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WORKING PAPER SERIES

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Working Paper Number	2025-021A
Creation Date	May 2025
Citable Link	https://doi.org/10.20955/wp.2025.021
Suggested Citation	Kalyani, A., Ozkan, S., 2025; Theory Meets Textual Analysis: Measuring Firm-Level Labor Cost Pressures and Inflation Pass-Through, Federal Reserve Bank of St. Louis Working Paper 2025-021. URL https://doi.org/10.20955/wp.2025.021

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Theory Meets Textual Analysis: Measuring Firm-Level Labor Cost Pressures and Inflation Pass-Through*

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First Version: July 6, 2025—This Version: July 6, 2025

Abstract

We develop a novel measure of firm-level marginal labor cost and investigate its pass-through to inflation. To construct this measure, we apply textual analysis to earnings calls to identify discussions of labor-related topics such as higher costs, shortages, and hiring. Leveraging the theoretical principle that cost-minimizing firms equate marginal costs across variable inputs, we project changes in firms' intermediate input revenue shares onto the intensity of labor-related discussions to quantify their contributions to marginal labor costs. This approach provides an economically-motivated way to reduce the multidimensional qualitative textual information into a single quantitative measure. An aggregate index from this measure tracks closely with conventional aggregate slack variables and outperforms them in forecasting inflation. When aggregated at the industry level, we find a significant but heterogeneous pass-through of marginal labor costs to PPI inflation, with the pass-through highest for service sector and near-zero for manufacturing. Consistent with the latter fact, firm-level data reveal that investment in automation mitigates the effects of higher labor cost pressures in manufacturing.

Keywords: Wage inflation, automation, textual data, machine learning
JEL codes: E24, J24, J31, J64.

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*We thank Mickenzie Bass and Mick Dueholm for excellent research assistance. The views expressed herein are those of the authors and do not reflect the ones of the Federal Reserve Bank of St. Louis, the Federal Reserve System or the Board of Governors. During the preparation of this work the authors used Claude LLM in order to improve language and readability. After using this tool, the authors reviewed and edited the content as needed and takes full responsibility for the content of the publication.

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1 Introduction

Labor cost pressures have long been recognized as a fundamental driver of inflation, dating back to Phillips (1958)'s seminal work. While several aggregate indicators such as unemployment rate, vacancy-to-unemployment ratios, and output gaps are commonly used to gauge shocks to marginal labor costs, there is little consensus on the most appropriate measure of slack (e.g., Barnichon and Shapiro (2024)) and neither measure fully captures the true marginal cost pressures. Moreover, their aggregate nature precludes analysis of firm-level responses to labor cost shocks. This paper addresses these limitations by developing a novel quantitative measure of labor cost pressures derived from textual analysis of corporate earnings calls with financial data from Compustat. We then use our measure to examine the pass-through from labor costs to inflation at the aggregate and industry level as well as heterogeneous firm-level responses to labor cost pressures. We find that our measure can explain two thirds of post-pandemic inflation surge.

Earnings calls are quarterly conference calls where company executives discuss financial results and business updates with investors and analysts, typically including both prepared remarks and a Q&A session. These calls often contain detailed discussions of operational challenges, including labor-related issues like hiring difficulties, wage pressures, and workforce management, making them valuable sources of real-time information about labor market conditions for each firm in each quarter. In our analysis we use more than 250,167 earnings call transcripts for about 6,237 public companies headquartered in the US between 2002 and 2025. About 86% of these earnings calls discuss labor relates issues.[1] The nature of these discussions varies with the economic cycle: during tight labor markets discussions are about hiring, higher labor costs and shortages, during recessions they shift to firing and reducing labor costs.

Our textual analysis methodology proceeds in three steps. First, based on a manual reading of transcript excerpts, we identify five primary topics of labor-related

[1] Other papers have used earnings calls to infer firms' cost of inputs. For example, Gormsen and Huber (2024) use them to measure firms' perceptions of their cost of capital. In a contemporaneous paper Harford *et al.* (2024) also extract information from earnings calls to develop a measure of labor shortage exposure. Furthermore, Gosselin and Taskin (2024) constructs demand and supply indicators for Canada and United States using earnings call transcripts.

discussions: 1) labor costs, 2) labor shortages, 3) headcount, 4) labor agreements, and 5) labor efficiency. When discussing labor costs, headcount and efficiency, the executives also qualify the discussion with the direction of shift—higher or lower—, leaving us with $J = 8$ topics. Second, to construct dictionaries for these topics, we begin with a few seed keywords that are directly indicative of these topics such as "labor shortage", "labor costs", and "wage inflation". Following Hassan *et al.* (2024a), we expand on these keywords using embeddings trained on earnings conferences calls to obtain other phrases which were used in similar context. Finally, to measure firm i's exposure to topic j of labor-related issues in quarter t, Λ_{it}^{j}, we count sentences containing these keywords and normalize it by the length of the call.

While our textual analysis provides rich descriptive evidence of labor market pressures, we need a more structured approach to quantify the economic importance of this qualitative data. We develop this framework through the firm's cost minimization problem that features materials as a variable input and generalized labor costs which capture both direct wage costs and indirect labor expenses, such as job posting, hiring, training, and retention costs. This model recognizes that firms facing labor market pressures incur multiple types of costs as they attempt to expand their effective workforce. We then leverage the fact that cost-minimizing firms equate marginal costs of one additional unit of output across all variable inputs to quantify the importance of various labor-related topics in driving marginal labor costs across firms. In our framework, an increase in marginal cost of labor while keeping revenue per employee and output elasticities constant should increase the share of spending on materials.

Therefore, we estimate each topic's contribution on marginal cost of labor by regressing firms' revenue shares of intermediate inputs on $\Lambda_{it} = [\Lambda_{it}^{1}, \Lambda_{it}^{2}, ..., \Lambda_{it}^{J}]$ while controlling for revenue per employee, and firm and time fixed effects, thereby exploiting the within-firm variation. This approach serves a dual purpose. First, it translates our high-frequency qualitative measure from earnings calls into quantitative estimates of labor cost pressures (ω_{it}). Second, it provides an economically-motivated way to reduce the multidimensional information from earnings calls into a single measure. The regression coefficients effectively determine the optimal weights for combining different aspects of labor topics mentioned in earnings calls into a unified measure of their impact on firm costs.

We first validate this measure by comparing a sales-weighted *average* of ω_{it} with traditional aggregate indicators. Our index exhibits strong correlations with them, for instance, 0.76 with labor market tightness, –0.55 with unemployment rate, and 0.63 with the Employment Cost Index (ECI). Furthermore, it reveals an intriguing nonlinear relationship with them, sharply increasing when unemployment falls below 5% and labor market tightness exceeds around 1.5. Notably, following a sharp but short-lived collapse during the Great Recession, our index remained persistently low throughout the subsequent recovery, consistent with the observed flattening of the Phillips curve (Powell (2018)). However, the measure surged dramatically during and after the COVID-19 pandemic, aligning closely with the steepening Phillips curve (Domash and Summers (2022)). Finally, when aggregated at the industry level, our measure maintains a robust correlation with labor market tightness and earnings growth of new hires across industries, further validating its relevance.

We next quantify the pass-through from labor cost pressures to inflation using industry-level variation in the Producer Price Index (PPI). We find a strong and statistically significant relationship between increased labor cost pressures (aggregated at the industry level) and subsequent PPI inflation even after controlling for industry and time fixed effects. Specifically, our estimates indicate that a 1.0 percentage point (pp) rise in labor cost pressures corresponds to approximately a 1.0 to 1.8 pp increase in PPI inflation over the following year. Importantly, the strength of this pass-through varies substantially across industries: sectors with higher labor intensity, such as wholesale trade, retail trade, and accommodation and food services, demonstrate stronger pass-through effects, whereas heavily regulated industries, like utilities and healthcare as well as manufacturing exhibit notably lower sensitivity.

Further, we evaluate the predictive power of the aggregate labor cost pressure measure for core PCE inflation using a Phillips curve framework, comparing its performance to traditional measures of labor market slack (à la Barnichon and Shapiro (2024)). We aggregate our quarterly industry-level measure using PCE weights and find that our measure outperforms traditional labor market indicators—such as unemployment rates, labor market tightness, the output gap, and the ECI—in explaining inflation dynamics. In fact, our measure can explain 19.5 pp of the 29.3 pp cumulative surge in inflation during the post-pandemic period. When included alongside these traditional measures, our indicator remains statistically significant, effectively subsuming their explanatory power. A particularly interesting finding is that while our measure leads inflation, the ECI tends to lag inflation by about three quarters, suggesting our measure could serve as a more timely indicator for predicting inflationary pressures. These results suggest that our labor cost pressure measure captures forward-looking critical information about inflationary pressures that conventional indicators might overlook, particularly during periods of extreme labor market tightness.

Finally, we exploit the disaggregated nature of our measure and examine how firms respond to labor cost pressures using firm-level data from Compustat. We analyze changes in several key firm outcomes, including investment rates, R&D spending, and productivity measures, in response to ω_{it}. Our empirical strategy employs a comprehensive set of controls including firm fixed effects, year fixed effects, industry characteristics, and other firm-specific variables to isolate the causal effect of labor cost pressures on firm behavior.

Firms experiencing higher labor cost pressures increase their investment, with this effect being particularly pronounced in industries that heavily employ routine manual tasks. These differential responses translate into productivity outcomes: firms facing labor cost pressures experience faster productivity growth, a one standard deviation increase in labor cost pressures corresponds to a 1.55 percentage point increase in productivity growth. However, this productivity gain is primarily driven by firms in routine-manual task-intensive industries, while firms in non-routine industries do not observe such increases. These findings suggest that labor cost pressures may accelerate automation and technological adoption, particularly in industries where human labor can be more readily substituted with capital. They also explain why the pass-through of marginal labor costs to PPI inflation is highest for service sector and near-zero for manufacturing.

Related Literature. Our paper contributes to a large literature that uses the Phillips curve to forecast inflation. Different researchers have advocated for various measures of slack as inflation predictors. Stock and Watson (1999) demonstrated that the unemployment rate outperforms other macroeconomic variables such as interest rates and commodity prices; Galí (2015) argued for the output gap; Moscarini and Postel-Vinay (2012) proposed the job-switching rate; and Barnichon and Shapiro (2024) recently showed that labor market tightness outperforms these alternatives. However, in several time periods, current inflation itself has proven to be the best predictor of future inflation (Atkeson *et al.* (2001); Stock and Watson (2008)). Our paper makes two contributions to this literature. First, whereas the existing work relies almost exclusively on aggregate indicators of slack—be it the unemployment rate, output gap, or the vacancy–unemployment ratio—we construct a novel, firm-level measure of labor cost pressures derived from textual analysis of earnings conference calls. Our measure directly captures the complaints of executives about labor market conditions. We therefore avoid assumptions about which aggregate variables reflect these conditions and whether these conditions uniformly affect all firms. The granularity also allows us to flexibly aggregate our measure using PCE weights which helps in quantifying labor cost pressures on prices of the representative consumption basket. As a result, our measure when aggregated performs better than all of these measures in Phillips curve estimation. Second, using firm-level granularity, we show that in usual times small changes in the unemployment rate or output gap do not materialize into widespread discussions of labor cost pressures at the firm level. However, during periods of extremely tight labor markets and extremely low rates of unemployment, these concerns are more widespread and thus translate into higher labor cost pressures and higher inflation.

Within the use of textual data in economics, our paper is relevant to two different literatures. First has used textual analysis to measure previously unobservable phenomena. For example, economic and political uncertainty (Hassan *et al.* (2019, 2020, 2024b, 2023) and Baker *et al.* (2016)), firm attention to macroeconomic variables or financial constraints (Song and Stern (2024)and Buehlmaier and Whited (2018)). We follow this literature in terms of methodology and develop a measure of labor cost pressures. Our approach follows this literature and we construct topic-specific dictionaries, using word embeddings trained on earnings calls, and then iteratively expanding on these dictionaries using manual reading. We add to this literature by embedding these firm-level textual measures in a theoretical framework that links them to marginal costs and ultimately quantifies the contribution of labor cost pressures to inflation. We show that our theoretical framework makes a material difference in predicting inflation and that a raw count of instances of labor discussions in earnings calls—which the previous literature used—is not correlated with either aggregate slack variables and inflation, whereas our measure is strongly correlated.

Second, a very recent literature uses natural language processing to forecast macroeconomic variables. Most of these studies time-aggregate their text signal—for example, by averaging a daily news-sentiment index or collapsing a quarterly central-bank press-conference transcript into one embedding—so that both left- and right-hand variables sit at the same monthly or quarterly frequency (e.g. Ashwin *et al.* (2024); Araujo *et al.* (2025)). Because the post-1990 sample offers at most 140 quarterly or 300 monthly observations, this top-down approach faces a severe degrees-of-freedom constraint. We instead discipline the text at the firm level, where the sample is orders of magnitude larger ($\approx$ 250,000 firm-quarters). Guided by a cost-minimization framework, we convert each firm's labour-related discussions into an economically interpretable statistic—its marginal labour-cost shock—and only then aggregate those shocks with theory-based weights. This micro-to-macro approach keeps the richness of the text while preserving statistical power.

This paper also relates to a growing literature on capital–labor substitution and productivity. Studies such as Acemoglu and Restrepo (2022b) and Graetz and Michaels (2018) show that automation can reduce firms' reliance on labor by increasing labor productivity. We show that labor cost pressures prompt capital-deepening investments—often spurring productivity gains—particularly in tight labor markets and mostly in industries with routine manual work. Our findings thus reinforce the importance of automation as a critical margin through which firms adapt to labor market shocks and have implications for aggregate productivity and optimal monetary policy.

The rest of the paper is organized as follows: In Section 3, we introduce the simple theoretical framework to fix the ideas. Section 2 presents the datasets we use in our analysis as well as the details of the empirical methodology. In Sections 2.2 and 5, we discuss validation of our labor cost pressure measure with respect to the aggregate data as well as its inflation implications. Section 6 presents our on how firms respond to changes in labor costs. Finally, Section 7 concludes.

2 Earnings Call Data and Empirical Methodology

Our main source of data is earnings conference calls. We use 443,870 transcripts of earnings conference calls held between 2002 and 2025 from S&P Global. For our baseline results, we focus on 248,437 earnings calls by US headquartered firms. We begin by constructing a dictionary of 104 labor-related terms (such as 'personnel', 'wage', 'workforce' etc.) and reading excerpts from these earnings conference calls that discuss these terms. In total, about 88% of earnings conference calls discuss labor-related terms. Table I shows sample excerpts from earnings calls that discuss labor issues. From our reading of a random sample of transcripts, we find that discussions revolve around five topics: labor costs, labor shortages, headcount, labor efficiency and labor agreements. When discussing labor costs, headcount and efficiency, the executives also qualify the discussion with the direction of shift: higher or lower. Therefore in total we have eight topics.

TABLE I – Sample Excerpts from Earnings Calls

Firm	Excerpt
Basic Energy Services Inc (2011)	We produced a sequential increase in revenue for the quarter, but only a modest increases in cash flow and earnings as **labor cost increases** jumped ahead of our ability to move pricing up in some segments.
KBR Inc (2013)	We had done forecast of **labor** availabilities and projects and had anticipated that market getting **tighter** in the first part of 2014. And candidly, it hit us faster than we anticipated.
US Foods Holding Corp (2019)	Third, on the cost side, we made substantial progress on our distribution initiatives. However, the higher than anticipated **wage pressure**, as a result of a very **tight** la**bor** market, did offset some of this progress.
Akumin Inc (2023)	So we have responded by like everybody and paying **more** sign-on **bonuses**, giving more than typical **wage increases**, particularly on the clinical labor side. ... as we discussed, there is a bit of a **headwind** resulting from those **labor costs**.

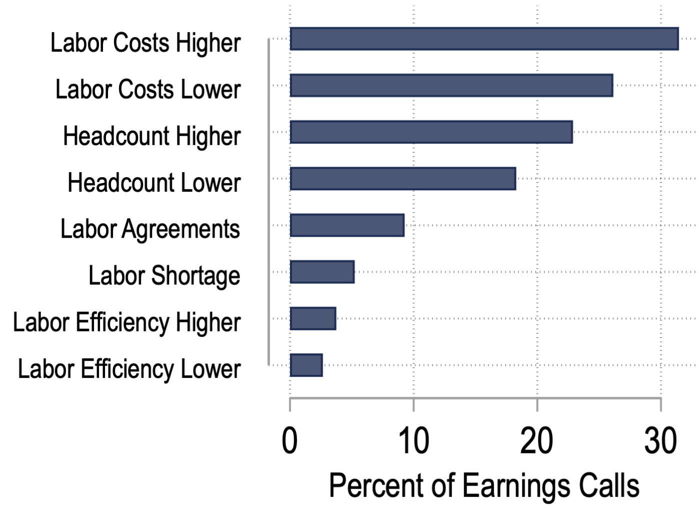
To label discussions of these automatically, we develop dictionaries for each topic following Hassan *et al.* (2024a). We began by identifying a small set of seed keywords that directly relate to each topic. For instance, for the topic of labor shortages, we started with words like labor and shortage. Similarly, for labor costs, we considered terms such as wage and compensation. To expand our initial keyword list, we employed word embeddings trained on the earnings call transcripts. This helped us identify additional words and phrases used in similar contexts. For example, the embedding model suggested terms like personnel shortage and staffing constraints as contextually similar to labor shortage. In parallel, we manually reviewed excerpts from earnings call transcripts to identify additional terms that were frequently used to discuss each topic but were not captured by the embedding model. To ensure the relevance of each keyword, we extracted 10 excerpts containing the keyword from our dataset and manually assessed whether they aligned with the intended topic. A keyword was retained in the dictionary for a topic if at least 70% of the sampled excerpts were correctly classified under that topic (i.e., they were true positives). If a keyword was found to be frequently ambiguous or misclassified, it was either discarded or reassigned to a different topic where it was more relevant. We repeated this process iteratively, adding to the keyword lists with each iteration. We finalized the lists when we could not find additional keywords through our process. Table A.1 shows top 20 keyword combinations used to identify conversations about each topic out of a total of 13,566 keyword combinations for all topics combined.

Our classification model operates at the sentence level. A sentence is assigned a topic if it contains all the constituent words from one of that topic's keyword combinations. For instance, a sentence is categorized under 'labor shortage' if it includes both the keywords 'labor' and 'shortage', regardless of the order or distance between them. We then aggregate over the earnings call transcript and define the percentage of sentence in an earnings call transcript which mention a topic τ. Figure 1 shows the incidence of these topics in earnings conference calls. These topics have significant overlaps. Executives discuss multiple topics in earnings conference calls. Altogether at least one of these topics is mentioned in 62% of earnings conference calls, accounting for 70.4% of overall executive discussions of labor-related terms. The four most prominent topics are higher and lower labor costs, and higher and lower head counts (hiring and firing). These four topics themselves are mentioned in 60% of earnings calls.

2.1 Discussion of Labor Topics Over Time

Figure 2 shows the percentage of earnings calls that contain labor-related discussions over time from 2002 to 2024. The time series reveals distinct patterns across different economic periods. During the pre-financial crisis period (2002-2007), around 85-90% of earnings calls consistently discussed labor issues. However, there was a notable decline following the 2008-2009 financial crisis, with the percentage dropping to

Figure 1 – Percentage of Earnings Calls, by Topic



Notes: The figures show percentage of earnings calls by labor topic between 2002 and 2025.

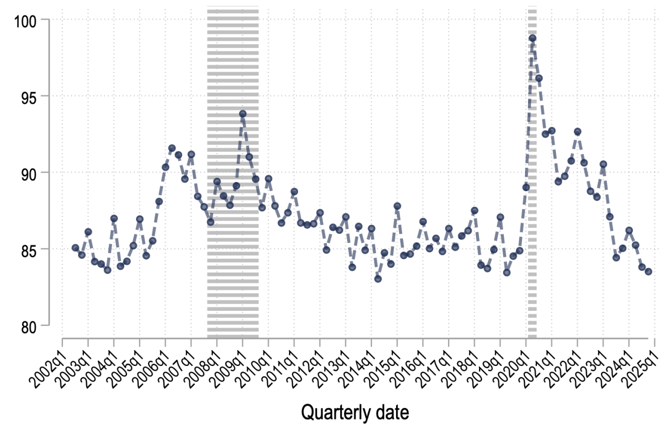
around 85% and remaining at this lower level through most of the 2010s. The data shows another significant shift during the COVID-19 pandemic, with the percentage of labor-related discussions spiking to almost 100% in 2021, reflecting the unprecedented labor market disruptions during this period. After this spike, the percentage has gradually declined but remained elevated and volatile, suggesting ongoing labor market adjustments in the post-pandemic period.

These patterns align with major economic events (e.g. recessions) and demonstrate how the intensity of labor-related discussions in earnings calls reflects attention paid to labor market conditions or decisions made around labor. However, the total count of labor issues mentions is not necessarily strongly correlated with aggregate slack, while, as we show next, some individual topics are. Therefore, it is important to classify discussions of labor issues into topics and quantify the importance of each topic for labor cost pressures separately.

2.2 Validation of Labor Topic Discussions

Figure 3 plots the evolution of each labor discussion topic from 2002 to 2025. The time series reveal distinct patterns across economic cycles. While discussions of higher labor costs were elevated before the crisis; during the Great Recession,

FIGURE 2 – Earnings calls with Labor mentions over time, %



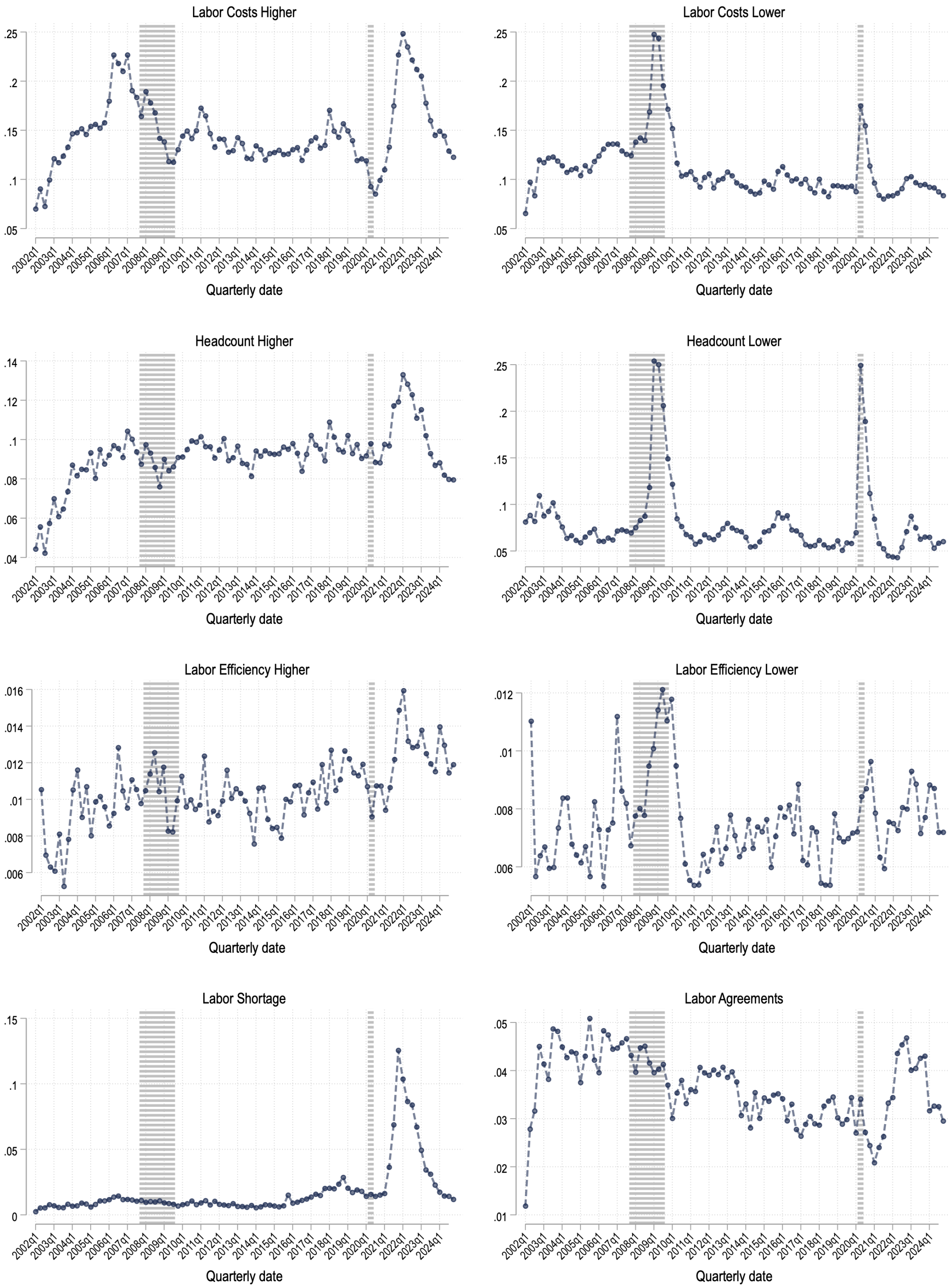
Notes: The figure shows the percentage of earnings calls that mention one of labor terms by quarter.

mentions of lower labor costs and headcount reductions peaked. Similar pattern was observed around the Covid pandemic recession. The post-pandemic period, in contrast, is defined by an unprecedented surge in labor shortage discussions in 2021-2022, with mentions reaching levels nearly four times higher than any previous peak. This highlights the unique severity of recent labor market tightness and validates that our textual measures capture critical, time-varying firm concerns.

Figure A.1 shows confirms these topics capture meaningful economic signals by correlating them with key macro variables. Unsurprisingly, first three panels show that discussions of labor shortages, higher costs, and increased headcount are positively correlated with labor market tightness (V/U ratio) and wage growth (ECI), while being negatively correlated with the unemployment rate. The opposite holds for discussions of lower costs and headcount reductions.

Finally, the bottom-right panel shows correlations with the output gap, where labor cost increases and efficiency decreases show the strongest positive correlations, suggesting these discussions are particularly sensitive to the overall state of the economy. Notably, labor shortage discussions show relatively modest correlation with the output gap compared to their strong correlations with direct labor market measures, suggesting they capture labor market-specific rather than general economic conditions.

Figure 3 – Discussion of Labor Topics over Time



Notes: The figures show the average percent share of sentences of a labor topic mentioned in earnings calls by quarter.

These correlation patterns validate our textual analysis approach by demonstrating that discussions of labor issues in earnings calls systematically align with traditional macroeconomic measures of labor market conditions and overall economic activity. The consistent and intuitive patterns across different measures suggest that earnings call discussions provide reliable signals about labor market conditions.

Table II – Discussion of labor topics and wage growth of new hires, at industry level

	$\Delta log(Earnings_{n,t})$		
	(1)	(2)	(3)
Labor Costs Higher (std.)$_{j,t}$	1.158***	1.572***	0.620***
	(0.249)	(0.281)	(0.208)
Labor Costs Lower (std.)$_{j,t}$	–1.388***	–1.194***	–0.469
	(0.333)	(0.293)	(0.281)
Headcount Higher (std.)$_{j,t}$	0.593***	–0.251	–0.121
	(0.180)	(0.326)	(0.329)
Headcount Lower (std.)$_{j,t}$	–1.096***	–1.352***	–0.948***
	(0.290)	(0.293)	(0.300)
Labor Shortage (std.)$_{j,t}$	0.677***	0.730***	0.206*
	(0.174)	(0.174)	(0.107)
Labor Efficiency Higher (std.)$_{j,t}$	0.078	0.242	0.029
	(0.155)	(0.183)	(0.159)
Labor Efficiency Lower (std.)$_{j,t}$	–0.215	–0.249	–0.155
	(0.268)	(0.236)	(0.177)
Labor Agreement (std.)$_{j,t}$	0.122	–0.009	0.129
	(0.198)	(0.251)	(0.201)
R^2	0.061	0.089	0.439
N	4,298	4,298	4,298
Time FE	N	N	Y
Industry FE	N	Y	Y

Notes: The table shows regression of changes in on discussion of labor topics by industry n in quarter t. Earnings denotes earnings for new hires observed in the quarterly workforce indicates aggregated over industry n at time t. Industry is at the NAICS 3-digit level. Each observation denotes a industry n and year t. To construct labor topic observations at the industry x year level we take averages across all quarters in a year. We exclude firms in financial and administrative industries (NAICS 52, 53 and 56). Topic variables are standardized. Regression is weighted by number of earnings calls in the industry. Standard errors are clustered by industry.

We also investigate how different labor-related discussions in earnings calls relate to wage growth for new hires at the industry level with time and industry fixed effects (Table II). Our results show economically significant relationships between labor-related discussions and wage growth. Discussions of higher labor costs are positively associated with wage growth, with coefficients ranging from 0.62 to 1.58 across specifications, all statistically significant. Conversely, mentions of lower labor costs are negatively associated with wage growth, with coefficients between –0.47 and –1.39. Similarly, discussions about decreasing headcount show negative associations (coefficients –0.95 to –1.35). These results are robust across specifications and remain significant even after controlling for both time and industry fixed effects. The R-squared increases substantially from 0.06 to 0.44 when including both time and industry fixed effects, indicating that industry-specific and time-varying factors explain a significant portion of the variation in wage growth. Discussions of labor shortages and efficiency show smaller coefficients, but their signs align with economic theory: labor shortages and higher efficiency discussions are positively associated with wage growth, while lower efficiency discussions show a negative association. Labor agreements is not significantly correlated with wage growth. Recall that firms also mention these topics less, suggesting these discussions may capture aspects of labor market conditions that are not directly related to wage growth.

3 Theoretical Framework

While our textual analysis of earnings calls provides rich descriptive evidence of labor market pressures, we need a more structured approach to quantify their economic importance on a firm's marginal costs. In this section we develop a framework through the firm's profit maximization problem with generalized labor costs, which capture both direct wage costs and indirect labor expenses, such as job posting, hiring, training, and retention costs. This comprehensive view recognizes that firms facing labor market pressures incur multiple types of costs as they attempt to expand their effective workforce as we have seen in the discussions of labor issues in the previous section.

We consider a firm's profit maximization problem with general labor costs capturing both direct wage costs and indirect labor expenses, such as job posting, hiring, training, and retention costs. Firm i in quarter t solves the following problem:

$$\begin{aligned} \max_{M_{i,t},L_{i,t}} & P(Y_{it})F_t(M_{it}, L_{it}, \Omega_{it}) - x_t^M M_{it} - w(\bar{L}_{it})L_{it} - C(\bar{L}_{it}) \\ \text{s.t. } & L_{it} \leq \mu_{it}\bar{L}_{it} \end{aligned}$$

Output (Y_{it}) is produced using two inputs, intermediate materials (M_{it}) and labor (L_{it}), according to the common production function (F_t). Ω_{it} denotes idiosyncratic productivity shocks. The firm faces a demand curve that determines the price (P_{it}) as a function of its output level. Firms make two key decisions: how much intermediate inputs (M_{it}) to purchase and how much labor to employ.[2] On the cost side, intermediate inputs are the flexible input (à la Gandhi *et al.* (2020)) and represent materials, supplies, and other variable inputs excluding labor and are purchased at price, x_t^M. However, the labor decision is more nuanced than in standard models. Firms must distinguish between two labor-related quantities: the number of positions they create or workers they aim to hire ($\bar{L_{it}}$) and the effective labor input that actually contributes to production (L_{it}). For labor costs, the wage function $w(\bar{L}_{it})$ determines the base wage costs and may reflect the firm specific labor supply curve and it's influence on wages, particularly in markets where it has significant hiring power. The function $C(\bar{L}_{it})$ captures additional labor-related expenses such as those for recruitment, vacancy posting, training, signing bonuses, etc.

This distinction between L_{it} and $\bar{L}_{it}$ captures several aspects of labor markets. A firm might post job openings but struggle to fill them, hire workers who need training before becoming fully productive, or face challenges in retaining employees. These frictions are captured through two types of costs: direct wages that depend on the number of positions created when labor supply is not perfectly elastic ($w(\bar{L}_{it})$), costs associated with posting vacancies and training workers, and potential wage adjustments needed to attract or retain workers ($C(\bar{L}_{it})$). The relationship between posted positions and effective labor is governed by a constraint, $L_{it} \leq \mu_{it}\bar{L}_i$, where μ_{it} represents idiosyncratic labor market pressure shocks—factors like tight local labor markets, low vacancy fill rates, or high training requirements that make it harder to convert posted positions into productive labor input. Shadow cost of this labor constraint is given by $\lambda_{i,t} = \frac{w_L(\bar{L}_{it})L^*_{i,t} + C_{\bar{L}}(\bar{L}_{it})}{\mu_{i,t}}$, where $L^*_{i,t}$ is the optimal choice of effective labor input and w_L and $C_{\bar{L}}$ are first derivatives.

Unlike the typical firm problem with only direct wage costs of labor, the marginal cost of labor ($MCL_{it} = w(\bar{L}_{it}) + \lambda_{it}$), includes both increase in direct wage costs and changes in indirect labor expenses such as job posting, hiring, training, and retention

[2]Capital is pre-determined in the previous period and for parsimony we only focus on firm's static decision.

costs. Changes in MCL_{it} is key for many firm decisions in this model. For example, from the first order condition (FOC) with respect to labor input L_{it}, one can show that under flexible prices the pass-through rate of changes in marginal cost of labor to prices is one:

$$\begin{aligned}
\log\left(P_{it}\right) &= \underbrace{\log\left(\frac{\epsilon_{it}+1}{\epsilon_{it}}\right)}_{\eta_{it},\ \text{Mark-up}} + \underbrace{\log\left(w\left(\bar{L}_{it}\right)+\lambda_{it}^{L}\right)}_{\text{Marginal cost of labor}} - \underbrace{\log\left(Y_{it}/L_{it}\right)}_{\text{Labor prod.}} - \underbrace{\log\left(\alpha_{it}^{L}\right)}_{\text{Elasticity}}, \\
\Delta\log\left(P_{it}\right) &= \Delta\log\left(w\left(\bar{L}_{it}\right)+\lambda_{i,t}^{L}\right) - \Delta\log\left(Y_{it}/L_{it}\right) - \Delta\log\left(\alpha_{it}^{L}\right) - \Delta\log\left(\eta_{it}\right) \qquad (1)
\end{aligned}$$

where ϵ_{it} is the price elasticity of demand and $\alpha_{it}^{L} = \frac{\partial Y_{it}}{\partial L_{it}}\frac{L_{it}}{Y_{it}}$ is the output elasticity of labor input.

Despite its central role in firm's decisions, measuring changes in marginal costs of labor presents a challenge since financial data does not provide such detailed breakdowns. To this end, we exploit the FOCs with respect to intermediate input and labor inputs:

$$\begin{aligned}
\frac{x_t^M}{P_{i,t}\frac{\partial Y_{i,t}}{\partial M}\left(\frac{\epsilon_{it}+1}{\epsilon_{it}}\right)} &= \frac{w\left(\bar{L}_{it}\right)+\lambda_{it}^{L}}{P_{i,t}\frac{\partial Y_{i,t}}{\partial L}\left(\frac{\epsilon_{it}+1}{\epsilon_{it}}\right)} \\
\frac{x_t^M M_{it}}{P_{i,t}Y_{it}} &= \frac{\left(w\left(\bar{L}_{it}\right)+\lambda_{it}^{L}\right)L_{it}}{P_{i,t}Y_{it}}\frac{\alpha_{it}^{M}}{\alpha_{it}^{L}} \\
\underbrace{\Delta\log s_{it}^{M}}_{M\text{-share}} &= \underbrace{\Delta\log\left(w\left(\bar{L}_{it}\right)+\lambda_{it}^{L}\right)}_{\text{Marginal cost of labor}} - \underbrace{\Delta\log\frac{P_{i,t}Y_{it}}{L_{it}}}_{\text{Revenue per worker}} + \underbrace{\Delta\log\frac{\alpha_{it}^{M}}{\alpha_{it}^{L}}}_{\text{output elasticities}}, \qquad (2)
\end{aligned}$$

where $\alpha_{it}^{M} = \frac{\partial Y_{it}}{\partial M_{it}}\frac{M_{it}}{Y_{it}}$ is the output elasticity of intermediate input and s_{it}^{M} is the revenue share of intermediate input cost.

Compustat data lacks direct measures of marginal cost of labor. Our methodology aims to quantify the latent labor cost pressures captured by the labor issues discussions by translating these qualitative mentions into estimated changes in the marginal costs labor, $\Delta\log\left(w\left(\bar{L}_{it}\right)+\lambda_{it}^{L}\right)$. In particular, we model changes in marginal labor cost as a function of labor issues discussions in earnings calls:

$$\Delta\log\left(w\left(\bar{L}_{it}\right)+\lambda_{it}^{L}\right) = f(\Lambda_{it}) + \varsigma_{it}, \qquad (3)$$

where $\Lambda_{it} = [\Lambda_{it}^1, \Lambda_{it}^2, ..., \Lambda_{it}^8]'$ is an array of firm i's exposure to topic k of labor-related issues in quarter t—Λ_{it}^k—, which is measured as the count of instances of keywords normalized by the length of the call (see Section 2). Therefore, in our empirical specification we project changes in firms' intermediate input revenue shares onto their exposure to labor topics and estimate $\omega_{it} = f(\Lambda_{it})$ in the below equation:

$$\underbrace{\Delta \log s_{it}^M}_{M\text{-share}} = \underbrace{f(\Lambda_{it})}_{\omega_{it}} - \underbrace{\Delta \log \frac{P_{i,t} Y_{it}}{L_{it}}}_{\text{Revenue per worker}} + \epsilon_{it}, \tag{4}$$

where $\epsilon_{i,t}$ denotes the error term which absorb changes in output elasticities and measurement error as well as possible variation in utilization of inputs.

This regression approach accomplishes two key objectives. First, it converts our textual data from earnings calls into quantifiable estimates of labor cost pressures. Second, it provides an economically grounded method for condensing the complex, multidimensional information in earnings calls into a single meaningful measure. By using the regression coefficients as weights, we create a composite measure that captures how different labor-related discussions contribute to overall firm costs. This approach yields a comprehensive labor cost pressure measure that weights each topic's mention according to its estimated impact on firms' cost structures, combining the rich qualitative information from earnings calls into a single, economically interpretable metric.

One might consider an alternative 'residual approach', where labor cost pressures are defined as the unobserved component from a regression of materials' revenue share on revenue per worker. However, such an approach suffers from a critical drawback. While our method uses an external, independently measured topic signals on the right hand side and only requires that this signal is not systematically correlated with other unobservables after including fixed effects. The residual approach requires a much stronger and less plausible assumption. Specifically, it assumes that any variation in materials' revenue share not explained by revenue per worker is the labor cost pressures shock, thereby mechanically conflating the signal with all sources of noise and misspecification.

4 Estimating labor cost pressures, ω_{it}

4.1 Compustat Data

Our estimation of each topic's contribution to the marginal cost of labor in equation 4 relies on financial data from Compustat. However, Compustat lacks direct measures of intermediate inputs, so we employ two alternative measurement approaches following the previous literature.

First, following Demirer (2022), we calculate materials as the sum of cost of goods sold (COGS) and selling, general and administrative expenses (SGA), minus depreciation (DP) and wage expenditures. Since our firm problem features indirect labor costs (such as recruitment and training costs) that may appear under SGA, we also construct an alternative measure that excludes SGA entirely. As shown in the next section, both measures of material expenditures measures yield remarkably similar results. Additionally, since Compustat does not report total wage expenditures directly, we approximate these by multiplying each firm's employee count by the average industry earnings from the Quarterly Census of Employment and Wages (QCEW). Although our earnings call data is quarterly, our intermediate input measures are available only annually, necessitating annual regression estimation.

Second, following Keller and Yeaple (2009), we use firm-level data on year-end raw materials inventory from Compustat as an alternative proxy for intermediate inputs. We again find remarkably similar results (as discussed in the next section). We calculate materials' revenue share by dividing materials cost by total annual sales. We exclude firms in financial and administrative industries (NAICS 52, 53 and 56). We only include firm level data till 2019 to exclude Covid-19 pandemic period.

4.2 Labor cost pressures (ω_{it}) estimates

We regress firms' revenue shares of variable intermediate inputs on labor issue topics while controlling for firm and time fixed effects. We also choose to flexibly control for employment growth and sales growth to account for measurement error in reporting employment. And, to account for flexible output elasticities—which have been shown to be functions of inputs and to vary over time (Hubmer *et al.* (2024))—

we control for industry-year fixed effects.[3] In particular, we estimate equation 4 at the annual level using the following regression specification.

$$\Delta \log s^M_{i,t} = \underbrace{\sum_k \beta^{topic}_k \Lambda^k_{i,t}}_{\omega_{it}} + \beta_1 \Delta log(Emp_{i,t}) + \beta_2 \Delta log(Sales_{i,t}) + \delta_{jt} + \varepsilon_{it}. \qquad (5)$$

where $s^M_{i,t}$ is the share of intermediate input and $Emp_{i,t}$ and $Sales_{i,t}$ are employee count and sales reported by firm i in year t. Each topic score for topic k by firm i in year t is constructed by averaging over the topic scores calculated quarterly for each earnings conference call. $\delta_{j,t}$ denotes various controls such as firm-level risk and sentiment scores, and industry, firm, and time fixed effects.

In this section we show the regression results when we use Demirer (2022)'s material measure (i.e., the sum of COGS and SGA minus DP and wage expenditures). The regression results for other measures of materials are remarkably similar (Table A.3). Table III shows the regression coefficients for different labor-related discussions in earnings calls relate to firms' cost structures. We present five different specifications with progressively more stringent controls, ranging from a basic specification to one that includes firm fixed effects, time fixed effects, and additional controls for risk and sentiment[4]. Using these coefficients, we calculate the estimated change in marginal costs of labor using:

$$\omega_{it} = \sum_k \hat{\beta}^{topic}_k \Lambda_{k,i,t} \qquad (6)$$

The results reveal overall robust and intuitive relationships between labor cost discussions and firms' cost structures. Discussions around higher labor costs, higher headcount, labor shortages and lower labor efficiency are associated with higher cost pressures. Whereas discussions around lower labor costs, lower headcount, and higher

[3]This specification choice is consistent with the marginal costs as specified in Gagliardone *et al.* (2023) who specify firm level marginal costs for firm i at time t as $MC_{i,t} = C_{i,t}A_{i,t}Y^v_{i,t}$where v is a scaling parameter and $A_{i,t}$is a firm level productivity shifter. This type of functional form assumption allows for more general production functions and nests Cobb-Douglas and CES cases.

[4]We find nearly identical coefficients when including firm fixed effects along with industry-year fixed effects.

labor efficiency are associated with lower cost pressures.

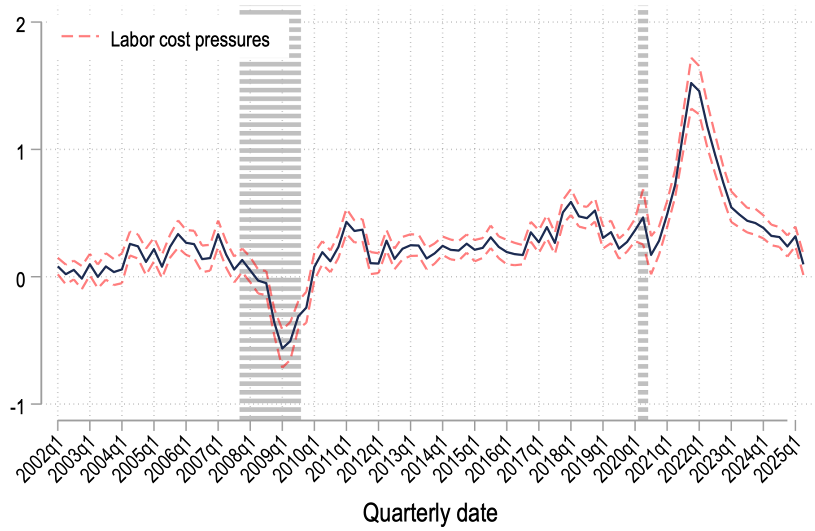
TABLE III – Estimation of labor cost pressures: Labor topics and variable input cost share, at firm x year level

	$\Delta log(Materials/Sales)_{i,t}$				
	(1)	(2)	(3)	(4)	(5)
Labor Costs Higher$_{i,t}$	4.270***	3.981***	3.427***	3.580***	3.854***
	(0.613)	(0.604)	(0.675)	(0.686)	(0.731)
Labor Costs Lower$_{i,t}$	–6.075***	–6.437***	–6.739***	–6.685***	–6.497***
	(0.973)	(0.971)	(1.008)	(1.044)	(1.014)
Headcount Higher$_{i,t}$	–0.788	–0.529	0.263	0.392	0.882
	(0.724)	(0.727)	(0.733)	(0.730)	(0.930)
Headcount Lower$_{i,t}$	–0.981	–0.365	–0.188	0.444	–0.764
	(1.032)	(1.029)	(1.038)	(1.075)	(1.162)
Labor Shortage$_{i,t}$	2.042	2.446	1.234	1.231	2.019
	(1.808)	(1.890)	(2.118)	(2.154)	(2.486)
Labor Efficiency Higher$_{i,t}$	–1.061	–1.838	–2.899	–2.883	–3.636
	(2.821)	(2.774)	(2.928)	(3.011)	(3.146)
Labor Efficiency Lower$_{i,t}$	6.885**	7.447**	7.494**	8.318**	1.373
	(3.291)	(3.287)	(3.464)	(3.608)	(3.398)
Labor Agreement$_{i,t}$	1.013	0.813	–0.425	–0.696	–0.441
	(1.102)	(1.082)	(1.112)	(1.167)	(1.247)
Residual category$_{i,t}$	0.374	0.286	0.520*	0.556*	1.056**
	(0.282)	(0.285)	(0.312)	(0.333)	(0.421)
R^2	0.050	0.060	0.099	0.099	0.223
N	23,790	23,790	23,714	21,500	21,240
Baseline Controls	Y	Y	Y	Y	Y
Time FE	N	Y	Y	Y	Y
Industry-Year FE	N	N	Y	Y	N
Sentiment and Risk	N	N	N	Y	Y
Firm FE	N	N	N	N	Y

Notes: The table shows regression of changes in on labor topics. Each observation denotes a firm i and year t. To construct labor topic observations at the firm x year level we take averages across all quarters in a year. All specifications include controls for yearly changes in sales and employment. Columns (4) and (5) include controls for risk and sentiment. We exclude firms in financial and administrative industries (NAICS 52, 53 and 56). We only include firm level data till 2019 to exclude Covid-19 pandemic period. Standard errors are clustered by firm.

Magnitudes and statistical significance of these coefficients exhibit interesting variations. Specifically, discussions of higher labor costs are consistently strongly associ-

Figure 4 – Labor Cost Pressure Index ($\bar{\omega}_t$)



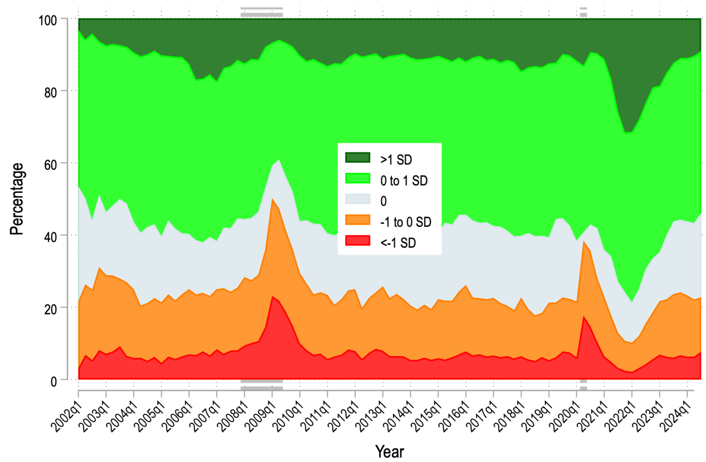
Notes: The figure shows the average change in estimated marginal cost of labor across firms by quarter along with bootstrapped confidence intervals. The estimation uses coefficients from Table III and topic specific scores by firm and by quarter. Bootstrapped confidence intervals are calculated by randomly leaving out 10% of the sample one at a time for the estimation procedure for 200 samples.

ated with increases in the materials-to-sales ratio. The estimated coefficients range from 4.270 (s.e. = 0.613) in the baseline model without any controls to 3.854 (s.e.= 0.731) in our most restrictive specification that includes firm and time fixed effects. In our most restrictive specification, the coefficient remains highly statistically significant at the 1% level. Similarly, mentions of lower labor costs are linked to significant negative coefficients, ranging from -6.075 (s.e.=0.973) to -6.497 (s.e.=1.014).

Appendix table A.4 shows regressions with individual topics. The table shows that individually discussion of higher and lower labor counts, and labor shortages are significantly associated with changes in materials-to-sales ratio. However, these associations are sufficiently summarized in the discussion of higher and lower labor cost pressures and therefore are not statistically significant in our baseline table.

The stability of key coefficients across specifications for labor costs discussions, suggests these relationships are robust and not driven by omitted variables at the firm, industry, or time level.

FIGURE 5 – Distribution of Labor Cost Pressures across firms (ω_{it})



Notes: The figure shows the distribution of change in estimated marginal cost of labor across firms by quarter. The estimation uses coefficients from Table III and topic specific scores by firm and by quarter. Different colors show the distributions of labor cost pressures separated by 1 standard deviation.

4.3 Time series variation of labor cost pressure (ω_{it})

We first construct an aggregate measure of labor cost pressures ($\bar{\omega}_t$) by creating a sales-weighted average of our firm-level measure (ω_{it}) to validate it against traditional macroeconomic indicators. Figure 4 shows our aggregate index. Following a sharp but short-lived collapse during the Great Recession, the index remained persistently low throughout the subsequent recovery. Consequently, it aligns more closely with the observed flattening of the Phillips curve (Powell (2018)). Furthermore, the index surged dramatically during and after the COVID-19 pandemic, surpassing its pre-recession peaks, a movement that corresponds to the steepening of the Phillips curve observed during this time (Domash and Summers (2022)).

Table IV presents correlations between our measure and four key macroeconomic indicators: unemployment rate, output gap, and the Employment Cost Index (ECI) (along with previously discussed labor market tightness). The results show strong and statistically significant correlations across all measures, with particularly robust relationships with labor market tightness (0.76) and the ECI (0.63). The positive correlation with different slack variables confirm that our measure effectively captures labor market conditions in a way that aligns with traditional indicators. However, the imperfect correlation suggests our measure captures critical information that conventional indicators might overlook.

TABLE IV – Correlation with labor cost pressure index, $\bar{\Lambda}_t$

Tightness	Unemp. Rate	Output gap	ECI
0.76***	–0.55***	0.29***	0.63***
(0.06)	(0.09)	(0.10)	(0.07)

What drives the variation in our aggregate index? Do all firms experience similar changes in labor cost pressures, or are these pressures concentrated among a small subset of firms? Figure 5 shows the distribution of labor cost pressures across firms over time. For each quarter, labor cost pressures at the firm level are split into five categories based on standard deviations. Notably, for more than 75% of of firms, labor cost pressures remain negligible between -1 to 1 standard deviations, indicating that substantial labor-related cost concerns are concentrated within a relatively small subset of firms at any given point. However, during periods of tight labor markets—particularly evident around 2005–2006 and again in 2021–2022—the number of firms experiencing meaningful labor cost pressures (more than one standard deviation to either side) increases more than two fold. Similarly, the slack in labor market after the Great recession between 2011 and 2019 was characterized by more firms not mentioning labor cost pressures. These patterns suggest that labor market tightness not only intensifies labor cost pressures among affected firms but also broadens their reach, causing more firms to encounter meaningful labor-related cost challenges.[5]

4.4 Industry variation of labor cost pressure (ω_{it})

We also construct a labor cost pressures index at the industry level ($\bar{\omega}_{n,t}$) by creating a sales-weighted average of our firm-level measure (ω_{it}) for each industry. Figure A.2 presents the evolution of the labor cost pressure index across 14 major industries from 2002 to 2024, revealing significant heterogeneity in both the timing and magnitude of labor market pressures across sectors. Several notable patterns emerge from this industry-level analysis. First, during the 2008-2009 financial crisis, many

[5]These findings echo those in Hassan *et al.* (2019), who use earnings conference calls to show that a large portion of the variation in political risk is at the firm quarter level rather than aggregate level. Similarly, Hassan *et al.* (2024b) show that the effects of Brexit varied largely by firm with large variation in winners, losers and unaffected firms.

industries experienced sharp declines in labor cost pressures. This is especially visible in construction with a major dip in labor cost pressures before the recession. Manufacturing and real estate showed steep downward movements during the recession. However, some service sectors like Administrative Services, and Healthcare and Social Assistance showed more resilience during this period, with less pronounced declines.

Second, the most dramatic jumps occur during the post-pandemic period (2020-2022). Accommodation and Food Services, Administrative Services, and Arts, Entertainment, and Recreation show unprecedented spikes in their indices, reaching levels 3-10 times higher than their historical averages. This likely reflects the acute labor shortages and wage pressures these sectors faced during the reopening phase of the economy. Health Care and Social Assistance also shows a notable spike during this period, consistent with widely reported healthcare worker shortages and increased labor costs. We next use this variation across industries to explore the pass through of labor cost pressures to PPI inflation.

5 Labor Cost Pressures and Inflation Pass-through

5.1 Estimating pass-through to PPI inflation

We now quantify the pass-through of labor cost pressures (ω_{it}) to inflation. For this purpose, we specify an equation by combining equation 3 with a log-linearized version of the pricing equation 1:

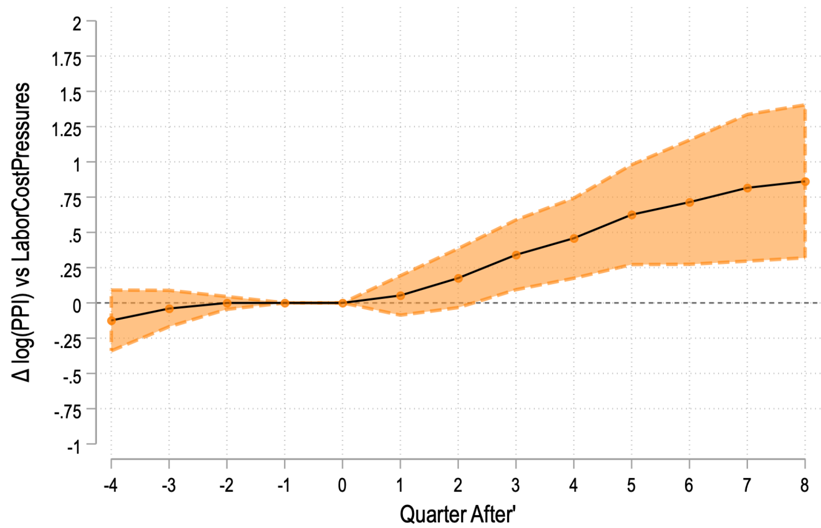
$$\hat{P}_{i,t} = \beta_p \omega_{it} - Y_{it} \hat{/} L_{it} - \hat{\alpha_{it}^L} - \hat{\eta_{it}},$$

where β_p is the pass-through of labor cost pressures to prices. We can then aggregate this equation at the industry level (under Cobb-Douglas preferences):

$$\hat{P}_{n,t} = \beta_p \sum_{i \in n} \theta_{i,t} \omega_{it} - Y_{nt} \hat{/} L_{nt} - \hat{\alpha_{nt}^L} - \hat{\eta_{nt}},$$

where the aggregate price index at the industry-level is $log(P_{n,t}) = \sum_{i,t} \theta_{i,t} log(P_{i,t})$ and $\theta_{i,t}$ are share of sales accounted for by firm i in industry n at time t. Therefore, by exploiting the disaggregated nature of our measure, we estimate $\beta_p$using variation in Producer Price Index (PPI) at the industry level.

Figure 6 – Labor cost pressures and industry inflation



Notes: The figure plots estimated pass-through of labor cost pressures by 2-digit NAICS industry. The plot shows estimates and 95% confidence intervals. Standard errors are clustered by industry. Estimated changes in MCL for industry in quarter is calculated by taking a sales weighted average of estimated changes in MCL across all firms in the industry in the Compustat. We exclude financial and administrative industries (NAICS 52, 53 and 56). Regression is weighted by number of firms observed within the industry. Inflation is winsorized at 2nd and 98th percentile.

To understand the dynamics of this response, we now study the response of PPI to labor cost pressures using the following Jorda projection specification.

$$log(PPI_{n,t+h})-log(PPI_{n,t}) = \alpha_h+\beta_h\bar{\omega}_{nt}+\sum_{k=1}^{3}\gamma_k(log(PPI_{n,t})-log(PPI_{n,t-k}))+\delta_{n,h}+\delta_{t,h}+\epsilon_{n,t+h}$$

where $\bar{\omega}_{n,t}$ is the sales weighted average of ω_{it} over firms in industry n at time t. $log(PPI_{n,t+h}) - log(PPI_{n,t})$ denotes PPI inflation between time t and t+h. $\delta_n$and $\delta_t$are industry and time fixed effects. We want to isolate domestic US labor cost pressures on U.S. inflation, so we exclude heavily import-dependent apparel and computer-electronics manufacturing industries (Borusyak and Jaravel (2021)). Estimating this equation without fixed effects runs into classic simultaneity problem. For example, an active monetary policy will look to offset increases in demand with an

Figure 7 – Pass-through of labor cost pressures by Industry

Notes: The figure plots estimated pass-through of labor cost pressures by 2-digit NAICS industry. The plot shows estimates and 95% confidence intervals. Standard errors are clustered by industry.

increase in interest rates. This could result in an increase in labor cost pressures and a subsequent fall in inflation. On the other hand, wage price spirals could introduce a mechanical association between labor costs and prices of the consumption basket which could introduce a positive association between labor cost pressures and inflation. Following Fitzgerald *et al.* (2014); Drechsel *et al.* (2019); Hazell *et al.* (2022), we use time fixed effects in our specification to address simultaneity due to simultaneous aggregate shocks. In our example, an active monetary policy cannot offset demand shocks individually across industries with one interest rate and any contemporaneous shocks across industries would be absorbed in the time fixed effect.

In our analysis we use a large panel of 2,832 industry-quarter observations (Table A.5). Considerably large sample size provides us more variation in inflation and labor cost pressures slack. Figure 6 shows that these labor cost pressures take about 6-8 quarters to pass through 86 percent of the increase in labor cost pressures to PPI inflation. Table A.5 shows a consistently positive and significant relationship between industry-level labor cost pressures and subsequent PPI inflation within the next four quarters across various specifications with and without fixed effects. The coefficient on the labor cost pressure measure ranges from 0.387 to 0.493, indicating that a one percentage point increase in labor cost pressures is associated with roughly 0.493 percentage points higher PPI inflation four quarters later.

Figure 7 shows the interaction of coefficient in Table 7 column 4 with a dummy for ten NAICS 2-digit industries. Each coefficient shows the estimated pass-through of labor cost pressures across a range of industries, along with corresponding confidence interval shown by dashed lines. Notably, industries with high labor shares such as Information, Wholesale Trade , and Accommodation and Food Services show higher pass-through estimates. We also find very small pass-through for manufacturing industry. These results are consistent with Heise *et al.* (2022), who find significant pass-through from wages to inflation in services industries for up to seven quarters but insignificant or negative in manufacturing. Though, they argue that rising import competition and increasing market concentration explain the disappearance of wage-price pass-through in manufacturing, whereas we argue in Section 6 that automation is a significant factor.

5.2 Labor Cost Pressure and PCE Inflation

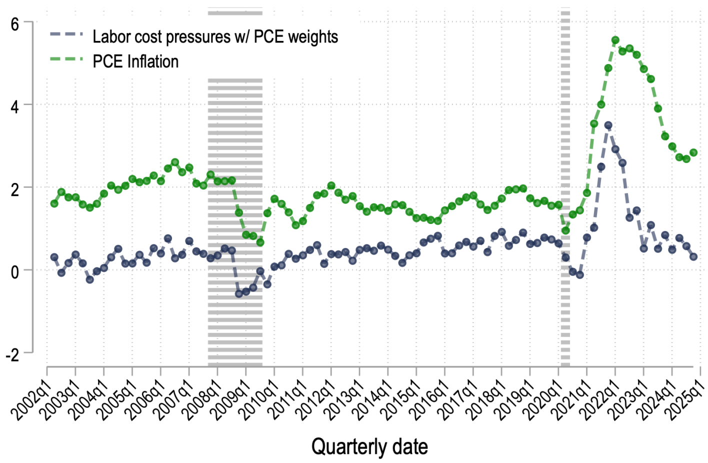
Using our estimate we obtained in the previous section, we now investigate the inflation predictions of our labor cost pressure measure, ω_{it}. We create our aggregate measure using PCE industry weights to our industry level measure—which is aggregated using sales weights within an industry. Figure 8 shows this aggregate index along with the PCE inflation. Our index and the PCE inflation are very strongly correlated. It can capture the short-lived decline in PCE during the Great recession as well as the pandemic surge. In fact, our measure can explain 19.5 pp of the 29.3 pp cumulative surge in inflation during the post-pandemic period.

Next, we test our measure within a standard Phillips Curve framework, comparing its performance to traditional measures of labor market slack. Following Barnichon and Shapiro (2024), we regress changes in core PCE inflation on a forcing variable controlling for long-run inflation expectations and control variables. Following the insight from Atkeson *et al.* (2001); Stock and Watson (2008)that in several time periods current inflation is the best forecast for future inflation, we add realized value of current inflation as controls:

$$\pi_t = \alpha + \beta_x \hat{x}_t + \beta_\pi E_t \pi_\infty + \beta_1 \pi_{t-4} + v_t,$$

where π_t is year-on-year change percent change in core PCE inflation between t and $t+4$, $E_t\pi_\infty$ denotes long-run inflation expectations obtained from Livingston survey,

FIGURE 8 – Labor Cost Pressure Index ($\bar{\omega}_t$) and PCE Inflation



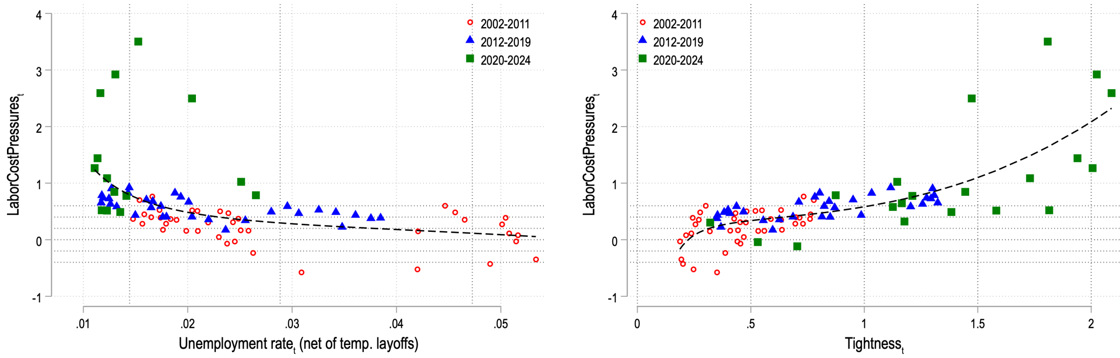
Notes: The figure shows our labor cost pressure index (weighted with PCE weights) and the PCE inflation. To aggregate with PCE weights, we use industry level aggregate at the NAICS 3 digit level and then aggregate up to quarterly level using PCE weights for each industry.

π_{t-4} is PCE inflation between t-4 and t, and $\hat{x}_t$ is the deviation from the steady state average of a forcing variable. We standardize all the push variables ($\hat{x}_t$) by their standard deviation, so that the coefficients are comparable. Along with our measure of labor cost pressures ($\bar{\omega}_t$), we consider the following commonly used forcing variables: (1) Unemployment rate, (2) Labor market tightness (V/U ratio), (3) Output gap (from the CBO), (4) Employment Cost Index (ECI). We employ "naive" ordinary least squares (OLS) regressions at the quarterly level using data from 2002-2025Q1.

This empirical approach is particularly valuable because it places our new measure in direct competition with established indicators within a well-understood framework. The use of a common specification across all measures enables clear comparison of their relative performance in explaining inflation dynamics, while the inclusion of long-run inflation expectations and current realized inflation helps control for the forward-looking component of price setting.

Panel A in Table V shows individual regressions for each forcing variable. The labor cost pressure measure exhibits the strongest relationship with future inflation, with a coefficient of 0.312 that is highly significant at the 1% level. The R-squared of 0.424 is higher than those of competing measures, indicating better explanatory power. Labor market tightness also shows a positive but statistically insignificant

Figure 9 – Correlation with unemployment rate, tightness and inflation



Notes: This figure plots unemployment rate (net of temporary layoffs), tightness and inflation observed at the quarter level against labor cost pressures.

relationship (0.078). Output gap, ECI and EE flows performs poorly, with an insignificant coefficient.

Panel B provides a more rigorous test by including the labor cost pressure measure alongside traditional forcing variables. The labor cost pressure coefficient remains remarkably stable and significant (ranging from 0.289 to 0.382) even when controlling for other measures. Importantly, when included alongside the labor cost pressure measure, the traditional forcing variables are statistically insignificant.

These results strongly support the value of the new labor cost pressure measure as a forcing variable in Phillips Curve estimations. Not only does it outperform traditional measures when tested individually, but it also subsumes their explanatory power in joint specifications. The high and stable R-squared values from specifications using the labor cost pressure measure suggest it captures important information about future inflation that is not fully reflected in traditional measures of slack in the economy. Figure 9 provides insight into why other labor cost pressures performs better at predicting inflation than other push variables. For a large range of unemployment and tightness, labor cost pressures inferred from executive conversations are largely unchanged. Only values of unemployment below 4 percent and tightness above 1.5 jobs per vacancies have a high correlation with labor cost pressures.

Table V – Phillips Curve Estimation

Panel A: Push variables and Inflation

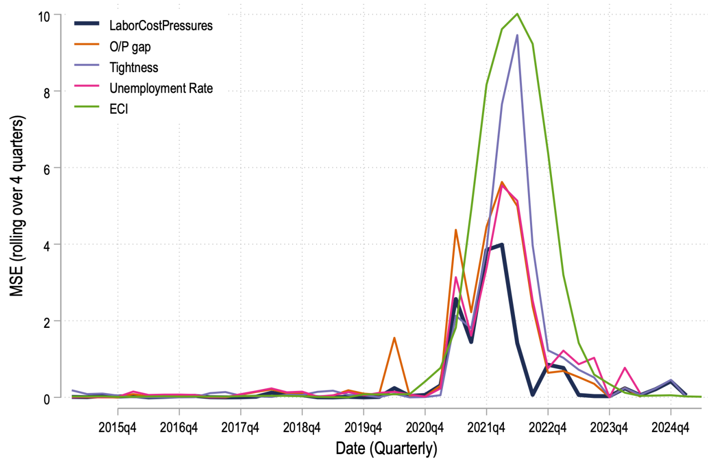
	PCE Inflation$_{t,t+4}$					
	(1)	(2)	(3)	(4)	(5)	(6)
Labor Cost Pressures$_t$	0.312***					
	(0.118)					
Tightness$_t$ (std.)		0.078				
		(0.114)				
Unemployment Rate$_t$ (std.)			0.056			
			(0.080)			
Output Gap$_t$ (std.)				–0.157		
				(0.116)		
ECI$_t$ (std.)					0.287	
					(0.196)	
E-E-Flows$_t$ (std.)						–0.266
						(0.219)
Inflation Expectations$_t$	–0.123	0.000	–0.079	–0.095	0.062	–0.075
	(0.200)	(0.240)	(0.246)	(0.217)	(0.291)	(0.213)
Inflation$_t$	0.470***	0.563***	0.690***	0.746***	0.363	0.726***
	(0.127)	(0.200)	(0.186)	(0.164)	(0.305)	(0.156)
R^2	0.424	0.385	0.385	0.398	0.401	0.397
N	88	88	88	88	88	88

Panel B: Comparison with Labor Cost Pressures

	PCE Inflation$_{t,t+4}$					
	(1)	(2)	(3)	(4)	(5)	(6)
Labor Cost Pressures$_t$	0.312***	0.382**	0.354***	0.343***	0.289**	0.311**
	(0.118)	(0.147)	(0.119)	(0.118)	(0.121)	(0.119)
Tightness$_t$ (std.)		–0.164				
		(0.150)				
Unemployment Rate$_t$ (std.)			0.126			
			(0.083)			
Output Gap$_t$ (std.)				–0.197*		
				(0.104)		
ECI$_t$ (std.)					0.231	
					(0.195)	
E-E-Flows$_t$ (std.)						–0.266
						(0.212)
Inflation Expectations$_t$ (std.)	–0.123	–0.225	–0.226	–0.202	–0.036	–0.159
	(0.200)	(0.217)	(0.205)	(0.178)	(0.264)	(0.183)
Inflation$_t$ (std.)	0.470***	0.601***	0.552***	0.581***	0.257	0.553***
	(0.127)	(0.177)	(0.149)	(0.132)	(0.274)	(0.132)
R^2	0.424	0.430	0.434	0.446	0.435	0.438
N	88	88	88	88	88	88

Notes: The table shows regression of PCE inflation observed in industry n between quarters t and t+4 on estimated changes in MCL for quarter t. Estimated changes in MCL quarter t is calculated by taking a PCE weighted average of estimated changes in MCL across all US headquartered firms in Compustat who hold earnings conference calls in quarter t. We exclude financial and administrative industries (NAICS 52, 53 and 56). Standard errors are robust.

FIGURE 10 – Labor Cost Pressure Index ($\bar{\omega}_t$) and PCE Inflation



Notes: The figure shows our labor cost pressure index (weighted with PCE weights) and the PCE inflation. To aggregate with PCE weights, we use industry level aggregate at the NAICS 3 digit level and then aggregate up to quarterly level using PCE weights for each industry.

Finally, we test the predictive power of our measure again using the Phillips Curve framework we developed by comparing its performance to other aggregate slack measures. To test this, we estimate the following model for rolling ten year windows and use the estimates to make prediction on inflation four quarters ahead:

$$\pi_t = \beta_x \hat{x}_t + \beta_\pi E_t \pi_\infty + \beta_1 \pi_{t-4} + v_t,$$

Using these window-specific coefficients—together with labour cost pressures computed only from data within the same 10-year window, so no future information leaks—we generate forecasts of core PCE inflation four quarters ahead. Figure 10 plots the 4-quarter average rolling mean-squared forecast errors (MSEs) of the different slack measures in predicting core PCE price inflation one year ahead over 2015–2025. The only serious inflationary period in our sample is the Covid pandemic era. Our measure displays the lowest MSE when compared with other slack variables. Again, these results strongly support the value of our labor cost pressure measure in predicting inflation.

6 How do firms respond to labor cost pressures?

Capital–labor substitution in production is central for many questions in economics, such as factor income shares (e.g., Karabarbounis and Neiman (2014)) or earnings distribution (e.g., Krusell *et al.* (2000)). Most models of labor demand imply that when firms face higher labor costs they adopt automation technologies (e.g., Acemoglu and Autor (2011); Acemoglu and Restrepo (2022a); Leduc and Liu (2024)).

We now exploit the disaggregated nature of our measure and examine how firms respond to labor cost pressures using a large panel of firm-quarter observations from Compustat data. We analyze changes in several key firm outcomes, including investment rates, R&D spending, and productivity measures, in response to ω_{it}. Our empirical strategy employs a comprehensive set of controls including firm fixed effects, year fixed effects, industry characteristics, and other firm-specific variables to isolate the causal effect of labor cost pressures on firm behavior. The results reveal intriguing patterns in how firms adapt to labor cost pressures, with notable differences across industry types. We use the following specification:

$$log(CapEx_{i,t,t+4}) = \alpha + \beta\omega_{i,t} + \gamma log(assets_{i,t-1}) + \chi_{i,t} + \delta_i + \delta_t + v_t,$$

where ω_{it} denotes labor cost pressures at the firm level observed in quarter t. $log(CapEx_{i,t,t+4})$ denotes log capital expenditures between quarter t and t+4. $\delta_i$and $\delta_t$are firm and time fixed effects. We control for risk and sentiment in expressed in earnings conference calls following Hassan *et al.* (2024a). We focus on heterogeneity across industries with different levels of routine manual task intensity (Table VI Panel A). The baseline specification (column 1) indicates that a percentage point increase in labor cost pressures is associated with a 2.58% increase in capital expenditure. The inclusion of various fixed effects and controls helps isolate the effect of labor cost pressures from other factors that might influence investment decisions, such as industry trends, macroeconomic conditions, and firm-specific characteristics.

Columns 2-3 reveal interesting heterogeneity across industry types based on their routine manual task intensity. High routine manual (HRM) industries show the strongest investment response to labor cost pressures (4.20%), followed by low routine manual (LRM) industries (2.24%), while medium routine manual (MRM) in-

TABLE VI – Labor Cost Pressures and Investment, Firm x time Level

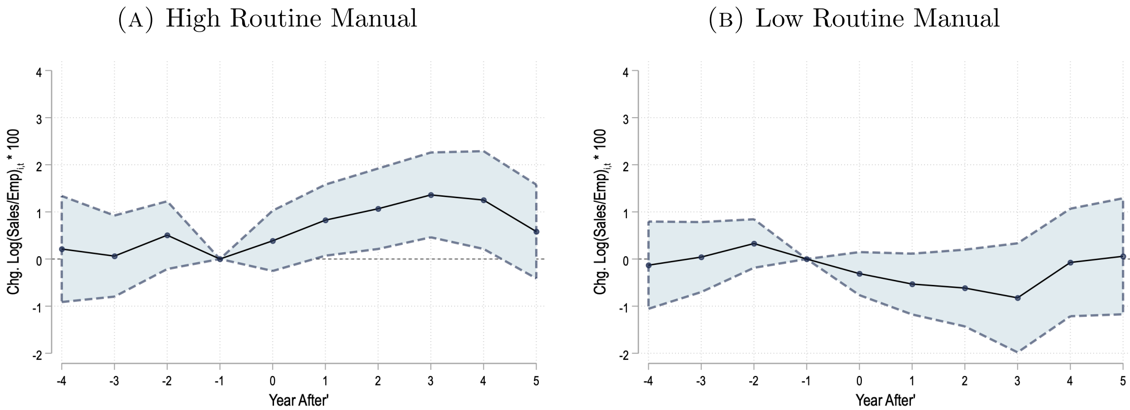
Panel A: Capital Investment				
	log(Capital Exp.$_{i,t:t+4}$) * 100			
	All	LRM	MRM	HRM
	(1)	(2)	(3)	(4)
Labor Cost Pressures$_{i,t}$	2.581***	2.238***	1.890***	4.203***
	(0.193)	(0.363)	(0.252)	(0.351)
R^2	0.920	0.889	0.934	0.914
N	148,510	45,360	61,459	41,532
Panel B: R&D Investment				
	log(R&D Exp.$_{i,t:t+4}$) * 100			
	All	LRM	MRM	HRM
	(1)	(2)	(3)	(4)
Labor Cost Pressures$_{i,t}$	0.556***	0.157	0.617**	0.967***
	(0.175)	(0.318)	(0.251)	(0.362)
R^2	0.959	0.960	0.960	0.957
N	53,582	15,624	22,968	14,966
Controls (Risk and Sentiment)	Y	Y	Y	Y
Time FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y

Notes: The table shows regression of log(Capital expenditures) reported by firm i between quarters t+1 and t+4 on labor topic scores of earnings conference calls held by firm i in quarter t. . Each observation denotes a firm i and year t. All columns include controls for risk, sentiment and log assets. We exclude firms in financial and administrative industries (NAICS 52, 53 and 56). Standard errors are clustered by firm.

dustries show the smallest response (1.89%). This pattern suggests that firms in industries with high routine manual task content are more likely to respond to labor cost pressures by increasing capital investment, consistent with greater opportunities for automation and capital-labor substitution in these industries.

We next examine how firms adjust their R&D expenditures in response to labor cost pressures, using a similar framework as the capital expenditure analysis (Table VI Panel B). For the full sample of firms (columns 1-3), labor cost pressures show a positive and significant relationship with R&D spending. The effect is substantial, with a one percentage point increase in labor cost pressures associated with a 0.56% increase in R&D expenditure in the baseline specification. We find similar results

Figure 11 – Productivity response to labor cost pressures, firm x time level



Notes: This figure plots the response of labor productivity growth measured as change in log of sales per employee. The sample includes an yearly panel of firms in Compustat. We control for firm and year fixed effects, and earnings call risk and net sentiment. Standard errors are clustered by firm.

to those observed for capital expenditures: firms in high routine manual industries invest in R&D at 7 times the rate compared to low routine manual industries. This finding, combined with the heterogeneous responses across industry types, indicates that firms' technological capabilities and industry characteristics significantly influence their choice between capital investment and R&D as responses to labor cost pressures.

How does an increase in capital investment and automation in response to labor cost shock affect labor productivity? Figure 9 presents an event study analyses showing how labor productivity (measured as revenue per employee) responds to labor cost pressure shocks from 4 years before to 5 years after the shock, with confidence intervals shown by the dotted lines. Panel A, focusing on HRM industries, reveals a clear pattern of productivity gains following labor cost pressure shocks. While there is no significant pre-trend before the shock (years -4 to 0), productivity begins to increase notably around year 1 and continues to rise, reaching a peak of nearly 1% higher productivity by year 3. The effect remains positive and statistically significant through year 5, suggesting persistent productivity improvements in these industries following labor cost pressures.

In contrast, Panel B shows that low routine manual industries exhibit no significant productivity response to labor cost pressure shocks. The point estimates fluctuate around zero throughout the post-shock period, and the confidence intervals consistently include zero. This stark difference between HRM and LRM industries aligns with the earlier findings on investment and automation responses, suggesting that firms in HRM industries are more successful at converting their technological responses to labor cost pressures into actual productivity gains, likely through successful automation and capital-labor substitution.

These productivity patterns align closely with and help explain our earlier findings about firms' differential responses to labor cost pressures across industry types. HRM firms successfully automate and achieve productivity gains. This heterogeneity in responses and outcomes highlights the important role of industry characteristics in determining the effectiveness of different strategies for dealing with labor cost pressures.

7 Conclusion

This paper develops and validates a novel approach to measuring labor cost pressures by combining textual analysis of earnings calls with Compustat data. Our measure offers several advantages over traditional indicators. First, it provides granular, firm-level data that captures both direct wage costs and indirect labor expenses. Second, it shows strong predictive power for inflation in both aggregate and industry-level analysis. Third, its disaggregated nature allows us to study how firms respond to labor cost pressures, revealing important heterogeneity across industries.

Our findings make three main contributions. First, we show that earnings calls contain valuable real-time information about labor market conditions and labor cost pressures. Second, we demonstrate that our measure outperforms traditional slack variables in Phillips curve estimations, suggesting it better captures inflationary pressures. Third, we document how labor cost pressures drive technological adoption differently across industries. Firms in routine manual industries respond through automation and achieve productivity gains.

These results have important implications for understanding both inflation dynamics and technological change. Our measure could help policymakers better anticipate inflationary pressures, while our firm-level findings suggest that labor cost pressures may accelerate automation and technological adoption, particularly in industries where human labor can be more readily substituted with capital. This highlights how labor market conditions can shape the pace and direction of technological change across different sectors of the economy.

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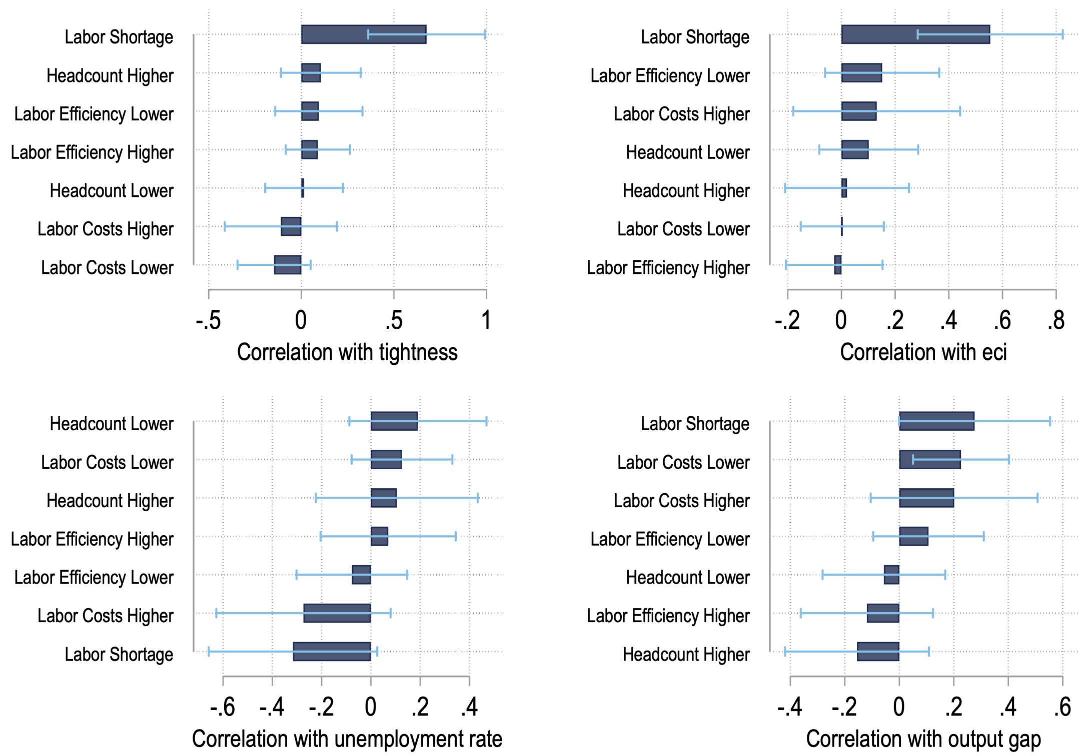
Appendix

Figure A.1 – Correlation of Labor Topic Discussions with Aggregate Variables



Notes: The table shows results of regressions of tightness (calculated as the ratio of postings to vacancies), unemployment rate, employment cost index, and output gap on labor topics. Observations are quarterly. To construct labor topic observations at the quarter level we take sales weighted averages across firms who hold earnings calls in a quarter. We exclude firms in financial and administrative industries (NAICS 52, 53 and 56). Standard errors are robust.

TABLE A.3 – Estimation of labor cost pressures: Labor topics and variable input cost share calculated using material inventories, at firm x year level

	$\Delta log(MaterialInventories/Sales)_{i,t}$				
	(1)	(2)	(3)	(4)	(5)
Labor Costs Higher (std.)$_{i,t}$	1.240***	0.963***	0.819***	0.808***	0.910**
	(0.283)	(0.279)	(0.290)	(0.306)	(0.359)
Labor Costs Lower (std.)$_{i,t}$	–1.166***	–1.188***	–1.185***	–1.070***	–1.108***
	(0.308)	(0.329)	(0.343)	(0.350)	(0.397)
Headcount Higher (std.)$_{i,t}$	0.152	0.079	0.229	0.357	0.295
	(0.414)	(0.408)	(0.432)	(0.470)	(0.569)
Headcount Lower (std.)$_{i,t}$	–0.624**	–0.417	–0.354	–0.372	–0.172
	(0.306)	(0.302)	(0.307)	(0.317)	(0.355)
Labor Shortage (std.)$_{i,t}$	0.484***	0.575***	0.444**	0.530***	0.683***
	(0.167)	(0.174)	(0.181)	(0.187)	(0.206)
Labor Efficiency Higher (std.)$_{i,t}$	0.227	0.145	0.146	0.155	–0.021
	(0.206)	(0.209)	(0.211)	(0.225)	(0.241)
Labor Efficiency Lower (std.)$_{i,t}$	0.170	0.241	0.165	0.176	0.148
	(0.191)	(0.190)	(0.189)	(0.194)	(0.213)
Labor Agreement (std.)$_{i,t}$	0.247	0.184	0.001	–0.011	–0.139
	(0.157)	(0.159)	(0.163)	(0.160)	(0.213)
R^2	0.040	0.048	0.051	0.049	0.156
N	27,750	27,750	27,749	24,999	24,830
Time FE	N	Y	Y	Y	Y
Industry FE	N	N	Y	Y	NA
Controls (Risk and Sentiment)	N	N	N	Y	Y
Firm FE	N	N	N	N	Y

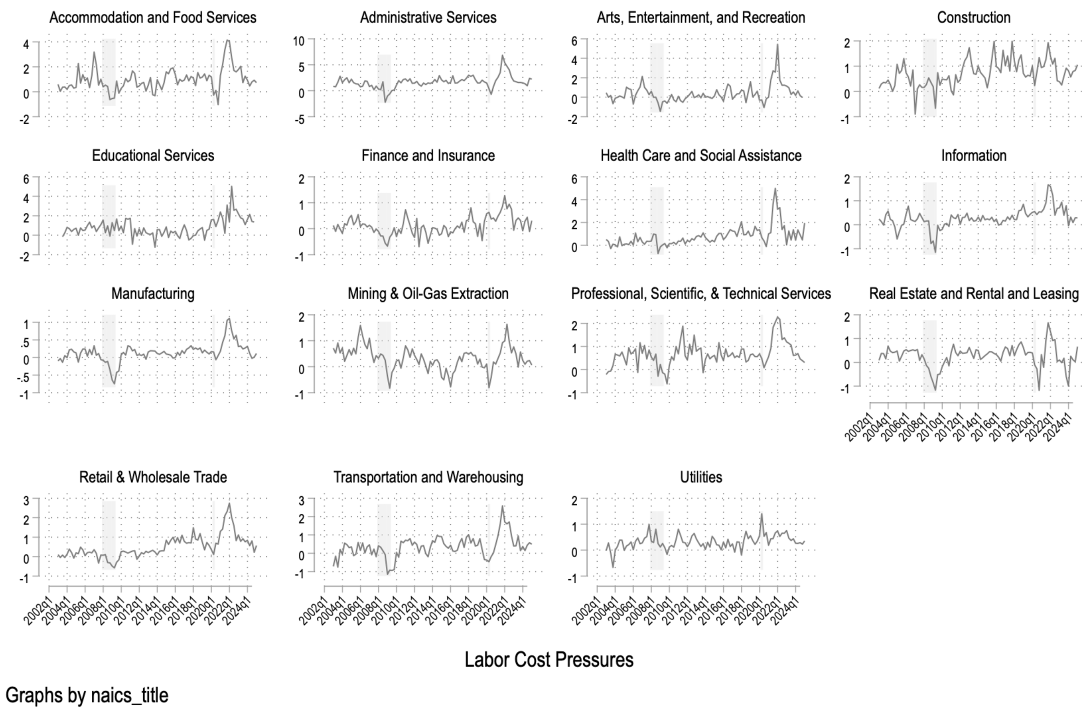
Notes: The table shows regression of changes in $log(MaterialInventories/Sales)_{i,t}$ on labor topics. Each observation denotes a firm i and year t. To construct labor topic observations at the firm x year level we take averages across all quarters in a year. All specifications include controls for changes in $log(Sales)_{i,t}$ and changes in $log(Emp)_{i,t}$. Columns (4) and (5) include controls for risk and sentiment. We exclude firms in financial and administrative industries (NAICS 52, 53 and 56). We only include firm level data till 2019 to exclude Covid-19 pandemic period. Standard errors are clustered by firm.

TABLE A.4 – Estimation of labor cost pressures: Labor topics and variable input cost share, at firm x year level

	$\Delta log(Materials/Sales)_{i,t}$				
	(1)	(2)	(3)	(4)	(5)
Labor Costs Higher$_{i,t}$	4.270***	3.981***	3.427***	3.580***	3.854***
	(0.613)	(0.604)	(0.675)	(0.686)	(0.731)
Labor Costs Lower$_{i,t}$	–6.075***	–6.437***	–6.739***	–6.685***	–6.497***
	(0.973)	(0.971)	(1.008)	(1.044)	(1.014)
Headcount Higher$_{i,t}$	–0.788	–0.529	0.263	0.392	0.882
	(0.724)	(0.727)	(0.733)	(0.730)	(0.930)
Headcount Lower$_{i,t}$	–0.981	–0.365	–0.188	0.444	–0.764
	(1.032)	(1.029)	(1.038)	(1.075)	(1.162)
Labor Shortage$_{i,t}$	2.042	2.446	1.234	1.231	2.019
	(1.808)	(1.890)	(2.118)	(2.154)	(2.486)
Labor Efficiency Higher$_{i,t}$	–1.061	–1.838	–2.899	–2.883	–3.636
	(2.821)	(2.774)	(2.928)	(3.011)	(3.146)
Labor Efficiency Lower$_{i,t}$	6.885**	7.447**	7.494**	8.318**	1.373
	(3.291)	(3.287)	(3.464)	(3.608)	(3.398)
Labor Agreement$_{i,t}$	1.013	0.813	–0.425	–0.696	–0.441
	(1.102)	(1.082)	(1.112)	(1.167)	(1.247)
Residual category$_{i,t}$	0.374	0.286	0.520*	0.556*	1.056**
	(0.282)	(0.285)	(0.312)	(0.333)	(0.421)
R^2	0.050	0.060	0.099	0.099	0.223
N	23,790	23,790	23,714	21,500	21,240
Baseline Controls	N	N	N	N	N

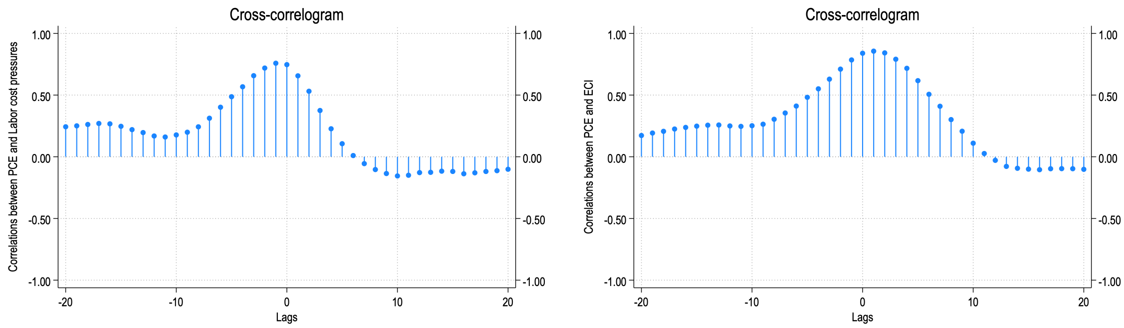
Notes: The table shows regression of changes in $log(Materials/Sales)_{i,t}$ on labor topics. Each observation denotes a firm i and year t. To construct labor topic observations at the firm x year level we take averages across all quarters in a year. All specifications include controls for yearly changes in $log(Sales)_{i,t}$ and changes in $log(Emp)_{i,t}$. Columns (4) and (5) include controls for risk and sentiment. We exclude firms in financial and administrative industries (NAICS 52, 53 and 56). We only include firm level data till 2019 to exclude Covid-19 pandemic period. Standard errors are clustered by firm. firm.

FIGURE A.2 – Labor Cost Pressure Index ($\bar{\omega}_t$) across Industries



Notes: The figures show the average change in estimated marginal cost of labor across firms by industry and by quarter. The estimation uses coefficients from Table III and topic specific scores by firm and by quarter. We then aggregate these by taking a sales weighted average across firms by industry and quarter.

Figure A.3 – Dynamics of Correlation with PCE, Labor cost pressures and ECI



Notes: This figure plots correlation of leads and lags of labor cost pressures rate and ECI with inflation observed at the quarter level.

Table A.5 – Labor Cost Pressures and Inflation, Industry x time Level

	PPI Inflation$_{n,(t-4,t)}$		
	(1)	(2)	(3)
Labor Cost Pressures$_{n,t}$	0.387*	0.642***	0.493**
	(0.227)	(0.234)	(0.241)
R^2	0.001	0.338	0.362
N	2,832	2,832	2,832
Industry FE	N	N	Y
Time FE	N	Y	Y

Notes: The table shows regression of PPI inflation observed in industry n between quarters and on estimated changes in MCL for industry in quarter . Industry is one of NAICS 3-digit industries. Estimated changes in MCL for industry in quarter is calculated by taking a sales weighted average of estimated changes in MCL across all firms in Compustat in the industry. We exclude financial and administrative industries (NAICS 52, 53 and 56). Regression is weighted by number of firms observed within the industry. Standard errors are clustered by industry. Inflation is winsorized at 2nd and 98th percentile.

Table A.1 – Top 20 keywords by topic

Topic	Keywords
headcount higher	training; hiring; hired; hire; staffing; recruiting; hires; recruitment; recruit; headcount increase; headcount growth; headcount increased; employees growth; employees increase; talent growth; headcount higher; employees increased; employees higher; headcount increases; workforce growth
headcount lower	headcount reduction; headcount reductions; headcount reduced; headcount down; headcount lower; layoffs; workforce reduction; employees down; employees reduction; headcount reduce; employees less; employees lower; furlough; workforce reductions; employees reduced; headcount reducing; furloughs; headcount decrease; employees reduce; workforce reduced
labor agreements	labor contract; labor contracts; labor agreement; employees contract; contractor contract; employees agreement; labor agreements; compensation agreement; labor union; labor negotiations; compensation contract; staff contract; contractors contract; employees contracts; contractors contracts; employees union; labor unions; employee contract; compensation contracts; personnel contract
labor costs higher	compensation increase; compensation higher; compensation increased; wage inflation; wage increases; compensation increases; labor costs higher; wage increase; salary increase; salary increases; salaries increase; wage higher; labor cost higher; labor costs increased; labor cost inflation; personnel costs increase; personnel expenses increase; labor costs increase; labor cost increase; wages increase
labor costs lower	compensation lower; compensation decrease; compensation reduction; compensation down; compensation decreased; compensation reduced; labor costs lower; compensation decline; labor cost lower; compensation reductions; bonus lower; compensation savings; compensation improvement; headcount cost reduction; wage lower; personnel costs lower; salaries lower; salary lower; headcount cost reductions; salary reductions
labor efficiency higher	labor productivity higher; labor productivity increase; labor productivity increased; labor efficiencies higher; headcount productivity growth; labor efficiency increase; labor efficiency higher; labor productivity increases; labor efficiencies increase; labor efficiencies increased; labor productivity growth; labor efficiency increased; employee productivity increase; headcount productivity increase; employee productivity increased; employee productivity higher; labor efficiencies growth; labor productivity increasing; employees productivity increase; labor efficiencies increases
labor efficiency lower	labor productivity lower; labor efficiencies lower; labor efficiency lower; labor inefficiencies higher; labor productivity reduce; labor productivity reduction; headcount efficiency reduction; labor efficiency reduce; labor productivity reduced; headcount efficiencies reductions; labor productivity down; headcount efficiencies reduction; labor efficiencies reduction; headcount efficiency reductions; headcount productivity reduction; labor productivity reductions; labor productivity reducing; labor efficiency reducing; labor efficiencies reductions; labor efficiency reduction
labor shortage	labor shortages; labor tight; labor shortage; labor constraints; staffing shortages; labor lack; labor tightness; labor tightening; labor tighter; staff shortages; labor constraint; labor scarcity; staff shortage; hiring tight; workers shortage; employees tight; staffing constraints; headcount tight; labor bottlenecks; staffing shortage

Notes: This table shows top 20 keywords used for each of our labor topics.

Table A.2 – Summary Stats

	Mean	SD	p1	p50	p99	N
Panel A: Firm x Quarter Level						
labor costs higher$_{i,t}$	0.17	0.34	0.00	0.00	1.52	248,437
labor shortage$_{i,t}$	0.02	0.12	0.00	0.00	0.53	248,437
headcount higher$_{i,t}$	0.10	0.26	0.00	0.00	1.19	248,437
labor efficiency higher$_{i,t}$	0.01	0.07	0.00	0.00	0.34	248,437
labor costs lower$_{i,t}$	0.13	0.28	0.00	0.00	1.23	248,437
headcount lower$_{i,t}$	0.08	0.24	0.00	0.00	1.11	248,437
labor efficiency lower$_{i,t}$	0.01	0.06	0.00	0.00	0.29	248,437
labor agreements$_{i,t}$	0.03	0.16	0.00	0.00	0.68	248,437
labor cost pressures$_{i,t}$	0.33	1.95	-5.81	0.23	6.07	248,437

Notes: This table shows summary statistics - mean, standard deviation, 1st percentile, median, 99th percentile and number of observations - for the firm x quarter level (in panel A), industry x quarter level (in panel B) and quarter level (in panel C) data used in empirical results.