEO social connectedness. Table 12 shows that results still hold but become less pronounced. For example, in *SYNCHRO* specification coefficient of *DCENTRALITY* is 192.5016 and is highly significant at 1% level. In *LLORENTE* specification coefficient becomes -87.5211 that also show a negative relation between connectedness of CEO and stock price informativeness of the company similar to the main ones reported above.

Next, Cheong et al. (2021) and Hou and Moskowitz (2005) emphasize the importance of consistency in the companies' data. We follow their work and exclude all the firms that don't have at least 5 years of data during the period of 1995-2020. In specification (1) of Table 13 *LOGNETWORKSIZE* coefficient is positive 0.0483 and significant at 1% level while in (2) and (3) they are not significant. The negative association is found with *LLORENTE* (-0.0484) and *PIN* (-0.0055) proxies. They show that CEO connectedness is negatively associated with stock price informativeness and less firm-specific information is incorporated with an increase in CEO social capital.

Moreover, Bhojraj et al. (2003) argue that Global Industry Classifications Standard (GICS) developed by Standard & Poor's and Morgan Stanley Capital International (MSCI) is a preferable way to classify companies into groups. GICS classification is better in explaining stock return co-movements and is becoming more popular among researchers. We utilize this classification to make sure that the social capital variable is still significant after accounting for new industry fixed effects. In Table 14 *LOGNETWORKSIZE* coefficients are 0.0752 and 0.0904 significant at 1% level when synchronicity and crash proxies of informativeness are used with new fixed effects. *LLORENTE* specification shows *LOGNETWORKSIZE* coefficient of -0.0373 significant at 10% level, while *PRICEDELAY* and *PIN* return non-significant values. New classification points in the same direction of a negative association between social capital and informativeness.

Finally, Duarte et al. (2020) mention the placebo test as another way to show results robustness. In this case, real CEO connectedness is replaced by randomized connectedness measures (*RLOGNETWORKSIZE*). We perform this test in Table 15 and do not find any significant connection between CEO social capital and stock price informativeness as expected. It shows that results received before are not due to chance and there is indeed negative causal relation between connectedness and informativeness.

5.5. Split-sample analysis

First of all, we investigate whether the information asymmetry plays an important moderating role with the help of the following proxies: analyst coverage, and bid-ask spread.

We utilize split-sample analysis with the median value of the number of analysts following the company to run regression according to equation (8) for each of the sub-samples. Specification (4) in Table 16 shows *LOGNETWORKSIZE* coefficient of -0.0835 for companies with extensive coverage significant at 1% level compared to the insignificant coefficient of -0.0078. For *PIN* specification *LOGNETWORKSIZE* coefficient transforms from -0.0075 significant at 1% for sub-sample with a large analyst following to insignificant -0.0011. Similar transformation is also shown for *SYNCHRO* specification when coefficient changes from highly significant 0.0483 to insignificant 0.0056. More extensive analyst coverage leads to a more pronounced negative impact of CEO connectedness on stock price informativeness as a result.

In Table 17 we present split-sample results while using the median of another proxy for information asymmetry - bid-ask spread. The coefficient of *LOGNETWORKSIZE* for specification (1) equals 0.0887 significant at 1% level for high bid-ask spread companies and insignificant -0.0191 for others. For *LLORENTE* and *PIN* specifications coefficients of *LOGNETWORKSIZE* are as follows: -0.0490 significant at 10% compared to insignificant -0.0495, -0.0033 significant at 5% becomes insignificant 0.0047 for low bid-ask spread accordingly. Overall, even less firm-specific information is incorporated into stock prices through CEO social capital for companies with large information asymmetry proxied by the bid-ask spread. Both lower exposure to firm-

specific shocks explanation suggested by Faccio et al. (2021) and investors' discouragement mentioned in Manove (1989) are possible in this case. The further results help to distinguish between them.

Next, we investigate the impact of financial constraints and split the sample by the median value of the companies' sizes. Table 18 shows that in *LLORENTE* and *PIN* specifications there is indeed a more negative relation between CEO connectedness and stock price informativeness with an increase in the company's size. The coefficient of *LOGNETWORKSIZE* is negative -0.0752 in *LLORENTE* specification and negative -0.0073 when *PIN* is used as a dependent variable. All of them significant at 1% level compared to insignificant coefficients in a small size sub-sample being -0.0508 and 0.0036. Overall, a negative effect of CEO connectedness on stock price informativeness is more pronounced for companies with lower financial constraints. That doesn't support lower exposure to firm-specific shocks explanation.

CEO's tenure can moderate the observed negative effect of social capital on stock price informativeness. We split the sample according to CEO's tenure median value to show whether there is a significant difference between the two groups. In Table 19 we find that the negative impact of CEO social capital on stock price informativeness is much more pronounced if CEO is short-tenured. In *SYNCHRO* and *CRASH* specifications coefficient of *LOGNETWORKSIZE* is larger and for short-tenured directors being 0.1161 and 0.0995 compared to 0.0393 and insignificant 0.0304 for CEO with longer tenure. When we use *PIN* as the main dependent variable results are also similar: -0.0062 significant at 10% level for short-tenured CEO compared to insignificant -0.0022 for others. Recently appointed CEOs may not have had the time to create meaningful connections that can positively influence informativeness. As before, this finding cannot be explained by lower exposure to firm-specific shocks.

The geographic position of the firms in the US can also play an important role while explaining the effect of CEO social capital on informativeness. That's why we split the sample and analyze 12 states with the highest index of social capital according to Lee (2018) and all others

separately. Table 20 shows that companies located in the states with a high level of social capital do not experience an adverse effect of increased CEO connectedness on informativeness. Others located in regions with lower social capital demonstrate a much more negative tendency. Coefficients of *LOGNETWORKSIZE* in high and low social capital states equal to 0.0693 significant only at 10% and 0.0481 significant at 1% in specification (1). For *LLORENTE* and *PIN* specifications coefficients for those two sub-groups are different even in terms of the sign and equal to 0.3679 and -0.0685 as well as 0.0104 and -0.0034. External information environment as proxied by the state in which CEOs of the companies make their respective connections and form networks matters for the total impact of social capital on informativeness. Based on this analysis, discouragement of outside investors explanation is preferred.

Finally, we use the 2002 SOX Act to split the sample and analyze whether there is a significant difference between social capital's influence on stock price informativeness before and after that event. Results of this analysis are presented in Table 21. In the post-SOX period, an increase in CEO connectedness becomes a much more negative factor for stock price informativeness than before SOX. In other words, even less firm-specific information is present in stock prices of the companies with connected CEO after SOX. In *SYNCHRO* specification coefficient of *LOGNETWORKSIZE* is positive and significant at 10% 0.0411 before SOX while highly significant at 1% level 0.0538 afterward. Similar numbers are also found for specification (2) with -0.1958 coefficient before and 0.0771 significant at 1% level after SOX implementation. Specifications (4) and (5) also show that negative relation is stronger for the post-SOX time interval with -0.0414 and -0.0028 coefficients significant at 10% and 5% levels. In this case, SOX discourages investors and makes them more cautious to collect and act upon private information to avoid possible scandals.

6. Conclusion

We investigate the association between CEOs' connectedness and stock price informativeness in a sample of US companies. Using five proxies for stock price informativeness,

We find that an increase in CEO connectedness is associated with lower stock price informativeness. Results survive endogeneity tests and a battery of other robustness tests. There is strong evidence that there is less private information incorporated into stock prices when the CEO has more social capital. Moreover, we show that diversity of CEO network in terms of gender and nationality leads to a negative impact on stock price informativeness while the positive relation is found instead when members are more diverse from professional and educational perspectives.

We also find that companies with more information asymmetry exhibit a stronger negative association between stock price informativeness and CEO connectedness, which is consistent with two possible explanations. First, that investors perceive more connected firms as being less exposed to firm-specific shocks because of the benefits of the network, such as alleviating information asymmetry problems or financial constraints. Second, that investors are discouraged from doing research and trading on more connected firms. Inconsistent with the first possible explanation, we uncover that the negative relation is stronger for firms with CEOs of a shorter tenure and for firms with lower level of financial constraints. Furthermore, we also find stronger (more negative) results for US states with low social capital and for the post-Sarbanes-Oxley Act (SOX) implementation. Overall, the results suggest that outside investors become discouraged from collecting, doing research, and trading on information about more connected companies, which leads to a decrease in stock price informativeness.

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Table 1

Summary Statistics.

This table presents summary statistics for firm-level variables. The sample represents firms from Compustat/CRSP from 1985 to 2020 with available information about the CEO's connections.

Variable	Obs	Mean	Std. Dev.	Min	Max
lognetworksize	94554	7.633	1.407	3.485	10.691
logmve	169570	4.998	2.638	-1.196	11.094
q	168482	5.182	18.042	.098	155.102
loghhi	197376	-2.681	1.156	-3.81	1.143
stdroa	168228	.361	1.175	.001	8.346
analysts	72011	6.908	6.676	1	31
loginst	98799	15.989	3.878	2.144	21.748
loginside	87157	11.548	2.276	5.991	17.002
disclosure	158984	-.306	1.32	-11.079	.523
prevRET	76437	.014	.056	-.129	.287
turnover	142452	.211	.508	0	3.653
tenure	33782	6.536	4.859	0	24
spread	17030	.304	.462	.01	3
genderdiversity	34056	.187	.08	0	.789
educdiversity	33976	.518	.092	0	.667
profdiversity	34047	.424	.107	0	.727
natdiversity	33345	.158	.185	0	1
synchro	71427	1.606	1.877	-5.028	6.187
crash	197379	-9.394	6.114	-29	-1
Llorente	91853	.022	3.049	-13.242	14.861
pricedelay	104435	.768	.272	0	1
PIN	45251	.233	.142	0	.699

Table 2

Regression results – Synchronicity measure.

This table shows relation between social capital of CEO of the company and synchronicity proxy of stock price informativeness. Standard errors are in parenthesis *** p<0.01, ** p<0.05, * p<0.1

	(1) Synchro	(2) Synchro	(3) Synchro	(4) Synchro	(5) Synchro	(6) Synchro	(7) Synchro
lognetworksize	-0.4187***	-0.4490***	-0.0709***	-0.0836***	0.0937***	-0.1182***	0.0486***
	(0.006)	(0.005)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)
logmve			-0.4729***	-0.4364***	-0.3389***	-0.4373***	-0.3402***
			(0.007)	(0.008)	(0.008)	(0.008)	(0.008)
q			0.0944***	0.1046***	0.0460***	0.0891***	0.0284***
			(0.004)	(0.005)	(0.004)	(0.005)	(0.004)
loghhi			-0.1127***	-0.1080***	-0.0656***	-0.3470***	-0.0426
			(0.011)	(0.013)	(0.012)	(0.035)	(0.032)
stdroa			-0.0414	-0.0392	-0.0438	-0.0233	-0.0537
			(0.036)	(0.045)	(0.040)	(0.045)	(0.040)
analysts			-0.0059***	0.0047**	0.0005	0.0094***	0.0055***
			(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
loginst			0.2031***	0.1348***	-0.1157***	0.1435***	-0.1051***
			(0.002)	(0.004)	(0.006)	(0.004)	(0.006)
loginside			0.0186***	0.0186***	0.0212***	0.0165***	0.0197***
			(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
disclosure			0.3119***	0.3257***	0.0202	0.2749***	-0.0325
			(0.046)	(0.060)	(0.054)	(0.059)	(0.053)
prevRET				1.7604***	0.1437	1.8348***	0.2888
				(0.219)	(0.208)	(0.215)	(0.204)
turnover				-0.4925***	0.0101	-0.4414***	0.0539***
				(0.021)	(0.021)	(0.021)	(0.021)
_cons	4.5019***	4.4226***	0.4936***	1.5294***	4.1689***	-0.3788	4.3836***
	(0.046)	(0.043)	(0.071)	(0.091)	(0.109)	(0.520)	(0.143)
N	48445	48445	30467	22588	22588	22588	22588
R^2	0.094	0.480	0.450	0.491	0.595	0.515	0.601
Year FE	No	Yes	No	No	Yes	No	Yes
Industry FE	No	Yes	No	No	No	Yes	Yes

Table 3

Regression results – Crash frequency.

This table shows relation between social capital of CEO of the company and crash proxy of stock price informativeness. Standard errors are in parenthesis *** p<0.01, ** p<0.05, * p<0.1

	(1) Crash	(2) Crash	(3) Crash	(4) Crash	(5) Crash	(6) Crash	(7) Crash
lognetworksize	0.1517***	0.1927***	-0.2557***	-0.2294***	0.0866***	-0.2931***	0.0331
	(0.013)	(0.015)	(0.018)	(0.020)	(0.023)	(0.021)	(0.023)
logmve			-0.5083***	-0.5360***	-0.5134***	-0.5026***	-0.4836***
			(0.015)	(0.018)	(0.019)	(0.018)	(0.019)
q			0.0940***	0.1219***	0.1065***	0.0756***	0.0649***
			(0.007)	(0.010)	(0.010)	(0.010)	(0.010)
loghhi			-0.4908***	-0.4472***	-0.3602***	-0.5894***	-0.3129***
			(0.023)	(0.027)	(0.026)	(0.078)	(0.077)
stdroa			-0.0358	0.0202	0.0368	0.0080	0.0035
			(0.068)	(0.096)	(0.093)	(0.095)	(0.093)
analysts			0.0679***	0.0681***	0.0556***	0.0716***	0.0578***
			(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
loginst			0.0519***	0.0869***	0.0314**	0.0992***	0.0356**
			(0.005)	(0.008)	(0.015)	(0.008)	(0.015)
loginside			0.0824***	0.0591***	0.0466***	0.0529***	0.0416***
			(0.008)	(0.010)	(0.010)	(0.010)	(0.009)
disclosure			-0.0293	0.3689***	0.2848**	0.3583***	0.2988**
			(0.098)	(0.125)	(0.122)	(0.124)	(0.122)
prevRET				-1.3252***	-1.4306***	-1.5125***	-1.6905***
				(0.492)	(0.505)	(0.486)	(0.500)
turnover				0.2243***	0.3657***	0.2554***	0.3906***
				(0.047)	(0.052)	(0.047)	(0.051)
_cons	-10.9149***	-10.4800***	-6.6706***	-6.9079***	-7.2552***	-5.5467***	-6.8553***
	(0.101)	(0.128)	(0.163)	(0.208)	(0.270)	(1.353)	(0.352)
N	94554	94554	42389	29433	29433	29433	29433
R^2	0.001	0.006	0.069	0.072	0.130	0.107	0.115
Year FE	No	Yes	No	No	Yes	No	Yes
Industry FE	No	Yes	No	No	No	Yes	Yes

Table 4

Regression results – Price delay measure.

This table shows relation between social capital of CEO of the company and price delay proxy of stock price informativeness. Standard errors are in parenthesis *** p<0.01, ** p<0.05, * p<0.1

	(1) Price Delay	(2) Price Delay	(3) Price Delay	(4) Price Delay	(5) Price Delay	(6) Price Delay	(7) Price Delay
lognetworksize	-0.0045***	-0.0007	-0.0070***	-0.0038**	-0.0014	-0.0054***	-0.0029
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
logmve			-0.0014	-0.0005	0.0011	-0.0006	0.0009
			(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
q			0.0011*	0.0025***	0.0023***	0.0019**	0.0018**
			(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
loghhi			0.0108***	0.0111***	0.0113***	0.0157***	0.0165***
			(0.002)	(0.002)	(0.002)	(0.006)	(0.006)
stdroa			-0.0457***	-0.0408***	-0.0424***	-0.0449***	-0.0465***
			(0.007)	(0.008)	(0.008)	(0.008)	(0.008)
analysts			0.0004	0.0003	-0.0000	0.0005*	0.0003
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
loginst			0.0011***	-0.0026***	-0.0041***	-0.0025***	-0.0039***
			(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
loginside			-0.0029***	-0.0021***	-0.0022***	-0.0014*	-0.0014*
			(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
disclosure			0.0106	0.0180*	0.0146	0.0100	0.0069
			(0.008)	(0.010)	(0.010)	(0.010)	(0.010)
prevRET				-0.0029	-0.0450	-0.0024	-0.0456
				(0.039)	(0.042)	(0.039)	(0.042)
turnover				-0.0276***	-0.0246***	-0.0285***	-0.0259***
				(0.004)	(0.004)	(0.004)	(0.004)
_cons	0.8159***	0.7962***	0.9007***	0.9383***	0.9529***	0.8345***	0.9670***
	(0.005)	(0.007)	(0.012)	(0.016)	(0.021)	(0.098)	(0.027)
N	75075	75075	40099	28317	28317	28317	28317
R^2	0.001	0.002	0.005	0.007	0.011	0.025	0.009
Year FE	No	Yes	No	No	Yes	No	Yes
Industry FE	No	Yes	No	No	No	Yes	Yes

Table 5

Regression results – Llorente measure.

This table shows relation between social capital of CEO of the company and Llorente proxy of stock price informativeness. Standard errors are in parenthesis *** p<0.01, ** p<0.05, * p<0.1

	(1) Llorente	(2) Llorente	(3) Llorente	(4) Llorente	(5) Llorente	(6) Llorente	(7) Llorente
lognetworksize	-0.0205**	-0.0266***	-0.0472***	-0.0336*	-0.0397*	-0.0414**	-0.0483**
	(0.008)	(0.009)	(0.016)	(0.018)	(0.021)	(0.019)	(0.022)
logmve			-0.0387***	-0.0454***	-0.0585***	-0.0522***	-0.0703***
			(0.014)	(0.016)	(0.018)	(0.017)	(0.019)
q			0.0015	0.0026	0.0049	0.0030	0.0062
			(0.008)	(0.009)	(0.010)	(0.010)	(0.010)
loghhi			-0.0032	-0.0154	-0.0151	-0.0088	-0.0128
			(0.020)	(0.024)	(0.024)	(0.069)	(0.070)
stdroa			0.0815	0.1169	0.1202	0.1323	0.1362
			(0.093)	(0.112)	(0.113)	(0.113)	(0.113)
analysts			0.0070**	0.0082**	0.0084**	0.0082**	0.0084**
			(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
loginst			0.0085*	-0.0024	0.0211	0.0009	0.0322**
			(0.004)	(0.008)	(0.015)	(0.008)	(0.015)
loginside			-0.0021	0.0006	0.0003	-0.0004	-0.0007
			(0.007)	(0.009)	(0.009)	(0.009)	(0.009)
disclosure			0.1015	0.0992	0.1160	0.1148	0.1318
			(0.101)	(0.126)	(0.127)	(0.127)	(0.128)
prevRET				-0.4144	-0.3346	-0.4088	-0.3313
				(0.475)	(0.509)	(0.475)	(0.510)
turnover				-0.0603	-0.1050**	-0.0450	-0.1038**
				(0.046)	(0.052)	(0.046)	(0.053)
_cons	0.1692***	0.1765**	0.4229***	0.4875***	0.1606	-0.4226	0.1311
	(0.063)	(0.080)	(0.144)	(0.187)	(0.253)	(1.159)	(0.328)
N	68359	68359	37533	26855	26855	26855	26855
R^2	0.000	0.000	0.001	0.001	0.001	0.012	0.002
Year FE	No	Yes	No	No	Yes	No	Yes
Industry FE	No	Yes	No	No	No	Yes	Yes

Table 6

Regression results – PIN measure.

This table shows relation between social capital of CEO of the company and PIN proxy of stock price informativeness. Standard errors are in parenthesis *** p<0.01, ** p<0.05, * p<0.1

	(1) PIN	(2) PIN	(3) PIN	(4) PIN	(5) PIN	(6) PIN	(7) PIN
lognetworksize	-0.0132***	-0.0156***	-0.0012	-0.0009	-0.0013	-0.0025**	-0.0029**
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
logmve			-0.0055***	-0.0063***	-0.0061***	-0.0046***	-0.0043***
			(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
q			0.0006	0.0004	0.0004	0.0002	0.0001
			(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
loghhi			0.0080***	0.0085***	0.0082***	0.0033	0.0023
			(0.001)	(0.001)	(0.001)	(0.004)	(0.004)
stdroa			-0.0031	-0.0063	-0.0062	-0.0043	-0.0041
			(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
analysts			-0.0008***	-0.0005**	-0.0005**	-0.0008***	-0.0007***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
loginst			-0.0015***	-0.0022***	-0.0028***	-0.0015***	-0.0023***
			(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
loginside			0.0025***	0.0021***	0.0019***	0.0020***	0.0019***
			(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
disclosure			0.0014	-0.0045	-0.0047	-0.0036	-0.0039
			(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
prevRET				-0.0383	-0.0361	-0.0381	-0.0356
				(0.026)	(0.027)	(0.025)	(0.027)
turnover				-0.0041	-0.0037	-0.0015	-0.0007
				(0.003)	(0.003)	(0.002)	(0.003)
_cons	0.3145***	0.3131***	0.2746***	0.2940***	0.3007***	0.2618**	0.2773***
	(0.004)	(0.005)	(0.009)	(0.011)	(0.015)	(0.104)	(0.020)
N	28443	28443	15203	10560	10560	10560	10560
R^2	0.024	0.028	0.030	0.033	0.035	0.080	0.027
Year FE	No	Yes	No	No	Yes	No	Yes
Industry FE	No	Yes	No	No	No	Yes	Yes

Table 7

IV regression – number of social organizations

This table investigates endogeneity issues. Instrument used in this case is the number of local social organizations in the area where the company is located. Endogeneity was not detected in PIN regression, so it's omitted. Standard errors are in parenthesis *** p<0.01, ** p<0.05, * p<0.1

	(1) Synchro	(2) Crash	(3) Price Delay	(4) Llorente
lognetworksize	0.1174*	1.0741***	0.0480***	-0.3578***
	(0.069)	(0.160)	(0.012)	(0.107)
logmve	-0.4999***	-0.8239***	-0.0190***	0.0737*
	(0.025)	(0.053)	(0.004)	(0.039)
q	0.1191***	0.1906***	0.0057***	-0.0189*
	(0.007)	(0.015)	(0.001)	(0.010)
loghhi	-0.0526**	-0.1121**	0.0203***	-0.0517*
	(0.021)	(0.045)	(0.003)	(0.027)
stdroa	-0.0865	-0.3990***	-0.0497***	0.2913***
	(0.058)	(0.116)	(0.010)	(0.104)
analysts	0.0055**	0.0478***	0.0004	0.0091***
	(0.002)	(0.005)	(0.000)	(0.003)
loginst	0.1229***	-0.0382**	-0.0074***	0.0302***
	(0.007)	(0.016)	(0.001)	(0.008)
loginside	0.0130**	0.0076	-0.0037***	-0.0016
	(0.006)	(0.013)	(0.001)	(0.008)
disclosure	0.5209***	0.9422***	0.0460***	0.0287
	(0.086)	(0.168)	(0.013)	(0.108)
prevRET	1.7932***	-0.6441	0.0157	
	(0.245)	(0.546)	(0.044)	
turnover	-0.4990***	0.0522	-0.0392***	
	(0.026)	(0.060)	(0.005)	
_cons	0.7108***	-12.1836***	0.7702***	1.6775***
	(0.238)	(0.587)	(0.041)	(0.423)
N	18912	25204	24158	32350

Table 8

Diversity (gender)

This table shows how gender diversity in CEO network influences stock price informativeness. Standard errors are in parenthesis *** p<0.01, ** p<0.05, * p<0.1

	(1) Synchro	(2) Crash	(3) Price Delay	(4) Llorente	(5) PIN
lognetworksize	0.1423***	0.1038***	-0.0088***	-0.0985***	-0.0079***
	(0.015)	(0.036)	(0.003)	(0.037)	(0.002)
logmve	-0.3634***	-0.4637***	0.0004	-0.0716**	-0.0034*
	(0.013)	(0.029)	(0.003)	(0.031)	(0.002)
q	0.0450***	0.0624***	0.0026*	0.0082	-0.0010
	(0.007)	(0.017)	(0.001)	(0.018)	(0.001)
loghhi	-0.0078	-0.2654**	-0.0153	0.2265*	0.0179**
	(0.054)	(0.121)	(0.010)	(0.124)	(0.007)
stdroa	-0.0862*	-0.1310	-0.0552***	0.0513	-0.0050
	(0.048)	(0.125)	(0.011)	(0.157)	(0.006)
analysts	0.0077***	0.0415***	0.0005	-0.0060	0.0001
	(0.002)	(0.005)	(0.000)	(0.006)	(0.000)
loginst	-0.1629***	0.1174***	-0.0024	0.0971***	-0.0062***
	(0.013)	(0.031)	(0.003)	(0.033)	(0.002)
loginside	0.0223***	0.0261**	-0.0003	-0.0172	0.0016**
	(0.005)	(0.012)	(0.001)	(0.013)	(0.001)
disclosure	-0.0242	0.1273	-0.0116	0.0782	-0.0116
	(0.081)	(0.167)	(0.014)	(0.181)	(0.008)
prevRET	0.4865	-0.5803	0.0067	1.0548	-0.0079
	(0.341)	(0.856)	(0.074)	(0.938)	(0.048)
turnover	0.0879*	0.9654***	-0.0221*	0.1947	0.0255***
	(0.052)	(0.127)	(0.011)	(0.142)	(0.007)
genderdiversity	0.2536*	-0.2070	0.1138***	0.6465*	0.0308
	(0.145)	(0.348)	(0.029)	(0.361)	(0.022)
_cons	4.9669***	-8.4529***	0.8717***	0.6140	0.4246***
	(0.259)	(0.610)	(0.052)	(0.633)	(0.037)
N	9493	13826	13503	12699	5064
R^2	0.465	0.111	0.011	0.005	0.046
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes

Table 9

Diversity (nationality)

This table shows how nationality diversity in CEO network influences stock price informativeness. Standard errors are in parenthesis *** p<0.01, ** p<0.05, * p<0.1

	(1) Synchro	(2) Crash	(3) Price Delay	(4) Llorente	(5) PIN
lognetworksize	0.1518***	0.0924***	-0.0068**	-0.0816**	-0.0068***
	(0.015)	(0.036)	(0.003)	(0.037)	(0.002)
logmve	-0.3631***	-0.4721***	0.0014	-0.0755**	-0.0033*
	(0.013)	(0.029)	(0.003)	(0.031)	(0.002)
q	0.0450***	0.0651***	0.0027*	0.0098	-0.0008
	(0.007)	(0.017)	(0.001)	(0.018)	(0.001)
loghhi	-0.0100	-0.2688**	-0.0158	0.2578**	0.0164**
	(0.054)	(0.122)	(0.010)	(0.124)	(0.007)
stdroa	-0.0788	-0.1385	-0.0556***	0.0786	-0.0036
	(0.048)	(0.125)	(0.011)	(0.157)	(0.006)
analysts	0.0069***	0.0436***	0.0006	-0.0047	-0.0000
	(0.002)	(0.005)	(0.000)	(0.006)	(0.000)
loginst	-0.1560***	0.1186***	-0.0045	0.1104***	-0.0052***
	(0.013)	(0.031)	(0.003)	(0.033)	(0.002)
loginside	0.0228***	0.0272**	-0.0002	-0.0152	0.0016**
	(0.005)	(0.012)	(0.001)	(0.013)	(0.001)
disclosure	-0.0055	0.1463	-0.0101	0.0880	-0.0124
	(0.081)	(0.168)	(0.014)	(0.181)	(0.008)
prevRET	0.3813	-0.9006	-0.0108	0.4294	0.0200
	(0.347)	(0.872)	(0.076)	(0.950)	(0.049)
turnover	0.0872*	0.9504***	-0.0214*	0.1413	0.0313***
	(0.052)	(0.128)	(0.011)	(0.141)	(0.007)
natdiversity	-0.0492	-0.2475	0.0126	-0.7185***	-0.0069
	(0.076)	(0.176)	(0.015)	(0.183)	(0.010)
_cons	4.8432***	-8.4511***	0.9026***	0.5757	0.3993***
	(0.261)	(0.616)	(0.052)	(0.637)	(0.037)
N	9394	13699	13382	12596	5006
R^2	0.461	0.112	0.011	0.006	0.042
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes

Table 10

Diversity (professional)

This table shows how professional diversity in CEO network influences stock price informativeness. Standard errors are in parenthesis *** p<0.01, ** p<0.05, * p<0.1

	(1) Synchro	(2) Crash	(3) Price Delay	(4) Llorente	(5) PIN
lognetworksize	0.1448***	0.1016***	-0.0079***	-0.0873**	-0.0054**
	(0.015)	(0.036)	(0.003)	(0.037)	(0.002)
logmve	-0.3625***	-0.4669***	0.0006	-0.0719**	-0.0030*
	(0.013)	(0.029)	(0.003)	(0.031)	(0.002)
q	0.0453***	0.0624***	0.0027*	0.0096	-0.0005
	(0.007)	(0.017)	(0.001)	(0.018)	(0.001)
loghhi	-0.0102	-0.2618**	-0.0153	0.2208*	0.0195***
	(0.054)	(0.121)	(0.010)	(0.124)	(0.007)
stdroa	-0.0878*	-0.1298	-0.0553***	0.0475	-0.0054
	(0.048)	(0.125)	(0.011)	(0.158)	(0.006)
analysts	0.0078***	0.0417***	0.0005	-0.0052	0.0001
	(0.002)	(0.005)	(0.000)	(0.006)	(0.000)
loginst	-0.1652***	0.1226***	-0.0031	0.0930***	-0.0057***
	(0.013)	(0.031)	(0.003)	(0.033)	(0.002)
loginside	0.0224***	0.0262**	-0.0002	-0.0169	0.0016**
	(0.005)	(0.012)	(0.001)	(0.013)	(0.001)
disclosure	-0.0242	0.1249	-0.0113	0.0837	-0.0122
	(0.081)	(0.167)	(0.014)	(0.181)	(0.008)
prevRET	0.4752	-0.5787	0.0042	1.0314	-0.0225
	(0.341)	(0.856)	(0.075)	(0.939)	(0.048)
turnover	0.0840	0.9687***	-0.0211*	0.1923	0.0285***
	(0.052)	(0.127)	(0.011)	(0.142)	(0.007)
posdiversity	-0.0857	0.1162	-0.0420**	-0.0351	0.1227***
	(0.104)	(0.252)	(0.021)	(0.262)	(0.015)
_cons	5.0604***	-8.5908***	0.9133***	0.7183	0.3494***
	(0.266)	(0.629)	(0.053)	(0.652)	(0.038)
N	9487	13824	13501	12698	5056
R^2	0.465	0.112	0.011	0.004	0.058
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes

Table 11

Diversity (educational)

This table shows how educational diversity in CEO network influences stock price informativeness. Standard errors are in parenthesis *** p<0.01, ** p<0.05, * p<0.1

	(1) Synchro	(2) Crash	(3) Price Delay	(4) Llorente	(5) PIN
lognetworksize	0.1457***	0.0991***	-0.0062**	-0.0950**	-0.0078***
	(0.015)	(0.035)	(0.003)	(0.037)	(0.002)
logmve	-0.3610***	-0.4687***	-0.0001	-0.0642**	-0.0036**
	(0.013)	(0.029)	(0.003)	(0.031)	(0.002)
q	0.0448***	0.0628***	0.0031**	0.0066	-0.0009
	(0.007)	(0.017)	(0.001)	(0.018)	(0.001)
loghhi	-0.0107	-0.2619**	-0.0153	0.2202*	0.0186***
	(0.054)	(0.121)	(0.010)	(0.124)	(0.007)
stdroa	-0.0887*	-0.1278	-0.0547***	0.0401	-0.0048
	(0.048)	(0.125)	(0.011)	(0.158)	(0.006)
analysts	0.0077***	0.0418***	0.0006	-0.0058	0.0001
	(0.002)	(0.005)	(0.000)	(0.006)	(0.000)
loginst	-0.1653***	0.1230***	-0.0028	0.0905***	-0.0058***
	(0.013)	(0.031)	(0.003)	(0.033)	(0.002)
loginside	0.0221***	0.0263**	-0.0002	-0.0167	0.0016**
	(0.005)	(0.012)	(0.001)	(0.013)	(0.001)
disclosure	-0.0254	0.1286	-0.0106	0.0747	-0.0118
	(0.081)	(0.167)	(0.014)	(0.181)	(0.008)
prevRET	0.4838	-0.5787	0.0012	1.0293	-0.0096
	(0.341)	(0.856)	(0.074)	(0.938)	(0.048)
turnover	0.0808	0.9711***	-0.0189*	0.1763	0.0274***
	(0.052)	(0.127)	(0.011)	(0.142)	(0.007)
educdiversity	0.1500	-0.1747	-0.0980***	0.8689***	-0.0083
	(0.119)	(0.294)	(0.025)	(0.306)	(0.018)
_cons	4.9384***	-8.4347***	0.9309***	0.3195	0.4287***
	(0.264)	(0.623)	(0.053)	(0.646)	(0.038)
N	9485	13822	13499	12696	5054
R^2	0.465	0.112	0.012	0.005	0.046
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes

Table 12

Degree of centrality

We include centrality measure of CEO connectedness rather than more direct one of the network size. Standard errors are in parenthesis *** p<0.01, ** p<0.05, * p<0.1

	(1) Synchro	(2) Crash	(3) Price Delay	(4) Llorente	(5) PIN
dcentrality	192.5016***	31.3378	-6.9483*	-87.5211*	-4.1052
	(19.039)	(54.393)	(4.091)	(50.152)	(2.920)
logmve	-0.3378***	-0.6042***	0.0004	-0.0836***	-0.0001
	(0.009)	(0.025)	(0.002)	(0.023)	(0.001)
q	0.0240***	0.0613***	0.0022***	-0.0003	-0.0011*
	(0.004)	(0.011)	(0.001)	(0.011)	(0.001)
loghhi	-0.0375	-0.3149***	0.0137**	0.0294	0.0007
	(0.034)	(0.088)	(0.007)	(0.080)	(0.005)
stdroa	-0.0379	-0.1218	-0.0500***	0.0956	-0.0102**
	(0.035)	(0.106)	(0.008)	(0.116)	(0.005)
analysts	0.0066***	0.0550***	0.0004	0.0076*	-0.0007***
	(0.002)	(0.005)	(0.000)	(0.004)	(0.000)
loginst	-0.1529***	0.1771***	-0.0041**	0.0456*	-0.0086***
	(0.010)	(0.027)	(0.002)	(0.025)	(0.001)
loginside	0.0166***	0.0298***	-0.0006	-0.0046	0.0015***
	(0.004)	(0.010)	(0.001)	(0.009)	(0.001)
disclosure	-0.0394	0.2753**	0.0013	0.1241	-0.0098*
	(0.048)	(0.127)	(0.010)	(0.132)	(0.005)
prevRET	0.5125**	-2.8969***	-0.0570	-0.2823	-0.0126
	(0.219)	(0.653)	(0.049)	(0.612)	(0.034)
turnover	-0.1703***	1.3315***	-0.0471***	0.1455	0.0144**
	(0.044)	(0.127)	(0.010)	(0.118)	(0.007)
_cons	4.9493***	-8.4269***	0.9598***	0.1089	0.3557***
	(0.172)	(0.460)	(0.035)	(0.424)	(0.024)
N	19981	26129	25736	24446	9466
R^2	0.434	0.120	0.009	0.002	0.033
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes

Table 13

Minimum 5 years of data

We include into consideration only companies that have at least 5 years of data available for analysis. Standard errors are in parenthesis *** p<0.01, ** p<0.05, * p<0.1

	(1) Synchro	(2) Crash	(3) Price Delay	(4) Llorente	(5) PIN
lognetworksize	0.0483***	0.0304	-0.0029	-0.0484**	-0.0055**
	(0.009)	(0.024)	(0.002)	(0.022)	(0.002)
logmve	-0.3398***	-0.4812***	0.0009	-0.0703***	-0.0026
	(0.008)	(0.019)	(0.002)	(0.019)	(0.002)
q	0.0284***	0.0651***	0.0018**	0.0062	-0.0007
	(0.004)	(0.010)	(0.001)	(0.010)	(0.001)
loghhi	-0.0430	-0.3075***	0.0165***	-0.0127	0.0182***
	(0.032)	(0.077)	(0.006)	(0.070)	(0.007)
stdroa	-0.0539	-0.0586	-0.0465***	0.1364	-0.0038
	(0.040)	(0.098)	(0.008)	(0.113)	(0.006)
analysts	0.0054***	0.0577***	0.0003	0.0084**	-0.0000
	(0.002)	(0.004)	(0.000)	(0.004)	(0.000)
loginst	-0.1050***	0.0368**	-0.0039***	0.0322**	-0.0047**
	(0.006)	(0.015)	(0.001)	(0.015)	(0.002)
loginside	0.0198***	0.0398***	-0.0014*	-0.0007	0.0015**
	(0.004)	(0.009)	(0.001)	(0.009)	(0.001)
disclosure	-0.0342	0.2770**	0.0069	0.1318	-0.0131
	(0.053)	(0.122)	(0.010)	(0.128)	(0.008)
prevRET	0.2864	-1.7366***	-0.0456	-0.3299	0.0088
	(0.204)	(0.500)	(0.042)	(0.510)	(0.049)
turnover	0.0541***	0.4069***	-0.0259***	-0.1038**	0.0325***
	(0.021)	(0.052)	(0.004)	(0.053)	(0.007)
_cons	4.3804***	-6.8355***	0.9670***	0.1313	0.2965***
	(0.144)	(0.352)	(0.027)	(0.328)	(0.040)
N	22578	29395	28317	26854	5003
R^2	0.601	0.115	0.009	0.002	0.057
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes

Table 14

GICS industry classification

New classification is utilized in this regression to better capture industry fixed effects. Standard errors are in parenthesis *** p<0.01, ** p<0.05, * p<0.1

	(1) Synchro	(2) Crash	(3) Price Delay	(4) Llorente	(5) PIN
lognetworksize	0.0752***	0.0904***	0.0001	-0.0373*	-0.0008
	(0.009)	(0.023)	(0.002)	(0.021)	(0.001)
logmve	-0.3364***	-0.4357***	0.0006	-0.0574***	-0.0067***
	(0.008)	(0.019)	(0.002)	(0.019)	(0.001)
q	0.0287***	0.0635***	0.0026***	0.0036	0.0009*
	(0.004)	(0.010)	(0.001)	(0.010)	(0.001)
loghhi	-0.0275**	-0.2781***	0.0062***	0.0009	0.0046***
	(0.013)	(0.029)	(0.002)	(0.026)	(0.002)
stdroa	-0.0811**	-0.1009	-0.0432***	0.0943	-0.0048
	(0.040)	(0.093)	(0.008)	(0.113)	(0.004)
analysts	0.0024	0.0433***	0.0001	0.0076**	-0.0004*
	(0.002)	(0.004)	(0.000)	(0.004)	(0.000)
loginst	-0.1111***	0.0177	-0.0043***	0.0212	-0.0030***
	(0.006)	(0.015)	(0.001)	(0.015)	(0.001)
loginside	0.0197***	0.0382***	-0.0014**	-0.0009	0.0021***
	(0.004)	(0.009)	(0.001)	(0.009)	(0.001)
disclosure	-0.0660	0.1887	0.0123	0.1145	-0.0034
	(0.053)	(0.121)	(0.010)	(0.128)	(0.005)
prevRET	0.3099	-1.7123***	-0.0416	-0.3402	-0.0359
	(0.204)	(0.501)	(0.042)	(0.510)	(0.027)
turnover	0.0143	0.2990***	-0.0241***	-0.1151**	-0.0037
	(0.021)	(0.051)	(0.004)	(0.053)	(0.003)
_cons	4.3586***	-6.9709***	0.9224***	0.2104	0.2883***
	(0.109)	(0.273)	(0.021)	(0.258)	(0.015)
N	22588	29433	28317	26855	10560
R^2	0.601	0.108	0.009	0.001	0.033
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes

Table 15

Placebo test

This table shows relation between randomized CEO connectedness (rlognetworksize) and all five proxies of stock price informativeness. Standard errors are in parenthesis *** p<0.001, ** p<0.01, * p<0.05

	(1) Synchro	(2) Crash	(3) Llorente	(4) PIN
rlognetworksize	-0.0004	0.0010	-0.0070	0.0001
	(0.004)	(0.009)	(0.008)	(0.000)
logmve	-0.3278***	-0.4760***	-0.0823***	-0.0049***
	(0.008)	(0.018)	(0.018)	(0.001)
q	0.0261***	0.0634***	0.0086	0.0003
	(0.004)	(0.010)	(0.010)	(0.001)
loghhi	-0.0415	-0.3126***	-0.0143	0.0022
	(0.032)	(0.077)	(0.070)	(0.004)
stdroa	-0.0421	0.0099	0.1218	-0.0046
	(0.040)	(0.093)	(0.113)	(0.004)
analysts	0.0064***	0.0584***	0.0076*	-0.0008***
	(0.002)	(0.004)	(0.004)	(0.000)
loginst	-0.0983***	0.0401***	0.0252*	-0.0027***
	(0.006)	(0.015)	(0.014)	(0.001)
loginside	0.0204***	0.0422***	-0.0015	0.0018***
	(0.004)	(0.009)	(0.009)	(0.001)
disclosure	-0.0502	0.2884**	0.1483	-0.0033
	(0.053)	(0.121)	(0.128)	(0.005)
prevRET	0.3138	-1.6802***	-0.3570	-0.0360
	(0.204)	(0.500)	(0.509)	(0.027)
turnover	0.0561***	0.3921***	-0.1055**	-0.0009
	(0.021)	(0.051)	(0.053)	(0.003)
_cons	4.5108***	-6.7730***	0.0594	0.2688***
	(0.144)	(0.352)	(0.329)	(0.019)
N	22588	29433	26855	10560
R^2	0.601	0.115	0.002	0.027
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes

Table 16

Information asymmetry. Split-sample analysis (analyst coverage)

This table shows relation between CEO social capital and informativeness for the firms with above (high) and below (low) the median analyst coverage. Standard errors are in parenthesis *** p<0.01, ** p<0.05, * p<0.1

	(1) Synchro		(2) Crash		(3) Price Delay		(4) Llorente		(5) PIN	
	Low	High	Low	High	Low	High	Low	High	Low	High
lognetworksize	0.0056	0.0483***	0.0981**	0.0379	-0.0011	-0.0018	-0.0078	-0.0835***	-0.0011	-0.0075***
	(0.015)	(0.011)	(0.041)	(0.033)	(0.003)	(0.002)	(0.031)	(0.026)	(0.002)	(0.002)
logmve	-0.4001***	-0.3080***	-0.5072***	-0.4406***	-0.0082***	0.0048**	-0.0701***	-0.0105	-0.0030*	-0.0082***
	(0.013)	(0.008)	(0.037)	(0.027)	(0.003)	(0.002)	(0.027)	(0.018)	(0.002)	(0.001)
q	0.0277***	0.0229***	0.0258	0.0371***	0.0062***	-0.0002	0.0249	-0.0146	0.0007	-0.0009
	(0.008)	(0.004)	(0.020)	(0.012)	(0.001)	(0.001)	(0.017)	(0.010)	(0.001)	(0.001)
loghhi	-0.1772***	0.0646*	0.1713	-0.5170***	0.0065	0.0137*	0.0484	-0.0498	0.0081	0.0010
	(0.054)	(0.038)	(0.144)	(0.107)	(0.010)	(0.008)	(0.107)	(0.083)	(0.007)	(0.005)
stdroa	-0.0127	-0.0587	-0.1057	-0.0059	-0.0632***	-0.0319***	-0.0828	0.0945	-0.0087	-0.0003
	(0.054)	(0.043)	(0.139)	(0.121)	(0.010)	(0.009)	(0.152)	(0.108)	(0.005)	(0.006)
loginst	-0.1070***	-0.1287***	0.1815***	0.2503***	0.0029	-0.0066***	-0.0097	0.0379**	-0.0065***	-0.0039***
	(0.011)	(0.006)	(0.038)	(0.026)	(0.003)	(0.002)	(0.024)	(0.016)	(0.001)	(0.001)
loginside	0.0217***	0.0096**	-0.0101	0.0473***	-0.0017	-0.0001	0.0044	-0.0072	0.0006	0.0011*
	(0.006)	(0.005)	(0.016)	(0.012)	(0.001)	(0.001)	(0.013)	(0.010)	(0.001)	(0.001)
disclosure	0.1083	0.0009	0.1701	0.1791	-0.0068	0.0035	-0.0120	0.0517	-0.0098	-0.0053
	(0.069)	(0.051)	(0.156)	(0.132)	(0.012)	(0.010)	(0.153)	(0.129)	(0.006)	(0.007)
prevRET	0.1395	0.9073***	-1.6629**	-2.2010***	-0.0379	-0.0290	-0.5328	0.1360	-0.0550	-0.0201
	(0.278)	(0.246)	(0.825)	(0.777)	(0.059)	(0.056)	(0.629)	(0.598)	(0.037)	(0.032)
turnover	-0.0222	0.1471***	1.8096***	1.5355***	-0.0017	-0.0517***	-0.1936**	-0.0148	-0.0093*	-0.0080**
	(0.036)	(0.024)	(0.232)	(0.144)	(0.017)	(0.010)	(0.084)	(0.060)	(0.005)	(0.003)
_cons	4.5183***	5.1287***	-7.5779***	-11.3470***	0.8650***	0.9618***	0.6650	-0.0642	0.3654***	0.3686***
	(0.238)	(0.155)	(0.679)	(0.465)	(0.049)	(0.034)	(0.490)	(0.349)	(0.031)	(0.021)
N	8913	16576	10348	19202	10153	18962	10492	19810	4030	7851
R^2	0.601	0.613	0.113	0.102	0.015	0.008	0.004	0.002	0.019	0.080
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 17

Information asymmetry. Split-sample analysis (bid-ask spread)

This table shows relation between CEO social capital and informativeness for the firms with above (large) and below (small) the median bid-ask spread. Standard errors are in parenthesis *** p<0.01, ** p<0.05, * p<0.1

	(1) Synchro		(2) Crash		(3) Price Delay		(4) Llorente		(5) PIN	
	Small	Large	Small	Large	Small	Large	Small	Large	Small	Large
lognetworksize	0.0191	0.0887***	0.0668	0.0265	-0.0042	-0.0024	-0.0495	-0.0490*	0.0047	-0.0033**
	(0.031)	(0.010)	(0.051)	(0.027)	(0.005)	(0.002)	(0.050)	(0.025)	(0.004)	(0.001)
logmve	-0.1941***	-0.3433***	-0.2082***	-0.5829***	0.0042	0.0013	-0.0347	-0.0815***	-0.0023	-0.0012
	(0.034)	(0.009)	(0.054)	(0.024)	(0.005)	(0.002)	(0.055)	(0.023)	(0.004)	(0.001)
q	0.0371*	0.0281***	0.0853***	0.0605***	0.0007	0.0020**	0.0891**	-0.0005	0.0023	-0.0009
	(0.022)	(0.004)	(0.028)	(0.011)	(0.003)	(0.001)	(0.036)	(0.011)	(0.002)	(0.001)
loghhi	-0.1425	-0.0399	-0.2795	-0.3063***	-0.0189	0.0143**	-0.1731	0.0273	0.0067	0.0009
	(0.348)	(0.034)	(0.446)	(0.087)	(0.037)	(0.007)	(0.388)	(0.080)	(0.029)	(0.005)
stdroa	-0.2451	-0.0452	0.2200	-0.1119	0.0346	-0.0499***	0.5149	0.1159	0.0049	-0.0089*
	(0.298)	(0.036)	(0.194)	(0.106)	(0.048)	(0.008)	(0.527)	(0.117)	(0.009)	(0.005)
analysts	0.0060	0.0052***	0.0134	0.0577***	0.0003	0.0004	0.0051	0.0085**	-0.0004	-0.0006***
	(0.008)	(0.002)	(0.014)	(0.005)	(0.001)	(0.000)	(0.013)	(0.004)	(0.001)	(0.000)
loginst	0.0106	-0.1291***	0.0015	0.1306***	-0.0021	-0.0059***	0.0426*	0.0463**	0.0038**	-0.0066***
	(0.016)	(0.009)	(0.026)	(0.025)	(0.002)	(0.002)	(0.026)	(0.023)	(0.002)	(0.001)
loginside	0.0827***	0.0159***	0.0471	0.0328***	-0.0057**	-0.0007	0.0038	-0.0031	0.0052**	0.0016***
	(0.019)	(0.004)	(0.030)	(0.010)	(0.003)	(0.001)	(0.031)	(0.009)	(0.002)	(0.001)
disclosure	0.0679	-0.0366	0.7593**	0.2470*	0.0891*	0.0009	0.3676	0.1181	-0.0200	-0.0070
	(0.337)	(0.048)	(0.316)	(0.133)	(0.051)	(0.010)	(0.545)	(0.132)	(0.017)	(0.006)
prevRET	-0.2161	0.5689***	0.2271	-2.8213***	-0.0093	-0.0553	-0.9601	-0.0822	-0.0858	0.0011
	(0.581)	(0.219)	(0.842)	(0.644)	(0.088)	(0.049)	(0.953)	(0.611)	(0.056)	(0.033)
turnover	0.0918**	-0.0845**	0.1975***	1.1206***	-0.0230***	-0.0387***	-0.1209*	0.0123	-0.0050	0.0060
	(0.041)	(0.038)	(0.065)	(0.107)	(0.006)	(0.008)	(0.066)	(0.103)	(0.005)	(0.006)
_cons	1.3125	4.6161***	-9.3362***	-7.8098***	0.9284***	0.9812***	-0.7253	0.1002	0.1458	0.3360***
	(1.448)	(0.166)	(2.269)	(0.444)	(0.184)	(0.034)	(1.930)	(0.412)	(0.132)	(0.023)
N	2568	20020	3247	26186	2563	25754	2391	24464	1069	9491
R^2	0.385	0.459	0.036	0.121	0.014	0.009	0.016	0.002	0.050	0.032
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 18

Financial constraints. Split-sample analysis (company size)

This table shows relation between CEO social capital and informativeness for larger and smaller firms compared to the median size. Standard errors are in parenthesis *** p<0.01, ** p<0.05, * p<0.1

	(1) Synchro		(2) Crash		(3) Price Delay		(4) Llorente		(5) PIN	
	Small	Large	Small	Large	Small	Large	Small	Large	Small	Large
lognetworksize	0.0027	-0.0588***	0.3065***	-0.2093***	0.0030	-0.0027	-0.0508	-0.0752***	0.0036	-0.0073***
	(0.023)	(0.010)	(0.052)	(0.025)	(0.004)	(0.002)	(0.050)	(0.024)	(0.003)	(0.001)
q	-0.0084	0.0044	-0.1081***	0.0196*	0.0036	0.0015*	0.0130	-0.0027	0.0022	-0.0007
	(0.013)	(0.004)	(0.028)	(0.011)	(0.002)	(0.001)	(0.027)	(0.011)	(0.002)	(0.001)
loghhi	-0.2498***	-0.0187	0.3545*	-0.3776***	0.0115	0.0175***	-0.0904	-0.0301	-0.0039	0.0040
	(0.094)	(0.034)	(0.185)	(0.086)	(0.015)	(0.006)	(0.176)	(0.078)	(0.011)	(0.005)
stdroa	-0.0025	0.2165***	0.3020**	0.6385***	-0.0539***	-0.0379***	-0.0666	0.3302**	-0.0105*	0.0105*
	(0.060)	(0.060)	(0.129)	(0.133)	(0.011)	(0.012)	(0.158)	(0.164)	(0.006)	(0.006)
analysts	-0.0883***	-0.0325***	0.1065***	0.0048	-0.0004	0.0005*	-0.0171	0.0002	-0.0031*	-0.0011***
	(0.013)	(0.001)	(0.028)	(0.004)	(0.002)	(0.000)	(0.027)	(0.003)	(0.002)	(0.000)
loginst	-0.1427***	-0.1111***	0.0043	-0.0797***	0.0061**	-0.0057***	-0.0316	0.0327**	-0.0097***	-0.0021**
	(0.017)	(0.007)	(0.035)	(0.017)	(0.003)	(0.001)	(0.035)	(0.017)	(0.002)	(0.001)
loginside	0.0234**	0.0147***	0.0137	0.0307***	-0.0017	-0.0014*	-0.0044	-0.0010	0.0013	0.0020***
	(0.010)	(0.004)	(0.023)	(0.010)	(0.002)	(0.001)	(0.021)	(0.010)	(0.001)	(0.001)
disclosure	-0.0202	-0.4204***	0.1410	-0.6327***	-0.0058	0.0306*	-0.0546	0.1487	-0.0078	-0.0132
	(0.079)	(0.081)	(0.151)	(0.202)	(0.013)	(0.016)	(0.168)	(0.196)	(0.007)	(0.011)
prevRET	-0.2602	0.6617***	-1.8824**	-0.2672	0.0052	-0.0655	-0.6452	-0.0439	-0.0690	0.0060
	(0.381)	(0.250)	(0.819)	(0.624)	(0.069)	(0.052)	(0.824)	(0.639)	(0.050)	(0.032)
turnover	0.0774	0.1729***	0.6326***	0.4265***	-0.0155	-0.0287***	-0.3435**	-0.0562	-0.0111	0.0031
	(0.061)	(0.022)	(0.123)	(0.057)	(0.012)	(0.005)	(0.141)	(0.058)	(0.007)	(0.003)
_cons	3.4338***	3.4324***	-7.5106***	-5.9305***	0.7733***	1.0021***	0.6621	-0.1164	0.3373***	0.2790***
	(0.399)	(0.167)	(0.827)	(0.419)	(0.066)	(0.032)	(0.782)	(0.388)	(0.051)	(0.022)
N	3831	18757	4758	24675	4516	23801	4193	22662	1676	8884
R^2	0.475	0.561	0.100	0.095	0.022	0.009	0.007	0.001	0.039	0.027
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 19

Personal characteristics. Split-sample analysis (tenure)

This table shows relation between CEO social capital and informativeness for CEOs with long and short tenures split by median. Standard errors are in parenthesis *** p<0.01, ** p<0.05, * p<0.1

	(1) Synchro		(2) Crash		(3) Price Delay		(4) Llorente		(5) PIN	
	Short	Long	Short	Long	Short	Long	Short	Long	Short	Long
lognetworksize	0.1161***	0.0393***	0.0995*	0.0304	-0.0099**	-0.0015	-0.0958	-0.0549**	-0.0062*	-0.0022
	(0.023)	(0.010)	(0.056)	(0.026)	(0.005)	(0.002)	(0.066)	(0.024)	(0.003)	(0.001)
logmve	-0.3513***	-0.3355***	-0.5741***	-0.4769***	0.0092**	-0.0014	-0.1622***	-0.0641***	-0.0029	-0.0031***
	(0.020)	(0.009)	(0.047)	(0.021)	(0.004)	(0.002)	(0.055)	(0.020)	(0.003)	(0.001)
q	0.0411***	0.0273***	0.0665**	0.0682***	0.0053**	0.0019**	0.0507	0.0012	0.0003	-0.0001
	(0.011)	(0.005)	(0.027)	(0.011)	(0.002)	(0.001)	(0.031)	(0.011)	(0.002)	(0.001)
loghhi	0.1405	-0.0582*	-0.4392**	-0.3428***	-0.0147	0.0174***	0.9777***	-0.0900	0.0145	-0.0002
	(0.088)	(0.035)	(0.206)	(0.084)	(0.017)	(0.006)	(0.233)	(0.074)	(0.011)	(0.005)
stdroa	-0.0985	-0.0416	-0.1141	0.0382	-0.0686***	-0.0394***	-0.1100	0.2000	-0.0197**	0.0004
	(0.061)	(0.049)	(0.168)	(0.108)	(0.014)	(0.010)	(0.266)	(0.127)	(0.008)	(0.005)
analysts	0.0099***	0.0049**	0.0503***	0.0580***	-0.0020***	0.0006*	-0.0101	0.0123***	0.0006	-0.0011***
	(0.003)	(0.002)	(0.008)	(0.005)	(0.001)	(0.000)	(0.010)	(0.004)	(0.000)	(0.000)
loginst	-0.1683***	-0.1003***	0.1340***	0.0247	0.0081*	-0.0054***	0.2542***	0.0195	-0.0083***	-0.0017**
	(0.022)	(0.006)	(0.051)	(0.016)	(0.004)	(0.001)	(0.059)	(0.015)	(0.003)	(0.001)
loginside	0.0202***	0.0196***	0.0216	0.0418***	-0.0012	-0.0015*	-0.0174	0.0027	0.0030***	0.0017***
	(0.008)	(0.004)	(0.019)	(0.011)	(0.002)	(0.001)	(0.023)	(0.010)	(0.001)	(0.001)
disclosure	-0.0626	-0.0241	0.3788*	0.2875**	-0.0299	0.0183	0.1829	0.0889	-0.0281***	0.0018
	(0.118)	(0.060)	(0.217)	(0.142)	(0.018)	(0.012)	(0.268)	(0.150)	(0.010)	(0.006)
prevRET	1.7041***	0.1535	0.4394	-1.8961***	0.0662	-0.0570	2.1435	-0.6336	-0.1327*	-0.0212
	(0.540)	(0.221)	(1.391)	(0.537)	(0.121)	(0.044)	(1.660)	(0.529)	(0.077)	(0.029)
turnover	-0.0335	0.0595***	0.9583***	0.3638***	-0.0199	-0.0263***	0.0217	-0.1185**	0.0136	-0.0013
	(0.090)	(0.022)	(0.219)	(0.054)	(0.019)	(0.004)	(0.266)	(0.053)	(0.013)	(0.003)
_cons	5.5898***	4.2940***	-8.4424***	-6.8196***	0.6729***	0.9964***	0.4559	0.0721	0.4177***	0.2540***
	(0.428)	(0.156)	(1.023)	(0.383)	(0.086)	(0.029)	(1.163)	(0.343)	(0.059)	(0.021)
N	3799	18789	5453	23980	5329	22988	5022	21833	1996	8564
R^2	0.468	0.613	0.128	0.113	0.019	0.010	0.010	0.002	0.046	0.025
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 20

Geographic characteristics. Split-sample analysis (US states)

This table shows relation between CEO social capital and informativeness for firms located in 12 states with high social capital versus other states. Standard errors are in parenthesis *** p<0.01, ** p<0.05, * p<0.1

	(1) Synchro		(2) Crash		(3) Price Delay		(4) Llorente		(5) PIN	
	Low	High	Low	High	Low	High	Low	High	Low	High
lognetworksize	0.0481***	0.0693*	0.0386	0.0742	-0.0017	-0.0105	-0.0685***	0.3679***	-0.0034**	0.0104**
	(0.010)	(0.038)	(0.024)	(0.080)	(0.002)	(0.007)	(0.023)	(0.104)	(0.001)	(0.005)
logmve	-0.3348***	-0.3505***	-0.4618***	-0.8513***	0.0014	-0.0067	-0.0663***	0.1330	-0.0040***	-0.0053
	(0.008)	(0.039)	(0.020)	(0.076)	(0.002)	(0.007)	(0.019)	(0.100)	(0.001)	(0.005)
q	0.0280***	0.0224	0.0603***	0.1987***	0.0014*	0.0136***	0.0073	-0.1746***	0.0001	0.0046*
	(0.004)	(0.022)	(0.011)	(0.043)	(0.001)	(0.004)	(0.010)	(0.058)	(0.001)	(0.002)
loghhi	-0.0487	-0.0262	-0.3367***	0.1539	0.0150**	0.0240	-0.0229	0.1017	0.0032	-0.0038
	(0.033)	(0.131)	(0.080)	(0.240)	(0.006)	(0.021)	(0.072)	(0.310)	(0.004)	(0.010)
stdroa	-0.0493	-0.2763	0.0247	-2.5913***	-0.0468***	-0.0287	0.1173	0.6861	-0.0039	-0.0490
	(0.041)	(0.260)	(0.095)	(0.533)	(0.008)	(0.046)	(0.114)	(0.677)	(0.004)	(0.038)
analysts	0.0044**	0.0168**	0.0531***	0.0483***	-0.0000	0.0022*	0.0057	0.0672***	-0.0009***	0.0020**
	(0.002)	(0.007)	(0.004)	(0.014)	(0.000)	(0.001)	(0.004)	(0.018)	(0.000)	(0.001)
loginst	-0.1019***	-0.2231***	0.0200	0.5134***	-0.0037***	0.0094	0.0462***	-0.6355***	-0.0020**	-0.0101**
	(0.006)	(0.039)	(0.015)	(0.080)	(0.001)	(0.007)	(0.015)	(0.103)	(0.001)	(0.005)
loginside	0.0196***	0.0248*	0.0415***	-0.0141	-0.0016**	-0.0011	0.0012	-0.0049	0.0020***	0.0008
	(0.004)	(0.013)	(0.010)	(0.028)	(0.001)	(0.002)	(0.009)	(0.036)	(0.001)	(0.002)
disclosure	-0.0624	0.4423**	0.3024**	-0.4949	0.0064	0.0067	0.1513	-0.1544	-0.0048	0.0419
	(0.055)	(0.212)	(0.125)	(0.447)	(0.010)	(0.039)	(0.131)	(0.570)	(0.005)	(0.028)
prevRET	0.2742	0.6979	-1.8715***	0.5978	-0.0527	0.1178	-0.4755	4.0049*	-0.0385	0.0044
	(0.211)	(0.798)	(0.515)	(1.808)	(0.043)	(0.156)	(0.518)	(2.324)	(0.028)	(0.093)
turnover	0.0542***	-0.0682	0.3760***	2.3035***	-0.0247***	0.0401	-0.1093**	1.0251*	0.0001	0.0407
	(0.021)	(0.192)	(0.052)	(0.410)	(0.004)	(0.035)	(0.053)	(0.527)	(0.003)	(0.025)
_cons	4.2873***	6.3975***	-6.6715***	-13.1068***	0.9530***	0.7925***	-0.0620	8.4111***	0.2753***	0.3138***
	(0.149)	(0.680)	(0.366)	(1.333)	(0.028)	(0.116)	(0.335)	(1.719)	(0.020)	(0.073)
N	21034	1554	27330	2103	26241	2076	24857	1998	9856	704
R^2	0.606	0.424	0.118	0.118	0.009	0.032	0.002	0.040	0.029	0.047
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 21

Split-sample analysis (SOX implementation)

This table shows relation between CEO social capital and informativeness before and after SOX implementation in 2002. Standard errors are in parenthesis *** p<0.01, ** p<0.05, * p<0.1

	(1) Synchro		(2) Crash		(3) Price Delay		(4) Llorente		(5) PIN	
	Before	After	Before	After	Before	After	Before	After	Before	After
lognetworksize	0.0411*	0.0538***	-0.1958***	0.0771***	0.0008	-0.0031	-0.0811	-0.0414*	0.0000	-0.0028**
	(0.022)	(0.010)	(0.058)	(0.026)	(0.004)	(0.002)	(0.058)	(0.024)	(0.004)	(0.001)
logmve	-0.2646***	-0.3568***	-0.5336***	-0.4975***	-0.0110**	0.0020	-0.0659	-0.0667***	-0.0044	-0.0043***
	(0.026)	(0.009)	(0.066)	(0.020)	(0.005)	(0.002)	(0.066)	(0.020)	(0.004)	(0.001)
q	-0.0091	0.0656***	0.0495***	0.0704***	0.0024*	0.0022**	0.0062	0.0041	-0.0014	0.0013*
	(0.007)	(0.005)	(0.018)	(0.012)	(0.001)	(0.001)	(0.018)	(0.013)	(0.001)	(0.001)
loghhi	0.3824**	-0.0410	0.3324	-0.3002***	0.0127	0.0233***	0.1491	-0.0128	0.0090	0.0071
	(0.192)	(0.039)	(0.500)	(0.094)	(0.037)	(0.007)	(0.501)	(0.085)	(0.031)	(0.005)
stdroa	-0.3031***	-0.0279	0.3444	-0.0430	-0.0601***	-0.0457***	-0.0065	0.1572	-0.0087	-0.0045
	(0.102)	(0.043)	(0.278)	(0.099)	(0.021)	(0.009)	(0.288)	(0.124)	(0.017)	(0.004)
analysts	-0.0099**	0.0068***	0.0223*	0.0606***	-0.0000	0.0002	0.0149	0.0074*	-0.0015*	-0.0007***
	(0.005)	(0.002)	(0.012)	(0.005)	(0.001)	(0.000)	(0.012)	(0.004)	(0.001)	(0.000)
loginst	-0.0617**	-0.1102***	0.3316***	0.0218	-0.0014	-0.0033***	-0.0023	0.0336**	-0.0032	-0.0021**
	(0.026)	(0.006)	(0.064)	(0.016)	(0.005)	(0.001)	(0.065)	(0.015)	(0.004)	(0.001)
loginside	-0.0199**	0.0284***	0.0457*	0.0359***	0.0031*	-0.0021**	0.0095	-0.0016	0.0019	0.0019***
	(0.009)	(0.004)	(0.024)	(0.010)	(0.002)	(0.001)	(0.024)	(0.010)	(0.001)	(0.001)
disclosure	-0.2232	0.0464	0.0679	0.3373***	0.0387	0.0038	0.6937*	0.0558	0.0078	-0.0033
	(0.140)	(0.058)	(0.366)	(0.129)	(0.027)	(0.011)	(0.368)	(0.137)	(0.021)	(0.006)
prevRET	0.1706	0.4144*	-2.7615**	-1.6191***	-0.4902***	0.0696	0.1569	-0.4367	0.0227	-0.0477
	(0.416)	(0.231)	(1.104)	(0.556)	(0.083)	(0.047)	(1.110)	(0.577)	(0.066)	(0.029)
turnover	-0.8062***	0.0829***	2.1945***	0.3459***	-0.0534**	-0.0248***	-0.0140	-0.1082**	-0.0075	-0.0006
	(0.117)	(0.021)	(0.313)	(0.053)	(0.023)	(0.004)	(0.317)	(0.054)	(0.018)	(0.003)
_cons	5.2440***	4.1524***	-8.2758***	-6.7414***	0.9209***	0.9650***	1.2510	0.1160	0.3039***	0.2858***
	(0.678)	(0.165)	(1.732)	(0.402)	(0.129)	(0.031)	(1.741)	(0.372)	(0.109)	(0.022)
N	3722	18866	3969	25464	3968	24349	3947	22908	1408	9152
R^2	0.370	0.596	0.081	0.104	0.022	0.009	0.003	0.002	0.047	0.026
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes