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ARTICLE

Accounting for employee flows

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Abstract

This paper examines employee flows and the association with firm earnings and interest rates. We use administrative employer–employee matched panel data from Denmark spanning 17 years and hence exploit actual data on employee arrivals (labor inflows) and departures (labor outflows). Three main findings emerge. First, we condition by firms' economic conditions. Departures predict earnings increases for prior-year loss firms, while they predict earnings decreases for prior-year profit firms, suggesting that this conditioning can help explain the mixed results in the literature. Arrivals predict earnings increases, though only for prior-year profit firms. These effects are stronger for high-paid employees than for low-paid ones. Second, the effects of departures are generally larger than the effects of arrivals, consistent with departures disrupting operations. Third, we find that lenders price employee flow information but only for departures of high-paid employees, despite the predictive ability of the flow of other employees for future earnings. Overall our results suggest that employee flows predict firm financial performance but are only partially priced by lenders.

KEYWORDS
credit markets, hires, human capital, labor flows, turnover

JEL CLASSIFICATION
M41, M54, M12, J24, L25, G12

1 | INTRODUCTION

Human capital management matters for firm operations and is recognized as a key parameter in environmental, social and governance (ESG) ratings (Kotsantonis & Serafeim, 2020; Sustainalytics, 2021; Thomson Reuters, 2017). Yet firms have traditionally not been required to disclose much human capital information, beyond employee counts, in their annual reports. This has caused investors to request new rules mandating disclosure of human capital management practices (SEC, 2017). In response, regulatory initiatives have been undertaken in the United Kingdom (FRC, 2018), the United States (SEC, 2020) and the European Union (EFRAG, 2021). Most notably, the US Securities and Exchange Commission (SEC) has adopted amendments requiring companies to disclose a description of the human capital aspects material to understanding their businesses (SEC, 2020 item 101(c)). The SEC has provided examples of material human capital disclosures, such as "the *attraction*, development, and *retention* of personnel" (SEC, 2020, p. 50). What is more, Haslag et al. (2022) show that "attract and retain" is one of the human capital topics discussed most frequently in US firms' 10-K filings.

Interest from investors and regulators has motivated several recent accounting studies on human capital, especially regarding employee flows, such as employee arrivals (*attraction*) and departures (*retention*), and the attendant informational value about firm performance and capital market responses.[1] Regarding arrivals, Gutiérrez et al. (2020) find that increases in the number of job postings predict 1-year-ahead increases in employee numbers, revenues, expenses and earnings, indicating that the intention to hire signals good performance. Regarding departures, Li et al. (2022) find that they are negatively associated with 1-year-ahead return on assets for moderate or high levels of departures.

The common view among human resource researchers, who have studied employee flows longer than accounting researchers, is that arrivals are good while departures are bad (Allen et al., 2010; Li et al., 2022). However, the empirical evidence is inconsistent. Hancock et al. (2013) conduct a meta-analysis and find that the correlation between departures and firm performance is negative but small and insignificant and that several variables moderate this correlation. More than 25% of the effect sizes in prior studies are positive (i.e., contradicting the common view on departures). This indicates that the association between employee flows and firm performance likely varies based on the conditions of individual firms. Furthermore, the association between employee inflows and outflows, on the one hand, and firm performance, on the other, may depend on the little investigated interplay between inflows and outflows.

We examine the predictive ability of employee flows for firm performance and extend this literature in several ways. First, we examine employee departures and arrivals together, instead of examining each in isolation. We expect that the inclusion of both measures will improve predictions of performance. In this manner, we empirically consider (1) the extent to which inflows and outflows result in replacements of employees versus contraction or expansion of the workforce and (2) the differential effects of departures versus arrivals. Second, we examine whether the associations between future performance and departures and arrivals differ with firms' economic conditions. We hypothesize that poorly performing firms could benefit from downsizing or changing their operating setup, by separating from employees responsible for poor performance, but could lose from levering their operations, by hiring, when expenses exceed income. Conversely, good performers could lose from downsizing or changing successful operations but gain from levering them. Finally, we examine whether lenders adjust their required interest rates based on employee flows.

To obtain information about employees and their dates of employment, we use Denmark's Integrated Database for Labor Market Research (IDAN), an economy-wide employer-employee-matched administrative database.[2] Thus, rather than using survey data,[3] job postings (e.g., Gutiérrez et al., 2020) or employees' self-reported LinkedIn profiles

[1] Employee arrivals denote employees entering a firm. The literature also labels this construct as hires, employee entry and (gross) labor inflows. Employee departures denote employees leaving a firm. The literature also labels this as separations, turnover, employee exit and (gross) labor outflows.

[2] The IDAN database is used by a range of papers published in prestigious journals on employee-related issues within accounting, finance, management and innovation (e.g., Dahl, 2011; Dahl et al., 2012; Bennedsen et al., 2019; Regenburg and Seitz, 2021; Jensen et al., 2022).

[3] Most research on employee flows and firm performance relies on surveys, which lack panel data, are subject to low response rates and cover small samples (Li et al., 2022).

(Agrawal et al., 2021; Li et al., 2022), we can count the actual annual number of employees arriving and departing for a significant proportion of Danish limited liability firms across the period of 1998–2016. The data also provide information on salary, position within the firm, tenure, age, gender and education, data that allow us to control for (and condition on) various factors not found in most other settings. We merge these data with financial information from the Orbis database, available because of the requirement that all Danish limited liability firms must provide rudimentary accrual-based income statements (starting with gross profit, for most firms) and balance sheets.

We find that economic conditions for individual firms influence the predictive ability of employee flows. We split on the prior year's net earnings being either above or below zero, since the zero earnings benchmark captures differences in the performance of the operating setup. Furthermore, this benchmark serves as a cue known in the accounting literature to influence investment decisions in general (Graham et al., 2005) and human capital investments and divestments in particular (Pinnuck & Lillis, 2007).[4]

For firms displaying poor recent financial performance (prior-year loss firms), departures relate *positively* to 1-year-ahead earnings changes, while arrivals are *not* associated with earnings changes. For firms displaying good recent financial performance (prior-year profit firms), the results are the opposite. Departures relate *negatively* to earnings changes, while arrivals relate *positively*. That is, the sign on departures switches when we condition by the prior year's earnings being below or above zero, while arrivals predict earnings increases only for the prior-year profit firms. In economic terms, a one standard deviation change in the statistically significant employee flow variables is associated with a change in earnings, relative to the sample mean level of earnings, ranging between 7% for departures and arrivals for prior-year *profit firms* and 16% for departures in prior-year *loss firms*. We predict earnings changes more accurately when conditioning by prior year's earnings being above or below zero than when not conditioning, and both departures and arrivals, incremental to each other, help predict earnings. This makes sense because they predict earnings changes differently for prior-year loss and profit firms.

Two sets of results suggest that the effects of departures are larger than the effects of arrivals. First, the absolute coefficients on departures in estimating changes in gross profits and earnings are larger than the coefficients on arrivals are. Second, we find that departures relate positively (negatively) to operating earnings for prior-year loss firms (profit firms), even when departures are replaced by new hires of the same position within the firm, although the effects are larger when they are not replaced.

We also explore what drives our results by distinguishing between the flows of high- and low-paid employees. Our results suggest that the effects of departures and arrivals on earnings changes are larger for high-paid employees than for low-paid ones. This suggests that loss firms benefit from replacing managers (presumably managers receive the highest salaries), while profit firms are harmed when (presumably) well-performing managers leave. Although high-paid employees drive the results, each layer of employees incrementally improves out-of-sample prediction accuracy, suggesting that flows of all employees contain useful information for the prediction of earnings.

Finally, we investigate whether lenders adjust their interest rates based on employee flow information. We find that lenders charge lower (higher) interest rates the following year for loss (profit) firms experiencing departures of high-paid employees. This suggests that lenders reward poorly performing firms when their managers leave, by charging lower interest rates, and penalize good performers when their managers leave. We do not find consistent evidence that lenders price information on other employee flows, despite their ability to predict earnings. For the generally small enterprises that comprise our sample, the findings are consistent with lenders only pricing employee flows of those employees likely to be known by the lenders, that is, existing employees likely to have some public visibility and likely to interact with the lenders.

This study has limitations regarding generalizability. First, we use data from Denmark. The Danish labor market is characterized as "flexicurity": It provides high flexibility (little protection against dismissals) coupled with security (generous unemployment benefits and active labor market policies) (Viebrock & Clasen, 2009). Consequently, Danish

[4] We also conduct tests using alternative measures of firms' economic conditions, such as ROA bins using several years of ROA information, as well as the number of consecutive losses and profits. The results from these tests further support our prediction.

workers change jobs more often than workers in other countries, suggesting lower average tenure.[5] Our additional tests suggest that the effects of departures are larger for high-tenured employees than for low-tenures ones, and we conjecture that the effects of departures could be larger in other countries with higher average tenure. Second, most sample firms are small and medium-sized enterprises. However, our robustness tests suggest that our results hold across firms of different sizes. Despite these limitations, our access to proprietary administrative data allows us to provide insights that are difficult to provide elsewhere.

With these caveats in mind, this paper contributes along three dimensions. First, the empirical results support our prediction that the information provided by employee flows about future performance differs according to firms' economic situations. Since the association between earnings growth, on the one side, and employee inflows and outflows, on the other, changes for profit firms, compared with loss firms, conditioning on firms' economic situation could help explain the mixed results in the literature (e.g., Hancock et al., 2013).

Second, the paper combines two concepts treated in isolation in the literature, departures (Li et al., 2022) and arrivals (Gutiérrez et al., 2020). Our results suggest that both contain distinct information cues, each of which helps predict earnings when added to the other. Our additional tests also show that departures and arrivals predict earnings better than net employee flows (a metric consistently disclosed by firms), likely because the effects of departures are larger than those of arrivals are.

Finally, our results complement research suggesting that equity investors do not fully incorporate employee flow information into their assessments (e.g., Agrawal et al., 2021; Lev & Wu, 2022; Li et al., 2022). Our specific contribution lies in showing that departures of high-paid employees are priced while other employee flows are not, despite their ability to predict earnings changes. While we conjecture that this result is a consequence of lenders being aware of only the departures of high-paid employees, how employee information affects interest rates is uncertain, as are potential consequences of disclosure of employee flows at all levels. Thus future research might investigate what human capital information lenders collect and how they use it.

Our results could have implications for regulators, ESG rating agencies, investors and creditors. Our paper provides valuable information particularly in the context of current endeavors of the European Commission and EFRAG to propose changes to the EU Corporate Sustainability Reporting Directive, which requires certain large companies to disclose information on their management of social and environmental challenges (EFRAG, 2022b; EU, 2014). Specifically our results are relevant to the financial materiality domain of the double materiality perspective according to which companies should report about sustainability issues with effects on not only people and the environment (impact materiality) but also on the business (financial materiality) (EFRAG, 2022a, Appendix 2.6). We document significant impact of employee matters on future firm profitability and provide insights that inform regulators about which information companies should disclose and how investors and creditors can use this information to improve forecast accuracy.

2 | BACKGROUND, INSTITUTIONAL SETTING AND HYPOTHESIS DEVELOPMENT

2.1 | Background

Zingales (2000) characterizes human capital as firms' most valuable asset. Human capital encompasses the management and execution of companies' day-to-day work—whether that is research and development, marketing of new products or maintaining property, plant and equipment. Human capital is also recognized as an important parameter when assessing the social dimension of a firm's ESG rating. Some of the largest providers of ESG ratings, including MSCI, Sustainalytics and Thomson Reuters, all include human capital as part of their ratings.[6] For example,

[5] According to Eurostat data, Denmark ranks four of 35 European countries on the proportion of workers starting new jobs. Section 2.2 elaborates on this.

[6] Thomson Reuters (2017) refers to human capital as workforce.

Sustainalytics (2021, p. 5) argues that "the common thread behind all Human Capital topics is attracting and retaining qualified employees." Yet financial statements do not include much information on human capital, and other disclosures on human capital remain scant (Gutiérrez et al., 2020).

This lack of disclosure in the United States prompted a group of institutional investors to submit a rulemaking petition to the Securities and Exchange Commission (SEC, 2017). The petition stated that there is a broad consensus that "human capital management is important to the bottom line." This led the SEC to add new requirements for disclosures about human capital resources in 2020 (SEC, 2020). In Europe, different regulatory initiatives have been undertaken to improve disclosures on human capital. Through the Non-Financial Reporting Directive, the European Union has established an objective for nonfinancial reporting that should provide "an understanding of the undertaking's development, performance, position and impact of its activity, relating to, as a minimum, environmental, social and *employee matters*" (EFRAG, 2021, pp. 33–34). In the United Kingdom, the Financial Reporting Council (FRC) has developed guidance on the strategic report, including information about the entity's employees (FRC, 2018). The analysis in the strategic report must include financial and, where appropriate, nonfinancial key performance indicators, including information relating to employee matters—all information that provides insight into financial prospects and progress in managing risks and opportunities (FRC, 2018).[7]

In summary, regulators around the world are implementing or working on implementing regulations that require financial reporting preparers to disclose information about their human capital. This calls for research on human capital metrics and their relation to firm outcomes.

2.2 | Institutional setting

We examine data from Denmark, which has adopted flexicurity as the governance model for the labor market (The Danish Ministry of Employment, 2021). Viebrock and Clasen (2009) describe the flexicurity model in general and specifically how it plays out in Denmark. Flexicurity is characterized as offering flexible labor markets (via low employment protection), generous unemployment support and a strong emphasis on activation (helping unemployed people into the labor market). Testifying to the flexibility of the Danish labor market, Denmark ranks four of 35 European countries based on the proportion of workers starting new jobs.[8] The Danish labor market is comparable to liberal labor markets, like those of the United Kingdom and the United States, in terms of employment protection (little protection against dismissal) but differs by offering high income security (generous unemployment insurance) and high employment security (right for retraining).

2.3 | Hypothesis development

While accounting studies—in line with the studies conducted by human resource researchers—have focused on either departures or arrivals, we seek to examine different effects of the two constructs. We conjecture that, while they are mathematically exactly opposite of each other (e.g., if two employees leave and two are hired the number of employees remains unchanged) their effects are not.

Employee departures, also labelled *employee turnover*, *separations*, *exits* or (gross) *outflows* (employees leaving a firm) entail the loss of firm-specific human and social capital and disrupt operations (Hausknecht & Trevor, 2011; Moon et al., 2022). The empirical prediction is (usually) that employee departures are negatively associated with performance.[9]

[7] Other organizations work on improving the disclosure on human capital. For example, the Global Reporting Initiative advocates for disclosure of hiring rates and employee replacement (https://www.globalreporting.org/standards/gri-standards-download-center/).

[8] See the Eurostat dataset LFSI_STA_Q (Recent job starters by sex and age - quarterly data). Rankings based on average new employments, as percentage of total employment, for the period Q1 2009 to Q1 2022.

[9] The literature tends to use one of the following outcome measures: Customer outcomes, productivity, financial measures and quality/safety.

However, departures could also have benefits. For instance, unhappy employees leaving may improve morale, low-productivity employees leaving could be replaced by high-productive ones and departures of high-level employees may make room for lower rank employees to develop and thrive.

Employee arrivals, also labelled *hires*, *entries* or (gross) *inflows* (employees arriving in a firm) can bring in new ideas and energy and can over time contribute positively to dynamics among existing employees. Allen et al. (2010) even argue that, when arriving employees replace departing ones, the benefits may more than outweigh the often-touted loss of firm-specific human capital of departing employees. However, arrivals are also associated with initial low productivity and recruitment and training costs (Muehlemann & Leiser, 2018), suggesting that the effects of arrivals differ from the effects of departures, at least on the short term.

In summary, we expect differential effects of departures versus arrivals on firm performance. Departures, on the one hand, entail that some of the existing human capital leaves, for better or worse, while arrivals, on the other hand, are new to the organization, are initially costly and will not duplicate departed or remaining employees in terms of age, education, salary, work experience and most obviously firm-specific human and social capital (Hausknecht & Trevor, 2011; Moon et al., 2022). Moreover, departures can occur on the initiative of the employee, while arrivals are typically initiated by the firm and therefore they are likely to carry different information about the state of the organization and hence future financials. Thus departures and arrivals are unlikely to have similar effects on firm performance, and we therefore hypothesize the following.

H1 While employee arrivals and departures are mathematically opposite, their effects are not, and therefore employee arrivals and departures together predict operating earnings significantly better than either does in isolation.

We conjecture that the relative weight of the positive and negative effects associated with departures and arrivals differ, conditional on firms' economic situations. On the one hand, well-managed firms seem likely to *suffer* from departure of employees, since this can disrupt well-functioning operations (Hausknecht & Trevor, 2011, p. 360). Conversely, firms that are poorly managed seem likely to *benefit* from departures, as this may serve as the response to poorly functioning operations (Hausknecht & Trevor, 2011, p. 381; Shah, 2007, p. 503).[10] Though similar notions are present in the literature as a potential explanation of the mixed results (e.g., Allen et al., 2010), these relations have not been investigated empirically. We identify poorly managed firms as those that experienced a loss in the prior year and well-managed firms as those that made a profit in the prior year. We hypothesize the following.

H2a) For prior-year loss firms, employee departures are positively associated with future operating earnings.

H2b) For prior-year profit firms, employee departures are negatively associated with future operating earnings.

In the same vein, we expect that prior-year loss firms and prior-year profit firms experience different outcomes of levering their operations through hiring. Prior-year loss firms as well as prior-year profit firms likely experience growth in revenue as well as expenses when hiring, but the relation between the growth in revenue and in expenses is likely unfavorable for firms with a poor operational setup and likely favorable for firms with a good operational setup. We therefore hypothesize the following.

H2c) For prior-year loss firms, employee arrivals are negatively associated with future operating earnings.

H2d) For prior-year profit firms, employee arrivals are positively associated with future operating earnings.

[10] Shah (2007) notes, in a discussion, that "other possibilities for future work include identifying a pool of poor-performing firms and comparing the subsequent performance of those firms which did downsize and those that did not" (p. 503), suggesting that prior performance moderates the relation between employee flows and firm financial performance.

As hypothesized above, we expect that employee flows are leading indicators of firms' performance and could matter to banks and influence loan pricing. Whether banks have the relevant information is not obvious. On one hand, gross employee flows are not consistently publicly disclosed, and banks may not be aware of their potential to predict firm performance. For example, the literature suggests that equity investors do not fully incorporate employee flow information into their assessments (Agrawal et al., 2021; Lev & Wu, 2022; Li et al., 2022). On the other hand, banks have more direct access to firms than equity investors do and could request private information (Bharath et al., 2008). Banks could, in line with other market participants who request more human capital information (e.g., the investors behind the SEC rule-making petition), appreciate this information and seek it either formally or informally and factor it into loan pricing particularly where information would affect bank estimates of downside risk.

Employee departures could influence firm risk in two opposing ways. On the one hand, they could disrupt operations and entail loss of firm-specific human and social capital (Hausknecht & Trevor, 2011), increasing risk. For example, Li et al. (2022) find that employee departures are associated with future earnings volatility, and Gassen and Fülbier (2015) find that earnings volatility is positively associated with interest rates. On the other hand, departures could help the firm cut expenses, decreasing risk. We argue that the net effect of these opposing forces depends on firms' economic situations. For prior-year loss firms, we expect the latter effect to be larger than the former. The average employee in these firms does not generate profits, and hence a reduction in the workforce could help the firm cut expenses and mitigate downside risk (in line with H2a). Moreover, we expect banks to appreciate the changes occurring in loss firms. For prior-year profit firms, we expect the former effect to be larger than the latter. The average employee in these firms generates profits and employee departures could disrupt well-performing operations (in line with H2b). We expect that, while banks recognize the benefits of decreased salaries, they are concerned about any changes occurring in profit firms. We therefore hypothesize the following.

H3a) For prior-year loss firms, employee departures are negatively associated with future interest rates.
H3b) For prior-year profit firms, employee departures are positively associated with future interest rates.

Regarding employee arrivals, we also expect two opposing effects. On the one hand, employee arrivals indicate increases in operating expenses via salary increases, initial low productivity and recruitment and training costs (Muehlemann & Leiser, 2018). This should impact interest rates upwards. On the other hand, banks could perceive employee arrivals as a signal of firm management optimism, which should impact interest rates downwards. While it is unclear which effect dominates for loss firms, we expect that banks monitor salary expenses closely and weigh these higher than the potential future increases in income signaled via the arrival of new employees. Thus, we expect employee arrivals to be associated with higher interest rates for loss firms. For profit firms, it is also unclear which effect dominates. Banks dislike larger salary expenses but also see the signal of future income, and, in the case of profit firms, they are likely to trust the signal, due to credence of prior signals. But banks hold no residual claim in the firm and care more about the downside risk than the upside potential (Jiang, 2008), and therefore we expect that, also for profit firms, arrivals are associated with higher interest rates. We therefore hypothesize the following.

H3c) For prior-year loss firms, employee arrivals are positively associated with future interest rates.
H3d) For prior-year profit firms, employee arrivals are positively associated with future interest rates.

3 | RESEARCH DESIGN

3.1 | Employee flows and firm performance

Our empirical design regarding H1 and H2 (firm performance and employee flows) closely follow the work of Gutiérrez et al. (2020) to ensure comparability. We regress future changes in performance (changes from year t to year $t+1$) on current (year *t*) employee flow variables outlined by following equation.

$$
\begin{aligned}
&\Delta\text{Operating Earnings}_{j,t+1}\ (\Delta\text{gross Profit}_{j,t+1},\ \text{or}\ \Delta\text{other Operating Expenses}_{j,t+1})\\
&= \alpha_0 + \beta_1 \text{Employee Departures}_{j,t} + \beta_2 \text{Employee Arrivals}_{j,t} + \gamma_3 \text{Accounting Controls}_{j,t}\\
&+ \gamma_4 \text{Employee Controls}_{j,t} + \sum \text{‹ Industry} + \sum \text{’ Year} + \text{"}_{j,t},
\end{aligned}
\tag{1}
$$

for firm *j* in year *t*. Appendix A defines all variables. Our independent variables of interest in equation 1 are Employee Departures and Employee Arrivals. Employee Departures measures separations, scaled by the number of employees at the beginning of the period, and captures a comparable construct to Turnover used by Li et al. (2022). Employee Arrivals measures hires, scaled by the number of employees at the beginning of the period, and captures a comparable construct to Job Postings used by Gutiérrez et al. (2020). Accounting Controls include variables such as ΔOperating Earnings and ΔcapEx, in line with the work of Gutiérrez et al. (2020). However, our dataset does not include the exact same variables, and we hence drop a few of their control variables (e.g., Δrevenue, ΔSG&A and Δemployees) and add others (e.g., ΔGross Profit, ΔOther Operating Expenses and Δln(TA)).[11] Employee Controls include factors used by the literature to explain departures, including work-related (e.g., pay (ΔaverageSalary) and advancement opportunities (Δpromotion)) and personal factors (e.g., age (ΔaverageAge), gender (ΔaverageFemale) and education (ΔaverageHighEduc)) (Cotton & Tuttle, 1986).

We also examine whether employee inflows and outflows would help predict earnings out-of-sample. Specifically, we use rolling estimation windows and estimate equation 1 in year one and use the estimated coefficients to predict earnings in year two. Overall, we predict earnings using (1) a restricted version of equation 1 excluding any employee flow variables, (2) equation 1 using employee arrivals and departures and (3) several variations of equation 1, where we only include one of the employee flow variables to examine which variables add incremental information.

We benchmark the predictive accuracy by comparing mean squared prediction errors (MSPE). For non-nested models (e.g., when we compare a model with departures to a model with arrivals), we use the Diebold-Mariano (DM) MSPE statistic (Diebold & Mariano, 1995; Nallareddy et al., 2020).

$$
\begin{aligned}
\text{DM}_{t+1} = &\left(\Delta\text{Operating Earnings}_{t+1} - \Delta\text{Operating }\widehat{\text{Earnings}}_{\text{Model }1,t+1}\right)^2\\
&- \left(\Delta\text{Operating Earnings}_{t+1} - \Delta\text{Operating }\widehat{\text{Earnings}}_{\text{Model }2,t+1}\right)^2.
\end{aligned}
\tag{2}
$$

For the nested models (e.g., when we compare a model with departures and arrivals to a model with arrivals only) we use the Clark-West (CW) MSPE adjusted statistic (Clark & West, 2007; Nallareddy et al., 2020). Model 1 is the restricted model and Model 2 is the model augmented with employee flow variables.

$$
\begin{aligned}
\text{CW}_{t+1} = &\left(\Delta\text{Operating Earnings}_{t+1} - \Delta\text{Operating }\widehat{\text{Earnings}}_{\text{Model }1,t+1}\right)^2\\
&- \left[\begin{array}{l}\left(\Delta\text{Operating Earnings}_{t+1} - \Delta\text{Operating }\widehat{\text{Earnings}}_{\text{Model }2,t+1}\right)^2\\ - \left(\Delta\text{Operating }\widehat{\text{Earnings}}_{\text{Model }1,t+1} - \Delta\text{Operating }\widehat{\text{Earnings}}_{\text{Model }2,t+1}\right)^2\end{array}\right].
\end{aligned}
\tag{3}
$$

A positive CW or DM statistic indicates that Model 2 is more accurate than Model 1.

[11] As noted above, most companies are not mandated to report revenue, and therefore gross profit is the first income statement variable for which observations are not generally missing. We cannot control for ΔEmployees since Employee Arrivals minus Employee Departures equals ΔEmployees. To control for size, we add the change in the logarithm of assets.

3.2 | Employee flows and interest rates

We examine whether the employee flow variables are associated with interest rates with the following equation.

$$\begin{aligned}\Delta \text{InterestRate}_{j,t+1} = \alpha_0 + \beta_1 \text{Employee Departures}_{j,t} + \beta_2 \text{Employee Arrivals}_{j,t} \\ + \gamma_2 \text{Interest Rate Controls}_{j,t} + \gamma_3 \text{Employee Controls}_{j,t} + "_{j,t},\end{aligned} \quad (4)$$

for firm *j* in year *t*. We estimate equation 5 as a changes specification as in our main analyses (equation 1). Appendix A defines the variables in detail. The dependent variable ΔInterestRate measures the change in a firm's interest rate. We follow Minnis (2011) and calculate the interest rate from income statement items. Specifically, we estimate the interest rate as a firm's financial expenses scaled by average interest-bearing debt (we calculate this as total liabilities net of trade payables), truncate this variable at the fifth and 95th percentiles and remove observations that are 10 percentage points above the interest rate of Danish government bonds for the year.[12]

We use comparable control variables to Minnis (2011); however, we use the variables as changes. Interest Rate Controls includes the changes in the following variables: EBIT coverage (Δln(EBIT/FiExp)),[13] current assets to current liabilities (ΔCA/CL), property, plant and equipment scaled by assets (ΔPPE), leverage (ΔTL/TA), an indicator for negative equity (ΔNegEquity), size (Δln(TA) and growth (ΔGPgrowth).[14]

4 | DATA, SAMPLE SELECTION AND DESCRIPTIVE STATISTICS

We use Statistics Denmark's Integrated Database for Labor Market Research (IDAN database) to obtain information about firms' employees and their dates of employment. The IDAN database keeps annual data on employment spells (firm-employee-year links), including data on salary received from the firm over the year, days of employment over a year, position codes of employees' positions in the company hierarchy (STILL codes) and six-digit occupation codes (DISCO codes) describing the nature of the employment.[15] Timmermans (2010) provides an excellent description of the database targeted an English speaking audience.[16] Several papers published in prestigious journals within accounting, finance, management and innovation rely on this dataset (e.g., Bennedsen et al., 2019; Dahl, 2011; Dahl et al., 2012; Jensen et al., 2022; Regenburg & Seitz, 2021).

We combine this with financial statement information obtained from the Orbis database, managed by Bureau Van Dijk. All limited liability firms in Denmark must produce balance sheets and rudimentary accrual-based income statements, which, for most firms, are limited to items after and including gross profits. The data enable insights based on data ranging from information on many small firms to information on a few large firms.

Using employment spells in the IDAN database, for each firm, we count the number of arriving and departing employees. Arriving employees are individuals who receive salary from the firm for the first time in year *t*. Departing employees are individuals who receive salary from the firm in year *t* but do not receive salary from the firm in year *t* + 1. We count only employees who at some point received the minimum salary from the firm to avoid temporary positions influencing our measures of arrivals and departures. Related literature using comparable data also keeps only

[12] Minnis (2011) uses the prime rate. We use the interest rate of government bonds in lieu of the prime rate because the prime rate is not available for Denmark.

[13] We take the logarithm of the interest coverage because interest coverage is highly skewed with many extreme values (e.g., Jiang 2008). Because interest coverage can be negative, we calculate the logarithm by adding the absolute value of the minimum of the variable (e.g., Amir et al. 2014).

[14] Because most firms do not disclose revenues we use gross profits.

[15] STILL codes are described here: https://www.dst.dk/da/Statistik/dokumentation/Times/ida-databasen/ida-ansaettelser/still (in Danish only). DISCO codes are described here: https://www.dst.dk/en/Statistik/dokumentation/nomenklaturer/disco. DISCO codes are available from 2008.

[16] Aarhus University in Denmark also describes the IDAN dataset and its variables in English here: https://econ.au.dk/the-national-centre-for-register-based-research/danish-registers/the-integrated-database-for-labour-market-research-ida

TABLE 1 Sample selection

Screening criterion	Firm-year observations dropped	Resulting sample size: Firm-year observations	Firms	Years per firm
Firm-year observations with employer-employee link		1,325,130	189,397	7.0
Employee Departures or Employee Arrivals missing	137,932	1,187,198	154,079	7.7
Missing values for test variables	448,506	738,692	105,779	7.0
Less than 10 employees	495,239	243,453	33,873	7.2

This table shows the sample selection.

full-time employees (e.g., Bennedsen et al., 2019; Jinkins & Morin, 2018).[17] Employee Arrivals (Employee Departures) is the number of arriving (departing) employees scaled by the lagged number of employees.

Using the position codes (STILL) provided by the IDAN database, we also calculate the proportion of departing employees who are replaced by new hires of similar positions. Departures Replaced hence measures the number of replacing employees scaled by the number of departing employees. If, for instance, 10 employees depart within middle-level employees and six arrive, six are counted as replacements. If four employees depart within lower-level employees and eight arrive, four are counted as replacements. In this example, Departures Replaced is [(6 + 4)/(10 + 4)] 0.71. Appendix A defines all variables.

Table 1 presents details of the sample selection. We begin with a dataset of 1,325,130 firm–year observations. We remove observations for which either Employee Arrivals or Employee Departures is missing. We also remove observations with insufficient data to estimate our main regression (equation 1). We finally remove firm-year observations with fewer than 10 employees to ensure variation in employee flows and to prevent mom-and-pop operations from driving our results.[18] The final sample comprises 243,453 firm–year observations for 33,873 firms for the period from 1999 to 2015.[19] It comprises 13,754,951 person-firm-year observations for 1,722,690 unique individuals over the sample period. For comparison, the Danish workforce was 3,082,000 individuals in the fourth quarter of 2021.[20]

4.1 | Descriptive statistics

Table 2 presents descriptive statistics for the sample. Panel A shows descriptive information about the size of the sample firms. The firms are typically small, with a median number of employees of 21 and total assets around €1.9 million. The means for the accounting variables (gross profit, operating earnings, net earnings and total assets) are above the medians, due to firm size skewness in sample.

Panel B shows descriptive statistics for the test and control variables. The means of Employee Arrivals (hires scaled by employees at the beginning of the year) and Employee Departures (separations scaled by the number of employees at the beginning of the year) are 17 and 13%, respectively. These figures suggest that the firms in our sample on average

[17] We validate our data by comparing departures and arrivals to publicly available population-level data from Eurostat and the Danish Agency for Labor market and Recruitment for the period 2009–2015. We find few differences in the arrivals/departures rates (less than one percentage points) using all employee unconditional on minimum salary. Conditioning on minimum salary our sample arrival/departure rates are lower than publicly available data are, likely because full-time employees change jobs less often than temporary workers do.

[18] Our inferences regarding employee flows and future firm performance remain unchanged when using a sample of firms with less than ten employees (untabulated). Online Appendix H also presents results across size deciles and testifies to the robustness of the results across firms of different sizes.

[19] The data for this period include lagged and leading variables. For example, the data for 2015 include ΔOperating Earnings$_{t+1}$ (growth in operating earnings from 2015 to 2016).

[20] https://www.dst.dk/en/Statistik/emner/arbejde-og-indkomst/befolkningens-arbejdsmarkedsstatus

TABLE 2 Summary statistics

	Full sample							Prior-year's net income: Loss	Prior-year's net income: Profit
	Mean	SD	p10	p25	p50	p75	p90	Mean	Mean
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Size variables ($N = 243{,}453$)								**($N = 53{,}767$)**	**($N = 189{,}686$)**
Employees_t	56	257	11	13	21	40	90	49	58
Gross Profit_t (EUR thousand)	3653	9126	451	702	1214	2571	6567	2862	3877
$\text{Operating Earnings}_t$ (EUR thousand)	578	2081	−137	24	136	416	1248	−23	749
Net earnings_t (EUR thousand)	397	1705	−161	3	81	285	911	−156	553
CapEx_t (EUR thousand)	560	2356	−14	8	54	228	886	443	593
TA_t (EUR thousand)	9651	30996	508	893	1910	4934	15601	8898	9865
Panel B: Test variables ($N = 243{,}453$)								**($N = 53{,}767$)**	**($N = 189{,}686$)**
$\text{Employee Arrivals}_t$	0.17	0.18	0.00	0.06	0.12	0.22	0.36	0.17	0.17
$\text{Employee Departures}_t$	0.13	0.09	0.00	0.07	0.12	0.18	0.25	0.16	0.12
$\text{Departures Replaced}_t$ ($N = 210{,}975$)	0.52	0.38	0.00	0.14	0.50	1.00	1.00	0.46	0.54
$\Delta\text{Gross profit}_{t+1}$	0.03	0.28	−0.22	−0.07	0.02	0.12	0.30	0.03	0.03
$\Delta\text{Other Operating Expenses}_{t+1}$	0.02	0.23	−0.16	−0.04	0.01	0.08	0.21	−0.01	0.03
$\Delta\text{Operating Earnings}_{t+1}$	0.01	0.16	−0.15	−0.06	0.00	0.07	0.17	0.04	0.00
$\text{Operating Earnings}_t/\text{Assets}_{t\text{-}1}$	0.10	0.19	−0.07	0.02	0.08	0.17	0.31	−0.02	0.13
ΔCapEx_t	−0.01	0.21	−0.20	−0.06	−0.00	0.04	0.15	−0.02	−0.01
$\Delta\ln(\text{TA})_t$	0.05	0.26	−0.22	−0.08	0.03	0.17	0.35	0.02	0.06
$\Delta\text{AverageSalary}_t$ (EUR thousand)	0.84	5.27	−5.13	−1.94	0.81	3.53	6.74	0.65	0.90
$\Delta\text{Promotion}_t$	0.00	0.13	−0.10	−0.02	0.00	0.03	0.10	0.00	0.00
$\Delta\text{AverageAge}_t$	0.36	1.93	−1.86	−0.64	0.40	1.42	2.56	0.38	0.36
$\Delta\text{AverageFemale}_t$	0.00	0.05	−0.06	−0.02	0.00	0.03	0.06	0.00	0.00
$\Delta\text{AverageHighEduc}_t$	0.00	0.04	−0.04	−0.01	0.00	0.01	0.04	0.00	0.00
Panel C: Interest rate variables ($N = 160{,}189$)								**($N = 36{,}065$)**	**($N = 124{,}132$)**
$\text{Employee Arrivals}_t$	0.15	0.14	0.00	0.06	0.11	0.20	0.30	0.14	0.15
$\text{Employee Departures}_t$	0.13	0.08	0.00	0.07	0.12	0.17	0.24	0.15	0.12
$\Delta\text{InterestRate}_{t+1}$	−0.00	0.02	−0.02	−0.01	−0.00	0.01	0.02	−0.00	−0.00
$\text{InterestRate}_{t+1}$	0.04	0.02	0.01	0.02	0.04	0.05	0.07	0.045	0.039
$\Delta\ln(\text{EBIT/FiExp})_t$	−0.01	0.35	−0.20	−0.05	0.00	0.05	0.18	0.10	−0.05
$\Delta\text{CA/CL}_t$	0.02	0.41	−0.36	−0.12	0.02	0.16	0.39	0.03	0.02
ΔPPE_t	−0.00	0.07	−0.07	−0.03	−0.01	0.02	0.07	−0.01	−0.00
$\Delta\text{TL/TA}_t$	−0.00	0.11	−0.11	−0.05	−0.01	0.04	0.11	0.01	−0.00
$\Delta\text{NegEquity}_t$	0.00	0.19	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$\Delta\ln(\text{TA})_t$	0.04	0.26	−0.21	−0.08	0.03	0.15	0.31	−0.00	0.05
$\Delta\text{GPgrowth}_t$	−0.02	0.37	−0.39	−0.14	−0.01	0.11	0.33	0.11	−0.06

This table shows the summary statistics for the sample. Size variables are converted from DKK to EUR using an exchange rate of 7.45. Appendix A defines the variables. All test and interest rate variables are winsorized at the first and 99th percentiles. $\text{InterestRate}_{t+1}$ is truncated at the 5th and 95th percentiles.

grow their workforce by 4%. About 52% of departing employees are replaced by new hires (Departures Replaced). Prior-year profit firms replace departing employees (54%) to a higher extent than prior-year loss firms do (47%).

Panel C presents descriptive statistics for the variables used for the interest rate estimations. This sample size is smaller because we truncate the interest rate variable, as is standard in the literature (e.g., Gassen & Fülbier, 2015; Minnis, 2011; Regenburg & Seitz, 2021; vander Bauwhede et al., 2015). Section 3.2 elaborates on this. Prior-year loss firms pay higher interest rates (4.5%) than prior-year profit firms do (3.9%).

5 | RESEARCH DESIGN AND RESULTS

5.1 | Pooled regressions

We initially estimate equation 1 (firm performance as a function of employee flows) for the pooled sample to compare our results to those obtained in the literature. We later estimate the regressions separately for prior-year loss and profit firms. Panel A of Table 3 presents the regression results. Columns 2, 5 and 8 of Panel A include human capital inflows (Employee Arrivals) and thus present the results for the regressions most comparable to those of Gutiérrez et al. (2020; Table 5). The results are in line with theirs: We find that Employee Arrivals (they use ΔJob Postings) relate positively to future changes in gross profit (they use revenue), other operating expenses (they use SG&A) and operating earnings (they use a comparable measure). Likewise, we find that ΔOperating Earnings is negatively associated with next-year ΔOperating Earnings. We hence replicate the results of Gutiérrez et al. (2020), despite large sample differences.

Columns 1, 4 and 7 of Panel A include human capital outflows (Employee Departures) and thus present the results for the regressions most comparable to those of Li et al. (2022). The relation of Employee Departures to ΔGross Profit and ΔOther Operating Expenses is negative. This is not surprising: when more employees leave, the firm's gross profit and expenses decrease. More surprising, however, is the positive relation of Employee Departures to ΔOperating Earnings. While this last result is inconsistent with the findings of Li et al. (2022; Table 3) and disagrees with the widely held managerial conception that turnover is inherently bad (Allen et al., 2010; Hancock et al., 2013), it comports with 25% of the effect sizes of the meta-analytical review of Hancock et al. (2013), which indicates a positive relation between employee turnover and firm performance.

Finally, columns 3, 6 and 9 of Panel A include both employee inflows (Employee Arrivals) and outflows (Employee Departures). The inferences from the above do not change when we include both variables together. Both significantly predict operating earnings (column 9), indicating that both variables contain information for the prediction of earnings.

5.2 | Results by prior performance

We then condition our estimations on the economic situation of the firm. We address the intuitive notion that poorly performing and well-performing firms could have different potentials for laying off and hiring employees. Specifically, we rerun equation 1 (firm performance as a function of employee flows) on subsamples consisting of prior-year loss firms and prior-year profit firms. We base the split on the prior year's net earnings, since the zero earnings benchmark captures differences in the performance of the operating setup. Furthermore, this benchmark serves as a cue known in the accounting literature to influence investment decisions in general (Graham et al., 2005) and human capital investments and divestments in particular (Pinnuck & Lillis, 2007).

Panel A of Table 4 reports the regression results of estimating equation 1 conditioned by prior-year earnings being below (columns 1 through 3) and above (columns 4 through 6) zero. As expected, we find that Employee Arrivals (Employee Departures) is positively (negatively) associated with ΔGross Profit and ΔOther Operating Expenses for

TABLE 3 Future performance regressed on current employee departures and arrivals

Panel A: Regression results ($N = 243{,}453$)

	ΔGross Profit$_{t+1}$			ΔOther Operating Expenses$_{t+1}$			ΔOperating Earnings$_{t+1}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Employee Departures$_t$	−0.39***		−0.50***	−0.46***		−0.56***	0.05***		0.04***
	(−39.80)		(−44.02)	(−26.77)		(−33.51)	(4.29)		(3.63)
Employee Arrivals$_t$		0.35***	0.39***		0.31***	0.36***		0.04***	0.04***
		(24.20)	(27.15)		(22.32)	(26.18)		(7.99)	(8.04)
ΔOperating Earnings$_t$	−0.06**	−0.04	−0.06**	0.13***	0.15***	0.13***	−0.27***	−0.27***	−0.27***
	(−2.33)	(−1.58)	(−2.31)	(7.12)	(7.36)	(6.61)	(−18.80)	(−18.72)	(−18.85)
ΔGross Profit$_t$	−0.12***	−0.13***	−0.12***	−0.01	−0.02	−0.01	−0.03**	−0.03**	−0.03**
	(−4.71)	(−5.08)	(−4.92)	(−0.62)	(−0.87)	(−0.54)	(−2.23)	(−2.18)	(−2.23)
ΔOther Oper. Expenses$_t$	0.14***	0.07**	0.05*	0.03	−0.03	−0.05**	0.02	0.01	0.02
	(4.14)	(2.54)	(1.83)	(1.30)	(−1.47)	(−2.47)	(1.57)	(0.95)	(1.07)
ΔCapEx$_t$	0.01	0.01**	0.01*	0.01**	0.01***	0.01***	−0.00	−0.00	−0.00
	(1.10)	(2.52)	(1.71)	(1.98)	(3.75)	(2.79)	(−1.50)	(−1.51)	(−1.44)
Δln(TA)$_t$	0.12***	0.05***	0.04***	0.15***	0.10***	0.08***	−0.03***	−0.04***	−0.04***
	(24.77)	(7.92)	(5.79)	(38.12)	(16.39)	(16.56)	(−7.36)	(−8.01)	(−8.05)
ΔAverageSalary$_t$	−0.00***	0.00***	−0.00***	−0.00***	0.00***	−0.00***	−0.00**	−0.00**	−0.00
	(−19.21)	(3.15)	(−5.99)	(−17.76)	(3.87)	(−5.17)	(−2.31)	(−2.30)	(−0.30)
ΔPromotion$_t$	0.02***	0.01	0.00	0.01***	0.00	−0.00	0.01**	0.01*	0.01*
	(4.38)	(1.38)	(0.71)	(3.21)	(0.02)	(−1.14)	(2.49)	(1.75)	(1.88)
ΔAverageAge$_t$	−0.00***	−0.00***	−0.00***	−0.00***	−0.00***	−0.00**	−0.00***	−0.00	−0.00
	(−9.49)	(−3.75)	(−3.03)	(−9.11)	(−3.43)	(−2.44)	(−2.65)	(−1.39)	(−1.54)
ΔAverageFemale$_t$	−0.01	−0.02	−0.02	0.01	0.00	−0.00	−0.02***	−0.02***	−0.02***
	(−0.46)	(−1.20)	(−1.42)	(1.02)	(0.18)	(−0.07)	(−2.59)	(−2.84)	(−2.81)
ΔAverageHighEduc$_t$	−0.00	0.02*	0.04***	0.01	0.03***	0.05***	−0.01	−0.00	−0.01
	(−0.14)	(1.79)	(2.79)	(0.67)	(3.09)	(4.81)	(−0.75)	(−0.33)	(−0.44)
Year and industry fix. effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.06	0.08	0.11	0.10	0.12	0.16	0.10	0.10	0.11
F-test	1v3	2v3		4v6	5v6		7v9	8v9	
p-Value	<0.01***	<0.01***		<0.01***	<0.01***		<0.01***	<0.01***	
H0: Employee Departures + Employee Arrivals = 0									
p-Value			<0.01***			<0.01***			<0.01***

Panel B: Out-of-sample ΔOperating Earnings$_{t+1}$ prediction accuracy, rolling estimation windows ($N = 230{,}887$)

	(1)	(2)	(3)	(4) (H1)	(5) (H1)	(6)
Model 1						
Control variables	X	X	X	X	X	X
Employee Arrivals				X		X
Employee Departures					X	
Model 2						
Control variables	X	X	X	X	X	X
Employee Arrivals	X		X	X	X	

(Continues)

TABLE 3 (Continued)

Panel B: Out-of-sample ΔOperating Earnings$_{t+1}$ prediction accuracy, rolling estimation windows (N = 230,887)						
	(1)	(2)	(3)	(4) (H1)	(5) (H1)	(6)
Employee Departures		X	X	X	X	X
Test statistic	CW	CW	CW	CW	CW	DM
MSPE diff (1 minus 2) × 100	0.0080***	0.0041***	0.0107***	0.0027***	0.0065***	−0.0031***
	(13.99)	(8.27)	(14.89)	(6.02)	(12.54)	(−4.38)

This table reports the results of estimating equation 1. The independent variables of interest, Employee Arrivals and Employee Departures, is the number of arriving and departing employees scaled by the lagged number of employees, respectively. The dependent variables are changes in the income statement line items scaled by assets. Panel A shows the regression results. Panel B shows the out-of-sample ΔOperating Earnings$_{t+1}$ prediction accuracy measures of different models using rolling prediction windows. We use rolling estimation windows and estimate equation 1 in year one and use the estimated coefficients to predict earnings in year two. The prediction accuracy is measured by the mean squared prediction error (MSPE). Clark-West, CW, (Diebold-Mariano, DM) statistics are used to compare out-of-sample predictions for nested (non-nested) models. MSPE diff is adjusted for CW models. A positive (negative) test statistic implies that Model 2 (Model 1) is the superior prediction model. Appendix A defines all variables. All variables are winsorized at the first and 99th percentiles. Values in brackets represent t-statistics. ***, ** and * indicate statistical significance at the 1, 5 and 10% levels, respectively, using two-tailed tests. Standard errors in Panel A are clustered by firm and year. The regressions are estimated with industry and year fixed effects in Panel A and industry fixed effects in Panel B.

both profit (columns 1 and 2) and loss (columns 4 and 5) firms. However, arrivals and departures are differently associated with the resulting change in earnings, presented in columns 3 and 6.

For prior-year loss firms, Employee Departures is negatively associated with ΔGross Profit (coefficient −0.48) and ΔOther Operating Expenses (−0.69), resulting in a positive association with ΔOperating Earnings (0.18). Employee Arrivals is positively associated with ΔGross Profit (0.36) and ΔOther Operating Expenses (0.36), resulting in an insignificant association with ΔOperating Earnings (0.01). This indicates that firms with poor performance experience improved earnings when employees separate from the firm (consistent with H2a) but no change in earnings when hiring new employees (inconsistent with H2c). In economic terms, a one standard deviation increase in Employee Departures is associated with an increase in ΔOperating Earnings of 1.62 percentage points or about 16.2% of the unconditional sample mean of operating earnings scaled by assets.

For prior-year profit firms, the associations between ΔOperating Earnings and the employee flow variables are different: the results regarding Employee Departures are the opposite, that is, the sign on Employee Departures switches. For these firms, Employee Departures is negatively associated with ΔGross Profit (−0.54) and ΔOther Operating Expenses (−0.47), resulting in a negative association with ΔOperating Earnings (−0.08). Employee Arrivals is positively associated with ΔGross Profit (0.40) and ΔOther Operating Expenses (0.36), resulting in a positive association with ΔOperating Earnings (0.04). These results indicate that well-performing firms experience lower earnings growth when employees separate from the firm (consistent with H2b) but higher earnings growth when hiring employees (consistent with H2d). In economic terms, a one standard deviation increase in Employee Departures (Employee Arrivals) is associated with a decrease (increase) in ΔOperating Earnings of 0.72 (0.72) percentage points or about 7.2% (7.2%) of the unconditional sample mean of operating earnings scaled by assets.

The absolute coefficients on Employee Departures are significantly larger than the absolute coefficients on Employee Arrivals across all estimations, hence indicating that the effects of employee departures are larger than the corresponding effects of employee arrivals, consistent with H1.

Estimating equation 1 separately for each subsample increases the explanatory power of the estimations. Specifically, the adjusted R^2 in predicting ΔOperating Earnings increases from 0.11 in the pooled estimations (column 9 of

TABLE 4 Future performance regressed on current employee departures and arrivals, conditional on prior-year net earnings

Panel A. Regression results ($N = 243{,}420$)	Prior-year loss firms (Net earnings$_{t-1} < 0$) $N = 53{,}768$			Prior-year profit firms (Net earnings$_{t-1} \geq 0$) $N = 189{,}652$		
	ΔGross Profit$_{t+1}$ (1)	ΔOther Operating Expenses$_{t+1}$ (2)	ΔOperating Earnings$_{t+1}$ (3)	ΔGross Profit$_{t+1}$ (4)	ΔOther Operating Expenses$_{t+1}$ (5)	ΔOperating Earnings$_{t+1}$ (6)
Employee Departures$_t$	−0.48***	−0.69***	0.18***	−0.54***	−0.47***	−0.08***
	(−25.68)	(−33.50)	(9.04)	(−42.22)	(−29.27)	(−10.78)
Employee Arrivals$_t$	0.36***	0.36***	0.01	0.40***	0.36***	0.04***
	(24.85)	(32.82)	(0.87)	(24.19)	(23.07)	(11.49)
ΔOperating Earnings$_t$	−0.03	0.23***	−0.31***	−0.13***	0.13***	−0.35***
	(−0.71)	(10.23)	(−16.11)	(−3.14)	(3.00)	(−11.95)
ΔGross Profit$_t$	−0.13***	−0.04*	−0.02*	−0.12***	0.00	−0.02
	(−3.74)	(−1.65)	(−1.85)	(−3.43)	(0.04)	(−0.86)
ΔOther Operating Expenses$_t$	0.07**	−0.02	0.01	0.06	−0.07*	0.03
	(2.15)	(−0.76)	(0.69)	(1.37)	(−1.68)	(0.91)
ΔCapEx$_t$	0.01	0.01	0.00	0.01	0.01***	−0.01***
	(1.22)	(1.03)	(0.80)	(1.22)	(3.15)	(−3.22)
Δln(TA)$_t$	0.03***	0.14***	−0.10***	0.06***	0.05***	0.01**
	(4.42)	(26.87)	(−18.13)	(7.23)	(10.65)	(2.09)
ΔAverageSalary$_t$	−0.00***	−0.00***	0.00	−0.00***	−0.00***	−0.00**
	(−5.80)	(−6.39)	(0.27)	(−4.41)	(−3.39)	(−2.54)
ΔPromotion$_t$	0.02	0.00	0.01	−0.00	−0.00	0.00***
	(1.59)	(0.25)	(0.58)	(−0.32)	(−1.16)	(2.59)
ΔAverageAge$_t$	−0.00	−0.00	0.00	−0.00***	−0.00**	−0.00***
	(−0.68)	(−0.61)	(0.42)	(−3.76)	(−2.54)	(−3.60)
ΔAverageFemale$_t$	−0.04	−0.02	−0.03**	−0.01	0.00	−0.02**
	(−1.61)	(−0.62)	(−2.13)	(−0.85)	(0.39)	(−2.10)
ΔAverageHighEduc$_t$	0.06	0.04	0.01	0.04**	0.05***	−0.01
	(1.58)	(1.29)	(0.46)	(2.34)	(3.69)	(−0.60)
Year and industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.09	0.20	0.15	0.12	0.14	0.12
F-test (vs. departures only), *p*-value	<0.01***	<0.01***	0.38	<0.01***	<0.01***	<0.01***
F-test (vs. arrivals only), *p*-value	<0.01***	<0.01***	<0.01***	<0.01***	<0.01***	<0.01***
H0: Employee Departures + Employee Arrivals = 0						
p-Value	<0.01***	<0.01***	<0.01***	<0.01***	<0.01***	<0.01***

Panel B. Out-of-sample ΔOperating Earnings$_{t+1}$ prediction accuracy, rolling prediction windows ($N = 230{,}887$)

	(1)	(2)	(3)	(4) (H1)	(5) (H1)	(6)	(7) (H2)
Model 1							
Conditioning by prior-year loss/profit?	Yes	Yes	Yes	Yes	Yes	Yes	NO

(Continues)

TABLE 4 (Continued)

Panel B. Out-of-sample ΔOperating Earnings$_{t+1}$ prediction accuracy, rolling prediction windows ($N = 230{,}887$)	(1)	(2)	(3)	(4) (H1)	(5) (H1)	(6)	(7) (H2)
Control variables	X	X	X	X	X	X	X
Employee Arrivals				X		X	X
Employee Departures					X		X
Model 2							
Conditioning by prior-year loss/profit?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	X	X	X	X	X	X	X
Employee Arrivals	X		X	X	X		X
Employee Departures		X	X	X	X	X	X
Test statistic	CW	CW	CW	CW	CW	DM	DM
MSPE diff (1 minus 2) × 100	0.0059***	0.0181***	0.0249***	0.0192***	0.0069***	0.0046***	0.0841***
	(11.80)	(19.52)	(23.25)	(20.20)	(13.14)	(4.35)	(28.37)

This table reports the results of estimating equation 1. The independent variables of interest, Employee Arrivals and Employee Departures, is the number of arriving and departing employees scaled by the lagged number of employees, respectively. The dependent variables are changes in the income statement line items scaled by assets. Panel A shows the regression results for subsamples of prior-year loss firms (columns 1 through 3) and prior-year profit firms (columns 4 through 6). Panel B shows the out-of-sample ΔOperating Earnings$_{t+1}$ prediction accuracy measures of different models using rolling prediction windows. Columns 1 through 6 of Panel B use rolling estimation windows, for the subsamples prior-year loss firms and profit firms, and estimate equation 1 in year one and use the estimated coefficients to predict earnings in year two. Column 7 compares predictions conducted conditional on prior-year loss firms and profit firms (Model 2) to predictions conducted without conditioning (Model 1) (i.e., not conditioned by prior-year profit/loss, like in Panel B of Table 3). The prediction accuracy is measured by the mean squared prediction error (MSPE). Clark-West, CW, (Diebold-Mariano, DM) statistics are used to compare out-of-sample predictions for nested (non-nested) models. MSPE diff is adjusted for CW models. A positive (negative) test statistic implies that Model 2 (Model 1) is the superior prediction model. Appendix A defines all variables. All variables are winsorized at the first and 99th percentiles. Values in brackets represent t-statistics. ***, ** and * indicate statistical significance at the 1, 5 and 10% levels, respectively, using two-tailed tests. Standard errors in Panel A are clustered by firm and year. The regressions are estimated with industry and year fixed effects in Panel A and industry fixed effects in Panel B.

Table 3) to 0.15 for prior-year loss firms (column 3 of Table 4) and 0.12 for prior-year profit firms (column 6 of Table 4). Our interpretation of the results is that conditioning on prior year's earnings being above or below zero can help explain the mixed results in the literature (e.g., Hancock et al., 2013), since the signs on the coefficients switch and the explanatory power increases when we condition by prior year's earnings being above or below zero.

We then examine whether the employee inflows and outflows help predict earnings out-of-sample. Specifically, we use rolling estimation windows (see Section 3.1) and estimate equation 1 separately for prior-year profit and loss firms (as we do in Panel A of Table 4) and combine the predictions generated for each subsample into one vector containing all the firm-year predictions. Panel B of Table 4 presents the results. A positive CW or DM statistic indicate that Model 2 is more accurate than Model 1. Conditioning by prior year earnings being below or above zero, both employee departures and arrivals significantly improve the out-of-sample predictive ability of the models, incremental to each other, consistent with our prediction in H1. Notably, column 6 shows that employee departures predict earnings better than arrivals do. This result is opposite to what we find in Table 3 using the pooled sample. Allowing the coefficients on Employee Departures and Employee Arrivals to differ for prior-year loss and profit firms hence reveals this relationship. We also find that conditioning by prior year's earnings being below or above zero significantly improves the ΔOperating Earnings prediction accuracy compared with not conditioning (column 7). This is not surprising, since the employee flow variables predict earnings differently for profit and loss firms (see Panel A of Table 4).

In summary, our findings are consistent with most of our hypothesized expectations. The effect of employee departures is larger than the effect of employee arrivals and both, incremental to each other, help predict earnings (H1). Loss firms (profit firms) experience positive (negative) earnings growth following employee departures. Only profit firms experience positive earnings growth following hires. This is consistent with H2a, b and d but inconsistent with H2c.

5.2.1 | Prior year ROA bins

We further explore the notion that the relation between employee flows and earnings growth is conditional on firms' economic situations, by estimating equation 1 on 10 different subsamples formed according to Net Earnings$_{t-1}$/TA$_{t-1}$ = ROA$_{t-1}$. Specifically, we include all observations with ROA$_{t-1}$ in the range between −25 and 25% and split these into 10 subsamples, based on intervals of five percentage points. We do this using last year's ROA as well as the average of the last three and five years' ROA, to better identify well and poorly performing firms. To preserve space, we show the results using only ΔOperating Earnings$_{t+1}$ as dependent variable. To efficiently illustrate the findings of the resulting 30 regressions (10 ROA$_{t-1}$ bins × 3 conditions), we plot the 60 key coefficients (10 ROA$_{t-1}$ bins × 3 conditions × 2 coefficients) in Panel A of Figure 1. The horizontal axis depicts the bins created by partitioning on ROA, and the vertical axis depicts the estimated coefficient values.

Panel A of Figure 1 shows that the association between ΔOperating Earnings$_{t+1}$ and Employee Departures$_t$ generally decreases with each ROA$_{t-1}$ bin, while the opposite is true for the association between ΔOperating Earnings$_{t+1}$ and Employee Arrivals$_t$. Thus, the results in Table 4 become more pronounced the further ROA is from 0. These effects also get more pronounced when we average ROA over 3 and 5 years. This indicates that the phenomenon unveiled develops in line with our hypothesis section: the poorer (better) the prior-year performance, the more firms will increase (decrease) operating earnings when experiencing employee departures and the more they will decrease (increase) operating earnings when experiencing employee arrivals. Panel A also graphically illustrates that the effect of departures is larger than the effect of arrivals across most ROA bins.

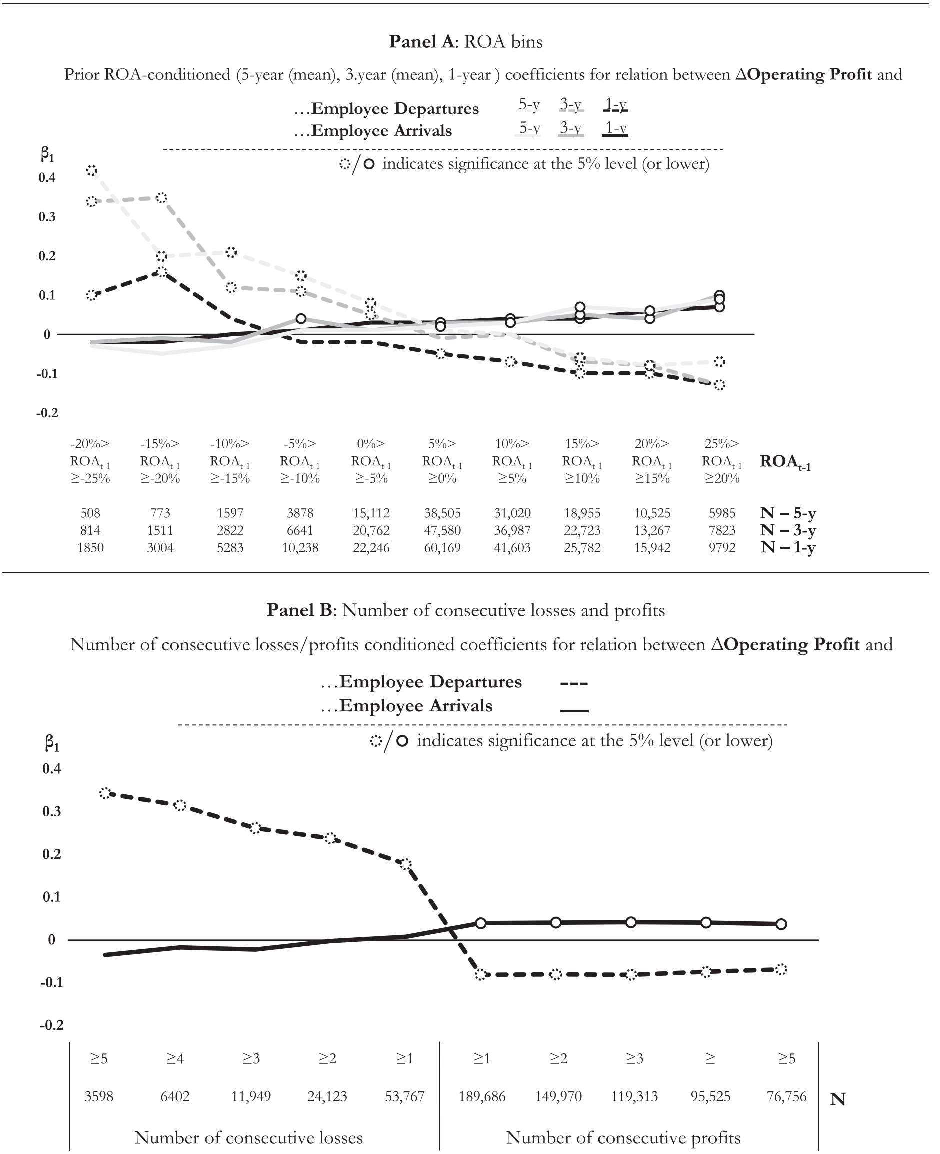
5.2.2 | Consecutive losses and profits

In addition to conditioning on ROA bins, Panel B of Figure 1 conditions by the number of consecutive losses and profits in year $t-1$. For loss firms, we find that the coefficients on Employee Departures increase with the number of consecutive losses (coefficient of 0.18 for ≥1 year of losses versus 0.32 for ≥5 years of consecutive losses), while the coefficients on Employee Arrivals decrease with the number of consecutive losses, although these coefficients are not statistically different from zero (coefficient of 0.01 for ≥1 year of losses versus −0.04 for ≥5 years of consecutive losses). For profit firms, the coefficients do not change much depending on the number of consecutive profits.

There is a large change in the coefficients for Employee Departures going from 1 year's loss (0.18) to 1 year's profit (−0.08), indicating that last year's earnings being above or below zero serves as a good benchmark for our study. The results suggest that the association between employee flows and earnings changes increases with poor historical performance. Also, like Panel A, Panel B graphically illustrates that the effect of departures is larger than the effect of arrivals.

5.3 | Employee departures and departures being replaced by new hires

We explore the interrelation between employee departures and arrivals by measuring the proportion of departing employees that are replaced by new hires of the same position. Departures could be replaced by new employees or could represent negative employee growth. We expect that an increase in the proportion of departures replaced by new hires attenuates the effect of employee departures on gross profit changes, expenses changes and earnings



This figure shows the coefficient estimates on the independent variables of interest of estimating equation 1 for subsamples of prior-year ROA bins (Panel A) and the number of consecutive losses and profits (Panel B). ROA is net earnings scaled by assets.

FIGURE 1 Regression coefficients for 10 subsamples based on ROA and 10 subsamples based on the number of consecutive losses and profits. This figure shows the coefficient estimates on the independent variables of interest of estimating equation 1 for subsamples of prior-year ROA bins (Panel A) and the number of consecutive losses and profits (Panel B). ROA is net earnings scaled by assets

changes. However, since our results this far suggest that the effect of departures is larger than the effect of arrivals, we expect that departures are positively (negatively) associated with earnings changes for prior-year loss (profit) firms even when all departures are replaced by new hires.

Specifically, we estimate a modified version of equation 1 substituting Employee Departures and Employee Departures × Departures Replaced for Employee Departures and Employee Arrivals. Departures Replaced captures the proportion of departing employees who are replaced by new hires. We measure this by counting the number of departures and arrivals within each position in the firm and summing up the number of arrivals that replace departures and dividing that by the total number of departures. Section 4 and Appendix A describe Departures Replaced in more detail.

Table 5 presents the results. The results confirm our expectations: (1) The association between Employee Departures and the dependent variables is attenuated when more departing employees are replaced by new hires (captured by the coefficient on the interaction term Employee Departures × Departures Replaced). (2) Even when all departures are replaced by new hires (Departures Replaced = 1) departures are positively associated with earnings changes for prior-year loss firms (the absolute coefficient on Employee Departures is larger than the absolute coefficient on Employee Departures × Departures Replaced in column 3). We find similar results regarding prior-year profit firms (column 6) however with opposite effects on earnings growth.

5.4 | High-paid versus low-paid employees

We explore the channels that drive our results by distinguishing between flows of high- and low-paid employees. We argue that high-paid employees could harm the profitability of prior-year loss firms, because they impose high costs and that these firms cannot generate profits given these high costs. Reversely, we argue that high-paid employees could benefit the profitability of prior-year profit firms, because these employees are likely the ones who contributed to these firms' ability to make profits.

We sort firms by industry-years and allocate each employee into four quartiles based on the salary they receive from the firm. For arriving employees, we use the salary they receive from the firm in year $t + 1$, because they do not receive a full year's salary in year t. (Recall that our dataset provides annual-level information on salary). For departing employees, we likewise use the salary they receive from the firm in year t – 1 because this salary covers a full year of salary. For the remaining employees (not arriving or departing) we use their salary in year t.

Panel A of Table 6 outlines our regression estimates and shows that high-paid employees drive our results. For loss firms, the coefficient on departures of employees in the highest salary quartile (0.34) is significantly larger than the coefficients on the departures of employees in the other salary quartiles (in the range from 0.14 to 0.22). That is, departures of high-paid employees benefit earnings growth more than departures of low-paid ones for loss firms. We find a similar pattern for employee arrivals. For loss firms, the arrival of high-paid employees (−0.06) is associated with significantly lower earnings growth than the arrival of low-paid employees (in the range from 0.03 to 0.04).

For profit firms, we find similar results, however with opposite effects on earnings growth (like we find in Section 5.2, Table 4). For profit firms, the coefficient on departures of employees in the highest salary quartile (−0.10) is larger than the coefficients on the departures of employees in the other quartiles (in the range from −0.07 to −0.08), although these differences are not statistically significant. For employee arrivals in profit firms, the coefficient on arrivals of employees in the highest salary quartile (0.08) differs from some of the coefficients on arrivals in the other salary quartiles (in the range from −0.01 to 0.06).[21]

Panel B of Table 6 examines whether employee flow information of each layer of employees helps predict earnings out-of-sample. We first compare a base model (using the accounting variables only) to a model including information on employee arrivals and departures of high-paid employees (SalaryQuartile = 4) and find that this information improves the prediction accuracy (column 1 of Panel B of Table 6). We then add each layer of employees (SalaryQuartile = 3, 2 and 1, columns 2 through 4 of Panel B of Table 6), one at a time, and find that employee flows from each layer help predict earnings changes.

[21] The difference between arrivals in the fourth salary quartile is statistically different from arrivals in the first salary quartile, marginally significantly different from arrivals in the second quartile, and insignificantly different from arrivals in the third quartile.

TABLE 5 Employee departures and departures being replaced by new hires

Panel A. Regression results ($N = 210,975$)	Prior-year loss firms (Net earnings$_{t-1} < 0$) $N = 48,330$			Prior-year profit firms (Net earnings$_{t-1} \geq 0$) $N = 162,645$		
	ΔGross Profit$_{t+1}$	ΔOther Operating Expenses$_{t+1}$	ΔOperating Earnings$_{t+1}$	ΔGross Profit$_{t+1}$	ΔOther Operating Expenses$_{t+1}$	ΔOperating Earnings$_{t+1}$
	(1)	(2)	(3)	(4)	(5)	(6)
Employee Departures$_t$	−0.62***	−0.90***	0.25***	−0.77***	−0.70***	−0.09***
	(−23.48)	(−34.86)	(12.51)	(−60.80)	(−39.56)	(−9.93)
Employee Departures$_t$	0.71***	0.81***	−0.09***	0.77***	0.72***	0.05***
× Departures Replaced$_t$	(20.40)	(31.00)	(−4.84)	(25.28)	(24.93)	(5.67)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year and industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.06	0.18	0.16	0.09	0.11	0.13
H0: Employee Departures + Employee Departures × Departures Replaced = 0						
p-Value	<0.01***	<0.01***	<0.01***	0.93	0.25	<0.01***

Panel B. Out-of-sample ΔOperating Earnings$_{t+1}$ prediction accuracy, rolling prediction windows, estimations conducted for each subsample of prior year loss-makers and profit-makers ($N = 200,164$)			
	(1)	(2)	(3)
Model 1			
Control variables	X	X	X
Employee Departures			X
Employee Departures			
× Departures Replaced			
Model 2			
Control variables	X	X	X
Employee Departures	X	X	X
Employee Departures		X	X
× Departures Replaced			
Test statistic	CW	CW	CW
MSPE diff (1 minus 2) × 100	0.0199***	0.0263***	0.0046***
	(20.36)	(20.68)	(6.86)

This table estimates equation 4 and examines the interplay between employee departures and arrivals, by interacting Employee Departures (the number of departing employees scaled by lagged employees) with the proportion of departures that are replaced by new hires of the same position (Departures Replaced). Panel A shows the regression results for subsamples of prior year loss-makers (columns 1 through 3) and prior year profit-makers (columns 4 through 6). Panel B shows the out-of-sample ΔOperating Earnings$_{t+1}$ prediction accuracy measures of different models using rolling prediction windows. We use rolling estimation windows for the subsamples prior-year loss firms and profit firms and estimate equation 1 in year one and use the estimated coefficients to predict earnings in year two. The prediction accuracy is measured by the mean squared prediction error (MSPE). Clark-West, CW, statistics are used to compare out-of-sample predictions for the nested models. MSPE diff is adjusted. A positive (negative) test statistic implies that Model 2 (Model 1) is the superior prediction model. We use the same control variables as in Tables 3 and 4. Appendix A defines the variables. All variables are winsorized at the first and 99th percentiles. Values in brackets represent t-statistics. ***, ** and * indicate statistical significance at the 1, 5 and 10% levels, respectively, using two-tailed tests. Standard errors in Panel A are clustered by firm and year. The regressions are estimated with industry and year fixed effects in Panel A and industry fixed effects in Panel B.

TABLE 6 Employee departures and arrivals, by industry-year salary quartiles

Panel A: Regression results ($N = 243{,}453$)	Dependent variable: ΔOperating Earnings$_{t+1}$			
Prior-year net earnings	Loss $N = 53{,}767$		Profit $N = 189{,}686$	
	Regression results	Coeff. = Q4? *p*-value	Regression results	Coeff. = Q4? *p*-value
	(1)	(2)	(3)	(4)
Employee Departures$_t$				
SalaryQuartile = 1 (small salary)	0.14***	<0.01***	−0.08***	0.16
	(7.37)		(−7.67)	
SalaryQuartile = 2	0.16***	<0.01***	−0.07***	0.13
	(5.84)		(−6.74)	
SalaryQuartile = 3	0.22***	<0.01***	−0.07***	0.22
	(5.94)		(−6.10)	
SalaryQuartile = 4 (large salary)	0.34***		−0.10***	
	(9.87)		(−5.35)	
Employee Arrivals$_t$				
SalaryQuartile = 1 (small salary)	0.04***	<0.01***	−0.01	<0.01***
	(3.34)		(−1.01)	
SalaryQuartile = 2	0.04**	<0.01***	0.05***	0.05*
	(2.11)		(5.23)	
SalaryQuartile = 3	0.03	<0.01***	0.06***	0.22
	(1.47)		(7.38)	
SalaryQuartile = 4 (large salary)	−0.06***		0.08***	
	(−2.58)		(10.25)	
Control variables	Yes		Yes	
Year and industry fixed effects	Yes		Yes	
Adjusted R^2	0.15		0.12	
H0: Employee Departures + Employee Arrivals = 0				
SalaryQuartile = 1, *p*-value	<0.01***		<0.01***	
SalaryQuartile = 2, *p*-value	<0.01***		0.12	
SalaryQuartile = 3, *p*-value	<0.01***		0.51	
SalaryQuartile = 4, *p*-value	<0.01***		0.20	

Panel B: Out-of-sample ΔOperating Earnings$_{t+1}$ prediction accuracy, rolling prediction windows, estimations conducted for each subsample of prior-year loss and profit firms ($N = 230{,}852$)				
	(1)	(2)	(3)	(4)
Model 1				
Control variables	X	X	X	X
Employee Arrivals & Departures, SalaryQuartile = 4		X	X	X
Employee Arrivals & Departures, SalaryQuartile = 3			X	X
Employee Arrivals & Departures, SalaryQuartile = 2				X
Employee Arrivals & Departures, SalaryQuartile = 1				

(Continues)

TABLE 6 (Continued)

Panel B: Out-of-sample ΔOperating Earnings$_{t+1}$ prediction accuracy, rolling prediction windows, estimations conducted for each subsample of prior-year loss and profit firms ($N = 230{,}852$)	(1)	(2)	(3)	(4)
Model 2				
Control variables	X	X	X	X
Employee Arrivals & Departures, SalaryQuartile = 4	X	X	X	X
Employee Arrivals & Departures, SalaryQuartile = 3		X	X	X
Employee Arrivals & Departures, SalaryQuartile = 2			X	X
Employee Arrivals & Departures, SalaryQuartile = 1				X
Test statistic	CW	CW	CW	CW
MSPE diff (1 minus 2) × 100	0.0051***	0.0030***	0.0036***	0.0057***
	(8.96)	(7.70)	(8.56)	(11.45)

This table shows the results of estimating a modified version of equation 1. We distinguish Employee Arrivals and Employee Departures by each industry-year salary quartile. For example, Employee Departures, SalaryQuartile = 1 measures the number of departing employees, whose salary fall in the first (i.e., lowest) salary quartile for the industry-year, scaled by the number of employees at the beginning of the year. Panel A shows the regression results. Columns 2 and 4 of Panel A test for coefficient equality between the coefficient in question and the fourth quartile for the related measure. For example, the *p*-value in the first row of column 2 of Panel A (<0.01) test whether the coefficient on Employee Departures, SalaryQuartile = 1 (0.14) is equal to the coefficient on Employee Departures, SalaryQuartile = 4 (0.34). Panel B shows the out-of-sample ΔOperating Earnings$_{t+1}$ prediction accuracy measures of different models using rolling prediction windows. We use rolling estimation windows for the subsamples prior-year loss firms and profit firms and estimate equation 1 in year one and use the estimated coefficients to predict earnings in year two. The prediction accuracy is measured by the mean squared prediction error (MSPE). Clark-West, CW, statistics are used to compare out-of-sample predictions for nested models. A positive (negative) test statistic implies that Model 2 (Model 1) is the superior prediction model. We use the same control variables as in Tables 3 and 4. Appendix A defines the variables. All variables are winsorized at the first and 99th percentiles. Values in brackets represent t-statistics. ***, ** and * indicate statistical significance at the 1, 5 and 10% levels, respectively, using two-tailed tests. Standard errors in Panel A are clustered by firm and year. The regressions are estimated with industry and year fixed effects in Panel A and industry fixed effects in Panel B.

In summary, high-paid employees drive our results, although employee flows from each salary layer incrementally improve prediction accuracy. This suggests that loss firms benefit from divesting and avoiding high-paid employees and thus cutting costs, while profit firms are harmed when (presumably) well-performing key personnel leave but benefit from attracting new high-paid employees.

5.5 | Employee flows and interest rates

We next examine whether the employee flow variables are associated with capital market outcomes as predicted in hypothesis 3a–3d by estimating equation 4 (interest rates as a function of employee flows). Table 7 presents the results. Consistent with H3a, employee departures are associated with lower interest rates for loss firms. However, H3b regarding the association between employee departures and interest rates in profit firms is not supported in this initial test. For employee arrivals H3c and H3d predict two opposing effects in the loss firm sample as well as the profit sample (increased operating expenses vs. signals of optimism). No effect dominates in the loss firm sample, while the positive effect on interest rates dominates in the profit firm sample.

We then examine whether lenders price employee flow information of different employees, specifically high and low-paid ones. We do this because our results discussed in Section 5.4 (Table 6) suggest that arrivals and departures of high-paid employees contain more information about future earnings than those of low-paid ones. Table 8 reports

TABLE 7 Interest rates

Sample: Current year earnings?	Expected sign: Loss firms (1)	Expected sign: Profit firms (2)	Dependent variable: ΔInterestRate [*t*; t+1] Loss firms $N = 37{,}171$ (3)	Dependent variable: ΔInterestRate [*t*; t+1] Profit firms $N = 122{,}958$ (4)
Employee Departures$_t$	(-) H3a	(+) H3b	−0.0042***	−0.0004
			(−3.55)	(−0.76)
Employee Arrivals$_t$	(+) H3c	(+) H3d	0.0005	0.0011*
			(0.58)	(1.84)
Δln(EBIT/FiExp)$_t$			−0.0046***	0.0046***
			(−11.03)	(14.37)
ΔCA/CL$_t$			−0.0012***	−0.0002
			(−4.95)	(−0.92)
ΔPPE$_t$			0.0035**	0.0075***
			(2.35)	(5.81)
ΔTL/TA$_t$			0.0012	0.0060***
			(1.00)	(5.36)
ΔNegEquity$_t$			−0.0005	0.0019***
			(−1.32)	(5.63)
Δln(TA)$_t$			−0.0008**	−0.0020***
			(−2.00)	(−4.57)
ΔGPgrowth$_t$			−0.0015***	−0.0033***
			(−3.76)	(−14.09)
ΔAverageSalary$_t$			−0.0000**	−0.0000***
			(−2.38)	(−3.72)
ΔPromotion$_t$			0.0004	−0.0002
			(0.59)	(−0.56)
ΔAverageAge$_t$			−0.0001*	−0.0000
			(−1.88)	(−0.53)
ΔAverageFemale$_t$			−0.0013	−0.0003
			(−0.49)	(−0.23)
ΔAverageHighEduc$_t$			−0.0016	0.0007
			(−0.72)	(0.37)
Year and Industry fixed effects			Yes	Yes
Adjusted R^2			0.0425	0.0337

This table reports the results of estimating equation 5. Appendix A defines the variables. All explanatory variables are winsorized at the first and 99th percentiles. Values in brackets represent t-statistics. ***, ** and * indicate statistical significance at the 1, 5 and 10% levels, respectively, using two-tailed tests. Standard errors are clustered by firm and year. The regressions are estimated with industry and year fixed effects.

TABLE 8 Interest rates and industry-year salary quartiles

Sample: Current year earnings?	Expected sign		Dependent variable: ΔInterestRate [t; t+1]			
	Loss	Profit	Loss $N = 37{,}171$		Profit $N = 122{,}958$	
			Regression results	Coeff. = Q4? *p*-value	Regression results	Coeff. = Q4? *p*-value
	(1)	(2)	(3)	(4)	(5)	(6)
Employee Departures$_t$						
SalaryQuartile = 1	(–) H3a	(+) H3b	–0.0035**	<0.01***	–0.0003	0.15
			(–2.17)		(–0.25)	
SalaryQuartile = 2	(–) H3a	(+) H3b	–0.0045***	<0.01***	–0.0005	<0.10*
			(–3.35)		(–0.40)	
SalaryQuartile = 3	(–) H3a	(+) H3b	0.0004	<0.01***	–0.0023	0.04**
			(0.21)		(–1.20)	
SalaryQuartile = 4	(–) H3a	(+) H3b	–0.0151***		0.0030**	
			(–6.17)		(1.97)	
Employee Arrivals$_t$						
SalaryQuartile = 1	(+) H3c	(+) H3d	–0.0015	0.37	0.0009	0.65
			(–1.31)		(1.19)	
SalaryQuartile = 2	(+) H3c	(+) H3d	–0.0009	0.67	0.0003	0.51
			(–0.43)		(0.30)	
SalaryQuartile = 3	(+) H3c	(+) H3d	0.0042*	0.24	0.0014	0.86
			(1.84)		(1.35)	
SalaryQuartile = 4	(+) H3c	(+) H3d	0.0002		0.0019	
			(0.14)		(0.90)	
Control variables			Yes		Yes	
Year and industry fixed effects			Yes		Yes	
Adjusted R^2			0.0430		0.0338	

This table reports the results of estimating a modified version of equation 5. We distinguish Employee Arrivals and Employee Departures by each industry-year salary quartile. For example, Employee Departures, SalaryQuartile = 1 measures the number of departing employees, whose salary fall in the first (i.e., lowest) salary quartile for the industry-year, scaled by the number of employees at the beginning of the year. Columns 2 and 4 test for coefficient equality between the coefficient in question and the fourth quartile for the related measure. For example, the *p*-value in the first row of column 2 (<0.01) test whether the coefficient on Employee Departures, SalaryQuartile = 1 (–0.0035) is equal to the coefficient on Employee Departures, SalaryQuartile = 4 (–0.0151). We use the same control variables as in Tables 7. Appendix A defines the variables. All variables are winsorized at the first and 99th percentiles. Values in brackets represent *t*-statistics. ***, ** and * indicate statistical significance at the 1, 5 and 10% levels, respectively, using two-tailed tests. Standard errors are clustered by firm and year. The regressions are estimated with industry and year fixed effects.

the results. We find that departures of high-paid employees (Employee Departures$_t$, SalaryQuartile = 4) are associated with lower (higher) interest rates the following year for loss (profit) firms. This is consistent with hypotheses 3a and 3b. We generally do not find consistent evidence that departures of other (lower paid) employees are associated with interest rates.[22] We find little evidence that lenders price employee arrivals and find no evidence that high-paid arrivals are priced differently than low-paid arrivals. This suggests lack of dominance of any of the arguments outlined in the theory section (increased operating expenses vs. signals of optimism). Our interpretation of the results is that lenders reward poorly performing firms by decreasing their interest rates when their managers (presumably managers receive the highest salary) leave. Likewise, lenders penalize well-performing firms, by increasing their interest rates, when their managers leave.

In summary, lenders adjust their interest rates to the information contained in departures of high-paid employees but to a lesser extent than the information on arrivals and departures of other employees, despite this information's ability to predict earnings changes. For the generally small enterprises that comprise our sample, it is likely that exactly those individuals, that is, existing employees with relatively high status and visibility, are those known by the lenders. Therefore the lenders are likely to learn about their departures either directly or via social and professional networks. This suggests that lenders do price the information they have but fail to recognize the potential from obtaining other employee flow information directly from the firm.

5.6 | Additional tests

We conduct a range of robustness tests, present them in the Online Appendix, and describe the results briefly below.

Additional insights (Online Appendices A and B): We find that using the information on employee arrivals and departures predict operating earnings changes better out-of-sample than using information on net employee growth, the information that is currently consistently disclosed in annual reports. We also find evidence of a positive curvilinear relationship between employee departures and firm performance, consistent with the meta-analysis of Hancock et al. (2013). However curvilinearity is mostly pronounced using gross profit changes as dependent variable (and less pronounced using earnings changes).

Cross-sectional variation (Online Appendices C, D, E, F and G): We generally find that the effect of employee departures on firm performance is more pronounced for firms with a high labor intensity, young firms, prior-year loss firms with low growth (very poor performance) and prior prior-year profit firms with high growth (very good performance). The effect is also more pronounced for employees with a long tenure and employees who leave late in a year (they should have most impact on next-year performance). The effect of departures is generally more positive for firms' performance when firms shift from labor to capital in their production function. Departures that are likely voluntary are associated with larger effects on gross profit changes than departures that are likely involuntary are. However, we also find differential effects on changes in expenses, resulting in little or no differential effects on earnings changes.

Robustness tests for subsamples (Online Appendices H and I): We rerun our analyses for 10 different firm sizes (size deciles based on the number of employees), 10 different industries (NACE Rev. 2 sections) and for each year in our sample. We generally find that the results reported in Section 5.2 (Table 4, our main results per prior-year profit and loss firms) are robust across industries, firm sizes and years.

Other robustness tests (Online Appendices J and K): Our results reported in Section 5.3 (Table 5), regarding departures and departures who are replaced by new hires, are largely robust to using three alternative identifiers of employees' within-firm position (one-digit DISCO codes, two-digit DISCO codes and salary quartiles),[23] although we find no differential effect between departures and replacements using DISCO codes for prior-year profit firms. Our results are robust to scaling all variables by the number of employees instead of scaling accounting figures by assets, as we do in our main analysis.

[22] For loss firms, Employee Departures in the first and second salary quartiles are significantly associated with interest rate changes with the expected sign. Any other employee departures are not associated with interest rate changes.

[23] DISCO codes describe the nature of the employment and are described in Section 4 and here: https://www.dst.dk/en/Statistik/dokumentation/nomenklaturer/disco

6 | CONCLUSION AND DISCUSSION

This paper examines whether employee flows predict earnings changes and whether lenders price these flows. Overall our results suggest that information on employee flows helps predict earnings and is to some extent priced by lenders.

We find that conditioning on firms' economic situations helps in predicting earnings. Employee departures are associated with earnings increases for loss firms but earnings decreases for profit firms (the sign switches). Employee arrivals do not predict earnings changes for loss firms but predict earnings increases for profit firms. The effect of employee departures is larger than the effects of arrivals, consistent with the notion that departures disrupt operations. The effect of employee flows on earnings changes is larger for high-paid employees than for low-paid ones. Finally, we find that lenders adjust their interest rates in the direction that we would expect when high-paid employees leave their firms.

Our results contribute to the literature in several ways. First, our findings regarding the conditioning on firms' economic situations could help explain the mixed results in the literature (e.g., Hancock et al., 2013). Second, we document differential effects of employee departures versus arrivals. Consequently, using information on both employee gross inflows and outflows yields better earnings predictions than using only one measure (e.g., Gutiérrez et al., 2020; Li et al., 2022) or a net measure. Finally, our results show that lenders, like equity investors (Agrawal et al., 2021; Lev & Wu, 2022; Li et al., 2022), do not fully incorporate employee flow information into their assessments. Our results could help regulators in deciding which information on employees financial reporting preparers should disclose to alleviate informational problems. Our results also demonstrate how investors and creditors can use employee flows to improve forecast accuracy.

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CONFLICT OF INTEREST

The authors have no conflicts of interest to disclose.

DATA AVAILABILITY STATEMENT

This study employs proprietary registry data from Statistics Denmark on the firm and the personal level. The use of confidential data prohibits the authors from sharing the data and conveying micro-data such as minimum and maximum values.

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REFERENCES

Agrawal, A., Hacamo, I., & Hu, Z. (2021). Information dispersion across employees and stock returns. *The Review of Financial Studies*, *34*(10), 4785–4831. https://doi.org/10.1093/rfs/hhaa105

Allen, D. G., Bryant, P. C., & Vardaman, J. M. (2010). Retaining talent: Replacing misconceptions with evidence-based strategies. *Academy of Management Perspectives*, *24*(2), 48–64. https://doi.org/10.5465/amp.24.2.48

Amir, E., Kallunki, J.-P., & Nilsson, H. (2014). The association between individual audit partners' risk preferences and the composition of their client portfolios. *Review of Accounting Studies*, *19*(1), 103–133. https://doi.org/10.1007/s11142-013-9245-8

Bennedsen, M., Tsoutsoura, M., & Wolfenzon, D. (2019). Drivers of effort: Evidence from employee absenteeism. *Journal of Financial Economics*, *133*(3), 658–684. https://doi.org/10.1016/j.jfineco.2018.12.001

Bharath, S. T., Sunder, J., & Sunder, S. v. (2008). Accounting quality and debt contracting. *The Accounting Review*, *83*(1), 1–28. https://doi.org/10.2308/accr.2008.83.1.1

Clark, T. E., & West, K. D. (2007). Approximately normal tests for equal predictive accuracy in nested models. *Journal of Econometrics*, *138*(1), 291–311. https://doi.org/10.1016/J.JECONOM.2006.05.023

Cotton, J. L., & Tuttle, J. M. (1986). Employee turnover: A meta-analysis and review with implications for research. *Academy of Management Review*, *11*(1), 55–70. https://doi.org/10.5465/amr.1986.4282625

Dahl, M. S. (2011). Organizational change and employee stress. *Management Science*, *57*(2), 240–256. https://doi.org/10.1287/mnsc.1100.1273

Dahl, M. S., Dezső, C. L., & Ross, D. G. (2012). Fatherhood and managerial style. *Administrative Science Quarterly*, *57*(4), 669–693. https://doi.org/10.1177/0001839212466521

Diebold, F. X., & Mariano, R. S. (1995). Comparing predictive accuracy. *Journal of Business & Economic Statistics*, *13*(3), 253–263. https://doi.org/10.1080/07350015.1995.10524599

EFRAG. (2021). Proposals for a relevant and dynamic EU sustainability reporting standard-setting. https://ec.europa.eu/info/sites/default/files/business_economy_euro/banking_and_finance/documents/210308-report-efrag-sustainability-reporting-standard-setting_en.pdf

EFRAG. (2022a). Double materiality conceptual guidelines for standard-setting (Appendix 2.6). *January*, 1–31. https://www.efrag.org/Assets/Download?assetUrl=/sites/webpublishing/SiteAssets/Appendix 2.6 - WP on draft ESRG 1.pdf

EFRAG. (2022b). PTF-ESRS Batch 1 working papers – Cover note and next steps. *January*, 1–10. https://www.efrag.org/Assets/Download?assetUrl=/sites/webpublishing/SiteAssets/Cover note for Batch 1 WPs.pdf

EU. (2014). Directive 2014/95/EU of the European Parliament and of the Council of22 October 2014amending Directive 2013/34/EU as regards disclosure of non-financial and diversity information by certain large undertakings and groups. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A32014L0095

FRC. (2018). Guidance on the strategic report (Issue July). https://www.frc.org.uk/accountants/accounting-and-reporting-policy/clear-and-concise-and-wider-corporate-reporting/narrative-reporting/guidance-on-the-strategic-report

Gassen, J., & Fülbier, R. U. (2015). Do creditors prefer smooth earnings? Evidence from European private firms. *Journal of International Accounting Research*, *14*(2), 151–180. https://doi.org/10.2308/jiar-51130

Graham, J. R., Harvey, C. R., & Rajgopal, S. (2005). The economic implications of corporate financial reporting. *Journal of Accounting and Economics*, *40*(1–3), 3–73. https://doi.org/10.1016/j.jacceco.2005.01.002

Gutiérrez, E., Lourie, B., Nekrasov, A., & Shevlin, T. (2020). Are online job postings informative to investors? *Management Science*, *66*(7), 3133–3141. https://doi.org/10.1287/mnsc.2019.3450

Hancock, J. I., Allen, D. G., Bosco, F. A., McDaniel, K. R., & Pierce, C. A. (2013). Meta-analytic review of employee turnover as a predictor of firm performance. *Journal of Management*, *39*(3), 573–603. https://doi.org/10.1177/0149206311424943

Haslag, P. H., Sensoy, B. A., & White, J. T. (2022). Human capital disclosure and workforce turnover. *SSRN (working paper)*. https://doi.org/10.2139/ssrn.3991257

Hausknecht, J. P., & Trevor, C. O. (2011). Collective turnover at the group, unit, and organizational levels: Evidence, issues, and implications. *Journal of Management*, *37*(1), 352–388. https://doi.org/10.1177/0149206310383910

Jensen, T. L., Leth-Petersen, S., & Nanda, R. (2022). Financing constraints, home equity and selection into entrepreneurship. *Journal of Financial Economics*, *145*(2), 318–337. https://doi.org/10.1016/j.jfineco.2021.10.012

Jiang, J. (2008). Beating earnings benchmarks and the cost of debt. *The Accounting Review*, *83*(2), 377–416. https://doi.org/10.2308/accr.2008.83.2.377

Jinkins, D., & Morin, A. (2018). Job-to-job transitions, sorting, and wage growth. *Labour Economics*, *55*, 300–327. https://doi.org/10.1016/j.labeco.2018.10.008

Kotsantonis, S., & Serafeim, G. (2020). Human capital and the future of work: Implications for investors and ESG integration. *Journal of Financial Transformation*, *51*, 115–130. https://www.capco.com/Capco-Institute/Journal-51-Wealth-and-Asset-Management/Human-Capital-And-The-Future-Of-Work-Implications-For-Investors-And-ESG-Integration

Lev, B. I., & Wu, X. (2022). Identifying overvalued stocks with corporate job postings. *SSRN (working paper)*. https://doi.org/10.2139/ssrn.4112800

Li, Q., Lourie, B., Nekrasov, A., & Shevlin, T. (2022). Employee turnover and firm performance: Large-sample archival evidence. *Management Science*, *68*(8), 5667–5683. https://doi.org/10.1287/mnsc.2021.4199

Minnis, M. (2011). The value of financial statement verification in debt financing: Evidence from private U.S. firms. *Journal of Accounting Research*, *49*(2), 457–506. https://doi.org/10.1111/j.1475-679X.2011.00411.x

Moon, K., Loyalka, P., Bergemann, P., & Cohen, J. (2022). The hidden cost of worker turnover: Attributing product reliability to the turnover of factory workers. *Management Science*, *68*(5), 3755–3767. https://doi.org/10.1287/mnsc.2022.4311

Muehlemann, S., & Leiser, M. S. (2018). Hiring costs and labor market tightness. *Labour Economics*, *52*, 122–131. https://doi.org/10.1016/J.LABECO.2018.04.010

Nallareddy, S., Sethuraman, M., & Venkatachalam, M. (2020). Changes in accrual properties and operating environment: Implications for cash flow predictability. *Journal of Accounting and Economics*, *69*(2–3). https://doi.org/10.1016/j.jacceco.2020.101313

Pinnuck, M., & Lillis, A. M. (2007). Profits versus losses: Does reporting an accounting loss act as a heuristic trigger to exercise the abandonment option and divest employees? *The Accounting Review*, *82*(4), 1031–1053. https://doi.org/10.2308/ACCR.2007.82.4.1031

Regenburg, K., & Seitz, M. N. B. (2021). Criminals, bankruptcy, and cost of debt. *Review of Accounting Studies*, *26*(3), 1004–1045. https://doi.org/10.1007/s11142-021-09608-6

SEC. (2017). Rulemaking petition to require issuers to disclose information about their human capital management policies, practices and performance. https://www.sec.gov/rules/petitions/2017/petn4-711.pdf

SEC. (2020). Modernization of regulation S-K items 101, 103, and 105, final rule. https://www.sec.gov/rules/final/2020/33-10825.pdf

Shah, S. Z. A. (2007). Discussion of employee layoffs, shareholder wealth and firm performance: Evidence from the UK. *Journal of Business Finance and Accounting*, *34*(3–4), 495–504. https://doi.org/10.1111/j.1468-5957.2007.02046.x

Sustainalytics. (2021). ESG risk ratings—Methodology abstract about sustainalytics. *Special Report*, *January*, 1–15. https://connect.sustainalytics.com/hubfs/INV/Methodology/Sustainalytics_ESG_Ratings_Methodology_Abstract.pdf

The Danish Ministry of Employment. (2021). The labour market in Denmark. https://bm.dk/media/19251/the-labour-market-in-denmark.pdf

Thomson Reuters. (2017). Thomson Reuters ESG Scores. *Thomson Reuters*, *March*. https://www.esade.edu/itemsweb/biblioteca/bbdd/inbbdd/archivos/Thomson_Reuters_ESG_Scores.pdf

Timmermans, B. (2010). The Danish integrated database for labor market research: Towards demystification for the English speaking audience. *DRUID Working Papers*. http://webdoc.sub.gwdg.de/ebook/serien/lm/DRUIDwp/10-16.pdf

vander Bauwhede, H., de Meyere, M., & van Cauwenberge, P. (2015). Financial reporting quality and the cost of debt of SMEs. *Small Business Economics*, *45*(1), 149–164. https://doi.org/10.1007/s11187-015-9645-1

Viebrock, E., & Clasen, J. (2009). Flexicurity and welfare reform: A review. *Socio-Economic Review*, *7*(2), 305–331. https://doi.org/10.1093/ser/mwp001

Zingales, L. (2000). In search of new foundations. *The Journal of Finance*, *55*(4), 1623–1653. https://doi.org/10.1111/0022-1082.00262

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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APPENDIX A: VARIABLE DEFINITIONS

Variable	Definition			
Size descriptives				
Employees	Headcount. The number of employees who received salary during the year. We count employees who at least once received a salary that was above the minimum salary from the firm.			
Gross profit (tDKK)	Gross profits in thousand Danish Kroner (DKK)			
Operating earnings (tDKK)	Operating earnings (EBIT, earnings before interest and tax) in thousand Danish Kroner (DKK)			
Net earnings (tDKK)	Net earnings in thousand Danish Kroner (DKK)			
TA (tDKK)	Total assets in thousand Danish Kroner (DKK)			
Independent variables				
Employee Arrivals	The number of employees entering the firm in a given year scaled by the number of employees at the beginning of the year.			
Employee Departures	The number of employees leaving the firm in a given year scaled by the number of employees at the beginning of the year.			
Departures Replaced	The proportion of employee departures that are replaced by new hires (i.e., replaced by arrivals). For each position for each firm-year observation we count the number of departures and the number of arrivals that replace a departing employee. The following example outlines our approach: A company has 10 departures and eight arrivals within 1 year, distributed across the following positions:			
		Departures (#)	Arrivals (#)	Departures Replaced (#)
	Position 1	5	3	3
	Position 2	4	0	0
	Position 3	1	5	1
	Total	10	8	4
	Departures Replaced for the firm-year obs. (4/10)			0.40
	We use the Statistics Denmark dataset STILL to identify positions. High STILL codes refer to higher positions in the hierarchy. We classify the STILL position codes into six categories:			
	Position category	Description (STILL codes)		
	1	Employer (11), top manager (30) (31)		
	2	Employee, highest level (32)		
	3	Employee, middle level (34)		
	4	Employee, basic level (35)		
	5	Employee, other (36)		
	6	Employee, without further specification (37) (39)		
	The STILL dataset is described here (in Danish only) https://www.dst.dk/da/Statistik/dokumentation/Times/ida-databasen/ida-ansaettelser/still			

Variable	Definition
Employee Growth	The net change in the number of employees scaled by the number of employees at the beginning of the year.
ΔGross Profit	The change in gross profits scaled by lagged assets.
ΔOther Operating Expenses	The change in operating expenses scaled by lagged assets. Operating expenses are defined as gross profit minus earnings before interest and tax (EBIT).
ΔOperating Earnings	The change in operating earnings (EBIT, earnings before interest and tax) scaled by lagged assets.
ΔCapEx	The change in capital expenditures (calculated as fixed assets minus lagged fixed assets plus depreciation) scaled by assets.
ΔAverageSalary	The change in employees' average salary.
ΔPromotion	The change in the propensity to be promoted. For each firm-year observation, we calculate the proportion of employees who got promoted, based on positions held within the firm. Specifically, we define a promotion as an increase in an employee's STILL code. We then calculate the change the proportion of employees being promoted.
ΔAverageAge	The change in employees' average age.
ΔAverageFemale	The change in the proportion of female employees.
ΔAverageHighEduc	The change in the proportion of employees with a college degree.
Arrivals and Departures based on salary	
Employee Departures$_t$, SalaryQuartile $= j$	Employee Departures, SalaryQuartile $= j$ denotes the number of departing employees, who fall in the jth salary quartile for the industry-year, scaled by number of employees at the beginning of the year.
Employee Arrivals$_t$, SalaryQuartile $= j$	Employee Arrivals, SalaryQuartile $= j$ denotes the number of arriving employees, who fall in the jth salary quartile for the industry-year, scaled by number of employees at the beginning of the year.
Interest rate variables	
ΔInterestRate	The change in the interest rate (InterestRate). InterestRate is the ratio of financial expenses scaled by the average of interest bearing debt. Interest bearing debt is calculated as total liabilities minus trade payables. InterestRate is truncated at the fifth and 95th percentile. Any observations more than 10 percentage points above the interest rate of Danish government bonds for the year are coded as missing.
Δln(EBIT/FiExp)	The change in the logarithm of a firm's interest coverage. We calculate EBIT/FiExp as earnings before interest and tax (EBIT) scaled by financial expenses. We then take the logarithm of EBIT/FiExp and add the absolute value of the minimum of EBIT/FiExp because EBIT/FiExp can be negative.
ΔCA/CL	The change in the ratio of current assets to current liabilities
ΔPPE	The change in the ratio of product, plant and equipment scaled by assets
ΔTL/TA	The change in the ratio of total liabilities to total assets
ΔNegEquity	The change in NegEquity, where NegEquity is an indicator for negative equity
Δln(TA)	The change in the logarithm of total assets
ΔGPgrowth	The change in a firms growth rate, where the growth rate is calculated as the change in gross profits scaled by lagged assets