The Role of Employees as Information Intermediaries: Evidence from Their Professional Connections*

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Abstract: This paper investigates whether employees in conjunction with their professional networks function as information intermediaries. Collectively, employees have access to value-relevant information that can be distributed through both their direct professional contacts and the contacts of their contacts. We find that firms with more highly connected employees have lower market reactions around earnings announcements. The transmitted information appears to be positive and firm-specific rather than negative and macroeconomic or industry-wide. We provide causal evidence using mergers of brokerage houses as a source of exogenous variation in the information environment. In addition, stock prices incorporate earnings-related information on a more-timely intra-period timeliness metric before and around the earnings announcement is greater. Overall, our findings suggest that employees and their professional connections play an important role as information intermediaries, thereby increasing the information efficiency of stock prices.

JEL codes: G12, G14, L14, M41

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1. Introduction

A firm's information environment is influenced by various market participants and information intermediaries (Beyer et al. [2010]). Early studies investigated the role of analysts and institutional investors as information intermediaries (Brennan et al. [1993], Brennan and Subrahmanyam [1995], El-Gazzar [1998], Yohn [1998], Roulstone [2003]). More recently, a growing stream of research has investigated the role of other types of information intermediaries, including the business press, social media, data providers, and the internet (Bushee et al. [2010], Blankespoor et al. [2014], Chen et al. [2014], Drake et al. [2017], Schaub [2018]). Collectively, this research finds that intermediaries are associated with greater price efficiency. In this paper, we analyze how employees, through their professional networks, function as information intermediaries by examining how employee connections are associated with the efficiency of stock prices with respect to earnings-related information. Understanding the role of employees as intermediaries is important not only because it affects stock price efficiency (and hence the efficient allocation of capital), but also because it represents private disclosures that are beyond the firm's control.[1]

We exploit a unique and proprietary dataset on interfirm employee connections from a dominant business card management application in Korea ("Remember"). As in many Asian countries, it is a pervasive and entrenched cultural practice in Korea to exchange business cards with a new professional contact during the first in-person interaction. This type of exchange is essential for building professional relationships. Remember's dominant market position provides us with a reliable and precise way to identify a near-comprehensive set of meaningful professional

[1] Hales et al. [2018] examine a similar reduction of firms' control over their disclosures due to employees' public opinions expressed on the Glassdoor.com website.

connections in Korea for both executive and non-executive employees.[2] With these data, we create employee-specific measures of first-order (i.e., direct) connections, along with second- and third-order (i.e., indirect) connections. Since the ability of a network to transmit information decays when the information must travel through more nodes, we accordingly discount higher-order connections relative to the first-order connections (Jackson [2008], Jackson and Wolinsky [1996]). Following the prior network literature (Cho et al. [2021], Omer et al. [2020]), we use the average number of connections per employee to calculate time-varying firm-level connection measures.

We expect that firms' employees play an important, but heretofore unexamined, role as information intermediaries for two primary reasons. First, information and knowledge are widely dispersed within organizations, and employees of all levels have privileged access to value-relevant information (Green et al. [2019], Huang et al. [2020], Huddart and Lang [2003], Radner [1992]). Second, employees have expansive professional networks, which consist of their direct and indirect professional connections, that allow them to widely (and privately) distribute their information outside of the firm and ultimately into stock prices. Accordingly, value-relevant information can be transmitted from employees to numerous market participants within a couple of steps (Milgram [1967]). Thus, the ability of employees to function as effective information intermediaries increases with the number of their professional connections. Therefore, we expect that employee connections contribute to stock price efficiency through the transmission of value-relevant information to stock market participants.[3]

[2] In contrast, the prior networking literature (e.g., Cohen et al. [2010], Engelberg et al. [2012], Guan et al. [2016]) often infers that connections exist if individuals have common educational or employment experiences (even if those experiences did not overlap temporally).

[3] The prior "word of mouth" literature finds that investors frequently make investment decisions based on information shared through personal connections (see Hwang [2022] for a review of this nascent literature). Thus, it is highly plausible that at least some investors who acquire value-relevant information through their professional connections make trades using this information.

We first examine whether employee connections are associated with lower stock price reactions to earnings surprises. We focus on earnings announcements because they are well-defined information events that occur for all firms and because they allow us to control for the expected level of earnings. If value-relevant information about upcoming earnings is transmitted through employees' professional connections, we expect that firms with more-connected employees have smaller market reactions around earnings announcements.

Our results show that the second- and third-order employee connection measures are negatively associated with the magnitude of the earnings response coefficient (ERC).[4] The associations are economically as well as statistically significant. For example, in one specification, the ERC decreases by about 18% if a firm's *2ndOrder* value moves from the mean to one-standard-deviation (within-firm) above the mean.[5] Examining the types of information, we find that positive (as opposed to negative) and firm-specific (as opposed to macroeconomic or industry-wide) earnings news are more likely to spread through employees' professional connections. Further analyses show that our results hold for both executive and non-executive connections, indicating that non-executives and their connections also act as information intermediaries. Overall, our results suggest that earnings-related information is transmitted through employees' professional networks during the pre-announcement period, lowering the market reactions upon earnings announcement. Together, these findings are consistent with employees' professional connections collectively acting as information intermediaries that increase the level of price efficiency around earnings announcements.

[4] We do not find a significant association between first-order connections and market reactions to earnings surprises.

[5] Our primary results are robust to using a propensity score matched sample. They are also inconsistent with an alternative explanation, discussed below, based on connections to traditional information intermediaries, such as media firms and analyst brokerage houses.

To draw a causal inference from our baseline results, we identify plausibly exogenous variation in the information environment using reductions in analyst coverage by three mergers of brokerage houses (Hong and Kacperczyk [2010]). These reductions would heighten the importance of employee networks as a channel of information diffusion. We define treated firms as those covered by analysts from both brokerage houses before the merger and by only one analyst after the merger. We expect our baseline effects to become stronger for treated firms after the mergers. Using a matched sample, we estimate the stacked regression developed by Cengiz et al. [2019] and recommended by Baker et al. [2022] to minimize estimation biases when the treatment effects vary over time or across groups (de Chaisemartin and D'Haultfœuille [2020]; Borusyak et al. [2021]). The results show that the relation between employee connections and ERC is stronger for the treated firms after the mergers, suggesting that market participants rely more heavily on the information diffused through employee networks when there are fewer alternative sources of information.

After having established the effects of employee connections on ERC, we aim to derive a more complete picture of the stock price discovery process over the quarterly earnings cycle by examining the post earnings announcement drift (PEAD) and the intra-period timeliness (IPT). If earnings-related information is impounded into stock prices during the pre-announcement period through employee connections, stock price adjustment in the post-announcement period should be more efficient when employees are more connected. Consistent with this expectation, the PEAD is significantly lower for more-connected firms. To provide more direct evidence that prices reflect earnings-related information earlier during the quarter when employees are more connected, we examine the association between employee connections and the intra-period timeliness (IPT) of earnings news (Bushman et al. [2010], Twedt [2016], Blankespoor et al. [2018], Guest [2021]).

The results show that IPT is significantly higher for more-connected firms, supporting the idea that employees act as information intermediaries through their professional connections.

One caveat to our study is that while we can precisely identify an employee's actual professional connections, we are unable to directly observe whether employees pass on value-relevant information to their connections, and if so, what information is transmitted.[6] Thus, we are only able to make inferences about whether employees and their professional connections act as information intermediaries and what types of information they transmit based on the associations between employee connections and price efficiency. As such, our results should be interpreted accordingly.

We contribute to the literature in at least three ways. First, we contribute to the broad literature on how value-relevant information is incorporated into stock prices, thereby improving stock price efficiency. Prior studies examine the role of voluntary and mandatory disclosures (Beyer et al. [2010], Brown et al. [2004], Byard et al. [2011], Leuz and Wysocki [2016]),[7] analysts (Barth et al. [2001], Hong et al. [2000], Mola et al. [2013]), institutional investors (Ayers and Freeman [2003], Boone and White [2015]), and the media (Blankespoor et al. [2014], Bushee et al. [2010], Li et al. [2011]) in disseminating and incorporating information into prices. We identify and analyze a new and economically important mechanism – employees' private, professional connections – through which value-relevant information flows from inside firms to the capital markets. Thus, this study expands our understanding of how information is disseminated to the capital markets.

[6] This limitation applies to other network studies (Akbas et al. [2016], Cohen et al. [2010], and Engelberg et al. [2012]) because the private transmission of information along a network cannot be directly observed.

[7] Traditional firm-initiated disclosures represent the intentional dissemination of information to the capital markets by the firm's top executives (i.e., management forecasts, press releases, conference calls, tweets, etc.). In contrast, the information transmitted or "disclosed" through professional networks is collectively determined by the firm's employees, and executives may find it difficult, if not impossible, to control, monitor, or curtail the flow of information.

Second, we add to the literature on the collective private information of employees and how it is associated with their firms' future operating and stock performance (Babenko and Sen [2016], Green et al. [2019], Hales et al. [2018], Huang et al. [2020], Huddart and Lang [2003]). We extend this literature by examining whether employees' private information is incorporated into stock prices, thereby enhancing price efficiency.

Finally, we add to the social networking literature that has focused on the connections of top executives and board members (Akbas et al. [2016], Cohen et al. [2010], Engelberg et al. [2012], Guan et al. [2016], Larcker et al. [2013]). In contrast, we find that the connections of both executive and non-executive employees are associated with information dissemination and price efficiency.

This paper is organized as follows. We develop our hypothesis in Section 2 and describe our connection measures and empirical methodology in Section 3. Section 4 presents our results. Section 5 summarizes and concludes the paper.

2. Hypothesis Development

Information intermediaries provide or transmit information that is useful to other parties, either because it has not been publicly released or because it has not been widely disseminated (Bushee et al. [2010]). Prior research has shown that information intermediaries are associated with more informationally efficient prices. For example, higher levels of institutional ownership (El-Gazzar [1998]) and analyst coverage (Dempsey [1989], Shores [1990]) are associated with lower market reactions to earnings surprises. Similarly, Twedt [2016] finds that newswire dissemination increases the speed with which the information contained in management earnings forecasts is impounded into prices. Thus, the presence of information intermediaries is associated with more earnings-related information being incorporated into prices during the pre-announcement period, and hence, smaller investor reactions during the announcement periods.

In order for an economic actor to function as an information intermediary, it must both have access to value-relevant information and play a direct or indirect role in incorporating that information into stock prices. For example, institutional investors and analysts have private information about firms. Institutions' private information is directly incorporated into prices through their trading activities. In contrast, analysts first disseminate their information through their forecasts and recommendations, which in turn are incorporated into stock prices through the trading activities of investors. Other types of intermediaries, such as data providers, play a smaller role in discovering new information but a larger role in quickly and widely disseminating information that has not yet been incorporated into prices (Schaub [2018], Twedt [2016]). As we argue below, we posit that a firm's employees act as information intermediaries in conjunction with their professional connections.

While it is not surprising that top-level executives have private information about their firms, recent research shows that lower-level employees are also privately informed about their firms' prospects (Babenko and Sen [2016], Green et al. [2019], Hales et al. [2018], Huang et al. [2020], Huddart and Lang [2003]). Babenko and Sen [2016] and Huddart and Lang [2003] find that employees' aggregate stock purchases and option exercises, respectively, predict future returns. Similarly, employees' collective opinions expressed publicly on Glassdoor.com are predictive of future accounting and stock performance (Green et al. [2019], Huang et al. [2020]) and future firm disclosures (Hales et al. [2018]).[8] Therefore, employees collectively possess value-

[8] These results are consistent with information and knowledge being widely dispersed in large organizations, a conjecture that goes back to at least Coase [1937] and Hayek [1945].

relevant information about their firms' future operating performance, and as such, potentially act as information intermediaries.

The mere possession of private information is not sufficient for employees to act as information intermediaries. In addition, there must be a mechanism through which this information is incorporated into stock prices. Prior research provides evidence indicating that firm-specific private information is transmitted through the connections of top executives and board members (Akbas et al. [2016], Cohen et al. [2010], Engelberg et al. [2012]). For example, Engelberg et al. [2012] find that personal connections between the executives and directors of borrowers and banks are associated with lower interest rates. These results are consistent with information flowing through these connections. Accordingly, we expect that employees disseminate their private information, at least in part, through their professional connections.

The theoretical models of Grossman and Stiglitz [1980] and Hong and Stein [1999] suggest that prices reflect a weighted average of investor beliefs, and prices adjust to new information gradually as the information diffuses among investors. Thus, the speed with which information becomes incorporated into prices depends on how quickly and widely the information is distributed (Blankespoor et al. [2014], Hong et al. [2000], Li et al. [2011], Twedt [2016]). Given that the average number of direct professional connections tends to be small, one could be skeptical about how effective employee connections are in widely disseminating information. However, this view ignores the network aspects of employee connections, whereby their connections also have connections, and so forth. Thus, the collective reach of employees' direct and indirect connections is potentially very large.[9] Accordingly, we expect that employees' private information is more widely disseminated through their connections as the size of their networks increases.[10]

Finally, in order for the information transmitted through employee networks to increase stock price efficiency, it must be impounded into stock prices through trading by investors. The nascent "word of mouth" literature finds that investors frequently make investment decisions based on information shared through connections (see Hwang [2022] for a review). Thus, we expect that at least some investors trade based on value-relevant information obtained through their professional connections. Furthermore, we expect that the amount of this type of trading increases with the size of the professional network, and hence, the speed with which employees' private information is incorporated into prices.

In summary, we expect that 1) employees have value-relevant information about their firms; 2) their information passes through their professional connections; 3) the information is impounded into stock prices by the trading activities of investors. Thus, we posit that employees in conjunction with their connections act as information intermediaries. As such, larger networks result in higher price efficiency. Hence, we make the following hypothesis:

Hypothesis: Firms with more-connected employees have more efficient stock prices.

Despite the arguments above, our hypothesis is not without tension. There are at least two reasons why employees' professional connections might not be associated with greater price efficiency. First, if not enough private information is transmitted through employee connections and/or if the transmitted information does not ultimately spur sufficient trading, then employees'

[9] A well-documented and extensively studied stylized fact in the network literature is that large networks, such as the employee network examined here, tend to have small average path lengths (Milgram [1967]). Thus, information can be disseminated to a very large number of individuals in just a few steps.

[10] Employees can directly provide their professional connections with value-relevant information, such as about future operating performance, planned capital expenditures, and the result of R&D projects. In addition, they can assist their connections in assimilating information disclosed and/or obtained from other sources (Chapman et al. [2019]).

professional connections will not meaningfully enrich a firm's information environment.[11] Second, information transmitted through employees' networks may induce a crowding-out effect, whereby the acquisition of private information by other market participants is reduced. Han and Yang [2013] theoretically show that information sharing through social networks may crowd out private information production because agents can free-ride on their informed contacts rather than engage in their own costly private information production. Halim et al. [2019] provide experimental evidence for this type of free-riding behavior in social networks. If large enough, these crowding-out effects could offset any increases in price efficiency due to employees' professional connections. However, given the prior empirical evidence that information flows between professional connections and the dearth of archival evidence supporting the crowding-out effects, we predict that employees' connections are positively associated with stock price efficiency.

3. Research Methodology

3.1. Employee Network Data from a Professional Networking App

We exploit a pervasive cultural practice in Korea to identify professional networks: exchanging business cards with new contacts during their first in-person interaction. Exchanging business cards in face-to-face meetings is essential for building professional relationships in Korea. In business meetings, the exchange of business cards is a formal self-introduction that facilitates remembering the new professional contact's name and role, acts as an ice breaker, helps create a positive first impression, and even boosts professional credibility. Business cards also serve as a physical reminder that one has met someone rather than learned about them indirectly (such as

[11] For instance, it is illegal for a non-employee (tippee) in Korea to trade on material non-public information that was provided by an employee (tipper). However, there is no explicit prohibition on a non-employee (tippee) trading on information provided by another non-employee (tippee). Thus, while trading by direct, first-order connections is specifically prohibited, trading by second- and third-order connections is not. See Article 174 (Prohibition on Use of Material Nonpublic Information) of the Financial Investment Services and Capital Markets Act for more details. In addition, it is not clear how frequently individual investors are investigated for illegal insider trading, and thus, to what extent this prohibition would inhibit trading based on information transmitted through professional networks.

through an internet search), thereby encouraging future interactions. Hence, tracing the exchange of business cards is a reliable and precise way to identify Korean professional networks.

We use a unique proprietary database from the professional networking app “Remember.” The app allows users to upload the business cards they have collected by scanning and uploading the business cards. Professional typists hired by the app developer manually check the information on the scanned cards, which renders the network data virtually free of errors. Remember has had a near-monopoly of professional business card management apps in Korea since its launch in January 2014. The database begins in January 2015 and extends through December 2018. It contains over 140 million cards uploaded by over 2.5 million users, approximately 18 percent of the total number of full-time employees in Korea. 88.7% of all users are non-executive employees, while only 11.3% represent executive employees. Thus, the professional networks in our database are dominated by non-executive employees.

We obtain detailed information about the professional contacts, including an individual identifier (uniquely defined by a coded name and mobile phone number to comply with user privacy laws), email domain, firm name, job position, and a timestamp indicating when the card was uploaded. The unit of observation in the raw data is at the connection level—that is, a pair consisting of the app user and the business contact whose card is uploaded. Our goal is to measure to what extent employees are connected to people outside of the firm, and thus, their potential to act as information intermediaries. Thus, we focus on connections between employees at different firms, so each relationship involves two employees at different firms.[12] Appendix B illustrates the network data and how we construct the employee connection measures (discussed below).

[12] A further advantage of this unique dataset is that employees are likely to upload only the connections they consider essential and want to maintain. Thus, the verified nature of these connections provides plausible links for the transmission of value-relevant information.

3.2. Employee Connection Measures

Following the network literature (e.g., Jackson [2008]), we measure each employee's direct or first-order connections (*1stOrder*), which is a function of the number of direct links an employee has to employees of other firms (*Degree1*) and a discount parameter, $p \in (0,1)$, that captures the probability that an observed employee connection is active (i.e., one through which information is plausibly distributed):

$$1stOrder_i(\boldsymbol{g}, p) = p \times Degree1_i(\boldsymbol{g}) = p \sum_j g_{ij}, \tag{1}$$

where $\boldsymbol{g}$ is an $n \times n$ adjacency matrix (n is the total number of employees in the network) where $g_{ij} = 1$ if employee i is directly connected with employee j in another firm, and $g_{ij} = 0$ otherwise.[13] We then average the employee-level first-order connection measure ($1stOrder_i$) over all employees of the firm who appear in the network to construct a firm-level first-order connection measure for firm f, $1stOrder_f$.

Our hypothesis relies on value-relevant information flowing from employees of a focal firm (i.e., insiders) to employees outside the firm (i.e., outsiders). Hence, it is essential to capture an employee's ability to spread information to other people in their professional network beyond their immediate, first-order connections.[14] To this end, we use two additional measures that capture second- and third-order connections. These measures are a more comprehensive way of measuring connections as information transmitted by employees to their direct (first-order)

[13] The choice of p is irrelevant for our analyses based on *1stOrder* because our inferences will be exactly the same for any value of p. Nevertheless, we opt to use this definition so that it is consistent with the definitions of *2ndOrder* and *3rdOrder*, which are provided below.

[14] This type of connection measure is referred to as "information capital" in the taxonomy of Jackson [2019] and is a member of the "closeness-based" measures of network centrality. These measures are appropriate for our study because our focus is on measuring the potential for information to flow from inside the firm to the capital markets. In contrast, other measures of network centrality, such as betweenness and eigenvector, are not appropriate because they do not capture the outward flow of employees' information along their professional networks.

connections can be further shared with the connections of their connections (second-order). However, information transmission among higher-order connections is likely to be less effective than among direct connections (Jackson [2008], Jackson and Wolinsky [1996]). The ability of a network to transmit information decays when the information must travel through more nodes (i.e., more people). Accordingly, we further discount higher-order degrees relative to the first-order degree to capture how quickly the information decays as the distance between the two employees increases. Specifically, we define our higher-order connection measures as follows:[15]

$$\mathit{2ndOrder}_i(\boldsymbol{g}, p) = \mathit{1stOrder}_i(\boldsymbol{g}, p) + p^2 \times \mathit{Degree2}_i(\boldsymbol{g}) \tag{2}$$

$$\mathit{3rdOrder}_i(\boldsymbol{g}, p) = \mathit{2ndOrder}_i(\boldsymbol{g}, p) + p^3 \times \mathit{Degree3}_i(\boldsymbol{g}), \tag{3}$$

where $\mathit{2ndOrder}_i(\boldsymbol{g}, p)$ ($\mathit{3rdOrder}_i(\boldsymbol{g}, p)$) captures the discounted number of unique first- and second-order (first-, second-, and third-order) connections. $\mathit{Degree2}_i(\boldsymbol{g})$ enumerates the number of unique second-order connections (i.e., friends of friends) who are not directly connected (i.e., not first-order connections). Likewise, $\mathit{Degree3}_i(\boldsymbol{g})$ enumerates the number of unique third-order connections who are not first- or second-order connections. We then average the employee-level measures over all employees who appear on the network to construct the firm-level connection measures for firm *f*, $\mathit{2ndOrder}_f$ and $\mathit{3rdOrder}_f$.

One limitation of our connection measures is that the probability of information transmission (p) is not determined by the inherent structure of the network, but rather is a research design choice. In order to minimize this limitation, we use three different values for p (0.1, 0.5, and 0.9) to assess the robustness of our results to this choice. As discussed below, our results are robust to the choice of p.

[15] Jackson [2008] refers to these measures as "decay centrality" due to the discounting of higher-order connections. We prefer our terminology because it emphasizes how many degrees of separation the measure considers when enumerating connections.

3.3. Employee Connections and Market Reactions around Earnings Announcements

Extensive literature in accounting and finance has used stock returns around earnings announcements to capture changes in investors' assessments of firm value (Verrecchia [2001]). Stock price changes reflect investors' belief revisions and are proportional to the unexpected portion of the earnings announcement (Ball and Brown [1968], Kim and Verrecchia [1991]). The literature documents that the amount of information available to investors prior to the earnings announcements affects market reactions to the earnings announcements. Using various proxies for the availability of predisclosure information, prior studies find smaller return reactions to the earnings announcements for larger firms (Atiase [1985]) and firms with higher analyst coverage (Dempsey [1989], Shores [1990]) or institutional ownership (El-Gazzar [1998]). Accordingly, we examine abnormal returns around quarterly earnings announcements.

Considering the disclosure rules and practices in Korea, we follow prior studies to determine the date when earnings news is first released to the capital market (Sohn et al. [2009], Baik et al. [2012]). Specifically, for each firm-quarter, we use the earliest date among the following five filing dates (if available) for 1) Report on preliminary business performance (fair disclosure); 2) Changes of 30% or more in sales or profits/losses; 3) Submission of audit report; 4) Calling shareholders' meeting; 5) Quarterly (Annual) financial statements; in addition to 6) the date of annual shareholders' meeting.[16]

We estimate the following regression model where *f* indexes firms, *q* indexes year-quarters, and *y* indexes years:

$$\begin{aligned} AbRet_{[-2,+2],f,q} = {} & \alpha_f + \alpha_y + \alpha_f \times SUE_{f,q} + \alpha_y \times SUE_{f,q} \\ & + \beta_1 SUE_{f,q} + \beta_2 SUE_{f,q} \times Connection_{f,q\text{-}1} + \beta_3 Connection_{f,q\text{-}1} \\ & + \gamma_1 Y_{f,q\text{-}1} + \gamma_2 Y_{f,q\text{-}1} \times SUE_{f,q} + \varepsilon_{f,q}. \end{aligned} \tag{4}$$

[16] The percentage of each date that provides the earliest disclosure date is as follows: 1) 22.4%, 2) 18.6%, 3) 0.3%, 4) 2.4%, 5) 56.3%, and 6) 0.0%.

The dependent variable, $AbRet_{[-2,+2]}$, is the market-adjusted cumulative returns during the five-day window [−2, 2] around the quarterly earnings announcement (i.e., day zero). *SUE* is standardized unexpected earnings, which is measured as the difference between the reported quarterly earnings per share and expected quarterly earnings per share generated by the seasonal random walk with a drift model using the most recent 12 quarters of data. The difference is scaled by the standard deviation of forecast errors over the estimation period. *Connection* is the natural logarithm of one plus one of our connection measures (*1stOrder*, *2ndOrder*, *3rdOrder*).

The earnings response coefficient (β_1) in Equation (4) reflects the association between stock returns and earnings surprise for a benchmark firm in which employees do not have any external connections (i.e., $Connection = 0$). β_2 captures the marginal change in the earnings response coefficient of a firm with $Connection > 0$, relative to the benchmark firm. If earnings news is preempted through employee networks, our hypothesis predicts that the earnings response coefficient will be lower for firms with better-connected employees (i.e., $\beta_2 < 0$).

Following Bartov et al. [2018], we include a vector (*Y*) of time-varying, firm-level controls that affect the information environment of a firm, including the market value of equity at the end of quarter $q-1$ (*Size*), the book value of equity divided by the market value of equity at the end of the quarter $q-1$ (*BM*), the number of analysts issuing at least one earnings forecast for quarter q made within 90 days of the earnings announcement (*Coverage*), the percentage of shares outstanding owned by block holders at the end of quarter $q-1$ (*BlockOwn*), an indicator variable that equals one if earnings per share for quarter q is negative (*Loss*), an indicator variable that equals one if management issues an earnings forecast before the earnings announcement date of quarter q (*Guidance*), an indicator variable that equals one if quarter q is the firm's fourth fiscal quarter (*Q4*). We also include the interactions of these controls with *SUE*. To absorb unobservable time-invariant firm heterogeneity and macroeconomic conditions in ERC, we also include a set of firm (α_f) and year (α_y) fixed effects as well as their interactions with *SUE* (Gipper et al. [2020], deHaan [2021]). Detailed definitions of all variables are provided in Appendix A.

3.4. Sample Selection and Other Data Sources

Our primary sample consists of all non-financial Korean firms listed in the KOSPI (Korea Composite Stock Price Index) and KOSDAQ (Korea Securities Dealers Automated Quotations) markets. We obtain financial statement information, stock returns, trading volume, analyst data, and block ownership data from Data Guide provided by FnGuide. The sample period is from 2015 to 2018. This database is similar to the merged CRSP-Compustat database in the U.S., with additional information specific to the Korean capital markets. We drop firm-quarter observations with missing data for the main variables. To reduce the effects of outliers, we winsorize all unbounded variables at the 1st and 99th percentiles of the distribution. The final sample consists of 17,789 firm-quarter observations and covers 1,284 unique firms.

Table 1 contains descriptive statistics for the main variables used in the study. *Degree1* has a mean of 7.44 and a median of 5.93; *Degree2* has a mean of 1,220 and a median of 948.4; *Degree3* has a mean of 38,187 and a median of 27,181. These numbers indicate that an employee of a firm, on average, has 7.44 direct connections with employees of other firms, 1,220 second-order connections (i.e., friends of friends), and 38,187 third-order connections. *Degree2* and *Degree3* increase exponentially, reflecting the expansive nature of the business network, and exhibit substantial variation (the standard deviation is 1,007 and 37,031, respectively).[17] Moreover, 81%

[17] Note that the second-order and third-order degree increases exponentially because more-connected employees have a disproportionately larger influence on others' second-order and third-order degrees. Consider a star network in which one employee is connected to all other 99 employees, and these 99 employees are only connected to that employee. The average *Degree1* is $(99\times1+1\times99)$ / 100 = 1.98, and the average *Degree2* is $(0\times1+98\times99)$ / 100 = 97.02.

(78% and 80%) of *Degree1* (*Degree2* and *Degree3*) connections are due to non-executive employees (results untabulated). These observations confirm the importance of considering higher-order relationships in measuring an employee's ability to spread information in the network. When we set the probability of information transmission as 0.5, *1stOrder*, *2ndOrder*, and *3rdOrder* have a mean of 3.72, 308.8, and 5,081, respectively.[18] The three measures are highly correlated. The untabulated correlation between *2ndOrder* and *3rdOrder* is 0.967, while the correlation between *1stOrder* and *2ndOrder* (*3rdOrder*) is 0.833 (0.796).

4. Results

4.1. Employee Connections and Market Reactions around Earnings Announcements

In this section, we provide evidence on whether earnings-related news is transmitted to investors through employees' professional connections. If some of the upcoming earnings news is transmitted to investors through employees' connections and incorporated into stock prices before earnings are announced, our hypothesis predicts that announcement period stock returns will be smaller for firms with more-connected employees.

We examine the association between employee connections and the magnitude of the earnings response coefficient around earnings announcements. The results from estimating Equation (4) are presented in Table 2.[19] Columns 1, 4, and 7 report the results where employee connections are measured using *1stOrder*, which only captures the direct connections of a firm's employees. The results show that while the *SUE*×*Connection* coefficients are all negative, none of them are significant. Thus, we find no evidence that the magnitude of employees' direct

[18] There are substantial differences across industries. The industries with the highest connection measures are Real Estate Activities (17, 1,089, and 19,238 for *1stOrder*, *2ndOrder*, and *3rdOrder*, respectively) followed by Financial and Insurance Activities (7, 576, and 8,891). Among the lowest connection industries are Construction (4, 227, 3,484) and Membership Organizations, Repair & Other Personal Services (3, 232, 3,893).

[19] Note that *SUE* is fully absorbed by the interaction terms of the fixed effects and *SUE*.

connections is associated with the amount of earnings-related information that is incorporated into prices during the pre-announcement period.

The results when we use second-order (third-order) connections are reported in Columns 2, 5, and 8 (3, 6, and 9). For both connection measures, all three of the *SUE*×*Connection* interaction coefficients are negative and significant. The results are qualitatively (and mostly quantitatively) similar across all three values of *p*. These results support our hypothesis that firms with more-connected employees have more efficient stock prices. In addition, the insignificant coefficients for *1stOrder* emphasize the importance of considering the expansive nature of professional networks in capturing employees' ability to spread information. The second- and third-order coefficient estimates are also economically significant. For example, in Column 5 (6), where the connection measure is *2ndOrder* (*3rdOrder*) with a probability of information transmission of 0.5, the estimated *SUE*×*Connection* coefficient is −0.258 (−0.325). To assess the economic magnitude of the effects, we first estimate a baseline ERC without fixed effects or their interactions with *SUE*. The untabulated baseline ERC for an average firm (estimated at the average values of all covariates) is 0.269. As a firm's *2ndOrder* value moves from the mean to one-standard-deviation (within-firm) above the mean, the ERC decreases by 0.050 ($= [-0.258 \times [\ln(1{+}308.8{+}172.2) - \ln(1{+}308.8)]]$, an 18.4% decrease relative to the baseline ERC. Similarly, the same increase in *3rdOrder* is associated with a decrease in ERC by 0.078 ($= [-0.325 \times [\ln(1{+}5{,}081{+}3{,}724) - \ln(1{+}5{,}081)]]$, a 28.8% decrease relative to the baseline ERC. Thus, our evidence suggests that a substantial portion of the earnings-related news is incorporated into prices before the earnings announcement period for firms with more-connected employees.

4.1.1. Alternative explanations

Our regressions include firm fixed effects and year fixed effects and their interactions with *SUE*. Thus, the results in Table 2 should not be affected by either time-invariant firm-specific factors or general time trends in ERC. However, it is possible that our results could be driven by omitted firm-specific time-varying variables that are correlated with both the *Connection* variables and the ERC. We think these concerns are lessened in our setting for two reasons. First, they apply more to our first-order connection measures than to the higher-order connection measures because any omitted variables (e.g., the characteristics of the firms and/or their employees) are most likely to be reflected in the first-order connection measures.[20] Thus, the combination of the insignificant results for *1stOrder* along with the significant results for *2ndOrder* and *3rdOrder* partially alleviates concerns about correlated omitted variables. Second, when we repeat the analyses in Table 2 without the interaction terms (results untabulated), none of the *Connection* coefficients are significant. Thus, the number of (direct or indirect) employee connections *per se* is not associated with market reactions around earnings announcements. These results help rule out alternative explanations that involve omitted correlated variables.[21]

Nonetheless, we repeat our main analyses using a propensity score matched sample to improve the covariate balance between firms with high and low employee connections. Every quarter, we assign each firm to a top- or bottom-quartile connection group based on *1stOrder*, *2ndOrder*, and *3rdOrder*. We then run a probit regression to estimate the probability of being a highly connected firm (treated firm) using the same set of control variables in Equation (4). We match each treated firm to a bottom-quartile control firm with replacement, using nearest neighbor

[20] For example, if business professionals prefer to connect with employees in more popular firms, then those firms will have more highly connected employees. In addition, investors may be more focused on or attracted to more popular firms, and therefore, these firms will have weaker market reactions around earnings announcements. However, the higher-order measures are less likely to be subject to this concern than the first-order measure.

[21] One limitation of many word-of-mouth studies is that they are subject to self-selection issues and common-shock problems (Hwang [2022]). For example, investors may make similar decisions because they receive a common information shock or share similar attributes, and not because they are sharing information. Common-shock concerns are lessened in our setting because they would affect both retail and institutional investors, whereas we only find significant trading volume results for retail investors. Furthermore, self-selection concerns are lessened because we include firm fixed effects that control for common attributes among retail investors (such as an affinity for a particular firm or industry).

matching with a maximum difference of 0.01. Panel A of Table 3 shows that there are no significant differences in our control variables between the treated and control firms in the matched sample using *1stOrder*, *2ndOrder,* or *3rdOrder*.

Using this matched sample, we then re-estimate Equation (4). The results presented in Panel B are qualitatively similar to the results in Table 2. Specifically, the interaction coefficients on *SUE*×*Connection* are negative and significant (at the 5% level) for *2ndOrder* and *3rdOrder*, but are insignificant for *1stOrder*. Overall, our findings are consistent with firms' employees playing an important role as information intermediaries as they transmit value-relevant information to the market through their professional connections. Based on the results in Tables 2 and 3, we focus on *2ndOrder* and *3rdOrder* as our connection measures in our subsequent analyses.[22]The evidence presented above suggests that firms' employees play an important role as information intermediaries. One concern with this interpretation is that firms with greater media and/or analyst coverage (i.e., traditional information intermediaries – TII hereafter) could mechanically have higher connection values. For example, employees of traditional information intermediaries could naturally have more connections to firms that receive more intensive media and/or analyst coverage. Thus, an alternative explanation is that information dissemination by TII is what drives the negative association between market reactions around earnings surprises and employee connections rather than information disseminated through the employees' connections.[23]

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[22] To distinguish between the roles of first-order, second-order, and third-order connections, we separately estimate Equation (4) using *Degree1*, *Degree2*, and *Degree3* as our *Connection* measures. The results, tabulated in the Internet Appendix, show that the *Degree1*×*SUE* coefficient are insignificant. In contrast, both *Degree2*×*SUE* and *Degree3*×*SUE* coefficients are significant at the 5% level or better. In addition, when we include *Degree1*, *Degree2*, and *Degree3* in the same regression model, only *Degree3*×*SUE* coefficient remains significant, suggesting the superior ability of higher-order connections in capturing the expansive nature of professional networks. Overall, these results are consistent with those in Tables 2 and 3.

[23] In addition to controlling for analyst coverage, our regressions include variables that are associated with media and analyst coverage choices, including *Size*, *BM*, *Loss*, and *Guidance*. This alternative explanation relies on associations between employee connections and TII coverage that are orthogonal to these control variables (and firm fixed effects).

In order to alleviate concerns regarding this alternative explanation, we split *2ndOrder* and *3rdOrder* measures into connections to employees of TII and connections to employees of non-information intermediaries (Non-TII). TII firms comprise media firms (KSIC 5812, 59114, 5912, 5913, 60, and 63910) and investment banking and security brokerage firms for which financial analysts work (KSIC 6612). If the alternative explanation is correct, then only TII connections are significantly associated with market reactions around earnings announcements.

We re-estimate Equation (4) and report the results in Table 4. Columns 1 and 3 show the results when connections are based only on TII connections. The coefficient on *SUE×Connection* is insignificant when connections are measured using *2ndOrder*, while it is negative and significant (at the 1% level) when connections are measured using *3rdOrder*. While this evidence is partly consistent with the alternative explanation, it does not discriminate between the two explanations. The reason is that TII could obtain value-relevant information via their connections to employees of the focal firm, which they then transmit to the market. In this case, these results provide further support for our hypothesis. However, it is not possible to directly discriminate between these two explanations because we do not observe the information sources of TII.

To provide more direct evidence on the information role of employees as information intermediaries, we use connections to Non-TII firms as the measure of *Connection* in Columns 2 and 4. The estimated coefficients on the interaction terms are both negative and significant at the 5% level or better. Our overall results, therefore, do not appear to be driven solely by any mechanical association between TII coverage and employee connections.[24] The evidence in Table 4 provides further support for our information intermediary hypothesis.

[24] To compare the economic magnitudes of the TII and Non-TII estimates, consider a change from the mean to one-standard-deviation (within-firm) above the mean of *3rdOrder*. The corresponding reduction in ERC relative to the baseline ERC is −21.6% for connections to TII (Column 3) and −29.2% for connections to Non-TII (Column 4). The

4.2. Further Analyses on How Employee Connections Are Associated with Market Reactions to Earnings Announcements

In this section, we report the results of additional analyses that provide further insights into how employees and their connections are associated with market reactions to earnings announcements. First, we analyze what types of information are transmitted via employees' professional connections. Second, we examine the importance of employee rank.

4.2.1. Types of Information

We conduct two sets of analyses to investigate which types of value-relevant information are transmitted through employees' professional connections. First, employees and their connections might be more likely to share positive than negative information, as is the case for the media content transmitted through social networks (Berger and Milkman [2012]). To examine this possibility, we separate the quarterly earnings surprise (*SUE*) into positive (*PSUE*) and negative (*NSUE*) earnings surprises and re-estimate Equation (4). Specifically, *PSUE* (*NSUE*) equals *SUE* if *SUE* is positive (negative) and zero otherwise. We interact *PSUE* and *NSUE* with firm fixed effects, year fixed effects, and control variables.

The estimation results are presented in Columns 1 and 3 of Table 5. Consistent with our conjecture, the *PSUE×Connection* coefficients are negative and significant for both *2ndOrder* and *3rdOrder*, whereas the *NSUE×Connection* coefficients are negative and insignificant. These asymmetric results indicate that good, earnings-related news is more likely to spread over the network, thereby contributing to the bias in social transmission (Hirshleifer [2020]).

Second, as insiders have the relative advantage of accessing firm-specific information over other market participants (Piotroski and Roulstone [2004], Hutton et al. [2012]), employees and

similarity in magnitudes provides further support that our results are driven by information transmitted through employees' connections.

their connections are more likely to spread firm-specific earnings-related information rather than industry-wide or macroeconomic news. Following Bhojraj et al. [2020], we decompose the earnings surprise into the macroeconomic, industry, and idiosyncratic components. For each firm *i*, we construct the macroeconomic earnings surprise (*MacroSUE*) as a weighted average of the surprises across all other firm *j* that announced earnings within the past 30 days of firm *i*'s earnings announcement date. We define the weight as the market capitalization of firm *j* divided by the gap between the earnings announcement dates of firms *i* and *j*. Using the same weighting methodology, we construct the industry earnings surprise by focusing on firms within the same two-digit KSIC industry. As the industry earnings surprise contains the macroeconomic component, we define the pure industry component (*IndSUE*) as the difference between the industry and macroeconomic components. Finally, we construct the idiosyncratic component (*IdioSUE*) by subtracting *MacroSUE* and *IndSUE* from *SUE*. We then replace *SUE* with *MacroSUE*, *IndSUE*, and *IdioSUE*, and re-estimate Equation (4). We interact *MacroSUE*, *IndSUE*, and *IdioSUE* with firm fixed effects, year fixed effects, and control variables.

The results are presented in Columns 2 and 4 of Table 5. The results show that the coefficients on the interactions between *Connection* and the three components of earnings surprise are negative and significant only for the idiosyncratic component, indicating that the information transmitted through the network is likely to be firm-specific. In summary, these additional analyses can shed light on the nature of value-relevant information (i.e., firm-specific and positive news) transmitted through the employee network, resulting in higher price efficiency.

4.2.2. Connections of Executives vs. Non-Executives

The prior literature on professional connections primarily focuses on personal connections between upper-level executives and/or directors and various outside parties (Akbas et al. [2016], Cohen et al. [2010], Engelberg et al. [2012], Guan et al. [2016], Larcker et al. [2013]). This focus is unavoidable because most data sources used in prior studies track only high-level executives and directors (e.g., BoardEx). With the exception of Cho et al. [2021], however, the importance of mid- and lower-level employee connections relative to those of higher-level employees has not been examined.[25] Despite this dearth of evidence, other studies provide evidence that non-top-level employees have access to value-relevant information (Green et al. [2019], Huang et al. [2020], Huddart and Lang [2003]). Collectively, their results suggest that lower-level employees have access to value-relevant private information. Accordingly, we expect that private, earnings-related information is transmitted to the capital markets through the professional connections of both executive and non-executive employees.

We categorize employees as executives or non-executives based on their job titles, where the chairman, vice chairman, president, deputy president, executive vice president, and senior vice president are classified as executives. All other employees are considered non-executives. We calculate *2ndOrder* and *3rdOrder* separately for executives and non-executives. We then re-estimate Equation (4) and present the results in Table 6.

The results in Columns 1 and 3 show that executive connections are negatively associated with market reactions around earnings announcements. Specifically, the *SUE×Connection* coefficients are significantly negative (at the 5% and 1% levels, respectively). These results are consistent with those in the prior literature that document the importance of top executives' connections. In addition, Columns 2 and 4 show that the associations are similar using non-executive connections. The *SUE×Connection* coefficients are significantly negative (both at the 1% levels). In addition, the absolute value of the interaction coefficients is somewhat larger for non-

[25] Cho et al. [2021] examine the first-order connections of both executive and non-executive employees. They find that firms with more-connected employees perform better.

executive measures (−0.215 vs. −0.297 and −0.214 and −0.355, respectively). To compare the economic magnitudes, a one-standard-deviation (within-firm) increase in *3rdOrder* from the mean is associated with an 18.6% decrease in ERC for executive connections (Column 3) and a 33.1% decrease for non-executive connections (Column 4). Thus, our evidence suggests that both executive and non-executive employees and their professional connections act as information intermediaries.

4.3. Exogenous Variation in Information Environment: Mergers of Brokerage Houses

A potential concern is that both a firm's information environment and its employees' connections (and their networking activities) are endogenous. To draw a causal inference from our baseline results, we exploit the exogenous variation in the information environment induced by mergers of brokerage houses. This setting, which is motivated by Hong and Kacperczyk [2010], identifies exogenous reductions in analyst coverage for stocks covered by both merging brokerages before the merger. The underlying assumption is that such mergers result in the firing of redundant analysts, which is unrelated to some underlying unobservable. These exogenous decreases in analyst following would increase the importance of employee networks as a channel of information diffusion.

There were three mergers in Korea during the sample period: (i) Mirae Asset Securities merged with Miare Asset Daewoo in December 2016, (ii) Hyundai Securities merged with KB Investment & Securities in December 2016, and (iii) Meritz Securities merged with I'M Investment & Securities in May 2015. We divide the sample of firms into treatment and control groups: the treatment group includes all firms covered by analysts from both brokerage houses before the merger and by only one analyst after the merger, whereas the control group includes all the remaining firms.

Since a two-way fixed effect difference-in-differences regression (or its variants) may yield biased estimates when the treatment effects vary over time or across groups (de Chaisemartin and D'Haultfœuille [2020], Sun and Abraham [2021], Borusyak et al. [2021]), we employ the stacked regression approach developed by Cengiz et al. [2019] and recommended by Baker et al. [2022]. Specifically, we create three event-specific datasets, including the treated and control firms within the 9-quarter event window ([-4, 4]). We then stack all three event-specific data sets by aligning merger events by event time (not calendar time). We require control firms not to be treated within the 9-quarter event window to avoid "forbidden" comparisons (i.e., "bad" controls). To ensure that firm characteristics are similar between treated and control firms, we construct a propensity score matched sample based on the firm characteristics before the mergers using 5-nearest neighbor matching with a maximum difference of 0.1. We then estimate the following difference-in-difference model where *m* indexes merger events:

$$
\begin{aligned}
AbRet_{[-2,+2],m,f,q} = {} & \alpha_{m,f} + \alpha_{m,y} + \alpha_{m,f} \times SUE_{m,f,q} + \alpha_{m,y} \times SUE_{m,f,q} \\
& + \beta_1 Connection_{m,f,q\text{-}1} + \beta_2 Post_{m,f,q} + \beta_3 SUE_{m,f,q} \times Connection_{m,f,q\text{-}1} \\
& + \beta_4 SUE_{m,f,q} \times Post_{m,f,q} + \beta_5 Connection_{m,f,q\text{-}1} \times Treated_{m,f,q} \\
& + \beta_6 Connection_{m,f,q\text{-}1} \times Post_{m,f,q} + \beta_7 Treated_{m,f,q} \times Post_{m,f,q} \\
& + \beta_8 SUE_{m,f,q} \times Connection_{m,f,q\text{-}1} \times Treated_{m,f,q} \\
& + \beta_9 SUE_{m,f,q} \times Connection_{m,f,q\text{-}1} \times Post_{m,f,q} \\
& + \beta_{10} SUE_{m,f,q} \times Treated_{m,f,q} \times Post_{m,f,q} \\
& + \beta_{11} Connection_{m,f,q\text{-}1} \times Treated_{m,f,q} \times Post_{m,f,q} \\
& + \beta_{12} SUE_{m,f,q} \times Connection_{m,f,q\text{-}1} \times Treated_{m,f,q} \times Post_{m,f,q} \\
& + \gamma_1 Y_{m,f,q\text{-}1} + \gamma_2 Y_{m,f,q\text{-}1} \times SUE_{m,f,q} + \varepsilon_{m,f,q}
\end{aligned}
\tag{5}
$$

where $\alpha_{m,f}$ and $\alpha_{m,y}$ are event-specific firm and year fixed effects; *Post* is an indicator variable that equals one for quarters after the mergers; *Treated* is an indicator variable that equals one for treated firms.[26] In estimating Equation (5), we exclude observations in the event quarter. The coefficient of primary interest is β_{12}, which captures the incremental change in the effect of employee

[26] Note that *SUE*, *Treated* and *SUE*×*Treated* are fully absorbed by the fixed effects and the interaction terms of the fixed effects and *SUE*.

connections on the ERC for firms that experienced an exogenous decrease in analyst coverage. A negative coefficient indicates that a response to earnings news is smaller for the treated firms, given the same change in employee connections. The estimation results are documented in Panel A of Table 7. The estimated coefficient β_{12} is negative and significant at the 1% level for both *2ndOrder* and *3rdOrder*. Thus, it appears that the role of professional networks as information intermediaries is more important when there are fewer alternative channels for value-relevant information to become impounded in stock prices.

To estimate the dynamic effect, we replace *Post* with a full set of relative-time indicators in Equation (5). The results are reported in Panel B of Table 7. The estimated coefficients on $Connection \times SUE \times Treated \times d_{q+t}$ are insignificant for $t < 0$ for both *2ndOrder* and *3rdOrder*. In contrast, those coefficients for $t > 0$ are negative and largely significant at the 10% level. These results clearly show no apparent difference of pre-trend in the effect of employee connections on the ERC between the treated and control firms. The results further indicate that the importance of employee connections in improving price efficiency increases right after a firm's information environment weakens after an exogenous reduction in its analyst coverage.

4.4. Employee Connections and Price Discovery Before and After Earnings Announcements

In this section, we provide a more complete picture of how employee connections affect stock price discovery over the quarterly earnings cycle, that is, before and after the earnings announcement period. To this end, we examine post-earnings announcement drift (PEAD) and the intra-period timeliness metric (IPT) before and around the earnings announcements.

4.4.1. Employee Connections and Post Earnings Announcement Drift

A large body of literature has investigated the well-documented post-earnings announcement drift anomaly whereby stock prices predictably move in the same direction as the earnings surprises over the subsequent months (e.g., Bernard and Thomas [1989, 1990], Livnat and Mendenhall [2006]). Among the various explanations suggested in the prior literature, the most widely accepted and empirically supported explanation is that PEAD is driven by mispricing due to investors' inability to fully understand the implications of current earnings for future earnings (Ball and Bartov [1996], Bartov et al. [2000], Bernard and Thomas [1989], Freeman and Tse [1989], Narayanamoorthy [2006]).

If earnings-related information is transmitted through employees' professional connections, the diffused information should assist investors in better understanding the implications of current earnings for future performances. This implies information dissemination through employees' connections should help mitigate PEAD and hence improve stock price efficiency during the post-earnings announcement period. Accordingly, we expect more-connected firms to exhibit lower PEAD.

To test this prediction, we estimate Equation (4) by replacing the dependent variable with $AbRet_{[+3,\ +62]}$, which is defined as the market-adjusted buy-and-hold abnormal returns following the quarterly earnings announcement for the window [+3, +62], where day zero is the earnings announcement date. We include the same set of control variables and fixed effects in Equation (4). The results are reported in Table 8. In Columns 1 and 2, the *SUE*×*Connection* coefficients are negative and significant at the 1% level. These results are consistent with our expectations that the information transmitted through employees' professional networks mitigates investors' underreactions to earnings news, hence lowering PEAD.

4.4.2. Employee Connections and Intra-period Timeliness over Quarterly Earnings Cycles

Thus far, the evidence is consistent with earnings-related information transmitted through employees' professional connections and incorporated into stock prices before the earnings announcement period. While we cannot directly observe when (or even if) information is disseminated from employees to their connections and impounded into stock prices, we can infer the arrival of private information about earnings in stock returns by estimating measures of intra-period price discovery. The speed of intra-period price discovery captures how quickly all of the information that becomes available over a given time period (i.e., a quarter) is reflected in the price. Thus, we expect that information becomes incorporated into stock prices earlier in the quarter for more-connected firms.

To provide evidence of this implication, we measure the speed of price formation using the intra-period timeliness metric (*IPT*) (Bushman et al. [2010], Guest [2021], McMullin et al. [2019]). *IPT* captures how quickly information is impounded into prices by holding constant both price response and information content. Intuitively, *IPT* increases when the higher portion of period returns is realized earlier in the period because it indicates faster price discovery. *IPT* equals the area under the cumulative price change curve over a given window. Following Bushman et al. [2010], we use a 63-day trading window to identify the entire span of the quarterly earnings cycle, ending two days after the quarterly earnings announcement.[27] This approach generates a large sample with standardized time periods that capture the total flow of earnings information into price starting after the prior earnings announcement and through the current quarterly earnings announcement. Specifically, *IPT* equals $\frac{1}{2}\sum_{\mathrm{t=-60}}^{2}\left(QAbRet_{t\text{-}1} + QAbRet_{t}\right)/QAbRet_{2} = \sum_{\mathrm{t=-60}}^{1} QAbRet_{t}/QAbRet_{2} + 0.5$, where $QAbRet_{t}$ is buy-and-hold market-adjusted returns from 60 trading days prior to the earnings announcement up to and including a given day *t*. A larger value of *IPT* indicates more timely, and hence, more efficient price formation.

[27] Following McMullin et al. [2019], we drop firm-quarter observations where a prior-period earnings announcement lies within the 63-day trading window to reduce the likelihood that prior-period earnings information is affecting *IPT*. Our results are qualitatively similar if we include the dropped observations.

We first perform graphical analyses by constructing *High Connection* and *Low Connection* portfolios based on the tercile of the corresponding employee connection measure (*2ndOrder* or *3rdOrder*). For each portfolio, we plot for each day in the earnings cycle the cumulative buy-and-hold market-adjusted abnormal returns, scaled by the cumulative buy-and-hold abnormal return for the entire 63-day period. Each point captures the proportion of the entire quarter's abnormal return realized up to and including a particular day. On the last day of the period, the plot equals one by construction since 100% of the quarter's abnormal returns must be realized by then.

Figure 1a (1b) presents the results for the *High Connection* (solid line) and *Low Connection* (dashed line) portfolios using *2ndOrder* (*3rdOrder*). Figure 1a shows that when a firm's employees are more connected, price discovery is faster. Starting about seven days after the beginning of the period, *IPT* is always higher for the more-connected portfolio than for the less connected portfolio. There is a large gap between the lines that begins around day −40 and generally persists to about day −10, when *IPT* for high-connection firms is almost 100%. After that, the gap between the two lines narrows until the two lines converge on day +2 (by construction). Figure 1b is similar.

While the results in Figure 1 indicate that earnings-related information is impounded into prices more quickly for high-connection firms, they do not show whether the differences are significant or not. Accordingly, we examine the association between employee connections and timeliness using regression analyses. To minimize the impact of outliers in *IPT*, we use a decile-ranked version of *IPT* as the dependent variable (Chapman et al. [2019], McMullin et al. [2019]). We include the same set of control variables in Equation (4). The estimation results are presented in Columns 1 and 2 of Table 9. Both *Connection* coefficients are positive and significant at the 1% level.

As pointed out by Blankespoor et al. [2018], the standard IPT measure could erroneously increases if overreactions and subsequent reversals occur when the intermediate and final cumulative returns are the same sign. To mitigate this concern, we use an adjusted IPT measure (*AdjIPT*) suggested by Blankespoor et al. [2018]. Specifically, when the buy-and-hold abnormal returns for any given day exceed the entire buy-and-hold abnormal returns for a 63-day trading window, the adjusted IPT subtracts the excess returns. This reduces adjusted IPT to account for the inefficient overreaction during the return measurement window. Under the simplifying assumption that each day's return accrues at the beginning of the day, *AdjIPT* can be calculated as $\sum_{t=-60}^{2}|AbRet_2 - AbRet_t|/|AbRet_2|$. The results using *AdjIPT* are reported in Columns 3 and 4. Similar to the results in Columns 1 and 2, the coefficients on *Connection* are positive and significant at the 5% level or better. [28] Overall, these findings are consistent with more-connected firms having faster price formation due to value-relevant information being transmitted through employees' professional connections. Thus, the evidence from our IPT analyses provides additional support for our hypothesis.

5. Conclusion

This paper examines whether employees in conjunction with their professional networks function as information intermediaries, and as such, serve to increase stock price efficiency. Employees have access to value-relevant information (Cohen et al. [2010], Engelberg et al. [2012], Green et al. [2019], Huang et al. [2020], Huddart and Lang [2003]). Employees also have expansive professional networks that allow their information to be widely distributed outside the firm. We hypothesize that the ability of employees to function as effective information

[28] When we exclude observations with absolute buy-and-hold abnormal returns less than 1%, 2%, or 3% over the 63-day window to mitigate a small denominator problem (Blankespoor et al. [2018]), our results remain qualitatively similar.

intermediaries increases with the size of their professional networks. We find that firms with more highly connected employees experience significantly lower price reactions to earnings news. The diffused information is more likely to be positive and firm-specific. Using mergers of brokerage houses as a source of exogenous variation in the information environment, we provide causal evidence for the effect of employee connections on the market reactions to earnings news. In addition, prices reflect earnings-related information on a timelier basis for more-connected firms. Taken together, our evidence indicates that employees act as information intermediaries through their connections and that the earnings-related information they transmit serves to increase the information efficiency of stock prices. Employees differ from other types of information intermediaries (e.g., analysts, media, investing websites) because their professional networks are not designed to disseminate information to the capital markets. The distributed, private, and unintentional nature of these professional networks has important implications for firms' disclosure policies (Hales et al. [2018]).

While we believe that we provide interesting and novel evidence regarding the role of employees and their professional networks as information intermediaries, there is a caveat that should be kept in mind. While we can precisely identify an employee's actual professional connections, we are unable to directly observe whether information is transmitted through their professional networks. Thus, our analyses provide indirect evidence on their role as information intermediaries. Holding aside these issues, we find strong and consistent evidence that the employees in conjunction with their professional networks function as an independent information intermediary and are an important factor in increasing stock price efficiency with respect to earnings-related information.

Appendix A: Variable Definitions

Variables	Definition
[Employee-Level Connection Measures]	
$Degree1_i(\boldsymbol{g})$	First-order degree which enumerates the number of direct connections of employee *i*, which is defined as $\sum_j g_{ij}$, where $\boldsymbol{g}$ is a $n \times n$ adjacency matrix (n is the total number of employees in the network) in which $g_{ij} = 1$ if employee *i* is directly connected with employee *j* in another firm, and $g_{ij} = 0$ otherwise
$Degree2_i(\boldsymbol{g})$	Second-order degree which enumerates the number of unique second-order connections (i.e., friends of friends) who are not directly connected (i.e., not first-order connections)
$Degree3_i(\boldsymbol{g})$	Third-order degree which enumerates the number of unique third-order connections who are not first- or second-order connections
$1stOrder_i(\boldsymbol{g}, p)$	First-order connection measure which is calculated as $p \times Degree1_i(\boldsymbol{g})$, where $p \in (0,1)$ is a probability of information transmission
$2ndOrder_i(\boldsymbol{g}, p)$	Second-order connection measure which is calculated as $1stOrder_i(\boldsymbol{g}, p) + p^2 \times Degree2_i(\boldsymbol{g})$
$3rdOrder_i(\boldsymbol{g}, p)$	Third-order connection measure which is calculated as $2ndOrder_i(\boldsymbol{g}, p) + p^3 \times Degree3_i(\boldsymbol{g})$
[Firm-Level Connection Measures]	
Degree1 (*2* or *3*)$_f$	Firm-level first- (second- or third-) order degree of firm *f*, which is calculated as the average of *Degree1* (*2 or 3*)$_i(\boldsymbol{g})$ over all employees of firm *f* who appear on the network
1st (*2nd* or *3rd*)*Order*$_f$	Firm-level first- (second- or third-) order connection measure of firm *f*, which is calculated as the average of *1st* (*2nd* or *3rd*)*Order*$_i(\boldsymbol{g}, p)$ over all employees of firm *f* who appear on the network
[Other Variables]	
$AbRet_{[-2, +2]}$	The market-adjusted cumulative returns (in percentage) around the quarterly earnings announcement for the window [−2, +2], where day zero is the earnings announcement date
$AbRet_{[+3, +62]}$	The market-adjusted buy-and-hold returns (in percentage) following the quarterly earnings announcement for the window [+3, +62], where day zero is the earnings announcement date
IPT	The intra-period timeliness measure of the speed of price discovery over the quarterly earnings cycle, which is calculated as $\frac{1}{2}\sum_{t=-60}^{2}(AbRet_{t-1} + AbRet_t)/AbRet_2 = \sum_{t=-60}^{1} AbRet_t/AbRet_2 + 0.5$, where $AbRet_t$ is buy-and-hold market-adjusted abnormal returns from 60 trading days prior to the earnings announcement up to and including a given day *t*
AdjIPT	IPT adjusted for overreactions and subsequent reversals during the return measurement window, which is calculated as $\sum_{t=-60}^{2}\lvert AbRet_2 - AbRet_t\rvert/\lvert AbRet_2\rvert$ with the simplifying assumption that returns accrue at the beginning of each trading day

SUE	Standardized unexpected earnings, which is the difference between the reported quarterly earnings per share and expected quarterly earnings per share generated by the seasonal random walk with drift model using the most recent 12 quarters of data. The difference is scaled by the standard deviation of forecast errors over the estimation period.
PSUE (*NSUE*)	Equals *SUE* if *SUE* is positive (negative) and zero otherwise
MacroSUE	The macroeconomic component of *SUE*, which is the weighted average of *SUE* across all other firm *j* that announced earnings within the past 30 days of firm *i*'s earnings announcement date. We define the weight as the market capitalization of firm *j* divided by the gap between the earnings announcement dates of firms *i* and *j*.
IndSUE	The pure industry component of *SUE*, which is the difference between the industry and macroeconomic components of *SUE*. The industry component of *SUE* is the weighted average of *SUE* across all other firms *j* in the same two-digit KSIC industry that announced earnings within the past 30 days of firm *i*'s earnings announcement date. We define the weight as the market capitalization of firm *j* divided by the gap between the earnings announcement dates of firms *i* and *j*.
IdioSUE	The idiosyncratic component of *SUE*, which is *SUE – MacroSUE – IndSUE*
Treated	An indicator variable that equals one for firms covered by analysts from both brokerage houses before the merger and by only one analyst after the merger
Post	An indicator variable that equals one for quarters after the merger
Size	The natural logarithm of one plus the market value of equity (*MktCap*) at the end of the quarter
BM	Book value of equity divided by market value of equity at the end of the quarter
Coverage	The natural logarithm of one plus the number of analysts making at least one earnings forecast for the quarter made within 90 days of the earnings announcement. When analyst following is not available, we set it to zero.
BlockOwn	Quarterly percentage of block ownership at the end of each quarter; when a person or group owns 5% or more of a company's shares, we categorize the corresponding shares as owned by block holders.
Loss	An indicator variable that equals one if earnings per share for the quarter is negative, and zero otherwise
Guidance	An indicator variable that equals one if the management issues the earnings forecast for the year before the earnings announcement date of the quarter
Q4	An indicator variable that equals one if the quarter *q* is the firm's fourth fiscal quarter

Appendix B: Illustration of the Network Data and Construction of Connection Measures

In this appendix, we provide a simple example to illustrate the data structure of our business card exchange network. Panel A of Table B.1 presents network data for this example where the unit of observation is at the connection level. Each connection links the app-user employee (Employee ID) who uploads the card and the employee (Business Card Employee ID) whose card is uploaded. For example, the first entry shows that employee A, a senior staff member at firm 1, has uploaded the card of employee C, a department head at firm 2. Panel B visualizes the connections in Panel A using a network graph. Employees A, C, and E (striped circles) are app users, and all other employees (hollow circles) are non-app users. Employee F does not appear in the network data because no one has uploaded the card of employee F.

Based on the connection-level data in Panel A, we construct firm-level employee connection measures as follows. As shown in Panel C, we first compute the raw (i.e., undiscounted) numbers of first-, second-, and third-order connections at the individual level. In calculating the number of second- and third-order connections (*Degree2* and *Degree3*), we do not include any paths that lead to a fellow employee (i.e., an employee at the same firm) because our focus is on the information diffusion to outsiders. For instance, employee A has two second-order connections, not three, because we exclude the path A−E−B.

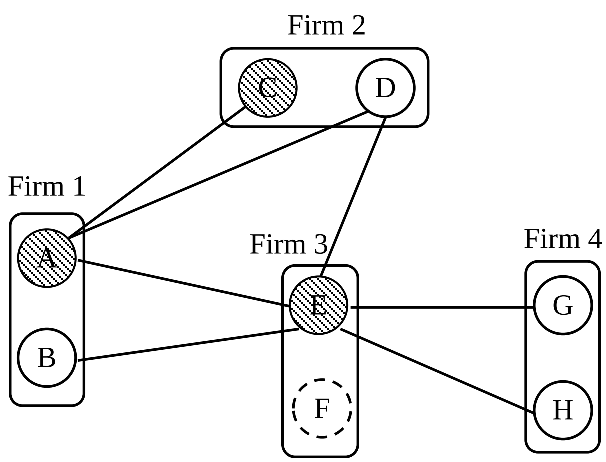
We then construct the *1stOrder*, *2ndOrder*, and *3rdOrder* at the firm level by averaging each respective employee-level connection measure across the firm's employees in the network. Panel D presents the calculations, where we use 0.9 as the probability of information transmission. Taking firm 2 as an example, the value of *1stOrder* is 1.35 (= 0.9×(1+2) / 2), *2ndOrder* is 2.97 (= 1.35 + [0.9^2×(1+3) / 2]), and *3rdOrder* is 4.06 (= 2.97 + [0.9^3×(3+0) / 2]). It is worth noting that firms with higher values of *1stOrder* do not necessarily exhibit higher values of *2ndOrder* or *3rdOrder*, as shown in the example for firms 2 and 4.

Table B.1. An Illustration of the Network Data and Construction of the Employee Connection Measures

Panel A. An Example of the Network Data

Employee ID	Firm ID	Job Position	Business Card Employee ID	Business Card Firm ID	Business Card Job Position
A	1	Senior staff	C	2	Department head
A	1	Senior staff	D	2	Executive vice president
A	1	Senior staff	E	3	Manager
C	2	Department head	A	1	Senior staff
E	3	Manager	A	1	Senior staff
E	3	Manager	B	1	Manager
E	3	Manager	D	2	Executive vice president
E	3	Manager	G	4	Staff
E	3	Manager	H	4	Vice president

Panel B. A Network Graph of the Example



Panel C. Non-Discounted Number of First-, Second-, and Third-Order Connections and the Number of Supported Connections at the Employee Level

Employee ID	Firm ID	*Degree1*	*Degree2*	*Degree3*
A	1	3	2	0
B	1	1	3	1
C	2	1	1	3
D	2	2	3	0
E	3	5	1	0
F	3	N/A	N/A	N/A
G	4	1	3	1
H	4	1	3	1

Panel D. Firm-Level Connection Measures

Firm ID	Number of Employees in the Network	*1stOrder* (p = 0.9)	*2ndOrder* (p = 0.9)	*3rdOrder* (p = 0.9)
1	2	1.80	3.83	4.19
2	2	1.35	2.97	4.06
3	1	4.50	5.31	5.31
4	2	0.90	3.33	4.06

Notes: This table illustrates the structure of our employee network data, determining the raw number of first-, second-, and third-order connections at the employee level and the construction of employee connection measures at the firm level (*1stOrder*, *2ndOrder*, and *3rdOrder*). Panel A presents the example network data in which the unit of observation is at the connection level. Panel B visualizes the connections in Panel A using a network graph. Striped circles indicate app users, and hollow circles indicate non-app users. Dotted hollow circles indicate employees who do not appear in the network data because no one has uploaded their business cards. Note that non-app users also appear in our network (e.g., employees B, D, G, and H) as long as app users upload their business cards. In Panel C, we compute the raw (i.e., undiscounted) numbers of first-, second-, and third-order connections at the individual level. Panel D reports the firm-level connection measures by averaging each employee-level connection measure across the firm's employees in the network.

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Figure 1. Speed of Price Discovery and Employee Connections

Figure 1a. High *2ndOrder* vs. Low *2ndOrder*

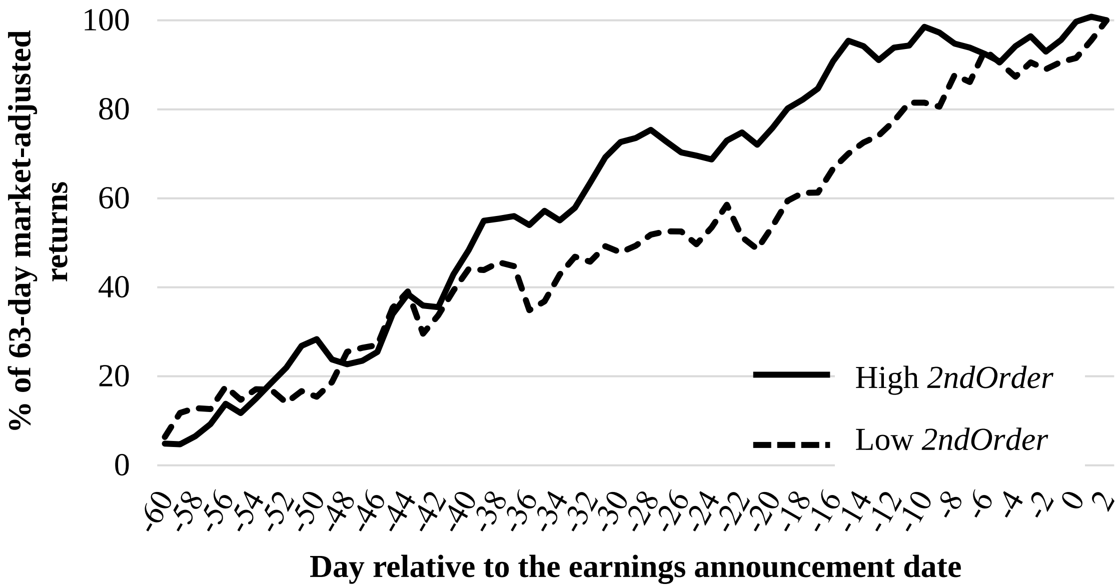
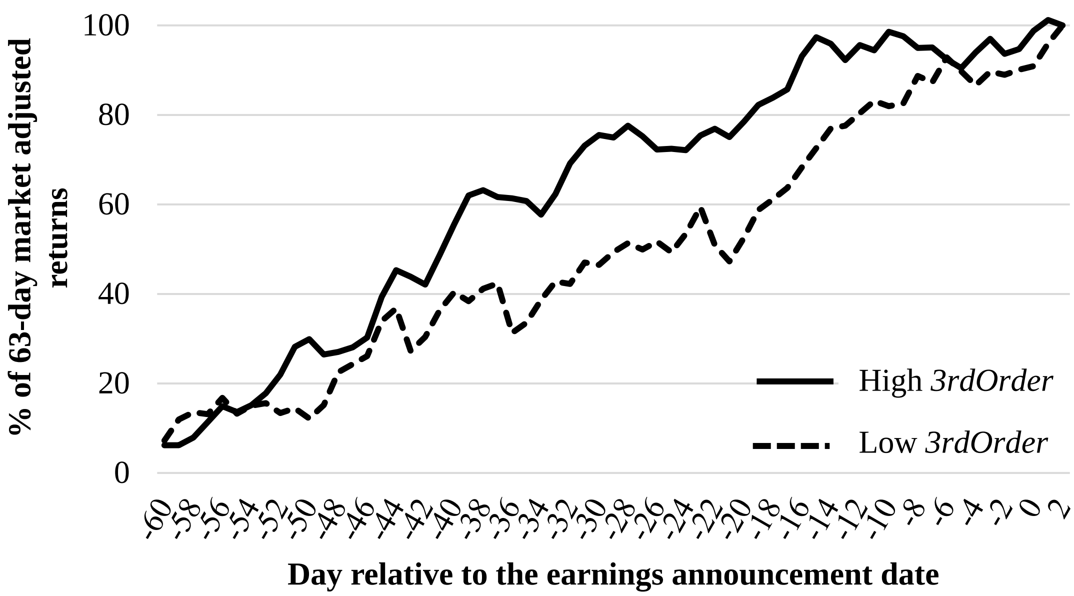


Figure 1b. High *3rdOrder* vs. Low *3rdOrder*



Notes: These figures present the percentage of 63-day buy-and-hold market-adjusted returns for each day from 60 trading days before the earnings announcement date to two trading days after it. We partition firm-quarter observations into three portfolios based on the tercile of employee connection measures and plot the percentage for the highest and lowest terciles. The solid (dashed) line represents high (low) employee connection portfolios. Figure 1a (1b) plots the graph based on *2ndOrder* (*3rdOrder*) with the probability of information transmission of 0.5. Detailed definitions of the variables are provided in the Appendix.

Table 1. Descriptive Statistics

Variables	N	Q1	Mean	Median	Q3	Std. Dev
[Firm-Level Connection Measures]						
Degree1	17,780	3.82	7.44	5.93	8.99	5.71
Degree2	17,780	542.4	1,220	948.4	1,560	1,007
Degree3	17,780	10,597	38,187	27,181	53,871	37,031
1stOrder (p = 0.5)	17,780	1.91	3.72	2.96	4.50	2.85
2ndOrder (p = 0.5)	17,780	138.0	308.8	240.1	394.0	254.1
3rdOrder (p = 0.5)	17,780	1,470	5,081	3,642	7,135	4,872
[Other Variables]						
$AbRet_{[-2,\,+2]}$	17,780	-3.47	0.149	-0.288	3.21	6.58
$AbRet_{[+3,\,+62]}$	17,780	-12.73	-1.16	-3.85	6.28	19.88
IPT	13,183	5.51	11.11	10.93	16.39	10.85
SUE	17,780	-1.83	-0.089	-0.044	1.73	3.86
Size	17,780	18.16	19.17	18.83	19.82	1.43
MktCap (₩KRW MN)	17,780	77,265	930,500	150,800	40,6500	2,809,000
BM	17,780	0.493	0.999	0.857	1.35	0.669
Coverage	17,780	0.000	0.567	0.000	0.693	0.859
BlockOwn	17,780	0.000	3.93	0.000	6.94	5.84
Loss	17,780	0.000	0.313	0.000	1.00	0.464
Guidance	17,780	0.000	0.066	0.000	0.000	0.248
Q4	17,780	0.000	0.251	0.000	1.00	0.433

Notes: This table provides summary statistics of the main variables used in this study. The sample period runs from 2015 to 2018. The definitions of all variables are provided in the Appendix. All continuous variables are winsorized at 1% and 99%.

Table 2. Employee Connections and Abnormal Returns around Earnings Announcements

Dep. Var. =	*AbRet*$_{[-2, +2]}$								
Prob. of Info Trans. (p) =	*0.1*			*0.5*			*0.9*		
Connection =	*1stOrder*	*2ndOrder*	*3rdOrder*	*1stOrder*	*2ndOrder*	*3rdOrder*	*1stOrder*	*2ndOrder*	*3rdOrder*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
SUE×Connection	0.023	-0.239*	-0.353***	-0.086	-0.258**	-0.325***	-0.108	-0.257**	-0.320***
	(0.243)	(0.141)	(0.115)	(0.153)	(0.124)	(0.090)	(0.139)	(0.122)	(0.088)
Connection	0.657	0.608	0.497	0.383	0.512	0.392	0.337	0.506	0.380
	(0.721)	(0.381)	(0.315)	(0.468)	(0.334)	(0.260)	(0.429)	(0.331)	(0.253)
Size	-1.686***	-1.690***	-1.699***	-1.687***	-1.687***	-1.701***	-1.687***	-1.687***	-1.702***
	(0.378)	(0.379)	(0.379)	(0.379)	(0.380)	(0.380)	(0.379)	(0.380)	(0.380)
BM	0.392	0.378	0.371	0.396	0.380	0.371	0.397	0.380	0.371
	(0.361)	(0.362)	(0.363)	(0.362)	(0.362)	(0.363)	(0.362)	(0.362)	(0.363)
Coverage	0.247	0.232	0.224	0.245	0.230	0.226	0.244	0.230	0.227
	(0.249)	(0.250)	(0.250)	(0.249)	(0.250)	(0.250)	(0.249)	(0.250)	(0.250)
BlockOwn	-0.027	-0.027	-0.027	-0.027	-0.027	-0.027	-0.027	-0.027	-0.027
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Loss	-1.707***	-1.710***	-1.711***	-1.708***	-1.710***	-1.711***	-1.708***	-1.710***	-1.711***
	(0.159)	(0.159)	(0.159)	(0.159)	(0.159)	(0.159)	(0.159)	(0.159)	(0.159)
Guidance	0.599	0.592	0.583	0.598	0.591	0.585	0.598	0.591	0.586
	(0.396)	(0.396)	(0.397)	(0.397)	(0.397)	(0.397)	(0.397)	(0.397)	(0.398)
Q4	0.005	-0.075	-0.112	-0.000	-0.070	-0.103	0.000	-0.069	-0.101
	(0.129)	(0.144)	(0.156)	(0.133)	(0.145)	(0.155)	(0.134)	(0.145)	(0.154)
SUE×Control Variables	Included								
Fixed Effects	Firm FEs, Year FEs								
SUE×Fixed Effects	Included								
Observations	17,780	17,780	17,780	17,780	17,780	17,780	17,780	17,780	17,780
Adj.R^2	0.061	0.062	0.062	0.062	0.062	0.063	0.062	0.062	0.063

Notes: This table reports regression estimates on the relation between employee connection measures and earnings response coefficient. We measure $AbRet_{[-2, +2]}$ as the market-adjusted cumulative returns (in percentage) around the quarterly earnings announcement for the window [−2, 2], where day zero is the quarterly earnings announcement date. We define *SUE* as the quarterly earnings surprise measured by standardized unexpected earnings from the seasonal random walk with drift model. We report results for the first-, second-, and third-order connection measures (*1stOrder*, *2ndOrder*, and *3rdOrder*, respectively) when the probability of information transmission (p) is 0.1, 0.5, or 0.9. *1stOrder* enumerates the number of direct connections, discounted by p. *2ndOrder* is defined as *1stOrder* plus the number of unique second-order relationships (i.e., friends of friends) discounted with p^2. *3rdOrder* is calculated as *2ndOrder* plus the number of unique third-order connections that are not first- or second-order connections discounted with p^3. The definitions of all variables are provided in the Appendix. All regressions include firm and year fixed effects, and their interaction terms with *SUE*. Standard errors in parentheses are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Table 3. Employee Connections and Market Reactions to Earnings Announcements Using a Propensity Score Matched (PSM) Sample

Panel A. Comparison of Covariates for Matched Sample

	Mean Comparison			
	Top Quartile *Connection*	Bottom Quartile *Connection*	Top – Bottom	*t*-stat
Connection = 1stOrder				
Size	19.266	19.294	-0.028	[-0.23]
BM	0.954	0.925	0.029	[0.65]
Coverage	0.543	0.576	-0.033	[-0.44]
BlockOwn	4.303	4.189	0.114	[0.27]
Loss	0.289	0.291	-0.002	[-0.09]
Guidance	0.059	0.063	-0.004	[-0.20]
Q4				
Connection = 2ndOrder				
Size	19.223	19.362	-0.139	[-1.11]
BM	0.845	0.856	-0.011	[-0.27]
Coverage	0.552	0.607	-0.054	[-0.74]
BlockOwn	4.132	4.102	0.031	[0.07]
Loss	0.333	0.329	0.005	[0.18]
Guidance	0.060	0.059	0.001	[0.05]
Q4				
Connection = 3rdOrder				
Size	19.245	19.375	-0.130	[-1.06]
BM	0.851	0.881	-0.031	[-0.72]
Coverage	0.550	0.616	-0.066	[-0.88]
BlockOwn	4.150	4.435	-0.285	[-0.63]
Loss	0.334	0.336	-0.001	[-0.05]
Guidance	0.064	0.066	-0.003	[-0.15]
Q4	0.252	0.253	-0.002	[-0.17]

Panel B. Market Reactions to Earnings Announcements Using PSM Approach

Dep. Var. =	$AbRet_{[-2, +2]}$		
Connection =	*1stOrder*	*2ndOrder*	*3rdOrder*
	(1)	(2)	(3)
SUE×Connection	0.087	-0.684**	-0.491**
	(0.269)	(0.292)	(0.207)
Connection	0.767	1.563	1.172
	(0.824)	(0.961)	(0.729)
Size	-1.375*	-2.893***	-2.238***
	(0.741)	(0.796)	(0.716)
BM	-0.047	-0.135	0.432
	(0.794)	(0.763)	(0.703)
Coverage	-0.276	0.322	1.102*
	(0.563)	(0.540)	(0.592)
BlockOwn	-0.049	0.003	-0.009
	(0.037)	(0.041)	(0.055)
Loss	-1.511***	-1.452***	-1.980***
	(0.335)	(0.360)	(0.352)
Guidance	1.237	0.957	1.062
	(0.844)	(0.885)	(1.029)
Q4	0.771***	-0.241	-0.364
	(0.278)	(0.363)	(0.396)
SUE×Control Variables		Included	
Fixed Effects		Firm FEs, Year FEs	
SUE×Fixed Effects		Included	
Observations	8,565	8,540	8,534
Adjusted R-squared	0.214	0.200	0.213

Notes: This table repeats the estimation in Table 2 using the propensity score matched sample. For each quarter, we assign each firm to a top- or bottom-quartile connection group based on *1stOrder*, *2ndOrder*, or *3rdOrder*. We run a probit regression to estimate the probability of being a highly connected firm (those with top-quartile connection measures) using the same set of control variables in Table 2. Each treated firm is matched to the nearest neighbor control firm using a caliper of 0.01 with replacement. Panel A tabulates the means of variables for the top- or bottom-quartile groups. We also report the mean differences between the two groups and their corresponding *t*-statistics based on standard errors clustered by firm. Panel B presents the results estimating the specifications in Table 2 using the matched sample. We measure $AbRet_{[-2, +2]}$ as the market-adjusted cumulative returns (in percentage) around the quarterly earnings announcement for the window [−2, 2], where day zero is the quarterly earnings announcement date. We include the same set of control variables in Table 2. The definitions of all variables are provided in the Appendix. All regressions include firm and year fixed effects, and their interaction terms with *SUE*. Standard errors in parentheses are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Table 4. Employee Connections and Market Reactions to Earnings Announcements: Traditional Information Intermediaries vs. Non-Information Intermediaries

Dep. Var. =	$AbRet_{[-2, +2]}$			
Connection =	*2ndOrder*		*3rdOrder*	
Connections to	TII	Non-TII	TII	Non-TII
	(1)	(2)	(3)	(4)
SUE×*Connection*	-0.047	-0.266**	-0.249***	-0.328***
	(0.106)	(0.123)	(0.083)	(0.090)
Connection	0.366	0.516	0.383	0.393
	(0.275)	(0.336)	(0.242)	(0.259)
Size	-1.694***	-1.686***	-1.705***	-1.701***
	(0.378)	(0.379)	(0.380)	(0.380)
BM	0.389	0.380	0.376	0.370
	(0.359)	(0.362)	(0.361)	(0.363)
Coverage	0.229	0.231	0.221	0.227
	(0.249)	(0.250)	(0.250)	(0.250)
BlockOwn	-0.027	-0.027	-0.027	-0.027
	(0.017)	(0.017)	(0.017)	(0.017)
Loss	-1.706***	-1.710***	-1.707***	-1.711***
	(0.159)	(0.159)	(0.159)	(0.159)
Guidance	0.593	0.591	0.590	0.585
	(0.397)	(0.397)	(0.398)	(0.397)
Q4	-0.025	-0.071	-0.085	-0.104
	(0.134)	(0.145)	(0.146)	(0.155)
SUE×Control Variables	Included			
Fixed Effects	Firm FEs, Year FEs			
SUE×Fixed Effects	Included			
Observations	17,780	17,780	17,780	17,780
Adjusted R-squared	0.062	0.062	0.062	0.063

Notes: This table repeats the estimation in Table 2 by splitting the connection measures into connections to employees of traditional information intermediaries (TII) and non-information intermediaries (Non-TII). We report the results using *2ndOrder* and *3rdOrder* measures with a probability of information transmission (p) equal to 0.5. TII include media firms (KSIC 5812, 59114, 5912, 5913, 60, and 63910) and firms in the investment banking industry (KSIC 6612), which consist of investment banks and security brokerage firms. We measure $AbRet_{[-2, +2]}$ as the market-adjusted cumulative returns (in percentage) around the quarterly earnings announcement for the window [−2, 2], where day zero is the quarterly earnings announcement date. We define *SUE* as the quarterly earnings surprise measured by the standardized unexpected earnings from the seasonal random walk with drift model. We include the same set of control variables in Table 2. Variable definitions are provided in the Appendix. All regressions include firm and year fixed effects, and their interaction terms with *SUE*. Standard errors in parentheses are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Table 5. Employee Connections and Market Reactions to Earnings Announcements: by Types of Information

Dep. Var. =	*AbRet*$_{[-2, +2]}$			
Connection =	*2ndOrder*		*3rdOrder*	
	(1)	(2)	(3)	(4)
PSUE×Connection	-0.529**		-0.481***	
	(0.265)		(0.186)	
NSUE×Connection	-0.070		-0.156	
	(0.260)		(0.190)	
MacroSUE×Connection		-0.546		-0.382
		(0.506)		(0.381)
IndSUE×Connection		-0.043		-0.232
		(0.273)		(0.204)
IdioSUE×Connection		-0.360**		-0.368***
		(0.154)		(0.111)
Connection	0.716	0.511	0.617	0.221
	(0.567)	(0.497)	(0.428)	(0.410)
Size	-0.627	-1.724***	-0.641	-1.727***
	(0.506)	(0.524)	(0.505)	(0.523)
BM	0.703	0.564	0.695	0.563
	(0.529)	(0.493)	(0.528)	(0.493)
Coverage	-0.076	0.171	-0.081	0.173
	(0.397)	(0.331)	(0.398)	(0.332)
BlockOwn	-0.006	-0.023	-0.006	-0.023
	(0.027)	(0.023)	(0.027)	(0.023)
Loss	-2.062***	-1.600***	-2.070***	-1.600***
	(0.247)	(0.197)	(0.247)	(0.196)
Guidance	0.388	0.644	0.378	0.642
	(0.588)	(0.496)	(0.586)	(0.496)
Q4	0.124	-0.261	0.040	-0.229
	(0.234)	(0.207)	(0.254)	(0.224)
Control Variables×*SUE* components	Included			
Fixed Effects	Firm FEs, Year FEs			
Fixed Effects× *SUE* components	Included			
Observations	17,780	16,756	17,780	16,756
Adjusted R-squared	-0.024	0.050	-0.023	0.050

Notes: This table repeats the estimation in Table 2 using the decomposition of earnings surprises (*SUE*) by different types of information. We report the results using *2ndOrder* and *3rdOrder* with a probability of information transmission (*p*) equal to 0.5. In Columns 1 and 3, we decompose *SUE* into positive (*PSUE*) and negative surprises (*NSUE*). *PSUE* (*NSUE*) equals *SUE* if *SUE* is positive (negative) and zero otherwise. In Columns 2 and 4, we decompose *SUE* into the macroeconomic, industry, and idiosyncratic components (*MacroSUE*, *IndSUE*, and *IdioSUE*, respectively). *MacroSUE* is the weighted average of *SUE* across all other firm *j* that announced earnings within the past 30 days of firm *i*'s earnings announcement date, where the weight is the market capitalization of firm *j* divided by the gap between earnings announcement dates of firms *i* and *j*. *IndSUE* is the difference between the industry and macroeconomic components of *SUE*, where the industry component of *SUE* is the weighted average of *SUE* across all other firms *j* in the same two-digit KSIC industry that announced earnings within the past 30 days of firm *i*'s earnings announcement date. *IdioSUE* is *SUE–MacroSUE–IndSUE*. We measure $AbRet_{[-2, +2]}$ as the market-adjusted cumulative returns (in percentage) around the quarterly earnings announcement for the window [−2, 2], where day zero is the quarterly earnings announcement date. We include the same set of control variables in Table 2. The definitions of all variables are provided in the Appendix. All regressions include firm and year fixed effects, and their interaction terms with *SUE* components. Standard errors in parentheses are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Table 6. Employee Connections and Market Reactions to Earnings Announcements: Executives vs. Non-Executives

Dep. Var. =	*AbRet*$_{[-2, +2]}$			
Connection =	*2ndOrder*		*3rdOrder*	
Connections of	Executive	Non-Executive	Executive	Non-Executive
	(1)	(2)	(3)	(4)
SUE×*Connection*	-0.215**	-0.297***	-0.214***	-0.355***
	(0.085)	(0.111)	(0.068)	(0.083)
Connection	0.279	0.303	0.167	0.321
	(0.260)	(0.310)	(0.218)	(0.239)
Size	-1.680***	-1.681***	-1.682***	-1.698***
	(0.380)	(0.379)	(0.379)	(0.380)
BM	0.394	0.390	0.390	0.372
	(0.362)	(0.361)	(0.362)	(0.361)
Coverage	0.236	0.239	0.233	0.230
	(0.250)	(0.249)	(0.251)	(0.250)
BlockOwn	-0.028	-0.027	-0.028	-0.027
	(0.017)	(0.017)	(0.017)	(0.017)
Loss	-1.704***	-1.709***	-1.705***	-1.709***
	(0.160)	(0.159)	(0.160)	(0.159)
Guidance	0.587	0.599	0.588	0.596
	(0.397)	(0.397)	(0.397)	(0.398)
Q4	-0.020	-0.025	-0.014	-0.080
	(0.138)	(0.143)	(0.147)	(0.151)
SUE×Control Variables	Included			
Fixed Effects	Firm FEs, Year FEs			
SUE×Fixed Effects	Included			
Observations	17,730	17,780	17,730	17,780
Adjusted R-squared	0.063	0.062	0.063	0.063

Notes: This table repeats the estimation of Table 2 using connections of executives and non-executives separately. We report the results using *2ndOrder* and *3rdOrder* measures with a probability of information transmission (p) equal to 0.5. Executive employees include the chairman, vice chairman, president, deputy president, executive vice president, and senior vice president. All other employees are considered non-executives. We measure *AbRet*$_{[-2, +2]}$ as the market-adjusted cumulative returns (in percentage) around the quarterly earnings announcement for the window [−2, 2], where day zero is the quarterly earnings announcement date. We define *SUE* as the quarterly earnings surprise measured by standardized unexpected earnings from the seasonal random walk with drift model. We include the same set of control variables in Table 2. Variable definitions are provided in the Appendix. All regressions include firm and year fixed effects, and their interaction terms with *SUE*. Standard errors in parentheses are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Table 7. Employee Connections and Market Reactions to Earnings Announcements: Causal Evidence from Mergers of Brokerage Houses

Panel A. Stacked Difference-in-Differences Regressions

Dep. Var. =	$AbRet_{[-2, +2]}$	
Connection =	*2ndOrder*	*3rdOrder*
	(1)	(2)
SUE×Connection×Treated×Post	-0.017***	-0.013***
	(0.006)	(0.005)
Connection	-0.091**	-0.040
	(0.039)	(0.025)
Post	0.013	0.148
	(0.086)	(0.129)
SUE×Connection	-0.016	-0.010
	(0.010)	(0.007)
SUE×Post	-0.072***	-0.086***
	(0.024)	(0.030)
Connection×Treated	0.021	0.004
	(0.025)	(0.015)
Connection×Post	0.006	-0.014
	(0.016)	(0.016)
Treated×Post	-0.126	-0.190
	(0.111)	(0.142)
SUE×Connection×Treated	0.013	0.009
	(0.012)	(0.007)
SUE×Connection×Post	0.015***	0.012***
	(0.005)	(0.004)
SUE×Treated×Post	0.093***	0.104***
	(0.031)	(0.038)
Connection×Treated×Post	0.020	0.022
	(0.021)	(0.018)
Control Variables	Included	
SUE×Control Variables	Included	
Fixed Effects	Event-specific Firm FEs, Year FEs	
SUE×Fixed Effects	Included	
Observations	3,898	3,898
Adjusted R-squared	0.402	0.395

Panel B. Dynamic Effects

Dep. Var. =	$AbRet_{[-2, +2]}$	
Connection =	*2ndOrder*	*3rdOrder*
	(1)	(2)
$SUE \times Connection \times Treated \times d_{q-3}$	0.032	0.021
	(0.024)	(0.025)
$SUE \times Connection \times Treated \times d_{q-2}$	-0.008	-0.016
	(0.014)	(0.011)
$SUE \times Connection \times Treated \times d_{q-1}$	0.010	0.003
	(0.019)	(0.017)
$SUE \times Connection \times Treated \times d_{q+1}$	-0.021	-0.018*
	(0.013)	(0.011)
$SUE \times Connection \times Treated \times d_{q+2}$	-0.007	-0.011
	(0.011)	(0.009)
$SUE \times Connection \times Treated \times d_{q+3}$	-0.019*	-0.020*
	(0.012)	(0.011)
$SUE \times Connection \times Treated \times d_{q+4}$	-0.025*	-0.022*
	(0.014)	(0.013)
Main, Two-, and Three-way Interacted Effects	Included	
Control Variables	Included	
SUE×Control Variables	Included	
Fixed Effects	Event-specific Firm FEs, Year FEs	
SUE×Fixed Effects	Included	
Observations	3,898	3,898
Adjusted R-squared	0.342	0.338

Notes: This table reports stacked difference-in-differences regression estimates on the relation between employee connection measures and ERC using mergers of brokerage houses as a quasi-natural experiment. We report the results using *2ndOrder* and *3rdOrder* measures with a probability of information transmission (p) equal to 0.5. *Treated* is an indicator variable that equals one for firms covered by analysts from both brokerage houses before the merger and by only one analyst after the merger. In Panel A, *Post* is an indicator variable that equals one for quarters after the mergers. In Panel B, we examine the dynamic effects by replacing *Post* with relative-time indicators d_{q+t} for $-3 \leq t \leq 4$. We measure $AbRet_{[-2, +2]}$ as the market-adjusted cumulative returns (in percentage) around the quarterly earnings announcement for the window [−2, 2], where day zero is the quarterly earnings announcement date. We define *SUE* as the quarterly earnings surprise measured by standardized unexpected earnings from the seasonal random walk with drift model. We include the same set of control variables in Table 2. Variable definitions are provided in the Appendix. All regressions include merger event-specific firm and year fixed effects, and their interaction terms with *SUE*. Standard errors in parentheses are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Table 8. Employee Connections and Post Earnings Announcement Drift

Dep. Var. =	$AbRet_{[+3, +62]}$	
Connection =	*2ndOrder*	*3rdOrder*
	(1)	(2)
SUE×Connection	-1.048***	-0.810***
	(0.357)	(0.254)
Connection	-0.109	0.254
	(1.046)	(0.744)
Size	-15.041***	-15.075***
	(1.423)	(1.426)
BM	1.802	1.745
	(1.140)	(1.143)
Coverage	-0.573	-0.596
	(0.750)	(0.750)
BlockOwn	-0.018	-0.016
	(0.045)	(0.045)
Loss	-1.166**	-1.161**
	(0.525)	(0.525)
Guidance	0.159	0.153
	(1.296)	(1.294)
Q4	-0.172	-0.287
	(0.467)	(0.502)
SUE×Control Variables	Included	
Fixed Effects	Firm FEs, Year FEs	
SUE×Fixed Effects	Included	
Observations	17,780	17,780
Adjusted R-squared	0.056	0.056

Notes: This table reports regression estimates on the relation between employee connection measures and post earnings announcement drift. We report the results using *2ndOrder* and *3rdOrder* measures with a probability of information transmission (p) equal to 0.5. We measure $AbRet_{[+3, +62]}$ as the market-adjusted buy-and-hold returns (in percentage) following the quarterly earnings announcement for the window [+3, +62], where day zero is the quarterly earnings announcement date. We define *SUE* as the quarterly earnings surprise measured by standardized unexpected earnings from the seasonal random walk with drift model. We include the same set of control variables in Table 2. Variable definitions are provided in the Appendix. All regressions include firm and year fixed effects, and their interaction terms with *SUE*. Standard errors in parentheses are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Table 9. Employee Connections and Intra-period Timeliness (IPT)

Dep. Var. =	Decile Ranking of *IPT*		Decile Ranking of *AdjIPT*	
Connection =	*2ndOrder*	*3rdOrder*	*2ndOrder*	*3rdOrder*
	(1)	(2)	(3)	(4)
Connection	0.231***	0.219***	0.169**	0.138**
	-0.065	-0.061	-0.064	-0.059
Size	0.076*	0.074*	-0.011	-0.012
	-0.04	-0.04	-0.04	-0.04
BM	-0.049	-0.045	-0.111*	-0.111*
	-0.061	-0.06	-0.057	-0.057
Coverage	-0.216***	-0.214***	-0.046	-0.045
	-0.07	-0.07	-0.057	-0.057
BlockOwn	-0.006	-0.006	-0.004	-0.004
	-0.005	-0.005	-0.005	-0.005
Loss	-0.132**	-0.135**	-0.029	-0.03
	-0.057	-0.057	-0.093	-0.093
Guidance	-0.008	-0.013	-0.009	-0.011
	-0.156	-0.156	-0.156	-0.156
Q4	-0.041	-0.073	-0.035	-0.049
	-0.059	-0.063	-0.052	-0.055
Fixed Effects	Industry FEs, Year FEs			
Observations	9,987	9,987	9,987	9,987
Adjusted R-squared	0.005	0.005	0.001	0.001

Notes: This table reports regression estimates on the relation between employee connection measures and *IPT*. We report the results using *2ndOrder* and *3rdOrder* measures with a probability of information as our connection measures. In Columns 1 and 2, *IPT* is a 63-day intra-period timeliness measure of the speed with which information is impounded into stock prices. Specifically, it is calculated as $\frac{1}{2}\sum_{t=-60}^{2}(QAbRet_{t-1}+QAbRet_{t})/QAbRet_{2}=\sum_{t=-60}^{1}QAbRet_{t}/QAbRet_{2}+0.5$, where $QAbRet_t$ is buy-and-hold market-adjusted abnormal returns from 60 trading days prior to the earnings announcement up to and including a given day *t*. In Columns 3 and 4, we use adjusted IPT measure (*AdjIPT*) to penalize for overreactions and subsequent reversals during the return measurement window. We use the decile rankings of *IPT* and *AdjIPT* as the dependent variable. Definitions of all variables are provided in the Appendix. We include industry (two-digit KSIC) and year fixed effects. Standard errors in parentheses are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Internet Appendix: Table IA.1. Employee Connections and Market Reactions to Earnings Announcements: Direct vs. Indirect Connections

Dep. Var. =	$AbRet_{[-2, +2]}$			
	(1)	(2)	(3)	(4)
SUE×log(1+*Degree1*)	-0.111			0.090
	(0.137)			(0.169)
SUE×log(1+*Degree2*)		-0.256**		0.150
		(0.122)		(0.207)
SUE×log(1+*Degree3*)			-0.314***	-0.420***
			(0.085)	(0.136)
log(1+*Degree1*)	0.331			0.049
	(0.424)			(0.522)
log(1+*Degree2*)		0.502		0.261
		(0.330)		(0.573)
log(1+*Degree3*)			0.365	0.209
			(0.245)	(0.386)
Size	-1.687***	-1.687***	-1.702***	-1.706***
	(0.379)	(0.380)	(0.380)	(0.380)
BM	0.398	0.380	0.371	0.356
	(0.362)	(0.362)	(0.363)	(0.364)
Coverage	0.244	0.230	0.227	0.224
	(0.249)	(0.250)	(0.250)	(0.250)
BlockOwn	-0.027	-0.027	-0.027	-0.026
	(0.017)	(0.017)	(0.017)	(0.017)
Loss	-1.708***	-1.710***	-1.711***	-1.708***
	(0.159)	(0.159)	(0.159)	(0.159)
Guidance	0.598	0.591	0.586	0.588
	(0.397)	(0.397)	(0.398)	(0.398)
Q4	0.000	-0.069	-0.099	-0.101
	(0.134)	(0.145)	(0.154)	(0.154)
Control Variables×*SUE*	Included			
Fixed Effects	Firm FEs, Year FEs			
Fixed Effects×*SUE*	Included			
Observations	17,780	17,780	17,780	17,780
Adj.R^2	0.062	0.062	0.063	0.063

Notes: This table repeats the estimation of Table 2 using *Degree1*, *Degree2*, and *Degree3* as our employee connection measures. *Degree1* is a first-order degree that enumerates the number of direct connections, *Degree2* is the second-order degree that counts the number of unique second-order connections (i.e., friends of friends) who are not directly connected, and *Degree3* is the third-order degree that counts the number of unique third-order connections who are not first- or second-order connections. We measure $AbRet_{[-2, +2]}$ as the market-adjusted cumulative returns (in percentage) around the quarterly earnings announcement for the window [−2, 2], where day zero is the quarterly earnings announcement date. We define *SUE* as the quarterly earnings surprise measured by the standardized unexpected earnings from the seasonal random walk with drift model. We include the same set of control variables in Table 2. Variable definitions are provided in the Appendix. All regressions include firm and year fixed effects, and their interaction terms with *SUE*. Standard errors in parentheses are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.