Labor shortage, Hiring and Stock Returns

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Abstract

This paper demonstrates how hiring constraints affect firm valuation through the discount rate channel in both cross-sectional and time-series analyses. I construct portfolios based on firms' labor shortage discussions in SEC filings and find that hiring-constrained firms exhibit low average stock returns. This return predictability is most pronounced among firms with high hiring activity. Similarly, among hiring--constrained firms, those with aggressive hiring demonstrate the lowest average stock returns. This pattern reflects a fundamental rule in corporate investment decisions: when firms continue to hire aggressively despite labor constraints, their cost of capital must be sufficiently low to justify these hiring, if profitability does not explain the behavior. I formalize this mechanism through a Q-theory-based model that incorporates varying adjustment costs of hiring, demonstrating how hiring frictions generate predictable patterns in stock returns and providing new insights into the relationship between labor market conditions and asset pricing.

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1 Introduction

Labor shortages represent one of the most persistent challenges facing modern businesses. Despite unemployment rates remaining near historic lows and Federal Reserve officials signaling labor market normalization through 2024, firms across industries continue reporting difficulties in attracting and retaining qualified workers. These constraints extend far beyond cyclical hiring challenges, reflecting structural shifts in skill requirements, geographic labor mobility, and worker preferences that fundamentally alter how firms approach human capital investment.

For finance researchers, labor market frictions represent a pressing valuation concern because human capital accounts for a large component of firm value. Labor shortages can link directly to firm valuation through two channels: cash flows and required returns. On the cash-flow side, scarcity can raise wage bills, compress margins, and create capacity constraints that cap revenue growth. On the discount-rate side, hiring constraints can load on aggregate conditions, generating co-movement that commands a risk premium. Together, these mechanisms imply that labor shortages may matter for both the level and the pricing of cash flows. However, testing which channel dominates requires firm-specific measures of labor market frictions. Traditional labor market indicators only capture aggregate economic status but cannot identify which specific firms face binding hiring constraints versus those that choose not to expand their workforce.

This paper addresses the measurement challenge by developing a text-based approach to identify labor shortage discussions in corporate SEC filings. I construct a comprehensive dictionary through an iterative process that combines large language model seed generation with Word2Vec embedding expansion, then apply this methodology to analyze over 300,000 corporate filings from 1997 to 2024. The resulting measure captures when firms explicitly discuss hiring constraints as material business challenges, providing granular firm-year indicators of hiring difficulties.

Using this measure, I document several key findings about how labor shortages affect stock returns in the cross-section. Firms experiencing labor shortages earn systematically lower returns, with a value-weighted portfolio strategy generating excess returns of 3.1 percentage points annually. The negative returns of labor-constrained firms reflect their exposure to fundamental risk factors rather than representing a distinct anomaly. Specifically, these firms exhibit negative loadings on both the profitability factor and investment factor in the Fama-French five-factor model, indicating weak current profitability combined with aggressive investment behavior.

The relationship between labor shortages and returns operates primarily through an interaction with hiring decisions. Portfolio analysis reveals that return predictability concentrates entirely among high-hiring firms. Among labor-constrained companies, those pursuing aggressive hiring strategies earn the lowest returns, while firms without labor constraints show no significant relationship between hiring activity and future performance. This asymmetry demonstrates that labor market frictions are necessary for generating the negative hiring-return correlation documented in prior research.

The cross-sectional patterns have important aggregate implications. To test whether the observed state-dependent relationships extend to market-level dynamics, I examine time-series patterns using aggregate hiring data rather than text-based measures. Historical analysis from 1950 to 2024 reveals that aggregate hiring growth negatively predicts market returns, with a one percentage point increase in hiring associated with a three percentage point decline in subsequent annual returns. Critically, this predictability varies significantly over time, with the strongest negative relationship occurring during periods of labor market tightness as measured by survey data on unfilled job openings.

The documented patterns across both cross-sectional and time-series analyses point to a consistent theoretical mechanism operating through discount rates rather than cash flows. When firms face binding labor constraints yet continue aggressive hiring, this behavior signals that their cost of capital must be sufficiently low to justify expensive talent acquisition in tight markets. Given that constrained firms simultaneously exhibit weak current profitability, their low returns reflect required return differences rather than expectations of superior future cash flows. Predictive regressions confirm this interpretation by showing that hiring among constrained firms predicts returns but not dividend growth.

The empirical results receive theoretical support from a Q-theory framework incorporating heterogeneous adjustment costs. The model demonstrates how varying degrees of labor market frictions generate the observed return patterns through their effects on optimal investment timing. Firms facing higher hiring constraints require lower discount rates to justify continued human capital investment, creating systematic differences in required returns that manifest as return predictability.

This research contributes to the asset pricing literature by establishing labor market frictions as a systematic determinant of cross-sectional return differences. The findings show that hiring constraints operate through existing risk factors rather than representing anomalous behavior, providing validation for investment-based models of asset pricing. The text-based measurement methodology offers a replicable approach for capturing firm-specific labor market conditions that can be applied to other research questions examining the intersection of labor economics and finance.

The results have practical implications for both portfolio managers and corporate executives. For investors, the documented patterns suggest that labor shortage information contains systematic risk exposures that may be useful for factor-based investment strategies. The predictability effects are economically significant and represent a natural extension of existing investment-based factors. For managers, the findings highlight how labor market conditions affect the cost of capital and optimal timing of hiring decisions, particularly during periods of aggregate labor market tightness.

This paper is organised as follows. In Section 2, I review relevant work. In Section 3, I set up a simple Q theory model to elaborate the theoretical foundation of labor shortage. In Section 4, I describe my sample of firms and empirical construction of labor shortage. In Section 5, I conduct portfolio sorting and predictive regression to show labor shortage is necessary for a negative hiring-return relationship. In Section 6, I show aggregate hiring predicts lower future return especially when labor market is tight. In Section 7, I present conclusions.

2 Literature

My paper contributes to the literature by constructing firm-level hiring constraint measures. Properly measuring the extent of hiring constraint across assets is critical to any study of firm hiring dynamics and its relation with the return of underlying assets. A growing body of literature studies the effects of labor market frictions on corporate decisions and performance, exploring variation in labor protection laws, hiring difficulties, competition, diversification, and job mismatch (Qiu (2019), Bai, Fairhurst, and Serfling (2020), Le Barbanchon, Ronchi, and Sauvagnat (2023), Bai, Eldemire, and Serfling (2024), Indriawan, Li, and Zurbruegg (2024), Beaumont, Hebert, and Lyonnet (2025), Coraggio, Pagano, Scognamiglio, and Tåg (2025)).

Measuring constraints. The paper builds directly on research that extracts information from corporate text regarding constraints or risks that are normally hard to directly infer from structured data. In the established literature on financing constraints, Lamont, Polk, and Saaá-Requejo (2001) manually read through subsamples of firm SEC filings and categorized them by the extent to which they expressed financing concerns. Hoberg and Maksimovic (2015) looked for expressions regarding delaying investment, equity and debt issuance in the management discussion and analysis section of 10-K filings, and assigned financing constraint scores to the entire sample based on cosine similarity. Buehlmaier and Whited (2018) took a naive Bayesian approach to evaluate firm's financing constraintedness as a function of word appearance in the 10-K[1]. For labor-related constraints, Harford, He, and Qiu (2023) used conference calls to construct firm level labor shortage measures. My paper proposes a simple and explicit two-step procedure to extract useful labor shortage information from firm's SEC filings, providing a granular, explicit firm-year hiring-constraint measure.

Labor and finance. Despite the rising application of textual analysis of corporate fil-

[1]Examples of using 10-K to obtain information includes product market competition Hoberg and Phillips (2016), product life cycle Hoberg and Maksimovic (2022), etc.

ings, few focus on production-related measures of constraintedness. The paper builds on asset pricing literature where certain forms of labor market friction are important in explaining return patterns. Belo, Lin, and Bazdresch (2014) and Belo, Donangelo, Lin, and Luo (2023) documented the negative hiring-return relationship and interpreted it as differential risk associated with the existence of labor market friction. The intuition is that because of adjustment costs of labor, high hiring firms are those that incur high adjustment costs, and aggregate shocks that lower such costs benefit them most, therefore serving as a hedge. Chen, Kacperczyk, and Ortiz-Molina (2011) and Edmans, Pu, Zhang, and Li (2024) explored how labor costs and employee satisfaction affect asset pricing. Studies examining hiring constraints include Serfling (2016) on firing costs, Tuzel and Zhang (2017) on local wage pro-cyclicality as expense hedging, and Petrosky-Nadeau, Zhang, and Kuehn (2018) showing that searching friction in labor markets can give rise to rare disasters. My contribution quantifies how hiring constraints map into valuation, providing the first empirical findings that document both the relation between labor shortage and return, and more importantly how labor shortage strengthens the negative relation between labor hiring and return.

Q-theory of investment. The paper extends research on investment-return correlations within the framework of Q-theory. Titman, Wei, and Xie (2004), Li and Zhang (2010), Kogan and Papanikolaou (2012), Fedyk and Hodson (2023) and Indriawan et al. (2024) have documented negative correlations between various forms of investment and future returns. However, the interpretation of these patterns remains contested, with alternative explanations including limits to arbitrage, managerial overconfidence, and talent wars competing with Q-theory's adjustment cost mechanisms. For example, Fedyk and Hodson (2023) finds that within IT related industry, high hiring predicts lower future return and is stronger in tigher labor market, which they interpret as over-valuation. Few studies provide direct supporting evidence for the Q-theory explanation over these behavioral or market friction alternatives. My contribution addresses this gap by testing whether Q-theory with heterogeneous hiring constraints can explain the hiring-return correlation, using labor shortage measures to provide more direct evidence for the adjustment cost channel. The cross-sectional interaction between labor constraints and hiring decisions, combined with time-series validation during periods of aggregate labor market tightness, offers stronger identification for Q-theory mechanisms than previous investment-return studies.

3 Theoretical motivation

Before entering into empirics, it helps clarify the question by laying out the basic idea of Q theory, and most importantly, explaining how the following empirical tests are related to the theory. Much of the introduction borrows knowledge from Campbell (2017)[2] and Zhang (2017). In the context of human capital investment, at the core of Q theory, it concerns the optimal hiring decision[3] of a given firm. A value-maximising firm will keep hiring until its marginal benefit equal to marginal cost. Productivity is typically an important element that goes into the marginal benefit, whereas on the marginal cost side, it usually concerns production related real cost, which is also referred to as hiring adjustment cost. The theory thus establish a connection between optimal hiring and the level of labor market friction.

Once the optimal hiring is obtained, one can always define hiring return, which is next period output plus continuation value (stochastic), divided by today's total cost of hiring. The key message is that, expected investment return should be negatively related to the rate of hiring, because holding expected output fixed, the higher the expected return, the lower the present value the firm's human capital stock is, therefore the firm has less desire to hire. Finally, to tie hiring return to stock market return, additional assumptions are needed, for example constant returns to scale in both production and adjustment costs (Hayashi, 1982).

To sum up, the neoclassical Q theory of human capital investment allows stock return to be negatively related to hiring rate, under the presence of hiring adjustment cost as key friction embedded in the production process. The rest of this chapter conveys the same intuition in formal expressions.

3.1 Model setup

Consider a canonical two-period stochastic partial equilibrium model focusing on the production side of economy, a simplified version from Zhang (2017). Given that the paper focus

[2]Chapter 7, pg 207-215.

[3]A particular form of investment where capital is human.

on labor hiring, I characterise firms as pure human capital based productive units, but the main mechanism works through for physical investment as well. The defining feature of this neoclassical economics is firms maximise their market value of equity taken as given an exogenous stochastic discount factor M_{t+1}. There are two dates, t and $t+1$, firms produce a single commodity to be consumed or invested, the price of which is normalised to 1. Firm i starts with productive human capital, K_{it}, operates in both dates, and exits at the end of date $t+1$ with a liquidation value of zero. The rate of human capital depreciation is set to be 100% for simplicity. Firms differ in human capital, K_{it}, and profitability, X_{it}, both of which are known at the beginning of date t. The operating profits are given by $\Pi_{it} = X_{it}K_{it}$. Firm i's profitability at date $t+1$, X_{it+1}, is stochastic, and is subject to aggregate shocks affecting all firms simultaneously, and firm-specific shocks affecting only firm i. Let I_{it} be the among of labor hired for date t, then $K_{it+1} = I_{it}$. Hiring entails quadratic adjustment costs, $(a/2)\left(I_{it}/K_{it}\right)^2 K_{it}$, in which $a > 0$ is a constant parameter.

Generally speaking, hiring adjustment cost form the model is a catch-all term summarising the convex cost in installing new human capital. A firm facing such cost will find it increasing costly to hire as they increase hiring rate. This may arise from searching friction, or increasing expense in training the workers and getting them ready to work. The paper is agnostic about the exact micro foundation of giving rising to hiring adjustment cost. Instead, it takes the concept as a starting point of the test. Following the literature, I refer to I_{it}/K_{it} as hiring rate thereafter.

Firm i uses its operating profits at date t to pay hiring cost I_{it} and adjustment costs $(a/2)\left(I_{it}/K_{it}\right)^2 K_{it}$. Therefore, its free cash flow at date t, D_{it}, can be expressed as $X_{it}K_{it} - I_{it} - (a/2)\left(I_{it}/K_{it}\right)^2 K_{it}$. If D_{it} is positive, the firm distributes it back to the household. A negative D_{it} means external equity raised by the firm from the household. At date $t+1$, firm i uses capital, K_{it+1}, to obtain operating profits, which are in turn distributed as dividends, $D_{it+1} \equiv X_{it+1}K_{it+1}$. With only two dates, firm i does not invest in date $t+1, I_{it+1} = 0$, and the ex-dividend equity value, P_{it+1}, is zero. Taking the household's stochastic discount factor, M_{t+1}, as given, firm i chooses I_{it} to maximise the cum-dividend equity value at the beginning of date t:

$$P_{it} + D_{it} = \max_{\{I_{it}\}} \left[X_{it}K_{it} - I_{it} - \frac{a}{2}\left(\frac{I_{it}}{K_{it}}\right)^2 K_{it} + E_t\left[M_{t+1}X_{it+1}K_{it+1}\right]\right]$$

The first order condition of investment says that:

$$1 + a\frac{I_{it}}{K_{it}} = E_t\left[M_{t+1}X_{it+1}\right]$$

The left-hand side is the marginal cost of hiring: unit cost of human capital and marginal adjustment cost; and the right-hand side is the marginal benefit of hiring, or more popularly referred to as marginal Q: expected discounted present value of date $t+1$'s operating profit per unit of human capital. Firm i hires until marginal cost equal to marginal benefit. Next, I show what stock return has to do with this condition.

By definition, stock return of firm i from date t to date $t+1$ can be expressed as:

$$r^S_{it+1} \equiv \frac{P_{it+1} + D_{it+1}}{P_{it}} = \frac{X_{it+1}K_{it+1}}{E_t\left[M_{t+1}X_{it+1}K_{it+1}\right]} = \frac{X_{it+1}}{E_t\left[M_{t+1}X_{it+1}\right]} = \frac{X_{it+1}}{1 + a\left(I_{it}/K_{it}\right)} \qquad (1)$$

Here the second equality uses the fact that this is a two-period model where $P_{it+1} = 0$, $D_{it+1} \equiv X_{it+1}K_{it+1}$, and ex-dividend price of firm i at date t is its expected discounted present value of date $t+1$'s operating profit: $P_{it} = E_t\left[M_{t+1}X_{it+1}K_{it+1}\right]$, The third equality uses the fact that human capital depreciates fully such that at date $t+1$ capital is actually determined at date t: $K_{it+1} = I_{it}$, therefore K_{it+1} can be taken out of the expectation operator and gets cancelled out. The last equality substitutes the denominator by the first order condition of hiring obtained from above.

3.2 Model interpretation

The interpretation of this equation is, holding profitability X_{it+1} fixed, hiring rate I_{it}/K_{it} is negatively related to stock return r^S_{it+1}, which holds if one takes expectation on both sides. In the asset pricing terminology, it is equivalent so say if one constructs a characteristic-based portfolio that longs low hiring and shorts high investment firms, it will on average generate positive return, which was documented documented and explained explicitly in Belo et al. (2014) and Belo et al. (2023). As for physical investment, such investment spread has also been well documented, as early as in Titman et al. (2004) [4]. Given more consistent findings in follow-up studies, ``investment factor'' has been officially coined and become part of those main stream multi-factor models, such as Hou, Xue, and Zhang (2015), Fama and French (2015).

Despite ample empirical evidence of hiring and investment spread, no consensus has yet been reached on its explanation[5]. Regarding the debate between behavioural and neoclassical explanation, this paper intends to provide further supporting evidence of the neoclassical Q theory, by testing its additional prediction related to adjustment cost. To convey the full intuition, the paper allows previously constant convex adjustment cost parameter a from Equation 1 to be firm and time varying, such that the relationship between return and hiring:

$$r^S_{it+1} = \frac{X_{it+1}}{1 + a_{it}\,(I_{it}/K_{it})} \tag{2}$$

For the moment if a_{it} is fixed, then one obtains predictions between hiring and stock return:

Hypothesis 1. *The faster the firm hires (higher I_{it}/K_{it}), i.e., as the firm incurs higher marginal cost of hiring, the lower is the stock return such that the marginal benefit is large enough to compensate the cost, holding profitability and hiring constraint fixed.*

[4] By constructing five capital investment (CI) portfolios, they find the spread between lowest and highest is 0.168% per month.

[5] For instance, Titman et al. (2004) argues that over investment explains the pattern.

The paper is not the first to propose and test this prediction. For example, Belo et al. (2014) find consistent empirical evidence and explain it using a dynamic model with hiring adjustment cost. The main deviation of my paper from Belo et al. (2014) is that I allow a_it to be firm specific, and examine the following two novel predictions from the model.

Specifically, as both the hiring constraint and hiring rate show up as a product in the denominator of Equation 2, one can also examine how stock return moves as a_{it} varies, the prediction of which can be formulated as follows:

Hypothesis 2. *The larger is labor adjustment cost a_{it}, i.e., as hiring constraint gets more severe, the lower must the stock return be such that firm sticks with the same level of hiring rate, holding profitability fixed.*

The intuition is, as firm becomes increasingly hiring constrained, its hiring adjustment cost also increases. Should the firm not down scale its hiring, the rate of return must be lower to allow room for higher marginal benefit of hiring.

In addition, Equation 2 also gives predictions on how a_{it} moderates the relationship between stock return and hiring rate. First, imagine an extreme case where $a_{it} = 0$, stock return becomes irrelevant to hiring rate, $r^S_{it+1} = X_{it+1}$. When Q theory was first formulated by Tobin (1969), it is actually implicitly assumed that there is no adjustment cost, meaning $a_{it} = 0$. That's why sometimes people say that optimally firm hires (invests) until marginal $Q = 1$[6]. The bottom line is, without adjustment cost, the relationship between stock return and hiring disappears.

More formally, one can check whether as a_{it} becomes larger, i.e., as new labor is more costly to put into use, stock return is more negatively correlated to hiring rate. In model, it is equivalent to ask, whether the first order derivative of r^S_{it+1} with respect to I_{it}/K_{it}, is more negative as a_{it} increases. That is, whether the derivative of $\frac{\partial r^S_{it+1}}{\partial\left(\frac{I_{it}}{K_{it}}\right)}$ with respect to a_{it},

[6]Because once $a = 0$, the left-hand side of the first order condition $1 + a\frac{I_{it}}{K_{it}} = E_t\left[M_{t+1}X_{it+1}\right]$ becomes 1, which is also the value of marginal Q.

or the cross-second order derivative $\frac{\partial^2 r^S_{it+1}}{\partial\left(\frac{I_{it}}{K_{it}}\right)\partial a_{it}}$, is negative. Starting from Equation 2, one can show that it can be expressed as follows:

$$\frac{\partial^2 r^S_{it+1}}{\partial\left(\frac{I_{it}}{K_{it}}\right)\partial a_{it}} = X_{it+1}\frac{a_{it}\frac{I_{it}}{K_{it}} - 1}{(a_{it}\frac{I_{it}}{K_{it}} + 1)^3}$$

This derivative is negative if and only if $a_{it}\frac{I_{it}}{K_{it}} < 1$, which under ordinary parameterisation will be the case. For example in Belo et al. (2014) a takes value 1.2, and we know that hiring rate on average is about 0.15, so their product is well below 1. This idea can be summarised in the following hypothesis:

Hypothesis 3. *Without hiring constraint (hiring adjustment cost), stock return and hiring rate will not be related. Within reasonable parameter range, as hiring constraint gets more severe, return will be more negatively related to hiring rate.*

Therefore, it takes a good measure of labor hiring constraint to make this hypothesis testable. The next section describe the construction of the measure, and summarise its properties.

4 Sample construction

Human capital is central to firm value, yet systematic information on labor conditions is strikingly limited. Beyond the requirement to disclose year-end headcount, firms face no obligation to provide consistent or granular measures of their hiring activity. As a result, quantitative data on labor inputs remain sparse relative to other production factors such as capital expenditure or R&D.

The lack of labor information in structural data not only prevents any attempt in understanding the effect of labor market friction in finance, but also introduces bias in explaining firm behaviour. For instance, ignoring the heterogeneity in hiring constraint across firms, researchers may well attribute any gap in performance fully to factors from the demand, or to managerial and liquidity issues[7].

Therefore, the first and central task is to properly measure the extent to which firms face hiring constraint. Just as basing the measurement of implicit financing constraint upon textual analysis, leveraging large text data helps distinguish hiring constrained firms from their peers.

4.1 Constructing a Labor Shortage Indicator from SEC Filings

4.1.1 Why SEC filings?

SEC filings offer a qualitatively rich source of information. Within mandatory sections such as risk factors, management discussion and analysis, and the business description, firms routinely discuss operational challenges and strategic priorities in their own words. These narratives often include references to issues such as staffing shortages, recruitment difficulties, or retention concerns, which rarely appear in tabular form but that are highly relevant to understanding labor frictions.

The recent rise in investor and regulatory attention to human capital underscores this point. Rulemaking petitions and public statements to SEC leadership have called for greater disclosure of workforce-related metrics, precisely because filings are regarded as the primary channel through which investors learn about firms' labor conditions[8]. The push for more structured disclosure further recognises SEC filings as the natural and authoritative venue for communicating labor-related challenges[9].

[7]For example, the difference between what a firm says and who a firm hires can be explained by hiring constraint instead of managerial cheap talk.

[8]SEC (2017): ``Investors are interested in using human capital disclosure for different purposes depending on their investment strategy. Many investors favor more robust human capital disclosures to identify and invest in companies that manage their human capital most effectively. For these investors, human capital management is an input for fundamental analysis alongside more traditional inputs such as product quality, technological innovation, and distribution channels.''

[9]In 2020, responding to the demands of investors, the SEC issued amendments to Regulation S-K requiring filers to provide discussions related to their human capital management practices. See more detailed discussion in Demers, Wang, and Wu (2025).

4.1.2 How to capture meaningful words

The absence of firm level data on hiring frictions motivates the use of disclosure text to recover signals of labor scarcity. Prior research shows that wordlist based approaches can map language in filings to economic constructs but may conflate mechanisms. For example, Bodnaruk, Loughran, and McDonald (2015) develop a lexicon for financial constraints. Applied to The New York Times 10-K filed in February 2008, their method classifies the sentence ``we are required to negotiate the wages, salaries, benefits, and staffing levels'' as a financial constraint, although the passage reports that 47% of the workforce is unionized, which reflects a labor context. This illustrates how generic constraint lists can attribute labor topics to financial frictions.

This example highlights a broader point: general-purpose constraint lists can, at times, attribute labor-related issues to financial frictions. Rather than viewing this as a flaw, I take it as a useful signal. If the language that encodes constraints already reflects staffing challenges, then a more targeted approach can isolate and measure hiring constraint directly.

Two implementation families are available. One uses sentence level classifiers that are supervised or LLM based Li, Mai, Shen, and Yan (2021); Harford et al. (2023). The other relies on curated dictionaries with contextual checks Hoberg and Phillips (2016); Li, Shan, Tang, and Yao (2024). Both ultimately depend on domain specific phrases. Even supervised models require labeled text, and the labels are defined by researcher chosen terms. In practice their precision is close. Harford et al. (2023) report about 88% for a curated dictionary under human review and about 91% for fine tuned NLP. The incremental gain comes with costs in transparency and sensitivity to training. I therefore adopt a term based approach with explicit guardrails and validation so that the measure remains transparent, auditable, and portable across years and firms.

4.1.3 Term list

I construct the term list to reflect how firms actually write about hiring frictions. I begin with a compact set of seed phrases that clearly signal scarcity, for example ``labor shortage'', ``worker scarcity'', and ``difficult to hire''. Using these seeds, I retrieve sentences from 10--K filings and treat the matched sentences as a focused corpus on staffing. I then fit a Word2Vec model to this corpus so that words that appear in similar shortage contexts move closer in the embedding space. Querying nearest neighbors to the seeds surfaces natural variants that firms use in practice. I add the high quality neighbors, refresh the retrieval, and retrain. The loop stops when additional rounds deliver little new coverage. Figure 1 summarizes this workflow.

To keep the list disciplined and replicable, I apply three guardrails. First, a candidate term must be unambiguously about staffing in its sentence context. Ambiguous words enter only when the sentence contains clear employment cues such as hire, recruit, retain, train, vacancy, position, or role. Second, I collapse duplicates and near duplicates so that small spelling, plural, or hyphenation differences do not inflate counts. Third, I monitor head coverage to decide when the list has converged. In sample, the top five terms account for about 43% of matches and the top ten account for about 71%. This pattern indicates that the main phrases are well covered while the remainder forms a long and thin tail.

Implementation links the dictionary to firm year outcomes in a transparent way. I normalize each filing to plain text, lowercase the content, remove boilerplate delimiters, and segment the document into sentences so that the sentence is the unit of analysis. I then apply two matching layers. The first uses literal phrases from the dictionary written as regular expressions that allow minor variation in number and punctuation. The second uses template patterns that capture recurring structures such as ``unable to hire [role]'' and ``lack of qualified [workers]''. A sentence is flagged when either layer matches. Within a filing I collapse near duplicate hits so that repeated mentions of the same idea do not inflate counts. I aggregate to the firm year and set the indicator to one if any sentence in that year

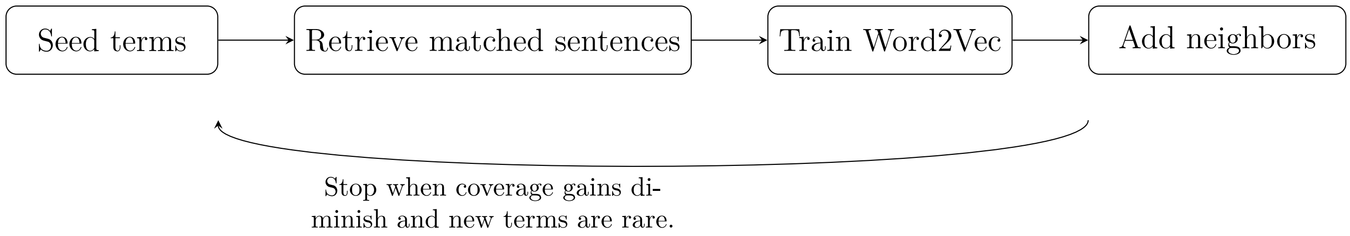

Figure 1: Iterative construction of the labor shortage dictionary

contains shortage language. I also retain the matched sentences for manual review, which enables spot checks, precision tracking, and consistent auditing over time. This design preserves precision through explicit patterns, improves recall through semantic expansion, and remains interpretable and portable across years and industries.

4.1.4 Top terms

Using a defined term list gives me the advantage of identifying which phrases drive most of the matches[10]. Table 1 reports the 30 most frequently occurring labor shortage--related terms in my 10-K sample. These 30 expressions account for 90.6% of all matched terms, with the top five alone making up over 42% of the total.

The distribution of matched terms is intuitive. Central phrases such as ``unable to retain,'' ``unable to attract,'' ``labor shortages,'' ``open positions,'' and ``unable to hire'' dominate the counts, while more specialized expressions (e.g., ``shortage of nurses,'' ``aging workforce'') form a plausible long tail. This heavy concentration of usage suggests that, as long as the dictionary successfully identifies the most common ways firms articulate hiring constraints, the risk of systematically missing implicit types of hiring difficulty is small.

Moreover, the fact that the empirical frequency distribution aligns closely with Zipf's law (see Figure A.2) provides reassurance that the dictionary captures a natural language process rather than being skewed by idiosyncratic construction. In other words, the relative frequencies across terms exhibit the expected power-law decay, reinforcing the comprehensiveness

[10]The probability distribution of words in the dictionary largely follows Zipf's law, as shown in Figure A.2, consistent with the observation in Bodnaruk et al. (2015).

and robustness of the constructed measure.

Term	Count	% of Total	Cumulative %
unable to retain	33090	9.51	9.51
unable to attract	31926	9.17	18.68
labor shortages	31284	8.99	27.67
open positions	28680	8.24	35.91
unable to hire	24080	6.92	42.83
inability to attract	23987	6.89	49.73
difficulties in staffing	21402	6.15	55.88
labor shortage	19500	5.60	61.48
inability to retain	16756	4.81	66.29
inability to hire	15188	4.36	70.66
difficulty in hiring	8680	2.49	73.15
high turnover	7564	2.17	75.33
inability to recruit	6661	1.91	77.24
difficulty in staffing	4756	1.37	78.61
unable to recruit	4624	1.33	79.93
staffing shortages	4238	1.22	81.15
difficulty in recruiting	3894	1.12	82.27
difficulties in recruiting	3772	1.08	83.36
difficulties in hiring	3562	1.02	84.38
tight labor market	2850	0.82	85.20
increased turnover	2670	0.77	85.96
aging workforce	2572	0.74	86.70
cannot retain	2433	0.70	87.40
staffing shortage	2287	0.66	88.06
difficult to retain	1924	0.55	88.61
vacant positions	1580	0.45	89.07
shortage of nurses	1546	0.44	89.51
higher turnover	1329	0.38	89.89
increased attrition	1300	0.37	90.27
unable to employ	1196	0.34	90.61

Table 1: Most Frequently Occurring Labor Shortage Terms in 10-Ks (1994-2024)

4.1.5 Evolution of narratives

Beyond documenting which terms are most frequent, the dictionary-based approach also allows me to track how the prominence of different expressions evolves over time. This dynamic perspective is important because it reveals not only the concentration of usage at

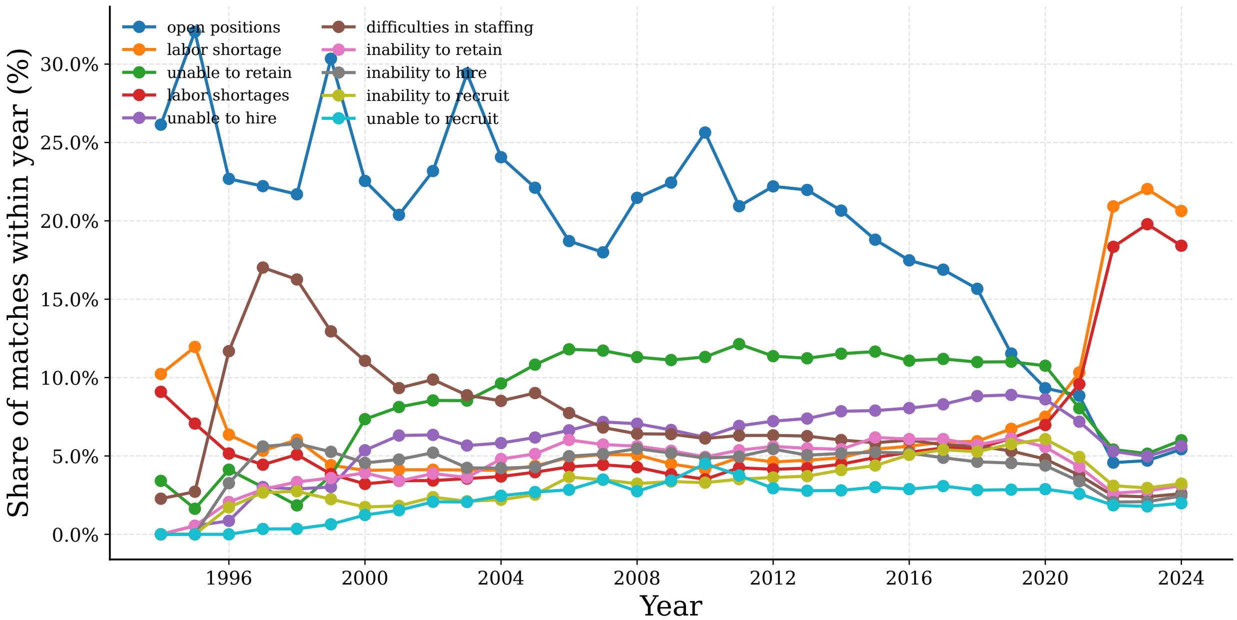

Figure 2: Evolution of labor-shortage narratives in 10-K filings (Top 10 terms, relative shares)

Note: Lines show the share of each of the Top 10 most frequent labor-shortage terms within all matched mentions in a given year. Shares are computed relative to the total number of matched phrases in 10-K filings within year.

any given point, but also how firms adapt their language when discussing hiring constraints. In other words, the method is informative both about the key phrases that dominate the narrative and about the shifts in emphasis that take place across different periods.

As shown in Figure 2, the early part of the sample is characterized by terms such as ``open positions,'' ``difficulties in staffing,'' or ``unable to retain,'' which account for most of the matched sentences. By contrast, the expressions ``labor shortage'' and ``labor shortages'' are virtually absent before 2010 but rise sharply after the COVID-19 outbreak, increasing from less than 5% of within-year mentions before 2020 to more than 20% by 2021.

These changes indicate that the dictionary is able to capture shifts in the way firms describe hiring constraints over time. This feature provides an additional justification for employing an expanded dictionary, which ensures that both established and newly emerging terms are covered and that the measure remains valid across historical episodes and disclosure practices.

4.1.6 Close terms

To address the concern that the dictionary might overlook salient expressions, I train a Word2Vec model on shortage-flagged sentences from 10-K filings and examine the terms that appear closest in the embedding space. The idea is that if the dictionary truly captures the semantic field of hiring constraint, then its nearest neighbors should be expressions that convey similar difficulties. Table A.1 shows that the closest phrases include ``retain,'' ``recruit,'' ``tight labor market,'' and ``staffing shortage(s),'' all of which are natural linguistic variants of labor shortage. Importantly, these neighbors are already well represented in the dictionary, which confirms that the list systematically covers the main ways firms articulate hiring constraint. This semantic coherence provides an external validation: the dictionary not only captures the most frequent formulations, but also anchors a neighborhood of related expressions, ensuring that the resulting measure is both comprehensive and theoretically meaningful.

4.1.7 Persistence and mobility in shortage mentions

After seeing what firms say and which phrases cluster together in meaning, a natural next step is to check how firms move across shortage states over time. The Markov transition matrix in Table 2 is designed for exactly this purpose and is worth a close look.

Two features stand out. First, persistence scales with intensity in a way that looks economically sensible: firms with ``multiple mention'' are likely to remain there in the following year (about 76%), while one-off mentions are notably more transitional (roughly 68%). Second, there is meaningful mobility on both margins: a nontrivial share of ``no mention'' firms begin to mention shortages in the next year, and intense mentioners sometimes step down to lighter mention or none. This is the pattern one would expect if shortage exposure is a time-varying constraint rather than boilerplate text.

In short, Table 2 shows a state variable with structure (persistence when constraints bite) and movement (entry and exit as conditions change). This complements the narrative evidence by showing that firms do not simply lock in a label, they transition as their hiring constraints evolve.

	no mention	mention only 1	multiple mention	exit
no mention	70.39	3.82	1.69	24.11
mention only 1	8.21	68.13	9.52	14.14
multiple mention	2.06	5.41	75.78	16.75

Table 2: Markov transitioning matrix (row %)

4.1.8 Industry and geographic patterns in shortage mentions

When normalized by firm and aggregated, the measure displays clear structure as in Table 3. In 2024, labor-intensive services (construction, air travel, lodging, restaurants) and several upstream goods producers rank highest, and many move up relative to 2019. Headquarters rankings show a similar reordering, mixing manufacturing-heavy states with financial domiciles. The aggregate view thus preserves informative variation across sectors and locations, complementing the firm-level dynamics.

4.1.9 Economic rationale

In frictionless models, hiring is instantaneous at the prevailing wage, without extra cost in the process of labor adjustment. But in reality recruiting is costly, time-consuming, and sensitive to labor market tightness. Textual disclosures that highlight labor shortages intend to capture signals for a higher cost of hiring, either because more resources must be devoted to recruiting, because vacancies take longer to fill, or because the quality of applicants does not meet the production need.

Importantly, the measurement by construction captures equilibrium states of firms in any given time. It by no means makes any clear cut supply and demand shock. When firms report that it is ``difficult to hire,'' that ``positions remain unfilled,'' or that there

Top-10 Industries (avg hits per firm, 2024)			Top-10 HQ Locations (avg hits per firm, 2024)	
Rank	Name	in 2019	Name	in 2019
1	Heavy Construction, Except Building	4	Alabama	26
2	Air Transportation	14	Cayman Islands	23
3	Hotels & Lodging	49	Mississippi	105
4	Eating & Drinking Places (Retail)	2	Bermuda	20
5	Misc. Manufacturing	35	Quebec	36
6	Lumber & Wood Products	10	District of Columbia	4
7	Leather & Leather Products	29	Ireland	33
8	Water Transportation	9	Wisconsin	62
9	Agricultural Production---Livestock	62	Missouri	56
10	Agricultural Services	11	Hawaii	29

Table 3: Top-10 industries and HQ locations by average shortage mentions

Notes - Average hits is defined to be total labor shortage matches of the SIC-2 industry or headquarter state divided by the number of firms (2024), with 2019 ranks shown for comparison.

is a ``lack of qualified workers,'', it can arise either from a positive demand shock to firm's marginal benefit of hiring, or a negative supply shock to firm's marginal cost of hiring.

Nevertheless, there is still value in this measurement. First of all, even if we do not have any definite prior on whether labor shortage is mainly driven by demand or supply, observing its association with key firm policies can still inform us how it takes place empirically. For example, if labor shortage can predict positive (negative) hiring growth, then it is likely that the dominating shock is positive demand (negative supply) shock. Second, The fact that we care so much about the nature of labor shortage already suggests that perhaps there is more to learn on the supply side, where variations in cost of labor adjustment may play important role potentially.

The logic is analogous to the way financial economists use textual mentions of ``financing constraints'' or ``liquidity shortages'' as indicators that the marginal cost of external finance is elevated. In both settings, the firm discloses the presence of a bottleneck that raises adjustment costs and restricts optimal investment[11]. Interpreting shortage language as a proxy for hiring constraints is therefore both consistent with textual evidence and grounded

[11] See for example, in Belo, Lin, and Yang (2019), financing constraints arise due to marginal cost of external financing.

in economic theory.

4.2 Labor shortage in text

4.2.1 Over time

In Figure 3, I plot labor shortage ratios over years. The ratio equals the number of 10-K filers that mention labor shortage in year t divided by the total number of 10-K filers in year t . Several features align with labor market conditions. First, the share is close to zero in the late 1990s and rises through the early 2000s, reaching roughly 12-15% by 2006-2007, consistent with tightening pre-crisis labor markets. Second, during the 2010–2019 expansion the series drifts from about 20% to around 25% as unemployment fell and hiring tightened. Third, there is a clear step up around 2021, with the share stabilizing near 30–32% in the early 2020s, consistent with post-pandemic hiring frictions, elevated job openings, and high quits.

Because gradual upward drift in text measures can also reflect longer filing trend rather than changing fundamentals[12], I interpret the secular rise with caution and focus on the timing and magnitude of the cyclical increases. Especially the post-2021 step-up indicates that managers' discussion in 10-Ks responds to prevailing labor conditions.

4.2.2 Where do firms disclose labor shortage?

I focus on 10-K disclosures because the analysis and portfolio formation are annual. The 10--K is the natural annual report where staffing capacity and hiring difficulties are systematically discussed. By contrast, 10-Q filings are interim and shorter. The appendix Figure A.1 shows that labor–shortage mentions occur predominantly in 10-Ks for most years, and their share rises to a clear majority in the 2010s. Figure A.3 plots the distribution of labor shortage mentions across sections from 1997 to 2024. Discussions of labor scarcity most often appear

[12] See for example, similar increasing pattern of text-based constraint measure from figure 1 in Bodnaruk et al. (2015), figure 2 in Buehlmaier and Whited (2018)

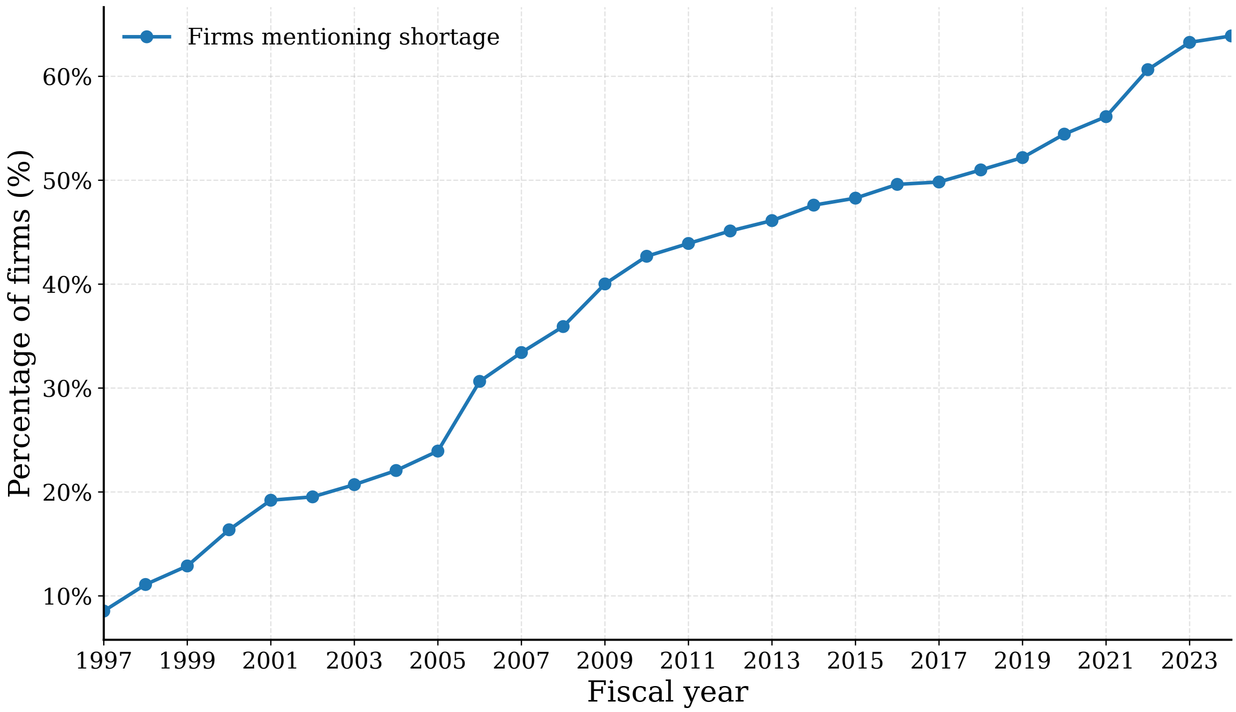

Figure 3: Share of firms mentioning labor shortage in 10-K

Note: For each fiscal year t (based on `rdate`: Jan-May $\rightarrow t-1$, Jun-Dec $\rightarrow t$); multiple sentences or filings within a year collapse to a single firm-year with indicator 1 if any sentence matches the dictionary, else 0. The variable equals the number of exact ``10-K'' filers with a labor-shortage mention divided by the total number of exact ``10-K'' filers in year t.

in three sections of the 10-K: Item 1 (Business), Item 1A (Risk Factors), and Item 7 (Management's Discussion and Analysis). Item 1 provides a qualitative overview of operations, inputs, and competitive conditions, and firms frequently describe staffing constraints here as part of their production capacity or service delivery. Item 1A, by contrast, is dedicated to material risks. When hiring frictions are seen as threats to growth or continuity, they are explicitly framed as risk factors alongside regulatory exposures, competitive pressures, or supply chain disruptions. Item 7 requires management to explain past performance and anticipate future developments, and firms often link higher labor expenses, delays, or unmet demand directly to difficulties in recruiting or retaining staff.

A striking feature is the sharp reallocation of disclosures from Item 1 to Item 1A beginning in 2006. This change reflects the SEC's 2005 amendment to Regulation S-K, which introduced Item 1A as a mandatory section devoted to risk factors. Before then, staffing constraints were commonly described within the general business overview. Afterwards, they were reframed and consolidated into the dedicated risk disclosure format. The pattern is highly persistent, with Item 1A accounting for the bulk of mentions in all subsequent years. In contrast, Item 7 remains a smaller but stable channel for reporting labor shortages, indicating that firms consistently view hiring constraints as both a forward-looking risk and an explanatory factor for operating results.

References to hiring challenges can also surface elsewhere, such as in the notes to the financial statements or in forward-looking statements when shortages materially affect costs or capacity. Across all of these sections, however, disclosure is narrative rather than tabular: firms do not report standardized measures of vacancies or turnover, but instead provide qualitative accounts of shortages, recruitment delays, and retention problems. This dispersion underscores the value of a textual approach. By systematically scanning filings, it becomes possible to capture the operational context (Item 1), the risk framing (Item 1A), and the financial implications (Item 7) of labor scarcity in a way that structured data alone cannot provide.

4.2.3 Examples of labor shortage discussion

Air transportation offers a clean illustration. In Table 3, the industry rises to the second highest incidence of shortage language. Comparing pre-- and post--COVID filings shows a shift from occasional tightness in FAA licensed roles to binding staffing constraints as networks scale back up. airline labor shortage language clusters Figure 4 visualises this shift: before COVID, narratives center on licensed occupations; after COVID, they stress the difficulty of rebuilding capacity with available flight and maintenance staff[13]. In practice, firms report that either hiring has become more costly and slower to scale, or demand has rebounded faster than staffing can adjust. The unifying statement is that firms lack sufficient qualified labor to meet the business need.

[13] Appendix Table A.1 provides two illustrative excerpts that anchor this pre-- and post--COVID contrast.

Figure 4: Air transportation shortage language, pre-- and post--COVID

Note: Slide level comparison of airline disclosure language before and after COVID based on clustered terms in 10--K text. The figure illustrates a shift from intermittent references to FAA licensed roles to broader constraints on restoring capacity.

4.3 Stock and firm data

Monthly stock returns are from the Center for Research in Security Prices (CRSP), and accounting information is from the CRSP/Compustat Merged Annual Industrial Files. The sample is from July 1997 to June 2022 and includes firms with common shares (shrcd = 10 and 11) and firms traded on the New York Stock Exchange, the American Stock Exchange, and NASDAQ (exchcd = 1, 2, and 3). I omit firms whose primary standard industrial classification is between 4900 and 4999 (regulated firms) or between 6000 and 6999 (financial firms) Following Belo et al. (2014), I require a firm to have a December fiscal year end to align the accounting data across firm. Latter I show relaxing such choice does not drive away the results. Following Fama and French (1993), I require each firm to have at least two years of data in Compustat before it is included in the sample. The data for the Fama-French factors (five factors plus momentum) are from WRDs.

4.3.1 Merge SEC filing data with accounting data

I merge the shortage signal from SEC filings to accounting data at the firm-year level and then carry it into the CRSP portfolio calendar. Within a fiscal year, multiple filings for the same CIK are treated as one information set: the texts are combined and all shortage mentions are counted once for that CIK--year, from which I build the annual indicators (``no mention,'' ``mention only 1,'' ``multiple mention''). The CIK--year panel is linked to COMPUSTAT and then to CRSP via the standard CCM bridge; when there are several possible links, I keep a single match using simple tie-breakers (primary link preferred, then availability of June market equity, then earlier link date). Following the usual convention, June market equity defines the sort year, I apply an NYSE $p20$ microcap screen by sort year, and portfolios run from July of year t through June of year $t+1$ using the shortage signal from fiscal year t.

4.4 Summary statistics

I compare firms that newly enter the shortage group with contemporaneous non--shortage firms and report medians by group. The final column shows the median difference scaled by the non--shortage median in percent, and stars denote significance[14]. Two organizing facts help read the table. First, profitability is lower for newly shortaged firms one year ahead. ROA is 0.03 versus 0.05 and operating cash flow over assets is 0.08 versus 0.10, and both gaps are statistically significant. Second, size and growth move in opposite directions. Log sales is lower by about 7% while sales growth is higher by about 78%.

Balance sheet positions and asset mix are consistent with a growth orientation. Cash over assets is higher by about 91% and book leverage is lower by about 15%. Tangibility is lower by about 32%, while R&D over assets is higher by about 116%. Hiring and investment are elevated in the event year and remain high one year ahead. The hiring rate is 0.08 versus 0.03 at time t and 0.06 versus 0.03 at time $t+1$. The investment rate is 0.23 versus 0.18 at time t and 0.22 versus 0.18 at time $t+1$. Taken together, newly shortaged firms appear smaller and faster growing, with more cash, less leverage, a tilt toward intangibles, and persistently strong factor demand alongside weaker near term profitability. It also suggests that despite persistent strong hiring from the time of labor shortage, future hiring gap becomes narrower

[14] Definitions and exact Compustat mappings for all variables appear in Appendix Table A.2.

Variable	Median (Newly)	Median (Non--LS)	Δ/Non--LS (%)
ROA (t+1)	0.03	0.05	**-34*****
OCF/Assets (t+1)	0.08	0.10	**-18*****
Log Sales	6.84	7.39	**-7*****
Sales Growth	0.15	0.08	**78*****
Cash/Assets	0.13	0.07	**91*****
Book Leverage	0.21	0.24	**-15*****
Tangibility (PPE/Assets)	0.16	0.24	**-32*****
R&D/Assets	0.05	0.02	**116*****
Hiring Rate (t)	0.08	0.03	**144*****
Hiring Rate (t+1)	0.06	0.03	**106*****
Investment Rate (t)	0.23	0.18	**25*****
Investment Rate (t+1)	0.22	0.18	**21*****

potentially due to binding hiring constraint. Of course all of the comparison is made without controls. Next I zoom into labor shortage and align the timing of labor shortage to offer a cleaner event study style analysis that sketches the dynamics of key firm policies over time.

4.4.1 Event time dynamics around the first shortage

To better characterize the happening of labor shortage, I adopt an event study comparison where I align the first labor shortage time of each firm afirst Figure 5 plots mean differences between newly shortaged firms and non--shortage firms by event time τ from -3 to $+3$, with $\tau = 0$ marking the first shortage year. Hiring and investment rise sharply at the event, step down afterward, and remain above pre event gaps for several years. Sales growth peaks at the event and then normalizes. Research and development increases at the event and stays elevated. Profitability troughs on impact. Both return on assets and operating cash flow over assets fall at $\tau = 0$ and recover gradually.

The series are constructed to compare like with like. Within each event time, I contrast newly shortaged firms with non--shortage firms in the same calendar year and SIC3 industry. I compute within cell treated minus control means and average across cells using weights that reflect the treated composition at that event time. The confidence bands are ± 1.96 standard errors of the aggregated series, and all panels share a common y axis scale to aid

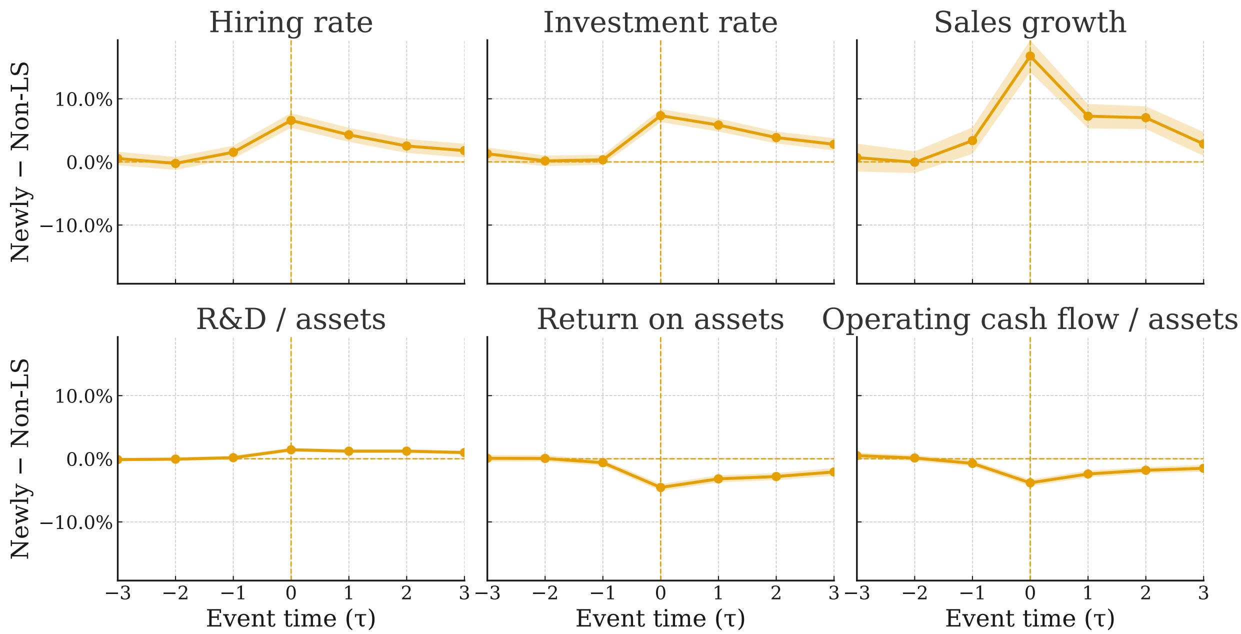

Figure 5: Event time differences, Newly minus Non--LS, industry--year fixed effects reweighting (SIC3)

Notes: $\tau = 0$ is the first year a firm is classified as newly shortaged. Within each treated cell (τ, Y, i) defined by event time, calendar year, and SIC3 industry, compute the treated minus control mean, then average across cells using weights equal to the treated share at that τ. Shaded bands show ± 1.96 standard errors. A common y axis scale is used across all six panels.

comparison. Read this as a difference profile that filters out shifts in industry mix and time.

Taken together, the profiles depict firms expanding capacity at the onset of a shortage while absorbing onboarding and training costs that compress near term profits. The sustained elevation in hiring, capital formation, and R&D, alongside a transitory spike in sales growth, points to binding staffing constraints during periods of strong demand rather than weak conditions. The same patterns obtain under alternative specifications, including industry--year matching without reweighting, SIC2 industries, and modest changes in the event window.

4.5 Learn from endogeneity

Endogeneity of labor shortage itself is not my *enemy*. Rather than eliminating it, I extract valuable insight from it. At least statistically, its association with hiring make it possible to probe deeper the nature of labor shortage. Intuitively, when labor shortage takes place when hiring is strong, it suggests that demand plays important role in causing firm to hit its bottleneck. Whereas if during labor shortage hiring dampens, probably cost of hiring matters more.

There are a few reasons why I use hiring instead of hiring cost proxy when it comes to distinguish supply from demand. First, wage is not directly observable in Compustat at firm level, missing values is a severe issue for labor cost, let along obtaining proxies for implicit cost of hiring adjustment. Second, even if I can obtain certain proxy for cost of hiring, the prediction of positive demand shock and negative supply shock will both push hiring cost up, making it hard to disentangle supply and demand.

Outcome panel	**Predictor**	**Pooled (no FE)**	**Year FE**	**Firm & industry×year FE**
A. Next-year hiring rate				
	Current labor shortage (binary)	0.0196***	0.0226***	−0.0093**
		(0.0029)	(0.0030)	(0.0042)
	Shortage matches (per 1 SD)	0.0126***	0.0141***	−0.0092***
		(0.0016)	(0.0016)	(0.0025)
	R^2	0.0036	0.0295	0.4425
	Observations	20,818	20,818	20,818
B. Next-year ROA				
	Current labor shortage (binary)	−0.0173***	−0.0146***	−0.0063**
		(0.0027)	(0.0028)	(0.0026)
	Shortage matches (per 1 SD)	−0.0091***	−0.0077***	−0.0025
		(0.0014)	(0.0014)	(0.0016)
	R^2	0.0069	0.0224	0.7004
	Observations	20,818	20,818	20,818

Table 4: Effects of Labor Shortages on Hiring and Performance

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. All models control for firm size and year effects as specified.

The empirical design uses increasingly saturated fixed effects to separate demand-driven comovement from firm-specific capacity constraints for *both* outcomes: next-year hiring and next-year profitability. Let $Y_{i,t+1} \in \{H_{i,t+1},\ \mathrm{ROA}_{i,t+1}\}$ denote, respectively, next-year hiring and next-year ROA for firm i observed at $t+1$. Let $S_{i,t}$ be the contemporaneous shortage signal (textual flag or shortage-matches). I estimate, for each outcome,

$$Y_{i,t+1} = \beta\, S_{i,t} + u_{i,t+1}, \tag{Pooled}$$

$$Y_{i,t+1} = \beta\, S_{i,t} + \delta_t + u_{i,t+1}, \tag{Year FE}$$

$$Y_{i,t+1} = \beta\, S_{i,t} + \alpha_i + \kappa_{s,t} + u_{i,t+1}, \tag{Firm FE + Industry×Year FE}$$

where δ_t are calendar-year effects, α_i are firm fixed effects, and $\kappa_{s,t}$ are industry×year effects for industry s in year t. Standard errors are clustered by firm. The purpose of this sequence is straightforward. Equations (Pooled) and (Year FE) leave common demand in the variation that loads on β. Equation (Firm FE + Industry×Year FE) differences out time-invariant firm traits and absorbs industry-year conditions, so any remaining association in β reflects a firm-specific constraint consistent with binding labor supply.

Table 4 reports the results. In the pooled specification and with year fixed effects, firms flagged as facing ``labor shortages'' subsequently show *higher* hiring. This aligns with the idea that the language partly tracks strong product-market conditions. Once the comparison is made within a firm and within an industry-year cell, the sign reverses for hiring. The shortage measures are associated with *lower* next-year hiring. The profitability outcome points in the same direction. Next-year ROA is lower when a shortage is flagged, and this is statistically significant for the primary shortage indicator under the most saturated specification. The contrast is informative. The positive association in the pooled and year-FE regressions reads as demand-driven comovement. The negative association in the firm and industry×year fixed-effects regression isolates an idiosyncratic capacity constraint that dampens subsequent headcount growth and operating performance.

4.6 Explain labor shortage

To better understand the relationship between firm-level labor shortage and the firm's accounting variables, I run Logit regression of the binary measure of labor shortage on contemporary hiring rate, investment rate, return on asset, book-to-market ratio, leverage and log of size.

Variable	**Coefficient (b)**	**%**	**%StdX**
hn	0.40***	49.8	9.0
ik	-0.03	-2.8	-0.9
roa	0.50***	65.5	10.8
bm	-0.06	-5.7	-4.1
lev	0.98***	167.6	24.6
size	0.06***	6.3	13.7
constant	-3.04***		

Table 5: Logit Regression Results

Note: this table reports results from running logistic regression to explain the binary variable of labor shortage that takes value 1 if the firm mentions labor shortage in that year. All sample includes all firms; hn: hiring rate; ik: physical capital investment rate; roa: return on assets; beme: book to market equity ratio; lev: book debt to market value of the firm; size: log of firm market value.

Table 5 studies how contemporary firm conditions are related to their labor shortage status. For better interpretation, I compute the percentage change in odds of being labor shortage for a unit change in each variable, reported in column (**%**), as well that for a standard deviation change in each variable, reported in column (**%StdX**). In the following text, I focus on interpreting the last column. Consistent with evidence from Table **??**, the first row shows that firm's hiring rate is an important factor explaining its labor shortage status. When the hiring rate increase by one standard deviation (17%), the odds of the firm to become labor shortage is 9% higher. Such relationship is absent from the second row, where investment rate is neither statistical nor economical significant, suggesting that firm's labor condition is not just a byproduct from its physical investment, instead, high hiring demand can make firm with tight hiring constraint more binding.

In addition, higher return on asset (one standard deviation being 10%) corresponds to 11% increase in the odds of labor shortage, this hints that firms may experience labor shortage while it is facing strong demand. Moreover, 10% higher leverage ratio is related to 25% percent increase in labor shortage, this can either be because financial constraint is interrelated to the tightness of firm's labor condition, or simply explained by high growth firm demanding both more capital and labor. Lastly, as a firm becomes bigger, its odds of being labor shortage is also higher, suggesting that labor shortage is not likely a small firm only thing. In Table A.3 I report robustness check with SIC industry identification code used as fixed effect, the coefficient and magnitude for hiring rate remain significant. This shows that variation in labor shortage is not likely to be mainly due to industry effect.

5 Labor shortage and stock returns

The aforementioned features imply that labor shortage is closely related to firm's operation, therefore can potentially affect asset price. This section focuses on testing the theory based hypotheses regarding the relation between labor shortage and stock return, using both portfolio sorting and predictive regression methods.

5.1 Does hiring predict lower return? Test of Hypothesis 1

Following the theoretical guidance formulated in Section 3, I start by testing Hypothesis 1, which entails investigating the link between hiring and future stock returns in the cross section. Specifically, I first perform one-way portfolio sorting on hiring rate, as is in Belo et al. (2014). To define the hiring rate breakpoints used to allocate firms into portfolios, I follow Fama and French (2008) and compute the deciles of the hiring rate cross-sectional distribution of all but micro cap firms in NYSE-AMEX, NASDAQ. The micro cap firms are defined as firms with a market capitalisation that is lower than the bottom 20th percentile of the market capitalisation cross-sectional distribution of NYSE firms. Every year, Ten portfolios are constructed based on the threshold. Firms with the lowest hiring rate are classified into L portfolio, and firms with the highest hiring rate are classified into H portfolios. The quantity of major economic interests is the average return of a long-short portfolio that longs L and shorts H, denoted as $L - H$.

Table 6 presents the results from one-way sorting on hiring rate. The highlighted column suggests that there is a strong negative hiring-return relation in the sample. As Hypothesis 1 implies, it takes certain level of labor hiring constraint on average among all firms such that one is able to observe the hiring spread. Quantitatively, $L - H$ (long low hiring short high hiring) portfolio yields a significant 16.6% equal-weighted annualised excess return and 7.2% (not statistically significant) value-weighted excess return. These results align well with the magnitude of Belo et al. (2014), if not larger.

Panel A: Returns

	Low	2	3	4	5	6	7	8	9	High	L-H	MAE
	Equal-Weighted Portfolios											
r^S	16.50	14.23	12.31	13.32	10.99	11.92	10.63	11.37	2.91	-0.08	16.58	
$[t]$	2.75	3.15	2.63	3.29	2.59	2.84	2.33	2.22	0.49	-0.01	4.64	
α	6.10	5.07	3.78	4.86	2.30	3.15	1.10	1.19	-7.88	-12.15	18.24	4.76
$[t]$	1.41	1.95	1.19	2.24	0.96	1.40	0.45	0.39	-1.97	-3.04	5.13	
α^{FF}	5.66	4.22	2.79	4.01	1.72	2.90	0.93	1.44	-7.21	-11.26	16.92	4.21
$[t]$	1.61	2.28	1.03	2.55	0.93	1.81	0.54	0.63	-2.21	-3.59	5.01	
	Value-Weighted Portfolios											
r^S	11.21	9.58	7.24	8.67	6.02	8.31	7.03	7.62	5.40	4.05	7.16	
$[t]$	2.19	2.82	1.92	2.71	1.80	2.55	1.77	1.70	1.13	0.73	1.33	
α	3.47	2.53	1.03	1.97	-0.75	1.34	-1.52	-1.57	-3.08	-7.00	10.46	2.43
$[t]$	0.84	1.36	0.36	1.14	-0.39	0.82	-0.77	-0.63	-0.93	-2.16	1.98	
α^{FF}	2.48	2.09	0.12	1.49	-0.73	1.05	-1.33	-0.91	-2.03	-5.20	7.67	1.74
$[t]$	0.61	1.16	0.04	0.91	-0.39	0.67	-0.69	-0.38	-0.65	-1.95	1.66	

Panel B: Accounting Variables

hn	-0.20	-0.06	-0.01	0.01	0.04	0.07	0.11	0.19	0.28	0.57	-0.77
ik	0.15	0.17	0.17	0.19	0.21	0.25	0.27	0.33	0.40	0.46	-0.31
roa	-0.06	0.02	0.03	0.04	0.04	0.04	0.04	0.03	0.02	-0.01	-0.05
lev	0.35	0.37	0.33	0.33	0.30	0.28	0.26	0.22	0.19	0.19	0.16
beme	0.68	0.59	0.57	0.53	0.49	0.47	0.46	0.43	0.35	0.37	0.31
size	11.63	12.56	12.73	13.24	13.23	13.07	12.94	13.01	12.94	12.69	-1.06

Table 6: One way sorting portfolio on hiring rate

This table reports the average equal- and value-weighted portfolio excess stock returns and abnormal returns of 10 portfolios one-way sorted on hiring rate. 1 is the lowest hiring rate portfolio. The term r^S is the average annualized ($\times 1,200$) portfolio excess stock return; $[t]$ are heteroscedasticity consistent t-statistics. α and α^{FF} are portfolio average abnormal returns, obtained as the intercept from monthly CAPM or Fama and French (1993) regressions, MAE is the mean absolute pricing errors (average of absolute values of α or α^{FF}). $L-H$ stands for the low-minus-high hiring portfolio. Panel B keeps track of the mean of the median of accounting variables of the portfolio over time series.

5.2 Does labor shortage predict lower return? Test of Hypothesis 2

Next, I test Hypothesis 2, which entails investigating the link between labor shortage and future stock returns in the cross section. To do so, I construct three portfolios orderly classified on the firm's current labor shortage mentioning state, and compare these portfolios' post-formation average stock returns. Specifically, at the end of June of year t, I sort the universe of common stocks into three portfolios based on the firm's hiring rate at the end of year $t-1$. Once the portfolios are formed, their returns are tracked from July of year t to June of year $t+1$, the average of which are computed. The procedure is repeated at the end of June each year. I report both average equal- and value-weighted portfolio returns across all firms to mitigate concerns over small firm bias, leaving a more comprehensive picture of the link between labor shortage and stock returns in the overall economy.

Table 7 reports the result from previous portfolio sorting. I denote non labor shortage firms as N, firms with only one time mentioning as S, and firms with multiple times mentioning as $S+$. The economic object of interests is the average return from long-short portfolio made out of $(S+) - N$, that is to long the multiple mentioning $S+$ and to short the non labor shortage N. This long-short portfolio's return is highlighted in the left half of Panel A from the Table 7. Consistent with Hypothesis 2, labor shortage portfolio indeed on average makes lower return than the non labor shortage portfolio. Such relationship is robust if one use both S and $S+$ to construct the long leg of the portfolio, and is robust for both weighting methods. For example, when value-weighted, labor shortage portfolio makes over 4% less annually than the non labor shortage portfolio, which is significant at 90% confidence level. The fact that one finds stronger pattern in value weighted portfolio sorting, suggests that the result is robust to small firm bias, therefore conveys economics significance.

Admittedly, the one-way sorting comes with a few caveats. First, it does not control for other characteristics that can potentially determine return, therefore, there is no guarantee to all else equal. Second, the result is marginally statistical significant. I argue that these two concerns can be two sides of the same coin. Because the omitted variable can go both way in affecting return. For example, in Panel B of Table 7, leverage is larger for labor shortage firms, which can potentially make it harder for the return of $(S+) - N$ to be significantly negative[15]. Later in the predictive regression, I mitigate this concern by adding controls to the regression.

In addition, one may wonder whether firms with shortage in production in general deliver lower return, or it is unique to hiring constraint. To mitigate the concern of false positive, I redo the one-way sorting analysis, this time on the state of shortage mentioning other than labor, as a placebo test. Meaning, if a firm discusses shortage other than labor, be it inventory, raw material or working capital, then the firm is categorised as S or $S+$ if mentioning multiple times. The rest firms go into N portfolio. In the right half of Panel A from the Table 7, I show that neither the weighting scheme deliver consistent sign on such zero-cost portfolio return, which are far from significant.This evidence conveys an important reminder that by simply pooling together multiple types of shortage, the economic meaning gets blurred, making it hard to obtain any clear shortage-return pattern, let along holding all else equal.

To sum up, I test Hypothesis 2 through one-way portfolio sorting on labor shortage, and find that labor shortage predicts lower future return in the cross section. In addition, the distinct comparison between labor shortage and the rest type of shortage suggests that the measure of labor shortage is uniquely informative of labor hiring constraint. In the next subsection, I test Hypothesis 3 by checking whether the hiring spread is larger for labor shortage firms, compared to non labor shortage firms.

[15]Several papers in asset pricing explicitly discuss the issue with sorting conditioning on key confounders to better examine the mechanism, see for instance Li (2011) and Kilic, Yang, and Zhang (2022)

Panel A: Returns

	N	S	S+	(S+)-N	MAE	N	S	S+	(S+)-N	MAE
	Labor Shortage					Nonlabor Shortage				
	Equal-Weighted Portfolios									
r^S	11.17	7.50	11.05	-0.12		10.91	9.70	12.09	1.18	
[t]	2.42	1.37	1.93	-0.05		2.38	1.96	2.28	0.79	
α	1.95	-2.93	0.62	-1.33	1.83	1.84	-0.05	1.51	-0.33	1.13
[t]	0.80	-0.91	0.17	-0.62		0.75	-0.02	0.54	-0.24	
α^{FF}	1.59	-3.38	-0.09	-1.68	1.69	1.51	-0.79	1.13	-0.38	1.14
[t]	1.01	-1.52	-0.03	-0.80		0.94	-0.42	0.55	-0.28	
	Value-Weighted Portfolios									
r^S	7.70	3.15	3.47	-4.23		7.80	5.76	9.45	1.64	
[t]	2.49	0.68	0.73	-1.31		2.55	1.61	2.18	0.62	
α	0.65	-5.87	-4.78	-5.43	3.77	0.88	-1.98	0.77	-0.11	1.21
[t]	0.98	-2.21	-1.49	-1.68		1.13	-1.45	0.34	-0.04	
α^{FF}	0.68	-6.08	-4.80	-5.47	3.85	0.84	-2.01	1.40	0.56	1.42
[t]	1.06	-2.31	-1.58	-1.83		1.12	-1.46	0.65	0.23	
	Panel B: Accounting Variables									
hn	0.05	0.06	0.07	0.02		0.05	0.05	0.04	-0.01	
ik	0.23	0.25	0.26	0.03		0.23	0.22	0.23	0.00	
roa	0.02	0.02	0.01	-0.01		0.02	0.03	0.02	0.00	
beme	0.49	0.49	0.49	0.00		0.49	0.49	0.48	-0.01	
lev	0.28	0.30	0.33	0.05		0.28	0.29	0.26	-0.02	
size	12.66	12.86	13.03	0.37		12.59	13.06	13.01	0.42	

Table 7: One way sorting portfolio on shortage

This table reports the average equal- and value-weighted portfolio returns based on labor shortage and nonlabor shortage state. Here, nonlabor shortage represents shortage type other than labor. The term r^S is the average annualised ($\times 1,200$) portfolio excess stock return; [t] are heteroscedasticity consistent t-statistics. α and α^{FF} are portfolio average abnormal returns, obtained as the intercept from monthly CAPM or Fama and French (1993) regressions, MAE is the mean absolute pricing errors (average of absolute values of α or α^{FF}). N is the portfolio of firms do not mention labor shortage of the year, S of firms mentioning labor shortage only once of the year, and $S+$ as multiple labor shortage mentioning portfolio. Panel B keeps track of the mean of the median of accounting variables of the portfolio over time series.

5.3 Does labor shortage strengthen the negative relation of hiring-return? Test of Hypothesis 3

Section 5.1 has documented that the negative relation between hiring rate and return persists in the full sample. This subsection, instead, concerns if labor shortage as a moderator strengthens such negative relation. To do so, I move onto the two-way portfolio sorting test. Specifically, in each year, six portfolios are formed based their hiring rate and labor shortage state independently. For hiring rate, firms are classified into low hiring L, median hiring M and high hiring H subgroups. For labor shortage state, firms are classified into labor shortage S and non labor shortage N subgroups. Together a firm will fall into one of the $2 \times 3 = 6$ portfolios among the two dimensions of classification. I compute the average return of these portfolios and display the result in Table 8.

The economic quantity of interests is the average return of $L - H$ across two labor shortage subgroups S and N, which are the highlighted rows in Table 8. Focusing on value-weighted, it shows that the $L - H$ spread is 9.7% for labor shortage group S. In comparison, such spread goes below zero to -1.15% for the non labor shortage group N. Further investigation at each leg of the $L - H$ portfolio for labor shortage group S reveals that the high excess return can be mainly explained by the rather low return of the HS leg, that is the high-hiring and labor shortage portfolio. This is exactly the prediction from Equation 2: holding all else equal, the product of high hiring and high adjustment cost implies a high marginal cost of hiring in the denominator, corresponding to a low return.

Symmetrically, one can examine the labor shortage $S - N$ spread across different hiring rate subgroups. According to Equation 2, the labor shortage spread should be wider for the high hiring subgroup H, which is also confirmed in the data. Quantitatively, the highlighted row shows that the labor shortage $S - N$ spread is only significantly negative for high hiring subgroup H (-10.6% excess return with $t = -2.37$), yet that for low hiring subgroup L is

0.3% and not significant.

Lastly, the middle and lower part of Table 8 report risk adjusted returns from CAPM and Fama-French three factor model. The results are consistent with findings from excess return, suggesting that such spread contains independent risk beyond market, size and value. This is important because it rules out the concern that confounding characteristics such as large size and growth can potentially explain the rather low return from the HS leg. In addition, in all hypotheses, one implicit but important assumption is that all else especially profitability should be held equal. Although it is hard to verify directly, but there is preliminary evidence from Figure 5, which suggests that return on asset does not have significant differential changes between labor shortage firms and non labor shortage firms (see the last subplot). In unreported robustness check, I vary the breakpoint of hiring rate, as well as conduct two way sorting based on size or value and labor shortage, and I find the main results still hold.

After offering evidence of negative relation between labor shortage and return, and the relative stable negative relation between hiring rate and return, I move on to two-way sorting test, which is robust to extreme values. I display the result in Table 8. Focusing on value-weighted, it shows that the $L-H$ spread is 9.7% for labor shortage group, but goes below zero to -1.15% for no labor shortage group. When investigating each leg of the zero-cost portfolio, I find that the high hiring and labor shortage portfolio's rather low return drives the difference. From a risk perspective, it says that high hiring firms are only less risky when their labor supply constraint is more binding, which is exactly aligned with the idea that it takes labor market friction to obtain the negative hiring-return relationship. Conversely, the $S-N$ spread is only significantly negative for high hiring group (-10.6% excess return with $t=-2.37$), yet that for low hiring is 0.3% and not significant. The result from CAPM and Fama-French three factor models looks similar, suggesting that such spread contains independent risk beyond size and value, this is important in that it rules out the concern on confounding characteristics such as large size and growth. In unreported robustness check, I vary the breakpoint of hiring rate, as well as conduct two way sorting based on size or value and labor shortage, and I find the main results still hold.

Hiring and Labor Shortage Portfolios

	Equal-Weighted				Value-Weighted			
	N	S	S-N	[t]	N	S	S-N	[t]
	Excess Return r^e							
L	15.08	10.95	-4.14	-1.79	7.51	7.83	0.31	0.07
M	12.35	11.72	-0.63	-0.4	7.18	5.95	-1.23	-0.39
H	4.06	3.92	-0.14	-0.05	8.66	-1.87	-10.53	-2.37
L-H	11.03	7.02			-1.15	9.70		
[t]	4.25	1.83			-0.33	1.55		
	CAPM α							
MAE	3.61				1.13			
L	6.27	1.12	-5.15	-2.25	1.15	-0.69	-1.84	-0.42
M	4.43	2.64	-1.79	-1.2	1.01	-1.66	-2.67	-0.85
H	-5.90	-6.9	-1.0	-0.4	0.15	-10.9	-11.05	-2.47
L-H	12.17	8.02			1.00	10.21		
[t]	4.75	2.08			0.30	1.61		
	Fama-French α^F							
MAE	2.61				1.25			
L	5.08	-0.35	-5.43	-2.4	0.81	-1.21	-2.01	-0.47
M	3.54	1.48	-2.07	-1.46	1.00	-1.99	-2.99	-1.01
H	-6.09	-7.47	-1.38	-0.56	1.03	-10.54	-11.57	-2.59
L-H	11.17	7.12			-0.22	9.33		
[t]	4.93	1.92			-0.09	1.49		

Table 8: Two way sorting portfolio on hiring and labor shortage

This table reports the average equal- and value-weighted portfolio excess stock returns and abnormal returns of portfolios two-way sorted on hiring rate and labor shortage. Specifically, S represents labor shortage, N represents not mentioning labor shortage portfolio. Independently I sort hiring into three groups, with breakpoint at 20% and 80% of NYSE non-micro cap. L is the low hiring rate portfolio, M as middle and H as the high. The term r^S is the average annualized $(\times 1,200)$ portfolio excess stock return; [t] are heteroscedasticity consistent t-statistics. α and α^{FF} are portfolio average abnormal returns, obtained as the intercept from monthly CAPM or Fama and French (1993) regressions, MAE is the mean absolute pricing errors (average of absolute values of α or α^{FF}). $L-H$ stands for the low-minus-high hiring portfolio. $S-N$ stands for the labor shortage-minus-not shortage portfolio. Panel B keeps track of the mean of the median of accounting variables of the portfolio over time series.

5.4 Evidence from predictive regression

Previous portfolio sorting analyses are known to be robust to outliners, whereas the downside of which is their limited space to control for other objects of interests. Therefore, I supplement the above portfolio sorting with predictive regression including an interaction term between hiring and labor shortage. Estimation is achieved following the classical procedure of the first-stage of Fama-Macbeth regression. Specifically, I treat each year as an independent cross-section, the coefficients of which are the average from all the cross-section estimates, which are reported in Table 9.

The main economic quantities of interests are the two level effects of hiring rate and labor shortage, as well as the heterogenous effect from the interaction term. First, in terms of labor shortage, its level effect remains a significant predictor of stock returns in the cross section as is highlighted in the table, even after controlling for size, and hiring rate, across all specification. Quantitatively, when firm mentions labor shortage, its next year's return decrease by 3% on average, which is consistent with results of labor shortage based one-way portfolio sorting, as is shown in Table 7. This result also provides supporting evidence for Hypothesis 2. Second, in terms of hiring rate, it seems to be insignificant in predicting return in the cross section on average, as is indicated by the first row of Table 9. At the first glance, the result does not directly support Hypothesis 1. Nevertheless, hiring can only be negatively correlated with stock return if there is large enough hiring constraint, as suggested by Hypothesis 3. Quantitatively, column 4 of Table 9 shades light on the relative strengthening of the negative relation as hiring constraint gets more sever. In particular, the coefficient on the interaction term is four times larger than the level effect of hiring rate. Despite the lack of significance of the negative coefficient on the interaction term between hiring rate and labor shortage state (-4% with $t = -0.84$). This may be explained by extreme values and insufficient sample size. In unreported results, I show that the results are robust to adding controls.

Firm-Level Stock Return Predictability Regression

	Fama-Macbeth				
	1	2	3	4	5
hn_{t-1}	-0.02		-0.02	-0.01	-0.01
[t]	-0.78		-0.78	-0.62	-0.42
$labor1_{t-1}$		-0.03	-0.03	-0.03	-0.04
[t]		-2.02	-2.16	-2.22	-2.00
$micro_{t-1}$				0.03	0.03
[t]				0.88	0.88
$hnxlabor1_{t-1}$					-0.04
[t]					-0.84
$microxlabor1_{t-1}$					0.02
[t]					0.55

Table 9: Firm-level stock return predictability regression

This table reports the coefficient of the following specification. Each month, stock return is regressed on the latest right hand side variables. Then I take the average of the estimate from the cross section as the final estimates reported in the table. *micro* here is a dummy variable of firm size being below the NYSE 20% breakpoint. The coefficent of interest are b and e.

$$r^s_{it} = a + b \times HN_{it-1} + c \times labor_{it-1} + d \times \text{ Micro }_{it-1} + e \times labor \times HN_{it-1} + f \times \text{ Micro } \times labor_{it-1} + e_{it}$$

5.5 Economic interpretation

Findings above are largely consistent with predictions from the neoclassical hiring model with heterogeneous hiring adjustment cost. This two-period model is convenient in relating firm hiring to return. In fact, one can take a step further to rationalize this feature in a dynamic framework, where expected return is determined by the product of price of risk and risk loading. First of all, from a risk interpretation, high-hiring firms with labor hiring constraint should be a good hedge to certain aggregate variation to make such low average return. In particular, in Belo et al. (2014), they show that with hiring adjustment, firms incur high adjustment cost when they intend to make high hiring. These firms thus benefit the most from shocks that lower aggregate hiring adjustment cost. Assuming that low aggregate hiring adjustment cost corresponds to the bad state of the world (imagine more commodity can be directed to production, lowering aggregate consumption), then aggregate adjustment cost shock comes with positive price of risk. As high hiring firms' value increases during low aggregate hiring adjustment cost, their risk loading on the shock is negative, making them a good hedge.

To further explore this mechanism, I conduct a comparative static analysis using the dynamic model of Belo et al. (2023), varying the coefficient of hiring adjustment cost (c_H) and estimating the slope coefficient of future returns on current hiring rate. Figure 6 presents the results for both one-year and three-year horizons. The pattern confirms the theoretical prediction: as hiring adjustment costs increase, the negative relationship between hiring and future returns becomes substantially more pronounced. At low adjustment costs, the relationship is nearly flat, but it steepens monotonically as frictions intensify. The effect is stronger and more persistent at the three-year horizon. These findings confirm that the observed hiring-return relationship is not merely an empirical artifact but a fundamental implication of costly labor adjustment: firms facing higher frictions exhibit stronger negative comovement between hiring and subsequent returns, consistent with the risk-based interpretation where constrained high-hiring firms serve as hedges against adverse aggregate shocks.

The empirical evidence presented here represents more than a marginal contribution to existing theory. While prior work has documented negative correlations between investment and future returns Titman et al. (2004); Li and Zhang (2010); Kogan and Papanikolaou (2012); Indriawan et al. (2024), the interpretation of these patterns remains contested. Alternative explanations ranging from limits to arbitrage and managerial overconfidence to talent wars compete with Q-theory's adjustment cost mechanisms, and few studies provide direct evidence distinguishing among these channels. My contribution addresses this identification challenge by leveraging labor shortage measures as observable proxies for binding hiring constraints. The key insight is that Q-theory makes sharp predictions about *when* and *for whom* the hiring-return relationship should strengthen: firms facing tight labor supply constraints should exhibit more negative hiring-return slopes, and this pattern should intensify during periods of strong hiring. The comparative static analysis in Figure 6 confirms that adjustment cost heterogeneity generates precisely this cross-sectional variation. Crucially, behavioral alternatives such as overconfidence or market friction explanations offer no clear prediction for why labor shortages should systematically moderate the hiring-return relationship. By directly measuring hiring constraints and showing that they interact with hiring decisions in ways consistent with costly adjustment, this evidence furthers our understanding of the source of return predictability and provides supporting evidence that would otherwise be difficult to reconcile with non-Q-theory interpretations.

6 Aggregate Evidence

This section complements the earlier cross-sectional analysis by examining whether labor demand conditions at the aggregate level help forecast the equity risk premium, or if they are more closely related to future profitability. In the essence, Q theory suggests that hiring be a forward-looking decision based on discount rate and/or cash flow, the degree of which is an empirical question.

6.1 Hiring and Risk Premium

As in Kothari and O'Doherty (2023), I use the job openings-to-employment ratio (JOE) as a proxy for aggregate labor demand and assess its predictive power for future excess returns on the aggregate stock market. While job openings are not a direct measure of labor market tightness, the finding that higher labor demand today is associated with lower future returns

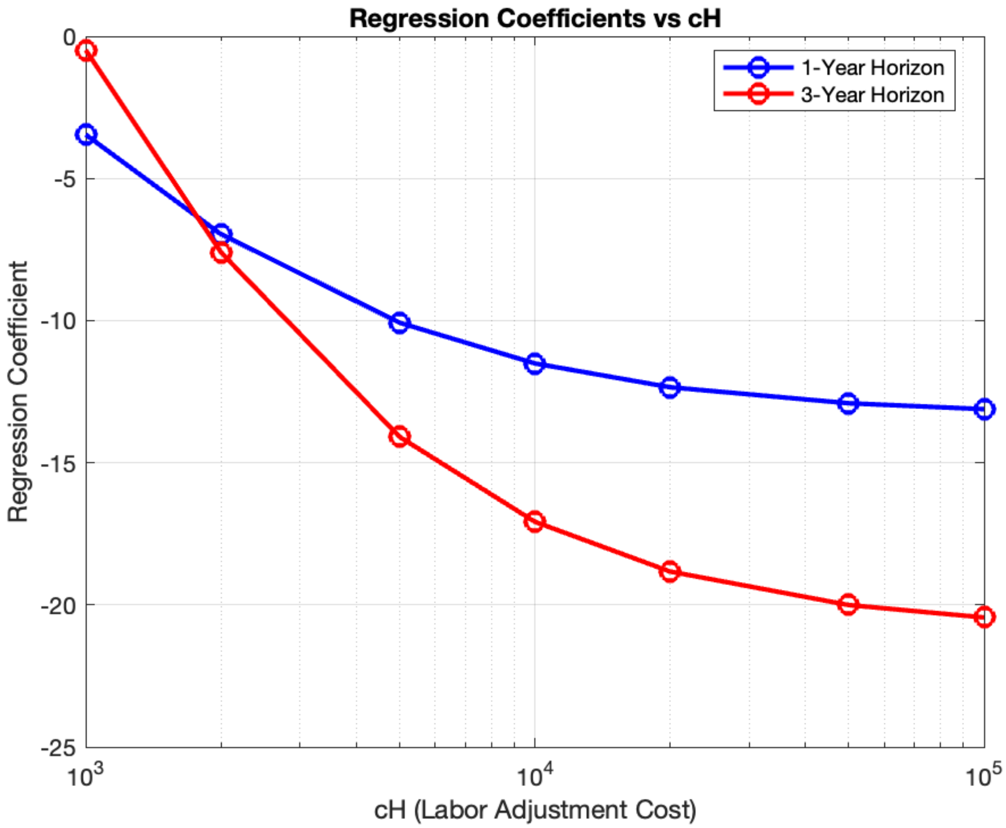

Figure 6: Regression Coefficients of Future Returns on Hiring Rate across Adjustment Cost Levels

Notes: This figure plots the regression coefficient of future returns on current hiring rate as a function of the hiring adjustment cost parameter (c_H) in the dynamic model of Belo et al. (2023). The blue line (circles) shows results for the one-year horizon, while the red line (circles) shows results for the three-year horizon. The x-axis is on a logarithmic scale. Higher adjustment costs lead to steeper negative relationships between hiring and future returns.

suggests that hiring conditions may be systematically linked to time variation in expected returns. This pattern is consistent with the idea that hiring frictions---such as adjustment costs or wage pressures---may affect firms' discount rates through their impact on marginal costs.

The predictor variable is the job openings-to-employment ratio (JOE), constructed at monthly frequency from 1951 to 2021. For the pre-2001 period, it uses the composite help-wanted index developed by Barnichon (2010), which combines the Conference Board's Help Wanted Index (1951--1994) and the Help Wanted Online Index (1995--2000). Post-2000, it uses total nonfarm job openings from the BLS Job Openings and Labor Turnover Survey (JOLTS). In both periods, vacancy counts are normalized by the civilian employment level (FRED series CE16OV). I standardize the resulting JOE series to have zero mean and unit variance.

Monthly market returns and risk-free rates are obtained from the Fama-French data library. To construct the equity premium over an h-month horizon, I compound the monthly market return and the monthly risk-free rate separately and take the difference:

$$\text{Premium}_{t,t+h} = \left(\prod_{\tau=1}^{h}(1+\text{MKT}_{t+\tau})\right) - \left(\prod_{\tau=1}^{h}(1+\text{RF}_{t+\tau})\right)$$

For each forecast horizon $h = 1, 2, \ldots, 36$, I estimate the predictive regression:

$$\text{Premium}_{t,t+h} = \alpha_h + \beta_h \cdot \text{JOE}_t + \varepsilon_{t+h}$$

I lag JOE by one month to ensure that it is observable at the time of forecasting. Newey-West standard errors are used with lag length $h-1$ to account for serial correlation in the overlapping return horizons.

Figure 7 plots the estimated slope coefficients $\hat{\beta}_h$ and 95% confidence intervals across horizons from 1 to 36 months. The coefficients are negative and statistically significant across all horizons, including at the 1-month forecast window. Moreover, the magnitude of the coefficients increases with the forecast horizon, indicating stronger predictive power over longer periods. At the 36-month horizon, a one-standard-deviation increase in JOE is associated with a cumulative decline in the market risk premium of approximately 12%. These results suggest that periods of strong labor demand are robustly associated with lower subsequent expected returns on the aggregate stock market.

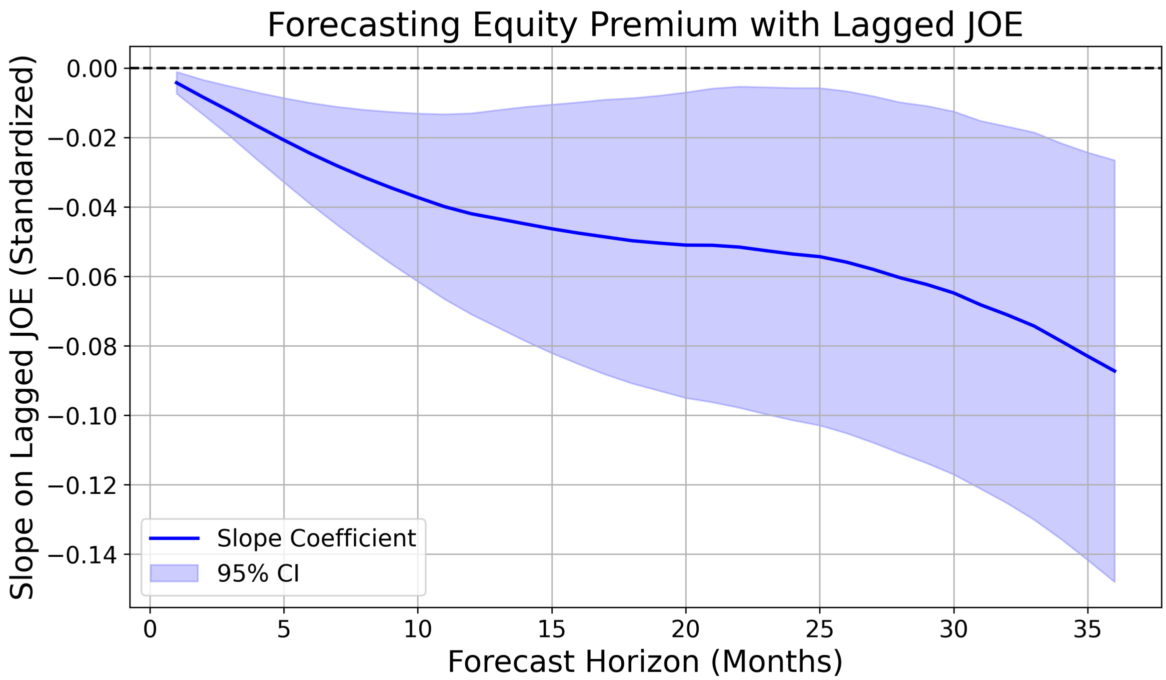

Figure 7: Forecasting coefficients of future equity premium on lagged JOE

Note: this figure plots slope coefficients and 95% confidence intervals from predictive regressions of the h-month ahead market risk premium on the lagged standardized job openings-to-employment ratio (JOE). The regressions are estimated separately for each forecast horizon $h = 1, 2, \ldots, 36$, using Newey-West standard errors with lag length $h-1$. The dependent variable is the compounded excess return over h months.

6.2 Hiring and Profitability

To complement the evidence on expected returns, I next examine whether aggregate hiring conditions predict future corporate profitability. If hiring reflects underlying business optimism or investment plans, then high labor demand today may signal stronger future earnings performance.

Following standard practice, I construct a quarterly measure of aggregate profitability as corporate profits after tax (CP) divided by the beginning-of-quarter book value of nonfinancial corporate assets (TAB). Specifically:

$$\text{Profitability Rate}_t = \frac{\text{CP}_t}{\text{TAB}_{t-1}},$$

where both CP and TAB are obtained from the FRED database (series IDs: CP and TABSNNCB, respectively). Profits are reported at seasonally adjusted annual rates in billions of dollars, while TAB is the book value of total assets reported at the end of each quarter.

To align the predictor and outcome frequencies, I aggregate the monthly JOE series into quarterly values by taking their average within each quarter. I then estimate the predictive regression:

$$\text{Profitability}_{t+k} = \alpha_k + \beta_k \cdot \text{JOE}_t + \varepsilon_{t+k},$$

where k ranges from 1 to 8 quarters (i.e., up to a two-year horizon). The JOE variable is standardized and lagged to ensure ex-ante observability. Standard errors are Newey-West adjusted for serial correlation with lag length $k-1$.

Figure 8 plots the estimated slope coefficients $\hat{\beta}_k$ and associated 95% confidence intervals from predictive regressions of future aggregate profitability on lagged JOE. The results indicate that JOE is a statistically significant predictor of future profitability starting from the third forecast quarter. The coefficients are negative across all horizons and become statistically significant at the 5% level for horizons $k = 3$ through $k = 6$. At its peak effect, a one-standard-deviation increase in JOE is associated with a 0.32 percentage point decline in the profitability rate over a five-quarter horizon ($\hat{\beta}_5 = -0.0032$, $p < 0.01$). This negative association suggests that elevated labor demand may signal rising cost pressures or diminishing marginal returns to hiring and investment, consistent with theories of hiring frictions. These findings reinforce the notion that hiring conditions affect not only expected returns (via discount rates), but also expected cash flows.

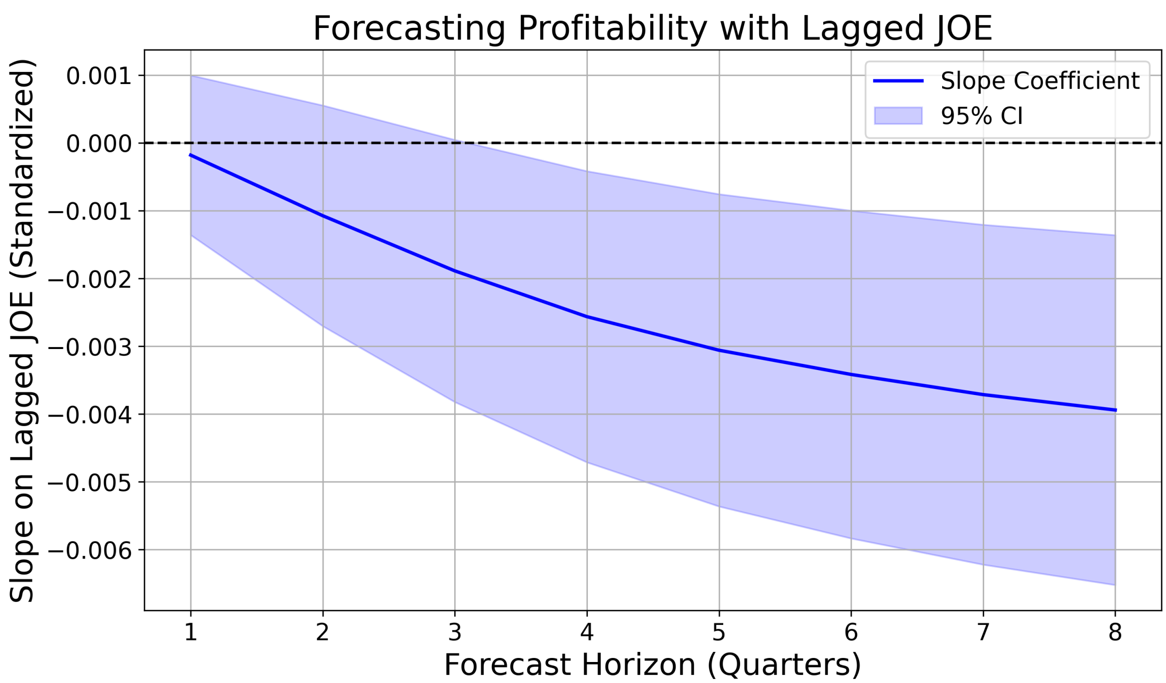

Figure 8: Forecasting coefficients of future profitability on lagged JOE

Note: this figure plots slope coefficients and 95% confidence intervals from predictive regressions of future aggregate profitability (CP over lagged TAB) on lagged standardized JOE. The regressions are estimated separately for each forecast horizon $k = 1, 2, \ldots, 8$, using Newey-West standard errors with lag length $k - 1$.

Taken together, the results in this section demonstrate that aggregate labor demand conditions, as proxied by the job openings-to-employment ratio (JOE), predict variation in stock returns and profitability in ways consistent with the discount rate channel of hiring. Specifically, high labor demand today forecasts lower future equity risk premia, but is not associated with higher future profitability. This pattern echoes the findings of Belo et al. (2023), who show that fluctuations in aggregate hiring are primarily driven by changes in discount rates and short-term expected cash flows, with negligible contribution from long-term cash flow variation. Our evidence reinforces the interpretation that hiring is a forward-looking decision shaped by time-varying risk, rather than a simple response to improved profitability prospects. These aggregate patterns complement our earlier firm-level analysis and underscore the macro-finance implications of labor market frictions.

6.3 Time Varying Relationship between Hiring and Risk Premium

This section explores the relationship between labor market tightness-proxied by the vacancy rate (JOE)-and expected equity market returns. We construct forward-looking returns and estimate rolling predictive regressions to assess how JOE correlates with and forecasts future market conditions.

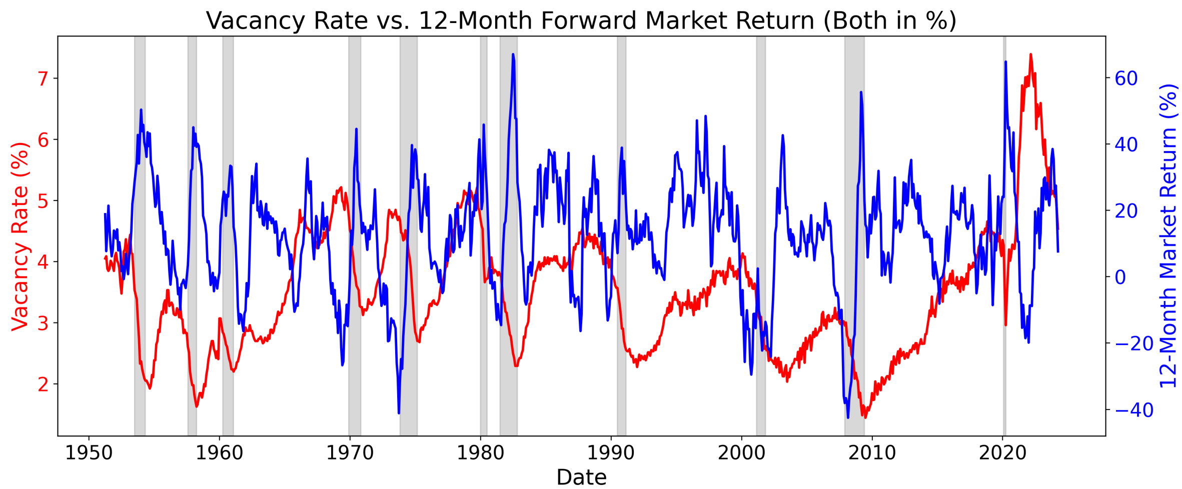

Figure 9: Vacancy Rate and 12-Month Forward Market Return

Note: this figure plots the vacancy rate (JOE) and the 12-month ahead cumulative market return over time. Both series are expressed in percent and smoothed using monthly frequency. The vacancy rate is plotted on the left axis in red, and the forward market return is plotted on the right axis in blue.

Figure 9 displays the time series of the vacancy rate (JOE) and the 12-month forward market return. The overall correlation between the two series is modestly positive, at approximately 0.20. However, this average masks substantial variation across time. In particular, a more nuanced relationship emerges when conditioning on the state of the labor market. Periods of historically tight labor markets-when the vacancy rate reaches local peaks-are often followed by pronounced declines in market returns.

For example, in the late 1960s, the vacancy rate peaked prior to the onset of the 1970 recession, with a noticeable subsequent drop in forward returns. A similar pattern is observed in the late 1990s, where a sustained rise in labor market tightness precedes the collapse of the dot-com bubble. Likewise, in the years immediately preceding the COVID-19 recession, the vacancy rate stood at post-crisis highs, followed by a sharp drawdown in equity markets. These episodes are consistent with the notion that tight labor markets may coincide with rising marginal costs, diminished slack, and depress future equity returns.

Figure 10 provides more formal evidence based on rolling 60-month predictive regressions of future market returns on lagged JOE. The figure displays estimated slope coefficients for four forecast horizons: one-month ahead, and cumulative returns over 1--3, 1--6, and 1--12 months. While the 1-month and 1--3 month betas tend to hover near zero, the coefficients become more substantially negative for the 1--6 and especially the 1--12 month horizons. These longer-horizon betas exhibit marked declines during periods of elevated vacancy rates, such as the late 1960s, early 1980s, and late 2010s. The 95% confidence intervals for the 1--12 month beta (shaded area) indicate that these negative values are statistically significant in several of these episodes, particularly during tight labor market conditions. These patterns highlight the state-dependent predictive power of JOE for future equity returns.

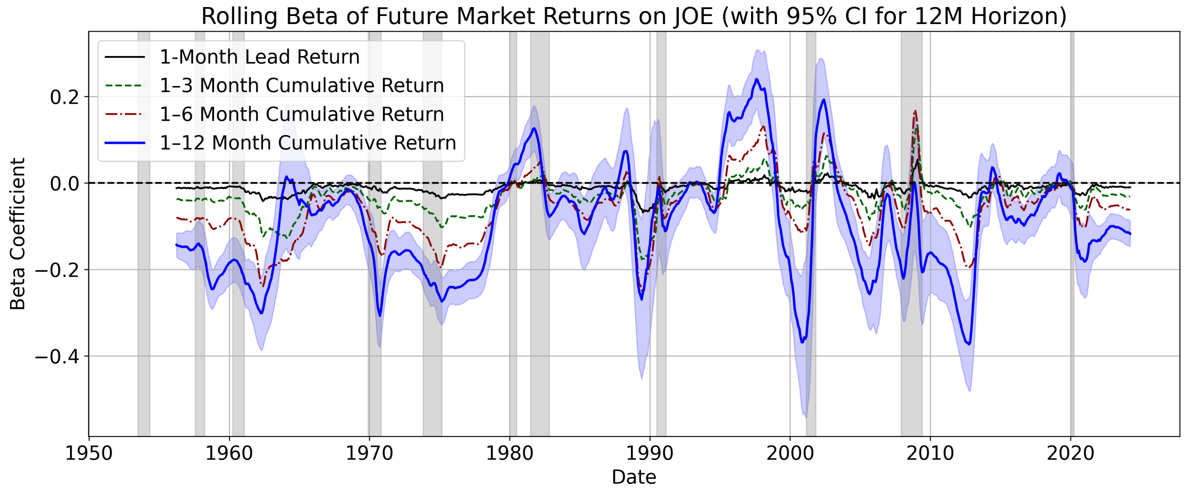

Figure 10: Rolling Beta of Future Market Returns on JOE

Note: this figure plots the rolling 60-month beta coefficients from regressions of future market returns on the job openings-to-employment ratio (JOE). The solid blue line shows the 1-12 month ahead cumulative market return, along with its 95% confidence interval (shaded area). The black, green, and red lines show the betas for the 1-month, 1-3 month, and 1-6 month horizons, respectively. Shaded gray areas represent NBER recessions.

These results highlight a state-dependent relationship between labor market hiring and future equity returns, where the state is labor market tightness. The negative association between JOE and subsequent returns strengthens during periods of exceptionally tight labor markets, suggesting that high hiring activity in such states signals lower expected equity premia, consistent with Q theory.

6.4 Beta Dynamics and Long--Term Labor Market Tightness

The previous analysis establishes two main findings. First, higher hiring activity---as measured by the job openings--to--employment ratio (JOE)---is associated with lower subsequent market returns. Second, the strength of this negative association is not constant over time. In this subsection, I examine whether variation in the predictive power of JOE reflects changes in labor market tightness. Specifically, I test whether the relationship between hiring and future equity returns strengthens during periods of persistently tight labor markets.

Figure 11 presents evidence on this point by plotting the rolling 12-month beta of future market returns on lagged JOE alongside a 60-month smoothed vacancy rate. The beta series is shown in blue and plotted on the left axis, while the long--term vacancy rate is in red on the right axis. The figure reveals a strong inverse relationship: during periods when the labor market is persistently tight, the rolling beta becomes more negative. This suggests that elevated job openings are more strongly associated with lower expected returns precisely when labor demand is high and slack is limited.

To formally test this relationship, I regress the rolling 12-month beta on the 60-month smoothed vacancy rate. The results indicate a statistically significant negative relationship: a one percentage point increase in the long--term vacancy rate is associated with a 3.06 percentage point decline in the beta coefficient ($t = -4.17$). In other words, the tighter the labor market, the more strongly hiring activity forecasts lower future returns.

These results reinforce the interpretation that the return implications of hiring are state--dependent. The predictive power of JOE strengthens precisely when the labor market is already tight---a pattern consistent with the logic of Q theory, in which marginal hiring becomes more costly and informative about declining risk premia when slack is scarce.

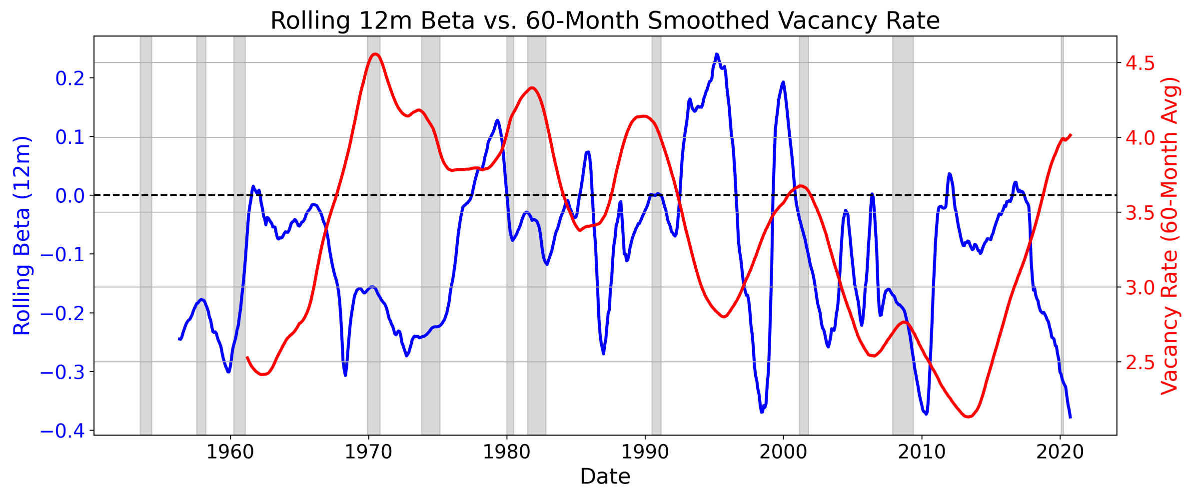

Figure 11: Rolling 12-Month Beta vs. Long--Term Smoothed Vacancy Rate

Note: this figure plots the 60-month rolling beta of 12-month cumulative market returns on lagged JOE (blue line, left axis), alongside the 60-month smoothed vacancy rate (red line, right axis). The rolling beta measures the strength of the predictive relationship between hiring and future returns in a moving window of 60 months. The dashed black line indicates a zero beta. Gray shaded areas correspond to NBER recession periods.

6.5 Time-Varying Labor Adjustment Cost via Structural Estimation

This section develops and estimates a structural model of hiring under adjustment costs, with a key feature: the marginal cost of hiring is allowed to vary with the state of the labor market. This approach enables me to directly test whether labor adjustment costs are higher in tight labor markets and whether this variation helps explain fluctuations in expected equity returns.

6.5.1 Model Setup

I consider a frictional labor market with a continuum of identical firms operating under perfect competition. Each firm hires a homogeneous labor input and takes all prices as given. Firms maximize their value by choosing optimal labor input L_t, subject to wage payments and hiring frictions. Output is produced according to a Cobb-Douglas production function:

$$Y_t = A_t L_t^{\alpha}, \tag{3}$$

where A_t is aggregate productivity and α is the output elasticity of labor. Firms pay a real wage W_t per worker and face a real hiring cost.

The key innovation lies in the specification of the adjustment cost. Let H_t denote the number of new hires, and define the hiring rate per worker as $h_t = H_t/L_t$. Let h_t^{60} denote the 60-month backward-looking average of the hiring rate, capturing long-run labor market tightness. The total adjustment cost per worker is assumed to take the form:

$$\text{AdjCost}(h_t) = c_{H2} \cdot h_{t+1}^{60} \cdot h_{t+1} + \frac{1}{2} c_{H3} \cdot h_{t+1}^{60} \cdot h_{t+1}^2, \tag{4}$$

where c_{H2} and c_{H3} are parameters governing the convexity and state-dependence of the adjustment cost. In particular, the interaction term $c_{H3} \cdot h_{t+1}^{60} \cdot h_{t+1}^2$ implies that marginal hiring costs increase more sharply when hiring activity is sustained at high levels, capturing persistent labor market tightness.

Firms choose L_{t+1} to maximize their expected present discounted value of profits:

$$\max_{L_{t+1}} \mathbb{E}_t \sum_{s=0}^{\infty} M_{t,t+s} \left[A_{t+s} L_{t+s}^{\alpha} - W_{t+s} L_{t+s} - L_{t+s} \cdot \text{AdjCost}\left(h_{t+s}\right) \right], \tag{5}$$

where $M_{t,t+s}$ is the stochastic discount factor.

The model features the following main variables. A_t denotes total factor productivity, L_t is labor employed at time t, and H_t is the number of new hires. The hiring rate per worker is $h_t = H_t/L_t$, and its 60-month moving average is h_t^{60}. Firms pay real wage W_t and discount future profits using the stochastic discount factor $M_{t,t+s}$. The elasticity of output with respect to labor is α, and labor attrition occurs at rate δ. The function $\text{AdjCost}(h_t)$ captures per-worker hiring frictions, governed by two parameters: c_{H2} for baseline convexity and c_{H3} for state-dependence. The marginal value of labor is denoted q_t^L, and its empirical proxy is labeled MC_t.

6.5.2 First Order Condition and Euler Equation

Using the envelope condition and applying dynamic programming, I derive the Euler equation for optimal hiring:

$$q_t^L = \mathbb{E}_t \left\{ M_{t,t+1} \left[\alpha A_{t+1} - W_{t+1} + c_{H2} h_{t+1}^{60} h_{t+1} + \frac{1}{2} c_{H3} h_{t+1}^{60} h_{t+1}^2 + (1-\delta) q_{t+1}^L \right] \right\} \quad (6)$$

where $q_t^L = \left(c_{H2} + c_{H3} h_t^{60}\right) h_t$ represents the marginal cost of hiring one additional worker today.

6.5.3 Estimation and Moment Conditions

I estimate the model using a two-step Generalized Method of Moments (GMM). The key moment condition is based on the residual from the Euler equation:

$$\epsilon_t(\theta) = \left(c_{H2} + c_{H3} h_t^{60}\right) h_t - \mathbb{E}t \left\{ M_{t,t+1} \left[\alpha A_{t+1} - W_{t+1} + \text{AdjCost}_{t+1} + (1-\delta) q_{t+1}^L \right] \right\} \quad (7)$$

Lagged values of h_t are used as instruments to construct moment conditions.

The estimation proceeds in two stages. First, I minimize the quadratic form of average moments using the identity matrix. Then, I compute a Newey-West adjusted optimal weighting matrix based on residuals. In the second stage, I re-estimate parameters using this efficient weighting matrix, enforcing the constraint that the marginal cost of hiring $\partial q_t^L / \partial h_t = c_{H2} + c_{H3} h_t^{60} \geq 0$ for all t. Multi-start optimization is applied to ensure robustness.

Estimation results suggest that labor adjustment costs are both economically significant and time-varying. The parameter c_{H2} is estimated to be positive and statistically significant, indicating a baseline convex cost of adjusting labor. More importantly, c_{H3} is estimated to be nonzero and large in magnitude, with statistical significance at conventional levels.

To interpret these coefficients, I construct the marginal cost of labor adjustment:

$$MC_t = \left(c_{H2} + c_{H3} h_t^{60}\right) h_t, \tag{8}$$

where h_t^{60} is the 60-month rolling average of H/L.

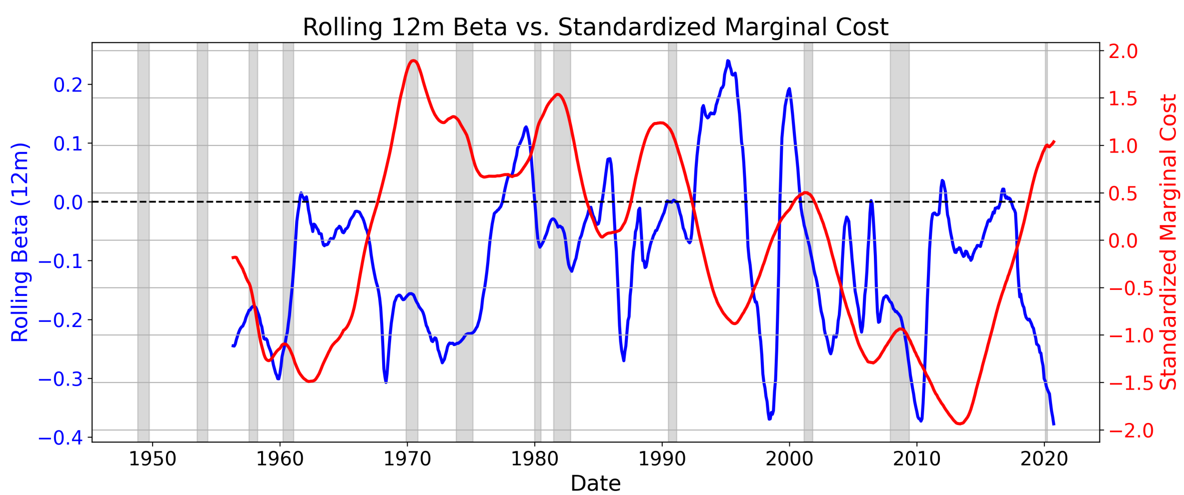

Figure 12: Marginal Labor Adjustment Cost over Time

Note: This figure plots the time series of marginal labor adjustment costs implied by the structural GMM estimation. The series is calculated using the estimated parameters and a 60-month smoothed hiring rate. The shaded gray regions indicate NBER recessions.

The marginal cost exhibits considerable variation across time, increasing substantially during tight labor market periods such as the late 1960s, early 2000s, and late 2010s. These results support the hypothesis that labor adjustment costs are state-dependent, rising when labor market slack is scarce.

Furthermore, I regress the 12-month forward market return beta on the standardized marginal cost of hiring and find a negative and statistically significant relationship. The estimated coefficient on standardized marginal cost is -0.0098 with a t-statistic of -2.16 and a p-value of 0.031. This implies that a one standard deviation increase in marginal labor adjustment costs is associated with a 1 percentage point decline in the 12-month beta coefficient. Although the R^2 of the regression is modest (0.006), the statistical significance supports the notion that higher labor adjustment costs predict lower risk premia over a one-year horizon. This suggests that higher marginal labor costs---which proxy for reduced hiring flexibility---are associated with lower expected risk premia. The structural estimates reinforce the time-varying predictive power of hiring for asset returns, consistent with the Q-theoretic interpretation developed earlier.

6.6 Cost of labor adjustment estimates revisit

Lastly, I revisit the key structural estimates of Merz and Yashiv (2007) to examine the functional form of hiring adjustment costs. The question is whether the marginal cost of hiring varies with the firm's hiring rate and investment activity, or remains constant as in the standard quadratic specification. This distinction matters because time-varying adjustment costs can rationalize cross-sectional heterogeneity in how hiring decisions affect firm value.

Consider a general adjustment cost function $g(\cdot)$ that depends on the hiring rate h_t/n_t (new hires scaled by employment) and the investment rate i_t/k_t (investment scaled by capital). The marginal adjustment cost of hiring is the derivative $\partial g/\partial(h_t/n_t)$. Under the conventional quadratic specification with $\eta_2 = 2$ and no interaction terms, this marginal cost takes the form $(e_2 \cdot h_t/n_t + f_2) \cdot f(z_t, n_t, k_t)$, where e_2 and f_2 are fixed parameters and

$f(\cdot)$ captures scale effects. The key feature is that e_2 is constant: a firm hiring at 10% of its workforce faces the same marginal cost coefficient as a firm hiring at 5%.

Merz and Yashiv (2007) relax this restriction by estimating a flexible specification that allows for higher-order polynomial terms and interactions between hiring and investment. Specifically, they parameterize the adjustment cost function to include terms like $(h_t/n_t)^{\eta_2}$ and $(i_t/k_t \cdot h_t/n_t)^{\eta_3}$, where η_2 and η_3 are estimated rather than imposed. The marginal cost of hiring then becomes

$$\frac{\partial g}{\partial(h_t/n_t)} = \left(e_2\left(\frac{h_t}{n_t}\right)^{\eta_2-2} + e_3\left(\frac{i_t}{k_t}\right)^{\eta_3}\left(\frac{h_t}{n_t}\right)^{\eta_3-2}\right)\cdot\frac{h_t}{n_t}\cdot f(z_t,n_t,k_t) + f_2\cdot f(z_t,n_t,k_t).$$

The crucial insight is that the effective marginal cost coefficient $a_t \equiv e_2(h_t/n_t)^{\eta_2-2}+e_3(i_t/k_t)^{\eta_3}(h_t/n_t)^{\eta_3-2}$ now varies over time with hiring and investment rates. Their GMM estimates, which match both quantity moments (first-order conditions for hiring and investment) and price moments (asset values), strongly reject the quadratic benchmark. The unrestricted specification yields $\eta_2 = 1.4$ and includes a negative interaction term, producing an estimated adjustment cost function of approximately $2900(h_t/n_t)^{1.4} - 101700(i_t/k_t)^2$. The fact that the effective adjustment cost coefficient is a positive function of hiring rate again aligns well we my finding.

Why does this matter? Figure 13 plots the observed aggregate asset value scaled by output (black solid line) alongside predictions from the unrestricted model (red dashed line) and the quadratic model (blue dash-dot line). The contrast is stark. The unrestricted model with time-varying adjustment costs achieves a correlation of 0.86 with observed valuations, successfully tracking the dramatic run-up during the late 1990s and the subsequent decline. The quadratic model with constant coefficients fails completely, producing a correlation of -0.04 and missing all major movements in firm value.

The economic interpretation ties directly to my empirical findings. Firms facing high hiring rates or binding labor constraints operate on steeper portions of their marginal cost curves-they have higher effective values of a_t. These are precisely the firms for which the negative hiring-return relationship should be strongest. The structural evidence from Merz and Yashiv (2007) confirms that adjustment cost heterogeneity, whether across firms or over time, is essential for understanding how hiring decisions map into asset prices. My contribution is to provide direct microeconomic evidence of this heterogeneity through observable labor shortage measures, validating the mechanism that their aggregate estimates implicitly require.

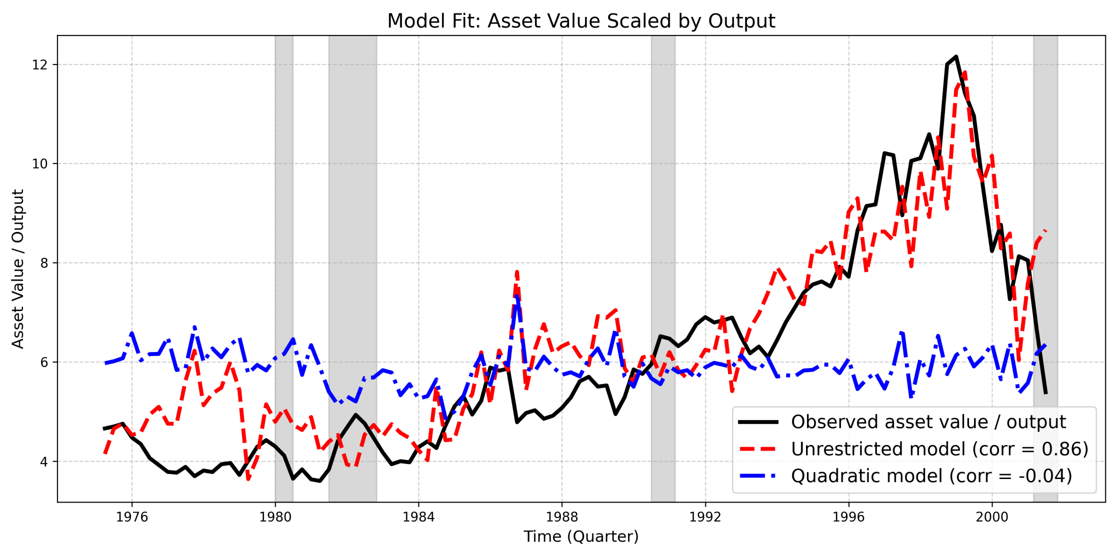

Figure 13: Model Fit: Asset Value Scaled by Output

Notes: This figure compares the time-series fit of two adjustment cost specifications from Merz and Yashiv (2007). The black solid line shows observed aggregate asset value scaled by output. The red dashed line shows the unrestricted model with higher-order adjustment costs, achieving a correlation of 0.86. The blue dash-dot line shows the quadratic model with constant adjustment cost coefficients, achieving a correlation of -0.04. Gray bars indicate NBER recession periods.

7 Conclusion

This paper establishes labor shortages as a systematic source of cross-sectional return differences, providing new evidence for Q-theory mechanisms in asset pricing. The research addresses a critical measurement gap by developing a text-based approach to identify firm-level hiring constraints, enabling direct testing of theoretical predictions about how labor market frictions transmit to financial markets.

The measurement contribution extends beyond methodology to reveal substantive economic relationships. Labor shortage intensity correlates meaningfully with observable labor market conditions and predicts changes in firm-level wages, hiring policies, and operational performance. These validation results demonstrate that corporate disclosures contain systematic information about employment constraints that traditional aggregate indicators cannot capture at the firm level.

The asset pricing analysis uncovers a state-dependent relationship between hiring decisions and stock returns. Labor market frictions serve as a necessary condition for the negative hiring-return correlation, with predictability effects concentrated among firms facing binding constraints. This finding resolves an identification challenge in prior research by directly observing the constraint rather than inferring it from investment behavior alone. The portfolio evidence shows that constrained firms exhibit factor loadings consistent with theoretical predictions about adjustment costs and systematic risk.

The temporal dimension adds important context to these cross-sectional patterns. Time-series analysis reveals that hiring predictability for market returns intensifies during periods of aggregate labor market tightness, suggesting that firm-level mechanisms aggregate to influence broader market dynamics. This relationship provides external validation for the cross-sectional findings while demonstrating the systematic nature of labor market effects on asset prices.

The theoretical interpretation connects these empirical patterns to established investment theory. The evidence supports Q-theory's prediction that adjustment costs create systematic differences in required returns, with the mechanism operating through discount rates rather than cash flow expectations. The state-dependent nature of the relationships aligns with models featuring time-varying adjustment costs, where constraint severity affects the sensitivity of investment decisions to market conditions.

Several implications emerge for both academic research and practical applications. The findings suggest that labor market information represents an underexplored source of systematic risk that complements existing factor models without requiring new theoretical frameworks. The text-based measurement approach offers a template for capturing firm-specific aspects of macroeconomic conditions that aggregate data cannot reveal.

For portfolio managers, the results indicate that employment-related constraints contain systematic risk exposures with measurable return implications. The predictability patterns suggest potential applications in factor-based investment strategies, particularly during periods when labor market conditions diverge significantly across firms or regions.

Corporate finance applications include improved understanding of how macroeconomic labor conditions affect firm-specific cost of capital. The evidence suggests that hiring decisions during constrained periods signal lower required returns, with implications for optimal timing of human capital investments and strategic workforce planning.

The research framework extends naturally to other forms of firm-specific constraints that may not be captured in traditional financial data but are disclosed through corporate communications. Future applications could examine supply chain disruptions, regulatory constraints, or technological bottlenecks using similar text-based measurement approaches combined with asset pricing analysis.

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A Appendix

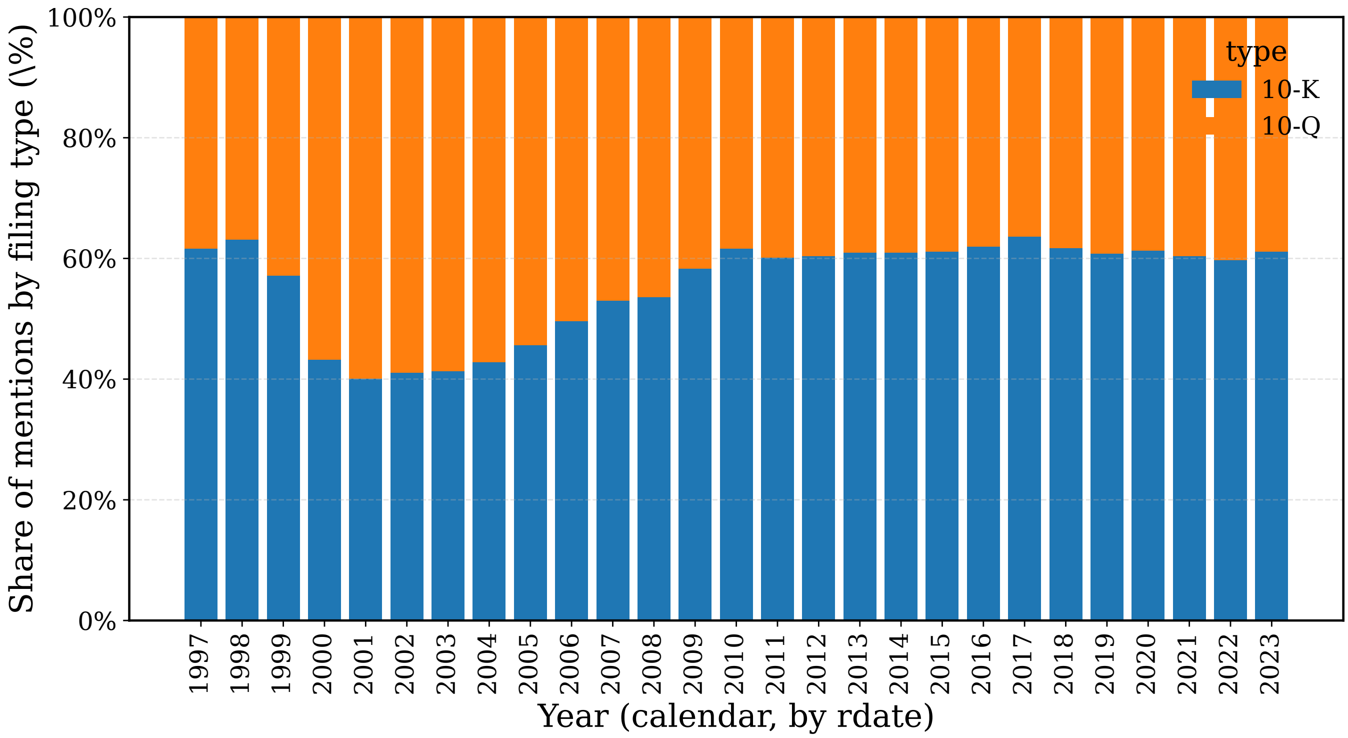


Figure A.1: Composition of labor shortage mentioning across SEC filing types

Note: this figure shows the composition of labor–shortage–mentioning filings across SEC types over time. For each calendar year (based on `rdate`), I count unique filings with at least one labor–shortage mention and compute the share by form type (10–K vs 10–Q). Percentages sum to 100% within each year.

Pre--COVID	``The airline industry has from time to time experienced a shortage of personnel licensed by the FAA, especially pilots and mechanics.'' -- Delta, 2018 10--K
Post--COVID	``As demand for air travel returns following the COVID--19 pandemic, we face shortages of qualified pilots and technicians, which may limit our ability to increase capacity and meet customer demand.'' -- United, 2021 10--K

Table A.1: Air transportation: illustrative shortage language, pre-- and post--COVID

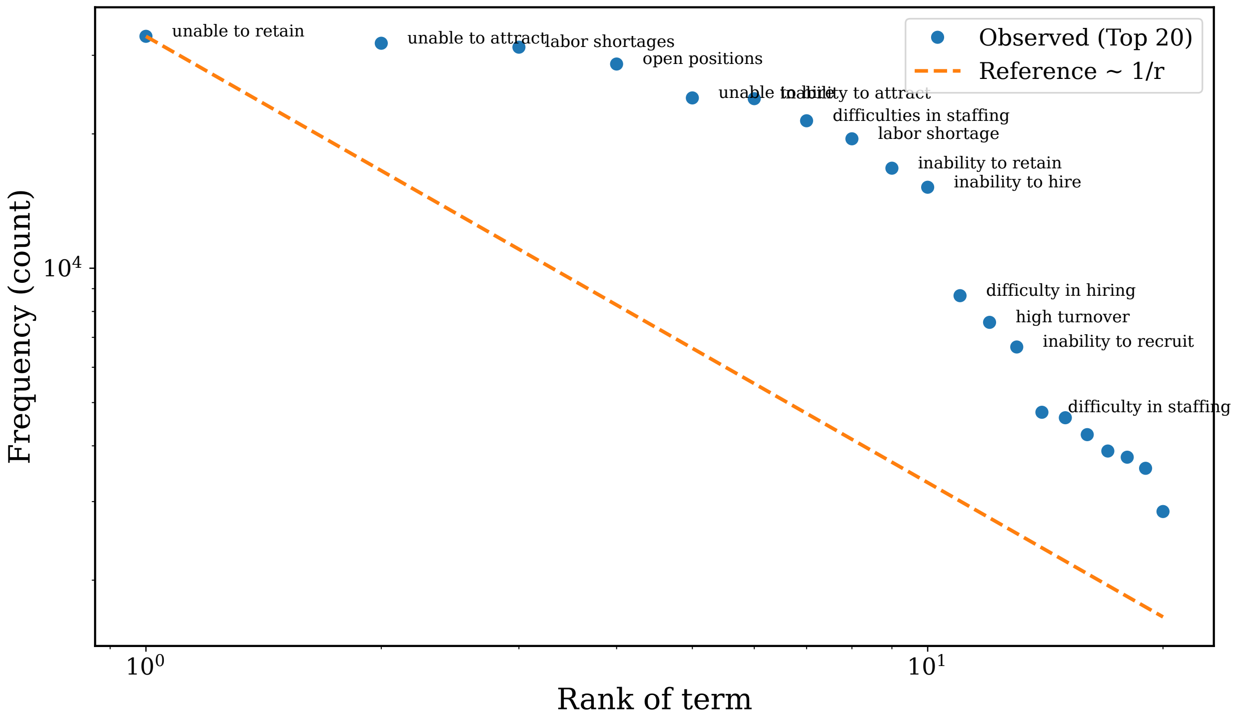


Figure A.2: Zipf plot of labor-shortage term frequencies (Top 20)

Note: points show term frequency (y-axis) against rank (x-axis) on log--log scales for the top 20 phrases matched in 10-K filings. Frequencies are raw counts of phrase occurrences across all sentences and years; multiple occurrences within a filing are counted multiple times. Ranks are assigned after sorting terms by descending frequency (ties broken by first appearance). The dashed line is a $1/r$ reference (slope -1) to illustrate the Zipf benchmark.

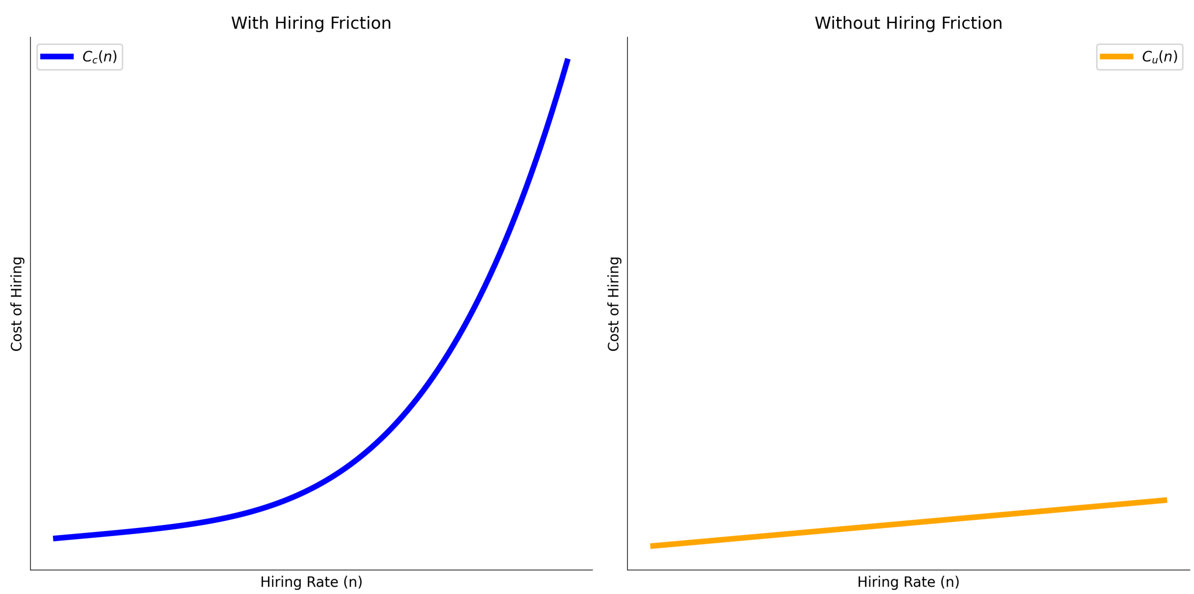


Figure A.4: Illustration of hiring friction

The figure shows the marginal cost of hiring curves of two hypothetical firms. The firm on the left faces hiring friction, whereas the firm right does not. Such characterisation relies on the difference of elasticity of supply of labor.

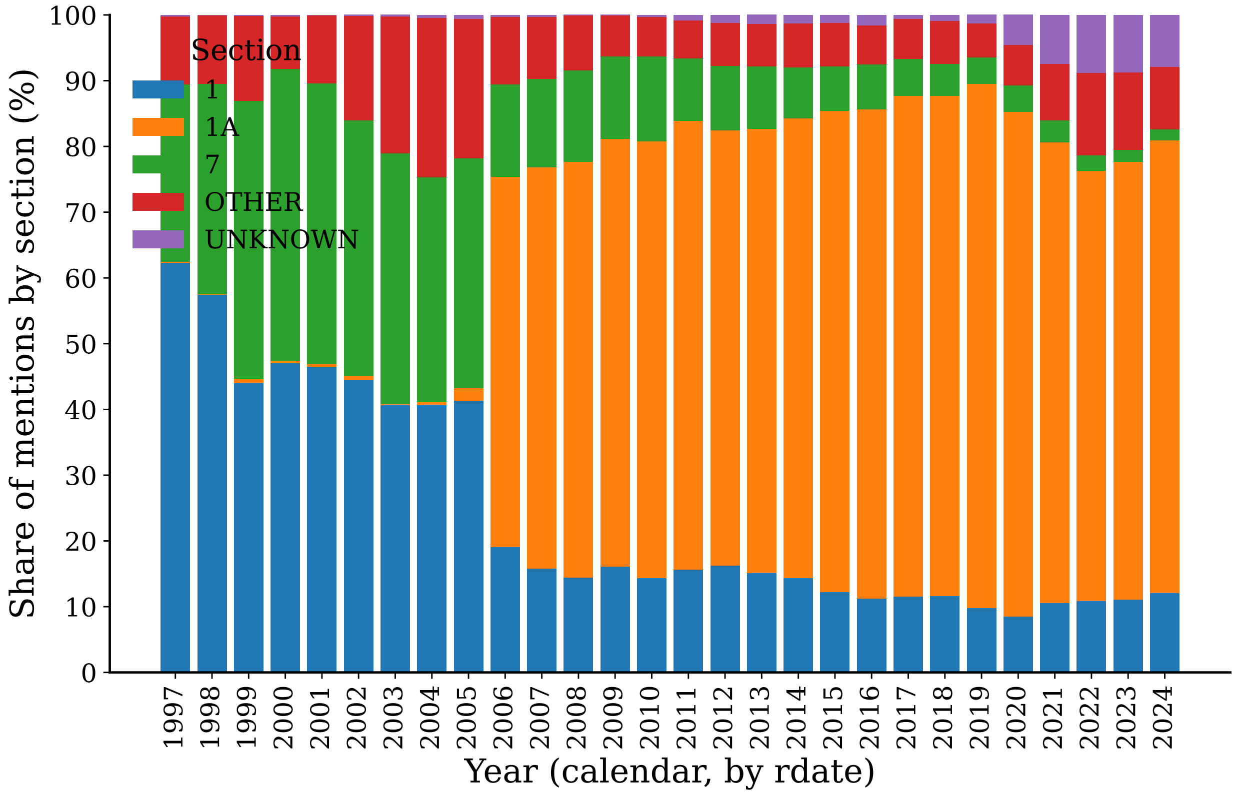


Figure A.3: Share of labor shortage mentions by section in 10-K filings, 1997--2024.

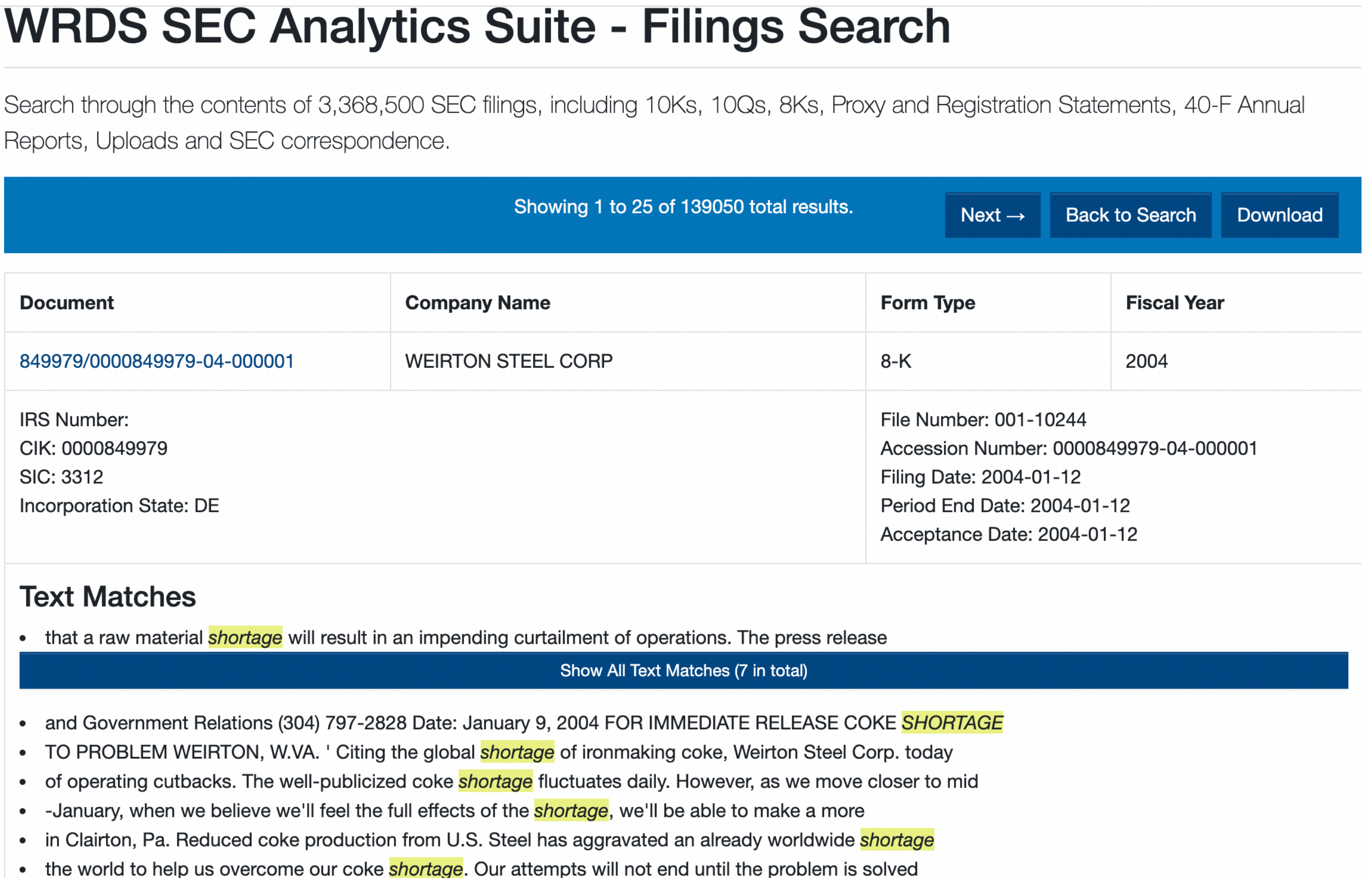
Notes - Shares are normalized to 100 within each year. The figure highlights the shift of disclosures from Item 1 (Business) to Item 1A (Risk Factors) after the SEC's 2005 rule change.

LABOR SHORTAGES ARE ADVERSELY AFFECTING PATTERSON'S DRILLING OPERATIONS.

The increase in domestic drilling demand from mid-1995 through the third quarter of 1997 and related increase in contract drilling activity caused a shortage of qualified drilling rig personnel in the industry. This increase adversely impaired our ability to attract and retain sufficient qualified personnel and to market and operate our drilling rigs. Further, the labor shortages resulted in wage increases, which impacted our operating margins. The return to higher demand levels in the contract drilling industry has reinstated the problems associated with labor shortages. Of particular concern to us is that these problems are more severe than those previously experienced by Patterson and were reinstated at a much lower rig utilization rate than experienced in the past. These labor shortages are adversely effecting Patterson's operations. They are impeding Patterson's ability to place additional drilling rigs into operation and are causing delays in the drilling of new wells for Patterson customers.

Figure A.5: Example of labor shortage in 10-K

This screenshot captures the exact wording where labor shortage is mentioned in Patterson's 10-K filing.



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Document	Company Name	Form Type	Fiscal Year
849979/0000849979-04-000001	WEIRTON STEEL CORP	8-K	2004

IRS Number:
CIK: 0000849979
SIC: 3312
Incorporation State: DE

File Number: 001-10244
Accession Number: 0000849979-04-000001
Filing Date: 2004-01-12
Period End Date: 2004-01-12
Acceptance Date: 2004-01-12

Text Matches

- that a raw material *shortage* will result in an impending curtailment of operations. The press release

Show All Text Matches (7 in total)

- and Government Relations (304) 797-2828 Date: January 9, 2004 FOR IMMEDIATE RELEASE COKE *SHORTAGE*
- TO PROBLEM WEIRTON, W.VA. ' Citing the global *shortage* of ironmaking coke, Weirton Steel Corp. today
- of operating cutbacks. The well-publicized coke *shortage* fluctuates daily. However, as we move closer to mid
- -January, when we believe we'll feel the full effects of the *shortage*, we'll be able to make a more
- in Clairton, Pa. Reduced coke production from U.S. Steel has aggravated an already worldwide *shortage*
- the world to help us overcome our coke *shortage*. Our attempts will not end until the problem is solved

Figure A.6: Example of labor shortage in WRDs SEC Analytics Suite

This screenshot captures the output structure from searching ``shortage''. It provides information about the firm, filing type, state, and most importantly, it outputs all text matches within the document.

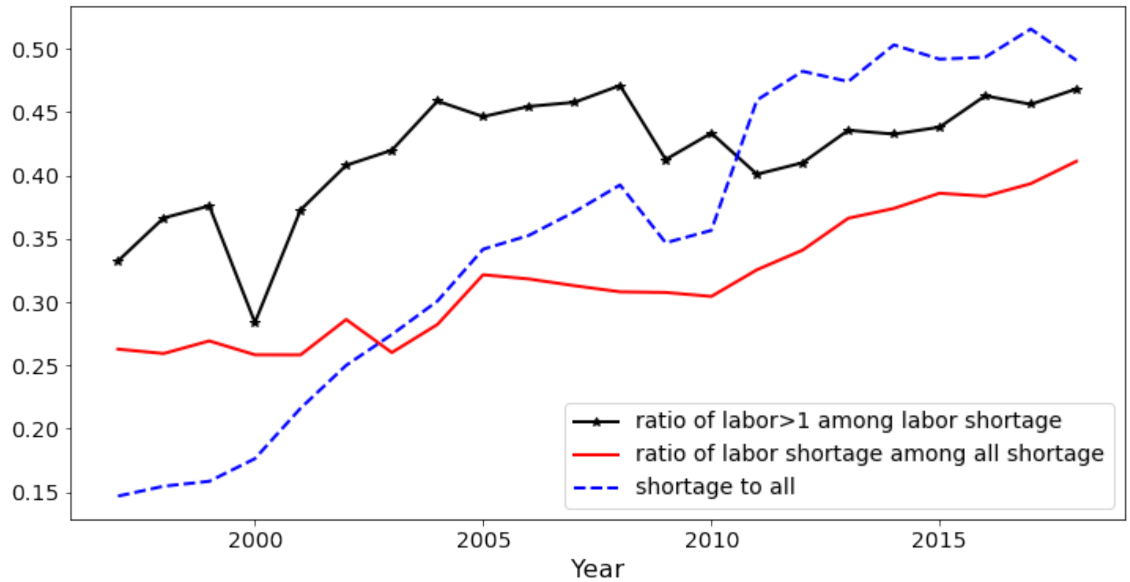

Figure A.7: Time series of labor shortage ratios

Note: the red solid line represents annual aggregate labor shortage ratio, defined as the ratio between labor shortage total mentioning and shortage total mentioning. The blue dashed line is annual aggregate shortage ratio, defined as the ratio between total firms mentioning shortage, and total firms in the year. The black stared line is the annual ratio between amount of firms mentioning labor shortage more than once in the year, and that of firms mentioning only one time.

Variable	**Definition**	**Compustat items and formula**	**Timing**
ROA (t+1)	Net income over average total assets.	$\frac{\texttt{NI}_{t+1}}{\frac{1}{2}\left(\texttt{AT}_{t+1}+\texttt{AT}_t\right)}$; require $\texttt{AT} > 0$.	t+1
OCF/Assets (t+1)	Operating cash flow over average total assets.	$\frac{\texttt{OANCF}_{t+1}}{\frac{1}{2}\left(\texttt{AT}_{t+1}+\texttt{AT}_t\right)}$; if OANCF missing, set $\texttt{OCF} = \texttt{IB} + \texttt{DP} - \Delta\texttt{WC}$ when components are available.	t+1
Log Sales	Natural log of annual net sales.	$\ln(\texttt{SALE}_t)$; drop non-positive SALE.	t
Sales Growth	Year over year sales growth.	$\frac{\texttt{SALE}_t - \texttt{SALE}_{t-1}}{\texttt{SALE}_{t-1}}$; require $\texttt{SALE}_{t-1} > 0$.	t
Cash/Assets	Cash and short term investments over total assets.	$\frac{\texttt{CHE}_t}{\texttt{AT}_t}$.	t
Book Leverage	Book debt over total assets.	$\frac{\texttt{DLTT}_t + \texttt{DLC}_t}{\texttt{AT}_t}$.	t
Tangibility (PPE/Assets)	Net property, plant, and equipment over total assets.	$\frac{\texttt{PPENT}_t}{\texttt{AT}_t}$.	t
R&D/Assets	Research and development expense over total assets.	$\frac{\texttt{XRD}_t}{\texttt{AT}_t}$; set XRD to 0 when missing.	t
Hiring Rate (t)	Employment growth within the fiscal year.	$\frac{\texttt{EMP}_t - \texttt{EMP}_{t-1}}{\texttt{EMP}_{t-1}}$; require $\texttt{EMP}_{t-1} > 0$.	t
Hiring Rate (t+1)	Employment growth in the following year.	$\frac{\texttt{EMP}_{t+1} - \texttt{EMP}_t}{\texttt{EMP}_t}$; require $\texttt{EMP}_t > 0$.	t+1
Investment Rate (t)	Asset growth as a proxy for investment.	$\frac{\texttt{AT}_t - \texttt{AT}_{t-1}}{\texttt{AT}_{t-1}}$; require $\texttt{AT}_{t-1} > 0$.	t
Investment Rate (t+1)	Next year asset growth.	$\frac{\texttt{AT}_{t+1} - \texttt{AT}_t}{\texttt{AT}_t}$; require $\texttt{AT}_t > 0$.	t+1

Table A.2: Construction of variables used in summary statistics

Notes: All variables are computed at the fiscal year level. Unless noted, ratios use end of year denominators or the average of adjacent totals as indicated. Extreme values are winsorized at the 1% and 99% tails by year. When the reporting date falls in January through May, observations are assigned to $t-1$; otherwise to t.

Neighbor term	Weighted score
retain	17.6
labor shortages	14.2
personnel	12.9
cannot retain	12.1
labor shortage	11.8
recruit	11.0
skilled	10.9
teamstaff	10.2
shortage	9.9
tight labor market	8.6
retaining	8.3
staffing shortages	8.2
hire	8.0
shortages	7.2
labor	7.0
talented	6.8
increased turnover	6.5
staffing shortage	6.1
wage	5.9
talents	5.3
turnover	4.9
employees	3.3
wages	3.2
skillsets	3.1
recruiting	2.9
high turnover	2.8
recruitment	2.3
aging workforce	2.1
unskilled	1.9
collaborations	1.9

Table A.1: Weighted nearest neighbors to top labor-shortage terms (Word2Vec).

Notes: The table reports the top 30 nearest neighbor phrases to the highest-frequency labor-shortage terms in 10-K text, obtained from a Word2Vec model trained on shortage-flagged sentences from 10-K filings in 1993--2024. ``Weighted score'' equals $\sum_j w_j \cdot \cos(\text{neighbor}, \text{term}_j)$, where w_j is the top term's share (in percent) in the Top-Terms table and $\cos(\cdot,\cdot)$ is cosine similarity from the trained embeddings. The model is trained using a skip-gram architecture with vector size 300, window 5, min_count 10, negative sampling 10, subsampling 10^{-3}, and 15 epochs. Neighbors are filtered to remove stopwords, numerics, very short tokens, and off-domain terms.

	labor	labor score	shortage	shortage score
0	labour	0.84	shortages	0.94
1	employment	0.79	scarcity	0.78
2	reform	0.79	cope	0.76
3	unions	0.78	supply	0.76
4	employers	0.76	alleviate	0.75
5	wage	0.76	chronic	0.74
6	union	0.75	severe	0.74
7	policies	0.75	supplies	0.73
8	policy	0.74	affected	0.72
9	wages	0.74	scarce	0.71
10	government	0.74	problems	0.71
11	workers	0.74	suffer	0.71
12	jobs	0.72	food	0.71
13	economic	0.72	reduce	0.70
14	welfare	0.72	skyrocketing	0.70
15	reforms	0.72	ease	0.70
16	social	0.72	experiencing	0.70
17	industry	0.70	fuel	0.70
18	unemployment	0.70	costs	0.69
19	non	0.70	drought	0.69
20	civil	0.69	demand	0.69
21	sector	0.69	caused	0.69
22	spending	0.69	suffering	0.69
23	demand	0.69	acute	0.69
24	hiring	0.69	oversupply	0.69
25	current	0.69	increasing	0.69
26	economy	0.69	lack	0.68
27	pensions	0.69	influx	0.68
28	tax	0.69	pressures	0.68
29	poor	0.69	relieve	0.68

Table A.2: Word2vec words list

This table provides reference lists of the word ``labor''(left) and ``shortage''(right). The higher the score the more related the model thinks the word is related to the search word. Note that in my two-step procedure, I only use ``shortage'' to search for matched sentences, mainly to avoid confounding factors other than shortage. In the second step, I only use a selective set from labor list, again to reduce confounding meanings.

Variable	**Coefficient (b)**	**%**
hn	0.31***	36.6
ik	0.16**	17.3
roa	0.14	15.3
bm	-0.01	-1.1
lev	0.70***	101.4
size	0.11***	11.2

Table A.3: Logit Regression Results with Industry Fixed Effect

Note: this table reports results from running logistic regression to explain the binary variable of labor shortage that takes value 1 if the firm mentions labor shortage in that year. All sample includes all firms; hn: hiring rate; ik: physical capital investment rate; roa: return on assets; beme: book to market equity ratio; lev: book debt to market value of the firm; size: log of firm market value.