

# Internal Connectedness and Accrual Quality: Evidence from Employee LinkedIn Connections

Shelley Xin Li

*University of Southern California*

Aner Zhou

*San Diego State University*

**SYNOPSIS:** We investigate the impact of employee connectedness on a firm’s accrual quality. Using data from the largest professional network, LinkedIn, we measure the degree to which employees are connected—which we label “internal connectedness”—and are therefore likely to interact and share information. We hypothesize and find that a firm’s internal connectedness increases its accrual quality and that the positive effect is stronger when external monitoring or internal formal monitoring is weaker or when accrual estimation is more difficult. That is, the effects of internal connectedness are stronger when greater benefits can be expected from enhanced informal internal information sharing. Our results provide insights for academics and practitioners in understanding the determinants of financial reporting quality and the crucial yet often neglected role of the internal information environment.

**Data Availability:** Data are available from the sources cited in the text.

**Keywords:** accrual quality; employee social connections; internal connectedness; LinkedIn.

## I. SYNOPSIS AND CONTRIBUTION TO PRACTICE

Accrual accounting is required for all large companies (with average revenue of \$25 million or more over three years) to provide a better understanding of the relationship between revenues and expenses and better insights into profitability. However, unlike cash flows, accruals incorporate many assumptions and estimates. Accrual quality is a key indicator of financial reporting quality and has become an even more important topic of study due to the uncertainties caused by the COVID-19 pandemic (PricewaterhouseCoopers 2021). Low accrual quality, indicated by high discretionary accruals, reflects earnings that are less supported by cash flows and can indicate earnings management, subsequent restatements, or even fraud (Dechow, Sloan, and Sweeney 1995; Jones, Krishnan, and Melendrez 2008).

What determines accrual quality and, by extension, financial reporting quality? Accounting practice and research have focused largely on external monitoring forces such as high-quality auditing (e.g., the Big 4 auditing firms), information intermediaries (e.g., financial analysts), and executive incentive contracts (Baker, Collins, and Reitenga 2003; Yu 2008; Abernethy, Bouwens, and Kroos 2017; DeFond et al. 2017). However, accounting measurements are produced within a company by employees, both directly by the accountants who prepare the financial statements and indirectly by all employees who create the underlying economic performance and share their interpretation of this economic reality with the accountants. Although an emerging literature focuses on the role of employees in accrual quality (Call, Campbell, Dhaliwal, and Moon 2017), little attention has been paid to the internal information environment that

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Shelley Xin Li, University of Southern California, Marshall School of Business, Leventhal School of Accounting, Los Angeles, CA, USA; Aner Zhou, San Diego State University, Fowler College of Business, Charles W. Lamden School of Accountancy, San Diego, CA, USA.

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produces these accrual numbers. This is partly due to the difficulty of observing firms' internal information environments and measuring the degree to which information is shared among employees.

We aim to overcome this challenge using employee connection data from the largest professional network, LinkedIn, allowing us to measure the degree to which employees are connected to one another—which we label “internal connectedness”—and are therefore likely to interact and share information. We examine how internal connectedness influences accrual quality and how this relationship varies with the expected benefits to accrual quality from stronger internal connectedness; that is, when external monitoring or internal formal monitoring is weaker or when accrual estimation is more difficult.

We first hypothesize that increased internal connectedness among a firm's employees improves accrual quality. The increase in connectedness and information sharing could (1) reduce errors by making them more transparent and easier to identify or communicate and (2) enable more accurate accounting measurements and estimates by improving the understanding of a firm's economic activities and outcomes. This directly echoes a recent PricewaterhouseCoopers report that recommends improving estimation quality by gathering information from different facets of the organization rather than just the audit committee and finance team (PricewaterhouseCoopers 2021). We focus on accrual quality because it is a continuous measure of financial reporting quality that captures all biases and noise in the accounting estimation, not only extreme and infrequent cases like restatements and fraud. To account for the potential effect of the economic environment on accrual quality, we hold a firm's economic reality constant by including year fixed effects, firm fixed effects and controlling for various operational factors. Our findings are consistent with the hypothesis: a one standard deviation increase in employee internal connections is associated with a 0.07 standard deviation improvement in accrual quality. Furthermore, consistent with the mechanism of improved information sharing leading to improved accrual quality, we find that connections involving employees in the accounting function have a stronger impact on accrual quality.

We also hypothesize and find that the positive effects of internal connectedness on accrual quality are more pronounced when there is weaker external monitoring—measured by the absence of Big 4 auditors or by a low number of analysts following the firm—or when there is weaker internal formal monitoring (i.e., the presence of internal control deficiencies). We also find that the impact is stronger when there is higher measurement difficulty, which we measure by a smaller firm size or higher sales growth.

Our results shed light on the determinants of accrual quality and on the critical but often overlooked role of internal information sharing. The more closely connected the employees are, the more likely they are to be on the same page concerning the firm's economic reality and the less likely it is that a mistake would go unnoticed or uncorrected. Our results have implications for executives trying to improve accounting information quality and for investors examining corporate accounting information. As auditors incorporate data analytics into their practice (Kogan, Appelbaum, and Vasarhelyi 2017), these findings could help them focus on higher-risk areas.

We also make several contributions to the accounting literature. First, we contribute to the large literature on financial reporting quality by extending it in two directions: the firm's internal information environment and the role of ordinary employees' social connections (as a medium of information flow). In doing this, we demonstrate that the development of network technologies makes it possible to observe theoretically important but previously unobservable constructs (e.g., internal information sharing) that provide novel insights into traditional problems. This complements an emerging literature that leverages techniques such as machine learning to improve accounting estimates and detect misstatements (Cho, Miklos, Vasarhelyi, and Zhang 2020; Ding, Lev, Peng, Sun, and Vasarhelyi 2020; Bertomeu, Cheynel, Floyd, and Pan 2021).

Second, we contribute to the emerging literature at the intersection of human capital and accounting. Recent studies have examined how employee credentials, turnover, rank-and-file accountants' incentives, and the size of accounting departments can be linked to financial reporting quality (Chen, Cheng, Chow, and Liu 2021; Lee and Yu 2021; Armstrong, Kepler, Larcker, and Shi 2022). Although these studies focus on individual accounting employees' expertise or economic incentives, we focus on social connections among all employees, pointing to the importance of internal information flow or social interactions in producing high-quality financial information. This builds on the social capital theory that relationships developed over time could provide organizational advantages (Nahapiet and Ghoshal 1998; Lin 2017). In Section V, we carefully discuss some limitations of using LinkedIn data to measure internal connectedness.

## II. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Accrual accounting is a key component of the Financial Accounting Standards Board accounting concepts (Financial Accounting Standards Board 2021). Compared to cash-based earnings, accrual-based earnings can better match the timing of accounting recognition with the timing of a transaction's economic benefits or costs, thus providing

high-quality and timely accounting information. However, accruals are based on assumptions and estimations that could cause noise in the earnings numbers and reduce the benefit of accruals.

An extensive literature has focused on accrual quality as measured by departure from the predicted level of accruals. Scholars and practitioners have focused on the role of external monitoring in influencing the quality of accounting numbers. For example, firms working with a Big 4 auditor and firms with more analyst coverage have better accrual quality (Yu 2008; DeFond et al. 2017). To the extent that prior studies examine internal information-production, they tend to focus on how characteristics of senior executives (e.g., bonus plans, equity incentives) influence the quality of financial reporting (Baker et al. 2003).

The role of most employees in internal information-production has been largely ignored, yet they are either directly involved in the accounting and control processes, or at least indirectly involved by generating and interpreting the economic outcomes that accountants aim to measure.

Can ordinary employees really affect firms' financial reporting quality? On the one hand, accounting and internal control policies are largely decided by executives (influenced by regulations and other external monitoring) and not directly affected by ordinary employees. On the other hand, the production of high-quality accounting information requires a deep and timely understanding of firms' economic activities. Managers and employees who are involved in these activities would participate in information measurement, reporting, sharing, and interpretation. High-quality employees—as measured by the average education level of a firm's workforce—and more-satisfied employees have been found to be positively associated with accrual quality (Call et al. 2017; Khavis and Krishnan 2021). A recent working paper by Armstrong et al. (2022) links rank-and-file accountants' compensation to financial reporting quality. We argue that the informal network among employees (a conduit through which information flows) is yet another important determinant of a firm's internal information environment and could contribute to the quality of accounting numbers.

Internal information sharing has been shown to affect employee creativity, engagement, and performance (Li and Sandino 2018, 2023). In addition to the formal information-sharing systems, the degree to which employees are connected in general can improve information sharing within a company, representing a key form of organizational social capital based on employee social networks (Lin 2017). This can help improve the quality of accounting numbers by (1) reducing biases and errors through greater transparency and more opportunities to identify and correct mistakes, and (2) increasing measurement accuracy, as those directly responsible for generating the accounting numbers achieve a better understanding of the economic reality within the firm through connections with those on the frontline of business operations and with other accountants or control personnel. Industry reports confirm that information sharing across departments improves accounting estimates (PricewaterhouseCoopers 2021). We therefore hypothesize:

**H1:** Internal connectedness increases accrual quality.

H1 is not without tension. Some studies show that when employees are more connected, as in a reciprocal environment or in environments in which communication is more open and transparent, they are more like to collude on misreporting (Evans, Moser, Newman, and Stikeleather 2016; Maas and Yin 2022; Ferdiansah, Chong, Wang, and Woodliff 2023).

We then explore the channels through which employee internal connectedness can improve accrual quality. When developing H1, we propose two channels: (1) reducing biases and errors through greater transparency and internal monitoring and (2) increasing measurement accuracy through deeper understanding of the business's operations. These two channels lead to cross-sectional hypotheses about the impact of internal connectedness.

If enhanced internal information flow increases accrual quality by increasing the probability of catching and correcting mistakes, we argue that this effect will be particularly strong when alternative forms of monitoring are weaker (H2a and H2b). Employees, with their direct involvement in daily operations, are uniquely positioned to identify errors and misreporting (Stubben and Welch 2020). This discovery and dissemination process relies on social relationships organically developed from employee interactions (Morrison 2002), representing a form of informal internal monitoring that complements formal monitoring systems such as internal control systems and external monitoring from analysts and auditors.

If enhanced internal connectedness can also increase accrual quality by enabling employees to better understand and more accurately measure a firm's economic reality, this effect will be stronger the more difficult it is to measure the economic reality (H3). We develop each of these hypotheses in more detail.

The prediction that internal connectedness increases accrual quality more when alternative forms of monitoring is weaker builds on the extensive literature on how external and internal monitoring improve accrual quality via reduced opportunities for earnings management. For example, the literature on analysts shows that firms with more analyst following have less earnings management, as analysts interact directly with management and question suspicious estimates

during earnings release conferences (Yu 2008; Chen, Harford, and Lin 2015; Bradley, Gokkaya, Liu, and Xie 2017). Similarly, Big N auditors can constrain firms' earnings management behaviors, given their industry knowledge, information technology, and state-of-the-art techniques to detect earnings management (Krishnan 2003). Firms audited by Big N auditors have better accrual quality (Krishnan 2003; DeFond, Erkens, and Zhang 2017), whereas firms with internal control deficiencies have lower accrual quality (Ashbaugh-Skaife, Collins, Kinney, and LaFond 2008). When strong external monitoring (e.g., from analysts and Big N auditors) is absent or formal internal monitoring suffers from control weaknesses, well informed employees become one of the few parties able to detect and curb earnings management. We therefore predict that employee internal connectedness matters more in increasing accrual quality when external or internal monitoring is weaker, and we hypothesize:

**H2a:** Internal connectedness increases accrual quality more when external monitoring is weaker.

**H2b:** Internal connectedness increases accrual quality more when internal monitoring is weaker.

However, it is possible that rigorous external monitoring or internal control mechanisms (which could curb potential collusion activities) are complements to internal connectedness, making it *more* effective in enhancing accrual quality. Whether these alternative forms of monitoring enhance or weaken the effects of internal connectedness on actual quality, is therefore, an open empirical question.

Enhanced internal connectedness can also increase accrual quality by helping employees better understand and more accurately measure a firm's economic reality. Employees in different functions and subsidiaries gain information about different aspects of firm operations, creating information advantages among them (Aghion and Tirole 1997; Gupta and Govindarajan 2000). As the internal information environment improves, information flows better (Reitzig and Maciejovsky 2015; Li and Sandino 2018) and firms can make better accrual estimates. This effect might be particularly strong for firms with difficult-to-estimate accruals. For example, in firms with higher growth, cash flows deviate more from accruals (Dechow 1994; Robin and Wu 2015), leaving more room for accrual estimation errors. Thus, we expect internal connectedness to have a stronger impact for firms experiencing higher growth and a weaker impact for more stable and established firms. We therefore hypothesize:

**H3:** Internal connectedness increases accrual quality more when it is more difficult to estimate accruals.

### III. METHODOLOGY

#### Data Sources and Sample

Internal employee connection data is obtained through a partnership with LinkedIn, a professional social network platform on which users create profiles and connect with others by sending or accepting connection invitations.<sup>1</sup> We obtain data from the inception of LinkedIn in 2003 to 2018 for U.S. public firms, which forms our main sample. All relevant firm financial measures come from Audit Analytics, Compustat, and the International Brokers' Estimate System (I/B/E/S). Consistent with the literature, we exclude firms in the finance and utility industries, firms without sufficient variables for calculating accruals, and firms with missing control variables. As we focus on employee connections on LinkedIn, we also exclude firms without any LinkedIn users. Our final sample consists of 31,819 firm-year observations.

#### Empirical Models

To test our hypotheses, we use the modified Jones model below, which regresses the absolute value of discretionary accruals onto the number of internal connections. A higher value of  $|Discretionary\ accrual_{it}|$  indicates lower accrual quality (Jones 1991; Dechow et al. 1995).

$$|Discretionary\ accrual_{it}| = \beta_1 + \beta_2 \ln(\text{of internal connections})_{it} + \beta_3 \text{control variables} + \text{Fixed effects} \quad (1)$$

To account for economic factors and external monitoring forces that could affect accrual quality, we include several control variables and fixed effects in our analyses, covering various aspects of firm economic and operational factors. Variable definitions can be found in Appendix A, and more detailed discussion about the main variables and control variables can be found in Appendix B.

<sup>1</sup> Additional information about the LinkedIn data can be found in Appendix B.

## IV. RESULTS

## Descriptive Statistics

Table 1 presents the descriptive statistics of our sample. On average, each firm-year has 76 employees (median 67) using LinkedIn and each employee is connected with three coworkers. Note that these sample mean values are at the firm-year level, representing our entire sample period (2003–2018). In later years of the sample period, there are many more LinkedIn users and connections. For example, in our latest sample year, 2018, firms have an average of 330 employees on LinkedIn (median 403) and each employee is connected with 11 coworkers (median 15). Table 2 reports the correlation coefficients among the main variables. The association between employee internal connections and the absolute value of discretionary accruals is negative and significant.

## H1: Main Results

Table 3 reports our main results from testing H1, which posits a relationship between employee internal connections and accrual quality. Columns (1) and (2) include industry and firm fixed effects, respectively. In both columns, we find a negative and significant association between the number of employee connections and the absolute value of discretionary accruals (note that high values of discretionary accruals indicate *low* accrual quality). In terms of economic significance, a one standard deviation change in internal connections is associated with a 0.07 standard deviation change in accrual quality. The coefficients of the control variables are consistent with our expectations. For example, firm profitability (*ROA*) and the strength of external monitoring (*Big4* and *Ln(# of analysts following)*) are negatively associated with our measure of *low* accrual quality—that is, they are positively associated with accrual quality—supporting the validity of our model.

To mitigate concerns that factors other than employee internal connections may drive our results, Table 3, column (3) examines the incremental impact of connections involving an accountant. If employee connections facilitate information flow within a firm, we would expect their impact on accounting quality to be stronger when the connections involve accounting employees. To test this idea, we include an additional variable measuring the number of employee connections involving at least one accountant (*Ln(# of internal accounting connections)*). As reported in Table 3, column (3),

TABLE 1  
Summary Statistics

Variable	Obs.	Mean	Std. Dev.	Min.	P25	Median	P75	Max.
Discretionary accruals	31,841	0.14	0.27	0.00	0.03	0.06	0.14	2.00
<i>Ln(# of internal connections)</i>	31,841	1.41	1.14	0.00	0.20	1.42	2.37	3.74
<i>Ln(# of LI users)</i>	31,841	4.35	2.43	0.69	2.30	4.22	6.17	10.00
<i>Ln(# of emp)</i>	31,841	1.27	1.32	0.00	0.16	0.79	2.06	5.19
<i>Ln(assets)</i>	31,841	5.93	2.45	-0.87	4.33	6.03	7.66	11.16
Market-to-book ratio	31,841	3.03	7.84	-34.37	1.15	2.17	3.96	46.65
Leverage	31,841	0.23	0.30	0.00	0.00	0.15	0.33	1.93
Foreign	31,841	0.12	0.33	0.00	0.00	0.00	0.00	1.00
ROA	31,841	-0.21	0.92	-7.24	-0.11	0.03	0.07	0.30
Market cap	31,841	6.10	2.37	0.47	4.44	6.20	7.75	11.36
ICW	31,841	0.08	0.28	0.00	0.00	0.00	0.00	1.00
Big4	31,841	0.54	0.50	0.00	0.00	1.00	1.00	1.00
Loss	31,841	0.40	0.49	0.00	0.00	0.00	1.00	1.00
<i>Ln(# of analysts following)</i>	31,841	1.31	1.22	0.00	0.00	1.39	2.40	3.50
<i>Ln(# of internal accounting connections)</i>	31,841	0.23	0.30	0.00	0.00	0.10	0.39	2.48
Lagged IDD	31,145	0.42	0.49	0.00	0.00	0.00	1.00	1.00
Top sales growth	31,841	0.16	0.37	0.00	0.00	0.00	0.00	1.00

Table 1 provides descriptive statistics for our main sample of 31,841 firm-year observations. Continuous variables are Winsorized at the 1st and 99th percentiles.

Variables are defined in Appendix A.

**TABLE 2**  
**Correlations**

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Discretionary accruals	1	-0.09***	-0.21***	-0.35***	-0.36***	-0.08***	-0.06***
Ln(# of internal connections)	-0.13***	1	0.82***	0.21***	0.29***	0.13***	0.07***
Ln(# of LI users)	-0.23***	0.80***	1	0.56***	0.59***	0.17***	0.15***
Ln(# of emp)	-0.25***	0.17***	0.56***	1	0.87***	0.13***	0.29***
Ln(assets)	-0.43***	0.30***	0.61***	0.79***	1	0.16***	0.37***
Market-to-book ratio	-0.06***	0.07***	0.07***	0.03***	0.06***	1	-0.10***
Leverage	0.16***	0.01**	0.02***	0.07***	0.05***	-0.10***	1
Foreign	-0.05***	0.03***	0.07***	0.06***	0.10***	-0.00	-0.02***
ROA	-0.65***	0.11***	0.23***	0.26***	0.49***	0.12***	-0.23***
Market cap	-0.33***	0.32***	0.60***	0.73***	0.90***	0.15***	-0.02***
ICW	0.26***	-0.09***	-0.14***	-0.15***	-0.24***	-0.04***	0.07***
Big4	-0.22***	0.14***	0.29***	0.36***	0.48***	0.06***	0.00
Loss	0.26***	-0.04***	-0.24***	-0.42***	-0.46***	-0.03***	0.10***
Ln(# of analysts following)	-0.22***	0.23***	0.38***	0.41***	0.54***	0.07***	0.00

  

Variable	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Discretionary accruals	-0.03***	-0.26***	-0.33***	0.15***	-0.20***	0.29***	-0.21***
Ln(# of internal connections)	0.04***	0.06***	0.31***	-0.08***	0.14***	-0.05***	0.23***
Ln(# of LI users)	0.08***	0.25***	0.58***	-0.14***	0.28***	-0.23***	0.38***
Ln(# of emp)	0.09***	0.49***	0.78***	-0.19***	0.41***	-0.49***	0.45***
Ln(assets)	0.10***	0.46***	0.91***	-0.20***	0.47***	-0.46***	0.54***
Market-to-book ratio	0.01	0.27***	0.41***	-0.10***	0.16***	-0.18***	0.21***
Leverage	0.00	-0.02***	0.22***	-0.00	0.12***	-0.04***	0.12***
Foreign	1	0.06***	0.09***	-0.01**	0.05***	-0.05***	0.05***
ROA	0.06***	1	0.52***	-0.19***	0.18***	-0.85***	0.24***
Market cap	0.09***	0.36***	1	-0.21***	0.47***	-0.49***	0.57***
ICW	-0.01**	-0.26***	-0.22***	1	-0.15***	0.17***	-0.13***
Big4	0.05***	0.20***	0.47***	-0.15***	1	-0.19***	0.32***
Loss	-0.05***	-0.38***	-0.48***	0.17***	-0.19***	1	-0.22***
Ln(# of analysts following)	0.05***	0.21***	0.57***	-0.13***	0.32***	-0.22***	1

\*\*\*, \*\*, \* Indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

Table 2 reports Pearson and Spearman correlations for the main variables used in our analyses for our main sample of 31,481 firm-year observations. Variables are defined in [Appendix A](#).

the coefficient of *Ln(# of internal accounting connections)* is negative and significant, suggesting that connections involving accounting employees incrementally improve accrual quality, even after controlling for all employee connections.<sup>2</sup> Together, the findings in [Table 3](#) are consistent with H1: internal connectedness increases accrual quality.

## H2 and H3: Cross-Sectional Variation

In this section, we explore cross-sectional variation in the impact of employee internal connections on accrual quality. [Table 4](#) reports the results of testing the second set of hypotheses. First, we examine H2a, when strong external monitoring ensures high-quality reporting, is the impact of employee connections weaker? We create interactions between employee internal connections and proxies for stronger external monitoring (*Big4* and *Ln(# of analysts following)*). In [Table 4](#), we see a positive coefficient on the interaction terms, which means that the negative association between internal connectedness and discretionary accruals is weakened by stronger external monitoring. In other words, employee internal connectedness has a *stronger* impact (on reducing discretionary accruals) among firms with *weaker* external monitoring, consistent with H2a. In terms of economic significance, the impact of internal connectedness on accrual

<sup>2</sup> Our results are robust to an instrumental variable approach as reported in [Appendix B](#).

**TABLE 3**  
**H1: Employee Internal Connections and Accrual Quality**

	(1)	(2)	(3)
	<i> Discretionary accruals </i>		
<i>Ln(# of internal connections)</i>	-0.015*** (-4.55)	-0.014*** (-3.96)	-0.009** (-2.36)
<i>Ln(# of internal accounting connections)</i>			-0.022* (-1.78)
<i>Ln(# of LI users)</i>	0.004** (2.19)	-0.009* (-1.82)	-0.008* (-1.77)
<i>Ln(# of emp)</i>	0.009** (2.87)	-0.021** (-2.56)	-0.018** (-2.24)
<i>Ln(assets)</i>	-0.033*** (-8.14)	0.005 (0.52)	0.001 (0.13)
<i>Market-to-book ratio</i>	0.000 (0.73)	0.000 (0.54)	0.000 (0.65)
<i>Leverage</i>	0.030** (2.44)	0.001 (0.05)	-0.003 (-0.14)
<i>Foreign</i>	-0.005 (-1.70)	-0.004 (-1.45)	-0.003 (-1.37)
<i>ROA</i>	-0.143*** (-18.64)	-0.099*** (-11.89)	-0.102*** (-11.91)
<i>Market cap</i>	0.016*** (5.27)	0.008** (2.47)	0.009** (2.58)
<i>ICW</i>	0.077*** (7.11)	0.030*** (3.84)	0.030*** (3.83)
<i>Big4</i>	-0.015*** (-6.71)	-0.016** (-2.90)	-0.015** (-2.79)
<i>Loss</i>	-0.007 (-1.32)	-0.012** (-2.14)	-0.012** (-2.28)
<i>Ln(# of analysts following)</i>	-0.007*** (-7.03)	-0.006*** (-7.28)	-0.006*** (-7.15)
Constant	0.216*** (19.08)	0.148*** (4.73)	0.156*** (4.96)
Industry FE	Yes		
Firm FE		Yes	Yes
Year FE	Yes	Yes	Yes
n	31,841	31,841	31,841
Adjusted R <sup>2</sup>	0.449	0.556	0.556

\*\*\*, \*\*, \* Indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

Table 3 examines the relationship between employee internal connections and the absolute value of discretionary accruals. Fama-French 30 industry fixed effects are included in column (1) whereas firm fixed effects are included in columns (2) and (3). Column (3) also includes a variable measuring the number of employee connections involving an accountant. Standard errors are double-clustered by firm and year. t-statistics are reported in parentheses.

Variables are defined in [Appendix A](#).

quality is 45 percent lower for firms with Big 4 auditors than for firms without Big 4 auditors and 23 percent lower for firms with a median analyst following than for those with none.

In [Table 4](#), Panel B, we examine H2b, i.e., the moderating role of internal monitoring. Weak internal monitoring is proxied by a dummy variable measuring whether the firm reports internal control weaknesses in the current year (column (1)) or in the past three years (column (2)). The coefficient on the interaction term between internal connections and internal control weaknesses is negative, suggesting that internal connectedness has a stronger effect in reducing discretionary accruals when internal monitoring is weak, consistent with H2b.

**TABLE 4**  
**H2a and H2b: The Moderating Roles of External and Internal Monitoring**

**Panel A: External Monitoring (H2a)**

	(1)	(2)
	<i> Discretionary accruals </i>	
<i>Ln(# of internal connections) * Big4</i>	0.009** (2.48)	
<i>Ln(# of internal connections) * Ln(# of analysts following)</i>		0.003*** (4.24)
<i>Ln(# of internal connections)</i>	-0.019*** (-4.26)	-0.018*** (-4.74)
<i>Ln(# of LI users)</i>	-0.009* (-1.87)	-0.009* (-1.88)
<i>Ln(assets)</i>	0.001 (0.15)	0.001 (0.13)
<i>Ln(# of emp)</i>	-0.019** (-2.31)	-0.019** (-2.35)
<i>Market-to-book ratio</i>	0.000 (0.66)	0.000 (0.65)
<i>Leverage</i>	-0.004 (-0.18)	-0.004 (-0.18)
<i>Foreign</i>	-0.003 (-1.44)	-0.003 (-1.40)
<i>ROA</i>	-0.102*** (-11.92)	-0.102*** (-11.91)
<i>Market cap</i>	0.009** (2.52)	0.009** (2.54)
<i>ICW</i>	0.030*** (3.85)	0.031*** (3.90)
<i>Big4</i>	-0.028*** (-3.94)	-0.016*** (-2.96)
<i>Loss</i>	-0.012** (-2.29)	-0.012** (-2.30)
<i>Ln(# of analysts following)</i>	-0.006*** (-7.09)	-0.011*** (-5.73)
Constant	0.166*** (5.25)	0.166*** (5.27)
Firm FE	Yes	Yes
Year FE	Yes	Yes
n	31,841	31,841
Adjusted R <sup>2</sup>	0.556	0.556

**Panel B: Internal Monitoring (H2b)**

	(1)	(2)
	<i> Discretionary accruals </i>	
<i>Ln(# of internal connections) * ICW</i>	-0.012** (-2.26)	
<i>ICW</i>	0.045*** (3.83)	
<i>Ln(# of internal connections) * ICW_3year</i>		-0.014*** (-3.50)

(continued on next page)



TABLE 4 (continued)

	(1)	(2)
	Discretionary accruals	
<i>ICW_3year</i>		0.031*** (3.50)
<i>Ln(# of internal connections)</i>	-0.013*** (-3.79)	-0.014*** (-4.01)
<i>Ln(# of LI users)</i>	-0.008 (-1.74)	-0.008 (-1.74)
<i>Ln(# of emp)</i>	-0.018** (-2.20)	-0.018* (-2.10)
<i>Ln(assets)</i>	0.001 (0.10)	0.002 (0.16)
<i>Market-to-book ratio</i>	0.000 (0.67)	0.000 (0.63)
<i>Leverage</i>	-0.003 (-0.17)	-0.003 (-0.15)
<i>Foreign</i>	-0.003 (-1.41)	-0.003 (-1.41)
<i>ROA</i>	-0.102*** (-11.92)	-0.103*** (-11.91)
<i>Market cap</i>	0.009** (2.52)	0.008** (2.46)
<i>Big4</i>	-0.015** (-2.86)	-0.015** (-2.74)
<i>Loss</i>	-0.012** (-2.28)	-0.012** (-2.21)
<i>Ln(# of analysts following)</i>	-0.006*** (-7.14)	-0.005*** (-6.11)
Constant	0.157*** (5.00)	0.156*** (4.94)
Firm FE	Yes	Yes
Year FE	Yes	Yes
n	31,841	31,841
Adjusted R <sup>2</sup>	0.556	0.555

\*\*\*, \*\*, \* Indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

Table 4 examines the moderating roles of external and internal monitoring in Panels A and B, respectively. In Panel A, external monitoring is measured by a dummy variable indicating whether a firm is audited by a Big 4 audit firm (column (1)) and by the number of analysts following the firm (column (2)). In Panel B, weak internal monitoring is measured by a dummy variable indicating whether the firm reports internal control weaknesses in the current year (column (1)) or in the current year or past two years (column (2)). Firm fixed effects are included in all columns. Standard errors are double-clustered by firm and year. t-statistics are reported in parentheses. Variables are defined in [Appendix A](#).

In [Table 5](#), we report results of testing H3, which posits that the impact of employee internal connections on accrual quality is stronger when there is greater estimation difficulty. Estimation difficulty is higher for firms with high sales growth and lower for mature firms with more employees. We create interactions between internal connections and proxies for estimation easiness (*Ln(# of emp)*) and estimation difficulty (*Top sales growth*). The positive coefficient of *Ln(# of internal connections) \* Ln(# of emp)* suggests internal connections reduces discretionary accruals to a less extent among mature firms with more employees. Our results still hold when we use asset size or revenue as proxies for mature firms. The negative coefficient of *Ln(# of internal connections) \* Top sales growth* suggests that internal connections have a stronger impact on reducing discretionary accruals among firms experiencing high sales growth. These results are consistent with H3, internal connectedness increases accrual quality more (by decreasing discretionary accruals) when estimation difficulty is higher.

**TABLE 5**  
**H3: The Moderating Role of Estimation Difficulty**

	(1) <u> Discretionary accruals </u>	(2) <u> Discretionary accruals </u>
<i>Ln(# of internal connections) * Ln(# of emp)</i>	0.005*** (3.59)	
<i>Ln(# of internal connections) * Top sales growth</i>		-0.011** (-2.83)
<i>Ln(# of internal connections)</i>	-0.019*** (-4.68)	-0.012*** (-3.48)
<i>Ln(# of LI users)</i>	-0.010** (-2.26)	-0.008 (-1.72)
<i>Ln(# of emp)</i>	-0.025** (-2.65)	-0.015* (-1.78)
<i>Ln(assets)</i>	0.002 (0.24)	0.001 (0.10)
<i>Market-to-book ratio</i>	0.000 (0.49)	0.000 (0.54)
<i>Leverage</i>	-0.006 (-0.29)	-0.006 (-0.28)
<i>Foreign</i>	-0.003 (-1.26)	-0.003 (-1.32)
<i>ROA</i>	-0.103*** (-11.96)	-0.103*** (-12.00)
<i>Market cap</i>	0.006* (1.76)	0.007* (1.86)
<i>ICW</i>	0.030*** (3.84)	0.030*** (3.81)
<i>Big4</i>	-0.018*** (-3.21)	-0.016** (-2.88)
<i>Loss</i>	-0.010* (-1.94)	-0.011* (-1.97)
<i>Ln(# of analysts following)</i>	-0.005*** (-6.76)	-0.005*** (-6.77)
<i>Top sales growth</i>	0.040*** (9.15)	0.056*** (6.82)
Constant	0.177*** (5.87)	0.159*** (5.30)
Firm FE	Yes	Yes
Year FE	Yes	Yes
n	31,841	31,841
Adjusted R <sup>2</sup>	0.558	0.558

\*\*\*, \*\*, \* Indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

Table 5 examines the moderating role of estimation difficulty. Mature firms with more employees have lower estimation difficulty and firms that experience high sales growth face more estimation difficulty. The tests are reported in columns (1) and (2), respectively. Firm fixed effects are included in all columns. Standard errors are double-clustered by firm and year. t-statistics are reported in parentheses.

Variables are defined in [Appendix A](#).

## V. CONCLUSION

Research on accounting quality largely focuses on the impact of executive incentives or of external factors, such as monitoring from analysts and auditors. In this paper, we examine how internal employee connections could affect information flow within a firm and increase accrual quality. Using detailed data on employee professional connections on the

LinkedIn platform, we find evidence that firms with more-interconnected employees have higher accrual quality. The results are stronger when the connections involve employees in the accounting function, when firms have weaker external or internal formal monitoring, and when they have higher estimation difficulty.

Our study highlights the importance of using Big Data, such as data from professional networking platforms, to better understand firm behaviors and identify new factors affecting financial reporting quality. Although concepts such as corporate social capital has long existed (Nahapiet and Ghoshal 1998), Big Data now enables large-scale measurement of such constructs. Our study has implications for managers, auditors, and regulators, as it suggests that encouraging internal employee connections and information sharing is an important factor in improving financial reporting quality.

Our research is not without caveats. Although LinkedIn connections represent meaningful ties, there remains some ambiguity regarding the extent to which they reflect the interconnectedness among employees within an organization. LinkedIn primarily facilitates connections with external stakeholders (e.g., for job seeking). We do not expect that employees would rely on it for robust internal connections, such as those stemming from shared projects and physical proximity, as explored by Sias and Cahill (1998) and Sias, Tsetsi, Woo, and Smith (2020), or from internal networks, as examined by Li and Sandino (2018). Given the challenge of directly observing these internal communication patterns for a large sample of firms, we use LinkedIn connections as an *indirect* measure of internal connectedness—an approximation of the “true” connections between coworkers. We think that this approximation is reasonable for the large public firms in our sample, as people are more likely to form online connections with those with whom they have already become familiar by other means (Singh, Hansen, and Podolny 2010). To the extent that the connections on LinkedIn do not, as we acknowledge, fully capture robust communications within a firm, this measure would have more noise and less power; for example, dormant LinkedIn connections may dilute its power. We therefore urge caution in interpreting our findings. We consider our study an initial step in exploring the impact of employee connections on accounting estimation and information quality. Given the rapid advances in people analytics and the widespread adoption of electronic systems, as noted by Leonardi and Contractor (2018), we eagerly anticipate research using improved methods for assessing corporate internal information environments and their impact on firm information quality.

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## APPENDIX A

## Definitions of Variables

Variable	Definition	Data Source
$ Discretionary\ accruals $	The absolute value of the residuals from the modified Jones model.	Compustat
$Ln(\#\ of\ internal\ connections)$	The natural logarithm of 1 plus the number of LinkedIn connections between employees of a firm, scaled by the number of LinkedIn users in that firm.	LinkedIn
$Ln(\#\ of\ LI\ users)$	The natural logarithm of 1 plus the number of LinkedIn users employed by the firm.	LinkedIn
$Ln(\#\ of\ emp)$	The natural logarithm of 1 plus the number of employees employed by the firm (EMP), measured in thousands.	Compustat
$Ln(assets)$	The natural logarithm of total assets (AT).	Compustat
Market-to-book ratio	The market value of the stock (MKVALT) divided by the book value of the common stock (CEQ).	Compustat
Leverage	The sum of long-term debt and long-term debt due in one year (DLTT + DD1), scaled by total assets (AT).	Compustat
Foreign	A dummy variable equal to 1 if the firm has a positive foreign exchange income (FCA).	Compustat
ROA	Return on assets, calculated as income before extraordinary items (IB) divided by total assets (AT).	Compustat
Market cap	The natural logarithm of the product of the closing stock price (PRCC_F) and the number of common shares outstanding (CSHO).	Compustat
Big4	A dummy variable equal to 1 if the firm's auditor is one of the Big 4 accounting firms.	Compustat
Loss	A dummy variable equal to 1 if the firm has a negative income before extraordinary items (IB).	Compustat
$Ln(\#\ of\ analysts\ following)$	The natural logarithm of 1 plus the number of analysts following the firm.	IBES
ICW	A dummy variable equal to 1 if the firm reports internal control weaknesses.	Audit Analytics
ICW_3year	A dummy variable equal to 1 if the firm reports internal control weaknesses in the current year or past two years.	Audit Analytics
$Ln(\#\ of\ internal\ accounting\ connections)$	The natural logarithm of 1 plus the number of LinkedIn connections between employees of a firm, where at least one employee is an accountant, scaled by the number of LinkedIn users in that firm.	LinkedIn
Top sales growth	A dummy variable equal to 1 if the firm's industry-adjusted sales growth is in the top quantile of all the sample firms in that year.	Compustat
Lagged IDD	A dummy variable equal to 1 if the inevitable disclosure doctrine (IDD) was recognized by the firm's headquarter state in year $t-3$ .	Gao, H. Zhang, and J. Zhang (2018)

## APPENDIX B

## Methods and Supplementary Information

## Additional Information about the LinkedIn Data

This project is part of the LinkedIn Economic Graph Research Program, in which LinkedIn partnered with academic researchers by providing data requested in researchers' proposals. Detailed information about this program can be found here: <https://engineering.linkedin.com/blog/2017/03/announcing-the-economic-graph-research-program>. The use of LinkedIn data in our research builds on the growing literature on the use and impact of social media in professional contexts. For instance, a recent study by Meluch and Kallis (2023) reveals that 77.5 percent of the people who use LinkedIn are connected to their coworkers on that platform. Research by Rajkumar, Saint-Jacques, Bojinov, Brynjolfsson, and Aral (2022) has demonstrated that LinkedIn connections, encompassing both strong and weak ties, can have tangible implications such as enhancing job mobility.

## Main Variables

Our primary dependent variable is accrual quality. We measure it as the absolute value of discretionary accruals, which are the residuals from the modified Jones model estimated at the industry-year level (Jones 1991; Dechow et al. 1995). We focus on discretionary accruals because they exhibit cross-sectional variation, are continuous, and are likely affected by employee actions, thus providing a robust setting to test our hypotheses (Armstrong et al. 2022). Discretionary accruals are negatively related to earnings persistence and positively related to restatements or other measures of low accounting quality (Jones et al. 2008). More specifically, we estimate the following model for each SIC two-digit industry; the residuals are *Discretionary Accruals*:

$$\frac{Accrual_{it}}{Assets_{i,t-1}} = \beta_1 + \beta_2 \frac{1}{Assets_{i,t-1}} + \beta_3 \frac{\Delta Rev_{it} - \Delta AR_{it}}{Assets_{i,t-1}} + \beta_4 \frac{PPE_{it}}{Assets_{i,t-1}}, \quad (S1)$$

where  $Accrual_{it}$  is the difference between income before extraordinary items and net cash flow from operating activities;  $\Delta Rev_{it}$  and  $\Delta AR_{it}$  measure changes in revenues and accounts receivable, respectively; and  $PPE_{it}$  is the gross value of plant, property, and equipment. All variables are scaled by lagged assets,  $Assets_{i,t-1}$ .

Our main independent variable is employee internal connections, which we measure using  $Ln(\# \text{ of internal connections})$ , the natural logarithm transformation of 1 plus the number of LinkedIn connections between employees of a given firm. We scale the number of connections by the number of LinkedIn users in the firm to minimize concerns that our findings are influenced by firm size or LinkedIn usage.

## Control Variables

We control for the following variables in testing our main hypothesis (Equation (1)): the number of employees ( $Ln(\# \text{ of emp})$ ), the number of employees with a LinkedIn profile ( $Ln(LI \text{ users})$ ), firm size ( $Ln(assets)$ ), *Market-to-book ratio*, *Leverage*, a dummy variable indicating whether the firm has foreign income (*Foreign*), *ROA*, market capitalization (*Market cap*), and dummy variables indicating whether the firm has experienced a loss in the past year (*Loss*) and whether its industry-adjusted sales growth is in the top quartile of all sample firms in that year (*Top sales growth*). We also control for external monitoring from auditors and analysts by including dummy variables indicating whether the firm is audited by one of the Big 4 accounting firms (*Big4*) and the number of analysts following the firm ( $Ln(\# \text{ of analysts following})$ ). To control for the quality of internal control systems, we include a dummy variable indicating whether the firm reported internal control weaknesses in the current year (*ICW*) or in the past three years (*ICW\_3year*). In most specifications, we include both firm and year fixed effects. Standard errors are double-clustered by firm and year. Detailed definitions and data sources for the variables can be found in Appendix A.

## An Instrumental-Variable Test

To reduce concerns about omitted variables, we use state-level differences in the recognition of the inevitable disclosure doctrine (IDD) as an instrumental variable for internal connections. We first discuss the suitability of our instrumental variable using the three criteria for the instrument variable: (1) the instrument has a causal effect on the X variable (i.e.,  $Ln(\# \text{ of internal connections})$  in our study); (2) the instrument affects the outcome variable Y

(continued on next page)

## APPENDIX B (continued)

(i.e.,  $|Discretionary\ accruals|$ ) through X ( $Ln(\# \text{ of internal connections})$ ); (3) there is no confounding effect of the instrument on Y ( $|Discretionary\ accruals|$ ). Criterion (1) relates to the relevance of the instrument, whereas (2) and (3) speak to the exclusivity of the instrument.

**Relevance**

The relevance criterion requires that the instrument has a causal effect on the X variable ( $Ln(\# \text{ of internal connections})$ ). IDD is a legal doctrine that permits companies (plaintiffs) in a trade secret case to establish “harm” against them by showing that a former employee’s new employment will inevitably lead them to rely on the plaintiff’s trade secrets (without having to show evidence of *actual* harm). States whose trade secret laws appeared to have adopted this doctrine (as shown in a federal court survey which examined court cases across states; *Phoseon Tech., Inc. v. Heathcote* 2019 WL 7282497) are recognizing and enforcing a *de facto* noncompetition agreement even when no explicit agreement exists. Research has shown that in such states, employees are less likely to leave their company and work for a potential competitor, which increases an average employee’s tenure at a given company headquartered in that state (Seaman 2015).

In our paper, we use this variation across states as an instrument to our X variable  $Ln(\# \text{ of internal connections})$  because the longer an employee stays at a company, the more connections they are likely to form within the company. To test this assumption, we empirically examine whether IDD adoption has a significant impact on employee internal connections on the LinkedIn platform. Following the approach of Gao et al. (2018), we use a dummy variable indicating whether the firm is headquartered in a state that adopted IDD. We use *Lagged IDD* from year  $t-3$ , not the contemporaneous IDD (i.e., whether the IDD was adopted in the current year). We elaborate on why *Lagged IDD* is preferable in our situation in the “*Exclusivity*” section below, although our results remain qualitatively similar if we use the contemporaneous IDD variable.

We regress internal connections ( $Ln(\# \text{ of internal connections})$ ) onto *Lagged IDD* and report first-stage results in Table B1, column (1). The first-stage regression has an F-statistic of 91.67, much higher than the common standard for the first-stage F-statistic  $\geq 10$  (Staiger and Stock 1997), empirically confirming a significantly positive relationship between lagged IDD and internal connectedness. This shows that lagged IDD satisfies the relevance criterion and could be a strong instrument for internal connections.

**TABLE B1**  
An Instrumental Variable Approach

	(1) <u><math>Ln(\# \text{ of internal connections})</math></u>	(2) <u><math> Discretionary\ accruals </math></u>
<i>Lagged IDD</i>	0.047*** (3.09)	
$Ln(\# \text{ of internal connections})$		-0.099* (-1.80)
$Ln(\# \text{ of LI users})$	0.414*** (20.33)	0.039 (1.73)
$Ln(\# \text{ of emp})$	-0.296*** (-9.23)	-0.013 (-0.81)
$Ln(\text{assets})$	-0.006 (-0.74)	-0.036*** (-7.92)
<i>Market-to-book ratio</i>	0.001* (1.78)	0.000 (1.24)
<i>Leverage</i>	-0.009 (-0.54)	0.039*** (3.09)
<i>Foreign</i>	-0.034** (-2.64)	-0.006 (-1.75)
<i>ROA</i>	0.018**	-0.150***

(continued on next page)

## APPENDIX B (continued)

TABLE B1 (continued)

	(1) <i>Ln(# of internal connections)</i>	(2) <i> Discretionary accruals </i>
<i>Market cap</i>	(2.38) 0.011 (1.32)	(-19.97) 0.017*** (4.61)
<i>ICW</i>	-0.079*** (-4.71)	0.073*** (6.17)
<i>Big4</i>	0.049*** (3.62)	-0.011*** (-3.18)
<i>Loss</i>	0.083*** (6.16)	-0.007 (-0.97)
<i>Ln(# of analysts following)</i>	0.013*** (4.91)	-0.004*** (-4.23)
Constant	-0.132 (-1.30)	
Industry FE	Yes	Yes
Firm FE		
Year FE	Yes	Yes
n	31,145	31,145
Adjusted R <sup>2</sup>	0.830	0.416
F-statistic	91.67	

\*\*\*, \*\*, \* Indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

Table B1 provides robustness tests for our main results. Columns (1) and (2) use an instrumental-variable approach. Column (1) is the first-stage regression using state-level IDD recognition status in year  $t-3$  to predict internal employee connections. Column (2) reports the second-stage results from regressing the absolute value of discretionary accruals onto the instrumented employee connections. Fama-French 30 industry fixed effects are included. Standard errors are double-clustered by firm and year. t-statistics are reported in parentheses.

Variables are defined in [Appendix A](#).

### Exclusivity

Exclusivity dictates that the instrument affects the outcome variable Y through the X variable and has no confounding effect on Y; in other words, the instrument (lagged IDD) affects the dependent variable (accrual quality) through X (internal connectedness) and only through X (internal connectedness). To the extent that the adoption of IDD affects firms' real performance, it may affect accrual quality via channels besides employee internal connections. To mitigate this concern, we adhere to the methodology in prior literature ([Custódio, Ferreira, and Matos 2019](#)) and use IDD adoption from year  $t-3$  (*Lagged IDD*) to reduce its potential contemporaneous impact on accrual quality and thus better satisfy the exclusivity criteria.

We report the results in [Table B1](#), columns (1) and (2). *Lagged IDD* increases employee internal connections, and employee internal connections instrumented by *Lagged IDD* are negatively associated with low accrual quality (i.e., positively associated with accrual quality). As there is limited within-state variation of IDD, we control for industry fixed effects in this model instead of firm fixed effects.