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Information Dispersion Across Employees and Stock Returns[†]

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Abstract

Rank-and-file employees are becoming increasingly critical for many firms, yet we know little about how their employment dynamics matter for stock prices. We analyze new data from the individual CV's of public company employees, and find that rank-and-file labor flows can be used to predict abnormal stock returns. Accounting data and survey evidence indicate that workers' labor market decisions reflect information about future corporate earnings. Investors, however, do not appear to fully incorporate this information into their earnings expectations. The findings support the hypothesis that rank-and-file employees' entry and exit decisions convey valuable insight into their employers' future stock performance.

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1 Introduction

Rank-and-file employees are becoming an increasingly critical factor of production for many companies (Zingales, 2000). These changes suggest that firms' workforce dynamics have important consequences for firm performance. We know little, however, about how employee entry and exit matter for firms' stock prices. Investors may ignore these dynamics if they believe that the information contained in rank-and-file labor flows is sufficiently spanned by other sources of data that are used to value securities.

To date, there has only been limited study of the implications of labor flows for asset prices. The main difficulty in addressing this issue stems from the empirical challenge of collecting granular data on employment dynamics at the firm-level. Standard datasets that are typically used to analyze workers and firms, such as Compustat and matched employer-employee administrative data, often lack precise information on the timing of employee entry and exit. These limitations make it difficult to assess how the employment dynamics of rank-and-file workers matter for stock returns.

We overcome this challenge by collecting new data from LinkedIn, one of the world's largest online professional networks. We analyze the CV's of individual users of the platform, and identify the start and end dates of job spells to construct a sample of monthly labor flows at Russell 1000 firms. Using this data, we assess whether rank-and-file employees' entry and exit decisions reflect information that can be used to predict stock returns.

More concretely, we propose and test the hypothesis that rank-and-file labor flows reflect information observed by workers that is not incorporated into prices by investors. The intuition behind our hypothesis can be understood as a bridge between theories of worker job search and theories of investor behavior. We hypothesize that workers observe informative signals about the firm's future prospects, and use these signals to update their wage expectations at the firm. In response to negative (positive) signals, workers become more likely to exit (join) the firm. Net labor flows reflect the aggregation of this information across workers. If investors do not infer this information from labor flows and incorporate it into stock prices immediately, either because it takes time for information to percolate through the market (Hong and Stein, 1999) or because investors are subject to behavioral biases (Barberis et al., 1998; Daniel et al., 1998), then we will observe a link between labor flows and future stock returns.

We document a number of empirical findings that support our hypothesis. First, we use calendar-time analysis to show that labor flows can predict future abnormal stock returns. We evaluate a trading strategy in which we short (long) firms that experience high (low) net labor outflows, where net labor outflows are calculated as the difference between gross labor outflows and inflows over a given month, divided by total employment at the start of the month. The strategy yields a statistically significant abnormal return of 0.42% per month (or more intuitively, 4.98% per year). The results are robust to a variety of alternative specifications, such as strategies that use different sorting window lengths, sample period start dates, return weighting schemes, and different benchmark factor models.

Second, we present evidence that equity analysts and investors do not appear to fully incorporate information from labor flows into their corporate earnings expectations. Equity analysts, for example, consistently overestimate (underestimate) the earnings of firms that experience high (low) net labor outflows. The negative correlation that we observe between net labor outflows and analyst errors is robust to numerous explanatory controls for earnings surprises and analyst biases documented by prior studies such as Hughes et al. (2008) and So (2013). Additionally, event study evidence reveals that stock prices decrease (increase) significantly in response to negative (positive) earnings surprises. These findings suggest that investors behave similarly to equity analysts, and fail to adequately formulate earnings expectations to reflect the information contained in labor flows.

Third, we show that our results are stronger for firms that are financially opaque to investors. We construct a number of well-established proxies for financial transparency, and find that the link between labor flows and stock returns is especially pronounced for firms that are less transparent to investors. For example, for newly listed firms that are likely to be harder for investors to evaluate given their limited operating histories, we find that our trading strategy yields abnormal returns of approximately 1.1% per month in the immediate three years that follow an initial public offering (IPO). These and other findings suggest that the failure to account for labor flows is especially costly in instances where it is already difficult to value the firm's assets correctly.

Fourth, we show that the link between gross labor outflows and abnormal stock returns is more pronounced than the link between gross labor inflows and abnormal stock returns. Although our hypothesis pertains to both workers who enter and exit firms, the mechanisms by which these two types of workers obtain information about the firm's future prospects are likely to differ. For example, some studies argue that employees within a company observe information about the firm's future prospects while on the job (Baghai et al. (2018); Bassamboo et al. (2015); Brown and Matsa (2016); Cowgill and Zitzewitz (2015)). Other studies claim that prospective workers gather information about a firm through its current employees (for example, Bayer et al. (2008); Cingano and Rosolia (2012); Hacamo and Kleiner (2017); Harry (1987); Holzer (1988); Ioannides and Datcher Loury (2004)). Our results support both information mechanisms that underlie our hypothesis.

Fifth, we conduct a large-sample survey of the actual LinkedIn users who comprise our sample, and show evidence that workers themselves confirm making entry and exit decisions in accordance with our hypothesis. For example, workers report that their employers' future prospects factored heavily into their past entry and exit decisions, and were generally more important to their decisions than idiosyncratic factors such as family considerations. We also show that prospective employees frequently report gathering information about a firm through its existing employees before deciding whether to join the company. These findings indicate that the workers in our analysis corroborate behavior that reflects our hypothesis.

We also present evidence of one example of the types of information that rank-and-file workers may observe about the firm's future prospects (under our hypothesis, workers may observe a variety of signals that pertain to firm performance). We argue that workers who are central to the operations of a firm observe information about the firm's future production costs. To support this claim, we first show that increases in net labor outflows are predictive of reductions in corporate earnings, primarily through increases in operating expenses and SG&A; we do not observe any significant correlations between labor flows and revenues. We then show that the net labor flows of high-skilled workers such as engineers, scientists, and middle managers—workers who are central to the firm's operations and able to directly observe the firm's production process—are highly predictive of abnormal stock returns, whereas other types of labor flows in our sample are less informative about future performance.

We consider several alternative explanations for our findings, and present theoretical and empirical arguments to characterize their relevance. For example, we assess whether the abnormal stock returns that we document are transitory phenomena that are subject to reversal over longer time horizons; if so, then labor flows may not reflect fundamental information that is materially important for stock prices. In contrast to this hypothesis, however, we show that our main results are not subject to reversal over longer-time horizons. Instead, estimates suggest that investors slowly incorporate information contained in labor flows into stock prices over time.

A second alternative explanation for the findings is that labor flows may simply reflect the hiring and firing decisions of well-informed top executives who possess inside information about the firm's future prospects (Myers and Majluf, 1984), rather than information used by rank-and-file employees to make entry and exit decisions on their own. We show, however, that top executives' insider trading patterns do not correlate with labor flows in a manner that is consistent with this explanation. Moreover, if executives possess insider information that leads to hiring and firing decisions in ways that affect stock prices (as our results demonstrate), then executives would likely be required to disclose this information to comply with fair disclosure rules such as SEC Rule 10(b)-5. The fact that analysts and investors fail to accurately forecast earnings in line with labor flows, however, suggests that top executives do not communicate (and therefore likely: possess) such information.

A third alternative explanation for the findings is that the abnormal stock returns that we observe may simply reflect employment adjustment costs caused by worker flows. To refute this hypothesis, we present three arguments. First, we construct several proxies for employment adjustment costs across firms, and show that our results are actually stronger for firms that have low adjustment costs rather than high adjustment costs. Second, we present survey evidence that individual workers in our sample do not believe that hiring costs—a first-order component of adjustment costs—are significant enough to impact stock returns. Third, we argue that if labor flows simply reflect adjustment costs that are significant enough to impact stock returns, then presumably managers should be cognizant of these costs and communicate such issues to investors. Our findings on insider trading and analyst earnings forecasts, however, are inconsistent with such behavior.

A fourth alternative explanation for our findings is that the abnormal stock returns that we document may simply reflect missing risk factors in the benchmark models for the equity cost of capital. In contrast to this explanation, however, the accounting data and survey evidence indicate that labor flows contain information about earnings levels rather than discount rates alone. Moreover, if labor flows only reflected information about discount rates, then we should not observe our predicted links between labor flows and earnings surprises, nor should we observe our predicted market reactions to earnings announcements.

Finally, we argue that our results do not stem from labor flows constituting private information that is unavailable to investors. We demonstrate that labor flows are publicly observable and fairly straightforward to analyze in real-time. For example, labor flows for individual companies can be constructed at low cost using LinkedIn's own search engine, as well as many other sources of data such as social media platforms and news databases. Consistent with this assessment, we show that our results hold even when we limit our analysis to post-2005 and post-2010 sample years—time periods that follow the public launch of LinkedIn and its rise in popularity among workers.

Our paper adds to a nascent, but rapidly growing literature that seeks to understand how the firm's labor force dynamics matter for asset prices and corporate behavior. Some studies, for example, argue that labor mobility and hiring adjustment costs impact the firm's equity cost of capital (Belo et al., 2014, 2017; Donangelo, 2014). Fedyk and Hodson (2019) present a descriptive analysis of a firm's technical and social skillsets and its equity returns. Other related papers argue that employee satisfaction surveys can be used to predict stock prices (Edmans, 2011; Green et al., 2017; Sheng, 2019).

The unique contribution of this study is evidence supporting the hypothesis that rank-and-file labor flows reflect information observed by workers that is not incorporated into stock prices by investors. The findings are important because they illustrate the costs of asset valuations that ignore the labor market activities of rank-and-file workers. The scope of this problem is potentially large given the increasing reliance of many firms on human capital as a factor of production.

The remainder of this paper is as follows. Section 2 outlines the conceptual framework for our analysis. Section 3 details the construction and sampling properties of our data. Section 4 presents the empirical findings. Section 5 concludes.

2 Conceptual Framework

2.1 Hypothesis

We propose the hypothesis that rank-and-file labor flows reflect information observed by workers that is not immediately incorporated into prices by investors. The intuition behind our hypothesis can be understood as a bridge between canonical theories of job search in labor economics with standard theories of investor behavior in finance. Additionally, the microfoundations of our hypothesis are supported by a number of empirical studies in the labor and finance literatures.

In the canonical model of job search (Cahuc et al., 2014; Mortensen, 1986), workers face various labor market frictions and incur search costs when looking for a job. While conducting their search, individuals face an exogenously specified distribution of wage offers and may receive income during unemployment spells. Workers formulate expectations over the discounted stream of wages they expect to earn from an employer over time. In equilibrium, a worker obeys the following rule: accept any wage offer that exceeds her reservation wage, where the reservation wage is an endogenously determined threshold that reflects the exogenous parameters discussed above.

One of the standard comparative statics of the canonical search model is that a worker is more likely to take up (turn down) an alternative job, in response to an exogenous reduction (increase) in the income that she expects to earn from a given employer. In our setting, workers may observe various signals about a firm's future performance that influence their wage expectations at the firm. These signals may include information about the firm's production costs, information about the CEO's productivity, or any other factors that impact the total amount of firm surplus available to workers, where firm surplus is defined as the difference between revenues and non-labor production costs.[1]

Our hypothesis applies to both workers currently employed by the firm, as well as prospective workers who may join the firm. The specific channels through which each group of workers obtains information about the firm may differ, however. For example, a number of papers argue that rank-and-file employees of firms are able to observe information about a firm's future prospects through their on-the-job activities (Agrawal and Tambe, 2016; Baghai et al., 2018; Bassamboo et al., 2015; Brown and Matsa, 2016; Cowgill and Zitzewitz, 2015). Other studies show that outside workers also gather information about a prospective firm's prospects, through peer networks of workers who are already employed by the firm (Bayer et al., 2008; Cingano and Rosolia, 2012; Hacamo and Kleiner, 2017; Harry, 1987; Holzer, 1988; Ioannides and Datcher Loury, 2004).

[1]Workers may even use these signals to make inference about future stock prices, which could further impact their wage expectations.

The net sum of entry and exit decisions reached by workers at a given firm constitutes a firm's net labor flow. Labor flows, therefore, reflect an aggregation of the information observed by workers that pertains to the firm's future prospects. This information can be used to predict stock returns, if investors fail to extract this information from labor flows and immediately incorporate it into stock prices. There are several models of investor behavior that could give rise to such an outcome. For example, investors may not fully incorporate information contained in labor flows into asset prices because they are too conservative or too overconfident in their preexisting views about firms' future earnings (Barberis et al., 1998; Daniel et al., 1998). It may also be the case that the information reflected by labor flows simply takes time to permeate through financial markets (Hong and Stein, 1999).

2.2 Empirical Predictions

Our hypothesis generates a number of testable empirical predictions. First, our hypothesis predicts that high (low) net labor outflows reflect negative (positive) signals about future stock returns. High net labor outflows stem from workers observing negative net signals about a firm's future prospects. If investors fail to incorporate this information into their expectations, stock prices for high (low) net labor outflow firms will be higher (lower) than their fundamental values. Our hypothesis, therefore, predicts that higher net labor outflows will be associated with lower future abnormal stock returns, ceteris paribus.

Second, our hypothesis implies that net labor outflows will be predictive of corporate earnings surprises. As per the reasoning described above, investors will overestimate the earnings of firms that experience high net labor outflows, since investors do not infer that net labor outflows reflect negative signals about firm surplus. Similarly, our hypothesis implies that investors will underestimate the earnings of firms that experience high net labor inflows.

Third, our hypothesis has implications for how abnormal returns should vary across different types of firms. For example, we should expect to see a stronger link between labor

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flows and abnormal stock returns for firms that are less financially transparent to investors. If investors do not incorporate labor flows into their corporate valuations, then their ability to formulate accurate expectations for financially opaque firms—where investors already face difficulty in predicting corporate performance—will be especially poor.

Fourth, our hypothesis applies to both workers who are currently employed by a given firm, as well as prospective workers who may join a firm. The mechanisms through which information is collected by the two groups of workers are slightly different. Nevertheless, we should observe an empirical link between gross outflows and stock returns, as well as an empirical link between gross inflows and stock returns. Moreover, we should also observe that both current employees as well as outside workers report awareness of the firm's future prospects when they make entry and exit decisions.

2.3 Example of Information Content in Labor Flows: Production Costs

Under our hypothesis, labor flows may encompass a variety of signals that rank-and-file workers observe about the firm's future performance. The main contribution of our paper is to establish that investors do not immediately extract and incorporate this information into stock prices. The various types of information that workers observe cannot be directly measured or quantified, as workers' information sets are inherently intangible. However, we use our data to consider one potential source of information that may be reflected in labor flows which is unique to the literature.

Specifically, we conjecture that key workers in the firm's operations are able to observe information about the firm's non-labor production costs. Software engineers, for example, may observe unexpected production setbacks that cause the firm to increase operating expenses such as IT purchases or marketing costs. If workers observe signals about the firm's future production costs, then net labor outflows should correlate positively with future operating expenses, and correlate negatively with corporate earnings. Furthermore, the link between labor flows and stock returns should be especially pronounced for workers who perform tasks that are critical to the core operations of the firm, as these workers are more likely to directly observe non-labor production costs. We use our data to evaluate these predictions, and present additional findings to shed light on the types of information that is reflected in rank-and-file labor flows.

3 Data

To test our hypothesis, we sample data from LinkedIn, one of the largest online business networking platforms in the U.S. Our sampling procedures are designed to meet three competing constraints: computational feasibility, population representativeness, and economic relevance. In this section, we describe our data collection methods, we present descriptive statistics of our dataset, and we discuss various sampling issues that pertain to our empirical analysis. Further details are provided in the Appendix where indicated.

3.1 Dataset Construction

3.1.1 Worker-Firm Panel Dataset

We collect data on individual workers registered on LinkedIn, where users upload self-reported information from their CV's to the website. The typical information available for a user includes data on an individual's educational background and employment history (i.e. current and past employment spells). The educational background includes information on schools attended, start and end dates, degrees obtained, and educational specialties such as college major. Each employment spell record includes the job title, full name of the employer, start and end dates, detailed job description, and geographic location. Each employment spell is also linked to the employer's firm-level profile on LinkedIn; this profile contains information such as the location of the firm's headquarters, its industry, size, and number of employees on LinkedIn.

From the universe of individual worker profiles available on LinkedIn, we use a randomized sampling strategy to collect data for over 1 million employees who have worked for publicly traded companies in the U.S. Our main sample consists of Russell 1000 constituents as of 2018; we choose this sample for three reasons. First, the Russell 1000 covers more than 90% of all traded equities in the U.S., which ensures that our results generalize across a wide range of firms. Second, we identify firms in the Russell 1000 as of a recent time period, to maximize the number of employee records that we are able to observe on LinkedIn. Third, we use the Russell 1000 index to provide a sample definition that is unlikely to vary with labor flow data, thereby minimizing potential sample selection bias. To show that our results are not sensitive to the choice of firms in our sample, we also collect and analyze the labor flows of over 1 million employees of firms that are part of the Russell 1000 as of 2006, as well as labor flows for firms that undertake an initial public offering (IPO) between 1985 and 2016.[2]

We access data on LinkedIn using publicly-available search tools provided by online search engines such as Google and Yahoo. We use these tools to search for the profiles of workers on LinkedIn who report any instances of working for a sample firm in their employment histories. Specifically, the inputs that are entered into the search engines are text strings that contain company names followed by a randomly generated alphanumeric character. This procedure returns a sample of individual user profile results that we collect for our analysis.

Using this sample, we create an employee-employer matched panel dataset that covers employment histories for individual workers at Russell 1000 firms between 1985 and 2016. We then use this data to aggregate individual employment spells across firms, and construct sample measures of firm employment levels and employment entry and exit every month. The net labor outflow of workers in a given firm-month is defined as the ratio of the difference between the total number of employees who exit a firm minus the total number of employees who join the firm (during the month), divided by the total stock of employment at the firm at the beginning of the month. We construct these measures for all

[2]Due to computational constraints, we are unable to collect data on all Russell 1000 constituents across all sample years, however, these alternative samples provide useful evidence of the robustness of our results to the choice of sample firms. These data also help us address additional issues in Section 4.

workers in the sample, and also create these measures across various worker classifications, based on job descriptions and educational characteristics from LinkedIn profiles.

We merge our firm-labor sample to several other datasets. For example, we use CRSP and Compustat to obtain stock prices and employer-quarter measures of accounting variables such as balance sheet and income statement figures. We collect insider trading data for Russell 1000 executives from Thomson Reuters' Insider Filing database. We also gather data on equity analyst earnings forecasts from the Institutional Brokers Estimate System (I/B/E/S). Further details on our data construction are presented in the Appendix.

3.1.2 Survey Dataset

We conduct a large-sample survey of the individuals who appear in our worker-firm panel data, to provide additional findings that we use to test our hypothesis. We ask users questions that describe their decision-making process when they chose whether to exit or join firms in our sample. We randomly select 2,500 users from our worker-firm panel dataset, and contact each user individually using LinkedIn's e-messaging service. Each message contains a link to a survey hosted on Surveymonkey.com.

Each survey contains three questions, and the content of the questions differs for workers who comprise the inflow versus outflow samples (we survey 1,250 workers from each of these samples). The questions (detailed in the Appendix), pertain to the main hypothesis that we test, as well as alternative hypotheses that we consider in the empirical analysis. For example, we ask workers in our outflow sample about the importance of their employer's future prospects when deciding to leave their jobs.

The responses to the questions correspond to a numerical scale of 1 (Not important at all) to 5 (Very important). We are thus able to quantify the average score and the standard deviation of scores that correspond to each question. We obtained approximately 400 responses to our survey, for an overall response rate of 16%, over a period of six months.

3.2 Sample Descriptive Statistics

Our worker-firm panel dataset consists of 1,500,457 job records held by 1,028,356 employees across Russell 1000 firms. Table 1 (Panel A) presents summary statistics that describe the workers in our sample. The most frequently observed sample occupations are middle-managers, engineers, and office administrators, followed by consultants, scientists, and finance staff. In terms of education, approximately 37.7% (12.45%) of our sample reports earning a Bachelor's degree (high school degree) as their highest level of educational attainment. The average length of labor market experience for a worker in our sample is 5.63 years.

To place these statistics into the proper context and understand the population of workers that is represented by our sample, it is helpful to compare our sample with the LinkedIn population and the U.S. labor force. The population of workers on LinkedIn represents a substantial fraction of the U.S. workforce. Although exact figures are not available, there are more than 160 million past and current U.S. users on LinkedIn as of October 2019; the current U.S. labor force is approximately 164 million workers.[3]

LinkedIn contains a large absolute number of workers across a variety of occupations and industries, as illustrated in Figure 1. The differences in the total numbers of workers on LinkedIn compared to the U.S. labor force stem from a variety of factors. Most important is the fact that online professional networking is relatively less important for workers in certain segments of the labor force. For example, Figure 1 illustrates that LinkedIn represents a high fraction of workers in the U.S. labor force who are employed in the finance, information technology, and business services sectors. In contrast, LinkedIn contains smaller numbers of workers in the U.S. labor force who are employed in the manufacturing, trade, and transportation sectors. Though the absolute numbers of LinkedIn workers is still high in these sectors, online professional networking in these industries is likely to be of less importance.

[3]These figures are taken from: www.statista.com/statistics/272783/linkedins-membership-worldwide-by-country/; www.dlt.ri.gov/lmi/laus/us/usadj.htm.

LinkedIn is also more likely to represent younger, more educated workers than the U.S. labor force as a whole. In the U.S. labor force, for example, the fraction of workers whose highest level of educational attainment is a college (high school) degree is approximately 24% (26%) as per BLS statistics. Taken together, these data illustrate that the LinkedIn population represents a very large fraction of the U.S. labor force, with over- and under-sampling of various occupations and industries.

Our dataset represents a sample of workers that have been employed by Russell 1000 firms sometime between 1985 and 2016. Figure 2 depicts the industry distribution of workers in our sample, compared to the total population of Russell 1000 workers on LinkedIn and the total population of Russell 1000 workers on Compustat. Although each of these data sources is subject to measurement error and therefore inadequate for providing precise employment numbers for Russell 1000 firms, data comparisons across these sources provide a general sense of the data that we analyze.

Figure 2 illustrates that our sample contains a large cross-section of workers across many industries. The figure also shows that the distribution of workers across most industries is similar to that of the LinkedIn population and Compustat. There are differences across groups in the sampling rates of specific industries; for example, our data over-samples workers in information technology and financial services, and under-samples workers in trade, transportation, and utilities. As discussed below, we assess the importance of these sampling differences in our empirical analysis.

Table 1 (Panel B) describes the characteristics of companies in our sample. The average firm size is $25 billion in assets, while the average market capitalization is $12.3 billion in equity. Table 1 (Panel C) describes our measures of firm-level labor flows in the sample. The average number of labor outflows (inflows) over in a given month is 4.1 (5.4) outgoing (incoming) workers across firms in the sample. Standardized net labor outflows (which we refer to simply as net labor outflows for brevity) have an average value of -0.007, and a standard deviation of 0.049, across all firm-months in the sample. Intuitively, this figure implies that the average monthly change in employment observed for sample firms is roughly an increase of 0.7% over the sample period. The 5th percentile of net outflows is -0.056, while the 95% percentile of net outflows is 0.028. These figures illustrate wide heterogeneity in monthly labor flows observed across Russell 1000 firms.

3.3 Sampling Issues

The main strength of our data is granular information on employee entry and exit at public companies. Other commonly used datasets, such as Compustat and administrative employer-employee matched surveys, often lack precise information on the timing of labor flows. Our data enable us to test whether rank-and-file labor flows contain information that is useful for predicting abnormal stock returns at a monthly frequency. An important concern for our empirical analysis is assessing the extent to which measurement error, sample selection biases, and population representativeness impact the interpretation of our findings. We discuss each of these issues below and cite further analysis in Section 4.

3.3.1 Measurement Error

There are two potential sources of measurement error in our data. First, users may provide incorrect information about their employment histories on LinkedIn, for example, by changing the start and end dates of various positions. Second, our sample measures of labor flows may be imprecise, because we do not observe all workers in the LinkedIn population, and we are unable to observe workers in the labor force who are not on LinkedIn.

We perform several analyses that suggest that measurement error is unlikely to be a major concern for our results. First, we present evidence that users report accurate information to LinkedIn. Figure 3 illustrates that the lengths of employment spells implied by our dataset closely match the lengths of employment spells for workers in the U.S. labor force (based on Current Population Survey data).

Second, the veracity of LinkedIn data is supported by the fact that employers often run background checks on workers to verify employment histories and educational acheivements, and users can be identified for posting false information on LinkedIn because this data is publicly available. Third, as we discuss in our empirical analysis below, we characterize the degree of measurement error in our labor flow measures using employment data from other data sources such as Compustat, and we show that are our results are stronger for samples where measurement error is likely to be relatively low.

3.3.2 Sample Selection

Another important concern is the over- and under-sampling of particular workers at Russell 1000 firms. As discussed earlier, Figure 2 shows that our sample over-represents younger, more highly educated workers across specific occupations and industries, as compared to the general population of workers employed by Russell 1000 firms.

To address this concern, in our empirical analysis we conduct bootstrap procedures to re-create samples that more closely mirror the population of workers on LinkedIn. We also create subsamples of data that are restricted to specific types of workers, to control for worker characteristics which may be subject to uneven sampling. Finally, we examine subsamples of data where sampling rates of the population are relatively high versus relatively low. Using these different samples, we perform our main tests, and show that our findings are robust to these different sampling schemes, which suggests that our main results are unlikely to be driven by significant sample selection bias.

3.3.3 Population Representativeness

Our data represent a large, economically meaningful segment of the labor force employed by Russell 1000 firms. We do not observe workers who do not use LinkedIn, nor do we study all firms outside of the Russell 1000. These caveats imply that we are unable to assess whether the labor flows of all workers contain information that is useful for predicting stock returns, nor are we able to claim that our hypothesis holds for publicly traded firms outside the Russell 1000. Nevertheless, we believe the dataset that we analyze is important, because it captures the labor dynamics for a large segment of the workforce that is employed by firms that represent approximately 90% of all U.S. traded equities. As such, the data enable us to test whether there are *any* labor flows that contain information that is useful for predicting stock returns for Russell 1000 firms.

4 Empirical Findings

In this section, we present three sets of empirical findings. First, we present evidence that supports the main predictions of our hypothesis. Second, we provide suggestive evidence of one example of information content that is reflected in labor flows. Third, we evaluate a number of alternative explanations for our findings.

4.1 Labor Flows and Stock Returns

4.1.1 Calendar-Time Portfolio Analysis

The first prediction of our hypothesis is that labor flows contain information that can explain abnormal stock returns. To test this prediction, we evaluate a trading strategy that is based on firms' labor flows. Specifically, we measure the returns of a portfolio constructed each month that shorts firms that experience high net labor outflows, and longs firms that experience low net labor outflows, over the previous month.

The long-short portfolio returns are measured against factor models that are commonly used to estimate a firm's equity cost of capital. In our main specifications, we present results using the Fama-French five factor model (Fama and French, 2015).

$$R_{p,t} = \alpha + \beta \cdot MP_t + s \cdot SMB_t + h \cdot HML_t + p \cdot RMW_t + i \cdot CMA_t + \epsilon_t$$

where t denotes the calendar month, $R_{p,t}$ is the monthly return of our portfolio, and the monthly explanatory factors such as MP_t and SMB_t are defined as per Fama and French (2015). In our main specifications, we sort firms into quartiles based on their realized net labor outflows over a given month; the dependent variable captures the differences in returns between firms in the top and bottom quartiles. The main coefficient of interest is the intercept (i.e. the "alpha"). Intuitively, the intercept is a measure of the average monthly abnormal return generated by the portfolio.

The coefficient estimates and raw returns for our main specifications are presented in Table 2. In column 1, the alpha of 0.415% per month is statistically significant, and stems from raw returns of 1.813% per month for the long portfolio and 1.522% per month for the short portfolio. Intuitively, the results imply that a trading strategy based on net labor outflows generates abnormal returns of approximately 4.98% per year. Column 2 indicates that the alpha is similar in magnitude when measuring portfolio returns using a value-weighting scheme.

The results are robust to a variety of alternative specifications and sample restrictions. For example, in columns 3 and 4 of Table 2, we construct our portfolios by sorting firms into terciles rather than quartiles of realized net labor outflows. The significant alpha estimates in both columns indicate that our results are not sensitive to more coarse distributions of labor flows across firms. In columns 5 through 8, we restrict our sample to years when the LinkedIn platform is publicly available, and we also remove NBER-defined recessionary periods in the final two columns. The results across these columns indicate that our main findings are not driven by periods of time when labor flows are potentially harder to observe by investors using LinkedIn, nor are they driven by recessionary periods when stock returns are especially low.

We further illustrate our results' robustness by presenting regression estimates across a variety of alternative specifications in the Appendix. For example, the findings presented in Appendix Table A1 show that our trading strategy generates consistent abnormal returns irrespective of whether we alter the length of the sorting windows used to calculate labor flows (from one month to six months), the percentile ranking schemes used to allocate firms across the long and short portfolios (terciles to quintiles), or the sample start years (1985, 1995, 2005, and 2010).

We also show that our results do not appear to be adversely impacted by measurement error in our labor flow measures. Appendix Table A2 illustrates that the link between labor flows and stock returns is, in fact, stronger when we examine subsamples of data where measurement error in labor flows is likely to be low. In particular, when we restrict our sample of analysis to firms in which we observe relatively high fractions of the total worker population in our sample—as measured by either Compustat or LinkedIn—we observe greater return predictability of labor flows. Therefore, because our results grow stronger as measurement error decreases, it is likely that our full sample results understate the ability of labor flows to predict abnormal stock returns.

In Appendix Table A3, we show that our results are robust to sample selection concerns that pertain to the workers in our data. The sampling strategy that we develop to collect our dataset is designed to generate a random sample of workers across firms. However, because our sample is ultimately comprised of return results from internet search engines, it is possible that the sample of workers that we collect is non-random across dimensions such as unobservable worker quality. To explore the relevance of this concern, we perform bootstrap analyses to generate samples of data where the distribution of workers who attend highly ranked universities (a proxy for unobservable worker quality) in our samples match those of the population. We show that even for these samples, our results hold. These results suggest that our estimates do not appear to be significantly biased by sample selection issues at the worker-level.

Appendix Table A4 shows that our results hold using alternative benchmark models such as 6-factor specifications that control for momentum, liquidity, and investment behavior (Panels A and B). Panel C illustrates that our findings are also robust to alternative factor measurement methods (Hou et al., 2015). Appendix Table A5 shows that our results do not appear specific to the choice of firms that we analyze. For example, our calendar-time results remain similar if we analyze firms that comprise the Russell 1000 as of 2006; these results suggest that our main sample results are not subject to survivorship bias or any other unique features of firms that are in the Russell 1000 as of 2018. Finally, we show that our results persist even if we exclude firms that IPO between 1985 and 2016 from our analysis. Because our results hold for liquid stocks with low transaction costs, it is unlikely that our full sample findings are significantly impacted by trading costs.

Overall, these findings illustrate that rank-and-file labor flows can be used to predict abnormal stock returns in calendar-time portfolio analysis. Granular measures of employee entry and exit have significant explanatory power that is robust to a variety of specification choices. The findings support the hypothesis that rank-and-file labor flows contain information that investors do not fully incorporate into stock prices.

4.1.2 Labor Flows and Earnings Expectations

Our hypothesis posits that labor flows explain abnormal stock returns partly because investors do not fully incorporate information from labor flows into corporate earnings expectations. Therefore, a second empirical prediction of our hypothesis is that labor flows can predict investors' earnings forecast errors. We test this prediction in three ways.

First, we examine the earnings expectations of equity analysts. Equity analysts are a useful proxy for well-informed investors, as they are incentivized to formulate accurate forecasts of corporate earnings. Our hypothesis suggests that labor outflows can predict analyst forecast errors: in particular, net labor outflows should correlate negatively with future earnings surprises.

To measure earnings surprises, we compute the difference between analysts' earnings per share (EPS) forecasts with the realized earnings per share announced by firms in our sample. Specifically, for a given firm i in month t, we calculate the mean $\mu_{i,t}$ and standard deviation $\sigma_{i,t}$ of analysts' earnings per share forecasts for the firm's next upcoming quarterly earnings announcement. The standardized unexpected earnings (SUE) for firm i in month t is defined as:

$$SUE_{i,t} = \frac{actual_{i,t}^{ex\text{-}post} - \mu_{i,t}}{\sigma_{i,t}}$$

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Intuitively, the SUE is the difference between the actual EPS realized by the firm minus the mean forecasted EPS across all equity analysts in a given month, normalized by the standard deviation of the EPS forecasts observed for that month.

We use this measure to estimate firm-month panel regressions of earnings surprises on realized net labor flows, controlling for a variety of known predictors of earnings forecast errors, following So (2013).[4] The key measure of interest is the estimated coefficient for net labor outflows. We test whether the estimated coefficient is negative and statistically significant, as our hypothesis predicts.

The results are presented in Table 3. In column 1, the coefficient for net labor outflows is negative and statistically significant, consistent with our hypothesis: increases in net labor outflows lead to more negative earnings surprises. In columns 2 through 4, we add controls such as firm and month fixed effects and other known predictors of unexpected earnings, and the coefficient for net labor outflows remains similar in magnitude and statistical significance. The results also remain the same when we restrict the sample years to 2005 and afterwards, suggesting that our main results are not driven by the potential difficulty of observing labor flow data from LinkedIn.

The findings are consistent with our hypothesis. The data indicate that differences between analyst earnings forecasts and realized corporate earnings can be partly explained by net labor outflows. Higher net labor outflows reflect worsening earnings prospects, yet equity analysts do not appear to factor this information into their forecasts prior to earnings announcements.

To buttress this evidence, in our second analysis, we estimate market reactions to earnings announcements in our sample. According to our hypothesis, if investors fail to incorporate information from labor flows into earnings expectations, then we should see a negative (positive) stock price reaction to negative (positive) earnings surprises.

[4]See also Hughes et al. (2008) for work that documents predictable components of earnings forecast errors and analyst biases.

Such evidence would illustrate that investors behave similarly to equity analysts when forecasting corporate earnings and factoring their expectations into stock prices.

Figure 4 depicts event study analysis of earnings announcements for firms in our sample. We define the event window to be 10 days around earnings announcements, and we estimate factor loadings over daily returns for up to 100 days, starting 50 days before the start of the event window. We graphically depict average cumulative abnormal returns (CAR) and corresponding 95% confidence intervals generated each day of the event window.

The results in Figure 4 indicate that negative (positive) earnings surprises generate negative (positive) and significant cumulative abnormal returns in the immediate days surrounding earnings announcements. In results available upon request, we find that these conclusions hold even when we restrict our sample of earnings announcements to those in which firms report negative or positive net labor flows in the previous quarter. Additionally, we find that the size and significance of these CAR's remains the same when we vary specification parameters such as the lengths of the event and estimation windows. These results suggest that the market fails to anticipate realized earnings in a manner that mirrors equity analysts.

In our third analysis (also available upon request), we compare analysts' earnings forecast errors across firms in our trading strategy's long and short portfolios. We find that firms in the long portfolio are characterized by earnings surprises that are positive on average, while firms in the short portfolio exhibit earnings surprises that are negative on average. Moreover, the difference in average earnings surprises between the two portfolios is statistically significant.

Collectively, these results indicate that investors do not appear to incorporate information from labor flows into earnings expectations. Consistent with our hypothesis, we find that higher net labor outflows lead to more negative earnings forecast errors and lower abnormal stock returns. The patterns are robust to a variety of different empirical specifications, and highlight the value of earnings-related information that can be extracted from rank-and-file workers' entry and exit decisions.

4.1.3 Heterogeneity of Findings Across Firms

We demonstrate the heterogeneity of our calendar-time results across different types of firms in our sample. As discussed in Section 2, our hypothesis predicts that the link between net labor outflows and abnormal stock returns should be stronger for firms that are less financially transparent to investors. We test this prediction by examining our main results across firms that differ across measures of financial transparency that have been established by the prior literature.

For example, numerous accounting studies, such as Brown and Martinsson (2018), proxy for financial transparency by using well-cited measures of earnings reporting quality from Leuz et al. (2003). Like others, we assume that firms that engage in greater earnings management are less likely to be transparent to investors, since these firms exhibit greater discretion in reporting their accounting data to the public. The first measure we examine is the ratio of the firm's standard deviation of operating earnings divided by the standard deviation of the firm's cash flow from operations. Low values of this measure indicate that managers exercise greater discretion to smooth reported earnings; such behavior implies lower firm transparency.

The second measure of earnings management is the correlation between changes in accounting accruals and changes in operating cash flows for a given firm (larger magnitudes of this correlation imply greater earnings management and hence lower transparency). The third measure is the ratio of the firm's absolute value of accruals scaled by the absolute value of the firm's cash flow from operations. The fourth measure is the ratio of small profits to small losses, using after-tax earnings scaled by total assets. Increases in both the third and fourth measures imply greater earnings management and hence lower transparency.

The fifth measure of firm transparency that we employ is based on the firm's age. We analyze firms that IPO during the sample period, and perform our calendar-time analysis over different periods of time after an IPO. Underlying our analysis is the assumption that recent IPO firms are likely to be less transparent to investors than older companies with longer operating histories, as investors gather more information about the firm over time.

Using these five measures of firm transparency, we split our sample into firms with high vs. low levels of firm transparency, and we repeat our calendar-time analysis for firms in each of these subsamples. The results are reported in Table 4 and Appendix Table A6. Across the various measures of firm transparency that we employ, we report that the results appear stronger for firms that are less financially transparent to investors. In Table 4 for example, not only are the vast majority of alphas for the low financial transparency samples statistically significant and positive in magnitude, 22 out of the 32 alphas among low transparency firms are of larger economic magnitude than the alphas for correspondingly high transparency firms. In Appendix Table A6, we see that the alphas are particularly large immediately following the IPO date of newly listed firms—on the order of 1.1% per month—and that the abnormal returns slowly converge over time to the alphas of established firms.

4.1.4 Net Labor Flows and Gross Labor Flows

As explained in Section 2, our hypothesis is relevant for both the firm's existing employees as well as the firm's prospective workers, though the specific information transmission mechanisms are slightly different between the two types of workers. Existing employees may obtain information about firm prospects through their job activities, while outside workers may gather this information through their peer networks within firms. Net labor flows combine the information contained in gross labor outflows and gross labor inflows, thus, our main results are depicted using net labor flows because they are more informative than gross flows alone.

Nevertheless, to understand the relative empirical importance of gross labor outflows versus gross labor inflows, we perform our calendar-time analysis using each of these gross labor flows in isolation. For example, we repeat our portfolio construction and return analysis as per Section 4.1.1, but sort firms into quartiles based on their gross labor outflows rather than their net labor outflows. We also repeat these procedures using gross labor inflows. Our hypothesis predicts that we should observe positive abnormal returns when we long (short) firms with low (high) gross outflows and long (short) firms with high (low) gross inflows.

The results of these two sets of analyses are presented in Table 5. Panel A illustrates that our trading strategy generally leads to positive abnormal returns when we sort firms based on gross labor outflows. The results are statistically significant and similar in magnitude across our equal-weighted portfolio return specifications (the results are positive, but less significant in our value-weighted schemes, possibly because gross flows contain less information than net flows for large-cap companies).

Panel B illustrates that gross inflows appear to have some explanatory power for abnormal returns, though the empirical link is relatively weaker than the documented effects of gross outflows. The abnormal returns for the gross inflow strategies are only statistically significant in three out of eight specifications. Moreover, the abnormal returns for six out of eight gross inflow specifications in Panel B are smaller in magnitude than the returns for the corresponding gross outflow specifications in Panel A.

The findings indicate that gross labor flows can explain abnormal stock returns, consistent with our hypothesis. Moreover, the data show that gross labor outflows are more informative than gross labor inflows. This evidence suggests that the information observed by the firm's existing employees is likely to be more precise than then information gathered by prospective workers outside the firm.

4.1.5 Survey Evidence

In addition to the statistical findings presented above, we also present survey evidence that supports the hypothesis that rank-and-file labor flows contain information that investors do not incorporate into stock prices. As described in Section 3, we ask a random sample of the actual individuals in our dataset several questions that pertain to their past labor market

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decisions. The answers to these questions corroborate the mechanisms that underlie our hypothesis.

For employees whose exit decisions comprise the gross labor outflows in our sample, we asked on a scale of 1 (Not important at all) to 5 (Very important): "How important were the future prospects of your employer when deciding whether to leave and find a new job?" Of the 169 responses received, Figure 5 shows that the average score for this question was 4.39 (with a standard deviation of 0.74). To provide a benchmark against which this score can be compared, we also asked these workers: "How important were personal circumstances when choosing whether to leave your employer"? The average score for this question was 3.62 (with a standard deviation of 1.31). The difference in average scores between the two questions is statistically significant at the 5% level.

For workers whose entry decisions comprise the gross labor inflows in our sample, we asked on a scale of 1 (Not important at all) to 5 (Very important): "Did you gather information from existing (or former) employees before deciding whether to join a prospective employer"? Of the 230 responses received, the average score for this question was 3.92 (with a standard deviation of 1.19). For comparability, we also asked them: "How important was publicly available information in deciding whether to join a prospective employer"? The average score for this question was 3.76 (with a standard deviation of 1.10). There are no statistically significant differences in the average scores between the two questions.

The survey answers demonstrate several points that are consistent with the underlying premises of our hypothesis. First, the evidence illustrates that existing employees use information about their employer's future prospects when making exit decisions. This information is relatively important, as it is highly valued relative to idiosyncratic, personal factors that also drive employees' exit decisions.

Second, the evidence also shows that prospective workers make entry decisions based on information about an employer's future prospects. The survey answers indicate that many workers obtain information about a firm's future prospects through their network of contacts that are already employed by the firm, consistent with existing literature. Moreover, this information appears to be as important to workers as the information collected from publicly available sources about a firm's future prospects–information that investors presumably use when valuing stocks. The survey evidence thus supports the notion that labor flows reflect information that rank-and-file employees have about a firm's future prospects.

4.2 Example of Information Content in Labor Flows: Production Costs

The findings presented thus far support the main contribution our paper: we show that rank-and-file labor flows contain information that investors do not incorporate into stock prices. Under our hypothesis, labor flows may encompass a variety of signals that workers observe about the firm's future performance. Although these signals cannot be directly measured, as workers' information sets are inherently unobservable, we provide suggestive evidence of a unique information channel that is reflected in labor flows: we argue that workers who are central to the core operations of the firm possess valuable information about the firm's future production costs.

4.2.1 Labor Flows and Production Costs

We demonstrate that labor flows can predict future production costs in our sample by examining firm quarterly operating earnings and its components, such as SG&A (sales, general and administration expenses), operating costs, and revenues. Table 6 (Panel A) reports the coefficients on net labor outflows in the following regression specification:

$$y_{i,t+1} = a + b * NetLaborOutflow_{i,t} + FEs + \epsilon_{i,t+1}$$

where t denotes the fiscal quarter. The dependent variable $y_{i,t+1}$ is measured as either SG&A, operating costs, revenues, or earnings after depreciation and amortization (EBIT) in the next quarter. All dependent variables are normalized by the book value of the firm's assets. The key independent variable $NetLaborOutflow_{i,t}$ is the net labor outflow of the current quarter. We also include firm and year-quarter fixed effects.

Table 6 illustrates that higher net labor outflows predict higher future operating expenses in our sample. The results are driven by the positive correlation between net labor outflows and SG&A. There is little correlation between labor flows and revenues. The sum of these effects is the observed negative correlation between labor flows and future earnings depicted in the final columns of Panel A. As higher net labor outflows lead to lower firm wage bills without offsetting effects on revenues, the results in Table 6 imply that the link between net labor outflows and earnings is driven by increased non-labor production costs, part of which are reflected in SG&A and operating expenses.

4.2.2 Labor Flows of Employees Central to the Firm's Production

We also show that the labor flows of specific types of workers are particularly informative about future stock returns. In particular, we examine employees who are directly involved in the firm's day-to-day operations; these workers are likely to observe shocks to the firm's production capabilities. For example, engineers often witness production setbacks that require the firm to incur additional future expenditures. To the extent that these increased expenditures leave less revenue surplus to be distributed among employees—consistent with the results depicted in Panel A of Table 6—there is an increased likelihood that workers will exit the firm, ceteris paribus.

To examine this issue empirically, we exploit data from workers' job titles, educational backgrounds, and career paths, to examine the links between specific types of labor flows and stock returns in our sample. For example, we identify the following major occupational categories in our data: engineers, scientists, middle managers, finance staff, office administrators, and consultants. We evaluate our calendar time trading strategy using the net labor outflows of workers that belong to each of these occupational categories. We perform similar analyses using the labor flows of workers distinguished by their educational attainment levels and years of work experience, respectively.

The results of these analyses are presented in Panels B through D of Table 6. In Panel B, we observe positive abnormal stock returns for our trading strategy when we sort firms based on the net labor flows of engineers, scientists, and middle managers. In contrast, we observe statistically insignificant abnormal stock returns for our trading strategy when we sort on the flows of finance personnel, office administrators, and consultants. Within each class of occupations, the results are generally similar across columns and therefore robust to a variety of alternative specifications. Panels C and D show that we observe positive abnormal stock returns when we sort firms based on the flows of workers with high levels of work experience and workers with relatively higher levels of educational attainment; these workers likely possess human capital that is critical to the operations of the firm.

Taken together, the results in Table 6 support the view that rank-and-file labor flows partly reflect information that pertains to the firm's productive capabilities. The correlations between labor flows and various accounting figures illustrate that higher net labor outflows are predictive of increased production costs. Furthermore, the links between labor flows and stock returns are especially pronounced among workers who are central to the operations of the firm and most able to directly observe these costs during the production process.

4.3 Alternative Explanations

We consider a number of alternative explanations for our main findings. In this section, we detail each of these alternative explanations, and then present theoretical and empirical arguments to characterize their relevance.

4.3.1 Return Reversal or Return Persistence?

We assess whether the abnormal stock returns that we document are subject to reversal over longer time horizons or whether they persist over time. If the returns reverse over longer horizons, then labor flows may not contain fundamental information that is materially important for stock prices. Instead, labor flows may simply correlate with transitory phenomena that temporarily influence prices in the short-run.

To evaluate this possibility, we repeat our calendar-time sorting procedure, and estimate the long-short portfolio's returns over the subsequent months that follow the initial one-month period that generates the main results presented in Table 2. We test whether the trading strategy yields negative abnormal stock returns during these subsequent months. Table 7 presents the results of this analysis for each specification depicted in Table 2.

Each row in Table 7 corresponds to the specific month over which returns are calculated; the alphas in the first row reflect the main results presented in Table 2. As illustrated in the second and third rows, the alpha generally remains positive when we examine the long-short portfolio's returns during the second and third months following the initial one-month return period. The remaining rows, however, show that any subsequent abnormal returns are no longer statistically different from zero. These patterns are similar across all specifications (columns) of Table 7.

The data show little evidence of negative abnormal stock returns in any future periods. Instead, the data reveal gradually decreasing, positive abnormal returns for up to three months, followed by statistically insignificant abnormal returns. This evidence indicates that our main results are not subject to reversal over longer-time horizons. In fact, the findings suggest that investors slowly incorporate information contained in labor flows into stock prices over time.

4.3.2 Top Executive Inside Information

Another alternative explanation for the findings is that labor flows simply reflect the hiring and firing decisions of well-informed top executives who possess inside information about the firm's future prospects (Myers and Majluf, 1984). This explanation differs slightly from our hypothesis, in that labor flows reflect information possessed by top executives rather than information possessed by rank-and-file employees per se.

We present two arguments that suggest that the observed links between labor flows and stock returns do not simply reflect inside information possessed by top executives. First, we show that top executives' insider trades do not correlate with labor flows. If top-level

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executives make operating decisions such as hiring and firing that reflect inside information, then presumably top-level executives should also trade their holdings to capitalize on this information. Thus, we should expect to see a correlation between labor flows and insider trades.

To test this prediction, we aggregate executive insiders' monthly net sales (open market sales minus open market purchases), normalized by the total number of outstanding shares, and examine whether insider sales correlate with net labor flows. As Panel A of Table 8 illustrates, we find little evidence of any statistical link between labor flows and insider trades. Panel B shows that these results persist even when the analysis is limited to insider trades that are considered "opportunistic" (Cohen et al., 2012). Furthermore, in results available upon request, we find that insider trades are poor predictors of whether firms are in the high vs. low net labor outflow quartiles studied in our calendar time analysis.

Second, we note that top executives are generally required by fair disclosure rules such as SEC Rule 10(b)-5 to disclose material information that is relevant to investors. If executives receive information that causes them to make hiring and firing decisions in ways that impact stock prices (as our results already demonstrate), then executives would be compelled to disclose this information to investors. The fact that equity analysts systematically fail to forecast earnings accurately in line with labor flows suggests that top executives do not communicate (and therefore likely: possess) such information.

4.3.3 Do Labor Flows Measure Adjustment Costs?

Another alternative hypothesis is that the abnormal stock returns that we document may simply reflect employment adjustment costs caused by worker flows. For example, employee departures can cause firms to incur costs of worker replacement such as hiring and training expenses; these expenditures may lead to lower future stock returns. To address this "adjustment cost" hypothesis, we present three arguments.

First, we construct several proxies for employment adjustment costs across firms. Using these measures, we show that our results are slightly stronger for firms that actually have low adjustment costs rather than high adjustment costs. We proxy for employment adjustment costs by measuring the labor market tightness faced by firms in the sample. Firms in tighter labor markets will likely incur greater worker replacement costs, since it is relatively harder to replace workers in a labor market that is tight rather than slack.

To construct this proxy, we compute each state's share of the total unemployed labor force in the U.S.; we assume that firms in states with above-median shares of the unemployed labor force will have different (and most likely: lower) adjustment costs than firms in states with below-median shares of the unemployed labor force. Our assumption is based on the idea that firms in states with relatively high shares of the unemployed labor force will likely face lower labor search costs, and thus lower adjustment costs, when replacing workers, since these firms will more easily be able to find available workers with similar skills within local geographic proximity.

As Table 9 indicates, when we restrict our sample to firms in either group of states, we find results for each group that mirror our full sample findings. However, when comparing the estimates between the two groups, we see that the results are slightly stronger for firms in states with higher unemployed labor force shares (i.e. lower adjustment costs). This evidence suggests that employment adjustment costs are unlikely to account for our findings, since reasonable proxies for employment adjustment costs have little explanatory power for the labor flow-stock return patterns that we document.

Second, in our LinkedIn survey of individuals who comprise our dataset, we ask questions that pertain to the adjustment cost hypothesis, and present evidence that individual workers in our sample do not believe that hiring adjustment costs are a major determinant of stock returns. When we ask workers on a scale of 1 (Not important at all) to 5 (Very important), whether they perceived hiring costs to be significant enough to impact stock prices for their specific occupations, they reported an average score of 2.06. This low average score is identical for both subsamples of inflows and outflows, and suggests that workers do not consider hiring costs—a first-order component of adjustment costs—to be significant enough to impact stock returns.

Third, we argue that other reasonable implications of the adjustment cost hypothesis do not appear to be supported by the data. For example, if the adjustment cost hypothesis truly explains the observed connection between labor flows and firm performance, then presumably managers should be cognizant of these adjustment costs. Moreover, managers would be legally obligated by fair disclosure rules to communicate these costs to equity analysts and shareholders if these costs are materially important to investors.

Our findings on insider trading, analyst expectations, and market reactions to earnings announcements, however, fail to support these implications. The lack of any significant insider trading patterns suggests that managers do not act upon adjustment costs triggered by departing workers. The evidence we find on equity analyst expectations and market surprises to earnings announcements also suggests that neither analysts nor investors appear to incorporate adjustment costs into their earnings forecasts.

Collectively, these findings suggest that the adjustment cost hypothesis is unlikely to explain the evidence that we document. The statistical findings we show for firms facing labor market tightness are inconsistent with empirical implications of the adjustment cost hypothesis, the survey evidence shows that workers do not view hiring adjustment costs as significant, and many of our other findings are inconsistent with reasonable implications of the adjustment cost hypothesis.

4.3.4 Discount Rates or Cash Flows?

One alternative hypothesis for our findings is that the abnormal stock returns that we document may simply reflect missing risk factors in the benchmark models for the equity cost of capital. For example, Belo et al. (2014, 2017) and Donangelo (2014) argue that labor adjustment costs and labor mobility impact the firm's cost of capital in ways that are not captured by commonly-used factor models. These "missing" factors might fully explain the abnormal returns that we associate with labor flows.

We believe that this hypothesis is unlikely to be the sole explanation for our findings. Both the accounting data and the survey evidence indicate that labor flows contain infor-

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mation about earnings levels rather than discount rates alone. Moreover, if labor flows only reflected information about discount rates, then we should not observe any link between labor flows and analyst earnings forecast errors, nor should we observe our predicted market reactions to earnings announcements. The findings, however, show that labor flows partly reflect information about the *level* of firms' earnings, rather than the *riskiness* of firms' earnings alone. Thus, the link that we document between labor flows and stock returns is unlikely to simply represent cost of capital differences across firms.

4.3.5 Are Labor Flows Publicly Observable?

Another explanation for our findings is that labor flows may not be publicly observable to investors in real-time; instead, it may take time for investors to observe and trade upon information otherwise contained in labor flows. Our documented links between labor flows and abnormal returns may thus essentially reflect private information that investors are unable to utilize.

While it is inherently difficult to measure the real-time availability of historical data, we argue that this alternative hypothesis is unlikely to hold true. Labor flows for individual companies can be constructed in real-time at low cost using LinkedIn's own search engine, as the platform allows users to search for the total number of current or past employees at a firm using relatively few steps. There are also many other publicly available sources of data, aside from LinkedIn, which can be used to construct labor flows across firms. For example, patent data that is publicly available from the U.S. Patent Office contains information on key scientists and their company affiliations. Other sources of information, such as social media platforms, news databases, etc., can be used to collect information on key workers who enter and exit specific firms. Given the returns to collecting this data and the resources available to investors such as hedge funds and mutual funds, we believe that investors can collect this information and incorporate it into their trading strategies at low cost.

To further support our argument, we show in Table 2 that our results hold even when we limit our sample to labor flows that take place after 2005 (when LinkedIn is available for

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public searches, as verified by the internet archive Wayback Machine (web.archive.org)). We also show in Appendix Table A1 that our results hold if we analyze our sample using data from 2010 onwards, when significantly more users joined the platform and richer labor data becomes available. These findings indicate that our results hold in time periods when labor flow data is relatively easier to collect by investors; our findings are not driven by sample periods where it may have been harder for investors to observe worker flows.

5 Conclusion

This paper adds to a nascent, but rapidly growing literature that seeks to understand how the firm's labor force characteristics matter for asset prices and corporate behavior. The unique contribution of this paper is evidence that the firm's rank-and-file labor dynamics reflect information that can be used to explain stock returns. The findings in our paper suggest that workers observe information that investors fail to extract from employees' labor market decisions.

A natural next step for research is to shed light on other aspects of corporate behavior that are impacted by the firm's labor dynamics. Casual observation suggests that corporate investment and financing decisions are intimately related to the entry and exit decisions of rank-and-file employees. Formal study of these issues is lacking, however, and there are a number of poorly understood concerns that arise when evaluating the relationship between labor flows and firm behavior. For example, the hiring rates of specific workers likely impact the timing and choice of investment projects, while exit rates of key personnel likely impact security issuance decisions. The findings in our paper suggest that these issues are fruitful areas for further inquiry.

References

A. Agrawal and P. Tambe. Private equity and workers' career paths: the role of technological change. *The Review of Financial Studies*, 29(9):2455–2489, 2016.

R. Baghai, R. Silva, V. Thell, and V. Vig. Talent in distressed firms: Investigating the labor costs of financial distress. *Available at SSRN 2854858*, 2018.

N. Barberis, A. Shleifer, and R. Vishny. A model of investor sentiment. *Journal of Financial Economics*, 49(3): 307–343, 1998.

A. Bassamboo, R. Cui, and A. Moreno. Wisdom of crowds in operations: Forecasting using prediction markets. *Available at SSRN 2679663*, 2015.

P. Bayer, S. L. Ross, and G. Topa. Place of work and place of residence: Informal hiring networks and labor market outcomes. *Journal of Political Economy*, 116(6):1150–1196, 2008.

F. Belo, X. Lin, and S. Bazdresch. Labor hiring, investment, and stock return predictability in the cross section. *Journal of Political Economy*, 122(1):129–177, 2014.

F. Belo, J. Li, X. Lin, and X. Zhao. Labor-force heterogeneity and asset prices: The importance of skilled labor. *The Review of Financial Studies*, 30(10):3669–3709, 2017.

J. Brown and D. A. Matsa. Boarding a sinking ship? An investigation of job applications to distressed firms. *The Journal of Finance*, 71(2):507–550, 2016.

J. R. Brown and G. Martinsson. Does transparency stifle or facilitate innovation? *Management Science*, 65(4): 1600–1623, 2018.

P. Cahuc, S. Carcillo, and A. Zylberberg. *Labor Economics*. MIT press, 2014.

M. M. Carhart. On persistence in mutual fund performance. *The Journal of Finance*, 52(1):57–82, 1997.

F. Cingano and A. Rosolia. People I know: Job search and social networks. *Journal of Labor Economics*, 30(2): 291–332, 2012.

L. Cohen, C. Malloy, and L. Pomorski. Decoding inside information. *The Journal of Finance*, 67(3):1009–1043, 2012.

B. Cowgill and E. Zitzewitz. Corporate prediction markets: Evidence from Google, Ford, and firm X. *The Review of Economic Studies*, 82(4):1309–1341, 2015.

K. Daniel, D. Hirshleifer, and A. Subrahmanyam. Investor psychology and security market under-and overreactions. *The Journal of Finance*, 53(6):1839–1885, 1998.

A. Donangelo. Labor mobility: Implications for asset pricing. *The Journal of Finance*, 69(3):1321–1346, 2014.

A. Edmans. Does the stock market fully value intangibles? Employee satisfaction and equity prices. *Journal of Financial Economics*, 101(3):621–640, 2011.

E. F. Fama and K. R. French. A five-factor asset pricing model. *Journal of Financial Economics*, 116(1):1–22, 2015.

A. Fedyk and J. Hodson. Trading on talent: Human capital and firm performance. *Available at SSRN 3017559*, 2019.

T. C. Green, R. Huang, Q. Wen, and D. Zhou. Wisdom of the employee crowd: Employer reviews and stock returns. Technical report, Working paper, 2017.

I. Hacamo and K. Kleiner. Competing for talent: Firms, managers and social networks. *Kelley School of Business Research Paper*, (17-34), 2017.

H. Harry. Informal job search and black youth unemployment. *American Economic Review*, 77(3):446–52, 1987.

H. J. Holzer. Search method use by unemployed youth. *Journal of Labor Economics*, 6(1):1–20, 1988.

H. Hong and J. C. Stein. A unified theory of underreaction, momentum trading, and overreaction in asset markets. *The Journal of Finance*, 54(6):2143–2184, 1999.

K. Hou, C. Xue, and L. Zhang. Digesting anomalies: An investment approach. *The Review of Financial Studies*, 28(3):650–705, 2015.

J. Hughes, J. Liu, and W. Su. On the relation between predictable market returns and predictable analyst forecast errors. *Review of Accounting Studies*, 13(2-3):266–291, 2008.

Y. M. Ioannides and L. Datcher Loury. Job information networks, neighborhood effects, and inequality. *Journal of Economic Literature*, 42(4):1056–1093, 2004.

C. Leuz, D. Nanda, and P. D. Wysocki. Earnings management and investor protection: An international comparison. *Journal of Financial Economics*, 69(3):505–527, 2003.

D. T. Mortensen. Job search and labor market analysis. *Handbook of Labor Economics*, 2:849–919, 1986.

S. C. Myers and N. S. Majluf. Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics*, 13(2):187–221, 1984.

L. Pástor and R. F. Stambaugh. Liquidity risk and expected stock returns. *Journal of Political economy*, 111(3): 642–685, 2003.

J. Sheng. Asset pricing in the information age: Employee expectations and stock returns. *Available at SSRN 3321275*, 2019.

E. C. So. A new approach to predicting analyst forecast errors: Do investors overweight analyst forecasts? *Journal of Financial Economics*, 108(3):615–640, 2013.

L. Zingales. In search of new foundations. *The Journal of Finance*, 55(4):1623–1653, 2000.

FIGURES AND TABLES

Figure 1: Industry Distribution of Workers in Linkedin and the U.S. Labor Force

This figure depicts the distribution of employment across industries for workers in the LinkedIn population and workers in the U.S. Labor Force as of 2018. The horizontal axis corresponds to industries defined by 2-digit NAICS codes, while the vertical axis corresponds to employment figures reported in Millions. Labor force employment estimates are based on Census data maintained by the U.S. Bureau of Labor Statistics (BLS).

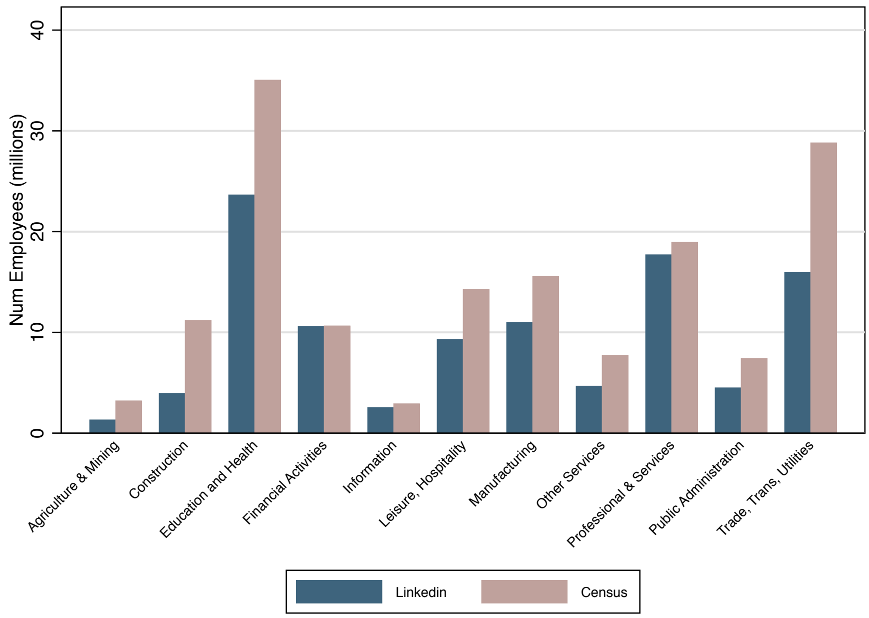


Figure 2: Industry Distribution of Workers at Russell 1000 Firms

This figure depicts the distribution of employment across industries for workers employed by *Russell 1000* firms, using three sources of data: the LinkedIn population, our LinkedIn sample, and Compustat. For each firm in the Russell 1000, we estimate the total size of the firm's workforce, and then assign all employees at the firm to the 2-digit primary NAICS code of the firm as measured in Compustat. The horizontal axis corresponds to 2-digit NAICS industries, while the vertical axis corresponds to the fraction of employees across industries within each data source.

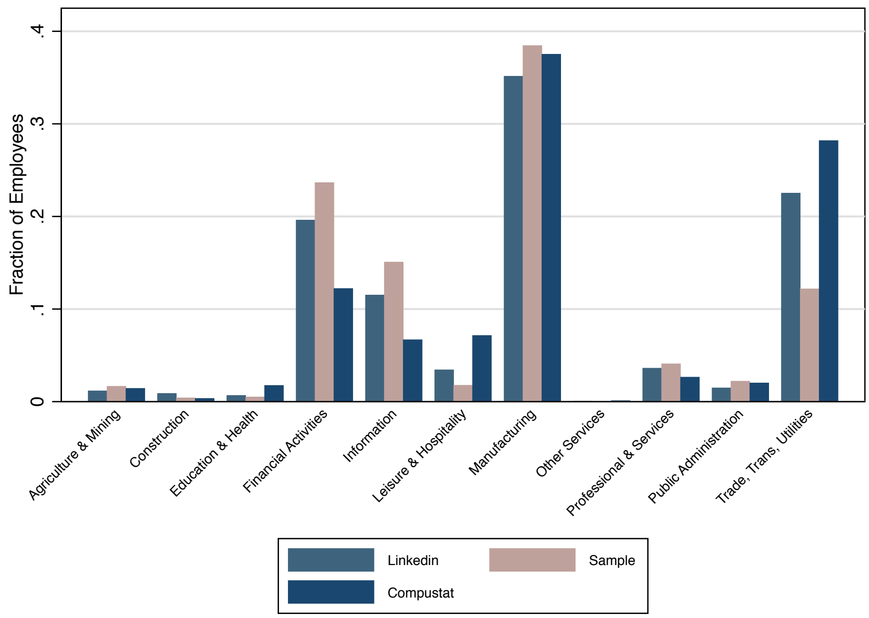


Figure 3: Job Tenures of Workers in LinkedIn and the U.S. Labor Force

This figure reports the lengths of job tenures for workers in our LinkedIn sample and workers in the U.S. labor force. Job tenures for workers in LinkedIn are measured using the start- and end- dates of employment spells listed on worker CV's. Job tenures for workers in the labor force are measured using the U.S. Current Population Survey (CPS) Job Tenure Supplement for respondents aged 15 years and older. The horizontal axis corresponds to the year of observed employment spell, while the vertical axis corresponds to the length of job tenure reported in years.

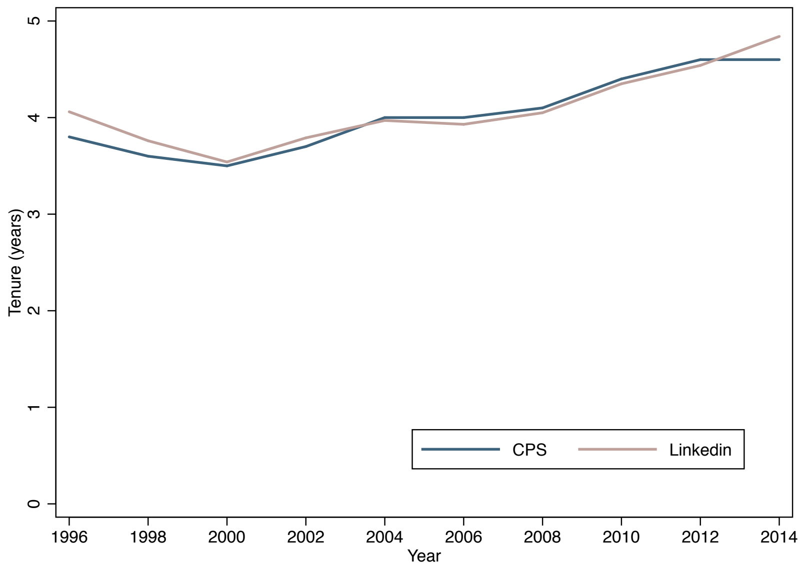
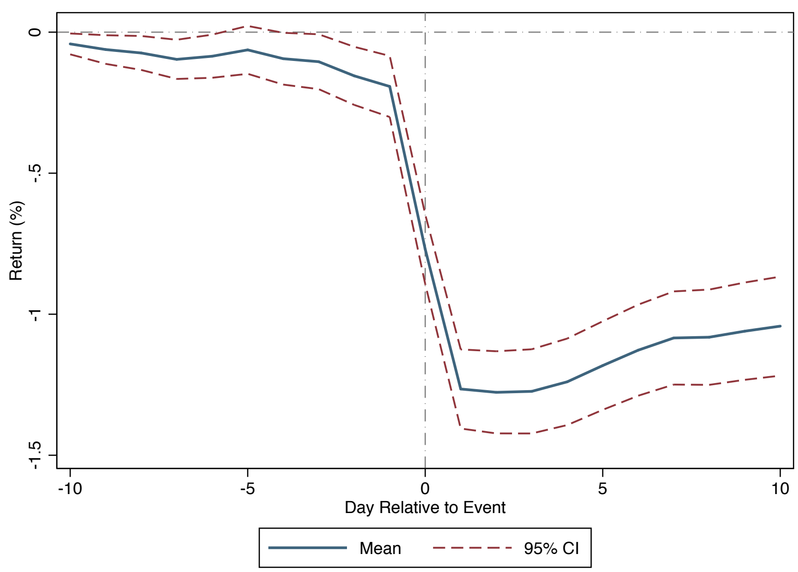


Figure 4: Stock Price Reactions to Corporate Earnings Announcements

This figure presents event study analysis of stock price reactions to earnings announcements of sample firms. Panel A (B) depicts the mean cumulative abnormal stock returns and 95% confidence intervals around negative (positive) earnings surprises, measured over ten-day event windows around earnings announcement dates. Earnings announcements in the sample are characterized as negative (positive) surprises if the average earnings-per-share (EPS) forecast of equity analysts in the quarter preceding the earnings announcement is lower (greater) than the realized EPS that is announced by the firm. Benchmark factor loadings are estimated using daily returns for 100 days, starting 50 days prior to the start of the event window. The horizontal axis corresponds to the day relative to the earnings announcement date, while the vertical axis corresponds to the average cumulative abnormal stock return measured in percentage terms.

Panel A: Negative Earnings Surprises



Panel B: Positive Earnings Surprises

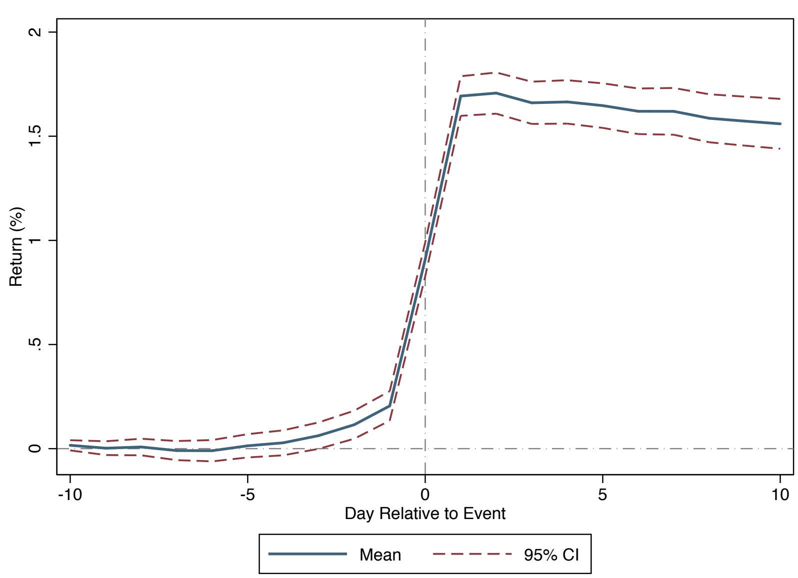


Figure 5: LinkedIn Survey Responses

This figure depicts the responses to survey questions administered to individual workers in our sample. Panel A (B) presents the average scores (and 95% confidence intervals) for each question asked of workers in our outflow (inflow) survey. Individual questions for each survey are listed in the Appendix. Scores are obtained for 230 (169) workers in the outflow (inflow) survey samples. The horizontal axis corresponds to the specific question asked in each survey, while the vertical axis presents the average response score.

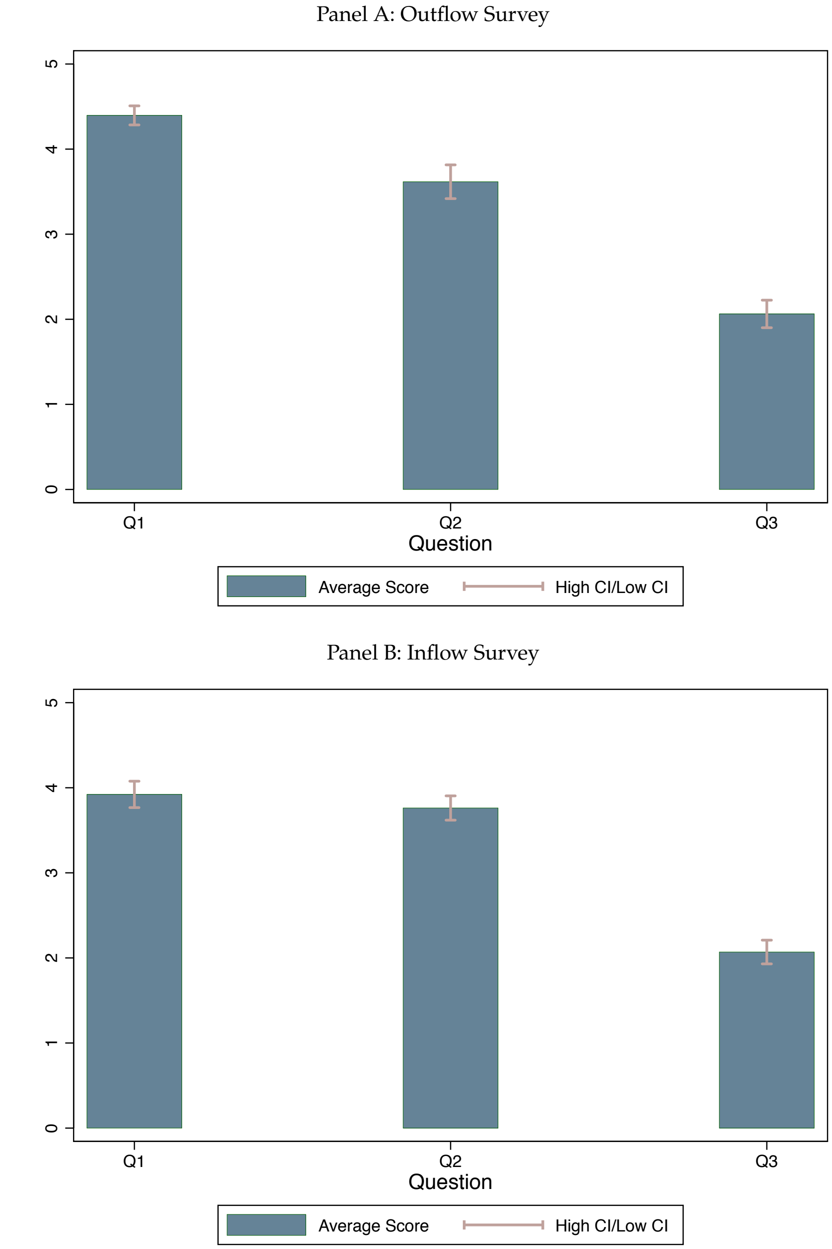


Table 1: Descriptive Statistics for Sample Workers and Firms

This table presents descriptive statistics that characterize the workers and firms in our sample. The sample contains 1,500,457 individual employment records for 1,028,356 employees at Russell 1000 firms between 1985 and 2016. Panel A summarizes data at the level of employment record. $Occupations$ are inferred from individuals' job titles as described in the Data section; Panel A shows six of the most common occupations in our sample. $Experience$ is the cumulative years worked for an individual prior to the start of an employment spell. $Education$ refers to the highest level of educational attainment reached by a given worker. Panel B presents summary statistics of firms in our dataset, averaged across all firm-years in the sample. *Total Assets* is the book value of assets. *Market Value of Equity* is the number of shares outstanding times the closing share price as of the most recent date for which data is available. *B/M of Equity* is the ratio of book value of equity to the market value of equity. *Return on Assets* is defined as the ratio of net income to the book value of assets. *Leverage* is defined as the ratio of total short-term and long-term debt obligations to total book value of assets. Panel C summarizes labor flows at the firm-level over a 1-month period. The $Outflow$ ($Inflow$) is computed as the total number of employees whose job spells at a given company ends (begins) in a given month. The $Net\ Outflow$ is computed as the difference between the $Outflow$ and $Inflow$. The $Standardized\ Net\ Outflow$ is $Net\ Outflow$ divided by the total number of employees that work at the firm as of the beginning of the month.

	Panel A: Employee Characteristics						
$Occupation$	Engineers	Scientists	Mid-Managers	Admin.	Finance	Consultants	Others
Obs.	215,111	93,620	326,228	145,196	20,853	92,085	607,364
Frac.	14.34%	6.24%	21.74%	9.67%	1.39%	6.14%	40.48%
$Education$	PhD	MBA	Master	Bachelor	High School	Unreported	
Obs.	58,210	218,314	193,708	565,256	186,859	278,110	
Frac.	3.88%	14.55%	12.91%	37.67%	12.45%	18.54%	
$Experience$ (years)	Mean	S.D.	5th pctl	25th pctl	50th pctl	75th pctl	95th pctl
	5.63	5.90	0.25	1.50	3.67	7.83	17.83
	Panel B: Firm Characteristics						
	Mean	S.D.	5th pctl	25th pctl	50th pctl	75th pctl	95th pctl
$Total\ Assets$ ($b)	25.19	117.52	0.19	1.37	4.51	14.26	82.58
$Equity\ Market\ Value$ ($b)	12.26	32.42	0.15	1.17	3.48	9.43	50.45
$B/M\ of\ Equity$	0.59	0.77	0.092	0.26	0.45	0.77	1.38
$Return\ on\ Assets$ (%)	1.14	4.13	-2.14	0.36	1.17	2.30	4.74
$Total\ Employees$ (,000s)	28.17	77.40	0.26	2.46	8.20	25.01	118.50
$Leverage$	0.59	0.23	0.19	0.45	0.59	0.74	0.93
	Panel C: Monthly Labor Flows						
	Mean	S.D.	5th pctl	25th pctl	50th pctl	75th pctl	95th pctl
$Outflow$	4.10	15.27	0	0	0	3	18
$Inflow$	5.43	18.13	0	0	1	4	23
$Net\ Outflow$	-1.33	9.89	-9	-2	0	1	4
$Standardized\ Net\ Outflow$	-0.0071	0.049	-0.056	-0.011	0	0.0014	0.028

Table 2: Results from Calendar-Time Portfolio Analysis

This table presents coefficient estimates from calendar-time portfolio analysis. Each month, firms are sorted into quartiles (or terciles) based on the net labor outflows realized over the previous one month. The long (short) portfolio consists of firms with the lowest (highest) realized net labor outflows. The long-short portfolios are rebalanced monthly and returns are computed using both value- (VW) and equal-weighted (EW) specifications. Abnormal returns are assessed using the five-factor model (Fama and French, 2015): $r_{p,t} = \alpha + \beta * MP_t + s * SMB_t + h * HML_t + r * RMW_t + c * CMA_t + \epsilon_t$, where MP is the market premium calculated as the value weighted market return on all NYSE-Amex-Nasdaq stocks minus the one-month T-bill rate, SMB (small minus big) is the average return of small firms minus the average return of big firms, HML (high minus low) is the average return of value (high book-to-market) firms minus the average return of growth (low book-to-market) firms, RMW (robust minus weak) is the average return of robust-profitability firms minus the average return of weak-profitability firms, and CMA (conservative minus aggressive) is the average return of firms with low investment minus the average returns of firms with high investment. Crisis periods are defined by NBER recession dates. Sample firms correspond to the Russell 1000 index as of June, 2018. Monthly returns and alphas are reported in percentages, and t-statistics are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
α (%)	0.415***	0.337**	0.316***	0.250*	0.389***	0.306**	0.364***	0.285**
	(3.546)	(2.114)	(2.868)	(1.818)	(3.685)	(2.080)	(3.501)	(2.003)
MP	-0.096***	-0.086*	-0.082***	-0.090**	-0.095**	0.042	-0.041	0.060
	(-3.057)	(-1.847)	(-2.750)	(-2.200)	(-2.515)	(1.003)	(-1.146)	(1.279)
SMB	0.130***	0.143**	0.077	0.074	0.085	0.126*	0.096*	0.084
	(2.603)	(2.070)	(1.592)	(1.285)	(1.208)	(1.752)	(1.699)	(1.086)
HML	-0.229***	-0.176**	-0.205***	-0.087	-0.312***	-0.287***	-0.276***	-0.212**
	(-3.505)	(-2.051)	(-3.299)	(-1.175)	(-4.499)	(-3.946)	(-4.167)	(-2.273)
RMW	0.030	0.018	0.051	0.020	-0.137	0.002	-0.135*	-0.128
	(0.316)	(0.145)	(0.569)	(0.208)	(-1.358)	(0.015)	(-1.763)	(-1.013)
CMA	-0.093	-0.304**	-0.102	-0.403***	-0.112	-0.191	-0.148	-0.248**
	(-0.738)	(-2.099)	(-0.860)	(-3.003)	(-0.933)	(-1.270)	(-1.510)	(-2.057)
R^2	0.162	0.146	0.132	0.135	0.351	0.214	0.322	0.191
Raw Long Return (%)	1.813	1.235	1.781	1.242	1.461	0.973	1.823	1.395
Raw Short Return (%)	1.522	1.067	1.569	1.115	1.188	0.662	1.576	1.126
Sorting Window	1 month	1 month	1 month	1 month	1 month	1 month	1 month	1 month
Starting Year	1985	1985	1985	1985	2005	2005	2005	2005
Portfolio Cutoff	quartile	quartile	tercile	tercile	quartile	quartile	quartile	quartile
EW/VW	EW	VW	EW	VW	EW	VW	EW	VW
Crisis Periods	Include	Include	Include	Include	Include	Include	Exclude	Exclude

Table 3: Net Labor Outflows and Earnings Surprises

This table reports coefficient estimates for an OLS model of corporate earnings surprises regressed on net labor outflows and various controls: $SUE_{i,t+j} = \beta_0 + \beta_1 NetOutflows_{i,t} + \beta_2 E^+_{i,t} + \beta_3 NEGE_{i,t} + \beta_4 ACC^-_{i,t} + \beta_5 ACC^+_{i,t} + \beta_6 AG_{i,t} + \beta_7 DD_{i,t} + \beta_8 DIV_{i,t} + \beta_9 PRICE_{i,t} + \beta_{10} BTM_{i,t} + \epsilon_{i,t}$. Standardized unexpected earnings ($SUE_{i,t+j}$) is defined as $(EPS^{actual}_{i,t+j} - \mu^{forecast}_{i,t})/\sigma^{forecast}_{i,t}$, where $EPS^{actual}_{i,t+j}$ is the next EPS of firm i announced in month $t+j$, $\mu^{forecast}_{i,t}$ is the mean of financial analysts' forecast reported in month t, and $\sigma^{forecast}_{i,t}$ is the standard deviation of the forecasts made in month t. $NetOutflows_{i,t}$ is the net labor outflows of firm i from month $t-1$ to t. Following So (2013), we include the following controls: earnings per share when earnings are positive and zero otherwise (E^+), a binary variable indicating negative earnings ($NEGE$), negative and positive accruals per share (ACC^-, ACC^+), the percent change in total assets (AG), a binary variable indicating zero dividends (DD), dividends per share (DIV), share price ($PRICE$) and book-to-market value (BTM). Firm and year-month fixed effects are also included. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$NetOutflows_{i,t}$	-0.706*	-0.889**	-0.892**	-1.233***	-0.906*	-0.741	-1.187**	-1.109**
	(0.426)	(0.421)	(0.384)	(0.375)	(0.493)	(0.484)	(0.461)	(0.448)
$E^+_{i,t}$			-0.029	0.048**			-0.069***	0.038*
			(0.018)	(0.019)			(0.019)	(0.020)
$NEGE_{i,t}$			-0.359***	-0.082*			-0.512***	0.130**
			(0.039)	(0.046)			(0.048)	(0.058)
$ACC^-_{i,t}$			-0.045***	-0.014			-0.023*	0.021
			(0.012)	(0.012)			(0.013)	(0.014)
$ACC^+_{i,t}$			0.002	-0.029**			-0.002	-0.057***
			(0.013)	(0.013)			(0.016)	(0.016)
$AG_{i,t}$			0.336***	0.270***			0.298***	0.094
			(0.066)	(0.065)			(0.084)	(0.083)
$DD_{i,t}$			0.506***	-0.160***			0.396***	-0.070
			(0.044)	(0.062)			(0.066)	(0.100)
$DIV_{i,t}$			-0.001	-0.004***			-0.003*	-0.003**
			(0.001)	(0.002)			(0.001)	(0.002)
$PRICE_{i,t}$			0.003***	-0.002***			0.002***	-0.003***
			(0.000)	(0.000)			(0.000)	(0.000)
$BTM_{i,t}$			0.007	0.006			0.014	0.008
			(0.010)	(0.010)			(0.011)	(0.011)
$Constant$	0.786***	0.785***	0.311***	1.087***	1.052***	1.053***	0.784***	1.315***
	(0.015)	(0.014)	(0.045)	(0.062)	(0.018)	(0.017)	(0.066)	(0.099)
R^2	0.000	0.078	0.005	0.113	0.000	0.095	0.003	0.124
Starting Year	1985	1985	1985	1985	2005	2005	2005	2005
Time FE	N	Y	N	Y	N	Y	N	Y
Firm FE	N	Y	N	Y	N	Y	N	Y

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Table 4: Calendar-Time Results Across Firms with Varying Financial Transparency

This table reports coefficient estimates from calendar-time portfolio analysis of firms characterized by high versus low measures of financial transparency. Following Leuz et al. (2003), we proxy for financial transparency using four measures of earnings reporting quality, and assume that firms that engage in greater earnings management are less likely to be transparent to investors. In Panel A, the transparency measure is the ratio of the firm's standard deviation of operating earnings divided by the standard deviation of the firm's cash flow from operations. In Panel B, we proxy for transparency using the correlation between changes in accounting accruals and changes in operating cash flows for the firm. In Panel C, the measure of transparency is the ratio of the firm's absolute value of accruals scaled by the absolute value of the firm's cash flow from operations. In Panel D, we compute transparency using the ratio of small profits to small losses, where small losses (profits) are defined as after-tax earnings scaled by total assets being in the range -0.01 to 0 (0 to 0.01). Across all four measures, higher values correspond to higher firm transparency. All other variables are defined as per Table 2. Abnormal returns are assessed using the five-factor model. For brevity, we do not report coefficient estimates for all factors. Alphas are in monthly percent, and t-statistics are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Financial Transparency Measure 1							
Low	0.538***	0.496**	0.418**	0.266	0.504***	0.332*	0.484***	0.422**
	(2.912)	(2.285)	(2.343)	(1.330)	(2.945)	(1.941)	(2.818)	(2.177)
High	0.454***	0.568***	0.340**	0.418**	0.452***	0.404*	0.445***	0.500**
	(3.118)	(2.645)	(2.497)	(2.245)	(3.202)	(1.862)	(2.880)	(2.161)
	Panel B: Financial Transparency Measure 2							
Low	0.424***	0.504***	0.324**	0.283*	0.474***	0.397*	0.437***	0.506**
	(2.779)	(2.641)	(2.336)	(1.664)	(3.634)	(1.886)	(3.225)	(2.537)
High	0.491***	0.169	0.382**	0.196	0.415***	0.132	0.435***	0.216
	(2.831)	(0.737)	(2.334)	(0.913)	(2.681)	(0.641)	(2.766)	(1.060)
	Panel C: Financial Transparency Measure 3							
Low	0.732***	0.553**	0.575***	0.406*	0.554***	0.268	0.487***	0.506**
	(3.765)	(2.226)	(3.235)	(1.776)	(3.415)	(1.212)	(2.807)	(2.446)
High	0.310**	0.529***	0.221*	0.371**	0.397***	0.378*	0.443***	0.393*
	(2.326)	(2.835)	(1.674)	(2.220)	(2.914)	(1.926)	(3.497)	(1.935)
	Panel D: Financial Transparency Measure 4							
Low	0.495***	0.430**	0.399***	0.326**	0.504***	0.291*	0.477***	0.443***
	(3.776)	(2.467)	(3.208)	(2.061)	(4.129)	(1.776)	(3.718)	(2.751)
High	0.431	0.564*	0.318	0.436	0.216	0.482	0.317	0.434
	(1.539)	(1.723)	(1.243)	(1.453)	(0.795)	(1.306)	(1.187)	(1.106)
Sorting Window	1 month	1 month	1 month	1 month	1 month	1 month	1 month	1 month
Starting Year	1985	1985	1985	1985	2005	2005	2005	2005
Portfolio Cutoff	quartile	quartile	tercile	tercile	quartile	quartile	quartile	quartile
EW/VW	EW	VW	EW	VW	EW	VW	EW	VW
Crisis Periods	Include	Include	Include	Include	Include	Include	Exclude	Exclude

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Table 5: Calendar-Time Portfolio Analysis Based on Gross Outflows and Gross Inflows

This table reports coefficient estimates from calendar-time portfolio analysis, where firms are sorted into long and short portfolios based on either gross labor outflows (Panel A) or (negative) gross labor inflows (Panel B) each month. Abnormal returns are assessed using the five-factor model (Fama and French, 2015): $r_{p,t} = \alpha + \beta * MP_t + s * SMB_t + h * HML_t + r * RMW_t + c * CMA_t + \epsilon_t$. The long (short) portfolio consists of firms with the lowest (highest) realized gross labor flows. Alphas are in monthly percent. All other variables are defined as per Table 2. For brevity, we do not report coefficient estimates for all factors. The t-statistics are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Outflows							
α (%)	0.208**	0.012	0.244***	-0.013	0.205**	0.175	0.199**	0.137
	(2.483)	(0.107)	(3.164)	(-0.119)	(2.043)	(1.122)	(2.002)	(0.928)
	Panel B: Negative Inflows							
α (%)	0.159*	0.383***	0.098	0.252**	0.092	-0.028	0.104	-0.011
	(1.902)	(3.005)	(1.276)	(2.411)	(0.911)	(-0.188)	(1.037)	(-0.080)
Sorting Window	1 month	1 month	1 month	1 month	1 month	1 month	1 month	1 month
Starting Year	1985	1985	1985	1985	2005	2005	2005	2005
Portfolio Cutoff	quartile	quartile	tercile	tercile	quartile	quartile	quartile	quartile
EW/VW	EW	VW	EW	VW	EW	VW	EW	VW
Crisis Periods	Include	Include	Include	Include	Include	Include	Exclude	Exclude

Table 6: Information Content in Labor Flows: Production Costs

Panel A of this table reports OLS regression coefficients of corporate fundamentals regressed on net labor outflows: $y_{i,t+1} = a + b * NetLaborOutflow_{i,t} + \lambda_i + \lambda_t + \epsilon_{i,t+1}$. The independent variable $NetLaborOutflow_{i,t}$ is the firm's net labor outflow of the current quarter, normalized by the total number of employees in the firm at the beginning of the quarter. The dependent variable $y_{i,t+1}$ is obtained from Compustat and is either: SG&A (sales, general and administration) expenses, operating expenses, revenues, or operating income after depreciation and amortization, in the following quarter. All dependent variables are normalized by book total assets at the beginning of the current quarter. Quarter-year and firm fixed effects are also included as independent variables. Panels B through D present the alphas from calendar-time portfolio analysis using labor flows of different subsets of workers. Each row corresponds to the worker characteristic that is used to compute labor flows. Panel B presents the results for long-short portfolios sorted by the net labor outflows of workers within specific occupations. Panel C presents the results for long-short portfolios sorted by workers with above versus below sample median levels of labor market experience. Panel D presents the results for long-short portfolios sorted by workers with different levels of educational attainment. Abnormal returns are assessed using the five-factor model (Fama and French, 2015), and alphas are in monthly percentage terms. All other variables are defined as per Table 2. The t-statistics are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Accounting Fundamentals							
	SGA Expense		Operating Expense		Revenues		Operating Income	
Net Labor Outflow	0.019***	0.016**	0.016**	0.013**	0.004	-0.006	-0.014***	-0.016***
	(3.167)	(2.286)	(2.011)	(1.857)	(0.410)	(-0.758)	(-4.603)	(-5.333)
Starting Year	1985	2005	1985	2005	1985	2005	1985	2005
	Panel B: Employee Occupation							
Engineers	0.414**	0.476**	0.414**	0.475**	0.339**	0.188	0.351***	0.090
	(2.575)	(2.509)	(2.572)	(2.504)	(2.459)	(0.952)	(2.623)	(0.484)
Scientists	0.268*	0.164	0.268*	0.164	0.333**	0.395*	0.393***	0.448**
	(1.793)	(0.918)	(1.793)	(0.918)	(2.579)	(1.945)	(2.812)	(2.187)
Managers	0.306***	0.434***	0.198*	0.321**	0.325***	0.389**	0.335***	0.502***
	(2.632)	(2.958)	(1.780)	(2.455)	(3.144)	(2.417)	(3.266)	(3.658)
Administration	0.113	0.057	0.105	0.056	0.161	0.045	0.220	-0.020
	(0.861)	(0.362)	(0.802)	(0.353)	(1.239)	(0.260)	(1.609)	(-0.115)
Finance	0.012	0.228	0.012	0.228	0.052	-0.131	0.198	-0.282
	(0.056)	(0.863)	(0.056)	(0.863)	(0.245)	(-0.397)	(1.188)	(-1.452)
Consultant	0.102	0.123	0.102	0.123	0.243*	0.228	0.293**	0.158
	(0.588)	(0.599)	(0.588)	(0.599)	(1.867)	(1.267)	(2.496)	(0.835)
	Panel C: Employee Work Experience							
High	0.241**	0.285**	0.228**	0.245**	0.332***	0.329*	0.432***	0.353**
	(2.398)	(2.049)	(2.343)	(1.991)	(2.859)	(1.658)	(3.938)	(2.164)
Low	0.144	0.234**	0.076	0.216*	0.318	0.330*	0.304	0.242
	(1.480)	(1.971)	(0.885)	(1.942)	(1.650)	(1.903)	(1.533)	(1.458)
	Panel D: Employee Education							
PhD/MBA/Master	0.359***	0.252**	0.372***	0.332**	0.358**	0.336*	0.344**	0.297
	(3.905)	(2.084)	(3.960)	(2.481)	(2.565)	(1.741)	(2.504)	(1.534)
Bachelor/High School	0.093	0.191*	0.060	0.210**	0.117	0.215	0.136*	0.146
	(1.297)	(1.677)	(0.928)	(2.048)	(1.591)	(1.644)	(1.840)	(1.202)
Sorting Window	1 month	1 month	1 month	1 month	1 month	1 month	1 month	1 month
Starting Year	1985	1985	1985	1985	2005	2005	2005	2005
Portfolio Cutoff	quartile	quartile	tercile	tercile	quartile	quartile	quartile	quartile
EW/VW	EW	VW	EW	VW	EW	VW	EW	VW
Crisis Periods	Include	Include	Include	Include	Include	Include	Exclude	Exclude

Table 7: Return Persistence in Calendar-Time Analysis

This table presents results from calendar-time portfolio analysis using monthly returns computed following N-month gaps between the trading period and the sorting period, where N ranges from 0 to 6 (N=0 corresponds to the main results presented in Table 2). Each month, firms are sorted into quartiles (or terciles) based on the net labor outflows realized over the previous $N+1$ month. The long (short) portfolio consists of firms with the lowest (highest) realized net labor outflows. Abnormal returns are assessed using the five-factor model (Fama and French, 2015). Each cell contains the coefficient estimate for alpha in monthly percentage terms. All other variables are defined as per Table 2. The t-statistics are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
0-month gap	0.415***	0.337**	0.316***	0.250*	0.389***	0.306**	0.364***	0.285**
	(3.546)	(2.114)	(2.868)	(1.818)	(3.685)	(2.080)	(3.501)	(2.003)
1-month gap	0.542***	0.346	0.439***	0.185	0.267	0.077	0.332**	0.087
	(3.242)	(1.638)	(2.929)	(1.056)	(1.590)	(0.325)	(2.277)	(0.376)
2-month gap	0.216*	0.215	0.105	0.176	0.187	-0.116	0.273**	-0.051
	(1.669)	(1.196)	(0.871)	(1.001)	(1.523)	(-0.542)	(2.335)	(-0.256)
3-month gap	0.103	0.258	-0.072	-0.005	0.064	0.041	0.163	0.212
	(0.743)	(1.138)	(-0.545)	(-0.025)	(0.453)	(0.212)	(1.231)	(1.099)
4-month gap	0.218	0.401**	0.098	0.141	0.071	0.314	0.135	0.238
	(1.506)	(2.254)	(0.793)	(0.968)	(0.488)	(1.463)	(0.985)	(1.088)
5-month gap	0.225	0.271	0.140	0.167	-0.117	0.043	-0.050	0.223
	(1.436)	(1.332)	(0.993)	(1.072)	(-0.862)	(0.231)	(-0.380)	(1.179)
6-month gap	0.309**	0.290	0.124	0.175	0.199	0.152	0.151	0.209
	(1.984)	(1.607)	(1.024)	(1.194)	(1.429)	(0.744)	(1.157)	(1.019)
Sorting Window	1 month	1 month	1 month	1 month	1 month	1 month	1 month	1 month
Starting Year	1985	1985	1985	1985	2005	2005	2005	2005
Portfolio Cutoff	quartile	quartile	tercile	tercile	quartile	quartile	quartile	quartile
EW/VW	EW	VW	EW	VW	EW	VW	EW	VW
Crisis Periods	Include	Include	Include	Include	Include	Include	Exclude	Exclude

Table 8: Insider Trading and Labor Flows

This table presents OLS regression estimates of insider trades as a function of net labor flows: $NetLaborOutflow_{i,t+L} = a + b * InsiderTrade_{i,t} + \lambda_i + \lambda_t + \epsilon_{i,t+L}$, where $L = 0, 1, 2, 3, 4, 5$, or 6 month(s). The main independent variable $InsiderTrade_{i,t}$ is the number of net shares sold by the insiders of firm i in month t, normalized by the number of outstanding shares at the beginning of the month. Insiders are categorized as either "routine traders" or "opportunistic traders" following Cohen et al. (2012). Panel A uses the sample of all insiders, while Panel B only uses "opportunistic traders", who are more likely to possess and exploit insider information. The dependent variable is the net labor outflows computed after L month(s) following the observed insider trades in a given month. All specifications include year-month fixed effects and firm fixed effects. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	Panel A: All Insiders						
$InsiderTrade$	0.001	-0.001	-0.006	-0.002	-0.006	-0.005	0.008
	(0.004)	(0.005)	(0.004)	(0.003)	(0.004)	(0.004)	(0.006)
R^2	0.060	0.058	0.054	0.060	0.060	0.057	0.054
L	0 month	1 month	2 months	3 months	4 months	5 months	6 months
	Panel B: Opportunistic Insiders						
$InsiderTrade$	0.020	0.065	0.008	0.035**	0.004	0.000	-0.036
	(0.023)	(0.044)	(0.021)	(0.015)	(0.021)	(0.020)	(0.028)
R^2	0.092	0.096	0.106	0.111	0.089	0.092	0.100
L	0 month	1 month	2 months	3 months	4 months	5 months	6 months

Table 9: Calendar-Time Analysis for Firms Facing Varying Labor Adjustment Costs

This table reports results of calendar-time analysis for firms that face high versus low labor adjustment costs. We proxy for labor adjustments costs using the share of total labor force unemployment that belongs to a state in which the firm's headquarters are located; above-median (below-median) unemployment shares correspond to low (high) labor adjustment costs faced by firms. Panel A (Panel B) reports the estimates for firms located in states with high (low) unemployment shares. Abnormal returns are assessed using the five-factor model (Fama and French, 2015). Alphas are in monthly percent. All other variables defined as per Table 2. The t-statistics are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: High Unemployment Share (Low Labor Adjustment Costs)							
α (%)	0.541***	0.627***	0.376**	0.556***	0.359**	0.338*	0.336**	0.277
	(3.207)	(2.947)	(2.422)	(3.146)	(2.210)	(1.720)	(1.993)	(1.419)
	Panel B: Low Unemployment Share (High Labor Adjustment Costs)							
α (%)	0.275**	0.131	0.213*	0.094	0.421***	0.333*	0.399***	0.389**
	(2.027)	(0.722)	(1.681)	(0.560)	(3.118)	(1.727)	(3.049)	(2.124)
Sorting Window	1 month	1 month	1 month	1 month	1 month	1 month	1 month	1 month
Starting Year	1985	1985	1985	1985	2005	2005	2005	2005
Portfolio Cutoff	quartile	quartile	tercile	tercile	quartile	quartile	quartile	quartile
EW/VW	EW	VW	EW	VW	EW	VW	EW	VW
Crisis Periods	Include	Include	Include	Include	Include	Include	Exclude	Exclude

TABLES APPENDIX

Table A1: Calendar-Time Results Under Alternative Specifications

This table presents results from calendar-time portfolio analysis under a variety of alternative specifications to the main sample results presented in Table 2. Each month, firms are sorted into quartiles/terciles/quintiles based on the net labor outflows realized over the previous one, two, three, and six month(s). The long (short) portfolio consists of firms with the lowest (highest) realized net labor outflows. The long-short portfolios are rebalanced monthly and returns are computed using both value- (VW) and equal-weighted (EW) specifications. The sample runs from January 1985 (or January 2005) to December 2016, including or excluding the NBER recession periods. Abnormal returns are assessed using the five-factor model (Fama and French, 2015): $r_{p,t} = \alpha + \beta * MP_t + s * SMB_t + h * HML_t + r * RMW_t + c * CMA_t + \epsilon_t$, where MP is the market premium calculated as the value weighted market returns of all NYSE-Amex-Nasdaq stocks minus the one-month T-bill rate, SMB (small minus big) is the average return of small firms minus the average return of big firms, HML (high minus low) is the average return of value (high book-to-market) firms minus the average return of growth (low book-to-market) firms, RMW (robust minus weak) is the average return of robust-profitability firms minus the average return of weak-profitability firms, and CMA (conservative minus aggressive) is the average return of firms with low investment minus the average returns of firms with high investment. Returns and alphas are in monthly percentages, and t-statistics are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

α (%)	0.431***	0.400**	0.475***	0.389**	0.289**	0.440***	0.327**	0.355*
	(3.035)	(2.129)	(3.226)	(2.032)	(2.345)	(2.650)	(2.614)	(1.990)
Sorting Window	1 months	1 months	1 months	1 months	1 months	1 months	2 months	2 months
Starting Year	1995	1995	1995	1995	2010	2010	2010	2010
Portfolio Cutoff	quartile	quartile	quartile	quartile	quintile	quintile	quintile	quintile
EW/VW	EW	VW	EW	VW	EW	VW	EW	VW
Crisis Periods	Include	Include	Exclude	Exclude	Include	Include	Include	Include
α (%)	0.389***	0.392**	0.406***	0.428***	0.380***	0.401**	0.348**	0.509**
	(3.062)	(2.425)	(3.134)	(2.675)	(3.169)	(2.462)	(2.366)	(2.450)
Sorting Window	2 months	2 months	2 months	2 months	3 months	3 months	3 months	3 months
Starting Year	1985	1985	1985	1985	1985	1985	1995	1995
Portfolio Cutoff	quartile	quartile	quartile	quartile	quartile	quartile	quartile	quartile
EW/VW	EW	VW	EW	VW	EW	VW	EW	VW
Crisis Periods	Include	Include	Exclude	Exclude	Include	Include	Include	Include
α (%)	0.405***	0.277*	0.505***	0.332**	0.574***	0.347*	0.442***	0.273*
	(4.226)	(1.704)	(5.394)	(2.332)	(4.782)	(1.958)	(4.322)	(1.714)
Sorting Window	3 months	3 months	6 months	6 months	6 months	6 months	6 months	6 months
Starting Year	2005	2005	1985	1985	1985	1985	2005	2005
Portfolio Cutoff	quartile	quartile	tercile	tercile	quartile	quartile	quartile	quartile
EW/VW	EW	VW	EW	VW	EW	VW	EW	VW
Crisis Periods	Exclude	Exclude	Include	Include	Include	Include	Exclude	Exclude

Table A2: Analysis of Measurement Error in Calendar-Time Results

This table presents analysis of measurement error in our calendar-time results. We perform our calendar-time portfolio analysis across firms for which our sample represents high versus low fractions of total employment, where total employment is measured using LinkedIn and Compustat. In panel A, we calculate the ratio of the total employees on LinkedIn for a given firm, divided by the total employees who work at the firm as reported by Compustat in 2018. In Panel B, we calculate the ratio of the firm's current and past employees in our sample, divided by the number of the firm's current and past employees in the LinkedIn population. Across both panels, we split our sample into firms with above versus below median employment coverage ratios, and we assume that firms with high (low) employment coverage ratios have less (more) measurement error in labor flow estimates. We repeat our calendar-time analysis (as per Table 2) for firms in each of these subsamples. Abnormal returns are assessed using the five-factor model (Fama and French, 2015). All other variables are defined as per Table 2. Alphas are presented in monthly percentages, and t-statistics are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: LinkedIn Population v.s. Compustat							
Above median	0.309*	0.406**	0.439**	0.521**	0.598***	0.348*	0.552***	0.314
	(1.685)	(2.043)	(2.135)	(2.271)	(3.655)	(1.679)	(3.500)	(1.386)
Below median	0.286**	0.195	0.315***	0.246	0.132	0.153	0.131	0.129
	(2.528)	(1.146)	(2.717)	(1.384)	(0.816)	(0.892)	(0.836)	(0.664)
	Panel B: LinkedIn Sample v.s. LinkedIn Population							
Above median	0.472***	0.482**	0.344**	0.316*	0.361**	0.360	0.345**	0.203
	(3.093)	(2.529)	(2.442)	(1.855)	(2.547)	(1.620)	(2.451)	(0.997)
Below median	0.367***	0.131	0.333**	0.228	0.347***	0.324*	0.332***	0.420**
	(2.711)	(0.743)	(2.517)	(1.356)	(3.636)	(1.939)	(3.362)	(2.424)
Sorting Window	1 month	1 month	1 month	1 month	1 month	1 month	1 month	1 month
Starting Year	1985	1985	1985	1985	2005	2005	2005	2005
Portfolio Cutoff	quartile	quartile	tercile	tercile	quartile	quartile	quartile	quartile
EW/VW	EW	VW	EW	VW	EW	VW	EW	VW
Crisis Periods	Include	Include	Include	Include	Include	Include	Exclude	Exclude

Table A3: Analysis of Worker Sample Selection Bias in Calendar-Time Results

This table presents two sets of bootstrapped analyses of our calendar-time trading strategy. The first analysis, depicted in Panel A, constructs a new sample of employee-weighted labor flows for each firm-month. Weights are calculated as the ratio of the number of firm employees in the LinkedIn population who belong to a specific category, divided by the number of firm employees in the LinkedIn population who do not belong to the same category; these weights are applied to individual workers in the sample who belong to categories that are undersampled by our dataset relative to the LinkedIn population. The second analysis, depicted in Panel B, resembles a Monte Carlo simulation method. From our original dataset of employment records by firm, we create a new sample by drawing (without replacement) employment records for workers who belong to categories that are undersampled by our dataset relative to the LinkedIn population, until the new sample distribution of workers across categories matches that of the LinkedIn population. The worker category that we examine in both analyses is whether a worker attended a college listed in the top 20 universities ranked by U.S News as of 2018. For each set of analyses, we draw 10,000 random samples of firm-month observations, and estimate the abnormal returns of our calendar-time trading strategy for each of these random samples. We calculate the average and standard deviation of the alpha estimates across all random samples, and report these values below. We estimate abnormal returns using the five-factor model (Fama and French, 2015). All variables are defined as per Table 2. Monthly alphas are in percentage terms, and t-statistics are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Resampling Method 1							
α (%)	0.391***	0.316**	0.308***	0.242*	0.366***	0.306**	0.360***	0.300**
	(3.301)	(1.979)	(2.906)	(1.784)	(3.491)	(2.151)	(3.548)	(2.201)
	Panel B: Resampling Method 2							
α (%)	0.347***	0.296***	0.284***	0.231***	0.312***	0.240***	0.316***	0.230***
	(6.732)	(4.139)	(6.405)	(3.506)	(6.792)	(3.358)	(8.281)	(3.752)
Sorting Window	1 month	1 month	1 month	1 month	1 month	1 month	1 month	1 month
Starting Year	1985	1985	1985	1985	2005	2005	2005	2005
Portfolio Cutoff	quartile	quartile	tercile	tercile	quartile	quartile	quartile	quartile
EW/VW	EW	VW	EW	VW	EW	VW	EW	VW
Crisis Period	Include	Include	Include	Include	Include	Include	Exclude	Exclude

Table A4: Calendar-Time Results using Alternative Factor Models

This table presents results of calendar-time portfolio analysis using alternative factor models. We repeat our analysis as per Table 2, but use different factors to estimate abnormal returns generated by our trading strategy. Each month, firms are sorted into quartiles (or terciles) based on the net labor outflows realized over the previous one month. The long (short) portfolio consists of firms with the lowest (highest) realized net labor outflows. The long-short portfolios are rebalanced monthly and returns are computed using both value- and equal-weighted specifications. Panel A adds the liquidity factor Pástor and Stambaugh (2003) to our benchmark Fama-French five-factor model. Panel B adds the momentum factor (Carhart, 1997). Panel C uses the q-factor model proposed by Hou et al. (2015). Monthly returns and alphas are in percentages, and t-statistics are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: FF 5-factor + liquidity							
α (%)	0.410***	0.328**	0.311***	0.242*	0.389***	0.305**	0.381***	0.290**
	(3.508)	(2.115)	(2.831)	(1.822)	(3.681)	(2.068)	(3.565)	(2.001)
MP	-0.084**	-0.067	-0.071**	-0.073*	-0.090**	0.036	-0.037	0.061
	(-2.511)	(-1.557)	(-2.216)	(-1.950)	(-2.288)	(0.848)	(-1.055)	(1.310)
SMB	0.132***	0.145**	0.078	0.075	0.082	0.129*	0.100*	0.085
	(2.611)	(2.124)	(1.601)	(1.326)	(1.198)	(1.771)	(1.759)	(1.104)
HML	-0.226***	-0.171**	-0.202***	-0.083	-0.313***	-0.285***	-0.267***	-0.209**
	(-3.468)	(-2.006)	(-3.240)	(-1.124)	(-4.615)	(-3.942)	(-4.016)	(-2.166)
RMW	0.033	0.023	0.054	0.024	-0.135	-0.001	-0.131*	-0.126
	(0.345)	(0.183)	(0.596)	(0.250)	(-1.312)	(-0.007)	(-1.715)	(-1.013)
CMA	-0.094	-0.307**	-0.104	-0.405***	-0.109	-0.195	-0.152	-0.250**
	(-0.748)	(-2.102)	(-0.868)	(-3.003)	(-0.920)	(-1.297)	(-1.550)	(-2.054)
LIQ	-0.029	-0.048	-0.027	-0.040	-0.012	0.014	-0.024	-0.009
	(-1.591)	(-1.491)	(-1.464)	(-1.242)	(-0.517)	(0.642)	(-1.041)	(-0.270)
R^2	0.168	0.156	0.138	0.143	0.353	0.216	0.328	0.192
	Panel B: FF 5-factor + momentum							
α (%)	0.282***	0.232	0.187**	0.173	0.363***	0.291**	0.333***	0.260*
	(2.816)	(1.559)	(2.001)	(1.295)	(3.445)	(1.997)	(3.170)	(1.789)
MP	-0.059**	-0.057	-0.047**	-0.069	-0.057*	0.063	-0.034	0.065
	(-2.320)	(-1.195)	(-1.974)	(-1.616)	(-1.928)	(1.626)	(-0.994)	(1.445)
SMB	0.106***	0.124**	0.054	0.060	0.075	0.120*	0.082	0.073
	(2.935)	(1.974)	(1.537)	(1.121)	(1.395)	(1.712)	(1.444)	(0.963)
HML	-0.064	-0.046	-0.046	0.007	-0.201***	-0.222***	-0.237***	-0.182**
	(-1.103)	(-0.619)	(-0.848)	(0.097)	(-3.207)	(-3.281)	(-3.472)	(-2.040)
RMW	-0.042	-0.039	-0.019	-0.021	-0.163**	-0.013	-0.155**	-0.143
	(-0.617)	(-0.344)	(-0.299)	(-0.233)	(-2.053)	(-0.105)	(-2.015)	(-1.126)
CMA	-0.224**	-0.408***	-0.230**	-0.478***	-0.164	-0.221	-0.142	-0.243**
	(-2.321)	(-3.332)	(-2.500)	(-3.752)	(-1.584)	(-1.518)	(-1.506)	(-2.018)
UMD	0.247***	0.195***	0.240***	0.142***	0.155***	0.090***	0.081**	0.062
	(7.875)	(3.837)	(8.186)	(3.658)	(4.236)	(2.813)	(2.139)	(1.225)
R^2	0.401	0.239	0.381	0.192	0.499	0.252	0.349	0.200

(Continued)

(Continued)

	Panel C: q-factor							
α (%)	0.272**	0.222	0.173	0.147	0.265**	0.263*	0.272**	0.194
	(2.220)	(1.414)	(1.530)	(1.066)	(2.085)	(1.802)	(2.328)	(1.307)
MP	-0.066**	-0.056	-0.052*	-0.056	-0.054	0.048	-0.030	0.073
	(-2.282)	(-1.211)	(-1.931)	(-1.339)	(-1.520)	(1.137)	(-0.833)	(1.610)
ME	0.207***	0.198**	0.148**	0.103*	0.105*	0.109	0.113	0.113
	(3.134)	(2.206)	(2.483)	(1.688)	(1.759)	(1.576)	(1.623)	(1.591)
IA	-0.315***	-0.492***	-0.289***	-0.459***	-0.391***	-0.428***	-0.310***	-0.364***
	(-3.942)	(-4.949)	(-3.860)	(-5.037)	(-4.020)	(-4.100)	(-3.164)	(-3.455)
ROE	0.244***	0.208**	0.257***	0.165**	0.256***	0.174**	0.124*	0.146*
	(3.258)	(2.480)	(3.567)	(2.176)	(2.666)	(2.427)	(1.757)	(1.689)
R^2	0.199	0.172	0.183	0.138	0.304	0.158	0.160	0.141
Sorting Window	1 month	1 month	1 month	1 month	1 month	1 month	1 month	1 month
Starting Year	1985	1985	1985	1985	2005	2005	2005	2005
Portfolio Cutoff	quartile	quartile	tercile	tercile	quartile	quartile	quartile	quartile
EW/VW	EW	VW	EW	VW	EW	VW	EW	VW
Crisis Periods	Include	Include	Include	Include	Include	Include	Exclude	Exclude

Table A5: Calendar-Time Results Across Alternative Firm Samples

This table reports the results of calendar-time analysis using alternative samples of firms. Columns 1 to 4 correspond to a sample of firms that are members of the Russell 1000 as of 2006. Columns 5 to 8 correspond to firms in the Russell 1000 as of 2018 (our main sample), but exclude firms that undertake an initial public offering (IPO) between 1985 and 2016. Abnormal returns are assessed using the five-factor model (Fama and French, 2015). All variables are defined as per Table 2. Monthly alphas are in percentages, and t-statistics are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
α (%)	0.370***	0.332**	0.325***	0.232*	0.375**	0.367***	0.252*	0.292**
	(2.869)	(2.004)	(2.887)	(1.669)	(2.443)	(3.054)	(1.789)	(2.582)
MP	-0.064*	-0.070	-0.062*	-0.051	-0.111**	-0.087**	-0.079*	-0.073**
	(-1.675)	(-1.562)	(-1.853)	(-1.320)	(-2.492)	(-2.561)	(-1.893)	(-2.245)
SMB	0.070	0.129*	0.066	0.113**	0.147**	0.110**	0.087	0.059
	(1.173)	(1.854)	(1.264)	(2.002)	(2.243)	(2.028)	(1.431)	(1.131)
HML	-0.222***	-0.244**	-0.183***	-0.174**	-0.173*	-0.211***	-0.048	-0.190***
	(-2.676)	(-2.446)	(-2.599)	(-2.302)	(-1.939)	(-3.049)	(-0.630)	(-2.900)
RMW	-0.056	-0.142	-0.007	-0.037	0.060	0.046	0.060	0.050
	(-0.574)	(-1.232)	(-0.083)	(-0.398)	(0.512)	(0.436)	(0.584)	(0.495)
CMA	-0.063	-0.155	-0.092	-0.160	-0.317**	-0.055	-0.432***	-0.052
	(-0.496)	(-1.040)	(-0.848)	(-1.276)	(-2.172)	(-0.403)	(-3.147)	(-0.417)
R^2	0.113	0.151	0.105	0.108	0.137	0.117	0.120	0.094
Sorting Window	1 month	1 month	1 month	1 month	1 month	1 month	1 month	1 month
Starting Year	1985	1985	1985	1985	1985	1985	1985	1985
Portfolio Cutoff	quartile	quartile	tercile	tercile	quartile	quartile	tercile	tercile
EW/VW	EW	VW	EW	VW	EW	VW	EW	VW
Crisis Periods	Include	Include	Include	Include	Include	Include	Include	Include

Table A6: Calendar-Time Results for IPO Firms

This table presents calendar-time results for a sample of 3,612 firms that undertake initial public offerings (IPO) between 1995 and 2016. We perform our calendar-time analysis over different periods of time after an IPO. Panel A (B) analyzes firms in the immediate three (five) years that follow an IPO. Panel C contains the full sample of firms across sample years. All variables are defined as per Table 2. Abnormal returns are assessed using the five-factor model (Fama and French, 2015). Monthly alphas are in percentages, and t-statistics are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	IPO less than 3 years				IPO less than 5 years				All IPO firms			
α (%)	1.183***	1.116**	1.104***	1.028**	1.178***	1.087***	1.150***	0.954**	0.993***	0.864**	0.935***	0.832**
	(2.948)	(2.240)	(2.840)	(2.158)	(3.343)	(2.636)	(3.395)	(2.449)	(3.159)	(2.203)	(3.063)	(2.214)
MP	0.048	0.164	0.068	0.132	-0.008	0.137	0.003	0.152	-0.020	0.064	-0.010	0.086
	(0.517)	(1.264)	(0.758)	(1.041)	(-0.098)	(1.215)	(0.044)	(1.419)	(-0.258)	(0.614)	(-0.133)	(0.851)
SMB	0.094	0.154	0.076	0.090	-0.023	-0.004	-0.036	-0.052	-0.055	0.037	-0.061	0.030
	(0.583)	(0.748)	(0.485)	(0.463)	(-0.159)	(-0.023)	(-0.253)	(-0.311)	(-0.400)	(0.221)	(-0.447)	(0.184)
HML	-0.382**	-0.677***	-0.334**	-0.506**	-0.445***	-0.750***	-0.433***	-0.551***	-0.361***	-0.611***	-0.354***	-0.557***
	(-2.299)	(-3.027)	(-2.137)	(-2.258)	(-3.087)	(-3.971)	(-3.183)	(-2.663)	(-2.773)	(-3.435)	(-2.836)	(-3.165)
RMW	0.371*	0.280	0.385*	0.192	0.413**	0.191	0.426**	0.193	0.227	0.122	0.262	0.151
	(1.670)	(0.913)	(1.775)	(0.669)	(1.984)	(0.826)	(2.122)	(0.921)	(1.201)	(0.516)	(1.468)	(0.673)
CMA	0.346	0.230	0.336	0.077	0.302	0.246	0.301	0.037	0.315	0.008	0.304	-0.048
	(1.085)	(0.621)	(1.092)	(0.230)	(1.018)	(0.754)	(1.061)	(0.128)	(1.157)	(0.023)	(1.172)	(-0.151)
R^2	0.030	0.060	0.029	0.044	0.063	0.093	0.066	0.072	0.045	0.099	0.048	0.094
Sorting Window	1 month	1 month	1 month	1 month	1 month	1 month	1 month	1 month	1 month	1 month	1 month	1 month
Starting Year	1985	1985	1985	1985	1985	1985	1985	1985	1985	1985	1985	1985
Portfolio Cutoff	quartile	quartile	tercile	tercile	quartile	quartile	tercile	tercile	quartile	quartile	tercile	tercile
EW/VW	EW	VW	EW	VW	EW	VW	EW	VW	EW	VW	EW	VW
Crisis Periods	Include	Include	Include	Include	Include	Include	Include	Include	Include	Include	Include	Include

DATA APPENDIX

5.1 Data

In this section, we provide additional details that describe our dataset construction. These details are organized by data sources.

5.1.1 LinkedIn Worker Data

We collect individual user data on employment histories and educational backgrounds from LinkedIn using publicly available search engines such as Google and Yahoo. The sample of firms that we use to present our main results corresponds to publicly traded firms listed in the Russell 1000 as of June, 2018 (the inception of this study). We also collect data for firms in the Russell 1000 as of 2006, as well as all firms that undertake an initial public offering after 1994; we describe the results for these samples in secondary analysis in the paper.

We define firm entry and exit based on the start and end dates of an employment spell at a given company. A typical job spell on a CV represents time spent in a specific role or position, but may not imply entry or exit from the firm, as a worker could be promoted or reallocated within the firm. For the purposes of our analysis, we construct job spells within the firm to correspond to a worker's entire contiguous working experience at the firm.

Worker occupations are gleaned from workers' self-reported job titles. Specifically, for each of the occupations listed in Table 1, we classify a worker as belonging to that occupation if the occupation appears anywhere in the worker's job title. For example, $Engineers$ consist of all individuals who list their job title as "computer engineer", "software engineer", etc. $Middle\ Managers$ consist of all individuals who list "Manager" in their job title.

5.1.2 Insider Trading Data

From Thomson Reuters' Insider Filing Database, we gather information on the reported changes in company holdings of directors and executives, as reported to the Securities and Exchange Commission (SEC). This information contains data on insiders' open market sales and open market purchases across all firms in our sample. We exclude all observations that are reported with low levels of confidence (using Thomson Reuters' cleanse indicator of "A" or "S"). We also exclude trades where the transaction price is either three times greater than the transaction day closing price or less than 33% of the transaction day closing price, as these observations are likely to be subject to measurement error.

5.1.3 Analyst Earnings Forecast Data

For each firm in our sample, we gather data on equity analyst forecasts from the Institutional Brokers Estimate System (I/B/E/S) unadjusted U.S. detail history file. We collect historical earnings per share (EPS) forecasts made by each analyst covered by I/B/E/S, and all non-split-adjusted realized EPS figures over time.

5.1.4 LinkedIn Survey Data

We conduct surveys of individual LinkedIn users who appear in our firm-worker matched dataset. Individual participants are selected at random, and are not offered any compensation for completing a survey. Workers who exit (join) Russell 1000 firms in the sample are given three questions in our "Outflow Sample Survey" ("Inflow Sample Survey") below. Survey participants are contacted to complete the surveys via LinkedIn's online messaging service, where each message contains a link to an online survey hosted by Surveymonkey.com. The answers to each question of the surveys correspond to a numerical scale, from 1 *Not Important At All* to 5 *Very Important*.

Outflow Sample Survey

Q1. In the past, how important were the future prospects of your employer when deciding whether to stay with your employer or join another company?

Q2. In the past, how important were personal reasons unrelated to your employer (eg. family considerations) when deciding whether to stay with your employer or join another company?

Q3. In the past, did you ever perceive that your employer's hiring costs were important enough to impact the firm's stock price?

Inflow Sample Survey

Q1. In the past, how important was information provided by current (or former) employees of your prospective employer in helping you determine whether to join the firm?

Q2. In the past, how important was information contained in publicly available news sources (such as newspapers, financial reports, etc.) in helping you determine whether to join a prospective employer?

Q3. In the past, did you ever perceive that your employer's hiring costs were important enough to impact the firm's stock price?