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

—Preliminary and Incomplete. Do Not Circulate—

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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. A sales-weighted average of 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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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)) as 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 and 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. Our findings shed light on flattening of Phillips curve (e.g., Powell (2018); Del Negro *et al.* (2020)) before the pandemic as well as the steeping in the aftermath (Domash and Summers (2022)).

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 184,802 earnings call transcripts for about 5,000 US public companies between 2002 and 2024. About 85% of these earnings calls discuss labor relates issues.[1] During tight labor markets discussions are about hiring, higher labor costs and shortages, during recessions they shift to firing and reducing labor costs.

We first employ textual analysis to identify and classify labor-related discussions in earning call transcripts. To this end, we undertake a two-step approach based on our reading of earnings calls and then constructing dictionaries for automated clas-

[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.

sification (à la Hassan *et al.* (2020)). First, we sample and read excerpts to identify the following topics of labor-related discussions: 1) labor costs, 2) labor shortages, 3) headcount, 4) labor agreements, 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 identify a few seed keywords that are directly indicative of these topics such as "labor shortage", "labor costs", and "wage inflation". 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 instances of 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 their economic importance. 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 with a common production function equate marginal costs across all variable inputs to quantify the importance of various labor-related topics in driving marginal labor costs across firms.

Specifically, we estimate the contribution of a topic on marginal cost of labor by regressing firms' revenue shares of intermediate inputs on a function of $\Lambda_{it} = [\Lambda_{it}^{1}, \Lambda_{it}^{2}, ..., \Lambda_{it}^{8}]$ while controlling for firm and time fixed effects.[2] This approach serves a dual purpose. First, it translates our high-frequency qualitative measure from earnings calls into quantitative estimates of labor cost pressures (∇_{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 men-

[2]To isolate the cost effects of intermediate inputs separate from labor costs, we face a data limitation in Compustat, which only reports the combined cost of goods sold (COGS) but not intermediate inputs. So, we employ two alternative measurement approaches following the previous literature. We find remarkably similar results in both cases.

tioned 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 ∇_{it} with traditional aggregate indicators. Our index exhibits strong correlations with them, such as 0.80 with labor market tightness, –0.50 with unemployment rate, and 0.74 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 2.0. 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). When aggregated at the industry level, we find a strong and statistically significant relationship between increased labor cost pressures 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)). Our measure outperforms traditional labor market indicators—such as unemployment rates, labor market tightness, the output gap, and the ECI—in explaining inflation dynamics. 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 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 ∇_{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. In contrast, firms in non-routine industries respond by increasing their R&D investment along with their physical capital investment. 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. First, our paper is relevant to a large literature which uses the Phillips curve to forecast inflation. Famously, Stock and Watson (1999) showed that inflation forecasts produced by Phillips curve using unemployment as a measure of slack are more accurate than forecasts using other macroeconomic variables, such as interest rates and commodity prices. However, they noted that aggregate slack measures based on output perform better than the rate of unemployment. Re-

cent papers have argued for various other measures of slack in the output gap (Galí (2015), the job-switching rate (Moscarini and Postel-Vinay (2012)), and the vacancy–unemployment ratio (Barnichon and Shapiro (2024)). 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 when aggregated performs better than all of these measures on the aggregate. 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.

A second strand of literature has used textual analysis applied to earnings conference calls (Hassan *et al.* (2019, 2020, 2024, 2023)), SEC filings (Song and Stern (2024)and Buehlmaier and Whited (2018)) and newspapers (Baker *et al.* (2016)) to produce various indicators about the state of economy. We follow this literature in terms of methodology and develop a measure of labor cost pressures. Our approach involves constructing 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.

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.

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

TABLE I – Sample Excerpts from Earnings Calls

Firm	Score (SD)	Excerpt
Basic Energy Services Inc (2011)	7.81	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)	7.75	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)	13.4	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** labor market, did offset some of this progress.
Akumin Inc (2023)	12.85	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**.

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 download 470,652 transcripts of earnings conference calls held between 2002 and 2024 from S&P Global. For our baseline results, we focus on 184,802 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. 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.

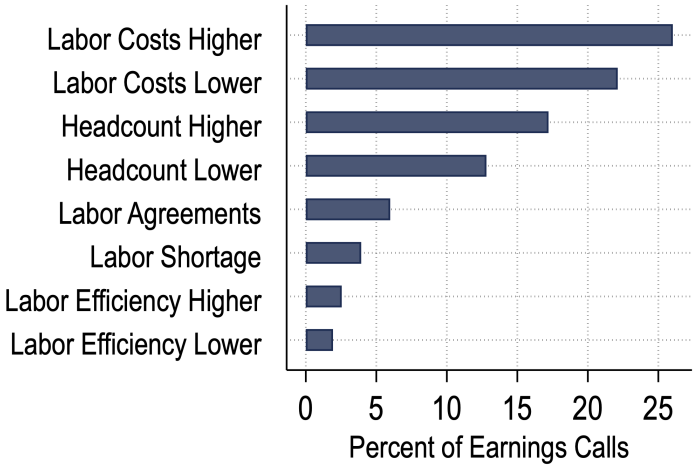
To label discussions of these automatically, we develop dictionaries for each topic. We began by identifying a small set of seed keywords that directly relate to each topic. For instance, for the topic of labor shortages, we started with words like labor and shortage. Similarly, for labor costs, we considered 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. In total, about 85% of earnings conference calls discuss labor-related terms. Table I shows sample excerpts from earnings calls that discuss labor issues. 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 49.60 percent of earnings conference calls, accounting for (49.60/85.0) 58.2 percent 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 44 percent 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 around 80% 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

FIGURE 1 – Percentage of Earnings Calls, by Topic

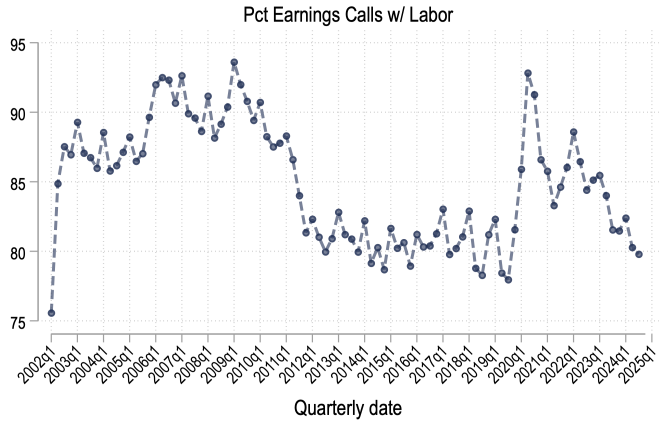


Notes: The figures show percentage of earnings calls by labor topic between 2002 and 2024.

of labor-related discussions spiking to over 90% in 2021, reflecting the unprecedented labor market disruptions during this period. After this spike, the percentage has gradually declined but remains volatile, suggesting ongoing labor market adjustments in the post-pandemic period. These patterns align with major economic events and demonstrate how the intensity of labor-related discussions in earnings calls reflects broader labor market conditions.

Figure A.1 provides a comprehensive view of how different labor-related topics are discussed in earnings calls from 2002 to 2024, broken down into our five aforementioned categories along with positive and negative mentions (except labor shortages), giving insight into the directional nature of firms' labor market experiences. The labor cost panels (top row) show notable spikes around the 2008-2009 financial crisis. Interestingly, while discussions of higher labor costs were elevated before the crisis, mentions of lower labor costs peaked during the financial crisis. The headcount panels (middle row) reveal similar patterns around the financial crisis but also show a marked asymmetry during the pandemic period—discussions of headcount reductions spiked dramatically in 2020, while mentions of headcount increases increased gradually after 2021. Perhaps most striking is the labor shortage panel at the bottom, which shows an unprecedented spike during the post-pandemic period of 2021-2022, reaching levels nearly four times higher than any previous period in the sample. This extraordinary

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



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

increase in labor shortage discussions aligns with widely reported hiring difficulties during the post-pandemic recovery and provides a unique perspective on the severity of recent labor market tightness.

These patterns across different labor-related topics and over time demonstrate the rich information content available in earnings calls and validate the our approach to measuring labor market pressures through textual analysis. The varying responses of different measures to major economic events suggest that each captures distinct aspects of labor market conditions, and their combination provides a more complete picture of the labor-related challenges firms face.

2.2 Validation of Labor Topic Discussions

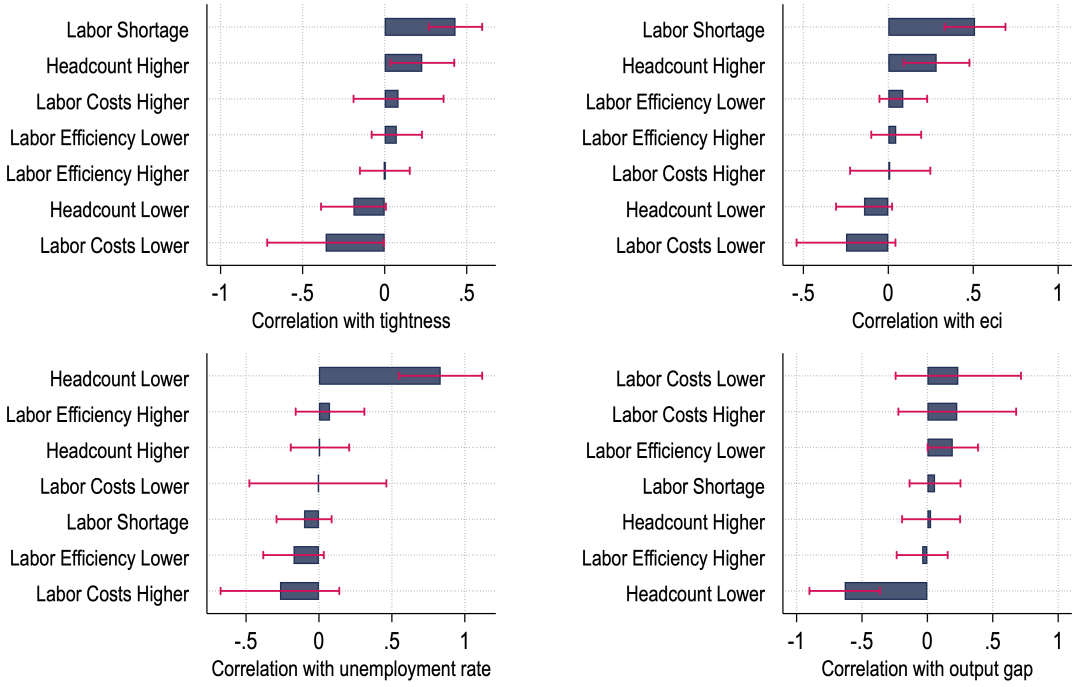
In this section, we validate our count of labor issues mentions by showing that they are consistent with other labor slack measures. Figure 3 presents a comprehensive analysis of how different labor-related discussions in earnings calls correlate with four key macroeconomic variables (along with 95% confidence bands): labor market tightness, the Employment Cost Index (ECI), the unemployment rate, and the output gap.

The top-left panel shows correlations with labor market tightness (vacancy-unemployment ratio). Labor shortages and discussions of higher headcount and labor costs show positive correlations with market tightness, while mentions of lower labor costs show a

strong negative correlation. This pattern aligns with economic intuition: when labor markets are tight, firms are more likely to discuss shortages and rising costs. The top-right panel, showing correlations with the ECI, reveals similar patterns, with labor shortages and higher labor costs showing strong positive correlations. This suggests that firms' discussions of labor issues in earnings calls align well with actual wage growth as measured by the ECI.

The bottom-left panel presents correlations with the unemployment rate, showing largely opposite patterns to the tightness correlations, as expected. Discussions of lower headcount and labor costs show positive correlations with unemployment, while labor shortages and higher costs show negative correlations.

FIGURE 3 – 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.

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.

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.)$_{j,t}$	0.927***	1.463***	0.421**
	(0.291)	(0.292)	(0.165)
Labor Costs Lower (std.)$_{j,t}$	–0.420*	–0.381	–0.535**
	(0.223)	(0.246)	(0.223)
Headcount Higher (std.)$_{j,t}$	0.770***	0.594***	0.323*
	(0.220)	(0.200)	(0.168)
Headcount Lower (std.)$_{j,t}$	–1.045***	–1.282***	–0.449**
	(0.239)	(0.268)	(0.199)
Labor Shortage (std.)$_{j,t}$	–0.017	0.021	0.228**
	(0.107)	(0.107)	(0.106)
Labor Efficiency Higher (std.)$_{j,t}$	0.066	0.245	0.005
	(0.171)	(0.169)	(0.127)
Labor Efficiency Lower (std.)$_{j,t}$	–0.331**	–0.253*	–0.103
	(0.149)	(0.151)	(0.096)
Labor Agreement (std.)$_{j,t}$	0.193	0.288***	0.074
	(0.130)	(0.108)	(0.089)
R^2	0.029	0.074	0.478
N	3,727	3,726	3,726
Time FE	N	N	Y
Industry FE	N	Y	Y

Notes: The table shows regression of changes in $log(Earnings)_{n,t}$on labor topics. 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 firm 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). Standard errors are clustered by industry.

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.

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 strong and 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 0.42 to 1.46 across specifications, all statistically significant. Conversely, mentions of lower labor costs are negatively associated with wage growth, with coefficients between -0.38 and -0.54. Similarly, discussions about increasing headcount show positive associations (coefficients 0.32 to 0.77), while decreasing headcount discussions show negative associations (coefficients -0.45 to -1.28). These results are robust across specifications and remain significant even with the inclusion of both time and industry fixed effects. The R-squared increases substantially from 0.031 to 0.484 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 show a consistently positive but modest relationship with wage growth, becoming significant only in specification (2) when industry fixed effects are included. 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:

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

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.[3] 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.

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

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 $\lambda_{i,t} = \frac{w_L\left(\bar{L}_{it}\right)L^*_{i,t}+C_{\bar{L}}\left(\bar{L}_{it}\right)}{\mu_{i,t}}$, 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 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 unity:

$$\log\left(P_{it}\right) = \underbrace{\log\left(\frac{\epsilon_{it}+1}{\epsilon_{it}}\right)}_{\eta_{it},\text{ Mark-up}} + \underbrace{\log\left(w\left(\bar{L}_{it}\right)+\lambda^L_{it}\right)}_{\text{Marginal cost of labor}} - \underbrace{\log\left(Y_{it}/L_{it}\right)}_{\text{Labor prod.}} - \underbrace{\log\left(\alpha^L_{it}\right)}_{\text{Elasticity}},$$

$$\Delta\log\left(P_{it}\right) = \Delta\log\left(w\left(\bar{L}_{it}\right)+\lambda^L_{i,t}\right) - \Delta\log\left(Y_{it}/L_{it}\right) - \Delta\log\left(\alpha^L_{it}\right) - \Delta\log\left(\eta_{it}\right) \quad (1)$$

where ϵ_{it} is the price elasticity of demand and $\alpha^L_{it} = \frac{\partial Y_{it}}{\partial L_{it}}\frac{L_{it}}{Y_{it}}$ 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 in earnings calls by translating these qualitative mentions into estimated changes in the marginal costs of labor, $\Delta\log\left(w\left(\bar{L}_{it}\right)+\lambda_{it}^L\right)$. In particular, we model changes in marginal cost of labor as a function of discussions of labor issues 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 $\nabla_{it} = f(\Lambda_{it})$ in the below equation:

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

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.

4 Estimating labor cost pressures, ∇_{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 shown 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.

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 (std.)$_{i,t}$	0.859***	0.687***	0.592***	0.583***	0.427***
	(0.114)	(0.113)	(0.117)	(0.122)	(0.140)
Labor Costs Lower (std.)$_{i,t}$	–0.824***	–0.857***	–0.876***	–0.819***	–0.629***
	(0.160)	(0.182)	(0.196)	(0.201)	(0.182)
Headcount Higher (std.)$_{i,t}$	0.125	0.097	0.206	0.293**	0.316**
	(0.139)	(0.137)	(0.134)	(0.142)	(0.150)
Headcount Lower (std.)$_{i,t}$	–0.645***	–0.595***	–0.554***	–0.543***	–0.302*
	(0.144)	(0.146)	(0.150)	(0.162)	(0.171)
Labor Shortage (std.)$_{i,t}$	0.260**	0.278**	0.216	0.267*	0.275**
	(0.129)	(0.135)	(0.140)	(0.147)	(0.136)
Labor Efficiency Higher (std.)$_{i,t}$	–0.089	–0.120	–0.123	–0.075	–0.135
	(0.101)	(0.100)	(0.102)	(0.104)	(0.112)
Labor Efficiency Lower (std.)$_{i,t}$	0.209**	0.227**	0.185*	0.123	0.037
	(0.104)	(0.104)	(0.104)	(0.107)	(0.116)
Labor Agreement (std.)$_{i,t}$	0.160	0.134	0.045	0.023	0.035
	(0.109)	(0.110)	(0.111)	(0.112)	(0.095)
R^2	0.099	0.108	0.112	0.113	0.227
N	28,195	28,195	28,194	25,463	25,305
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 $log(Materials/Sales)_{i,t}$ 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 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.

4.2 Labor cost pressures (∇_{it}) estimates

We regress firms' revenue shares of variable intermediate inputs on a flexible function of 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[4] for

[4]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 $MC_{i,t} = C_{i,t}A_{i,t}Y_{i,t}^{v}$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.

measurement error in reporting employment, and to account for changes in output elasticities—which have been shown to be functions of inputs and to vary over time (Hubmer *et al.* (2024)). We estimate equation 4 at the annual level using the following regression specification.

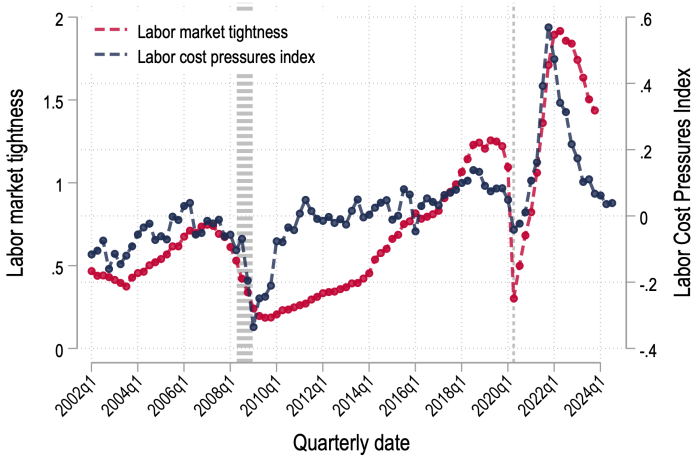
$$\Delta \log s_{i,t}^{M} = \underbrace{\sum_{k} \beta_{k}^{topic} \Lambda_{i,t}^{k}}_{\nabla_{it}} + \beta_1 \Delta log(Emp_{i,t}) + \beta_2 \Delta log(Sales_{i,t}) + \delta_{jt} + \varepsilon_{it}. \quad (5)$$

where $s_{i,t}^{M}$ 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.1). 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. Using these coefficients, we calculate the estimated change in marginal costs of labor using:

$$\nabla_{it} = \sum_{k} \hat{\beta}_{k}^{topic} \Lambda_{k,i,t} \quad (6)$$

FIGURE 4 – Labor Cost Pressure Index ($\bar{\nabla}_t$) and Labor Market Tightness



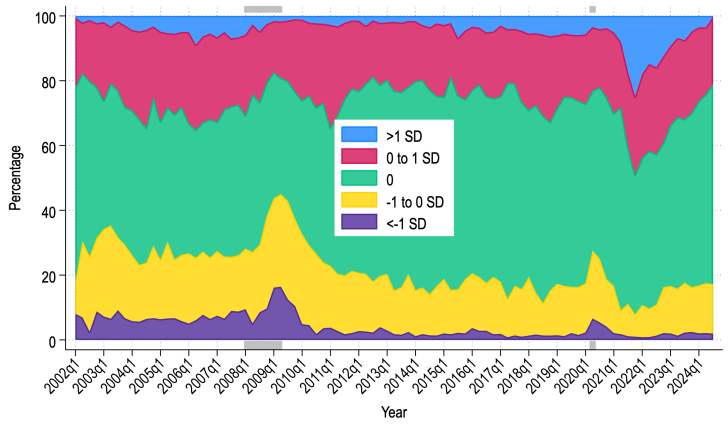
Notes: The figure shows the average change in estimated marginal cost of labor across firms by quarter. The estimation uses coefficients from Table III and topic specific scores by firm and by quarter.

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 labor efficiency are associated with lower cost pressures. Magnitudes of these coefficients exhibit interesting variations. Specifically, discussions of higher labor costs are consistently strongly associated with increases in the materials-to-sales ratio. The estimated coefficients range from 0.859 (s.e. = 0.114) in the baseline model without any controls to 0.427 (s.e.= 0.114) in our most restrictive specification that includes firm and time fixed effects. In our richest 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 -0.824 (s.e.=0.160) to -0.629 (s.e.=0.182). Higher and lower labor headcount is associated with increasing and decreasing materials-to-sales ratio.

Labor shortage discussions also emerge as a particularly robust predictor, with consistently positive and highly significant coefficients (around 0.216–0.275) across all specifications. This suggests that firms experiencing labor shortages tend to see increases in their cost ratios, even after controlling for various fixed effects and other

factors. Interestingly, labor efficiency and labor agreement discussions show generally small and statistically insignificant coefficients across all specifications.

FIGURE 5 – Distribution of Labor Cost Pressures across firms ($\bar{\nabla}_t$)



Notes: The figure shows the distribution of average 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.

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

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

We first construct an aggregate measure of labor cost pressures ($\bar{\nabla}_t$) by creating a sales-weighted average of our firm-level measure (∇_{it}) to validate it against traditional macroeconomic indicators. Figure 4 shows our aggregate index and the aggregate labor market tightness (measured as the ratio of job vacancies to unemployment, V/U). The time series plot demonstrates that both measures track each other closely throughout the sample period (2002-2024) with a striking correlation of 0.82 between two variables. They particularly co-move strongly during major economic events. Both measures show sharp declines during the 2008-2009 financial crisis and an unprecedented spike during the post-pandemic period of 2021-2022. The close relationship between these measures provides important validation for our textual-analysis approach, suggesting that discussions of labor issues in earnings calls effec-

tively capture the similar underlying labor market conditions measured by traditional vacancy-unemployment statistics.[5]

However, following a sharp but short-lived collapse during the Great Recession, our index remained persistently low throughout the subsequent recovery, while labor market tightness increased steadily during this period. Therefore, our measure aligns more closely with the observed flattening of the Phillips curve. Furthermore, our index surged dramatically during and after the COVID-19 pandemic, surpassing its pre-recession peaks, which corresponds closely with the steepening of the Phillips curve observed during this time. These result suggests that our labor cost pressure index captures critical information about labor market that conventional indicators might overlook.

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 (0.82) and the ECI (0.73). The strong 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 additional dimensions of labor market pressure beyond these variables can capture. This finding suggests our measure subsumes the information content of the ECI and other variables while providing additional insights into labor market conditions.

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

Tightness	Unemp. Rrate	Output gap	ECI
0.82***	–0.50***	0.46***	0.73***
(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

[5]However, our measure offers some advantages over the V/U ratio: it provides more granular firm-level variation and captures a broader range of labor market pressures beyond just hiring difficulties.

over time. Notably, for the majority of firms, labor cost pressures remain negligible, 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 increases significantly. 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.[6]

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

We also construct a labor cost pressures index at the industry level ($\bar{\nabla}_{n,t}$) by creating a sales-weighted average of our firm-level measure (∇_{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 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

[6]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.* (2024) show that the effects of Brexit varied largely by firm with large variation in winners, losers and unaffected firms.

period, consistent with widely reported healthcare worker shortages and increased labor costs.

5 Labor Cost Pressures and Inflation

5.1 Estimating pass-through to PPI inflation

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

$$\hat{P}_{i,t} = \beta_p \nabla_{it} - \hat{Y_{it}/L_{it}} - \hat{\alpha^L_{it}} - \hat{\eta_{it}},$$

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

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

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. In particular, we estimate the pass-through of our labor-cost pressure measures on to inflation using the following equation:

$$\hat{P}_{n,t} = \beta_p \hat{\nabla}_{nt} + \delta_n + \delta_t + \epsilon_{n,t}$$

where $\bar{\nabla}_{n,t}$ is the sales weighted average of ∇_{it} over firms in industry n at time t. $\hat{P}_{n,t}$ denotes PPI inflation between time t and t+4. $\delta_n$and $\delta_t$are industry and time fixed effects. 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 increase in interest rates. This could result in an increase in labor cost pressures and a subsequent fall in 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.

In our analysis we use a large panel of 3,359 industry-quarter observations (Table V). Our results show a consistently positive and significant relationship between industry-level labor cost pressures and subsequent PPI inflation across all specifications. The coefficient on the labor cost pressure measure ranges from 1.834 to 1.015, indicating that a one percentage point increase in labor cost pressures is associated with roughly 1.015-1.834 percentage points higher PPI inflation four quarters later. The relationship remains robust to the inclusion of both industry and time fixed effects, suggesting it is not driven by either industry-specific factors or common time trends and aggregate economic conditions. We interpret this number as the pass-through of labor cost pressures on inflation. Remember that on the aggregate during 2021-22, labor cost pressures increased by 0.61 percentage points. Given a passthrough ranging between 1.015 and 1.834, this implies that labor cost pressures can explain 0.62 to 1.12 percentage point increase in inflation during 2021-22.

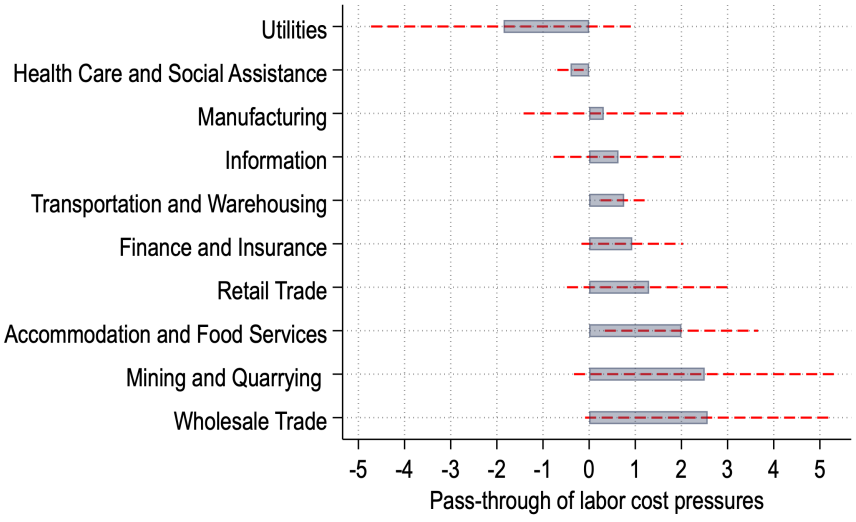
Figure 6 shows the interaction of coefficient in Table V column 4 with a dummy for ten NAICS 2-digit industries. Each coefficient shows the estimated pass-through of labor cost pressures across a range of industries, along with dashed lines which show corresponding the confidence interval. Notably, industries with high degree of regulation such as Utilities, and Health Care and Social Assistance exhibit lowest pass-through values. By contrast, industries with high labor shares such as Wholesale Trade (coef.=2.569), Retail Trade (coef. = 1.299), and Accommodation and Food Services (coef.=2.00) 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 show that automation is a significant factor.

TABLE V – Labor Cost Pressures and Inflation, Industry x time Level

	PPI Inflation$_{n,(t-4,t)}$			
	(1)	(2)	(3)	(4)
Labor Cost Pressures$_{n,t-4}$	1.834**	1.305**	1.628**	1.015**
	(0.802)	(0.618)	(0.626)	(0.489)
R^2	0.012	0.146	0.267	0.400
N	3,359	3,359	3,359	3,359
Industry FE	N	Y	N	Y
Time FE	N	N	Y	Y

Notes: The table shows regression of PPI inflation observed in industry n between quarters $t-4$ and t on estimated changes in MCL for industry n in quarter $t-4$. Industry is one of NAICS 3-digit industries. Estimated changes in MCL for industry n in quarter $t-4$ is calculated by taking a sales weighted average of estimated changes in MCL across all firms in Compustat who report their industry as n. 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.

FIGURE 6 – Pass-through of labor cost pressures by Industry

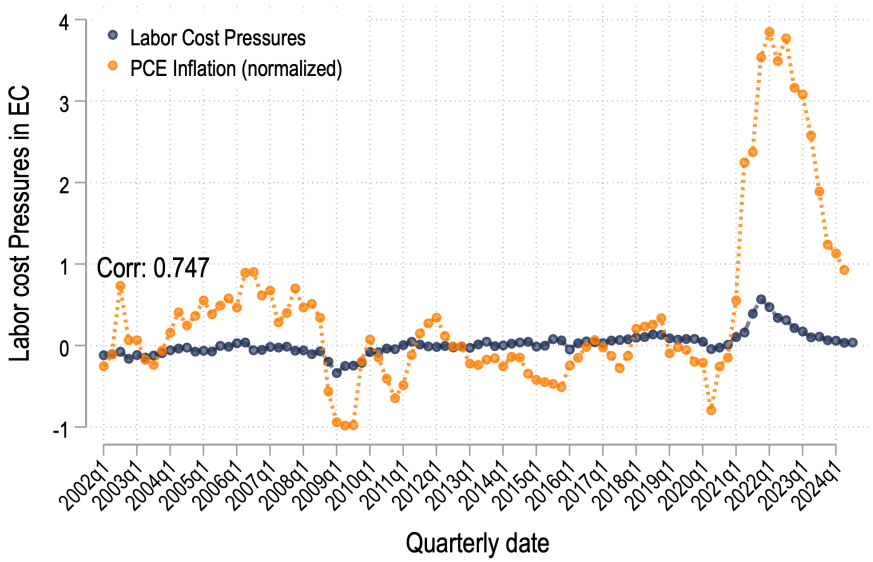


Notes: The figure plots estimated pass-through of labor cost pressures by 2-digit NAICS industry. The plot shows estimates and 95% confidence intervals. Standard errors are clustered by industry.

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, ∇_{it}. Figure 7 compares the evolution of the aggregate labor cost pressure index ($\bar{\nabla}_t$) (shown in blue) with PCE inflation (shown in orange) from 2002 to 2024, with both series standardized for comparison. The high correlation coefficient of 0.747 between the two series suggests a strong relationship between labor cost pressures and inflation dynamics. Our measure can capture the significant decline in inflation during the 2008-2009 financial crisis, followed by a period of relative stability from 2010 to 2019, where both measures remained close to their historical averages with limited volatility.

FIGURE 7 – Labor Cost Pressure and PCE Inflation



Notes: The figures show the average change in estimated marginal cost of labor across firms by quarter. We then aggregate these by taking a sales weighted average across firms by quarter. Inflation is normalized by its sample average of 1.7% before 2019 (PCE - 1.7%).

The most striking feature of the graph is the unprecedented spike in both series during the post-pandemic period (2020-2022). The labor cost pressure index shows a sharp increase that slightly precedes the surge in PCE inflation, reaching levels approximately five standard deviations above its historical mean. This leading relationship suggests that the labor cost pressure index might serve as an early indicator of inflationary pressures. The subsequent decline in labor cost pressures starting in late 2022 also appears to lead the moderation in PCE inflation, though both measures remain above their pre-pandemic levels in the most recent data.

This visualization provides compelling evidence that labor market pressures, as captured through earnings call discussions, may help predict inflation. 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:

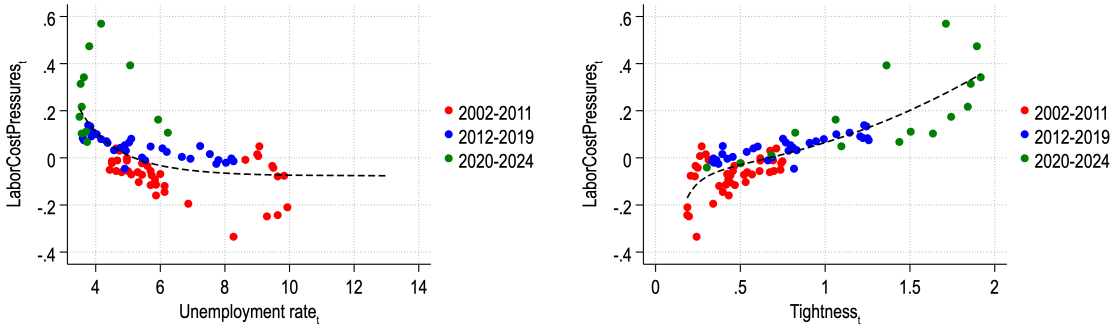
$$\pi_t = \alpha + \beta_x \hat{x}_{t-h} + \beta_\pi E_t \pi_\infty + v_t,$$

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, and $\hat{x}_{t-h}$ is the deviation from the steady state average of a forcing variable for $h = 4$. We standardize all the push variables ($\hat{x}_{t-h}$) by their standard deviation, so that the coefficients are comparable. Along with our measure of labor cost pressures ($\bar{\nabla}_t$), 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 2002-2024Q1.

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 helps control for the forward-looking component of price setting.

Panel A in Table VI shows individual regressions for each forcing variable. The

FIGURE 8 – Correlation with unemployment rate, tightness and inflation



Notes: This figure plots unemployment rate, tightness and inflation observed at the quarter level against labor cost pressures.

labor cost pressure measure exhibits the strongest relationship with future inflation, with a coefficient of 0.595 that is highly significant at the 1% level. The R-squared of 0.338 is substantially higher than those of competing measures, indicating better explanatory power. Labor market tightness also shows a significant positive relationship (0.595), while unemployment shows the expected negative relationship (-0.243). The output gap performs poorly, with an insignificant coefficient and the lowest R-squared (0.037).

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 0.595 to 0.665) even when controlling for other measures. Importantly, when included alongside the labor cost pressure measure, the traditional forcing variables become statistically insignificant, and their coefficients often change signs (for example, unemployment becomes positive and insignificant). The R-squared values remain stable around 0.37-0.38, suggesting that adding traditional measures provides little additional explanatory power beyond what is captured by the labor cost pressure measure.

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 8 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 VI – Phillips Curve Estimation

Panel A: Push variables and Inflation				
	PCE Inflation$_{t,t+4}$			
	(1)	(2)	(3)	(4)
Labor Cost Pressures$_t$	0.595***			
	(0.089)			
Tightness$_t$ (std.)		0.533***		
		(0.115)		
Unemployment Rate$_t$ (std.)			–0.243***	
			(0.072)	
Output Gap$_t$ (std.)				0.153
				(0.153)
Inflation Expectations$_t$ (std.)	0.280	0.334	0.397	0.249
	(0.259)	(0.286)	(0.300)	(0.273)
Constant	–0.897	–2.247	–1.522	–0.417
	(2.751)	(3.090)	(3.044)	(2.801)
R^2	0.338	0.237	0.075	0.037
N	84	84	84	84

Panel B: Comparison with Labor Cost Pressures				
	PCE Inflation$_{t,t+4}$			
	(1)	(2)	(3)	(4)
Labor Cost Pressures$_t$	0.595***	0.611***	0.624***	0.665***
	(0.089)	(0.167)	(0.105)	(0.099)
Tightness$_t$ (std.)		–0.021		
		(0.159)		
Unemployment Rate$_t$ (std.)			0.057	
			(0.075)	
Output Gap$_t$ (std.)				–0.166
				(0.128)
Inflation Expectations$_t$ (std.)	0.280	0.278	0.256	0.332
	(0.259)	(0.264)	(0.266)	(0.229)
Constant	–0.897	–0.847	–0.780	–1.567
	(2.751)	(2.893)	(2.782)	(2.403)
R^2	0.338	0.338	0.341	0.356
N	84	84	84	84

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 sales 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.

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 ∇_{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.

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

	log(Capital Exp.$_{i,t}$) * 100					
	All			LRM	MRM	HRM
	(1)	(2)	(3)	(4)	(5)	(6)
Labor Cost Pressures (std.)$_{i,t}$	3.276***	3.732***	2.764***	2.866***	2.015***	3.732***
	(0.610)	(0.473)	(0.332)	(0.715)	(0.403)	(0.498)
R^2	0.804	0.849	0.951	0.934	0.955	0.950
N	125,784	125,784	125,758	30,203	56,103	39,247
Controls (Risk and Sentiment)	Y	Y	Y	Y	Y	Y
Industry FE	N	Y	N/A	N/A	N/A	N/A
Time FE	Y	Y	Y	Y	Y	Y
Firm FE	N	N	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.

We start with examining how firms adjust their capital expenditure in response to

labor cost pressures, with a particular focus on heterogeneity across industries with different levels of routine manual task intensity (Table VII). The baseline specification (column 1) indicates that a one standard deviation increase in labor cost pressures is associated with a 4.06% increase in capital expenditure. This effect remains significant but moderates to 1.68% in the most demanding specification with firm and time fixed effects (column 3). 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 4-6 reveal interesting heterogeneity across industry types based on their routine manual task intensity (see also Figure A.4). High routine manual (HRM) industries show the strongest investment response to labor cost pressures (1.692%), followed by low routine manual (LRM) industries (1.141%), while medium routine manual (MRM) industries show the smallest response (0.702%). 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 VIII). 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 standard deviation increase in labor cost pressures associated with a 2.812% increase in R&D expenditure in the baseline specification, rising to 3.693% when including industry fixed effects, and moderating to 1.056% in the specification with firm fixed effects.

TABLE VIII – Labor Cost Pressures and R\& D expenditures, Firm x time Level

	log(R&D Exp.$_{i,t}$) * 100			
	All	LRM	MRM	HRM
	(1)	(2)	(3)	(4)
Labor Cost Pressures (std.)$_{i,t}$	0.879**	1.420**	0.372	0.687
	(0.376)	(0.702)	(0.480)	(0.735)
R^2	0.966	0.965	0.972	0.959
N	49,891	15,039	20,839	13,996
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(R&D 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 and sentiment. We exclude firms in financial and administrative industries (NAICS 52, 53 and 56). Standard errors are clustered by firm.

The industry heterogeneity analysis (columns 4-6) reveals a pattern that contrasts sharply with the capital expenditure results. LRM industries show the strongest and only statistically significant response, with a 1.723% increase in R&D spending for a one standard deviation increase in labor cost pressures. MRM and HRM industries show smaller and statistically insignificant responses (0.834% and 0.584% respectively). This pattern suggests that firms in industries with less routine manual work are more likely to respond to labor cost pressures by increasing R&D investment, possibly reflecting their focus on innovation and process improvements rather than direct automation.

The dramatic increase in R-squared values from the baseline (0.051) to specifications with firm fixed effects (>0.917) suggests that firm-specific factors play a crucial role in determining R&D responses to labor cost pressures. 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.

We further investigate firms' automation decision in earnings calls in response to labor cost pressures.[7] For this purpose, we again employing textual analysis to identify discussions of automation in earning call transcripts. Table IX shows how labor cost pressures relate to firms' discussions of automation in their earnings calls, providing direct evidence of firms' technological responses to labor market challenges. The analysis uses a dummy variable for automation mentions as the dependent variable and examines this relationship across different industry types based on routine manual task intensity. For the full sample (column 1), the results show that a one standard deviation increase in labor cost pressures is associated with a 0.293 percentage point increase in the probability of automation being mentioned in earnings calls, an effect that is highly statistically significant. This finding suggests that firms actively consider automation as a response to labor cost pressures.

The industry-level analysis (columns 2-4) reveals a striking pattern that aligns with economic intuition. HRM industries show the strongest response, with a 0.624 percentage point increase in automation mentions for a one standard deviation increase in labor cost pressures. This effect is more than twice the size of the full sample effect and highly significant. In contrast, medium routine manual MRM industries show virtually no response (0.025), while LRM industries show a moderate but insignificant response (0.310). This pattern suggests that firms in industries with more routine manual tasks are more likely to consider automation when facing labor cost pressures, presumably because their production processes are more amenable to automation.

These findings, combined with the earlier results on capital expenditure and R&D, paint a coherent picture of firms' technological responses to labor cost pressures: firms in high routine manual industries respond through automation and capital investment, while those in low routine manual industries tend to favor R&D investments, possibly reflecting the different technological opportunities available to them.

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

[7] Leduc and Liu (2024) develop a business cycle model with labor market search frictions, generalized to incorporate automation decisions to show that automation is procyclical.

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 2% 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.

TABLE IX – Labor Cost Pressures and Automation mentions, Firm x time Level

	Automation mention dummy $_{i,t}$ * 100			
	All	LRM	MRM	HRM
	(1)	(2)	(3)	(4)
Labor Cost Pressures (std.)$_{i,t}$	0.276**	0.445**	–0.063	0.546**
	(0.124)	(0.226)	(0.193)	(0.235)
R^2	0.410	0.461	0.390	0.387
N	139,437	33,926	62,278	43,002
Controls (Risk and Sentiment)	Y	Y	Y	Y
Industry FE	N/A	N/A	N/A	N/A
Time FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y

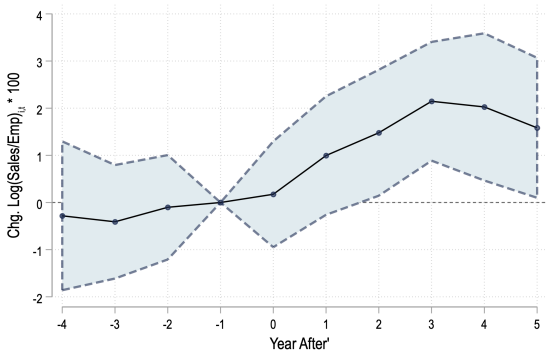
Notes: The table shows regression of changes in $Automation_{i,t}$on labor topics at the firm x quarter level. $Automation_{i,t}$ is a dummy which calculates if any earnings conference call during the next four quarters (between t and t +3) mentions one of automation keywords. Each observation denotes a firm i and year t. All columns include controls for risk and sentiment. We exclude firms in financial and administrative industries (NAICS 52, 53 and 56). Standard errors are clustered by firm.

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

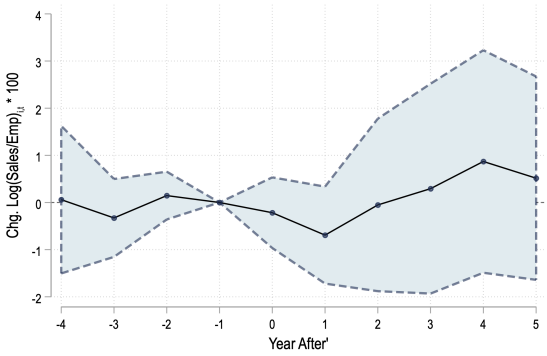
responses to labor cost pressures into actual productivity gains, likely through successful automation and capital-labor substitution.

FIGURE 9 – Productivity response to labor cost pressures, firm x time level

(A) High Routine Manual



(B) Low Routine Manual



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, while LRM firms invest in R&D but struggle to achieve short-term productivity improvements. 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, while firms in non-routine industries invest in R&D but see limited short-term productivity improvements.

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.

References

Acemoglu, D. and Autor, D. H. (2011). Skills, tasks and technologies: Implications for employment and earnings. *Handbook of Labor Economics*, **4**, 1043–1171. 6

— and Restrepo, P. (2022a). Demographics and automation. *The Review of Economic Studies*, **89** (1), 1–44. 6

— and — (2022b). Tasks, automation, and the rise in us wage inequality. *Econometrica*, **90** (5), 1973–2016. 1

Baker, S. R., Bloom, N. and Davis, S. J. (2016). Measuring economic policy uncertainty. *The quarterly journal of economics*, **131** (4), 1593–1636. 1

Barnichon, R. and Shapiro, A. H. (2024). Phillips meets beveridge. *Journal of Monetary Economics*, **148**, 103660. 1, 5.2

Buehlmaier, M. M. and Whited, T. M. (2018). Are financial constraints priced? evidence from textual analysis. *The Review of Financial Studies*, **31** (7), 2693–2728. 1

Del Negro, M., Lenza, M., Primiceri, G. E. and Tambalotti, A. (2020). What's up with the phillips curve? *Brookings Papers on Economic Activity*, **2020** (Spring), 301–373. 1

Demirer, M. (2022). Production function estimation with factor-augmenting technology: An application to markups. 4.1, 4.2

Domash, A. and Summers, L. H. (2022). *How tight are US labor markets?* Tech. rep., National Bureau of Economic Research. 1

Drechsel, T., McLeay, M. and Tenreyro, S. (2019). Monetary policy for commodity booms and busts. 5.1

Fitzgerald, T. J., Nicolini, J. P. *et al.* (2014). *Is there a stable relationship between unemployment and future inflation?: Evidence from US cities*. Citeseer. 5.1

Gagliardone, L., Gertler, M., Lenzu, S. and Tielens, J. (2023). *Anatomy of the Phillips curve: micro evidence and macro implications*. Tech. rep., National Bureau of Economic Research. 4

Galí, J. (2015). *Monetary policy, inflation, and the business cycle: an introduction*

to the new Keynesian framework and its applications. Princeton University Press. 1

Gandhi, A., Navarro, S. and Rivers, D. A. (2020). On the identification of gross output production functions. *Journal of Political Economy*, **128** (8), 2973–3016. 3

Gormsen, N. J. and Huber, K. (2024). *Firms' Perceived Cost of Capital*. Tech. rep., National Bureau of Economic Research. 1

Gosselin, M.-A. and Taskin, T. (2024). *Textual Economic Indicators for Canada and the United States: Insights From Earnings Calls*. Tech. rep., Bank of Canada Staff Discussion Paper. 1

Graetz, G. and Michaels, G. (2018). Robots at work. *Review of economics and statistics*, **100** (5), 753–768. 1

Harford, J., He, Q. and Qiu, B. (2024). Firm-level labor-shortage exposure. *Available at SSRN 4410126*. 1

Hassan, T. A., Hollander, S., Van Lent, L. and Tahoun, A. (2019). Firm-level political risk: Measurement and effects. *The Quarterly Journal of Economics*, **134** (4), 2135–2202. 1, 6

—, —, — and — (2020). *The global impact of Brexit uncertainty*. Tech. rep., National Bureau of Economic Research. 1

—, —, van Lent, L. and Tahoun, A. (2023). Firm-level exposure to epidemic diseases: Covid-19, SARS, and H1N1. *Review of Financial Studies*, **34** (6), 2409–2449. 1

—, —, — and — (2024). The global impact of Brexit uncertainty. *Journal of Finance*, **79**, 413–458. 1, 6

Hazell, J., Herreno, J., Nakamura, E. and Steinsson, J. (2022). The slope of the phillips curve: evidence from us states. *The Quarterly Journal of Economics*, **137** (3), 1299–1344. 5.1

Heise, S., Karahan, F. and Şahin, A. (2022). The missing inflation puzzle: The role of the wage-price pass-through. *Journal of Money, Credit and Banking*, **54** (S1), 7–51. 5.1

Hubmer, J., Chan, M., Ozkan, S., Salgado, S. and Hong, G. (2024). *Scalable versus Productive Technologies*. Tech. rep., Penn Institute for Economic Research, Department of Economics, University of Pennsylvania. 4.2

Karabarbounis, L. and Neiman, B. (2014). The global decline of the labor share. *The Quarterly journal of economics*, **129** (1), 61–103. 6

Keller, W. and Yeaple, S. R. (2009). Multinational enterprises, international trade, and productivity growth: firm-level evidence from the united states. *The review of economics and statistics*, **91** (4), 821–831. 4.1

Krusell, P., Ohanian, L. E., Ríos-Rull, J.-V. and Violante, G. L. (2000). Capital-skill complementarity and inequality: A macroeconomic analysis. *Econometrica*, **68** (5), 1029–1053. 6

Leduc, S. and Liu, Z. (2024). Automation, bargaining power, and labor market fluctuations. *American Economic Journal: Macroeconomics*, **16** (4), 311–349. 6, 7

Moscarini, G. and Postel-Vinay, F. (2012). The contribution of large and small employers to job creation in times of high and low unemployment. *American Economic Review*, **102** (6), 2509–2539. 1

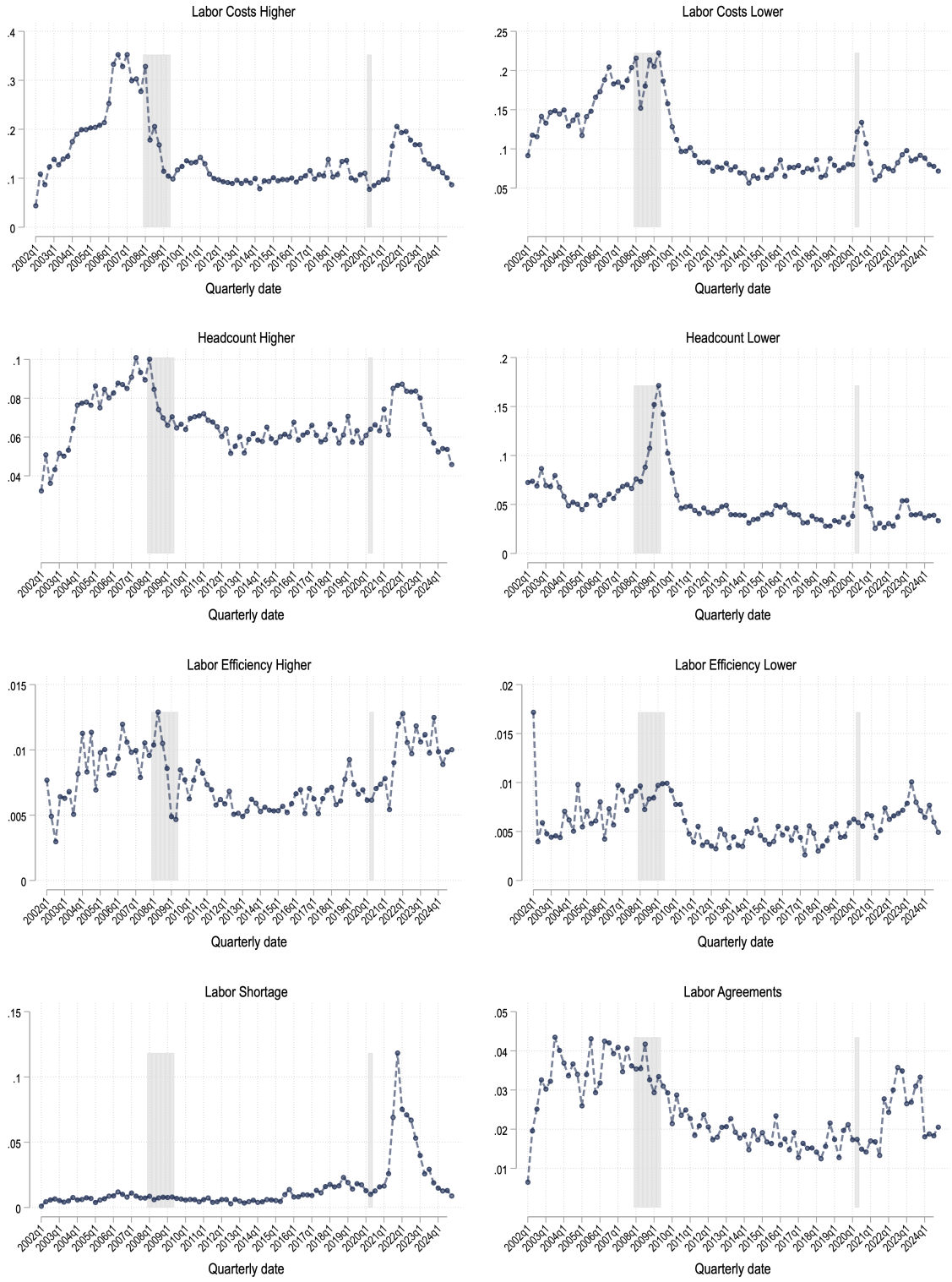
Phillips, A. W. (1958). The relation between unemployment and the rate of change of money wage rates in the united kingdom, 1861-1957. *economica*, **25** (100), 283–299. 1

Powell, J. H. (2018). Monetary policy and risk management at a time of low inflation and low unemployment. *Business Economics*, **53**, 173–183. 1

Song, W. and Stern, S. (2024). Firm inattention and the efficacy of monetary policy: A text-based approach. *Review of Economic Studies*, p. rdae102. 1

Stock, J. H. and Watson, M. W. (1999). Forecasting inflation. *Journal of monetary economics*, **44** (2), 293–335. 1

FIGURE A.1 – Discussion of Labor Topics over Time



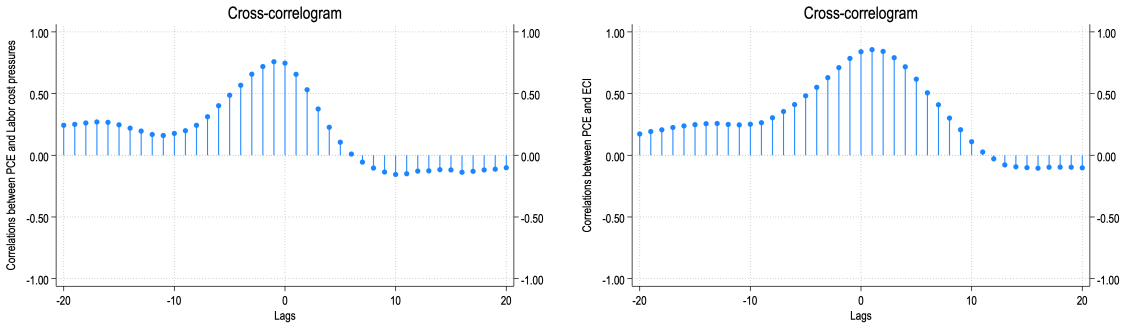
Notes: The figures show the average percentage of sentences about a labor topic mentioned in earnings calls by quarter.

TABLE A.1 – 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.

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.

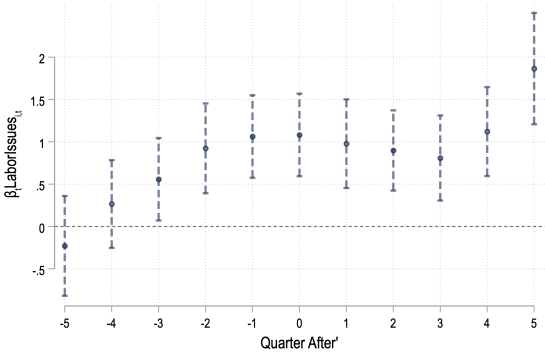
FIGURE A.2 – Labor Cost Pressure Index ($\bar{\nabla}_t$) across Industries



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.4 – Investment response to labor cost pressures, firm x time level

(A) High Routine Manual



(B) Low Routine Manual

