The Transfer of Corporate Disclosure Practices

Through Accounting Employee Movements

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ABSTRACT

We examine how individual accounting employee movements across firms impact the transfer of corporate disclosure practices. We employ a large dataset of employee movements across firms through employee disclosures sourced from a professional networking platform and apply GPT-4 to identify employees in accounting roles. We use narrative disclosures in 10-K filings to measure corporate disclosure practices, which offer rich and nuanced discretion within a disclosure. We first identify an increase in similarity between the qualitative disclosures of firms experiencing an employee movement relative to other firm pairs. This increase is observable for both rank-and-file and executive-level employees and varies in magnitude by employee tenure and the similarity of the old and new roles. Moreover, the increase in similarity is more substantial in firm pairs that are industry peers. In subsequent tests, we use a difference-in-differences design at the firm-year level to show that firms hiring employees with previous exposure to highly informative disclosures increase their disclosure informativeness. Collectively, we report evidence that individual accounting employees at all levels transfer disclosure practices across firms.

Keywords: accounting employees; disclosure preferences; GenAI; informativeness; labor market; qualitative disclosure; rank-and-file employees.

JEL Classification: J23, J24, J44, M41.

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I. INTRODUCTION

Corporate disclosures serve the purpose of conveying information about a firm to its stakeholders to reduce information asymmetries (Leuz & Verrecchia, 2000). Therefore, every disclosure decision contributes to understanding a firm's situation. Within an organization, various decision-makers have the capacity to influence the quality and extent of information disclosed. Prior research has established that managers exert a relevant influence on corporate disclosure decisions and other accounting outcomes (Bamber, Jiang, & Wang, 2010; Davis, Ge, Matsumoto, & Zhang, 2015; Dyreng, Hanlon, & Maydew, 2010; Ge, Matsumoto, & Zhang, 2011; Wells, 2020). More recent research shows that characteristics of accounting-related departments, such as the number of employees or year-to-year employee turnover, are significant determinants of the likelihood of restatements and material weaknesses, financial reporting quality, and tax outcomes (Chen, Cheng, Chow, & Liu, 2021; Dambra, Khavis, & Lin, 2021; Lee & Yu, 2021; Renschler, Ahn, Hoitash, & Hoitash, 2023; Armstrong, Kepler, Larcker, & Shi, 2024; Li & Zhou, 2024). These studies suggest that not only top management influences firm outcomes, but that the broader accounting workforce plays an economically important role too. However, it remains unclear whether these department characteristics reflect the incremental contribution of rank-and-file accounting individuals to corporate disclosures or firm-level investments in the accounting function that enable top executives to shape firm outcomes (e.g., through monitoring, reporting, or assurance).

To fill this void, we examine whether accounting employees possess individual disclosure preferences that they incorporate in their firms' disclosures. We define accounting employees' disclosure preferences as the subjective tendencies of members of the accounting function to structure or express information outputs for external stakeholders in one way or another. As such, we remain agnostic as to whether disclosure preferences reflect deliberate, explicit disclosure choices or unconscious, implicit differences in disclosure style.

We focus our analysis on changes in firms' textual disclosures made in the Management Discussion and Analysis (MD&A) of their 10-K filings following accounting employee movements. We focus on textual disclosures to utilize the discretion inherent to such qualitative contents as we argue that the disclosure preferences of rank-and-file employees may be relatively nuanced, which is why having a larger number of disclosure items (i.e., words and sentences) facilitates the identification of a measurable influence. We focus our analysis on the MD&A section as it consists primarily of qualitative information about a firm's operations, is one of the most individually shapeable sections of a firm's annual financial report, and serves as a decision-useful source of information for stakeholders (Clarkson, Kao, & Richardson, 1999).

We argue that individuals' disclosure preferences are not exogenously determined at the beginning of their careers but are shaped by their professional experiences. Therefore, we consider employees' disclosure preferences to be a function of their employment history. In other words, if accounting employees develop individual preferences based on prior employment, they could be responsible for the transfer of disclosure practices when moving from one employer to another. Consequently, if accounting employees obtain individual disclosure preferences through experience, move across firms, and incorporate their preferences into the subsequent employers' disclosures, we expect that corporate disclosures of the prior firm and the hiring firm converge after movements, relative to firms not exchanging employees and to periods prior to movements.

We begin our empirical analysis by employing a sample of firm-year pairs, which we build by linking every sample firm in a given year to all other sample firms in each of the three subsequent fiscal years. For each of the resulting firm-year pairs, we calculate the cosine similarity between the respective MD&A sections and measure changes in cosine similarity following the movement of an accounting employee from one firm to another. We

track employee movements across firms using data from a large professional social networking platform that allows its users to disclose their employment history. To identify positions held in the accounting functions of our sample firms, we use GPT-4, equipped with information about the respective types of jobs, to classify job positions. If employees are able to incorporate disclosure practices acquired at the previous employer in the hiring firm, we expect higher similarity scores for firm-year pairs that reflect a recent accounting employee movement. Our empirical strategy effectively captures the incremental effect of accounting employee movements on firm-year pairs' MD&A similarities.

We find a significantly positive effect of accounting employee movements on the similarity between the hiring and the departed firms' MD&A sections in the three years following the movement. Specifically, the magnitude corresponds to an average similarity increase of 12.94 % to 13.23 % of one standard deviation of the cosine similarity, relative to firm-year pairs without employee movements in the same period. This finding persists across different fixed effect structures and after controlling for observable differences between firm-year pairs. Furthermore, when disaggregating the treatment variable and considering each of the three subsequent years individually, we observe that the effect is concentrated in the second and third year following the movement, consistent with individuals requiring time to familiarize themselves with the new job before materially influencing their new employers' disclosures. To mitigate concerns that our results are attributable to differences between pairs that exchange accounting employees at any time versus those that do not, we further restrict our model to firm pairs that ever exchange an employee throughout the sample period and find similar coefficient estimates. In additional tests, we find that the effect of accounting employee movements on firm pairs' cosine similarities is concentrated in movements across peer firms. Collectively, these results align with employee movements facilitating the transfer of corporate disclosure practices across firms through the labor market.

Next, we focus on employee attributes that could affect their ability to incorporate preferences into their employers' disclosures. Specifically, we examine whether and how the implications of accounting employee movements depend on (1) moving employees' seniority and tenure and (2) the similarity between moving employees' previous and current roles within the accounting function. First, we differentiate movements by the accounting employees' seniority and tenure. We expect that employees with more work experience and in more senior positions exert a stronger influence on disclosure practices than lower-ranked employees. We find that non-executive employee movements positively affect the cosine similarity between the former and current employer, consistent with rank-and-file employees shaping disclosure outcomes. As anticipated, movements of accounting employees at the executive level exert a stronger impact on disclosure similarities, reflecting their greater weight in disclosure decisions. Moreover, we observe a more pronounced response to movements of employees with longer tenure before the movement. Both models suggest that employees at all stages can determine disclosure outcomes, although employees in more senior roles and with more experience exert a stronger influence on disclosure practices than rank-and-file and less experienced employees.

Second, we examine how the similarity of roles before and after transitioning affects the transfer of disclosure practices. We expect that employees moving into a similar job will have a more considerable impact on the hiring firm's disclosure than those changing their role, as the former are likely to possess stronger preferences. Consistently, our findings show that the increase in disclosure similarity associated with accounting employee movements is almost three times larger for movements into very similar positions relative to movements into very dissimilar positions. This finding is consistent with employees having a larger impact when they can apply more of their existing experiences and skills after a movement.

In additional analyses, we investigate whether the observed transfer of disclosure practices extends to the informativeness of corporate disclosures. Specifically, we focus on four attributes that indicate the amount of incremental and relevant information contained in a disclosure: the number of boilerplate sentences, readability, the stickiness of disclosures over time, and the uniqueness of a filing compared to other filings in the same year. We use a difference-in-differences design at the firm-year level to examine changes in disclosure informativeness when a firm hires an accounting employee from a firm that produces disclosures with high (low) informativeness. We find that the use of boilerplate language and sticky disclosures decreases, and that of unique language increases when firms hire employees from high-quality disclosers. However, we do not observe a significant change in readability and find no equivalent reactions to hiring from low-quality disclosers. This is consistent with a transfer of disclosure preferences associated with highly informative disclosures but not with lowly informative disclosures.

Our study contributes to the literature in several ways. First, we contribute to research examining the impact of the workforce on firms' accounting outcomes. Prior studies show that accounting department characteristics, including department size and composition (Chen, Cheng, Chow, & Liu, 2021; Dambra, Khavis, & Lin, 2021; Lee & Yu, 2021; Renschler, Ahn, Hoitash, & Hoitash, 2023), internal connectedness (Li & Zhou, 2024), and employee incentivization (Armstrong, Kepler, Larcker, & Shi, 2024; Call, Kedia, & Rajgopal, 2016) affect financial reporting. However, these studies focus on the overall relevance of the accounting function rather than individual contributions. One notable exception is Barrios & Gallemore (2024), who examine how hiring tax employees from tax-aggressive firms affects firms' tax planning activities. In contrast, our study broadens the scope by analyzing the entire accounting function and focusing on qualitative financial reporting outcomes, where the implications of individual disclosure preferences may not be directly observable or

controllable by the employee. In other words, our study relates more to subjective communication styles and implicit disclosure preferences than to a specific employee skill set used to optimize key performance indicators through instruction or incentivization.

Second, we contribute to research on individuals' roles in corporate disclosures, particularly qualitative ones. While some studies focus on executive-level employees' influence on financial reporting outcomes (Bamber, Jiang, & Wang, 2010; Wells, 2020; Davis, Ge, Matsumoto, & Zhang, 2015), others approach the role of managers in determining disclosures implicitly by assuming certain textual features to be the result of executives' discretionary choices (Dyer, Lang, & Stice-Lawrence, 2017). Several auditor-related studies show that attributes of the audit committee can influence MD&A tone (Lee & Park, 2019) and that accruals and textual disclosures are more similar when firms share the same auditor (De Franco, Fogel-Yaari, & Li, 2020; Francis, Pinnuck, & Watanabe, 2014; Mauritz, Nienhaus, & Oehler, 2023), indicating that other groups also influence corporate disclosures through specific styles. We extend this literature by examining individual rank-and-file employees, an understudied group in the context of corporate disclosure determinants.

Third, by showing that non-executive employee movements explain variation in firm disclosures, our findings are relevant to managers, investors, and other stakeholders interested in corporate disclosures. Given that the MD&A informs decision-making (Clarkson, Kao, & Richardson, 1999), our research highlights that top managers do not exclusively shape the presented information. Instead, the experience of rank-and-file employees contributes to the informativeness of qualitative disclosures as well. Our findings highlight the need for managers to incorporate individual employees' characteristics when entrusting them with specific disclosure preparation tasks. For investors and other stakeholders, our results highlight that the MD&A is not the exclusive product of top management's assessment of firm performance but the product of many individual preferences.

II. THEORY

Managerial Disclosure Preferences

Prior research provides largely consistent evidence that managerial preferences affect corporate behavior and disclosure outcomes. For instance, Bertrand & Schoar (2003) use a research design involving manager fixed effects to explicitly capture individual managerial styles and find that chief executive officers (CEOs) and other top executives (such as the chief financial officer (CFO)) incrementally explain firms' investing and financing behavior. Fee, Hadlock, & Pierce (2013), however, find that this effect does not persist when focusing on exogenous CEO departures through death, health issues, or retirement and conclude that significant manager fixed effects reflect endogenous choices by the firm. Dyreng, Hanlon, & Maydew (2010) add to this literature by showing that individual executives affect corporate tax outcomes. Turning the focus to corporate disclosures, Bamber, Jiang, & Wang (2010) show that top managers influence multiple aspects of management forecasts, consistent with manager-specific disclosure styles. More recently, Wells (2020) offers broader evidence that individual top executives influence their firms' accruals quality, further supporting the idea that managers set a "tone at the top" for accounting outcomes. Other studies show that individual managers and their characteristics explain accounting choices (Ge, Matsumoto, & Zhang, 2011; DeJong & Ling, 2013).

Relatedly, Davis, Ge, Matsumoto, & Zhang (2015) analyze whether optimism in conference calls related to earnings announcements is manager-specific and find a substantial manager-specific component in conference call tone. While this finding does not necessarily reflect CEOs' deliberate or strategic choice to steer external perceptions of firm performance, it demonstrates how individual styles shape corporate disclosures. Other recent studies examine the consequences of appointing a chief accounting officer (CAO) and find that having an executive accountant improves financial reporting quality (Mitsuda, 2020; Rhodes

& Russomanno, 2021; Chen, He, & Plumlee, 2023), emphasizing the relevance of top managers for accounting outcomes. In sum, these studies are consistent with upper echelons theory (Hambrick & Mason, 1984; Hambrick, 2007), which predicts that managers' individual experiences, values, and personality traits shape their preferences, resulting in manager-specific organizational outcomes, including disclosures of a particular style.

Other studies focusing on managerial disclosure styles place lower weight on measuring the idiosyncratic influence of individual managers through specific empirical strategies. Instead, these studies build their theoretical predictions on managerial discretion that results in observable disclosure practices, such as features of qualitative disclosures (Dyer, Lang, & Stice-Lawrence, 2017). For instance, Li (2008) argues that managers have incentives to obscure disclosures when their firm performs more poorly and finds that current earnings are positively related to 10-K and, in particular, MD&A readability and that firms with more readable disclosures have more persistent earnings. He controls for potential non-strategic determinants of readability but does not explicitly tailor the analysis to capture the effect of individuals on firm performance. Davis & Tama-Sweet (2012) compare managerial optimism in earnings press releases versus MD&A disclosures and find that press releases are more optimistic than the MD&A and that this relationship depends on the extent of strategic reporting incentives (e.g., when earnings forecasts are met or beat). Relatedly, Huang, Teoh, & Zhang (2014) examine tone management in earnings press releases, arguing and finding evidence consistent with managers strategically altering the tone of their disclosures to obfuscate negative financial performance. D'Augusta & DeAngelis (2020) show that the relationship between MD&A disclosure tone and earnings performance depends on earnings expectations, providing further evidence for managerial opportunism in MD&A disclosures.

Other studies capture managerial disclosure choices using disclosure features such as year-to-year disclosure changes (Brown & Tucker, 2011), the use of boilerplate language

(Lang & Stice-Lawrence, 2015), repetitious disclosure within 10-K filings (Cazier & Pfeiffer, 2017), and concurrent disclosure about unrelated events (Rawson, Twedt, & Watkins, 2023). While their findings generally differ based on the research objective, one common feature of these studies is that they demonstrate how disclosures attributed to a small group of individuals (such as top managers) are *strategically* related to other firm outcomes, indicating managerial exploitation of discretion. These studies assume that managers are responsible for "their" firms' disclosure decisions by (a) actively shaping a disclosure or (b) communicating specific expectations for the disclosure by establishing a "tone at the top."

Non-Executive Employees and Accounting Outcomes

A growing body of literature examines the role of the accounting workforce in jointly determining accounting outcomes. Much of this research focuses on the relationship between characteristics of the entire workforce or (parts of) the accounting function and specific features of their firms' financial statements. For example, rank-and-file employees can impact financial reporting quality by using their oversight function to detect corporate fraud (Dyck, Morse, & Zingales, 2010) or reduce the likelihood of annual report restatements (Lee & Yu, 2021) and material weaknesses (Renschler, Ahn, Hoitash, & Hoitash, 2023; Dambra, Khavis, & Lin, 2021). Call, Campbell, Dhaliwal, & Moon (2017) show that a higher-quality workforce, measured using the average educational level in a metropolitan statistical area, is associated with higher accruals quality, fewer internal control weaknesses, and fewer restatements. Jollineau, Vance, & Webb (2012) provide experimental evidence that subordinates can limit managerial opportunism in biasing financial reports. In contrast, Call, Kedia, & Rajgopal (2016) find that granting stock options to rank-and-file employees disincentivizes them from whistleblowing corporate fraud. In a tax-specific setting, Chen, Cheng, Chow, & Liu (2021) show that the size and composition of the tax department are

associated with tax planning and tax risk, and Jiang, Robinson, & Wang (2020) find that firms hiring former IRS employees report lower tax rate volatility and fewer penalties.

These studies show that specific features of the (accounting) workforce determine accounting outcomes. However, they do not attribute these outcomes to individual rank-and-file employees and their individual preferences. One notable exception to these department-oriented studies is the work of Barrios & Gallemore (2024), who examine how individual tax employee movements across firms affect their new employers' tax planning depending on the prior employers' tax outcomes. Their findings are consistent with tax employees obtaining specific tax planning knowledge and being responsible for the diffusion of such knowledge across firms by changing employers. However, it is unclear ex-ante whether the knowledge diffusion channel also extends to broader disclosure strategies. Specifically, the diffusion of tax planning knowledge only requires an employee to possess knowledge about specific strategies and suggest them to their new employer, leaving the firm's managers with the decision to implement the strategy. Therefore, the transfer of tax planning knowledge does not necessarily imply that the employees' individual and subjective preferences induce the shift in tax outcomes. Our study, instead, focuses on individual disclosure preferences as we examine individuals' direct contributions to corporate disclosures in a setting that offers substantial discretion for multiple agents, i.e., qualitative disclosures.

Hypothesis Development

The literature outlined above suggests a prominent role of the labor force in determining their firm's accounting outcomes. However, this evidence is limited mainly to the role of (1) high-level individuals such as CEOs, CFOs, and CAOs, and (2) the availability of a group of individuals, such as the workforce or the accounting function. These studies do not answer the relevance of individuals in non-executive positions ("rank-and-file employees") for observable disclosure outcomes. We argue that if managers influence

accounting outcomes primarily through strategic trend-setting decisions and their tone at the top but not through specific operational actions, rank-and-file employees gain discretion about task execution. For instance, if a CFO sets disclosure transparency and informativeness as a general principle instead of preparing such disclosures themselves, the individuals responsible for realizing said goal can act more independently as they gain individual decision-making authority.

Considering that top managers' role arguably relates more to oversight, guideline-setting, and broader decision-making rather than to the execution of single tasks (such as the formulation of financial statements) and assuming that subordinate-level employees have beliefs, values, and experiences of similar strength as top executives, discretion in disclosure decisions allows rank-and-file employees to incorporate individual preferences. The degree to which such discretion translates into observable changes in disclosure depends on the number of available levers. For instance, the decision to issue management guidance is a binary choice to increase the amount of voluntary disclosure, whereas the granularity and presentation format of qualitative disclosures reflect a large, discrete number of alternatives to choose from. We argue that the disclosure preferences of an individual (esp. of lower rank) are more likely to manifest when the number of options to choose from is larger. In other words, we expect that individuals in subordinate positions are more likely to contribute to elements of a disclosure package incrementally, whereas managers are more likely to choose binary disclosure outcomes themselves as parts of their strategic considerations. Consequently, we focus on the role of individuals in preparing textual disclosures, which involves an indefinite number of alternatives, i.e., different contents, phrases, and words, and therefore offers considerable potential for discretion to incorporate disclosure preferences.

However, it is also possible that rank-and-file individuals cannot exercise discretion over corporate disclosure outcomes. First, when the number of alternatives to choose from is

sufficiently large, the relative relevance of a single lever declines. For instance, the statistical and economic significance of changing only a single word in a longer discussion is possibly imperceptible. Therefore, even if employees exercise discretion to incorporate their disclosure preferences, the amount of individual disclosure amendments must be sufficiently large. Second, to the extent that employees are obliged to follow specific guidelines and rely on existing resources, their discretion is limited. Thus, firm-specific factors (e.g., disclosure policies or reviewing procedures) could diminish individuals' ability to incorporate individual preferences. In sum, whether individual employees are an observable determinant of corporate disclosure outcomes remains an open empirical question.

Extending Hambrick & Mason's (1984) upper echelons theory to any individual in a firm, we conjecture that rank-and-file accounting employees' disclosure preferences are a function of various personal traits, including experiences, norms, and values. Although many of these features are unobservable, we expect an employee's previous job(s) to be a central determinant of these preferences. Specifically, we expect individuals to assimilate the disclosure practices prevailing at the firms they work for and (at least partly) retain them when switching to another firm. In other words, we expect employees' individual preferences to be shaped by their employment history. Consequently, accounting employee movements from one firm to another result in transfers of disclosure practices across firms. Therefore, we state the following hypothesis:

H 1: The similarity of two firms' disclosures changes when accounting employees move from one firm to another.

III. METHODOLOGY AND DATA

Sample

Our analysis relies on three types of data: (1) financial statement data from Compustat North America; (2) text-based data (i.e., 10-K filings) from the SEC's EDGAR database; and

(3) data on accounting employee movements. We collect information about employee movements from resumes posted publicly on LinkedIn, a social network for professionals that allows its users to share information about their work experiences, educational background, and other attributes via their profiles. We begin our sample selection and data collection process by focusing on the set of companies listed in the S&P 500 between 1996 and 2021 with an official company page on the social networking platform. We restrict our analysis to S&P 500 firms due to the trade-off between financial data availability and employee data collection efforts. We also require an official company page on LinkedIn to facilitate identifying and matching employees with their employers. This procedure yields a set of 830 possible firms to include in our sample.

We further restrict our sample to firm-years between 2002 and 2021. Next, we retrieve all available 10-K filings of these firms from the SEC's EDGAR database to extract Item 7, the MD&A, from each 10-K filing. We require every MD&A section to have a minimum length of 500 words to ensure that (1) our analysis is not biased by fragmented or unreadable 10-K filings and (2) the disclosures under examination contain enough words to assume a meaningful discussion of relevant matters. We successfully obtain MD&A sections of 10,264 firm-years. Moreover, we require sufficient data availability to construct all relevant variables. Finally, we require firms to hire an accounting employee at least once during our sample period because firms that do not hire accounting employees could systematically differ from firms that do. Our final sample comprises 8,798 firm-years. The number of firm-years available in each year of our sample period is displayed in Table 1.

We build on this firm-year sample to construct a dataset of firm-year pairs by linking every firm in a given year with all other firm-years in the three fiscal years following the given year. Specifically, for any firm i operating in any year t, we create a discrete number of firm-year pairs by linking the firm-year to every other firm $j \neq i$ in the three subsequent years

t+1, *t+2*, and *t+3*, respectively. Thus, the total number of firm-year pairs for any firm *i* in year *t* is as follows:

$$Pairs_{it} = \sum_{j \neq i} \sum_{\tau=t+1}^{t+3} Firm_{j,\tau} \tag{1}$$

Assuming that any firm *i* with an available sample observation in year *t* will also appear in our sample in subsequent periods and taking into account that firms in the most recent years cannot be paired with other firms for each of the three roll-forward periods, the sample size *N* would be as follows:

$$\begin{aligned} \mathrm{N} = & \left(\sum_{t=2002}^{2018} n_t \times \sum_{\tau=t+1}^{t+3} (n_\tau - 1) \right) \\ & + \left(n_{2019} \times \sum_{\tau=2020}^{2021} (n_\tau - 1) \right) \\ & + n_{2020} \times (n_{2021} - 1) \end{aligned} \tag{2}$$

Here, n_t represents the number of firms *i* available in year *t*. Inserting the actual number of firm-years available in our sample and reported in Table 1 leaves us with 10,871,908 firm-year pairs. However, since not all firm-years are available every year of our sample period, we obtain a final sample size of 11,944,634 firm-year pairs.[1]

The design of this dataset follows the intuition that the last disclosure experienced by an accounting employee before a movement most closely resembles the employee's disclosure style. Specifically, the disclosure style of an accounting employee joining firm *i* from firm *j* during fiscal year *t+1* will be reflected the strongest in firm *i*'s disclosures for year *t*.[2] Moreover, if accounting employees transfer disclosure styles across firms, a movement in the months after the end of year *t* should only be able to shape their new employer's disclosures from year *t+1* onwards. Thus, in pairing firm-years across fiscal

[1] Mathematically, the larger factual sample size is due to the term "-1" becoming obsolete in cases where a firm that is available in one year is missing in subsequent period(s).

[2] This example assumes that both firms' fiscal years end on the same day. In our setting, we take into account the actual fiscal year ends as our dataset allows us to track accounting employee movements at the month level.

years, our research design reflects employee movements themselves, allowing for the identification of treatment firm-year pairs. We visualize the sample design in Figure 1.

Identification of Accounting Employee Movements

To obtain information on accounting employee movements, we search the social networking platform for user profiles that publicly report a movement from one sample firm to another and have held at least one position with a job title that broadly indicates involvement in the accounting function.[3] For each identified employee, we collect job titles, employer names, and start and end dates of each position reported in the employment history. We exclude work experiences where we cannot identify the employer or start/end dates.

Our identification of relevant accounting jobs involves two steps. First, we filter for positions held at any of our sample firms during the sample period. In matching job experiences to firms, we exploit hyperlinks embedded in user profiles that refer to the respective company websites on the social networking platform to ensure accuracy in our employee-employer matching. Second, we differentiate between accounting and non-accounting jobs using GPT-4, a large language model capable of processing large amounts of text inputs and generating matching outputs (OpenAI, 2023a). We use GPT-4 for job title classification due to its objectivity, replicability, and efficiency, which reduces researcher bias while maintaining high classification accuracy. Appendix A provides details on our utilization of GPT-4, including the prompt, model parameters, and a comparison of GPT-4 versus other classification techniques.

After identifying individuals employed in their firms' accounting functions, we select relevant accounting employee movements following Barrios & Gallemore (2024). Specifically, we focus on movements where the employee holds their respective pre- and post-movement position for at least twelve months and transitions within twelve months. We

[3] The broad terms we use for our initial search are "accounting," "accountant," "reporting", "tax," "treasury," "treasurer," "audit," "auditor," "controlling," controller," "cost," "payroll", "accounts payable," and "accounts receivable."

exclude movements where either position is an internship to ensure sufficient exposure to employer disclosures. This process results in 11,118 movements of accounting employees across 9,932 firm-year pairs.

We acknowledge that our sample cannot capture every relevant accounting employee movement as it is limited by employee coverage and their voluntary disclosure behavior on the social networking platform and by our identification of accounting jobs. However, any unobserved accounting employee movements (i.e., movements in the control group) would only bias our results downward as they contradict the magnitude of our coefficient estimates. Therefore, our findings are conservative estimates of the true relationship between accounting employee movements and disclosure similarities.

Figure 2 presents the 5 % most frequent movements of accounting employees by job title. As can be seen, many of the most frequent job titles include a version of the term "accountant." Other relevant accounting positions refer to operational tasks, audit and controlling jobs, and positions in the tax department. Moreover, we observe movements with and without promotion and across similar and dissimilar roles, illustrating the width of available career paths in accounting.

Empirical Strategy

We leverage the firm-year pair level of our data for a direct comparison of any two firms' disclosure practices. Specifically, we measure the degree of alignment between any two MD&A disclosures using the cosine similarity between these documents. The idea behind the cosine similarity is to translate a document, such as an individual MD&A section, into an *n*-dimensional vector representing the frequency of every word in the document and to compare this vector with that of another document. We follow Brown & Tucker (2011) and calculate the cosine similarity of two documents *i* and *j* as follows:

$$COS_SIM_{ij} = \frac{\vartheta_i \cdot \vartheta_j}{\|\vartheta_i\| \|\vartheta_j\|} \quad (3)$$

Here, ϑ_i and ϑ_j describe the *n*-dimensional vectors that represent two documents *i* and *j* as "bags of words" and $\|\vartheta_i\|$ and $\|\vartheta_j\|$ describe the lengths of the respective vectors. Therefore, the cosine similarity equals the dot product of both vectors divided by the product of the vector lengths. The measure is bound between zero and one such that higher values of cosine similarity represent more similar disclosures. We transform the raw document strings by deleting stopwords and stemming the remaining words before calculating the cosine similarities between any two MD&A sections using Equation (3). Moreover, instead of considering unigrams, i.e., vector elements being single words, we use word sequences of six adjacent words ("6-grams") to capture accounting employees' influence on disclosure formulations instead of mere wording choices.[4] In calculating each document vector, we multiply the frequency of every 6-gram by the inverse document frequency of the same 6-gram throughout the corpus of documents in the sample, thereby increasing the weight of less common phrases (Loughran & McDonald, 2016). The main advantage of this approach in our setting is that we emphasize the relevance of uncommon phrases, thereby aligning our measure more strongly to the idea of individuals transferring disclosure styles. After applying these steps and calculating the cosine similarity between every two documents in the corpus of MD&A sections, we multiply the variable by 100 for clarity. The resulting variable *COS_SIM* represents the cosine similarity between the MD&A sections disclosed by firm *i* in year *t* and by firm *j* in year $\tau = t+1, t+2, t+3$.

To test our predictions regarding disclosure strategy diffusion through employee movements, we employ an empirical design that exploits the firm-year pair-level dataset described above. Specifically, we create an indicator variable, *MOVEMENT*, that equals one if two firms *i* and *j* ever experience an accounting employee movement during our sample

[4] Our choice of word sequence dimensionality reflects a trade-off between measuring the formulation of single terms (e.g., unigrams and bigrams) and longer sentences (e.g., higher-order n-grams). In untabulated analyses, we find similar results to the ones displayed when using unigrams or 10-grams instead of 6-grams.

period, and zero otherwise. The indicator variable *TREAT* equals one if an accounting employee departs from firm *i* to join firm *j* in year *t+1*, such that year *t* is the last year the moving employee experiences at the former employer, and zero otherwise. Effectively, an employee exchange in year *t* sets *TREAT* to one for three observations (i.e., with $\tau = t+1$, $\tau = t+2$, and $\tau = t+3$). Since we pair every firm-year with all available firm-years in the three subsequent periods, *TREAT* effectively captures the effect of an accounting employee movement on the first three MD&A disclosures due after the movement. If individual accounting employees can influence the disclosure practices of their firms through disclosure styles, MD&A disclosures in future periods will resemble another firm's previous disclosures more strongly if an accounting employee joins the firm after being involved in the disclosure preparation of said prior disclosure, relative to other MD&A disclosures. Therefore, we test our main prediction using the following linear OLS regression model:

$$COS_SIM_{ij t\tau} = \beta_0 + \beta_1 \cdot MOVEMENT_{ij} + \beta_2 \cdot TREAT_{ijt} + \sum_{k=3}^{K} \beta_k \cdot Controls_{ijt\tau} \qquad (4)$$

We add a vector of covariates reflecting differences between any firm-years included in our sample that might affect the similarity of their disclosures. First, we include several continuous control variables, defined as the absolute difference between the two firm-years contained in a pair. Specifically, we include differences in the natural logarithms of total assets (*ASSETS*) and age (*AGE*), in the book-to-market ratio (*BTM*), in return on assets (*ROA*), in the ratio of long-term debt to total assets (*LEVERAGE*), in the relative sales growth from year *t-1* to *t* (*SALES_GROWTH*) and in research and development expenses scaled by total assets (*RND*) to capture dissents in disclosure practices attributable to differential size, profitability, the level of financial constraint, and the general business structure. Moreover, we include the difference in discretionary accruals, calculated following Jones (1991) and Dechow, Sloan, & Sweeney (1995), to control for differences in the degree of earnings management conducted by two firms (*DISC_ACCRUALS*) and control for differences in

disclosure length as proxied by the number of words contained in either MD&A section (*MDA_LENGTH*). We also account for variations in external oversight and market attention that may influence firms' disclosure practices using differences in institutional ownership (*IO*) and the number of analysts covering each firm (*ANALYST*). We winsorize these variables at the firm-year pair level at the 1st and 99th percentile.

Second, we use a set of indicator variables to substantiate our measurement of differences between firm-year pairs. We include an indicator variable equal to one if both firms were profitable or incurred an aggregate loss in the past two periods, and zero otherwise (*SAME_PL*). Also, we include an indicator variable equal to one, either if both firm-years in a pair or none of them reported merger and acquisition expenses (*SAME_MERGER*), and zero otherwise. To account for auditor-induced disclosure similarities (Francis, Pinnuck, & Watanabe, 2014; Mauritz, Nienhaus, & Oehler, 2023), we further include an indicator variable that is equal to if both firm-years share the same audit firm, and zero otherwise (*SAME_AUDITOR*). Moreover, we control for peer firm status by including an indicator variable equal to one if both firm-years in a pair belong to the same industry (classified using the Fama-French 17-industry classification), and zero otherwise (*SAME_FF17*). All variables are defined in Appendix B.

Given the firm-year pair structure of our sample, we expect that omitted (unobservable) variables beyond the described covariates influence our results along multiple dimensions. Therefore, we include several fixed effects to capture unwanted variation in the outcome variable of interest (i.e., disclosure similarity) across (1) departure years, (2) the number of roll-forward periods, and (3) prior firms and hiring firms. In constructing our fixed effects structure, we carefully evaluate the potentials and threats associated with their use for our analysis, e.g., related to correlated omitted variables versus inflation in the number of included regression parameters (Breuer & deHaan, 2024). We provide transparency over the

relevance of fixed effects for our main estimates by reporting a gradual forming of our fixed effects structure. We cluster standard errors by both firms in a pair to account for serial correlation across firm pairs.

Descriptive Statistics

We present descriptive statistics for our sample in Table 2. In Panel A, we show at the firm-year level the financial variables we use as covariates in our primary analysis. Consistent with the S&P 500 focus of our study, firms in our sample are relatively large and profitable and have little financial constraints and lengthy MD&A disclosures. In Panel B, we report all variables at the firm-year pair level. In our sample, the number of firm-year pairs exchanging an accounting employee during our sample period (*MOVEMENT*) comprises 2.37 % of all sample observations. Accordingly, the number of no-variation firm pairs (i.e., firm pairs that never experience a movement) concerning our main independent variable is relatively large in our sample. The number of firm-year pairs reflecting the timing of the movement (*TREAT*) is consistently lower, accounting for 0.23 % of all sample observations, or a total of 26,828 observations. This number is approximately three times larger than the raw number of movements reported above due to the structure of our firm-year pair dataset.[5] Notably, the number of firm-year pairs sharing their auditor or operating in the same industry is relatively high, as about 25.27 % of pairs share the same audit firm (*SAME_AUDITOR*), and 13.88 % of pairs are assigned to the same industry (*SAME_FF17*). When aggregating *SAME_AUDITOR* to a Big Four versus non-Big Four indicator variable in an untabulated test, we see that 97.83 % of observations share an auditor from the same status group.

In addition to these firm-oriented descriptive statistics, we report on important features of the accounting employees included in our analysis in Table 2, Panel C. We note that the

[5] The number of firm-year pairs where *TREAT* equals one underrepresents the hypothetical number of $3 \times 9{,}932 = 29{,}796$ firm-year pairs we would expect to obtain after extending the dataset to a three-year roll-forward period. The deviation is due to movements to firms that do not have three observable subsequent periods and to movements after 2018, which is the last year in which we could observe all three subsequent years at the moving employee's new employer.

variables are at the employee level in the first month of employment at the new employer, i.e., within twelve months after leaving the prior firm. As can be seen, our dataset captures the movements of accounting employees at different stages of their careers: While an accounting employee in the first quartile has 85 months of total job experience before joining their new employer, employees in the third quartile have 200 months of experience. We observe comparable variation with respect to employees' tenure in the position held before moving to the new firm: The average accounting employee in our sample spends almost 43 months in their most recent position at any of our sample firms before joining another sample firm, with a standard deviation of 36.29 months. Our sample mainly consists of movements of rank-and-file-employees, as only about 2.6 % of all movements reflect a movement of an employee holding a vice president or C-level position at either firm.

Regarding a potential change in the position being held, we compare the job titles held by each accounting employee before and after the movement. We find that about 8.1 % of movements are not associated with a change in the job title, which we interpret as consistent with these employees moving horizontally into similar positions as those they previously held. To allow for a more granular assessment of job title similarity, we approximate semantic differences in job titles using Jaccard Distances, which we calculate at the word level. The similarity between the two accounting job titles before and after movement averages at a balanced level of 50.7 % but with substantial variation, e.g., an interquartile range of 23.53 percentage points.

IV. RESULTS

Accounting Employee Movements and Disclosure Similarity

Table 3 reports the results from estimating Equation (4) in different settings. In Columns (1) and (2), we include the full sample of 11,944,634 firm-year pairs and consider every identified accounting employee movement with two different fixed effects structures

and the full set of covariates to mitigate concerns of omitted variable bias (Breuer & deHaan, 2024). Specifically, our fixed effects structure in Column (1) eliminates variation related to departure years and to either firm in a pair, whereas the structure in Column (2) isolates variation attributable to either firm-year in a pair. In both specifications, we find a significant and positive coefficient on our variable of interest, *TREAT*, indicating that an accounting employee movement from one firm to another is associated with a higher disclosure similarity. Notably, this pattern holds after controlling for differences between firm pairs that eventually exchange an accounting employee versus those that never do (*MOVEMENT*). We interpret the magnitude of *TREAT* in terms of the within-fixed effects standard deviation of the dependent variable (Mummolo & Peterson, 2018). Specifically, the coefficient estimates in Columns (1) and (2) indicate that an accounting employee movement increases *COS_SIM* by 13.23 % and 12.94 % of its (within-fixed effects) standard deviation, respectively, relative to non-exchanging firm-year pairs. We interpret this magnitude as economically important.[6]

Next, we re-estimate Column (2) but replace *TREAT* with three treatment indicator variables, i.e., one per time distance to departure year, allowing us to identify the treatment size over time. Thus, *TREAT1* (*TREAT2*) [*TREAT3*] indicates the first (second) [third] year after an accounting employee leaves one firm to join another, such that for any year *t* delineating the last fiscal year at the departed firm during which the respective employee participated in the preparation of the financial statements, the variable is equal to one in year *t+1* (*t+2*) [*t+3*] at the hiring firm. We further control for differences across distances-to-departure-year to allow for a better comparison of the annual treatment effects to *TREAT* in Column (2). We present the result from this re-estimation in Column (3). The treatment effect is the strongest in years two and three after the movement, consistent with a period of acclimatization and establishment at the new firm.

[6] In untabulated tests using firm-year pair fixed effects, we continue to find a significantly positive coefficient for *TREAT*, consistent with pair-specific differences not driving our findings.

To further corroborate our main findings, we limit our sample to firm pairs that ever exchange an accounting employee throughout our sample period (i.e., firm-year pairs where *MOVEMENT* equals one). This approach allows us to mitigate remaining concerns about bias related to systematic differences between firm pairs that exchange accounting employees at any time versus those that do not (i.e., no-variation fixed effects groups).[7] In Column (4), we demonstrate the result from this re-estimation in the specification employed in Column (2). The coefficient estimate for *TREAT* is comparable in significance and economic magnitude to our findings. Collectively, we interpret these findings as strong evidence for a positive relationship between accounting employee movements and MD&A disclosure similarities between former and current employers.

Peer Firms versus Non-Peer Firms

In addition to our primary analysis, we expect that moving accounting employees are more able to transfer their disclosure knowledge across firms when these firms are similar. Our main analysis controls for generally higher cosine similarities between firm pairs in the same industry. We extend Equation (4) by interacting *TREAT* and *SAME_FF17* to account for differences between same-industry versus across-industry movements.

We report the results in Table 4. Columns (1) and (2) use the same fixed effects structures as the respective columns of Table 3. In both specifications, we find a positive and significant coefficient only for the interaction term, i.e., for accounting employee movements across peer firms. This finding is consistent with the treatment effect being concentrated in movements of accounting employees across similar firms.

In Columns (3) and (4), we re-run the original empirical design established in Equation (4), including fixed effects for either firm-year in a pair, but separate the sample based on their status as same-industry versus different-industry pairs. We observe a positive

[7] Relatedly, limiting our sample to pairs for which we were able to identify accounting employee movements addresses concerns about bias stemming from incomplete identification of movements through the use of self-disclosed employee-level employment data.

and significant coefficient of *TREAT* in both specifications. However, using a Chi^2 test to assess the difference between the estimated coefficients of *TREAT* across both regressions, we see that the estimated coefficient is significantly larger in the peer firm subsample, consistent with the interaction terms estimated before. Overall, our finding is consistent with the similarity of prior and hiring firms being an important determinant of employees' ability to incorporate their individual disclosure preferences.

Employee Attributes

Seniority and Tenure

We expect that the extent to which accounting employees' disclosure preferences materialize in the hiring firm depends on the employees' attributes. In this section, we examine whether movements of accounting employees in more senior positions and with longer tenure result in stronger changes. We expect such a relationship because (1) individuals in higher positions are less likely to have their decisions overruled, making it more probable that their preferences manifest in the final disclosure, and (2) seniority and tenure reflect the individual's experience (Bochkay, Chychyla, & Nanda, 2019), which in turn affects the likelihood that a disclosure change induced by the employee prevails throughout the disclosure preparation process.

First, we differentiate between executive-level and non-executive-level movements. If an employee holds a job title indicating a senior management position at either firm (i.e., a C-level or vice-presidential role), we categorize the movement as executive. Thus, we extend Equation (4) by an interaction of *TREAT* with a splitting variable, *SV*, here representing whether a moving accounting employee holds an executive-level position at either position (*EXECUTIVE*). This amendment leads to the following regression equation, where the coefficient β_3 denotes the differential effect of executive movements relative to non-executive level movements:

$$COS_SIM_{ijt} = \beta_0 + \beta_1 \cdot MOVEMENT_{ij} + \beta_2 \cdot TREAT_{ijt} + \beta_3 \cdot TREAT \times SV_{ijt} + \sum_{k=4}^{K} \beta_k \cdot Controls_{ijt} \quad (5)$$

Second, we differentiate accounting employee movements by tenure. Specifically, we exploit moving accounting employees' work experience at the timing of the movement in months to portion movements into one out of five discrete tenure groups: (1) Zero to five years, (2) more than five to ten years, (3) more than ten to fifteen years, (4) more than fifteen years to twenty years, and (5) more than twenty years of experience.[8] In this setting, we split *TREAT* into five individual indicator variables, $TREAT_SV_1$ through $TREAT_SV_5$, resembling movements of accounting employees in the respective group of the splitting variable (*TENURE*). Thus, we modify regression Equation (4) as follows:

$$COS_SIM_{ijt} = \beta_0 + \beta_1 \cdot MOVEMENT_{ij} + \sum_{g=1}^{5} \beta_{g+1} \cdot TREAT_SV_{gijt} + \sum_{k=7}^{K} \beta_k \cdot Controls_{ijt} \quad (6)$$

We report the results of these regressions in Table 5. In Columns (1) and (2), our coefficient of interest, *TREAT* × *EXECUTIVE*, reports the extent to which executive-level accounting employees can affect disclosure similarities through movements relative to non-executive employees, whereas in Columns (3) and (4), we focus our interpretation on $TREAT_TENURE_1$ through $TREAT_TENURE_5$.

Non-executive employee movements significantly affect the cosine similarity between former and current employers' MD&A disclosures. In Column (2), the coefficient estimate translates into an average 11.26 % increase in cosine similarity of one standard deviation of

[8] If a firm-year pair is subject to more than one accounting employee movement, we use the average tenure of all moving accounting employees.

COS_SIM for firm-year pairs that exchange an accounting employee, relative to non-exchanging firm-year pairs. This is consistent with rank-and-file accounting employees being a relevant determinant of specific qualitative disclosure outcomes. However, executive-level movements exhibit approximately six times larger increases in cosine similarity (70.51 % of one standard deviation), reflecting higher-level employees' ability to incorporate disclosure preferences into their firms' disclosure practices.

Our results are consistent when differentiating employee movements by tenure. For instance, in Column (4), we observe consistently positive and significant coefficient estimates for tenure groups two to five, with progressively stronger magnitudes for movements of more experienced employees. This increase is statistically significant. We visualize the coefficient estimates in Figure 3, Panel A. We conclude that accounting employees in higher positions and with more experience can assert their disclosure preferences better than other accounting employees.

Shifts in Job Positions

We next examine how shifts in job responsibilities impact our main results. Specifically, if our main result reflects employees' individual disclosure preferences and their ability to integrate such preferences into their new employer's disclosure practices, we expect this effect to be concentrated in employee movements associated with little shifts in job responsibilities. This assumption follows the intuition that employees are most likely to have preferences in areas where they have more expertise. Therefore, if the employee's new job requires similar tasks, it is more likely that they will continue operating as they preferred doing at their prior firm. Moreover, if employees have disclosure preferences that they are willing to incorporate, they will presumably find it easier to fundamentally contribute to the new firm's disclosures if the new position resembles the old role more closely.

We repeat the framework established in Equations (5) and (6) to test the relevance of job position shifts. First, we create an indicator variable, *SAMETITLE*, that equals one if the moving employee holds the same title at both the new and the old firm, and zero otherwise.[9] Second, we establish a categorical measure to assess the relevance of job position switches. Specifically, we measure Jaccard Distances between job titles to proxy for job position similarity before and after hiring into a new firm. To facilitate our interpretation, we again replace our main variable of interest with five distinct indicator variables that reflect the degree to which a moving employee's job title changes relative to the last title held before the movement. $TREAT_TITLESIM_1$ to $TREAT_TITLESIM_5$ reflect quintiles of Jaccard Distances from low (i.e., very different job titles) to high (i.e., identical or very similar job titles).

Columns (5) to (8) of Table 5 present the corresponding results. We continue to observe a positive and significant treatment effect in Columns (5) and (6) for movements associated with a change in job titles. However, we fail to find a significantly different impact for movements involving the same job titles at both firms. However, Columns (7) and (8), as well as Figure 3, Panel B, show that the accounting employee movements lead to more similar disclosures when former and current job titles are more similar. In terms of economic magnitude, the coefficient estimates reported in Column (8) suggest an increase in cosine similarity of 5.63 % (22.38 %) of one standard deviation for very dissimilar (similar) job titles. Collectively, this finding reinforces our presumption that employees' ability to incorporate individual preferences in their new employers' disclosures is amplified when their new role reflects the previous position more strongly.

Firm-Specific Consequences

Our analyses thus far highlight the potential for employees to transfer corporate disclosure practices across firms through disclosure preferences. In this section, we examine

[9] When firm-year pairs experience more than one accounting employee movement, we only set *SAMETITLE* to one if all moving accounting employees retain their previous job title.

how accounting employee movements influence the informativeness of firms' qualitative disclosures. Specifically, we expect that if such movements are associated with a transfer of disclosure practices, firms will exhibit different disclosure characteristics after hiring, depending on the features of the prior firm's disclosures. Following this intuition, we assess whether employee hirings from firms with highly (lowly) informative disclosures are associated with more (less) informative disclosures at the hiring firm.

We focus on four distinct measures that capture the informativeness of the MD&A section of a firm-year's 10-K filing: (1) the use of boilerplate language, (2) readability, (3) stickiness, and (4) the uniqueness of a disclosure relative to other filings in the same year. By employing a difference-in-differences design following Barrios & Gallemore (2024), we estimate the change in disclosure informativeness following an accounting employee movement from a highly (lowly) informative discloser. Specifically, we expect that an accounting employee movement from firm i to firm $j \neq i$ in year t will result in more informative disclosures if firm j qualifies as a highly informative discloser in year *t-1* (i.e., the year before the movement), and vice versa. We use the following linear OLS model to implement this design:

$$INFORMATIVENESS_{it} = \beta_0 + \beta_1 \cdot TREATMENT_{it} + \beta_2 \cdot TREATMENT_{it} \times POST_{it} + \sum_{k=3}^{K} \beta_k \cdot Controls_{it} \quad (7)$$

In this model, *INFORMATIVENESS* refers to one of the four measures described above. First, we define *BOILER* as the proportion of words in the MD&A filing contained in sentences that include a boilerplate 6-gram, such that lower values indicate more individualized language (Lang & Stice-Lawrence, 2015). Second, *FOG* measures readability using the Gunning Fog index, where higher values denote lower readability (Li, 2008). Third, *STICKY* represents the cosine similarity between firm *i*'s MD&A filings in years *t* and *t-1*, where smaller values indicate less year-to-year repetition (Brown & Tucker, 2011). Finally,

CONFORM captures the mean cosine similarity between a firm's MD&A section and all other firms in the same year, with higher values indicating lower uniqueness.

TREATMENT is an indicator variable equal to one if a firm ever hires an accounting employee from a firm considered to be a highly (lowly) informative discloser in the year preceding the movement, and zero otherwise. We define prior firms as highly (lowly) informative disclosers if their MD&A filings in the year before the movement are in the top (bottom) two deciles of disclosure informativeness for the year. *POST* indicates years after the movement of an accounting employee, such that the interaction term captures the differential effect of firm-years hiring an accounting employee from a firm with highly (lowly) informative disclosures, relative to the pre-movement period and to firms not hiring such an employee. We omit the standalone term *POST* due to collinearity with year fixed effects. Furthermore, we control for industry-fixed effects and include a set of firm-year level covariates that account for size, profitability, financial reporting quality, and MD&A length, consistent with the main analysis.

We present the results from estimating Equation (7) in Table 6. Panel A reports firm responses to accounting employee hirings from firms with highly informative pre-movement disclosures (i.e., low boilerplate, low Fog index, low stickiness, and low conformity). As expected, we find significantly negative coefficients in three of the four specifications, indicating that hiring from firms with lower boilerplate, lower disclosure stickiness, and higher uniqueness results in more informative disclosures at the hiring firm. The magnitude of our estimates is economically relevant: For a sample firm with disclosure informativeness at the sample mean, hiring an employee from a highly informative discloser is associated with a decrease in boilerplate by 16.67 %, stickiness by 5.41 %, and conformity by 6.43 %. We do not observe a significant effect on readability. To address concerns about potential biases arising from the staggered timing of employee movements, we employ a stacked

difference-in-differences design following Cengiz, Dube, Lindner, & Zipperer (2019) and Barrios (2022). We report the results in Columns (5) and (8) of Panel A. Our findings are generally consistent with conventional difference-in-differences estimations but are weaker in two specifications.

In Panel B of Table 6, we replicate the analysis for movements from firms with low informativeness (i.e., high boilerplate, high Fog index, high stickiness, and high conformity). The results show no significant association between accounting employee hirings and the informativeness of hiring firms' disclosures for any of the four measures. Collectively, these findings suggest that accounting employees transfer disclosure practices associated with higher informativeness but do not with the transfer of less informative disclosure practices.

One assumption underlying the difference-in-differences design is that firms hiring an employee from a highly informative discloser would have followed a similar reporting trajectory as non-hiring firms absent the hiring. We examine this assumption by testing for parallel trends in disclosure behaviors before the movement. For this purpose, we amend Equation (7) by replacing the *POST* indicator with a vector of annual indicator variables relative to the year of the movement (years *t-4* through *t+3*, where *t* is the year of the movement). Figure 4 plots the coefficients for these annual interaction terms with 90% confidence intervals, using the year before the movement (i.e., *t-1*) as the baseline. None of the four specifications exhibits significant differences between treated and non-treated firms in the pre-movement period, supporting the validity of the parallel trends assumption.

An alternative explanation for our results is that accounting employee movements occur systematically based on the informativeness of the prior firm and the hiring firm, driven either by strategic hiring or job seeking. Therefore, we examine whether accounting employee movements follow specific patterns depending on both firms' disclosure practices. Figure 5 shows heat plots illustrating the frequency of accounting employee movements by

decile of each informativeness measure. We use the year before the accounting employee movement for both firms so that the implications of the movement itself are not depicted. The plots for each measure show relatively consistent movement patterns across all measures. We observe a concentration of departures from firms with medium informativeness (horizontal patterns). However, we do not find a similar pattern for movements into hiring firms (vertical patterns), indicating that pre-movement disclosure informativeness at the hiring firm does not affect movements. The corresponding correlation coefficients range between 1.39 % (*STICKY*) and 4.11 % (*CONFORM*), inconsistent with systematic movements across highly similar (antidiagonal patterns) or highly dissimilar (diagonal patterns) firms. We conclude that our sample does not appear susceptible to systematic movements based on the pre-movement disclosure features of the hiring firm.

V. CONCLUSION

We examine whether accounting employees incorporate their individual disclosure preferences in the preparation of firm filings. Combining financial statement data and textual data describing features of the MD&A with data on accounting employees, we investigate how employee movements affect firms' disclosures. Using a firm-year pair dataset, we find that accounting employee movements are associated with greater disclosure similarity, consistent with employees acquiring individual disclosure preferences through previous professional experiences. This finding holds across several sample specifications. Moreover, we find that the effect of accounting employee movements on MD&A similarity is concentrated in firm-year pairs that are relatively more similar, suggesting an interaction between employee-level preferences and company-level circumstances. We also examine how employee characteristics moderate the relationship between accounting employee movements and disclosure similarity. We find that both rank-and-file and higher-level employees shape disclosure outcomes and that the similarity increase associated with a

movement is stronger when the accounting employee is more experienced. Also, employees incorporate their disclosure preferences more strongly when their new role reflects the previous one more strongly, consistent with benefits from task-specific knowledge and skills.

In subsequent tests using a difference-in-differences design at the firm-year level, we find that firms hiring employees with previous exposure to highly informative disclosures (as indicated by boilerplate language, disclosure stickiness, and uniqueness) increase the informativeness of their disclosures. We do not observe a comparable pattern when examining the transferability of disclosure preferences coming from lowly informative disclosure environments. Collectively, our findings suggest that individual accounting employees are a relevant determinant of corporate disclosures.

We extend prior literature by showing that individual accounting employees can shape corporate disclosures. While prior research highlights the relevance of the accounting function overall (e.g., accounting department size), our findings indicate that firm-specific knowledge about disclosure practices transfers through labor market movements, facilitating the diffusion of disclosure styles across firms. Therefore, our results are relevant to academics, managers, and other stakeholder groups as we contribute to understanding how individuals within the firm shape their employers' financial reporting outcomes.

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APPENDIX

Appendix A: Classification of Accounting Jobs

Description of Classification Algorithm

In classifying individuals' self-disclosed job titles according to their belonging to the accounting function, we rely on computational power in the form of GPT-4, a transformer-based large language model capable of understanding user inputs and generating natural language text as a response (OpenAI, 2023a). For our analysis, we use GPT-4 Turbo, which is OpenAI's latest language model available at the time of our job title classification in December 2023 and is built on training data until April 2023 (OpenAI, 2023b), enabling the model to classify traditional job titles as well as contemporary ones.

Before prompting GPT-4 to classify job titles, we preprocess raw job titles to increase the uniformity of subsequent job title classifications. This step involves word capitalization, handling of special characters, standardization of common abbreviations (such as "Jr," "Sr," and "Mngr"), and deletion of company mentions. After preprocessing the job titles of all employee experiences accordingly, we create a list of unique job titles that we use as data basis for the classification algorithm.

For the classification of job titles, we develop a prompt giving the model additional information about the specifics of the accounting function. For this purpose, we subdivide the accounting function into six categories reflecting different types of job responsibilities. We label these categories (1) "Accounting and Financial Reporting," (2) "Controlling and Management Accounting," (3) "Tax Accounting," (4) "Treasury," (5) "Internal Audit and Revision," and (6) "Operational Accounting." We equip our prompt with broad information on each of these categories to improve the accuracy of GPT-4's classification. We also include a seventh category, "Finance," because GPT-4 tends to be less precise when faced with jobs related to investing and financing. The category "Other" captures all other jobs. For

our main analysis, we consider employees holding a position in their firm's respective accounting function if their reported job title is assigned to either of these accounting categories.

We iteratively prompt GPT-4 to classify a list of 25 distinct job titles into the most applicable of the eight categories listed above. We use more than one job title per request because we observed that the model tends to label job titles with greater precision when being given multiple elements to classify at once. However, we classify job titles in chunks of 25 job titles to avoid deterioration of classification accuracy due to GPT-4 "forgetting" the original task or category meanings. In prompting GPT-4 to categorize job titles, we set the "sampling temperature" parameter, which controls the randomness of generated outputs, of the model to zero to maximize consistency in GPT-4's generation of outputs.

Final Prompt

We iteratively run the following prompt through GPT-4's application programming interface, where we insert one chunk of 25 distinct job titles (separated by newline characters) per iteration within the braces in the second row of the prompt (*{title}*):

Here is a list of job titles:

<title>{title}
</title>

Which of the following job categories (irrespective of seniority) applies to each job title?
A. Accounting and Financial Reporting: Concerned with external reporting of their firm's financial performance in compliance with accounting standards. Prepare and analyze financial statements, such as the balance sheet, income statement, cash flow statement, and non-financial information, to communicate their firm's financial health to external stakeholders like investors, regulators, and creditors.
B. Controlling and Management Accounting: Focus on internal financial processes to assist in financial planning, budgeting, and controlling. They generate and analyze reports to provide insights into cost structures, budget variances, and overall performance for decision-makers within their firm.
C. Tax Accounting: Organize tax-related matters. Ensure compliance with tax regulations, prepare and calculate federal, state, and local taxes, and optimize their firm's overall tax positions through tax planning.

D. Treasury: Handle their firm's financial assets, liabilities, and liquidity. Oversee cash flows, investments, and debt to ensure that their firm has the necessary funds for its operations. Mitigate financial risks and ensure that their firm has the financial resources needed to operate efficiently.
E. Internal Audit and Revision: Evaluate and improve their firm's risk management and governance processes, primarily focusing on financial reporting. Provide oversight over their firm's accounting function by internally auditing financial and accounting procedures for compliance, mitigating fraud-related risks, and identifying areas for improvement concerning their firm's obligation to disclose accurate information.
F. Operational Accounting: Handle day-to-day financial activities within their firm, including bookkeeping, transaction processing, and maintaining accurate and timely records. Their work is essential for other accounting tasks as they provide the data foundation for many accounting analyses.
G. Finance: Responsible for their firm's investment and financing decisions, including capital acquisitions, M&A activities, and banking relationships. Not directly involved in the accounting function of their firm, but work closely with accounting colleagues and rely on their data outputs.
H. Other: All other jobs.

Please return the most applicable job category per job title in JSON format with the key "job_category" using the respective code for each job title (A-H). Please evaluate each job title diligently and independently.

GPT-4 Performance Relative to Manual Classification and Regular Expressions

In order to assess the quality of our job title classification algorithm, we extract a random subset of 500 job titles from the list of unique job titles and manually label each job title according to the category definitions also prompted to GPT-4. Specifically, two of the authors independently assign each title to one of the eight categories; when job titles were not classified equally by both authors, a third author made the final decision. We then use this pre-labeled subset to assess GPT-4's classification accuracy.[10] We also employ a set of regular expressions to compare the quality of GPT-4 to a more controlled job classification system relying on a list of keywords. We obtain the following results:

[10] For conciseness, we focus on the classification of accounting positions (i.e., categories A through F) versus non-accounting positions (i.e., categories G and H), but the relative quality of the different algorithms is similar when evaluating job title classifications at the more granular category level.

	True Positive	True Negative	False Positive	False Negative
GPT-4	159	308	25	8
Regular Expr.	69	324	9	98

Our manual classification assigns 167 job titles as belonging to the accounting function, whereas GPT-4 (the regular expressions algorithm) identifies 184 (78) accounting jobs. Considering the values above, we obtain an accuracy (i.e., percentage of correctly assigned values) of 93.40 % for GPT-4 and 78.60 % for regular expressions, a precision (i.e., the ratio of correctly predicted positives to total predicted positives) of 86.41 % for GPT-4 and 88.46 % for regular expressions, and a recall (i.e., the ratio of correctly predicted positives to true positives) of 95.21 % for GPT-4 and 41.32 % for regular expressions, we conclude that GPT-4 substantially outperforms the regular expressions algorithm (mostly due to its ability to identify true positives). Moreover, considering a baseline accuracy of 66.6 % when always selecting the most likely category (i.e., non-accounting), we evaluate our GPT-4-based classification algorithm as sufficiently precise to serve as a foundation for our analysis.

Appendix B: Variable Definitions

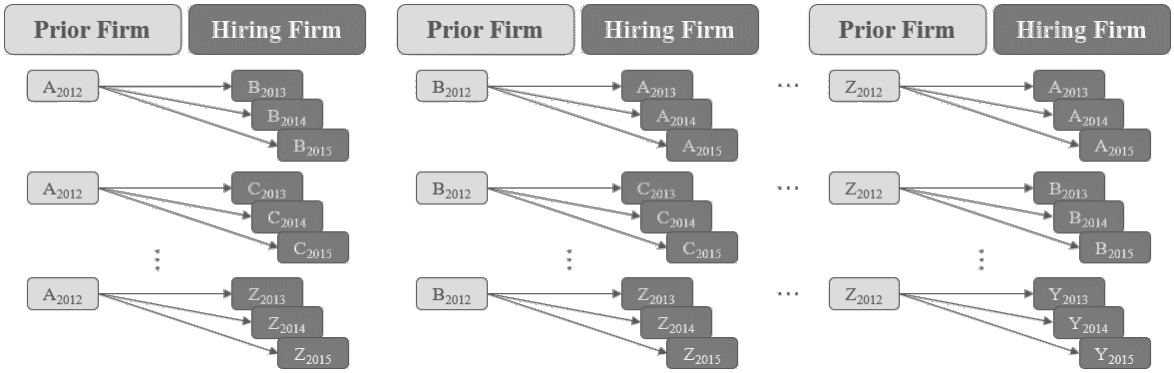
Variable Name	Variable Definition
Dependent Variables (Firm-Year Pair Analysis)	
COS_SIM	The cosine similarity of the MD&A sections of firm-years *i,t* and *j,τ*.
Dependent Variables (Firm-YearAnalysis)	
BOILER	The number of words in the MD&A of firm-year *i,t* from sentences containing at least one boilerplate phrases, divided by the number of words in the MD&A. Boilerplate phrases are 6-grams that occur in at least 60 % of all MD&A sections in the same year *t*, but not in more than 80 % of all documents because such phrases are likely to be innocuous grammatical phrases (Lang & Stice-Lawrence, 2015).
CONFORM	The mean cosine similarity between any firm-year *i,t* and all other sample observations available in year *t*, multipled by 100.
FOG	Gunning Fog index, calculated as the mean number of words per sentence plus the percentage of complex words in the document, multiplied by 0.4. Words are considered "complex" if they contain three or more syllables.
STICKY	The cosine similarity between the MD&A sections of firm *i* in year *t* and *t-1*, multipled by 100.
Main Variables	
MOVEMENT	An indicator variable equal to 1 if any employee movements occur between firms *i* and firm *j* throughout our sample period, and zero otherwise.
TREAT	An indicator variable equal to one in the three years $\tau = t+1$, $t+2$, and $t+3$, where *t* indicates the last year before an employee moves from firm *i* to firm *j*.
TREAT1 (*TREAT2*) [*TREAT3*]	An indicator variable equal to one in year $\tau = t+1$ ($t+2$) [$t+3$], where *t* indicates the last year before an employee moves from firm *i* to firm *j*.
Continuous Variables	
AGE	Firm-year: The natural logarithm of the distance between the current fiscal year (*t* for firm *i* and *τ* for firm *j*) and the respective firm's first financial year available in Compustat. Pair: The absolute difference between firm-years *i,t* and *j,τ*.
ANALYST	Firm-year: The number of analysts. Pair: The absolute difference between firm-years *i,t* and *j,τ*.
ASSETS	Firm-year: The natural logarithm of total assets. Pair: The absolute difference between firm-years *i,t* and *j,τ*.

BTM	Firm-year: The end-of-year book values of equity, divided by the end-of-year market value of equity. Pair: The absolute difference between firm-years *i,t* and *j,τ*.
DISC_ACCRUALS	Firm-year: The discretionary accruals of firm *i* [*j*] in year *t* [*τ*], calculated as per Jones (1991) in the modified version of Dechow et al. (1995). Pair: The absolute difference between firm-years *i,t* and *j,τ*.
IO	Firm-year: The end-of-year ratio of shares held by institutional owners to the number of total shares outstanding. Pair: The absolute difference between firm-years *i,t* and *j,τ*.
LEVERAGE	Firm-year: The reported long-term debt scaled by beginning-of-year total assets. Pair: The absolute difference between firm-years *i,t* and *j,τ*.
MDA_LENGTH	Firm-year: The number of words in the MD&A section of the 10-K filing. Pair: The absolute difference between firm-years *i,t* and *j,τ*.
RND	Firm-year: The research and development expenses scaled by beginning-of-year total assets. Research and development expenses are set to zero if missing. Pair: The absolute difference between firm-years *i,t* and *j,τ*.
ROA	Firm-year: The reported income before extraordinary items scaled by beginning-of-year total assets. Pair: The absolute difference between firm-years *i,t* and *j,τ*.
SALES_GROWTH	Firm-year: The percentage change in sales of firm *i* [*j*] from year *t-1* to *t* [*τ-1* to *τ*]. Pair: The absolute difference between firm-years *i,t* and *j,τ*.
Indicator Variables	
BIG4	Firm-year: Indicator variable equal to one if firm *i* is audited by Deloitte, Ernst & Young, KPMG, or PricewaterhouseCoopers in year *t*, and zero otherwise.
SAME_AUDITOR	Pair: An indicator variable equal to 1 if firm-years *i,t* and *j,τ* share the same audit firm, and 0 otherwise.
SAME_FF17	Pair: An indicator variable equal to 1 if firms *i* and *j* operate in the same industry as per the Fama-French 17 industry classification, which is based on SIC industry codes, and 0 otherwise.
SAME_MERGER	Firm-year: An indicator variable equal to 1 if firm *i* [*j*] reports non-zero acquisition expenses in year *t* or *t-1* [*τ* or *-1*], and 0 otherwise. Pair: The absolute difference between firm-years *i,t* and *j,τ*.
SAME_PL	Firm-year: An indicator variable equal to 1 if the sum of income before extraordinary items reported by firm *i* [*j*] in years *t* and *t-1* [*τ* and *τ-1*] is negative, and 0 otherwise. Pair: The absolute difference between firm-years *i,t* and *j,τ*.

Movement-Specific Heterogeneity	
EXECUTIVE	An indicator variable equal to one in the three years $\tau = t+1$, $t+2$, and $t+3$, where t indicates the last year before an employee in an executive-level position moves from firm i to firm j.
TREAT_TENURE	A set of five indicator variables $g = 1,\ldots,5$ equal to *TREAT* if the distance between the month of departure at the prior firm and the moving employee's start of the first reported job experience is in the range of zero to five years, more than five to ten years, more than ten to fifteen years, more than fifteen to twenty years, and more than twenty years, respectively, and zero otherwise.
SAMETITLE	An indicator variable equal to one in the three years $\tau = t+1$, $t+2$, and $t+3$, where t indicates the last year before an employee moves from firm i to firm j, retaining the same job title before and after the movement.
TREAT_TITLESIM	A set of five indicator variables $g = 1,\ldots,5$ equal to *TREAT* if the similarity of the job titles at the prior firm and the hiring firm is in the first, second, third, fourth, or fifth quintile, respectively, and zero otherwise.

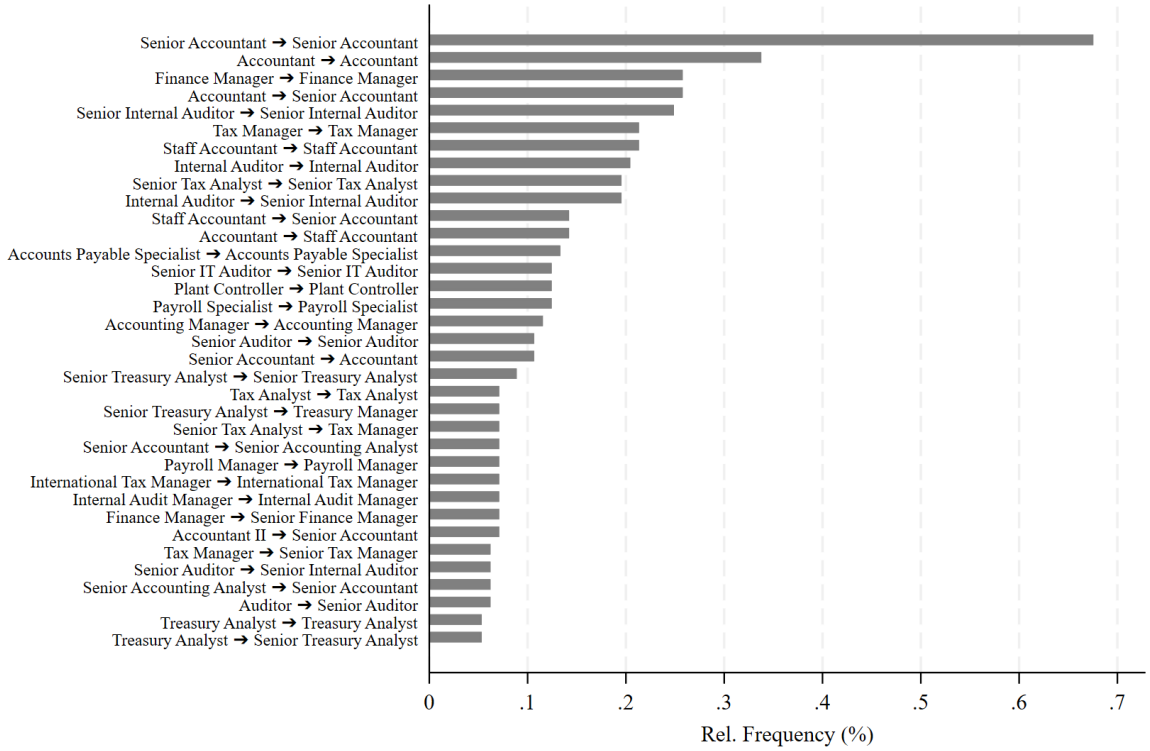
FIGURES AND TABLES

Figure 1: Sample Design



Notes: This figure visualizes our sample design for an exemplary fiscal year 2012. First, every hypothetical "prior firm" is paired with all other available firms in the sample in the subsequent three periods (i.e., 2013, 2014, and 2015). This approach is repeated for every other sample firm as another hypothetical "prior firm" in 2012. Thus, in each year of the sample period, every firm is paired with all other available firms in the three subsequent periods. To obtain our final sample, the same approach is repeated for all other departure years of the sample period.

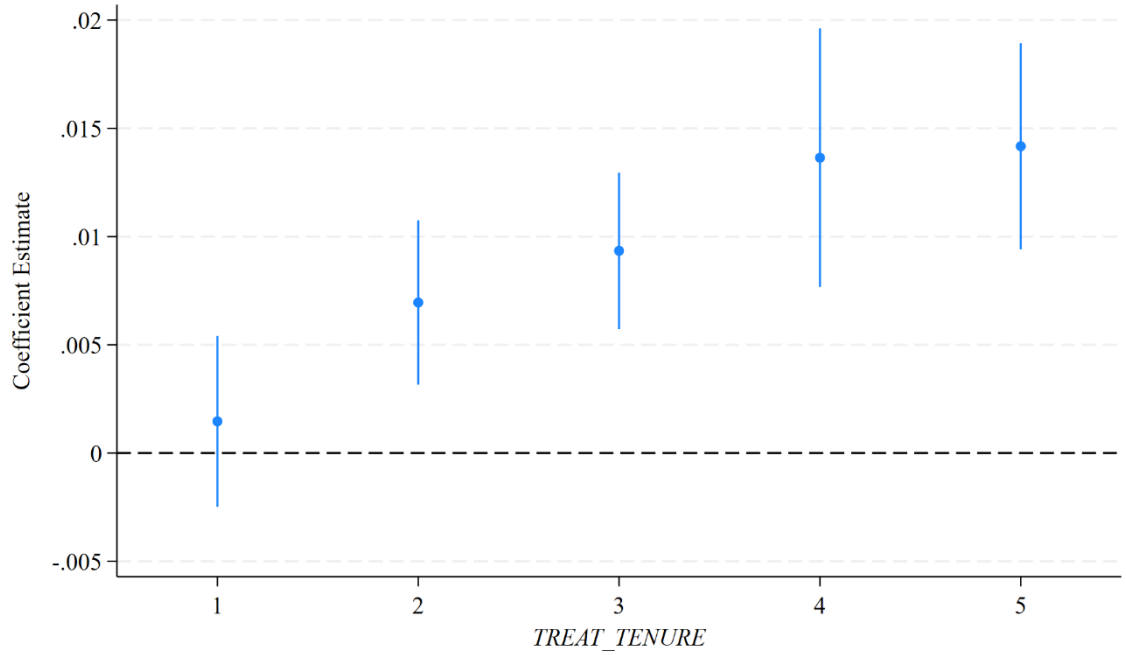
Figure 2: Most Frequent Accounting Employee Movements



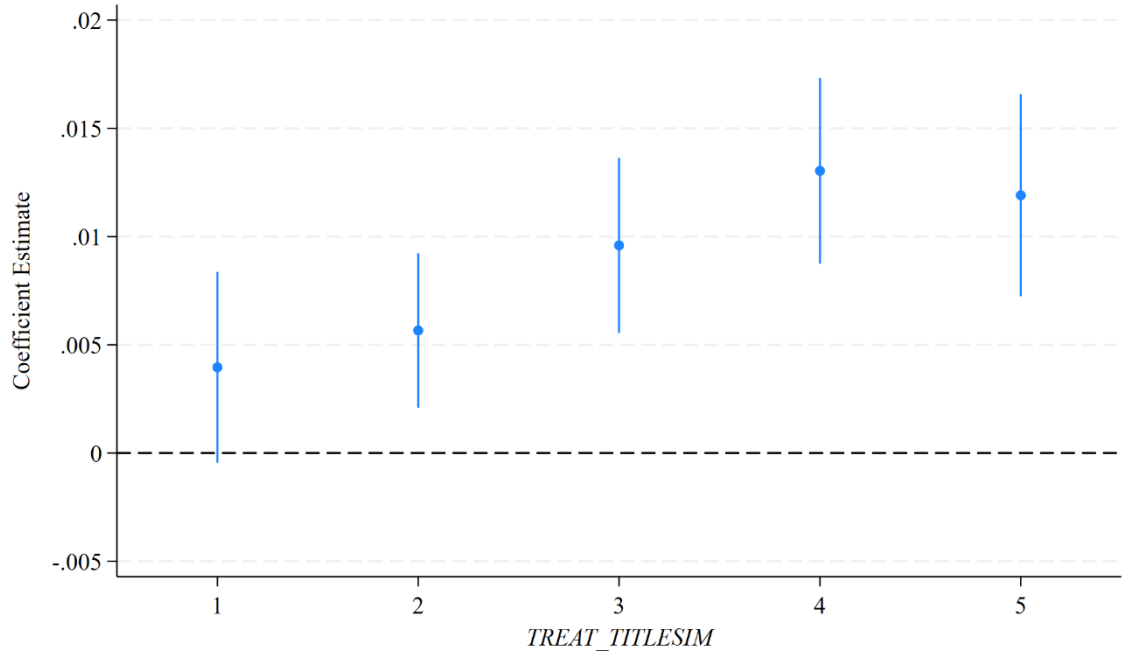
Notes: This figure summarizes the top 5 % most frequent movements of accounting jobs by job titles. While accounting positions are identified using the procedure described in Appendix A, we report non-standardized versions of the job titles.

Figure 3: Coefficient Magnitude by Tenure and Job Title Similarity

Panel A: Tenure

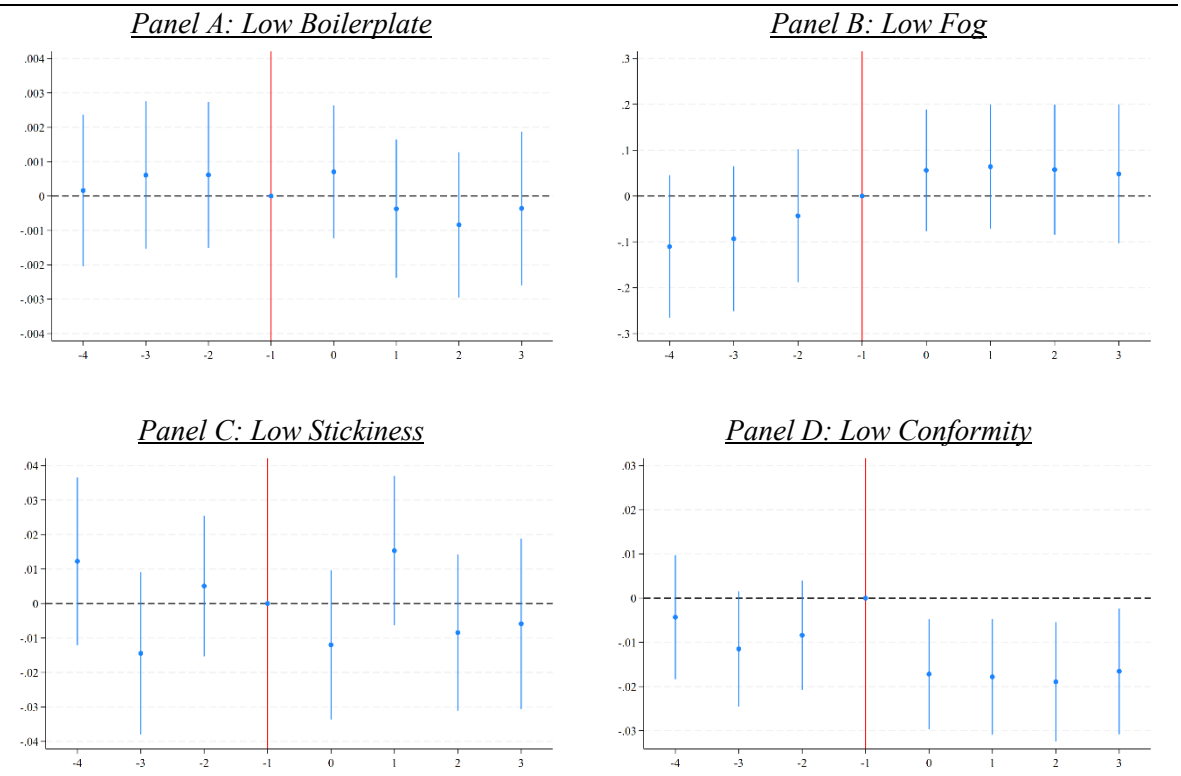


Panel B: Job Title Similarity



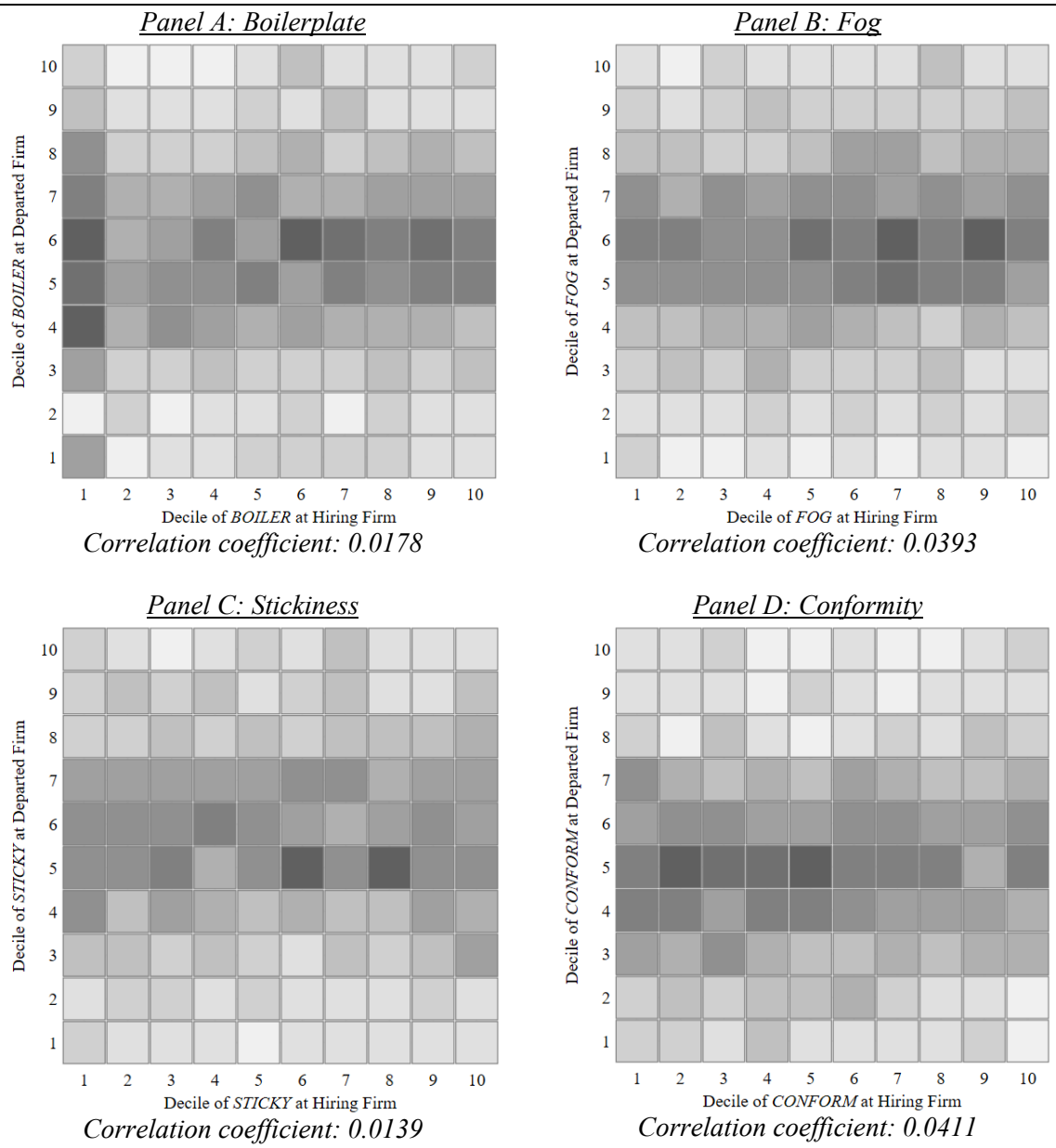
Notes: This figure presents the coefficient estimates for *TREAT_SV*$_1$ through *TREAT_SV*$_5$ tenure (Panel A) and job title similarity (Panel B), respectively. The blue lines represent point estimates with their corresponding 90% confidence intervals. The coefficient estimates are equivalent to those reported in Table 5, Columns (4) and (8), respectively.

Figure 4: Treatment Dynamics for Informativeness of Corporate Disclosures



Notes: This figure presents the treatment effects for different dimensions of corporate disclosures over time. The figure is divided into four panels, each focusing on a specific disclosure dimension. All dimensions are defined in Appendix B. The y-axis represents the effect sizes, while the x-axis represents time relative to the treatment event. The vertical red line indicates the treatment, and the blue lines represent point estimates with their corresponding 90% confidence intervals.

Figure 5: Movements by Level of Informativeness at Either Firm



Notes: This figure presents heatmaps depicting the movement of employees between firms, categorized by decile of informativeness in corporate disclosures at both the hiring and departed firms. The figure is divided into four panels, each corresponding to a specific dimension of disclosure informativeness: boilerplate, readability (using the Fog index), stickiness, and conformity.

Table 1: Sample Composition over Time

	# Firm-Years	# Firm-Year Pairs	# Movements
2002	301	409,539	117
2003	342	488,498	219
2004	387	565,155	307
2005	396	592,720	361
2006	422	627,345	445
2007	434	648,763	366
2008	445	659,498	269
2009	450	670,317	434
2010	450	684,807	558
2011	457	712,084	668
2012	463	739,449	724
2013	487	777,789	807
2014	495	785,498	1,026
2015	498	782,852	951
2016	496	767,680	953
2017	491	727,860	913
2018	490	685,799	886
2019	488	433,244	617
2020	423	185,737	497
2021	383	-	-
Total	8,798	11,944,634	11,118

Notes: This table presents the composition of our main sample per fiscal year. The first column reports the number of sample firms that meet our sample requirements in the respective year. The second column displays the number of firm-year pairs obtained by linking each firm in the respective year with every other firm observation in each of the three subsequent years. The sum of these firm-year pairs reflects our main sample. The actual values in this column deviate from the hypothetical value one would obtain when applying Equation (2) to the information in the first column because of firms with missing observations in individual years. The third column displays the number of movements per the last fiscal year a moving employee spent at their former employer.

Table 2: Summary Statistics

Panel A: Firm-Year Level Descriptive Statistics

	N	Mean	SD	P25	Median	P75
BOILER	8,798	0.018	0.018	0.005	0.012	0.024
FOG	8,798	19.185	1.332	18.297	19.157	20.050
STICKY	8,004	39.920	20.666	29.742	43.972	53.652
CONFORM	8,798	0.280	0.121	0.204	0.236	0.302
ASSETS	8,798	9.079	1.385	8.129	9.014	9.990
AGE	8,798	3.282	0.718	2.833	3.332	3.951
BTM	8,798	0.395	0.360	0.176	0.314	0.521
ROA	8,798	0.064	0.089	0.025	0.062	0.108
LEVERAGE	8,798	0.269	0.216	0.117	0.239	0.371
SALES_GROWTH	8,798	0.092	0.209	-0.003	0.068	0.157
RND	8,798	0.032	0.059	0.000	0.000	0.037
DISC_ACCRUALS	8,798	1.485	3.162	0.101	0.420	1.282
MDA_LENGTH	8,798	14745.848	7005.300	10054	13347.5	17754
ANALYST	8,798	19.430	9.389	13	18	25
IO	8,798	0.494	0.397	0.000	0.686	0.848
PL	8,798	0.119	0.324	0	0	0
MERGER	8,798	0.393	0.488	0	0	1
BIG4	8,798	0.989	0.103	1	1	1

Panel B: Firm-Year Pair Level Descriptive Statistics

	N	Mean	SD	P25	Median	P75
COS_SIM	11,944,634	0.043	0.076	0.007	0.020	0.046
MOVEMENT	11,944,634	0.024	0.152	0	0	0
TREAT	11,944,634	0.002	0.047	0	0	0
ASSETS	11,944,634	1.497	1.157	0.586	1.245	2.146
AGE	11,944,634	0.784	0.599	0.288	0.693	1.147
BTM	11,944,634	0.459	1.067	0.111	0.248	0.484
ROA	11,944,634	0.096	0.097	0.030	0.067	0.127
LEVERAGE	11,944,634	0.231	0.219	0.081	0.175	0.308
SALES_GROWTH	11,944,634	0.209	0.232	0.059	0.135	0.272
RND	11,944,634	0.050	0.074	0.000	0.021	0.069
DISC_ACCRUALS	11,944,634	2.323	4.536	0.215	0.718	2.380
MDA_LENGTH	11,944,634	7,495.153	7749.893	2,471	5,357	9,727
ANALYST	11,944,634	10.143	7.945	4	8	15
IO	11,944,634	0.198	0.256	0.015	0.103	0.243
SAME_PL	11,944,634	0.792	0.406	1	1	1
SAME_MERGER	11,944,634	0.579	0.494	0	1	1
SAME_AUDITOR	11,944,634	0.253	0.435	0	0	1
SAME_FF17	11,944,634	0.139	0.346	0	0	0

Panel C: Employee-Level Descriptive Statistics

	N	Mean	SD	P25	Median	P75
Total Tenure	11,118	152.652	93.122	85	135	200
Tenure at Prior Position	11,118	42.981	36.294	21	32	52
Executive-level Positions	11,118	0.026	0.158	0	0	0
Same Title	11,118	0.081	0.249	0	0	0
Jaccard Distance of Titles	11,118	0.507	0.196	0.373	0.476	0.608

Notes: This table provides descriptive statistics. Panel A provides descriptive statistics for the independent variables included in Equation (4) at the firm-year level. Panel B presents descriptive statistics for the dependent and independent variables included in Equation (4) at the firm-year pair level, where continuous variables are winsorized at the 1st and 99th percentile. Panel C describes relevant employee characteristics at the timing of the employee movement. All variables are as defined in Appendix B.

Table 3: Accounting Employee Movements and MD&A Disclosure Similarity

	Main Specification		*Annual*	*Restricted*
Dependent variable	*COS_SIM* (1)	*COS_SIM* (2)	*COS_SIM* (3)	*COS_SIM* (4)
MOVEMENT	0.0152***	0.0141***	0.0141***	
	(12.344)	(12.190)	(12.189)	
TREAT	**0.0094*** **	**0.0088*** **		**0.0067*** **
	(6.602)	**(6.324)**		**(5.448)**
TREAT1			**0.0076*** **	
			(4.344)	
TREAT2			**0.0095*** **	
			(5.959)	
TREAT3			**0.0095*** **	
			(5.000)	
ASSETS	-0.0016***	-0.0015***	-0.0015***	-0.0018**
	(-6.309)	(-5.943)	(-5.961)	(-1.982)
AGE	-0.0076***	-0.0079***	-0.0079***	-0.0071***
	(-9.426)	(-9.645)	(-9.652)	(-3.374)
BTM	-0.0002	-0.0027***	-0.0027***	-0.0084***
	(-0.476)	(-4.764)	(-4.662)	(-2.627)
ROA	0.0025	-0.0177***	-0.0177***	-0.0198
	(1.086)	(-6.102)	(-6.105)	(-1.598)
LEVERAGE	-0.0055***	-0.0101***	-0.0101***	-0.0218***
	(-5.029)	(-6.711)	(-6.723)	(-4.213)
SALES_GROWTH	-0.0017*	-0.0077***	-0.0070***	-0.0199***
	(-1.694)	(-7.112)	(-6.469)	(-5.931)
RND	-0.0845***	-0.1554***	-0.1555***	-0.2597***
	(-10.104)	(-11.620)	(-11.626)	(-7.069)
DISC_ACCRUALS	0.0001	-0.0005***	-0.0005***	-0.0006*
	(1.534)	(-6.172)	(-6.163)	(-1.909)
MDA_LENGTH	-0.0000***	-0.0000***	-0.0000***	-0.0000***
	(-5.126)	(-7.572)	(-7.577)	(-3.930)
ANALYST	-0.0001***	-0.0002***	-0.0002***	-0.0009***
	(-3.436)	(-6.320)	(-6.321)	(-5.581)
IO	-0.0023**	-0.0031***	-0.0031***	-0.0120**
	(-2.460)	(-4.053)	(-4.059)	(-2.495)
SAME_PL	0.0003	0.0029***	0.0029***	0.0053
	(0.404)	(3.340)	(3.342)	(1.017)
SAME_MERGER	0.0016***	0.0011***	0.0011***	0.0026**
	(6.104)	(6.488)	(6.548)	(2.576)
SAME_AUDITOR	0.0015***	0.0014***	0.0014***	0.0067***
	(6.725)	(6.293)	(6.294)	(3.637)
SAME_FF17	0.0146***	0.0131***	0.0132***	0.0327***
	(16.476)	(15.745)	(15.745)	(11.591)
Departure Year FE	Yes	No	No	No
Departed Firm FE	Yes	No	No	No
Hiring Firm FE	Yes	No	No	No
Departed Firm × Departure Year FE	No	Yes	Yes	Yes
Hiring Firm × Hiring Year FE	No	Yes	Yes	Yes
Departure Year × Hiring Year FE	No	No	Yes	No
Adjusted R^2	0.1300	0.2052	0.2081	0.2659
N	11,944,634	11,944,634	11,944,633	283,097

Notes: This table provides the results from estimating Equation (4). Columns (1) and (2) contain the main results on the full sample in different fixed effects specifications. In Column (3), we split the treatment indicator variable into three individual indicators to show the annual treatment effect. Column (4) reports the findings on a restricted sample of firm pairs that ever exchange an accounting employee (i.e., *MOVEMENT* = 1). We present t-statistics in parentheses. Standard errors are clustered by firm. *, **, and *** denote statistical significance at 10 percent, 5 percent, and 1 percent, respectively, based on two-tailed tests. All continuous variables are winsorized at the 1st and 99th percentile. All variables are as defined in Appendix B.

Table 4: Peer Firm versus Non-Peer Firm Movements

	Interaction		*Different Industries*	*Same Industries*
Dependent variable	*COS_SIM*	*COS_SIM*	*COS_SIM*	*COS_SIM*
	(1)	(2)	(3)	(4)
MOVEMENT	0.0152***	0.0141***	0.0076***	0.0270***
	(12.348)	(12.194)	(8.101)	(10.713)
TREAT	**-0.0014**	**-0.0018**	**0.0044*** **	**0.0168*** **
	(-1.186)	**(-1.590)**	**(4.947)**	**(4.843)**
TREAT × SAME_FF17	**0.0367*** **	**0.0362*** **		
	(7.729)	**(7.685)**		
ASSETS	-0.0016***	-0.0015***	-0.0016***	-0.0018***
	(-6.304)	(-5.937)	(-6.409)	(-3.486)
AGE	-0.0076***	-0.0079***	-0.0072***	-0.0107***
	(-9.430)	(-9.649)	(-9.181)	(-7.403)
BTM	-0.0002	-0.0027***	-0.0020***	-0.0067***
	(-0.470)	(-4.736)	(-3.701)	(-4.070)
ROA	0.0025	-0.0177***	-0.0162***	-0.0170***
	(1.086)	(-6.102)	(-5.521)	(-3.978)
LEVERAGE	-0.0055***	-0.0100***	-0.0069***	-0.0223***
	(-5.024)	(-6.705)	(-5.259)	(-6.917)
SALES_GROWTH	-0.0017*	-0.0077***	-0.0063***	-0.0103***
	(-1.693)	(-7.103)	(-6.089)	(-4.965)
RND	-0.0845***	-0.1554***	-0.1187***	-0.2274***
	(-10.107)	(-11.622)	(-9.972)	(-10.942)
DISC_ACCRUALS	0.0001	-0.0005***	-0.0002*	-0.0011***
	(1.542)	(-6.114)	(-1.869)	(-6.776)
MDA_LENGTH	-0.0000***	-0.0000***	-0.0000***	-0.0000***
	(-5.118)	(-7.559)	(-6.935)	(-6.371)
ANALYST	-0.0001***	-0.0002***	-0.0001***	-0.0004***
	(-3.425)	(-6.311)	(-3.471)	(-6.245)
IO	-0.0023**	-0.0031***	-0.0021***	-0.0082***
	(-2.457)	(-4.049)	(-3.019)	(-4.128)
SAME_PL	0.0003	0.0029***	0.0027***	0.0039***
	(0.406)	(3.340)	(2.896)	(3.712)
SAME_MERGER	0.0016***	0.0011***	0.0009***	0.0007**
	(6.102)	(6.483)	(5.681)	(2.180)
SAME_AUDITOR	0.0015***	0.0014***	0.0011***	0.0028***
	(6.714)	(6.283)	(5.083)	(3.781)
SAME_FF17	0.0144***	0.0130***		
	(16.365)	(15.633)		
$Chi^2_{TREAT = TREAT}$			14.86***	
Departure Year FE	Yes	No	No	No
Departed Firm FE	Yes	No	No	No
Hiring Firm FE	Yes	No	No	No
Departed Firm × Departure Year FE	No	Yes	Yes	Yes
Hiring Firm × Hiring Year FE	No	Yes	Yes	Yes
Adjusted R^2	0.1301	0.2053	0.1998	0.2464
N	11,944,634	11,944,634	10,287,074	1,657,558

Notes: This table provides the results from estimating Equation (4) extended such that we interact *TREAT* with an indicator variable for same-industry pairs. Columns (1) and (2) contain the main results on the full sample in different fixed effects specifications. In Column (3) [(4)], we report the findings on a restricted sample of firm pairs operating in the same industry [different industries]. We present t-statistics in parentheses. Standard errors are clustered by firm. *, **, and *** denote statistical significance at 10 percent, 5 percent, and 1 percent, respectively, based on two-tailed tests. All continuous variables are winsorized at the 1st and 99th percentile. All variables are as defined in Appendix B.

Table 5: Employee Attributes

Attribute	*Seniority*				*Shifts in Job Positions*			
Splitting variable (*SV*)	*EXECUTIVE*		*TENURE*		*SAMETITLE*		*TITLESIM*	
Dependent variable	*COS_SIM* (1)	*COS_SIM* (2)	*COS_SIM* (3)	*COS_SIM* (4)	*COS_SIM* (5)	*COS_SIM* (6)	*COS_SIM* (7)	*COS_SIM* (8)
MOVEMENT	0.0152***	0.0141***	0.0152***	0.0141***	0.0152***	0.0141***	0.0152***	0.0141***
	(12.341)	(12.187)	(12.351)	(12.197)	(12.344)	(12.190)	(12.340)	(12.186)
TREAT	**0.0085*** **	**0.0080*** **			**0.0089*** **	**0.0084*** **		
	(6.127)	**(5.820)**			**(6.135)**	**(5.907)**		
TREAT × SV	**0.0416*** **	**0.0421*** **			**0.0066**	**0.0062**		
	(4.116)	**(4.254)**			**(1.527)**	**(1.444)**		
TREAT_SV₁			**0.0018**	**0.0015**			**0.0045***	**0.0040**
			(0.745)	**(0.611)**			**(1.693)**	**(1.478)**
TREAT_SV₂			**0.0071*** **	**0.0070*** **			**0.0055** **	**0.0057*** **
			(3.068)	**(3.020)**			**(2.494)**	**(2.614)**
TREAT_SV₃			**0.0100*** **	**0.0093*** **			**0.0105*** **	**0.0096*** **
			(4.612)	**(4.262)**			**(4.066)**	**(3.910)**
TREAT_SV₄			**0.0148*** **	**0.0136*** **			**0.0136*** **	**0.0130*** **
			(3.967)	**(3.763)**			**(5.257)**	**(5.004)**
TREAT_SV₅			**0.0152*** **	**0.0142*** **			**0.0129*** **	**0.0119*** **
			(5.039)	**(4.901)**			**(4.585)**	**(4.204)**
$F_{TREAT_SV1 = TREAT_SV5}$			11.485***	11.025***			6.010**	5.3293**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Departure Year FE	Yes	No	Yes	No	Yes	No	Yes	No
Departed Firm FE	Yes	No	Yes	No	Yes	No	Yes	No
Hiring Firm FE	Yes	No	Yes	No	Yes	No	Yes	No
Departed Firm × Departure Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Hiring Firm × Hiring Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Adjusted R^2	0.1300	0.2052	0.1300	0.2052	0.1300	0.2052	0.1300	0.2052
N	11,944,634	11,944,634	11,944,634	11,944,634	11,944,634	11,944,634	11,944,634	11,944,634

Notes: This table provides the results from estimating Equation (5) in Columns (1), (2), (5), and (6) and Equation (6) in Columns (3), (4), (7), and (8) on the full sample in different fixed effects specifications. The splitting variable (SV) is used to examine the determinants influencing the effects of movements on disclosure similarities. These factors are categorized based on seniority, which includes *EXECUTIVE* and *TENURE*, and shifts in job positions, represented by *SAMETITLE* and *TITLESIM*. We present t-statistics in parentheses. Standard errors are clustered by firm. *, **, and *** denote statistical significance at 10 percent, 5 percent, and 1 percent, respectively, based on two-tailed tests. All continuous variables are winsorized at the 1st and 99th percentile. All variables are as defined in Appendix B.

Table 6: Informativeness of Corporate Disclosures

Panel A: High Informativeness

	Conventional Difference-in-Differences Design				*Stacked Difference-in-Differences Design*			
Dependent variable	*BOILER* (1)	*FOG* (2)	*STICKY* (3)	*CONFORM* (4)	*BOILER* (5)	*FOG* (6)	*STICKY* (7)	*CONFORM* (8)
***TREATMENT*$_{Low_Boiler}$**	**0.002**							
	(1.377)							
***TREATMENT*$_{Low_Boiler}$ × *POST*$_{Low_Boiler}$**	**-0.003****				**-0.001**			
	(-2.535)				**(-1.269)**			
***TREATMENT*$_{Low_Fog}$**		**-0.049**						
		(-0.519)						
***TREATMENT*$_{Low_Fog}$ × *POST*$_{Low_Fog}$**		**0.116**				**0.003**		
		(1.385)				**(0.064)**		
***TREATMENT*$_{Low_Sticky}$**			**0.750**					
			(1.010)					
***TREATMENT*$_{Low_Sticky}$ × *POST*$_{Low_Sticky}$**			**-2.160****				**-2.282****	
			(-2.488)				**(-2.401)**	
***TREATMENT*$_{Low_Conform}$**				**0.000**				
				(0.026)				
***TREATMENT*$_{Low_Conform}$ × *POST*$_{Low_Conform}$**				**-0.018****				**-0.007**
				(-2.383)				**(-1.585)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	No	No	No	No
Cohort × Firm FE	No	No	No	No	Yes	Yes	Yes	Yes
Cohort × Year FE	No	No	No	No	Yes	Yes	Yes	Yes
Adjusted R^2	0.1764	0.3144	0.0248	0.2206	0.5655	0.8063	0.1001	0.8112
N	8,798	8,798	8,004	8,798	44,005	49,613	45,226	43,340

Panel B: Low Informativeness

	Conventional Difference-in-Differences Design				*Stacked Difference-in-Differences Design*			
Dependent variable	*BOILER* (1)	*FOG* (2)	*STICKY* (3)	*CONFORM* (4)	*BOILER* (5)	*FOG* (6)	*STICKY* (7)	*CONFORM* (8)
$TREATMENT_{High_Boiler}$	**0.000**							
	(0.266)							
$TREATMENT_{High_Boiler} \times POST_{High_Boiler}$	**-0.000**				**0.001**			
	(-0.062)				**(0.655)**			
$TREATMENT_{High_Fog}$		**0.019**						
		(0.188)						
$TREATMENT_{High_Fog} \times POST_{High_Fog}$		**0.111**				**0.025**		
		(1.350)				**(0.543)**		
$TREATMENT_{High_Sticky}$			**-1.433***					
			(-1.902)					
$TREATMENT_{High_Sticky} \times POST_{High_Sticky}$			**0.424**				**0.248**	
			(0.508)				**(0.257)**	
$TREATMENT_{High_Conform}$				**-0.009**				
				(-1.017)				
$TREATMENT_{High_Conform} \times POST_{High_Conform}$				**0.000**				**0.002**
				(0.034)				**(0.537)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	No	No	No	No
Cohort × Firm FE	No	No	No	No	Yes	Yes	Yes	Yes
Cohort × Year FE	No	No	No	No	Yes	Yes	Yes	Yes
Adjusted R^2	0.1743	0.3152	0.0242	0.2174	0.5372	0.8203	0.1119	0.8140
N	8,798	8,798	8,004	8,798	48,905	45,075	42,469	50,230

Notes: This table provides the results from estimating Equation (7) using both Conventional Difference-in-Differences (Columns (1) through (4)) and Stacked Difference-in-Differences Design (Columns (5) through (8)) in different fixed effects specifications. We examine four different dependent variables: *BOILER*, *FOG*, *STICKY*, and *CONFORM*. We present t-statistics in parentheses. Standard errors are clustered by firm. *, **, and *** denote statistical significance at 10 percent, 5 percent, and 1 percent, respectively, based on two-tailed tests. All continuous variables are winsorized at the 1st and 99th percentile. All variables are as defined in Appendix B.