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 disseminated through both their direct and indirect professional contacts. We find that firms with more highly connected (executive and non-executive) employees have lower market reactions to earnings surprises. Using brokerage firm mergers, we provide evidence supporting a causal effect. Further analyses indicate that employees primarily disseminate information about positive earnings news and the firm-specific component of earnings news. Supporting employees' role as information intermediaries, we find that the stock prices of more connected firms incorporate information about forthcoming earnings on a timelier basis throughout the quarter as well as exhibit lower post-earnings announcement drift. Overall, our results suggest that more connected firms have more efficient stock prices because employees, in conjunction with their professional networks, act as information intermediaries.

JEL codes: G12, G14, L14, M41

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Data availability: The data on professional business connections is proprietary and cannot be shared. Other data is available from the data providers listed in the paper.

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I. INTRODUCTION

A firm's information environment is influenced by various market participants and information intermediaries (Beyer, Cohen, Lys, and Walther 2010). Early studies investigated the role of analysts and institutional investors as information intermediaries (e.g., Brennan and Subrahmanyam 1995; Roulstone 2003). More recently, the literature has investigated other types of information intermediaries, including the business press, data providers, and the internet (Bushee, Core, Guay, and Hamm 2010; Blankespoor, Miller, and White 2014; Drake, Thornock, and Twedt 2017; Schaub 2018). This research finds that intermediaries are associated with enhanced market liquidity and with information being impounded into stock prices more rapidly. In this paper, we investigate whether employees function as information intermediaries. We examine how employees' professional 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, but also because it represents a private disclosure channel that is beyond the firm's control.

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 connections in Korea for both executive and non-executive employees.[1] We create employee-

[1] In contrast, much of the prior networking literature (e.g., Cohen, Frazzini, and Malloy 2010; Engelberg, Gao, and Parsons 2012; Guan, Su, Wu, and Yang 2016) often infers that connections exist if individuals have common educational or employment experiences, even if those experiences did not overlap temporally.

specific measures of first-order (i.e., direct) connections, along with second- and third-order (i.e., indirect) connections. We discount higher-order connections relative to the first-order connections because the ability of a network to transmit information decays when the information must travel through more nodes (Jackson 2008; Jackson and Wolinsky 1996). Following the prior network literature (Cho, Choi, Hertzel, and Wang 2021; Omer, Shelley, and Tice 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 previously 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, Huang, Wen, and Zhou 2019; Huang, Li, and Markov 2020; Huddart and Lang 2003). Second, employees have expansive professional networks, which consist of their direct and indirect professional connections, that allow them to widely distribute their information outside of the firm and ultimately into stock prices. Accordingly, value-relevant information can be transmitted from employees to a large number of market participants within a couple of steps (Milgram 1967). Therefore, we expect that employee connections contribute to stock price efficiency through the transmission of value-relevant information to stock market participants.

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 allow us to control for the expected level of earnings. If value-relevant information about upcoming earnings is transmitted through employees' professional connections, then we expect that firms with more-connected employees have smaller market reactions to earnings surprises.

Our results show that both the second- and third-order connection measures are negatively associated with the magnitude of the earnings response coefficient (ERC).[2] Our results are robust to using a propensity score matched sample. 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. Additional analyses indicate that information related to positive (as opposed to negative) earnings surprises and information related to firm-specific (as opposed to macroeconomic or industry-wide) earnings news is more likely to be disseminated through employees' connections. We also find that our results hold for both executive and non-executive connections, indicating that non-executives also act as information intermediaries. Overall, these results suggest that earnings-related information is transmitted through employees' networks before the earnings announcement, which reduces the market reaction to earnings surprises. Together, these findings are consistent with employees, in conjunction with their professional connections, acting as information intermediaries that increase price efficiency around earnings announcements.

To provide evidence on whether the negative association between employee connections and ERCs represents a causal effect, we identify plausibly exogenous variation in the information environment using reductions in analyst coverage caused by brokerage mergers. We expect that reductions in analyst coverage increase the importance of employee networks in disseminating earning-related information. Using a matched sample, we estimate the stacked regression developed by Cengiz, Dube, Lindner, and Zipperer (2019) and recommended by Baker, Larcker, and Wang (2022) to minimize estimation biases when the treatment effects vary over time or across

[2] In contrast, we do not find a significant association between first-order connections and market reactions to earnings surprises. As discussed below, this combination of significant and insignificant results helps rule out alternative explanations related to self-selection effects as these explanations primarily related to first-order connections.

groups. The results show that during the post-merger period, the negative association between employee connections and ERCs is stronger for firms that experience exogenous reductions in analyst coverage. These results suggest that market participants increase their reliance on the information disseminated through employee networks when there are fewer alternative sources of information. As such, these findings indicate a causal relation between employees' connections and the dissemination of earnings-related information into stock prices.

The ERC results suggest that when employees have more connections, additional earnings-related information is impounded into stock prices during the pre-announcement period. To provide supporting evidence, we examine the stock price discovery process over the quarterly earnings cycle by examining both intra-period timeliness (IPT) (Blankespoor, deHaan, and Zhu 2018; Bushman, Smith, and Wittenberg-Moerman 2010; Guest 2021) during the pre-announcement period and the level of the post-earnings announcement drift (PEAD). Our results show that IPT is significantly higher for more-connected firms, which provides further support that employees act as information intermediaries. Second, we examine the association between connections and PEAD. If more earnings-related information is impounded into stock prices during the pre-announcement period through employee connections, then stock prices should more fully reflect the valuation implications of the earnings news by the end of the announcement period. In this case, more connected firms should have more efficient stock prices during the post-announcement period. Consistent with our expectations, we find that more connected firms have significantly lower PEAD following the earnings announcement.

We contribute to the literature in at least three ways. First, we add to the literature that shows that (mainly non-executive) employees collectively have access to private information about their firms' future operating and stock performance (Babenko and Sen 2016; Green et al.

2019; Hales, Moon, and Swenson 2018; Huang et al. 2020).[3] Importantly, we extend this literature by providing evidence that when disseminated through their professional connections, employees' private information about future earnings is associated with higher stock price efficiency. We also present evidence that speaks to the type of information that is disseminated by employees through their professional connections. Specifically, we show that they primarily disseminate information about positive earnings surprises and the idiosyncratic component of earnings.

Second, we add to the social networking literature that has focused on the connections of top executives and board members (Akbas, Meschke, and Wintoki 2016; Cohen, Frazzini, and Malloy 2010; Engelberg, Gao, and Parsons 2012; Guan, Su, Wu, and Yang 2016; Larcker, So, and Wang 2013). Among these, Akbas et al. (2016), Cohen, Frazzini, and Malloy (2008), Cohen et al. (2010), and Engelberg et al. (2012) examine the flow of information from top executives and board members to outside investors and analysts. Their evidence suggests that private information flows along inferred first-order connections, which results in more profitable trades and trade recommendations. However, it is unclear whether these private information flows increase stock price efficiency due to offsetting increases in information asymmetry and trading costs. For instance, Akbas et al. (2016) find that changes in board connectedness are positively associated with bid-ask spreads and the probability of informed trading. In addition to providing evidence that information dissemination through employee networks results in higher price efficiency, we also show the importance of higher-order connections in disseminating information to the capital markets, which are largely ignored by this literature (see Cai and Sevilir (2012) for an exception).

Finally, 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

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[3] We provide complementary evidence that does not rely on public comments made on a single website or has to be inferred from employee actions that could be driven by other factors, such as stock option exercises.

role of voluntary and mandatory disclosures (Beyer et al. 2010; Leuz and Wysocki 2016),[4] analysts (Brennan, Jegadeesh, and Swaminathan 1993; Hong, Lim, and Stein 2000; Mola, Rau, and Khorana 2013), institutional investors (Ayers and Freeman 2003; El-Gazzar 1998), and traditional and social media (Bartov, Faurel, and Mohanram 2018; Blankespoor et al. 2018; Bushee et al. 2010; Li, Ramesh, and Shen 2011) in disseminating and incorporating information into prices. We identify and analyze a new and economically important information intermediary – 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 more generally, as well as to the large body of research that examines the market response to earnings news.

II. 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 stock prices. For example, higher levels of institutional ownership (El-Gazzar 1998) and analyst coverage (Dempsey 1989) 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 to earnings surprises.

[4] 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.

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' private information is directly incorporated into prices through their trading activities. In contrast, analysts first disseminate their private information through their forecasts and recommendations, which in turn is incorporated into stock prices through the trading activities of investors. 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).

While it is not surprising that top-level executives have private information about their firms, 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). These results are consistent with value-relevant information about future performance being widely dispersed within organizations.

In addition to possessing private information, there must be a mechanism through which employees' private 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. Thus, we expect that employees disseminate their private information, at least in part, through their professional connections.

The speed that information becomes incorporated into prices depends on how quickly and widely the information is distributed (Blankespoor et al. 2014; Grossman and Stiglitz 1980; Hong et al. 2000; Hong and Stein 1999; Li et al. 2011; Twedt 2016). Given that the average number of direct professional connections tends to be small, one may question how effective are employees' professional networks in widely disseminating information. However, this view ignores the network aspects of employee connections, whereby an employee's connections also have connections, who also have their own connections. Thus, the collective reach of employees' direct and indirect connections is potentially very large. Thus, value-relevant information can be disseminated to a very large number of individuals in just a few steps (Milgram 1967). Accordingly, we expect that employees' private information is more widely disseminated through their connections as the size of their professional networks increases.[5]

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 personal interactions (Hvide and Östberg 2015; Hwang 2022; Knüpfer, Rantapuska, and Sarvimäki forthcoming). Thus, we expect that some investors trade based on value-relevant information obtained through their professional connections. Furthermore, we expect that the amount of trading increases with the size of the professional network, and hence, the speed with which employees' private information is incorporated into prices.

[5] Employees can directly provide their professional connections with value-relevant information, such as about future operating performance, planned capital expenditures, and the results of R&D projects. In addition, they can assist in understanding and assimilating information that is disclosed by and/or obtained from other sources.

In summary, we expect that 1) employees have value-relevant information about their firms; 2) their information is disseminated through their professional connections; and 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' private information will not be impounded into stock prices.[6] Second, information transmitted through employees' networks may induce a crowding-out effect. 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. Halim, Riyanto, and Roy (2019) provide supporting experimental evidence. If large enough, these crowding-out effects could offset any increases in price efficiency due to employees' professional connections. However, given the prior evidence that information flows along direct executive-level connections and the dearth of archival evidence supporting the crowding-out effects, we predict that employees' connections are positively associated with stock price efficiency.

[6] For instance, it is illegal for a non-employee (i.e., the tippee) in Korea to trade on material non-public information that was provided by an employee (i.e., the tipper). Thus, legal prohibitions may impede information diffusion. However, there is no explicit prohibition on a tippee trading on information provided by another 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.

III. RESEARCH METHODOLOGY AND SAMPLE

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. 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 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 scan and upload their 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. The professional networks in our database are dominated by non-executive employees: 88.7% (11.3%) of all users are non-executive (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 disseminate information to the capital markets. Thus, we focus on connections between employees at different firms, so each relationship involves two employees at different firms.[7] An illustration of the network data and how we construct the employee connection measures is presented in the Internet Appendix.

Employee Connection Measures

Following the network literature (Jackson 2008), we measure each employee's direct or first-order connections (*1stOrder*), which depends on 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 a connection is active (i.e., one through which information is plausibly distributed):

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

$\boldsymbol{g}$ is an $n \times n$ adjacency matrix, n is the total number of employees in the network and $g_{ij} = 1$ if employee i is directly connected with employee j, and $g_{ij} = 0$ otherwise.[8] $1stOrder_f$ is the average the employee-level first-order connection measure ($1stOrder_i$) over all employees i of firm 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.[9] To this end, we use two additional measures that capture

[7] 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.
[8] 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. We opt to use this definition so that it is consistent with the definitions of *2ndOrder* and *3rdOrder*.
[9] This type of connection measure is referred to as "information capital" in the taxonomy of Jackson (2020) 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 external capital

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) connections can be further shared with the connections of their connections (second-order), and so on. 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 to capture how quickly information decays. Specifically, we define our higher-order connection measures as follows:[10]

$$2ndOrder_i(\boldsymbol{g}, p) = 1stOrder_i(\boldsymbol{g}, p) + p^2 \times Degree2_i(\boldsymbol{g}) \tag{2}$$

$$3rdOrder_i(\boldsymbol{g}, p) = 2ndOrder_i(\boldsymbol{g}, p) + p^3 \times Degree3_i(\boldsymbol{g}), \tag{3}$$

where $2ndOrder_i(\boldsymbol{g}, p)$ ($3rdOrder_i(\boldsymbol{g}, p)$) captures the discounted number of unique first- and second-order (first-, second-, and third-order) connections. $Degree2_i(\boldsymbol{g})$ enumerates the number of unique second-order connections (i.e., friends of friends) that are not first-order connections. Likewise, $Degree3_i(\boldsymbol{g})$ enumerates the number of unique third-order connections who are not first- or second-order connections. $2ndOrder_f$ ($3rdOrder_f$) is the average of the employee-level measures for firm *f* over all employees *i* who appear on the network. The probability of information transmission (*p*) is not determined by the inherent structure of the network, but rather is a research design choice. Accordingly, we use three different values for *p* (0.1, 0.5, and 0.9). As discussed below, our results are robust to the choice of *p*.

Employee Connections and Market Reactions around Earnings Announcements

Extensive prior literature has used stock returns around earnings announcements to capture

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.

[10] Jackson (2008) refers to these measures as "decay centrality" because they discount higher-order connections. We use our terminology to emphasize how many degrees of separation the measure considers.

changes in investors' assessments of firm value (Verrecchia 2001). Stock price changes reflect investors' belief revisions and are proportional to unexpected earnings (Kim and Verrecchia 1991). The amount of information available to investors prior to the earnings announcements affects market reactions to the earnings announcements. Consistent with this idea, prior studies find smaller reactions to earnings announcements for larger firms (Atiase 1985) and firms with higher analyst coverage (Dempsey 1989) or institutional ownership (El-Gazzar 1998). Similarly, we examine how abnormal returns around quarterly earnings announcements vary with how connected firms' employees are.

Consistent with the disclosure rules and practices in Korea, we follow prior studies to determine the date when earnings news is first publicly disclosed (Baik, Kim, and Lee 2012; Sohn, Paik, and Goh 2009). For each firm-quarter, we use the earliest of the following filing dates: 1) Quarterly (Annual) financial statements; 2) Report on preliminary business performance (fair disclosure); 3) Changes of 30% or more in sales or profits/losses; 4) Calling shareholders' meeting; and 5) Submission of audit report. These filings represent the earliest disclosure date 56.3%, 22.4%, 18.6%, 2.4%, and 0.3% of the time, respectively.

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

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

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 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, Faurel, and Mohanram (2018) and others, 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*), and 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 control for known determinants of ERCs. To control for unobservable time-invariant firm heterogeneity and macroeconomic determinants of ERC, we also include a set of firm (α_f) and year (α_y) fixed effects as well as their interactions with *SUE* (deHaan 2021; Gipper, Leuz, and Maffett 2020). Thus, the main effect of *SUE* is fully subsumed by the interaction terms. Detailed definitions of all variables are provided in the Appendix.

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. This database is similar to the merged CRSP-Compustat database in the U.S., with additional information specific to the Korean capital markets. The sample period is from 2015 to 2018. 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 our primary variables. The mean (median) value of *Degree1* is 7.44 (5.93); 1,220 (948.4) for *Degree2* ; and 38,187 (27,181) for *Degree3*. These statistics indicate that an employee of a firm, on average, has 7.44 direct connections with employees of other firms, 1,220 second-order connections, 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). [11] These observations confirm the importance of considering higher-order relationships in measuring an employee's ability to disseminate information. When we set the probability of information transmission to 0.5, *1stOrder*, *2ndOrder*, and *3rdOrder* have a mean of 3.72, 308.8, and 5,081, respectively.[12] The three measures are highly correlated. The correlation

[11] The number of second- and third-order connections increases exponentially because more-connected employees have a disproportionately larger influence on the number of second- and third-order connections. For example, consider a star network in which a focal employee is connected to all other 99 employees, and these 99 employees are only connected to the focal employee. The average value of *Degree1* is $(99\times1+1\times99)/100 = 1.98$, while the average value of *Degree2* is $(0\times1+98\times99)/100 = 97.02$.
[12] 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

between *2ndOrder* and *3rdOrder* is 0.967, while the correlation between *1stOrder* and *2ndOrder* (*3rdOrder*) is 0.833 (0.796).[13]

IV. EMPIRICAL RESULTS

Employee Connections and Market Reactions around Earnings Announcements

If some of the upcoming earnings news is transmitted to investors through employees' connections and incorporated into stock prices before earnings are announced, then our hypothesis predicts that investors will respond less to earnings surprises for firms with more-connected employees. Accordingly, we examine the association between employee connections and the magnitude of the earnings response coefficient.

The results from estimating Equation (4) are presented in Table 2. Columns 1 – 3 report the results where employee connections are measured using *1stOrder*, where the probability of transmission, *p*, is set to 0.1, 0.5, and 0.9, respectively. The results show that none of the *SUE×Connection* coefficients are significant. Thus, we find no evidence that the magnitude of employees' direct connections is associated with the ERC.

The results when we use second-order (third-order) connections are reported in Columns 4 – 6 (7 – 9). For both connection measures, all three of the *SUE×Connection* coefficients are negative and significant. The results are qualitatively (and quantitatively) similar across all three values of *p*. Thus, our evidence is consistent with employees, in conjunction with their professional networks, acting as information intermediaries. These results support our hypothesis that firms with more-connected employees have more efficient stock prices. In addition, the insignificant

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). Our research design explicitly controls for time-invariant, firm-specific characteristics, including industry.

[13] See the correlation matrix in the Internet Appendix (Table IA.2).

coefficients for *1stOrder* emphasize the importance of considering the expansive nature of professional networks in capturing employees' ability to spread information.[14]

The second- and third-order coefficient estimates are also economically significant. For example, in Column 5 (8), the estimated *SUE*×*Connection* coefficient is −0.258 (−0.325). To assess the economic magnitude of the effects, we 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.

The evidence in Table 2 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, TII employees 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 employees drives our results.

[14] 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 are tabulated in Internet Appendix (Table IA.4). They show that while the coefficient on the interaction term with *SUE* is insignificant for *Degree1*, the coefficients for *Degree2* and *Degree3* are significant at the 5% level. In addition, when we include *Degree1*, *Degree2*, and *Degree3* in the same regression model, only the coefficient for *Degree3* remains significant. Overall, these results are consistent with those in Table 2 and further highlight the importance of higher order connections in disseminating and incorporating earnings-related information into stock prices.

In order to examine the validity of this alternative explanation, we split *2ndOrder* and *3rdOrder* measures into connections of TII and Non-TII employees.[15] 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 TII (Non-TII) connections will (not) be significantly associated with market reactions around earnings announcements. We re-estimate Equation (4) and report the results in Table 3.

Columns 1 and 2 show the results when connections are based only on Non-TII connections. The estimated *SUE×Connection* coefficients are both negative and significant (at the 5% and 1% levels, respectively). Thus, our results do not appear to be driven solely by a mechanical association between TII coverage and employee connections. The results in Column 3 for TII connections show that the coefficient on *SUE×Connection* is insignificant when connections are measured using *2ndOrder*. However, it is negative and significant (at the 1% level) in Column 4 when TII connections are measured using *3rdOrder*.[16] Overall, the evidence in Table 3 is inconsistent with the alternative explanation. Instead, the results provide further support for our information intermediary hypothesis.

The Types of Earnings News that are Disseminated through Employee Connections

In this section, we investigate which types of information are transmitted through employees' professional connections. First, we examine whether positive or negative earnings news is more likely to be disseminated through employees' connections. Prior literature provides mixed evidence on this issue. Berger and Milkman (2012) find that positive media content is more

[15] Given the similarity of results for different values of p, we only tabulate the results for $p = 0.5$ henceforth. In addition, given the insignificant *1stOrder* results, we do not tabulate the results for *1stOrder* going forward.
[16] 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 −29.2% for connections to Non-TII (Column 2) and−21.6% for connections to TII (Column 4). The similarity in magnitudes provides further support that our results are driven by information transmitted through employees' connections.

likely to be shared via social media, while Cohen et al. (2010) find that when analysts have educational connections to top executives, only their buy recommendations generate abnormal returns. In contrast, Akbas et al. (2016) find that a higher fraction of negative earnings news is impounded into stock prices before the earnings announcement when directors have more direct professional and social connections. Huang et al. (2020) find that employees' social media disclosures are more informative about future bad news than good news.

We separate the quarterly earnings surprise into positive and negative earnings surprises. Specifically, *Positive SUE* (*Negative SUE*) equals *SUE* if *SUE* is positive (negative), and zero otherwise. We re-estimate Equation (4), where we include *Positive SUE* and *Negative SUE* and their interactions with firm fixed effects, year fixed effects, and control variables. The results are presented in Columns 1 and 2 of Table 4.

The results show that both of the *Positive SUE×Connection* coefficients are negative and significant (at the 5% and 1% levels, respectively), whereas the *Negative SUE×Connection* coefficients are both insignificant. These asymmetric results indicate that positive earnings news is more likely to spread through employees' professional networks compared to negative earnings news.[17] This finding contrasts with the prior literature that finds that negative information is more likely to be transmitted through employees' opinions expressed on Glassdoor.com (Huang et al. 2020) or via more connected directors (Akbas et al. 2016).

Second, compared to other market participants, employees are better informed about firm-specific information, but are less likely to be better informed about industry-wide or

[17] These results are consistent with employees primarily sharing information about positive earnings surprises (and more generally, news about good performance) with their professional connections. They are also consistent with social transmission bias, which is the systematic directional modification of signals as they pass from person to person (Hirshleifer 2020). Thus, employees could share information about both good and bad earnings news, but their professional contacts and/or the individuals who ultimately trade on the information may exhibit a bias for transmitting and/or trading on positive earnings news. We are unable to distinguish between these explanations empirically.

macroeconomic conditions. Thus, we expect employees are more likely to spread firm-specific earnings-related information through their connections compared to industry and macroeconomic news. Following Bhojraj, Mohanram, and Zhang (2020), we decompose the earnings surprise into its macroeconomic, industry, and idiosyncratic components. Details on how each component of the earnings surprises are provided in the Appendix. We then replace *SUE* with *Macro SUE*, *Industry SUE*, and *Idiosyncratic SUE*, and re-estimate Equation (4), where the *SUE* variables are interacted with firm fixed effects, year fixed effects, and the control variables.

The results are presented in Columns 3 and 4. They 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. Thus, the earnings-related information disseminated through the network is likely to be firm-specific. In addition, these results provide more-nuanced insights into which types of value-relevant information (i.e., firm-specific and positive news) are disseminated through employees' professional networks.

Connections of Executive and Non-Executive Employees

The prior literature on professional connections generally finds evidence indicating that private information flows out of the firm through the inferred personal and/or professional connections of upper-level executives and/or directors to outside parties such as banks, auditors, and investors (Akbas et al. 2016; Cohen et al. 2010; Engelberg et al. 2012; Guan et al. 2016). In addition, non-top level employees also have access to value-relevant private information (Babenko and Sen 2016; Green et al. 2019; Huang et al. 2020). Accordingly, we expect that information is disseminated through the 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. The large majority of connections in our dataset are for non-executive employees. Specifically, 81% (78%) {80%} of *Degree1* (*Degree2*) {*Degree3*} connections are due to non-executive employees. We calculate *2ndOrder* and *3rdOrder* separately for executives and non-executives. We then re-estimate Equation (4) and present the results in Table 5.

The results in Columns 1 and 2 show that executive connections are negatively associated with market reactions around earnings announcements. 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. Columns 3 and 4 show that the *SUE×Connection* coefficients are significantly negative at the 1% level. In addition, the absolute value of the interaction coefficients is somewhat larger for non-executive measures (−0.297 vs. −0.215 and −0.355 vs. −0.214, 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 2) and a 33.1% decrease for non-executive connections (Column 4). Thus, our evidence suggests that both executive and non-executive employees, in conjunction with their professional connections, act as information intermediaries.

V. EXOGENOUS VARIATION IN THE INFORMATION ENVIRONMENT: EVIDENCE FROM BROKERAGE HOUSE MERGERS

Our regressions include firm and year fixed effects and their interactions with *SUE*. Thus, our results are unaffected by time-invariant firm-specific factors or general time trends in ERC. However, our results could be driven by omitted firm-specific time-varying variables that are correlated with our connection measures and the information environment (and hence, ERCs). For example, if professionals prefer to connect with employees of more popular firms, then more popular firms will have more highly connected employees. In addition, investors, analysts, and the business press may be more focused on or attracted to more popular firms. In this case, our findings may simply reflect unobservable time-series variations in popularity.

We think these concerns are lessened in our setting for three main reasons. First, they are more applicable to direct connections than higher-order connections because any omitted variables or self-selection issues (e.g., the characteristics of the firms and/or their employees) are most likely related to the number of direct connections relative to the higher-order measures. For example, while professionals may prefer to be connected to employees of popular firms, they are unlikely to prefer to be connected to professionals at non-popular firms who are connected to employees of popular firms. 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, the untabulated results show that the coefficients on *1stOrder*, *2ndOrder*, and *3rdOrder* are insignificant. Thus, the number of direct or indirect employee connections *per se* is not associated with market reactions around earnings announcements. Third, we use a propensity score matched sample to reduce the effects of any confounding differences between firms with different levels of *Connection*. The results are tabulated in Table IA.3). They show that both *SUE*×*Connection* coefficients are negative and significant. This evidence further reduces the likelihood that self-selection issues are driving our results.

To mitigate any remaining concerns about endogeneity, we follow Hong and Kacperczyk (2010) and exploit the exogenous variation in the information environment induced by mergers of brokerage houses. Specifically, we identify exogenous reductions in analyst coverage for stocks covered by two merging brokerages before the merger. Our underlying assumption is that such mergers result in the firing of redundant analysts, which is unrelated to both firms' information environments and their *2ndOrder* and *3rdOrder* connection measures. We predict that these exogenous decreases in analyst coverage will increase the importance of employee networks as an information intermediary, thereby strengthening the negative association between *Connection* and the market's reaction to earnings surprises.

There were three brokerage 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 other firm-quarter observations.

We employ the stacked regression approach developed by Cengiz et al. (2019) to avoid the potential biases in difference-in-differences regressions (or their variants) when the treatment effects vary over time or across groups. 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 in event 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 estimate the following difference-in-difference model where *m* indexes merger events:

$$
\begin{aligned}
AbRet_{[-2,+2],m,f,q} = {} & \alpha_{m,f} + \alpha_{m,y} + \alpha_{m,f} \times SUE_{m,f,q} + \alpha_{m,y} \times SUE_{m,f,q} + \beta_1 Connection_{m,f,q\text{-}1} \\
& + \beta_2 Post_{m,f,q} + \beta_3 SUE_{m,f,q} \times Connection_{m,f,q\text{-}1} + \beta_4 SUE_{m,f,q} \times Post_{m,f,q}
\end{aligned}
$$

$$
\begin{aligned}
&+ \beta_5 Connection_{m,\,f,q\text{-}1} \times Treated_{m,f,q} + \beta_6 Connection_{m,\,f,q\text{-}1} \times Post_{m,f,q} \\
&+ \beta_7 Treated_{m,f,q} \times Post_{m,f,q} + \beta_8 SUE_{m,\,f,q} \times Connection_{m,\,f,q\text{-}1} \times Treated_{m,f,q} \\
&+ \beta_9 SUE_{m,f,q} \times Connection_{m,\,f,q\text{-}1} \times Post_{m,f,q} + \beta_{10} SUE_{m,f,q} \times Treated_{m,f,q} \times Post_{m,f,q} \\
&+ \beta_{11} Connection_{m,\,f,q\text{-}1} \times Treated_{m,f,q} \times Post_{m,f,q} \\
&+ \beta_{12} SUE_{m,f,q} \times Connection_{m,f,q\text{-}1} \times Treated_{m,f,q} \times Post_{m,f,q} \\
&+ \gamma_1 Y_{m,f,q\text{-}1} + \gamma_2 Y_{m,f,q\text{-}1} \times SUE_{m,f,q} + \varepsilon_{m,f,q} \qquad (5)
\end{aligned}
$$

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; and *Treated* is an indicator variable that equals one for treated firms. In estimating Equation (5), we exclude observations in the event quarter. The coefficient of interest is β_{12}, which captures the incremental change in the effect of employee connections on the ERC for firms that experienced an exogenous decrease in analyst coverage. We predict that β_{12} will be negative.

The results are presented in Panel A of Table 6. Both of the *SUE*×*Connection*×*Treated*×*Post* coefficients are negative and significant at the 1% level. Thus, our results indicate that the role of employees and their professional networks as information intermediaries is more important when there are fewer alternative channels for value-relevant information to become impounded in stock prices. As such, this evidence indicates that there is a causal effect of how connected a firm's employees are on its information environment.

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 6. The estimated coefficients on *Connection*×*SUE*×*Treated*×d_{q+t} are insignificant for $t < 0$ for both *2ndOrder* and *3rdOrder*. These results indicate that there are no apparent differences in the effect of employee connections on the ERC between the treated and control firms during the pre-period. Thus, it appears that the parallel trends assumption is valid in our setting.

VI. EMPLOYEE CONNECTIONS AND PRICE EFFICIENCY BEFORE AND AFTER EARNINGS ANNOUNCEMENTS

In this section, we provide a more complete picture of how employee connections affect stock price efficiency before and after the earnings announcement period.

Employee Connections and Intra-period Timeliness before Earnings Announcements

The evidence discussed above is consistent with employees' earnings-related private information being disseminated through their professional connections and incorporated into stock prices before the earnings announcement period. While we cannot directly observe this process taking place, we can infer when private information about forthcoming earnings is impounded into stock prices by observing how quickly price discovery occurs during the quarter. Thus, if employees and their connections act as information intermediaries, then we expect that information becomes incorporated into stock prices earlier in the quarter for more-connected firms.

We measure the speed of price formation using the intra-period timeliness metric (*IPT*) (Bushman et al. 2010; Guest 2021; McMullin, Miller, and Twedt 2019). *IPT* captures how quickly information is impounded into prices by holding constant both price response and information content. Intuitively, *IPT* increases when more of the period returns are realized earlier in the period. 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.[18] 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. *IPT* equals the area under the cumulative price change curve over a given window. Specifically, *IPT* equals $\frac{1}{2}\sum_{\mathrm{t}=-60}^{2}\left(QAbRet_{t\text{-}1} + QAbRet_{t}\right)/QAbRet_{2} =$

[18] 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.

$\sum_{t=-60}^{1} QAbRet_t / QAbRet_2 + 0.5$, 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 timelier, and hence, more efficient price formation.

We first perform graphical analyses by constructing *High Connection* and *Low Connection* portfolios based on the tercile of the corresponding connection measure. For each portfolio, we plot for each day in the earnings cycle the cumulative buy-and-hold market-adjusted returns, scaled by the entire returns for the entire 63-day period. On the last day of the period, the plot equals one by construction since 100% of the quarter's abnormal returns are realized by then.

Figure 1a (1b) presents the results for the *High Connection* (solid line) and *Low Connection* (dashed line) portfolios using *2ndOrder* (*3rdOrder*). Both figures show that when a firm's employees are more connected, price discovery occurs earlier during the quarter. 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).

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. Therefore, 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, Miller, and White 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 7. Consistent with our conjecture, both *Connection* coefficients are positive and significant at the 1% level.

As discussed in Blankespoor et al. (2018), the standard IPT measure used above is biased upwards if overreactions and subsequent partial reversals occur during the quarter. If more connected firms were more likely to experience intra-quarter overreactions and reversals, perhaps due to inefficient trades based on information disseminated through employees' networks, then the results in Columns 1 and 2 could be biased. To mitigate this concern, we use an adjusted IPT measure (*AdjIPT*) suggested by Blankespoor et al. (2018). Specifically, when the buy-and-hold market-adjusted returns for any given day exceed the entire returns for a 63-day trading window, the adjusted IPT subtracts the excess returns. This reduction adjusts IPT to account for the inefficient overreaction during the return measurement window. We calculate *AdjIPT* 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 *IPT* results, the *Connection* coefficients are positive and significant at the 5% level or better. [19] These findings are consistent with more-connected firms having faster price formation due to value-relevant information being disseminated through employees' professional connections. These results also provide a mechanism for our prior ERC results: investors react less to earnings news during the announcement period for more connected firms because some of the earnings news was disseminated through employees' connections and incorporated into stock prices before the announcement period. Thus, this evidence provides additional support for our hypothesis that stock prices are more efficient for more connected firms.

Employee Connections and Post Earnings Announcement Drift

Collectively, the results above suggest that more connected firms have more efficient stock prices because employees, in conjunction with their professional networks, act as information intermediaries with respect to employees' private earnings-related information. Prior literature

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

indicates that information intermediaries are associated with lower levels of PEAD because they allow investors to better understand and more fully incorporate the time-series properties of earnings into prices in a timely and unbiased manner (Bartov, Radhakrishnan, and Krinsky 2000; Ben-Rephael, Da, and Israelsen 2017; Brennan et al. 1993; Zhang 2008). For example, Bartov et al. (2000) find that PEAD is negatively associated with institutional ownership. Thus, if our hypothesis is correct, then we expect PEAD will be lower among more-connected firms because the earnings-related information disseminated by employees should assist investors in better understanding the implications of current earnings for future earnings.

To test this prediction, we replace the dependent variable in Equation (4) with $AbRet_{[+3, +62]}$, which is defined as the buy-and-hold market-adjusted returns following the quarterly earnings announcement for the window [+3, +62], where day zero is the earnings announcement date. 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.

In addition, these results help rule out an alternative explanation whereby the lower ERCs experienced by more connected firms are due to an inefficient underreaction to earnings news among more connected firms. This explanation implies that more underreaction during the announcement period would result in higher drift during the post-announcement period. The fact that more connected firms experience less drift during the post-announcement period (and smaller reactions to earnings news during the announcement period) provides further evidence that employees, in conjunction with their professional networks, allow earnings-related information to be impounded into stock prices more quickly and completely than otherwise would occur.

VII. 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 both access to value-relevant information and 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 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. Additional analyses indicate that information related to positive (as opposed to negative) earnings surprises and information related to firm-specific (as opposed to macroeconomic or industry-wide) earnings news is more likely to be disseminated through employees' connections. 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. We also examine both IPT during the pre-announcement period and the level of PEAD during the post-announcement period. Our results show that IPT is significantly higher for more-connected firms, which indicates that prices reflect earnings-related information on a timelier basis for more-connected firms. We also find that more connected firms have significantly lower PEAD following the earnings announcement.

Overall, we find strong and consistent evidence that employees, in conjunction with their professional connections, act as an information intermediary and are an important factor in increasing stock price efficiency with respect to earnings-related information. 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 independent nature of these professional networks has important implications for firms' disclosure policies (Hales et al. 2018).

Appendix: 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 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 calculated as $1stOrder_i(\boldsymbol{g}, p) + p^2 \times Degree2_i(\boldsymbol{g})$
$3rdOrder_i(\boldsymbol{g}, p)$	Third-order connection measure 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
$Connection_f$	The natural logarithm of one plus one of the connection measures (*1stOrder*, *2ndOrder*, *3rdOrder*)
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 buy-and-hold market-adjusted 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 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 a

	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.
Positive SUE (*Negative SUE*)	Equals *SUE* if *SUE* is positive (negative) and zero otherwise
Macro SUE	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*.
Industry SUE	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*.
Idiosyncratic SUE	The idiosyncratic component of *SUE*, which is *SUE – Macro SUE – Industry SUE*
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

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Figure 1. Speed of Price Discovery and Employee Connections

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

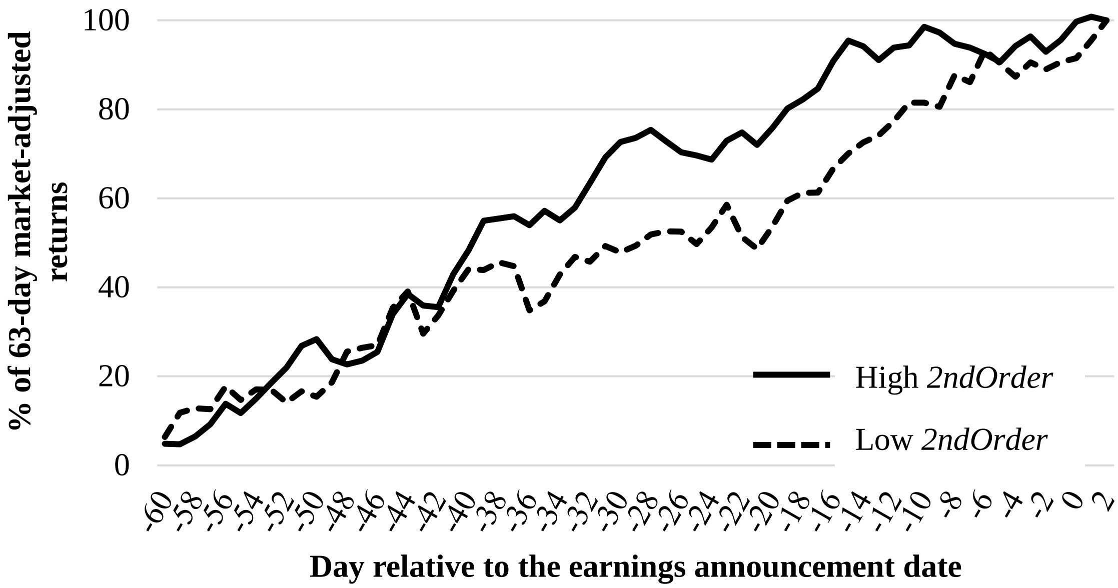
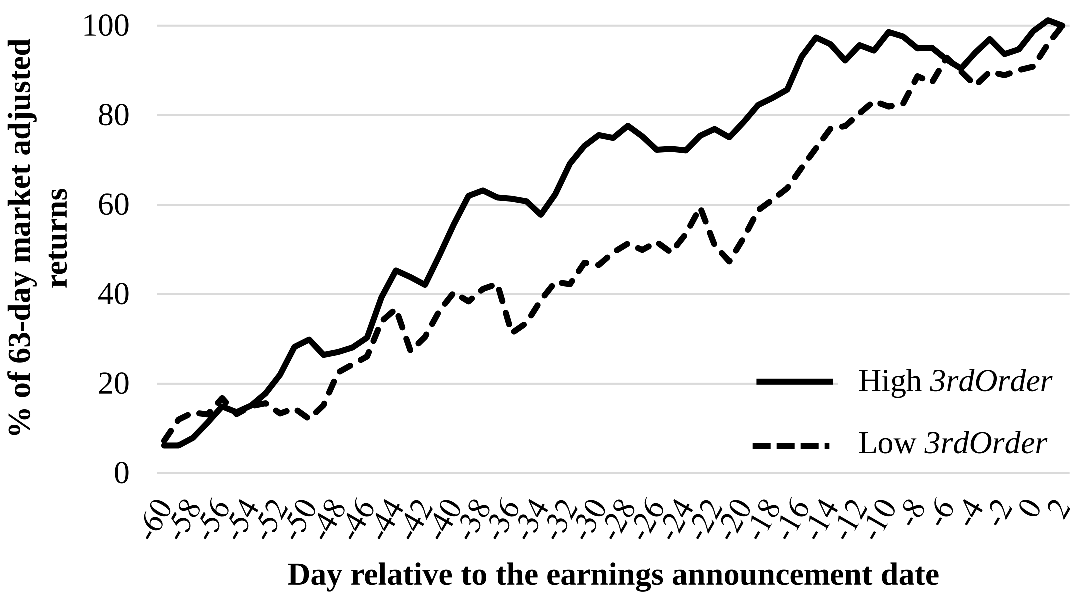


Figure 1b. High *3rdOrder* vs. Low *3rdOrder*



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	9,987	12.74	37.12	32.82	52.93	149.67
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. =	$AbRet_{[-2, +2]}$								
Connection =	*1stOrder*			*2ndOrder*			*3rdOrder*		
Prob. of Info Trans. (*p*) =	*0.1*	*0.5*	*0.9*	*0.1*	*0.5*	*0.9*	*0.1*	*0.5*	*0.9*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
SUE×*Connection*	0.023	-0.086	-0.108	-0.239*	-0.258**	-0.257**	-0.353***	-0.325***	-0.320***
	(0.243)	(0.153)	(0.139)	(0.141)	(0.124)	(0.122)	(0.115)	(0.090)	(0.088)
Connection	0.657	0.383	0.337	0.608	0.512	0.506	0.497	0.392	0.380
	(0.721)	(0.468)	(0.429)	(0.381)	(0.334)	(0.331)	(0.315)	(0.260)	(0.253)
Size	-1.686***	-1.687***	-1.687***	-1.690***	-1.687***	-1.687***	-1.699***	-1.701***	-1.702***
	(0.378)	(0.379)	(0.379)	(0.379)	(0.380)	(0.380)	(0.379)	(0.380)	(0.380)
BM	0.392	0.396	0.397	0.378	0.380	0.380	0.371	0.371	0.371
	(0.361)	(0.362)	(0.362)	(0.362)	(0.362)	(0.362)	(0.363)	(0.363)	(0.363)
Coverage	0.247	0.245	0.244	0.232	0.230	0.230	0.224	0.226	0.227
	(0.249)	(0.249)	(0.249)	(0.250)	(0.250)	(0.250)	(0.250)	(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***	-1.708***	-1.708***	-1.710***	-1.710***	-1.710***	-1.711***	-1.711***	-1.711***
	(0.159)	(0.159)	(0.159)	(0.159)	(0.159)	(0.159)	(0.159)	(0.159)	(0.159)
Guidance	0.599	0.598	0.598	0.592	0.591	0.591	0.583	0.585	0.586
	(0.396)	(0.397)	(0.397)	(0.396)	(0.397)	(0.397)	(0.397)	(0.397)	(0.398)
Q4	0.005	-0.000	0.000	-0.075	-0.070	-0.069	-0.112	-0.103	-0.101
	(0.129)	(0.133)	(0.134)	(0.144)	(0.145)	(0.145)	(0.156)	(0.155)	(0.154)
SUE×Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm & Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SUE×Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,780	17,780	17,780	17,780	17,780	17,780	17,780	17,780	17,780
Within Adj.R^2	0.018	0.018	0.018	0.019	0.019	0.019	0.019	0.020	0.020

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. *Connection* is the natural logarithm of one plus one of the connection measures (*1stOrder*, *2ndOrder*, *3rdOrder*). 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: Traditional Information Intermediaries vs. Non-Information Intermediaries

Dep. Var. =	$AbRet_{[-2, +2]}$			
Connections to	Non-TII		TII	
Connection =	*2ndOrder*	*3rdOrder*	*2ndOrder*	*3rdOrder*
	(1)	(2)	(3)	(4)
SUE×Connection	-0.266**	-0.328***	-0.047	-0.249***
	(0.123)	(0.090)	(0.106)	(0.083)
Connection	0.516	0.393	0.366	0.383
	(0.336)	(0.259)	(0.275)	(0.242)
Size	-1.686***	-1.701***	-1.694***	-1.705***
	(0.379)	(0.380)	(0.378)	(0.380)
BM	0.380	0.370	0.389	0.376
	(0.362)	(0.363)	(0.359)	(0.361)
Coverage	0.231	0.227	0.229	0.221
	(0.250)	(0.250)	(0.249)	(0.250)
BlockOwn	-0.027	-0.027	-0.027	-0.027
	(0.017)	(0.017)	(0.017)	(0.017)
Loss	-1.710***	-1.711***	-1.706***	-1.707***
	(0.159)	(0.159)	(0.159)	(0.159)
Guidance	0.591	0.585	0.593	0.590
	(0.397)	(0.397)	(0.397)	(0.398)
Q4	-0.071	-0.104	-0.025	-0.085
	(0.145)	(0.155)	(0.134)	(0.146)
SUE×Control Variables	Yes	Yes	Yes	Yes
Firm & Year Fixed Effects	Yes	Yes	Yes	Yes
SUE×Fixed Effects	Yes	Yes	Yes	Yes
Observations	17,780	17,780	17,780	17,780
Within Adj.R^2	0.019	0.020	0.018	0.019

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). 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. *2ndOrder* and *3rdOrder* are calculated with the probability of information transmission (p) set to 0.5. *Connection* is the natural logarithm of one plus one of the connection measures (*2ndOrder*, *3rdOrder*).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 4. Employee Connections and Market Reactions to Earnings Announcements by Different Types of Information

Dep. Var. =	$AbRet_{[-2, +2]}$			
Connection =	*2ndOrder*	*3rdOrder*	*2ndOrder*	*3rdOrder*
	(1)	(2)	(3)	(4)
Positive SUE×Connection	-0.529**	-0.481***		
	(0.265)	(0.186)		
Negative SUE×Connection	-0.070	-0.156		
	(0.260)	(0.190)		
Macro SUE×Connection			-0.546	-0.382
			(0.506)	(0.381)
Industry SUE×Connection			-0.043	-0.232
			(0.273)	(0.204)
Idiosyncratic SUE×Connection			-0.360**	-0.368***
			(0.154)	(0.111)
Connection	0.716	0.617	0.511	0.221
	(0.567)	(0.428)	(0.497)	(0.410)
Size	-0.627	-0.641	-1.724***	-1.727***
	(0.506)	(0.505)	(0.524)	(0.523)
BM	0.703	0.695	0.564	0.563
	(0.529)	(0.528)	(0.493)	(0.493)
Coverage	-0.076	-0.081	0.171	0.173
	(0.397)	(0.398)	(0.331)	(0.332)
BlockOwn	-0.006	-0.006	-0.023	-0.023
	(0.027)	(0.027)	(0.023)	(0.023)
Loss	-2.062***	-2.070***	-1.600***	-1.600***
	(0.247)	(0.247)	(0.197)	(0.196)
Guidance	0.388	0.378	0.644	0.642
	(0.588)	(0.586)	(0.496)	(0.496)
Q4	0.124	0.040	-0.261	-0.229
	(0.234)	(0.254)	(0.207)	(0.224)
SUE×Control Variables	Yes	Yes	Yes	Yes
Firm & Year Fixed Effects	Yes	Yes	Yes	Yes
SUE×Fixed Effects	Yes	Yes	Yes	Yes
Observations	17,780	17,780	16,756	16,756
Within Adj.R^2	0.020	0.020	0.019	0.019

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. *Connection* is the natural logarithm of one plus one of the connection measures (*2ndOrder*, *3rdOrder*). In Columns 1 and 2, we decompose *SUE* into positive and negative surprises. *Positive SUE* (*Negative SUE*) equals *SUE* if *SUE* is positive (negative) and zero otherwise. In Columns 3 and 4, we decompose *SUE* into the macroeconomic, industry, and idiosyncratic components (*Macro SUE*, *Industry SUE*, and *Idiosyncratic SUE*, respectively). *Macro SUE* 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*. *Industry SUE* 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. *Idiosyncratic SUE* is *SUE–Macro SUE–Industry SUE*. 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 inTable 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 5. Employee Connections and Market Reactions to Earnings Announcements: Executives vs. Non-Executives

Dep. Var. =	$AbRet_{[-2, +2]}$			
Connections of	Executive		Non-Executive	
Connection =	*2ndOrder*	*3rdOrder*	*2ndOrder*	*3rdOrder*
	(1)	(2)	(3)	(4)
SUE×Connection	-0.215**	-0.214***	-0.297***	-0.355***
	(0.085)	(0.068)	(0.111)	(0.083)
Connection	0.279	0.167	0.303	0.321
	(0.260)	(0.218)	(0.310)	(0.239)
Size	-1.680***	-1.682***	-1.681***	-1.698***
	(0.380)	(0.379)	(0.379)	(0.380)
BM	0.394	0.390	0.390	0.372
	(0.362)	(0.362)	(0.361)	(0.361)
Coverage	0.236	0.233	0.239	0.230
	(0.250)	(0.251)	(0.249)	(0.250)
BlockOwn	-0.028	-0.028	-0.027	-0.027
	(0.017)	(0.017)	(0.017)	(0.017)
Loss	-1.704***	-1.705***	-1.709***	-1.709***
	(0.160)	(0.160)	(0.159)	(0.159)
Guidance	0.587	0.588	0.599	0.596
	(0.397)	(0.397)	(0.397)	(0.398)
Q4	-0.020	-0.014	-0.025	-0.080
	(0.138)	(0.147)	(0.143)	(0.151)
SUE×Control Variables	Yes	Yes	Yes	Yes
Firm & Year Fixed Effects	Yes	Yes	Yes	Yes
SUE×Fixed Effects	Yes	Yes	Yes	Yes
Observations	17,730	17,730	17,780	17,780
Within Adj.R^2	0.019	0.019	0.019	0.020

Notes: This table repeats the estimation of Table 2 using connections of executives and non-executives separately. *2ndOrder* and *3rdOrder* are calculated with the probability of information transmission (p) set to 0.5. *Connection* is the natural logarithm of one plus one of the connection measures (*2ndOrder*, *3rdOrder*). 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 6. 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	Yes	Yes
SUE×Control Variables	Yes	Yes
Event-specific and Year FEs	Yes	Yes
SUE×Fixed Effects	Yes	Yes
Observations	3,898	3,898
Within Adj.R^2	0.160	0.150

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	Yes	Yes
Control Variables	Yes	Yes
SUE×Control Variables	Yes	Yes
Event-specific and Year FEs	Yes	Yes
SUE×Fixed Effects	Yes	Yes
Observations	3,898	3,898
Within Adj.R^2	0.212	0.207

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. *2ndOrder* and *3rdOrder* are calculated with the probability of information transmission (p) set to 0.5. *Connection* is the natural logarithm of one plus one of the connection measures (*2ndOrder*, *3rdOrder*). *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 7. 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
	(0.040)	(0.040)	(0.040)	(0.040)
BM	-0.049	-0.045	-0.111*	-0.111*
	(0.061)	(0.060)	(0.057)	(0.057)
Coverage	-0.216***	-0.214***	-0.046	-0.045
	(0.070)	(0.070)	(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)
Firm & Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	9,987	9,987	9,987	9,987
Within Adj.R^2	0.002	0.002	0.001	0.001

Notes: This table reports regression estimates on the relation between employee connection measures and *IPT*. *2ndOrder* and *3rdOrder* are calculated with the probability of information transmission (p) set to 0.5. *Connection* is the natural logarithm of one plus one of the connection measures (*2ndOrder*, *3rdOrder*). 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 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.

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	Yes	Yes
Firm & Year Fixed Effects	Yes	Yes
SUE×Fixed Effects	Yes	Yes
Observations	17,780	17,780
Within Adj.R^2	0.063	0.063

Notes: This table reports regression estimates on the relation between employee connection measures and post earnings announcement drift. *2ndOrder* and *3rdOrder* are calculated with the probability of information transmission (p) set to 0.5. *Connection* is the natural logarithm of one plus one of the connection measures (*2ndOrder*, *3rdOrder*). We measure $AbRet_{[+3, +62]}$ as the buy-and-hold market-adjusted 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.

Internet Appendix

Illustration of the Network Data and Construction of Connection Measures

In this section, we provide a simple example to illustrate the data structure of our business card exchange network. Panel A of Table IA.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.

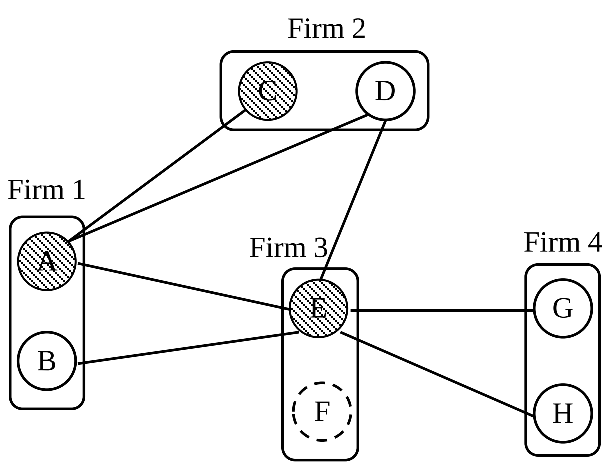
We then construct the *1stOrder*, *2ndOrder*, and *3rdOrder* at the firm level by averaging each respective employee-level connection measure across the firm's employees in the network. Panel D presents the calculations, where we use 0.9 as the probability of information transmission. Taking firm 2 as 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 IA.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.

Table IA.2. Correlation Matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) *1stOrder*	1.000													
(2) *2ndOrder*	**0.833**	1.000												
(3) *3rdOrder*	**0.796**	**0.967**	1.000											
(4) $AbRet_{[-2, +2]}$	-0.006	**-0.013**	**-0.014**	1.000										
(5) $AbRet_{[+3, +62]}$	0.003	0.008	0.008	0.008	1.000									
(6) *IPT*	0.014	0.015	0.018	0.003	-0.013	1.000								
(7) *SUE*	**-0.024**	**-0.027**	**-0.031**	**0.159**	**0.049**	0.000	1.000							
(8) *Size*	**0.074**	**0.045**	**0.034**	**0.024**	**-0.071**	-0.004	-0.007	1.000						
(9) *BM*	**-0.009**	**-0.032**	**-0.013**	**0.034**	**0.025**	-0.001	**0.012**	**-0.109**	1.000					
(10) *Coverage*	0.001	**-0.021**	**-0.025**	**0.027**	**-0.035**	-0.008	-0.002	**0.793**	**-0.068**	1.000				
(11) *BlockOwn*	**0.043**	**0.023**	**0.013**	**0.016**	**-0.021**	**-0.022**	-0.009	**0.292**	**0.059**	**0.281**	1.000			
(12) *Loss*	-0.005	**0.051**	**0.064**	**-0.134**	**-0.022**	**-0.018**	**-0.274**	**-0.229**	**-0.032**	**-0.201**	**-0.099**	1.000		
(13) *Guidance*	**-0.014**	**-0.019**	**-0.019**	**0.014**	-0.011	-0.004	-0.003	**0.314**	0.010	**0.318**	**0.090**	**-0.049**	1.000	
(14) *Q4*	**0.082**	**0.113**	**0.140**	-0.004	0.003	-0.003	**-0.061**	**-0.014**	**0.049**	0.004	-0.004	**0.150**	**0.018**	1.000

Notes: This table presents Pearson correlation coefficients for 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%. Bolded correlation coefficients are statistically significant at the 10% level. See the Appendix for additional variable definitions.

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

Panel A. Comparison of Covariates for Matched Sample

	Mean Comparison			
	Top Quartile *Connection*	Bottom Quartile *Connection*	Top – Bottom	*t*-stat
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	0.250	0.248	0.002	[0.19]
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. Employee Connections and Market Reactions to Earnings Announcements Using a PSM Sample Approach

Dep. Var. =	$AbRet_{[-2,+2]}$	
Connection =	*2ndOrder*	*3rdOrder*
	(1)	(2)
SUE×Connection	-0.684**	-0.491**
	(0.292)	(0.207)
Connection	1.563	1.172
	(0.961)	(0.729)
Size	-2.893***	-2.238***
	(0.796)	(0.716)
BM	-0.135	0.432
	(0.763)	(0.703)
Coverage	0.322	1.102*
	(0.540)	(0.592)
BlockOwn	0.003	-0.009
	(0.041)	(0.055)
Loss	-1.452***	-1.980***
	(0.360)	(0.352)
Guidance	0.957	1.062
	(0.885)	(1.029)
Q4	-0.241	-0.364
	(0.363)	(0.396)
SUE×Control Variables	Yes	Yes
Firm & Year Fixed Effects	Yes	Yes
SUE×Fixed Effects	Yes	Yes
Observations	8,540	8,534
Within Adj.R^2	0.024	0.026

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 *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. *2ndOrder* and *3rdOrder* are calculated with the probability of information transmission (p) set to 0.5. *Connection* is the natural logarithm of one plus one of the connection measures (*2ndOrder*, *3rdOrder*). 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 IA.4. Employee Connections and Market Reactions to Earnings Announcements: Direct vs. Indirect Connections

Dep. Var. =	$AbRet_{[-2, +2]}$			
	(1)	(2)	(3)	(4)
SUE×ln(1+*Degree1*)	-0.111			0.090
	(0.137)			(0.169)
SUE×ln(1+*Degree2*)		-0.256**		0.150
		(0.122)		(0.207)
SUE×ln(1+*Degree3*)			-0.314***	-0.420***
			(0.085)	(0.136)
ln(1+*Degree1*)	0.331			0.049
	(0.424)			(0.522)
ln(1+*Degree2*)		0.502		0.261
		(0.330)		(0.573)
ln(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)
SUE×Control Variables	Yes	Yes	Yes	Yes
Firm & Year Fixed Effects	Yes	Yes	Yes	Yes
SUE×Fixed Effects	Yes	Yes	Yes	Yes
Observations	17,780	17,780	17,780	17,780
Within Adj.R^2	0.018	0.019	0.020	0.019

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% and 5% level, respectively.