Firm-Level Labor-Shortage Exposure*

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Abstract

We use *FinBERT* to extract information from earnings conference call transcripts to develop a novel and reliable measure of labor-shortage exposure. We demonstrate the validity of the measure by showing that states with higher levels of labor-shortage exposure experience lower future unemployment rates but higher wage growth and local labor market tightness, while firms with higher labor-shortage exposure have greater growth in future per-employee staff expenses. Firms with labor-shortage exposures experience lower earnings call CARs, future stock returns and operating performance. Firms respond to labor shortages by substituting labor with capital and R&D investments, and by producing more production-process patents. Such measures mitigate the negative effects on future performance. Our results demonstrate a fruitful application of machine learning to finance and provide insight into labor-capital substitution in response to increasingly expensive and scarce labor.

Keywords: Labor-shortage Exposure, Machine Learning, *FinBERT*, Stock Returns, Operating Performance, Corporate Investment, Process Patent, COVID-19 Crisis

JEL classification: G12, G30, J2

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"*As anyone who has lost luggage or waited half an hour for a restaurant check can tell you, America needs way more workers in some parts of the economy.*"

— Gwynn Guilford, *August 14, 2022, The Wall Street Journal*

1 Introduction

Labor shortages are an increasingly pressing concern for firms, often driving up labor costs and impacting operations and financial performance. However, accurately measuring firm-level exposure to labor shortages is challenging due to data limitations, and no reliable measure currently exists in the literature. This paper proposes a novel approach using finance-specialized machine learning techniques to develop a comprehensive and reliable measure of labor-shortage exposure for a broad sample of U.S. firms. Our findings reveal the significant effects of labor-shortage exposure on firm performance and decision-making, showing how exposed firms adjust investment strategies and their capital-labor mix in response. These insights provide valuable guidance for firms and policymakers to better anticipate and mitigate the impact of labor shortages in an evolving labor market.

We use earnings conference call transcripts to capture a firm's exposure to labor shortages. Earnings conference calls typically take place quarterly after a public firm releases its financial results for the previous quarter. Such conference calls provide a forum for the firm to update investors and analysts on its financial performance and outlook. They also provide an opportunity for investors and analysts to ask questions and gain a deeper understanding of the firm's business and financial prospects. Because of the high volume of firm-level information contained in earnings conference calls, a growing strand of literature uses earnings conference call transcripts to measure a firm's material exposures, such as political risk (Hassan et al., 2019), corporate culture (Li et al., 2021), and climate change (Li et al., 2023; Sautner et al., 2023). Thus, we expect earnings conference call transcripts to be superior text data in capturing labor-shortage-related discussions from corporate executives.

To measure a firm's exposure to labor shortages, we split each transcript into sentences.

We then employ an advanced machine learning model, *FinBERT* (Huang et al., 2023), to help us efficiently identify whether a sentence is labor-shortage-related or not.[1] Our fine-tuned *FinBERT* model achieves an impressive 95% accuracy rate in detecting labor-shortage-related sentences. Based on the labor-shortage-related sentences identified by our machine learning model, we construct a firm-level measure of labor-shortage exposure for all U.S. public firms with available earnings conference call transcripts each year during the 2005-2021 period. After requiring non-missing stock returns and financial data, our final sample consists of 25,551 firm-year observations related to 100,588 earnings conference call transcripts and 3,829 unique firms.

To verify the reliability of our measure, we conduct various validation tests. First, we observe that the economy-wide aggregate labor-shortage exposure attained its highest level in 2021 due to the COVID-19 pandemic's impact on the labor market. Second, we rank the measure by 2-digit SIC industry and find that the construction, transportation, and service sectors are the most susceptible to labor shortages, given their labor-intensive nature. Third, we aggregate the firm-level measure to the state-level and find a negative (positive) relationship between state-level labor-shortage exposure and the state's future unemployment rate (the state's future wage growth and local labor market tightness), which aligns with economic theory (e.g., Dwayne et al., 2002). Fourth, we observe a positive relationship between the measure of firm-level labor-shortage exposure and a firm's future growth in per-employee staff expenses, which include wages and employee benefits.

Additionally, we exploit the 2017 U.S. immigration policy reforms, which almost halved annual foreign labor migration, as a quasi-natural experiment. We find that relative to capital-intensive firms, labor-intensive firms significantly increased their labor-shortage exposure following the immigration policy changes, further validating the measure. Finally, we leverage the variation in the stringency of state-level COVID-19 lockdown policies that primarily re-

[1] *FinBERT* is a machine learning model built upon *BERT* (Devlin et al., 2018). *BERT* is pretrained using a large amount of text data and can understand syntax and semantics of English language well, while *FinBERT* is finance-specialized model trained using financial text data (e.g., 10-K filings and earnings conference call transcripts). Huang et al. (2023) document that *FinBERT* yields better performance than *BERT* in detecting sentence sentiment and environmental, social, and governance (ESG) sentences in financial contexts. Please see section 3 for more information.

strict people's behavior during the COVID-19 health crisis. We find that a state's COVID-19 lockdown stringency significantly heightens local firms' labor-shortage exposure.

After validating the measure, we next investigate its implications. We find that firms with labor-shortage exposure experience significantly lower cumulative abnormal returns (CAR) within the three days following the earnings conference calls. Further, our measure robustly and negatively predicts one-year-ahead stock returns and corporate operating performance in the cross-section. Specifically, a one-standard-deviation increase in firm-level labor-shortage exposure, on average, predicts a 1.09-percentage-point lower one-year-ahead annual stock return, a 0.225-percentage-point decline in one-year-ahead return on assets (ROA), and a 0.156-percentage-point reduction in one-year-ahead operating cash flow. These findings suggest that exposure to labor shortages has significant implications on cross-sectional future stock returns and operating performance.

Next, we show that a firm's labor-shortage exposure has a positive (negative) relationship with its one-year-ahead capital expenditures and R&D expenses (change in the number of employees per million dollars of assets), implying that firms exposed to labor shortages substitute increasingly scarce and costly labor with capital. Our finding based on firm-level labor-shortage exposure complements the finding of Geng et al. (2022), who show that minimum wage policies prompt firms to increase capital investment as a substitute for labor.

Further, we find that exposure to labor shortages leads firms to pursue more production-process innovations to improve their production efficiency. Specifically, we show that firm-level labor-shortage exposure is positively related to a firm's production-process patent outputs in the next three years, while the relation between labor-shortage exposure and non-process patent outputs is statistically insignificant. These results suggest that firms exposed to labor shortages seek to develop more process patents in the future to improve their production efficiency and support their labor-capital substitution. These findings based on labor-shortage exposure are consistent with those of Bena et al. (2022) that increased labor dismissal costs lead firms to increase their process innovations and decrease their reliance on labor.

After observing that firms respond to labor-shortage exposure by increasing capital and

R&D expenses, as well as generating more production-process patents in the future, we next investigate whether these policy responses can help improve exposed firms' future stock performance. Our analysis reveals that increasing capital expenditure and/or process innovations helps mitigate the negative effect of labor-shortage exposure on firms' future stock performance. These findings suggest that replacing labor with capital and increasing process innovation are effective ways to deal with labor shortages.

A potential concern is that unobserved firm-level factors could simultaneously influence both a firm's exposure to labor shortages and its subsequent performance and investment decisions, leading to spurious correlations. To address this concern, we first replace the firm-year-level labor shortage measure with an industry-year-level measure in our analyses. Our results remain consistent: firms in industries highly exposed to labor shortages experience significantly lower stock returns and operating performance in the following year. These firms also respond by substituting labor with capital and R&D investments, as well as producing more process innovation outputs.

Second, we apply a Bartik shift-share instrumental-variable approach to isolate plausibly exogenous variation in firms' labor-shortage exposure (Bartik, 1991; Goldsmith-Pinkham et al., 2020). Specifically, we leverage the evolution of labor-shortage issues across different industries over time, which affects firms differently based on their preexisting industrial sales shares. The instrument, calculated as the inner product of common industry trends in labor shortages and a firm's industry segment sales shares, isolates firm-level variation in labor-shortage exposure from other firm characteristics. As expected, the first-stage regression results show a positive and significant relationship between the instrument and firm-level labor-shortage exposure. The second-stage results indicate that instrumented firm-level labor-shortage exposure continues to negatively impact future performance and leads firms to substitute capital and process innovations for labor. While it is impossible to prove causality, our findings, taken together, severely restrict the space for plausible alternative explanations.

We conduct multiple tests to verify the robustness of our findings. These tests include 1) excluding the COVID-19 period (2020 and 2021) from the analysis, 2) comparing the extensive and intensive margins of firm-level labor-shortage exposure on future stock returns, operating performance, and firm policy responses, 3) reconstructing the firm-level labor-shortage exposure using either the management presentation section or Q&A section of the earnings conference call transcripts,[2] 4) replacing the raw buy-and-hold stock returns of a firm with the Fama-French three-factor-adjusted or five-factor-adjusted stock returns, and 5) controlling for CEO fixed effects when investigating firm policy responses to labor shortages. We obtain qualitatively similar results across all these robustness tests. Importantly, we show that firms that are more geographically dispersed can partially alleviate the negative impact of labor-shortage exposure on future stock returns and operating performance, and that it is repeated exposure to labor shortages that leads firms to decrease their labor inputs and increase their investments in capital expenditures and process innovations.

Finally, we investigate the differential impact of the COVID-19 pandemic on the stock returns and operating performance of firms with labor-shortage exposure prior to the pandemic and those that were not. We find that the exposed firms experienced significantly lower stock returns and operating performance compared to the non-exposed firms during the pandemic. Thus, firms with greater preexisting exposure to labor shortages fared far worse during the pandemic.

Our study contributes to three strands of literature. First, it contributes to the literature on textual analysis in finance (e.g., Loughran and McDonald, 2011; Garcia and Norli, 2012; Hoberg and Phillips, 2016; Gentzkow et al., 2019; Florackis et al., 2023). Prior literature uses "bag-of-words" (keyword dictionary) approach to measure different topics of interest such as economic policy uncertainty (Baker et al., 2016), corporate epidemic disease exposure (Hassan et al., 2023a) and geopolitical risk (Caldara and Iacoviello, 2022). An emerging literature adopts machine learning techniques to broaden the scope of the dictionary. For example, Li et al. (2021)

[2] A potential concern is that managers may exaggerate or hide their firms' labor-shortage issues during conference calls. If managers were systematically manipulating their labor-shortage-related discussions in conference calls, then our measure would mainly capture such manipulations rather than the firm's true labor-shortage exposure. All of our validation and economic outcome tests suggest this is not the case. The fact that our results are also robust to using the Labor Shortage measure constructed from either the managerial presentation section or the Q&A section (Q&A is arguably more difficult to manipulate than managerial presentation) of the conference call further supports the validity of the measure.

apply *Word2vec* model to measure corporate culture. Sautner et al. (2023) adopt a keyword discovery algorithm to measure firm-level climate change exposure. This study leverages an advanced machine learning technique, *FinBERT*, to measure firm-level labor-shortage exposure from earnings conference call transcripts.

Second, the study contributes to the literature on the implications of labor frictions on firms (e.g., Danthine and Donaldson, 2002; Chen et al., 2012; Donangelo, 2014; Petrosky-Nadeau et al., 2018; Donangelo et al., 2019; Bena et al., 2022; Geng et al., 2022). This literature suggests that various labor frictions, such as wage rigidity, labor mobility, labor unions, minimum wages and labor dismissal costs, can affect firm risks and corporate policies. We contribute to the literature by developing a reliable and novel measure of labor-shortage exposure at the firm level for a broad sample of firms. In various validation tests, we show that the developed measure captures firm-level labor-shortage exposure well. We further show that greater exposure to labor shortages predicts lower operating performance and stock returns in the cross-section. In addition, complementing the findings on minimum wages and labor dismissal costs in the literature, we show that exposure to labor shortages can also lead to increased capital expenditures and greater process innovations to replace costly labor. The developed measure can be used by analysts, investors, and regulators to identify and address labor-shortage-related issues.

Third, the study contributes to the literature on the heterogeneous impacts of the COVID-19 pandemic on firms (e.g., Albuquerque et al., 2020; Ramelli and Wagner, 2020; Ding et al., 2021; Fahlenbrach et al., 2021; Liu et al., 2021). The literature suggests that various firm characteristics including environmental and social ratings, firm leverage, cash holdings, financial flexibility, debt rollover risk, ownership structure and other characteristics, affect the stock performance of firms during the pandemic. We contribute by documenting that firms exposed to labor shortages prior to the pandemic experienced significantly worse operating performance and produced significantly lower stock returns than the non-exposed firms during the pandemic, indicating that labor-shortage-exposed firms are particularly vulnerable to the pandemic's impact on the labor market (e.g., decreased labor supply due to sickness and increased difficulty in retaining and attracting workers).

The rest of the paper proceeds as follows. Section 2 describes the data and sample construction. Section 3 presents a detailed discussion on how we measure exposure to labor shortages at the firm level. Section 4 reports the results from various validation tests on the developed measure of firm-level labor-shortage exposure. Section 5 studies the implications of firm-level labor-shortage exposure on cross-sectional future stock returns and operating performance and the implications on corporate investment and innovations. Section 6 explores how labor-shortage-exposed firms performed during the COVID-19 Pandemic. Section 7 concludes. Appendix A provides variable definitions, the prediction performance of our fine-tuned *FinBERT* model, examples of the identified labor-shortage sentences using our machine learning model, and additional robustness results. Appendix B provides the results from additional validation tests.

2 Data and Sample

We use earnings conference call transcripts of U.S. public firms as text data to measure firm-level labor-shortage exposure. Earnings conference calls are generally held by public firms every quarter. It starts with a management presentation session in which the company executives discuss the firm's quarterly operating performance and business conditions, followed by a Q&A session in which financial analysts raise questions to the executives. Consistent with prior literature (e.g., Hassan et al., 2019; Li et al., 2021; Sautner et al., 2023), we use the entire earnings call transcript (including both the management presentation and Q&A session) to construct the measure of labor-shortage exposure. We collect transcripts from the Standard & Poor Capital IQ database (CIQ) during the 2005-2021 period. The raw dataset contains 136,169 earnings call transcripts of 4,869 U.S. public firms.

We further collect state-level employment and wage data from the U.S. Bureau of Labor Statistics (BLS), state-level economic statistics from the U.S. Bureau of Economic Analysis (BEA), the information on firm historical headquarters states from the header section of 10-K/Qs filed on EDGAR, stock return data from the Center for Research in Security Prices

(CRSP), and financial data from Compustat.[3] We obtain the corporate patent data from Kogan et al. (2017), and obtain the process vs. non-process patent classification data from Bena et al. (2022) based on patent claims text.[4] After merging the datasets and requiring non-missing variables, the final sample consists of 25,551 firm-year observations related to 100,588 earnings conference call transcripts and 3,829 unique firms. Table 1 reports the summary statistics of the variables used in this study. Table A1 in Appendix A provides detailed variable definitions and data sources.

[Please insert Table 1 about here]

3 Measuring Firm-level Labor-Shortage Exposure

Prior literature generally uses economic indicators, such as unemployment rate and wage, to measure the degree of labor market slack (e.g., Mortensen and Pissarides, 1994; Domash and Summers, 2022). However, these measures are usually available at only country- or state-level. A firm's exposure to labor shortages can arise from a variety of factors. Besides firm-level differences in production functions, production technologies and processes, firm-level differences in geographical locations, growth trajectories and labor-capital substitutions can all play a part in driving labor shortages in firms. For example, our later analyses show that variations in local restrictions on human mobility during the COVID-19 pandemic can drive firm-level labor shortages, and a firm's geographic dispersion helps mitigate the negative effects of labor-shortage exposure on the firm's future stock returns and operating performance. Bagger et al. (2022) also show that firms' growth in revenue and value added strongly predicts their job vacancy postings (which can lead to labor shortages given relatively fixed local labor supply). Since human capital is an important input in firms' production processes and exposure to labor shortage has become a growing concern for many firms in recent years, it is important to

[3] See https://sraf.nd.edu/data/augmented-10-x-header-data on firms' historical headquarters locations. We thank Bill McDonald for making the data publicly available.

[4] The patent data can be downloaded from Noah Stoffman's research website: https://kelley.iu.edu/nstoffma. The classification data can be downloaded from Jan Bena's research website: https://www.janbena.com/en/process-innovation-patent-dataset. We thank Noah Stoffman, Jan Bena and their research teams for generously sharing the data.

measure firm-level labor-shortage exposure.

To achieve this goal, we choose earnings conference call transcripts as text data to quantify a firm's discussion on labor-shortage-related topics. Earnings conference calls typically take place quarterly after a publicly traded firm releases its financial results for the previous quarter. Such conference calls provide a forum for the firm to update investors and analysts on its financial performance and outlook. They also provide an opportunity for investors and analysts to ask questions and gain a deeper understanding of the firm's business and financial prospects. Thus, earnings conference calls provide high volume of firm-level information. Importantly, Cao et al. (2023) find that, with the rapid growth of artificial intelligence, firms strategically avoid negative tones that can be detected by algorithms in their financial reports. In contrast to the regulatory filings that firms have sufficient time to edit, earnings conference calls require instant responses from corporate executives, which helps reduce their strategic behavior of hiding unfavorable information. Because of these advantages, a growing strand of literature uses earnings conference call transcripts to measure a firm's exposures to different issues, such as political risk (Hassan et al., 2019), corporate culture (Li et al., 2021), and climate change (Li et al., 2023; Sautner et al., 2023).

In this study, we use earnings conference call transcripts to measure a firm's labor-shortage exposure, which is a heated topic that has attracted significant investor attention in recent years, especially given the recent COVID-19 crisis and the related lockdown measures. If a firm is experiencing a significant labor shortage, we expect its earnings conference call transcripts to contain meaningful discussions on this issue. In the rest of this section, we explain in detail how we measure firm-level labor-shortage exposure.

3.1 The Challenge

Prior studies generally use two approaches to measure a firm's exposure to certain topics. The first approach is to develop a pre-specified keyword list (or dictionary). For example, Hassan et al. (2019) generate a politics-related dictionary by collecting keywords that only occur in political science textbooks but not in accounting and finance textbooks. On the other hand, keywords can also be generated based on common knowledge if the topics of interest are self-evident. For example, Hassan et al. (2023a,b) measure a firm's exposure to Brexit and epidemic diseases using obvious keywords (e.g., Brexit, SARS, and COVID-19). The exposure measure can then be constructed by counting the number of keyword occurrences in the text data. However, this approach can lead to underestimation if the keyword list is of limited scope. To address the underestimation issue, researchers start to apply the second approach, machine learning, to expand the scope of the topical dictionary. For example, Li et al. (2021) use *Word2Vec* model to obtain a broader list of words that have close similarity scores with the predetermined corporate-culture-related seed words. Similarly, Sautner et al. (2023) adopt a keyword discovery algorithm to identify climate-related keywords.

In our research context of measuring firm-level labor-shortage exposure, relying on a keyword list (either prespecified or expanded via *Word2Vec*) can be particularly challenging because language is colorful, versatile and constantly evolving, and corporate executives can express their concerns on labor-shortage issues in very flexible ways. Some sentences in earnings call transcripts may contain very clear statements about labor shortage and thus the dictionary approach can work well in such cases. For example, in Baker Hughes Inc's 2012Q1 earnings conference call, its CEO mentioned that "*But as highlighted in last quarter's call, labor shortages are limiting growth.*" However, in many cases, CEOs discuss the labor shortage concerns in ways that are difficult to be detected by the predetermined keywords. For example, in 2010Q3 earnings conference call, the CEO of Ariba Inc mentioned that "*I would like to have gotten there sooner, but I think we're finding the hiring environment is pretty intense out there.*"

To deal with this challenge, instead of relying on a keyword list, we use the Bidirectional Encoder Representations from Transformers (*BERT*), which is an advanced natural language processing (NLP) technique to more accurately measure a firm's labor-shortage exposure.

3.2 The Advantage of *BERT*

BERT is a deep-learning-based large language model (LLM) developed by Devlin et al. (2018). A deep learning model contains a neural network that is interconnected with an input layer, multiple hidden layers, and an output layer. To train such models, people need to first feed their raw text data (e.g., financial reports and earnings call transcripts) into the input layer, which will then further feed forward to the hidden layers. The hidden layers will use nonlinear functions to adjust the embedded parameter matrices and then feed forward to the final output layer. The output layer thus contains the prediction outcome (e.g., whether a sentence sentiment is positive, neutral, or negative). When the training starts, the model makes prediction error (the difference between the ground truth and the prediction outcome). However, the error is fed backward (backpropagation) to the hidden layers to further make adjustment to the parameter matrices. After rounds of iteration, the prediction error converges and parameter matrices will become stable. The trained model can then be employed in different NLP tasks.

Since the last decade, industry scientists and academic researchers have started to apply neural network to solve different NLP tasks. For example, Mikolov et al. (2013) use neural network to develop a *Word2Vec* model, which transforms words into quantifiable vectors (word embeddings) that can be used to discover similar words by comparing their cosine similarities.[5] However, such word vectors are represented by static numbers without considering the contextual information. For example, the word "running" will have the same vector in the sentences "She is running a company" and "She is running a marathon", while as human beings, we can see that it indicates different meanings by looking at the contexts.

The advantage of *BERT* is that it can provide contextualized word vectors (i.e., words have different vectors depending on the actual language contexts), because it is pretrained using large text data.[6] By reading the text sentences from left to right and right to left (the so-called "bidirectional") and using features of Masked Language Model and Next Sentence Prediction, *BERT*

[5] For example, "Man" and "King" are closer (more similar) in the vector space than "Man" and "Queen".

[6] *BERT* is pretrained using around 2.5 billion words from Wikipedia and 800 million words from Google's BooksCorpus.

can recognize the syntax and semantics of the English language well.[7] Another distinguishing feature of *BERT* is that although it requires a large amount of computational hours and text data to be pretrained, it can be flexibly finetuned (i.e., further train the model by using some specific training samples) to apply into downstream NLP tasks, such as classifying sentence sentiment.[8] Researchers have also start to apply *BERT* in finance research. For example, Rajan et al. (2023) use *BERT* to categorize corporate goals in shareholder letters. Bingler et al. (2022) develop a *ClimateBERT* to identify corporate climate commitments. Similarly, Chava et al. (2022) use *RoBERTa* to capture a firm's inflation exposure.

In this study, we use *FinBERT* to measure a firm's labor-shortage exposure. *FinBERT* is a *BERT*-based model. Instead of being pretrained using general text data (e.g., Wikipedia), it is pretrained using financial text data by Huang et al. (2023).[9] Thus, *FinBERT* yields better understanding in the finance-specialized contexts. The testing results by Huang et al. (2023) show that compared with the original *BERT*, *FinBERT* obtains higher accuracy rate when predicting sentence sentiment or identifying ESG sentences. Thus, we use *FinBERT* to detect labor-shortage-related sentences and expect that it can improve the performance of detecting labor-shortage-related sentences from earnings conference call transcripts.

3.3 Training Sample and Testing Sample for *FinBERT*

Before applying *FinBERT* to the downstream task of detecting labor-shortage-related sentences, we need to first construct a training sample to finetune *FinBERT*. We aim to use *FinBERT* to distinguish between labor-shortage-related sentences and non-labor-shortage-related sentences in earnings conference call transcripts. Thus, it is important to construct a training sample that includes these two types of sentences.

[7] Masked Language Model (MLM) is to first hide a word from a sentence and then ask *BERT* to fill up the masked word based on the surrounding words in this sentence. Next Sentence Prediction is to ask *BERT* to predict the next sentence based on the current sentence. These two mechanisms significantly improve *BERT*'s language reading ability. Please see https://huggingface.co/blog/bert-101 for more information.

[8] Training a *BERT*-base model (12 layers, 768 hidden size, 12 attention heads, and 110 million parameters) requires 4 days with 4 Cloud TPUs in Pod configuration (Devlin et al., 2018). Applying *BERT* to downstream tasks is also called transfer learning.

[9] The financial text data include 10-Ks and 10-Qs reports from Russel 3000 firms, analyst reports from S&P 500 firms, and earnings conference call transcripts.

We first use Stanza (Qi et al., 2020), a Python natural language processing toolkit for linguistic analysis, to split the earnings call transcripts into sentences. We call this sentence sample $\boldsymbol{A}$. Next, from the sentence sample $\boldsymbol{A}$, we collect labor-related sentences because only such labor-related sentences are likely to contain labor-shortage-related discussions.[10] Specifically, to identify the labor-related sentences, we construct a comprehensive labor-related keyword list. Similar to Li et al. (2021), we first generate nine labor-related seed words. We then use the *Word2Vec* model to obtain an expanded labor-related dictionary from these seed words. Panel A of Table A2 in Appendix A presents the expanded labor-related keyword list. Only the sentences that contain at least one of these labor-related keywords from the list (including the seed words and the *Word2Vec*-expanded words) will be included in the labor-related sentence sample $\boldsymbol{B}$, which eventually consists of 1,339,370 sentences.

Next, we randomly select 3,000 sentences from $\boldsymbol{B}$ as our *initial sample*, and manually classify whether each sentence is related to labor shortage or not. However, during this labeling process, we find that many of those sentences are non-labor-shortage related. We only detect 79 sentences that discuss labor shortage (labeled as *positive*), while the remaining 2,921 sentences are not labor-shortage-related (labeled as *negative*). The rare occurrence of positive sentences can lead to a sample imbalance issue (see, e.g., He and Garcia, 2009; Lemaître et al., 2017): when a class imbalance occurs in the training data, the model will tend to overclassify the majority class because of the higher prior probability. That is, if we use this imbalanced sample to train the *FinBERT*, it will tend to overclassify sentences as negative.

To address this sample imbalance issue, we further expand the initial 3,000 sentence sample by including 2,000 more sentences. To increase the probability of obtaining a labor-shortage-related sentence, for these 2,000 sentences, we require each of them to include at least one labor-shortage-related keyword. We similarly generate a keyword list of labor shortage using the *Word2Vec* model. We start with inputting nine labor-shortage-related seed words into the *Word2Vec* model. The model then expands the dictionary by selecting words that have close

[10] It is unlikely that labor-shortage-related discussions will occur in the sentences that do not contain any labor-related keywords.

cosine similarity with the seed words. Panel B of Table A2 in Appendix A presents the expanded labor-shortage-related dictionary. After obtaining the labor-shortage-related keyword list, we then randomly select 2,000 sentences containing one or more labor-shortage-related keywords from the sentence sample $\boldsymbol{A}$.[11] We then manually classify whether each of these 2,000 sentences is related to labor shortage or not. We find that 1,780 out of the 2,000 sentences are labor-shortage-related. Thus, our final sentence sample includes 5,000 (3,000 plus 2,000) sentences, with 1,859 (79 plus 1,780) are labor-shortage related and 3,141 are non-labor-shortage related.

Having constructed the sentence sample, we next follow prior literature to stratify the sample and use 90% as our training sample (4,500 sentences), which is used to adjust the parameters in *FinBERT*. The remaining 10% is the testing sample (500 sentences), which is used to evaluate the model prediction performance at the end.[12]

3.4 Model Prediction Performance

After using the training sample to finetune the *FinBERT* model, we next evaluate the finetuned *FinBERT* model's prediction performance using the testing sample. Table A3 in Appendix A presents the results. We report the overall accuracy, macro average accuracy, and weighted average accuracy for the testing sample. Moreover, for each sentence category (positive or negative), we report the precision rate (i.e., the ability of the trained model not to label as positive a sentence that is negative), recall rate (i.e., the ability of the model to identify all the positive sentences), and F1-score (i.e., a harmonic mean of the precision rate and recall rate).[13]

We find that our finetuned *FinBERT* model achieves very impressive predicting performance. The overall accuracy rate is 95%, which indicates that 475 sentences in the testing sample are correctly classified by the model.[14] In terms of the positive (i.e., labor-shortage-

[11] We also require that these 2,000 sentences should not be overlap with the 79 labor-shortage-related sentences that we find in the first stage.

[12] For the hyperparameters of the model, we follow Huang et al. (2023) to set the learning rate to 2e-5 with model finetuning for five epochs.

[13] Specifically, the precision rate is calculated as *TP/(TP+FP)*, where *TP* denotes the number of true positives and *FP* denotes as the number of false positives. The recall rate is calculated as *TP/(TP+FN)*, where *TP* denotes the number of true positives and *FN* denotes as the number of false negatives. The F1-score is calculated as 2×(precision×recall)/(precision+recall).

[14] Using *FinBERT*, Huang et al. (2023) achieve an accuracy of 88.2% in classifying sentence sentiment, 89.5%

related) sentences, the precision rate, recall rate, and f1-score are 91%, 95%, and 93%, respectively. It indicates that our finetuned *FinBERT* model works very well in identifying all positive sentences with high precision. Similarly, for the negative sentences, the precision rate, recall rate, and f1-score are all over 95%. Taken together, the superior testing performance shows that our finetuned *FinBERT* model can reliably detect the labor shortage discussions in the earnings conference call transcripts.

3.5 Measuring Firm-level Labor-shortage Exposure

Having finetuned the *FinBERT* model, we next apply it to measure firm-level labor-shortage exposure. Specifically, for each labor-related sentence in the sentence sample $\boldsymbol{B}$, we use *FinBERT* to determine whether it is related to the topic of labor shortage. We then use the following equation to compute firm-level labor-shortage exposure:

$$LS\ Exposure_{i,t} = \frac{LS\ Sentences_{i,t}}{Total\ Sentences_{i,t}} \times 100 \tag{1}$$

where *LS Sentences* is the average number of labor-shortage-related sentences contained in the earnings conference call transcripts of firm i in year t, and *Total Sentences* is the average number of all sentences of the transcripts of firm i in year t. We further multiply the raw measure by 100 for easier result interpretation. Table A4 in Appendix A further provides 20 randomly selected sentences that are detected as related to labor shortage by the finetuned *FinBERT* model. Table 1 provides the descriptive statistics for *LS Exposure*. The mean of *LS Exposure* is 0.062 in our sample, with its standard deviation being 0.173.

Moreover, in Appendix Table A5, we investigate how persistent over time a firm's labor-shortage exposure is. We report the correlation matrix of *LS Exposure* and its lags in Panel A) and the correlation matrix of *I (LS)* and its lags in Panel B. *LS Exposure* is a firm's labor-shortage exposure in a year. *I (LS)* is an indicator variable that equals one if the *LS Exposure* of a firm in that year is larger than zero, and equals zero otherwise. Panel A shows that *LS*

in detecting ESG-related sentences, and 85.3% in labeling forward-looking sentences.

Exposure is somewhat persistent over time: the correlation coefficient estimates between *LS Exposure* and its lags slowly decrease from 0.566 to 0.302 when moving from the first lag to the fourth lag. A similar but weaker pattern is observed using *I (LS)* in Panel B.

In Appendix Table A6, we further examine what firm characteristics are associated with labor-shortage exposure. We regress *LS Exposure* (*I (LS)*) on various firm characteristics measured in the same year. In columns 1 and 5, we do not include any fixed effects. In columns 2 and 6, we include year fixed effects. Columns 3 and 7 further include industry fixed effects. In columns 4 and 8, we replace year and industry fixed effects with industry-by-year fixed effects. In general, we find that firms that have higher sales growth, larger firm size, higher asset tangibility, greater labor intensity, lower ROA, lower leverage, lower cash holdings and/or lower R&D expenses, tend to have higher labor-shortage exposure. The finding that firms with higher sales growth tend to have higher labor-shortage exposure is consistent with Bagger et al. (2022) finding that firms' growth in revenue and value added strongly predicts their online vacancy postings.

4 Validation

In this section, we validate the *LS Exposure* measure and show that it performs very well capturing the labor-shortage exposures of firms.

4.1 Time-series and Industry Variation of Labor Shortage Measure

First, we examine the variation in the aggregate labor-shortage-exposure measure over time. Figure 1 illustrates the number of labor-shortage-exposed firms (red bars), the average labor-shortage exposure of firms (green line) and the proportion of labor-shortage-exposed firms (blue line) by year. All three elements indicate an increasing trend of labor-shortage exposure. The value of average *LS Exposure* is relatively stable between 2005 and 2013 and we observe some slight increase in *LS Exposure* from 2014 to 2016, likely due to the post-Great-Recession economic expansion and declining labor force participation.[15] However, since 2017 there have been two significant spikes in average firm-level labor-shortage exposure. The first spike occurs in 2018 when the then U.S. President Donald Trump tightened U.S. immigration policies, which significantly restricted the number of immigrants and led to a substantial reduction in foreign labor supply.[16] The second (and bigger) spike occurs in 2021, the year after the COVID-19 outbreak in the U.S, which produced long-lasting labor disruptions because: i) the virus negatively affected workers' health conditions; ii) the self-quarantine policy stopped employees from working; and iii) people did not want to return to pre-COVID work activities after the pandemic.[17] These two spikes indicate that the *LS Exposure* measure indeed captures economy-wide labor-shortage exposure. Similar patterns are observed for the number of labor-shortage-exposed firms (peaked at around 600 firms in 2021) and the proportion of labor-shortage-exposed firms (peaked at around 30%).

[Please insert Figure 1 about here]

Next, we examine the industrial variation of the labor-shortage measure. Figure 2 shows the top-10 industries (2-digit SIC) that are most exposed to labor shortages.[18] For comparison, we rank the industries using the full sample period (2005-2021, Figure 2A), the pre-COVID period (2005-2019, Figure 2B), and the COVID period (2020-2021, Figure 2C). Although the rankings change slightly across the three panels, there is no significant difference. Overall, the industries of *Special Trade Contractors*, *Lumber & Wood Products*, *General Building Contractors*, *Legal Services*, and *Motor Freight Transportation & Warehousing* are highly exposed to labor shortage. This finding is consistent with our expectation since these industries are labor-intensive. Interestingly, Panel C shows that during the COVID-19 crisis period, the industries of *Social Services* and *Eating & Drinking Places* climb up to the third and fourth places, which is consistent with the anecdotal evidence that the COVID-19 pandemic has exposed the service

[15] For example, see https://www.brookings.edu/blog/social-mobility-memos/2017/02/03/what-we-know-and-dont-know-about-the-declining-labor-force-participation-rate/.

[16] We discuss this immigration policy change in detail in Section 4.4

[17] For example, see https://www.wsj.com/articles/several-million-u-s-workers-seen-staying-out-of-labor-force-indefinitely-11650101400.

[18] Table A7 in Appendix A reports the bottom-10 industries (2-digit SIC) that are least exposed to labor shortages during the 2005-2021 sample period.

and hospitality sectors to significant labor shortage.[19]

[Please insert Figure 2 about here]

4.2 State-level Labor-shortage Exposure, Unemployment Rate, Wage Growth, and Local Labor Market Tightness

Another way to verify whether the *LS Exposure* measure indeed captures labor-shortage exposure or not is to examine how it correlates with unemployment rate, wage growth, and local labor market tightness (e.g., Domash and Summers, 2022). Specifically, when local labor markets are tight, the number of job openings available will exceed the number of people who are looking for jobs. Thus, it is easier for job seekers to find employment, and local unemployment rate should decrease. Moreover, facing tight local labor markets, firms will tend to increase wages to retain current employees and attract new employees, resulting in higher wage growth. Thus, if the *LS Exposure* measure indeed captures labor-shortage exposure of firms, we should expect a negative (positive) relation between a state's aggregate level of labor-shortage exposure and its future unemployment rate (future wage growth and labor market tightness).

To test this conjecture, we aggregate our measure of labor-shortage exposure from the firm level to the state level based on the information on historical headquarters states of the sample firms. We then use the following ordinary least squares (OLS) regression equation to investigate the relationship between a state's aggregate labor-shortage exposure and its future unemployment and wage conditions:

$$Y_{s,t+1} = \beta_1 LS\ Exposure^{state}_{s,t} + \beta_2 Controls_{s,t} + \omega_s + \mu_t + \epsilon_{s,t} \tag{2}$$

In Equation 2, Y indicates the unemployment rate, wage growth or labor market tightness of state s in year $t+1$; *LS Exposure*^{state} refers to the labor-shortage exposure of state s in year t, which is calculated by averaging the firm-level labor-shortage exposure to the state level based

[19] For example, see https://www.wsj.com/articles/customers-are-back-at-restaurants-and-bars-but-workers-have-moved-on-11626168601.

on firm headquarters state information. We follow the literature and use the natural logarithm of a state's number of job openings divided by the state's number of people unemployed in a year to proxy for the state's labor market tightness. We further control for three state-level economic variables, the natural logarithm of a state's GDP (*Log(GDP)*), the natural logarithm of a state's total population (*Log(Population)*) and the natural logarithm of a state's per capita income (*Log(Per Cap Income)*), to capture the state's economic dynamics that may correlate with its labor market condition. State fixed effects and year fixed effects are included to control for the time-invariant state characteristics and potential nationwide time trends. Table 2 presents the results.

[Please insert Table 2 about here]

In columns 1-2, we investigate the relationship between a state's labor-shortage exposure and its one-year-ahead unemployment rate (*Unemployment Rate*); in columns 3-4, we examine the association between a state's labor-shortage exposure and its one-year-ahead wage growth (*Wage Growth*); in columns 5-6, we further shed light on how a state's labor-shortage is related to its one-year ahead labor market tightness ($Log(\frac{\#Job\ Openings}{\#Unemployed})$). Columns 1, 3, and 5 only include year fixed effects, while columns 2, 4, and 6 further include state fixed effect.

Consistent with our expectation, columns 1-2 show a negative and significant (at the 5% level or better) relation between a state's aggregate labor-shortage exposure and its one-year-ahead unemployment rate. In terms of economic magnitude, a one-standard-deviation increase in $LS\ Exposure^{state}$, on average, leads to a 0.108 percentage point (= 0.057*0.019) decrease in the state unemployment rate (mean of 5.9%). Similarly, columns 3-4 indicate a positive and significant (at the 5% level) relation between a state's aggregate labor-shortage exposure and the state's one-year-ahead wage growth. On average, a one-standard-deviation increase in $LS\ Exposure^{state}$ leads to a 0.177 percentage point (= 0.057*0.031) increase in the local wage growth (mean of 3.4%). Finally, the results in columns 5-6 show that a state's aggregate labor-shortage exposure is also positively associated with next year's local labor market tightness. A one-standard-deviation increase in $LS\ Exposure^{state}$ is related to a 2.331% (= 0.057*0.409) increase in the state's labor market tightness (mean of 0.734). Panel A of Table A8 in Appendix

A further shows that the findings remain qualitatively unchanged when we exclude the COVID-19 period (2020 and 2021) from the regressions.

Overall, the results in this section confirm a negative (positive) relation between a state's labor-shortage exposure and its future unemployment rate (its future wage growth and local labor market tightness), supporting the validity of the labor-shortage exposure measure.

4.3 Firm-level Labor-shortage Exposure and Growth in Per-employee Staff Expenses

Next, we examine the relation between the measure of labor-shortage exposure and a firm's growth in per-employee staff expenses as another validity test of the measure. We conjecture that if a firm is exposed to significant labor shortages, such a situation should motivate the firm to raise per-employee wages and employment benefits to better retain the current workers and attract new workers to join the firm. Therefore, if our measure successfully captures a firm's labor-shortage exposure, we should expect to observe a positive relation between the measure and growth in future per-employee staff expenses of the firm. We use the following equation to investigate this conjecture:

$$Y_{i,j,t+1} = \beta_1 LS\ Exposure_{i,j,t} + \beta_2 Controls_{i,j,t} + \sigma_j + \mu_t + \epsilon_{i,j,t} \tag{3}$$

In Equation 3, Y is the growth in per-employee staff expenses (*Growth in Per-Employee Staff Expenses*) of firm i in industry j in year *t+1*, and *LS Exposure* indicates the labor-shortage exposure of firm i in industry j in year t. We further control for a variety of firm characteristics, such as return on assets (*ROA*), leverage ratio (*Book Leverage*), past stock return (*Stock Return*), capital expenditure (*CAPEX*), market to book ratio (*MTB*), sales growth (*Sales Growth*), firm size (*Firm Size*), cash holdings (*Cash*), asset tangibility (*Asset Tangibility*), stock return volatility (*Stock Volatility*), and research and development expenses (*R&D*). We also control for a firm's number of employees (in thousands) per million dollars of assets (*Employees/AT*) to capture the firm's labor efficiency. Industry fixed effects σ and year fixed effects μ are included. Table 3 presents the results.

[Please insert Table 3 about here]

Column 1 of Table 3 shows that the coefficient estimate of *LS Exposure* is significantly positive at the 5% level, confirming a positive relation between a firm's labor-shortage exposure and its one-year-ahead growth in per-employee staff expenses. A one-standard-deviation increase in *LS Exposure* is, on average, associated with a 0.260 percentage point increase (= 0.173*0.015) in the growth in per-employee staff expenses next year. The coefficient estimate of *LS Exposure* continues to be significantly positive at the 1% level when we control for industry-by-year fixed effects to account for potential confounding industry shocks (column 2). The results remain qualitatively the same when we instead control for firm and year fixed effects (column 3) or firm and industry-by-year fixed effects (column 4). Moreover, Panel B of Table A8 in Appendix A shows that the results remain qualitatively similar when we exclude the COVID-19 period (2020 and 2021) from the regressions.

Taken together, these findings are consistent with the expectation that when exposed to labor shortage, firms tend to raise their per-employee staff expenses to retain current employees and attract new employees. The findings further support the validity of the measure of labor-shortage exposure.

4.4 Shocks to Labor Supply

Our final validation of the measure comes from two shocks to the U.S. labor supply: The 2017 Trump Immigration Policy Reforms and variations in state-level restrictions on human mobility during the COVID-19 pandemic. The 2017 Immigration Policy Reforms severely tightened immigration eligibility, reducing net international migration to the U.S. rapidly from 1.07 million in 2016 to 569,000 by 2019 (see Cohen and Shampine, 2022). The variations in U.S. states' stringency in mobility restrictions are captured by the Oxford COVID-19 Government Response Tracker in a measure normalized to range from 0-100, where the interquartile range for U.S. states is more than 17.

We detail our empirical analyses using these two shocks in Appendix B. In short, after the enactment of the 2017 immigration policy reforms, the treated firms (labor-intensive firms) experience a sharp and significant increase in labor-shortage exposure relative to the control firms (capital-intensive firms). In the second test, we document clear evidence that a firm's discussion of labor shortage problems is directly related to evolution of its state's COVID-19 lockdown stringency. These findings further validate the measure of labor-shortage exposure.

5 Implications of Firm-level Labor-shortage Exposure

In this section, we examine the implications of firm-level labor-shortage exposure. We first shed light on how the stock market reacts to the discussions of labor shortage in earnings conference calls in the short term. We then investigate the relations between firm-level labor-shortage exposure and future stock returns and operating performance in the cross-section. Finally, we examine how firms adjust their corporate investment and innovation strategies in response to labor-shortage exposure.

5.1 Stock Market Reaction to Firm-level Labor-shortage Exposure

We first investigate how the stock market reacts to corporate labor-shortage exposure. We measure stock market reaction as a firm's CAR within the three days following the earnings conference call (i.e., *CAR (0, 2)*) using the market-adjusted model. We then conduct the firm-year-quarter panel regression analyses using the following specification:

$$Y_{i,j,q} = \beta_1 LS\ Exposure_{i,j,q} + \beta_2 Controls_{i,j,q-1} + \sigma_j + \mu_q + \epsilon_{i,j,q} \tag{4}$$

In Equation 4, Y represents the CAR of firm i in industry j within the three days following the earnings conference call (i.e., *CAR (0, 2)*) in year-quarter q, and *LS Exposure* is the labor-shortage exposure of firm i in industry j in year-quarter q. In addition to the firm-level control variables in Equation 3, we further control for the most recently disclosed earnings surprise of firm i (i.e., the earnings surprise of the firm for the past quarter *q-1* as disclosed in the current quarter q). Moreover, Industry fixed effects σ_i and year-quarter fixed effects μ_q are included. The results are reported in Table 4.

[Please insert Table 4 about here]

In column 1, we run a univariate OLS regression to examine the relation between firm-level labor-shortage exposure and the three-day CAR. In column 2, we further control for a variety of firm characteristics. In column 3, we include year-quarter fixed effects to account for the time-varying economic conditions. In column 4, we further add industry fixed effects to control for time-invariant industry characteristics. In column 5, we replace the year-quarter and industry fixed effects with industry-by-year-quarter fixed effects to account for the influence of industry shocks. We find that the coefficient estimates on *LS Exposure* are negative and statistically significant at the 1% level across all specifications, suggesting that the stock market reacts negatively to firms' labor-shortage exposure. In terms of the economic magnitude, column 5 implies that a one-standard-deviation increase in firm-level labor-shortage exposure is, on average, related to a 0.10-percentage-point reduction (= 0.173*0.006) in the three-day CAR.

We conduct a battery of additional tests to confirm the robustness of our finding that a firm's labor-shortage exposure elicits a negative reaction from the stock market. These robustness tests include 1) excluding the COVID-19 period (2020 and 2021) from the regression (column 1 in Panel C of Table A8 in Appendix A), 2) comparing the extensive margin (column 1 in Panel A of Table A9 in Appendix A) and intensive margin (column 1 in Panel B of Table A9 in Appendix A) of the labor-shortage exposure effect on CAR,[20] and 3) reconstructing the firm-level labor-shortage exposure using either the management presentation section or Q&A section in the earnings conference call transcripts (columns 1-3 in Panel A of Table A10 in Appendix A). We continue to obtain qualitatively similar results of negative stock price reaction

[20] We conduct the extensive margin analysis by replacing the continuous labor-shortage exposure measure with an indicator *I (LS)* that equals one if *LS Exposure* is larger than zero, and equals zero otherwise. We conduct the intensive margin analysis by restricting to the sample of firms that are exposed to labor shortages (i.e., *LS Exposure* is larger than zero in a firm-year).

to firm-level labor-shortage exposure.

Overall, the results in this section indicate that the stock market reacts negatively to a firm's revelation of labor-shortage exposure. In the next section, we examine whether the affects of firm-level labor-shortage exposure are then reflected in future operating performance as well as the cross-section of long-run stock returns.

5.2 Future Cross-sectional Stock Returns and Operating Performance

Our earlier results show that greater firm-level labor-shortage exposure is related to higher future growth in per-employee staff expenses, and that stock market investors react negatively to managers' discussion of labor shortage when the earnings conference call is held. On this basis, we expect that greater labor-shortage exposure of a firm should hamper its future operating performance, thereby leading to lower future stock returns in the cross-section. We use Equation 3 to examine the relation between labor-shortage exposure and future cross-sectional stock returns, with the dependent variable Y_{t+1} being the buy-and-hold stock return of a firm in the next four quarters after the quarter of the last earnings conference call of that firm in year t.

[Please insert Table 5 about here]

Table 5 reports the results. In column 1, we first run a univariate OLS regression to examine the relation between firm-level labor-shortage exposure and one-year-ahead cross-sectional stock returns. We find that the coefficient estimate on *LS Exposure* is significantly negative at the 5% level. Column 2 shows that the result does not change qualitatively when we further control for a variety of firm characteristics. In column 3, we add year fixed effects to account for time-varying economic conditions. In column 4, we further control for industry fixed effects as some time-invariant industry characteristics may drive the results. In column 5, we replace year fixed effects and industry fixed effects by industry-by-year fixed effects. The coefficient estimates on *LS Exposure* are negative and highly significant at the 1% level, confirming that *LS Exposure* strongly and negatively predicts one-year-ahead cross-sectional stock returns. The economic magnitude is considerable. Take column 5 as an example: a one-standard-deviation increase in firm-level labor-shortage exposure is, on average, related to a 1.09-percentage-point reduction (= 0.173*0.063) in one-year-ahead cross-sectional stock returns. Combined, the findings from columns 1 to 5 in Table 5 show that the measure of firm-level labor-shortage exposure can robustly and negatively predict one-year-ahead cross-sectional stock returns.

Next, we use the same regression specification as that in column 5 to investigate whether firm-level labor-shortage exposure can predict one-year-ahead cross-sectional operating performance, which is measured by return on assets (*ROA*) and operating cash flow (*Operating Cash Flow*). Columns 6-7 report the results. We find that the coefficient estimates on *LS Exposure* are negative and statistically significant at the 5% level or better in both regression models, indicating that the measure of firm-level labor-shortage exposure also robustly and negatively predicts future cross-sectional operating performance. In terms of economic magnitude, a one-standard-deviation increase in firm-level labor-shortage exposure on average predicts a 0.225-percentage-point decline (= 0.173*0.013) in one-year-ahead return on assets and a 0.156-percentage-point reduction (= 0.173*0.009) in one-year-ahead operating cash flow. These results support our expectation that greater exposure to labor shortage forces firms to increase wages and employment benefits to retain and attract workers, which ultimately hampers their future operating and stock performance.

We conduct multiple tests to verify the robustness of the negative predictive power of firm-level labor-shortage exposure on future cross-sectional stock returns and operating performance. These robustness tests include 1) excluding the COVID-19 period (2020 and 2021) from the regressions (columns 2-4 in Panel C of Table A8 in Appendix A), 2) comparing the extensive margin (columns 2-4 in Panel A of Table A9 in Appendix A) and intensive margin (columns 2-4 in Panel B of Table A9 in Appendix A) of the predictability of firm-level labor-shortage exposure on future cross-sectional stock returns and operating performance, 3) reconstructing the firm-level labor-shortage exposure using either the management presentation section or Q&A section of the earnings conference call transcripts (columns 4-12 in Panel A of Table A10 in Appendix A), and 4) replacing the raw buy-and-hold stock returns of a firm with the

Fama-French three-factor-adjusted stock returns (Panel A of Table A11 in Appendix A) or Fama-French five-factor-adjusted stock returns (Panel B of Table A11 in Appendix A). Across all these robustness tests, we continue to obtain qualitatively similar findings indicating that firm-level labor-shortage exposure negatively and significantly predict one-year-ahead stock returns and operating performance in the cross-section.

Additionally, we conjecture that a firm's geographic dispersion in its operations may help mitigate the negative effects of labor-shortage exposure on the firm's future stock returns and operating performance since the firm can shift some of its production to geographic areas less subject to (localized) labor shortages. To verify this conjecture, we follow Garcia and Norli (2012) and measure a firm's geographic dispersion by counting the number of unique states mentioned in the 10-K filing of a firm-year.[21] The results, reported in Table A12 in Appendix A, show that geographic dispersion indeed helps mitigate the negative effects of firm-level labor-shortage exposure on future cross-sectional stock and operating performance.

Moreover, in Panel A of Table A13 in Appendix A, we conduct additional analyses to determine if the impact of firm-level labor-shortage exposure on future stock returns and operating performance differs between those firms experiencing labor shortages for the first time and those with repeated exposure. We find that the estimates of the impact of first time exposure on returns and performance is smaller. These results imply that it is primarily repeated labor-shortage exposure that leads to lower future stock returns and operating performance.

Overall, the findings in this section show that the measure of firm-level labor-shortage exposure has robust predictability on future cross-sectional stock returns and operating performance, indicating that the exposure to labor shortage has implications for future firm profitability and shareholder wealth.

[21] We construct two variables to measure a firm's geographic dispersion in a year. In Panel A of Table A12 in Appendix A, the variable, *Geographic Dispersion*, is the natural logarithm of the number of unique states mentioned in the 10-K filing of a firm-year. In Panel B, the variable, $Geographic\ Dispersion^{decile\ rank}$, is measured as the decile rank of the number of unique states mentioned in the 10-K filing of a firm-year.

5.3 Corporate Investment

We next investigate whether firms alter their corporate investment strategies in response to their labor-shortage exposure. On the one hand, firms exposed to labor shortages are likely to substitute increasingly scarce and expensive labor with capital as well as pursue efficiency-increasing process innovation, resulting in increased capital expenditures and R&D expenses coupled with a reduction in labor inputs (e.g., Geng et al., 2022). On the other hand, due to the labor shortage, firms may be forced to delay or even give up planned investment projects, which can negatively affect their future capital investment (e.g., Gustafson and Kotter, 2023). Moreover, labor-shortage-induced operating costs can hamper a firm's operating performance, leading CEOs to cut capital expenditures and R&D projects. Table 6 presents the results on the relations of firm-level labor-shortage exposures with future capital expenditures, R&D expenses and labor inputs.

[Please insert Table 6 about here]

The dependent variables in Table 6 are one-year-ahead capital expenditures ($CAPEX$), R&D expenses (*R&D*), and the change in the number of employees (in thousands) per million dollars of assets ($\triangle Employees/AT$). In columns 1, 3, and 5, we regress each of these three dependent variables on firm-level labor-shortage exposure (*LS Exposure*) with a battery of firm-level control variables, firm fixed effects and year fixed effects. In columns 2, 4, and 6, we further replace year fixed effects with a more stringent industry-by-year fixed effects. We find a significantly positive relation between a firm's labor-shortage exposure and its one-year-ahead capital expenditures and a weakly positive relation between labor-shortage exposure and one-year-ahead R&D expenses. We further document a significantly negative relation between labor-shortage exposure and the change in the number of employees per million dollars of assets in the next year. Taken together, these findings suggest that, in response to their exposure to labor shortages, firms seek to substitute the increasingly costly labor inputs with capital inputs in their production processes.

Similarly, we perform various robustness tests for the findings on investment policy responses to labor shortages. These robustness tests include 1) excluding the COVID-19 period (2020 and 2021) from the regressions (columns 1-3 in Panel D of Table A8 in Appendix A), 2) comparing the extensive margin (columns 1-3 in Panel C Table A9 in Appendix A) and the intensive margin (columns 1-3 of Panel D of Table A9 in Appendix A) of the effects of firm-level labor-shortage exposure on future corporate investment strategies, 3) reconstructing the firm-level labor-shortage exposure using either the management presentation section or Q&A section of the earnings conference call transcripts (columns 1-9 in Panel B of Table A10 in Appendix A), and 4) further controlling for CEO fixed effects (CEO identities are obtained from Execucomp or earnings conference call transcripts) to account for the time-invariant CEO characteristics (columns 1 to 3 in Panels A and B of Table A14 in Appendix A). Across all these robustness tests, we continue to obtain qualitatively similar results suggesting that firms respond to labor shortages by replacing labor inputs with capital expenditure and R&D expenses.

Additionally, in columns 1-3 of Panel B in Appendix Table A13, we further compare the differences in corporate investment policy responses to labor-shortage exposure between firms that are experiencing labor shortages for the first time and firms that frequently face labor shortages. Our analysis shows that it is repeated exposure to labor shortages that leads firms to decrease their labor inputs and increase their investments in capital expenditures and research and development.

Artificial intelligence (AI) can replace human labor for certain types of tasks, potentially reducing reliance on labor (Agrawal et al., 2019; Webb, 2020). Consequently, although we observe a decrease in general employment in firms exposed to labor shortages, these firms may instead increase their investment in AI-related employees to accelerate the development of their AI infrastructure. Following Babina et al. (2024), we measure a firm's AI employee investment using current employees' resume data,[22] and generate a flow variable, $\triangle$*AI Employee Share*, which represents the change in a firm's AI-related employee share from year t to year t*+1*. The results reported in columns 1-2 in Appendix Table A15 indicate that firms exposed to labor shortages do indeed engage in more AI human capital investment.

[22] We thank Tania Babina and her research team for generously making the data publicly available.

5.4 Production-process Patents

Next, we examine the implications of a firm's labor-shortage exposure on its future production-process and non-process patent outputs. Prior literature suggests that firms facing higher labor rigidity (e.g., higher labor dismissal costs and worker wages) may be motivated to generate more production-process-related patents to support their substitution of capital for labor (e.g., Bena et al., 2022). As our previous results indicate that firms' exposure to labor shortages leads them to substitute costly labor with capital in the future, we conjecture that firms exposed to labor shortages may also have the incentive to develop more production-process patents to improve their production process efficiency and facilitate labor-capital substitution.

We follow Bena and Simintzi (2019) and Bena et al. (2022) to identify whether a patent is production-process related or not.[23] Specifically, a patent claim is defined as a process claim if it contains words such as "*A method for . . .*" or "*A process for . . .*", followed by a verb.[24] A patent is defined as a process patent if all claims of the patent are process claims. Different from process patents, non-process patents are generally innovations that could be sold to others, such as new products or devices. Non-process patent claims frequently contain words such as "*A system . . .*" or "*A device . . .*". A patent is defined as a non-process patent if all claims of the patent are non-process claims.

Following Bena et al. (2022), we use two measures to capture a firm's process patent outputs. The first measure is the share of process claims (*Process Claims Share*) of the firm, which is computed as the number of process claims divided by the number of total claims for all patents the firm has applied for (and later granted) in a year. The second measure is the citation-weighted process patents (*# CW Process Patents/AT*) a firm has applied for (and later granted) in a year, further scaled by the total assets of the firm (Kogan et al., 2017). For comparison, we also generate a third measure, which is the citation-weighted non-process patents (*# CW Non-Process Patents/AT*) scaled by total assets. As developing a patent can

[23] The process and non-process patent classification datasets are available at https://www.janbena.com/en/process-innovation-patent-dataset. We thank Jan Bena for generously sharing the data on his website.

[24] One example of process patent claim according to Bena et al. (2022) is Ford Motor's patent "Manufacturing assembly line and a method of designing a manufacturing assembly line" (US20050044700A1). The patent contains the claim "*A method of designing a manufacturing process line ...*", which is a process claim.

take a few years, it may not be possible for firms to immediately produce more process patents after being exposed to labor shortages. Hence, we examine the implication of a firm's labor-shortage exposure on its process patent outputs in the next three years. We also require firms to be active in innovation activities (i.e., produce at least one patent throughout the history of the firm) for this analysis. Table 7 reports the results.

[Please insert Table 7 about here]

The results in Table 7 show that there is a significantly positive relation between a firm's labor-shortage exposure and its process claims share (columns 1 and 2) and the number of citation-weighted process patents scaled by total assets (columns 3 and 4) in the next three years. The findings are robust to controlling for firm and year fixed effects or firm and industry-by-year fixed effects. In terms of economic magnitude, columns 1 and 3 indicate that a one-standard-deviation increase in *LS Exposure* leads to an average 0.727-percentage-point (= 0.173*0.042) increase in *Process Claims Share* and a 0.104-percentage-point (= 0.173*0.006) increase in *# CW Process Patents/AT* in the next three years, respectively. In addition, columns 5 and 6 further show that the relation between firm-level labor-shortage exposure and future non-process patent outputs is statistically insignificant.

Similarly, we perform various robustness tests for our findings on process patents. These tests include 1) excluding the COVID-19 period (2020 and 2021) from the regressions (columns 4 and 5 in Panel D of Table A8 in Appendix A), 2) comparing the extensive margin (columns 4 and 5 in Panel C of Table A9 in Appendix A) and intensive margin (columns 4 and 5 in Panel D of Table A9 in Appendix A) of the effects of firm-level labor-shortage exposure on future citation-weighted process patents and the share of process claims, 3) reconstructing the firm-level labor-shortage exposure using either the management presentation section or Q&A section of the earnings conference call transcripts (columns 10-15 in Panel B of Table A10 in Appendix A), and 4) further controlling for CEO fixed effects to account for the time-invariant CEO characteristics (columns 4 and 5 in Panels A and B of Table A14 in Appendix A). Across all these robustness checks, we continue to obtain qualitatively similar findings indicating that firms respond to labor shortages by developing more process patents (claims).

Moreover, in columns 4 and 5 of Panel B in Appendix Table A13, we further compare patenting responses to labor shortages between firms experiencing them for the first time and those facing repeated labor shortages. Our analysis shows that the patenting responses are significantly muted following first-time labor shortages. These results again indicate that it is repeated labor-shortage exposure that leads firms to produce more process patents (claims).

In addition to process-related innovation, we also examine whether firms exposed to labor shortages are likely to produce more AI-related patents. These patents are identified using a machine learning approach that analyzes the text and citations of each patent, as outlined by Giczy et al. (2022).[25] The results reported in columns 3-4 of Appendix Table A15 confirm our expectations: firms facing greater labor shortages tend to generate more AI patents in the future, potentially reducing their reliance on labor.

Taken together, the findings in this section show that firms exposed to labor shortages pursue production process efficiency improvements that would facilitate the substitution of labor with capital, resulting in more production-process patents. By contrast, we do not find any significant effect of labor-shortage exposure on non-process patent outputs, likely because such patents do not help address labor-shortage-related issues.

5.5 Corporate Policy Responses to Labor-shortage Exposure and Future Stock Returns

After observing that labor-shortage-exposed firms tend to respond by substituting expensive and scarce labor inputs with capital expenditures and R&D inputs, as well as producing more process patents, we then examine whether these policy responses translate into improved future stock performance.

To conduct the analyses, we measure $\triangle CAPEX$ as the change in a firm's capital expenditure from year *t-1* to year *t*, divided by the firm's capital expenditure in year *t-1*, $\triangle R\&D$ as the change in a firm's R&D expenses from year *t-2* to year *t-1*, divided by the firm's R&D expenses

[25] The AI patent data is also available on the USPTO's official website. Please see https://www.uspto.gov/ip-policy/economic-research/research-datasets/artificial-intelligence-patent-dataset.

in year *t-2*, and $\triangle$*CW Process Patent* as the change in a firm's number of citation-weighted process patents from year *t-2* to year *t-1*, divided by the firm's number of citation-weighted process patents in year *t-2*.[26] We then interact $\triangle$*CAPEX*, $\triangle$*R&D* and $\triangle$*CW Process Patent* with *LS Exposure*, respectively, in the one-year-ahead stock return regressions. If increasing investments in capital expenditures, R&D inputs, and process patents can mitigate the impact of labor shortages, we would anticipate a positive relationship between the three interaction terms and the firm's one-year-ahead stock return. The results are reported in Table 8.

[Please insert Table 8 about here]

Our analysis shows that all three interaction terms have positive coefficient estimates, and two of them, namely *LS Exposure* $\times\triangle$*CAPEX* and *LS Exposure* $\times\triangle$*CW Process Patent*, have statistically significant coefficient estimates. These findings show that corporate policy responses such as increasing capital expenditures and producing more process patents can mitigate the adverse impact of labor-shortage exposure and consequently lead to better future stock performance for labor-shortage-exposed firms.[27]

5.6 Addressing Endogeneity Concerns

Thus far, our findings suggest that firms exposed to labor shortages experience lower future stock and operating performance, and tend to substitute labor with capital while increasing process innovation to mitigate the negative effects on future performance. However, a potential concern is that unobserved firm-level factors may correlate with both a firm's exposure to labor shortages and its future performance, as well as its investments in capital and process innovation, potentially leading to spurious relationships. To address this concern and strengthen the causal interpretation of our findings, we i) replace the firm-level labor shortage exposure

[26] Note that we measure changes in a firm's CAPEX in year *t*, while changes in R&D and process patents are measured in year *t-1*. Doing so accounts for the longer lag between the R&D expenditures or patent filings and the realization of the benefits from those actions.

[27] Our untabulated results show that increasing AI innovation can significantly mitigate the negative impact of labor shortages on firms' future stock performance. Additionally, in Table A16 in Appendix A, we further investigate whether increasing CAPEX, R&D, and/or process patents can help reduce the likelihood of a firm experiencing labor shortages in the next one, two, or three years. We find significant negative effects for changes in CAPEX but generally insignificant effects for changes in R&D or process patents, likely because the impact of R&D and innovation changes on labor-shortage exposure tends to be long-term rather than short-term.

measure with an industry-level indicator, and ii) construct Bartik shift-share instruments.

5.6.1 Industry Labor-shortage Exposure and Firms' Operating Performance and Policy Responses

We first replace the firm-level labor-shortage exposure (*LS Exposure*) with an industry-year indicator in all regressions. The indicator, *I* $(LS^{ind\text{-}top20\%})$, equals one if a firm's industry (2-digit SIC) falls within the top quintile of industry-average *LS Exposure* across all industries in a given year, and zero otherwise. The results are presented in Table 9.

[Please insert Table 9 about here]

Consistent with the baseline results using firm-level labor-shortage exposure, we find that firms in the top quintile of labor-shortage industries also experience significantly lower stock returns, ROA, and operating cash flow in the following year. These firms again tend to respond to labor shortages by substituting labor with capital, increasing R&D investments, and producing more process innovations. By replacing the firm-level labor-shortage exposure with an industry-level measure, these results help alleviate the endogeneity concern that a firm's operating performance and policy responses may be driven by some unobserved firm-level factors.

One might argue that time-varying industry characteristics could drive our findings. For example, labor shortages in an industry-year might be due to factors that significantly increase industry growth and labor demand in that year. However, this alternative explanation is unlikely, as we find qualitatively similar results in our baseline regressions after controlling for industry-year fixed effects. Overall, our combined results suggest that both industry-level and firm-level variation in labor-shortage exposure drive firms' performance and investment responses. We have not been able to identify an economically plausible alternative explanation for all the documented results.

5.6.2 Bartik Shift-Share Instrument

To further address potential endogeneity concern on our findings, we construct a Bartik shift-share instrument (Bartik, 1991; Goldsmith-Pinkham et al., 2020). The Bartik instrument aims to identify the treatment effect by measuring the differential impact of common shocks on units with distinct predetermined exposures. For instance, Bartik (1991) instruments a county's employment rate by interacting the nationwide industry employment rate with the county's preexisting industry shares. Inspired by this, we utilize the granular information on a firm's segment sales from the Compustat Segments database to construct an instrument for the firm-level labor-shortage exposure.

Specifically, we construct an instrument *Bartik IV1*$_{\text{i,t}}$ by summing the products of *LS Exposure*$_{\text{j,t}}{}^{\text{Ind-Avg}}$ and *Segment Share*$_{\text{s,i,t-1}}$ for each firm i and year t. *LS Exposure*$_{\text{j,t}}{}^{\text{Ind-Avg}}$ is the average labor-shortage exposure for industry j (to which the segment s of firm i belongs) in year t.[28] *Segment Share*$_{\text{s,i,t-1}}$ is the predetermined sales share of segment s in firm i in year *t-1*. We then instrument *LS Exposure*$_{\text{i,t}}$ with *Bartik IV1*$_{\text{i,t}}$ in two-stage least squares (2SLS) regressions. That is, we use the aggregate industry-year labor shortage conditions weighted by a firm's predetermined segment sales shares to predict the firm's labor-shortage exposure. The rationale behind this instrument is that the preexisting segment sales shares indicate the firm's ex-ante reliance on specific industries. When labor-shortage issues impact certain industries, we expect a firm with higher preexisting sales in these industries to be more significantly affected. The approach allows us to isolate a firm's variation in labor-shortage exposure from firm characteristics. Panel A of Table 10 reports the results.

[Please insert Table 10 about here]

Column 1 (2) presents the first-stage regression results, where *LS Exposure*$_{\text{i,t}}$ is regressed on *Bartik IV1*$_{\text{i,t}}$, with controls for firm characteristics and industry (firm) and year fixed effects. As anticipated, we find that the instrument is positively and significantly related to firm labor-shortage exposure, with Cragg-Donald Wald F statistics exceeding 422 (229). Columns 3 to 10 present the second-stage results using the instrumented labor-shortage exposure, $LS\ \widehat{Exposure}_{\text{i,t}}$. Columns 3 to 5 explore the effects of instrumented labor-shortage exposure on future firm performance, while columns 6 to 10 examine corporate policy responses

[28] We only use the labor-shortage exposures of single-segment firms in industry j to calculate industry j's average labor-shortage exposure.

to labor-shortage issues. Consistent with our prior findings, the results suggest that firm-level labor-shortage exposure indeed negatively affects future firm performance, and firms seek to address labor-shortage issues by replacing labor with capital and process innovations.

In the spirit of Bartik (1991), we further strengthen the causal interpretation of our findings by constructing another instrument. We interact $LS\ Exposure_{j,t}{}^{M}$, the average labor-shortage exposure for *labor-shortage-mentioning firms* in industry j (to which firm i belongs) and year t, with $LS\ Exposure_{j,t\text{-}1}{}^{Fraction}$, the predetermined fraction of firms exposed to labor shortages in industry j and year $t\text{-}1$. The idea behind this instrument is that a firm is more likely to be affected by industry-wide labor shortages if the intensive margin of labor-shortage exposure in its industry is high currently and labor-shortage issues were pervasive in the industry previously. The first-stage results in columns 1 and 2 of Panel B in Table 10 confirm this hypothesis. Importantly, the second-stage results, reported in columns 3 to 10, indicate that the negative effects of firm-level labor-shortage exposure on future stock performance remain robust. Moreover, we continue to observe the substitution effects between labor and capital and process innovations.

In summary, the results from both sets of 2SLS regressions yield qualitatively similar findings: labor shortages decrease firms' future performance and motivate them to replace labor with capital and process innovations.

6 How Do Labor-shortage-exposed Firms Perform during the COVID-19 Pandemic?

Finally, we investigate whether labor-shortage-exposed firms and non-exposed firms performed differently during the COVID-19 pandemic. In 2020, the outbreak led to a contraction of the GDP growth by 3.5%, the largest drop since 1946. Additionally, the pandemic has magnified the labor-shortage exposure facing the U.S. economy (as shown in Figure 1). It is an empirical question whether firms that experienced labor shortages before the pandemic performed better or worse than those without labor-shortage exposure. While firms with prior labor-shortage experience may be better prepared for labor market disruptions during the pandemic (e.g., having developed more labor-efficient production processes), they may also be more vulnerable to labor market tightening.

We use a DiD regression framework to examine the differential effects of the pandemic on stock returns and corporate operating performance between the ex-ante labor-shortage exposed firms and non-exposed firms two years before and after the pandemic (i.e., from 2018 to 2021). The labor-shortage exposed firms are those that have already experienced labor-shortage-related issues before the onset of the pandemic; that is, their *LS Exposure* is non-zero in the two years (i.e., 2018 and 2019) before the pandemic. The non-exposed firms are those that have not been exposed to labor shortages during the entire 2005-2021 sample period.[29] We estimate the following regression specification:

$$Y_{i,t} = \beta_1 LS_{\mathrm{i}}^{\textit{ex-ante}} \times \textit{Post COVID}_t + \beta_2 \textit{Controls}_{i,t-1} + \omega_i + \mu_t + \epsilon_{i,t} \tag{5}$$

In Equation 5, the dependent variable Y is firm i's stock return or operating performance (*Stock Return*, *ROA*, or *Operating Cash Flow*) in year t. $LS^{\textit{ex-ante}}$ is an indicator that equals one if firm i has non-zero value of labor-shortage measure in the two years before the pandemic, and equals zero if firm i is never exposed to labor shortage during the sample period of the study. *Post COVID* is also an indicator that equals one if year t is 2020 or 2021, and equals zero otherwise. β_1 is our coefficient of interest that captures the differential effect of the COVID-19 shock on firm performance between the labor-shortage exposed firms and non-exposed firms. We further control for a battery of lagged firm characteristics, as well as firm fixed effects ω_i and year fixed effects μ_t. Panel A of Table 11 presents the results.

[Please insert Table 11 about here]

[29] We exclude firms that were only exposed to labor shortages during the pandemic from our analysis, but our results remain qualitatively unchanged when we include such firms. Furthermore, we find that firms that were only exposed to labor shortages during the pandemic did not underperform compared to unexposed firms during the 2020-2021 period. This is consistent with our earlier finding that the impact of labor-shortage exposure mainly comes from repeated exposure rather than first-time exposure

We control for firm and year fixed effects in columns 1, 3, and 5 of Panel A, while we further replace year fixed effects with industry-by-year fixed effects in columns 2, 4, and 6. The coefficient estimates of the DiD term are negative and statistically significant at least at the 10% level across all regression models. The results indicate a disproportionate impact of the COVID-19 shock on the stock returns and operating performance of firms with ex-ante labor-shortage exposure relative to non-exposed firms, suggesting that labor-shortage exposed firms have been hit harder than non-exposed firms. The economic magnitudes are sizable. During the pandemic, compared to non-exposed firms, labor-shortage exposed firms experienced stock returns that were 5.5 percentage points worse per year, and ROA that was 2.4 percentage points per year lower, and operating cash flow that was 1.5 percentage points lower per year.

We further estimate a dynamic regression specification where we replace the *Post COVID* indicator in Equation 5 with year indicators to allow for the differential effect to be varied by year. The results in Panel B show that the coefficient estimates of the interaction term between $LS^{ex\text{-}ante}$ and $Year_{-1}$, the year (i.e., 2019) before the onset of the pandemic, is insignificantly different from zero across all six regression models. The significant differential effects only show up in 2020 and especially 2021. These findings suggest that there are parallel performance trends immediately before the pandemic and the differential effect on *Stock Return*, *ROA* and *Operating Cash Flow* are likely caused by the pandemic.

In summary, the results in this section suggest that labor-shortage-exposed firms were particularly vulnerable to the tightened labor market during the pandemic, and that the significant pandemic-induced labor shortage further eroded these firms' stock returns and operating performance.

7 Conclusion

In this paper, we use earnings conference call transcripts and the machine learning model *FinBERT* to measure a firm's labor-shortage exposure, achieving a 95% accuracy rate in classifying labor-shortage-related sentences. Using these classifications, we construct a firm-level labor-shortage exposure measure spanning 2005-2021.

We validate this measure through multiple approaches: First, labor-shortage exposure peaked in 2021, aligning with the COVID-19 pandemic's labor market impact. Second, industry rankings reveal construction, transportation, and service sectors as most vulnerable due to their labor-intensive nature. Third, at the state level, labor-shortage exposure negatively correlates with future unemployment rates and positively with wage growth and labor market tightness. Fourth, firm-level exposure predicts future growth in per-employee expenses. Fifth, the 2017 U.S. immigration policy reforms, which reduced foreign labor supply, led to significant increases in labor-shortage exposure for labor-intensive firms. Finally, state-level COVID-19 lockdown stringency significantly increased local firms' labor-shortage exposure in the subsequent quarter, further validating the measure.

We then explore the implications of labor-shortage exposure. First, firms with higher labor-shortage exposure experience lower CAR within the three days following the earnings conference calls. Second, this exposure negatively predicts one-year-ahead stock returns and operating performance. Third, a firm's labor-shortage exposure correlates positively (negatively) with its one-year-ahead capital expenditures (change in the number of employees per million dollar of assets), suggesting substitution of costly labor with capital. Fourth, labor-shortage exposure is positively associated with increased process innovations over the next three years, indicating a focus on production efficiency. These adjustments help mitigate the negative impact of labor shortages on future stock performance.

Finally, we examine the COVID-19 pandemic's differential impact on firms exposed to labor shortages prior to the pandemic, finding that these firms suffered significantly lower stock returns and operating performance compared to non-exposed firms. While the study does not focus on the underlying causes of labor shortages, our labor-shortage exposure measure offers a valuable tool for practitioners, academics, and policymakers to address these critical issues.

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Figure 1. Annual Variation of Labor-shortage Exposure

This figure provides the number of labor-shortage-exposed firms (red bars), the equal-weighted aggregate firm-level labor-shortage exposure (green line), and the proportion of labor-shortage-exposed firms (blue line) by year from 2005 to 2021.

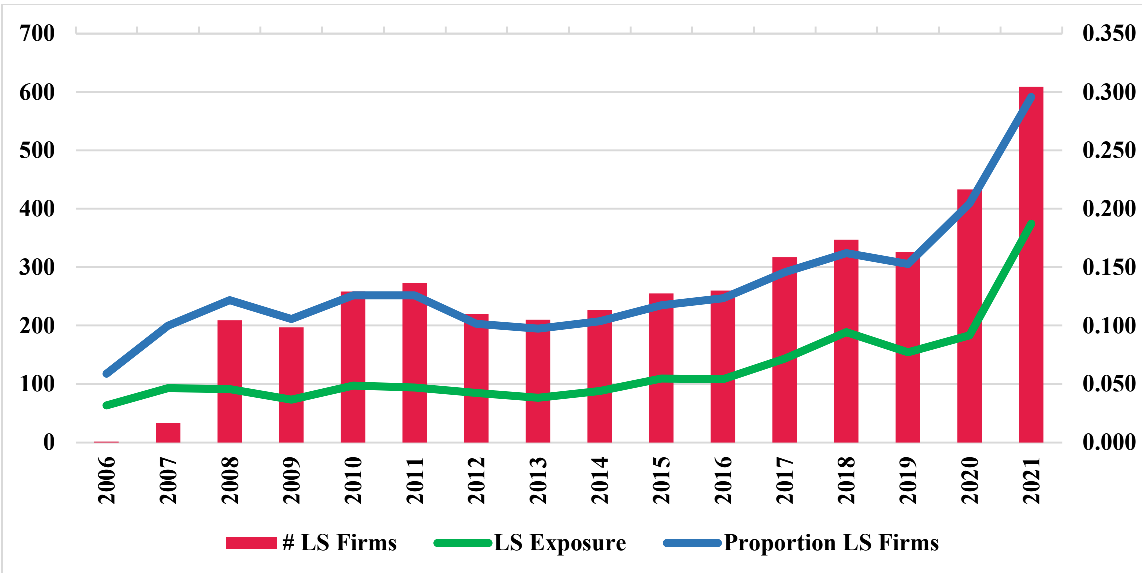

Figure 2. Top-10 Industries by Average Labor-Shortage Exposure

The figures illustrate the top-10 industries (2-digit SIC) that are most exposed to labor shortage. In figure 2A, we rank industries by average labor-shortage exposure over the full sample period (2005 to 2021); in figure 2B, we rank industries by average labor-shortage exposure over the pre COVID sample period (2005 to 2019); in figure 2C, we rank industry by average labor-shortage exposure over the COVID sample period (2020-2021). The y axis denotes the 2-digit SIC and the related industry classification, and the x axis reports the value of the labor-shortage exposure.

Figure 2A. Full sample period 2005-2021

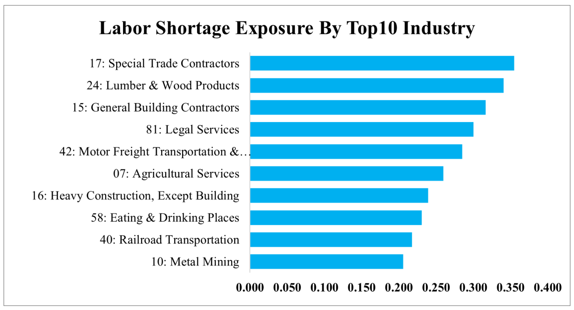

Figure 2B. Pre-COVID 2005-2019

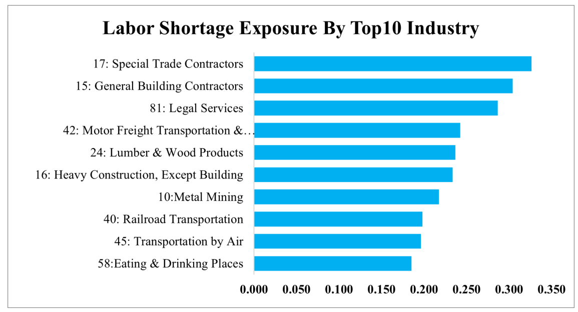

Figure 2C. During-COVID 2020-2021

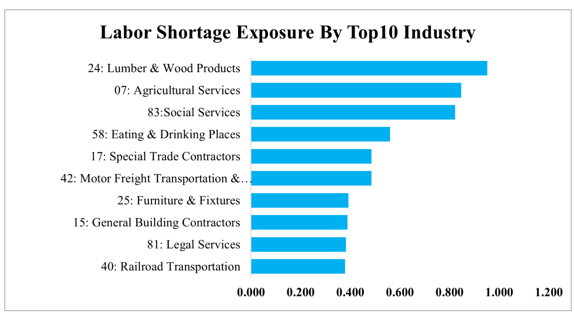

Table 1. Summary Statistics

This table reports the summary statistics for our final sample. The sample period spans from 2005 to 2021. We report the number of observations, mean, 25th percentile, median, 75th percentile, and standard deviation for each of the variables used in the study. All continuous variables are winsorized at the 1st and 99th percentiles. Table A1 in Appendix A provides detailed variable definitions.

Variables	Obs.	Mean	P25	Median	P75	STD
Labor Shortage Variables						
LS Exposure^{state}	726	0.058	0.024	0.045	0.077	0.057
LS Exposure	25,551	0.062	0.000	0.000	0.060	0.173
Dependent Variables						
Unemployment Rate	726	0.059	0.042	0.055	0.073	0.022
Wage Growth	726	0.034	0.022	0.036	0.049	0.030
Log(# Job Openings/# Unemployed)	702	-0.515	-1.008	-0.470	-0.002	0.660
Growth in Per-Employee Staff Expenses	4,040	0.025	-0.021	0.028	0.074	0.121
CAR (0, 2)	100,588	-0.000	-0.473	0.000	0.048	0.094
Stock Return	25,551	0.154	-0.115	0.100	0.325	0.479
ROA	25,551	-0.021	-0.027	0.032	0.073	0.216
Operating Cash Flow	25,551	0.053	0.036	0.082	0.131	0.179
CAPEX	25,551	0.043	0.014	0.028	0.055	0.048
R&D	25,551	0.055	0.000	0.003	0.063	0.110
△Employees/AT	25,510	-0.0001	-0.0003	-0.0000	0.0001	0.0011
Process Claims Share	16,231	0.167	0.000	0.037	0.327	0.210
# CW Process Patents/AT	16,231	0.013	0.000	0.000	0.004	0.098
# CW Non-Process Patents/AT	16,231	0.021	0.000	0.000	0.009	0.113
Independent Variables						
Log(GDP)	726	13.566	12.758	13.602	14.287	0.993
Log(Population)	726	15.137	14.398	15.302	15.748	1.006
Log(Per Cap Income)	726	10.710	10.567	10.697	10.842	0.197
COVID Stringencystate	11,841	58.705	50.460	59.720	67.590	14.312
Book Leverage	25,551	0.369	0.061	0.327	0.549	0.348
MTB	25,551	3.813	1.281	2.207	3.964	5.774
Sales Growth	25,551	0.065	-0.035	0.054	0.156	0.296
Firm Size	25,551	6.639	5.462	6.783	7.986	2.077
Cash	25,551	0.148	0.033	0.096	0.201	0.162
Asset Tangibility	25,551	0.254	0.069	0.159	0.370	0.243
Stock Volatility	25,551	0.484	0.296	0.419	0.597	0.270
Earnings Surprise	100,588	-0.004	-0.001	0.001	0.003	0.103

Table 2. Validation: State-level Labor-Shortage Exposure, Unemployment Rate, Wages Growth, and Labor Market Tightness

The table presents the regression results that investigate the effects of a state's labor-shortage exposure on the state's one-year-ahead unemployment rate, wage growth, and labor market tightness. The dependent variable *Unemployment Rate* is measured as a state's total number of people unemployed divided by the state's total labor force in a year; *Wage Growth* is measured as a state's total wage in year *t* minus the state's total wage in year *t-1*, further divided by the state's total wage in year *t-1*; $Log(\frac{\#Job\ Openings}{\#Unemployed})$ is measured as the natural logarithm of a state's number of job openings divided by the state's number of people unemployed in a year. The independent variable $LS\ Exposure^{state}$ is a state's labor-shortage exposure, which is the average labor-shortage exposure of all public firms headquartered in that state in a year. All specifications control for state economic variables, state fixed effects, and year fixed effects. Table A1 in Appendix A provides detailed variable definitions. Robust standard errors clustered at the state level are provided in parentheses. All financial variables are winsorized at the 1st and 99th percentiles. ***, **, and * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Unemployment Rate $_{t+1}$		Wage Growth $_{t+1}$		$Log(\frac{\#Job\ Openings}{\#Unemployed})_{t+1}$	
LS Exposure^{state}	**-0.040*** **	**-0.019** **	**0.033** **	**0.031** **	**0.858*** **	**0.409*** **
	(0.013)	**(0.008)**	**(0.015)**	**(0.014)**	**(0.265)**	**(0.149)**
Log(GDP)	0.025**	-0.010	0.007	-0.033	0.005	1.002**
	(0.012)	(0.028)	(0.008)	(0.072)	(0.183)	(0.436)
Log(Population)	-0.020*	0.045	-0.005	0.041	-0.165	-2.334***
	(0.011)	(0.033)	(0.007)	(0.094)	(0.173)	(0.676)
Log(Per Cap Income)	-0.040**	-0.071***	-0.008	0.065	0.404	1.213***
	(0.018)	(0.023)	(0.016)	(0.067)	(0.339)	(0.403)
State FE	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	726	726	726	726	702	702
Adj. R2	0.638	0.851	0.652	0.702	0.852	0.936

Table 3. Validation: Firm-level Labor-Shortage Exposure and Growth in Per-Employee Staff Expenses

The table presents the regression results that investigate the effects of a firm's labor-shortage exposure on the firm's one-year-ahead growth in per-employee staff expenses. The dependent variable *Growth in Per-Employee Staff Expenses* is measured as the growth rate in a firm's per-employee staff expenses from year *t-1* to year *t*. The independent variable *LS Exposure* is a firm's labor-shortage exposure in a year. All specifications include firm controls. Column 1 controls for year fixed effects and industry fixed effects. Column 2 controls for industry-by-year fixed effects. Column 3 controls for year fixed effects and firm fixed effects. Column 4 controls for industry-by-year fixed effects and firm fixed effects. Table A1 in Appendix A provides detailed variable definitions. Robust standard errors clustered at the firm level are provided in parentheses. All financial variables are winsorized at the 1st and 99th percentiles. ***, **, and * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)
VARIABLES	Growth in Per-Employee Staff Expenses $_{t+1}$			
LS Exposure	**0.015****	**0.020*****	**0.016***	**0.022****
	(0.007)	**(0.007)**	**(0.009)**	**(0.010)**
ROA	0.063*	0.087**	0.085	0.130**
	(0.038)	(0.043)	(0.056)	(0.054)
Book Leverage	0.005	0.007	-0.020	-0.025
	(0.008)	(0.008)	(0.016)	(0.018)
Stock Return	-0.000	-0.001	-0.003	-0.007
	(0.009)	(0.009)	(0.010)	(0.011)
CAPEX	-0.169**	-0.181***	-0.076	-0.187*
	(0.081)	(0.069)	(0.106)	(0.106)
MTB	0.000	-0.000	0.001	0.000
	(0.000)	(0.000)	(0.001)	(0.001)
Sales Growth	-0.039**	-0.034*	-0.029	-0.020
	(0.018)	(0.020)	(0.021)	(0.022)
Firm Size	-0.002	-0.002	-0.012	-0.016**
	(0.001)	(0.001)	(0.007)	(0.008)
Cash	0.046*	0.036	0.115**	0.134***
	(0.024)	(0.023)	(0.045)	(0.045)
Asset Tangibility	0.023	0.042**	-0.038	0.048
	(0.021)	(0.020)	(0.052)	(0.071)
Stock Volatility	0.039	0.020	0.122*	0.144*
	(0.047)	(0.049)	(0.066)	(0.074)
R&D	0.073	0.131	0.227	0.320**
	(0.101)	(0.092)	(0.154)	(0.134)
Employees/AT	-0.817**	-0.970**	-4.304***	-6.876***
	(0.387)	(0.408)	(1.336)	(1.860)
Industry FE	Yes	No	No	No
Year FE	Yes	No	Yes	No
Industry-Year FE	No	Yes	No	Yes
Firm FE	No	No	Yes	Yes
Obs.	4,040	3,864	4,033	3,848
Adj. R2	0.044	0.083	0.008	0.044

Table 4. Stock Price Reaction to Labor-shortage Exposure

This table reports the regression results that investigate the stock price reaction to labor-shortage exposure. The dependent variable *CAR (0, 2)* is cumulative abnormal stock returns during a three-day event window of (0, 2) following the earnings conference calls. We calculate cumulative abnormal returns using the market-adjusted model. The independent variable *LS Exposure* is a firm's labor-shortage exposure in that year-quarter (measured using the earnings conference call transcript). All regression specifications except Column 1 include firm control variables. Columns 1-2 do not include any fixed effect. Column 3 includes year-quarter fixed effects. Column 4 includes both year-quarter fixed effects and industry fixed effects. Column 5 includes industry-by-year-quarter fixed effects. Table A1 in Appendix A provides detailed variable definitions. Robust standard errors clustered at the firm level are provided in parentheses. All financial variables are winsorized at the 1st and 99th percentiles. ***, **, and * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)	(5)
VARIABLES			CAR (0, 2)		
LS Exposure	**-0.007*** **	**-0.006*** **	**-0.006*** **	**-0.006*** **	**-0.006*** **
	(0.001)	**(0.001)**	**(0.001)**	**(0.001)**	**(0.001)**
ROA $_{q-1}$		0.142***	0.133***	0.135***	0.135***
		(0.011)	(0.011)	(0.011)	(0.011)
Book Leverage $_{q-1}$		0.001	0.001	0.001	0.001
		(0.001)	(0.001)	(0.001)	(0.001)
Stock Return $_{q-1}$		0.124***	0.150***	0.151***	0.154***
		(0.002)	(0.002)	(0.002)	(0.002)
CAPEX $_{q-1}$		0.030***	0.004	0.006	0.004
		(0.011)	(0.012)	(0.012)	(0.013)
MTB $_{q-1}$		-0.000***	-0.000***	-0.000***	-0.000***
		(0.000)	(0.000)	(0.000)	(0.000)
Sales Growth $_{q-1}$		0.016***	0.016***	0.016***	0.016***
		(0.001)	(0.001)	(0.001)	(0.001)
Firm Size $_{q-1}$		0.000	-0.000	-0.000	-0.000
		(0.000)	(0.000)	(0.000)	(0.000)
Cash $_{q-1}$		-0.001	0.003	0.003	0.002
		(0.003)	(0.003)	(0.003)	(0.003)
Asset Tangibility $_{q-1}$		-0.001	0.002	0.002	0.002
		(0.002)	(0.002)	(0.002)	(0.002)
Stock Volatility $_{q-1}$		-0.030***	-0.042***	-0.042***	-0.046***
		(0.005)	(0.005)	(0.006)	(0.006)
R&D $_{q-1}$		0.051**	0.030	0.017	0.012
		(0.021)	(0.021)	(0.024)	(0.024)
Employees/AT $_{q-1}$		0.015	0.005	0.034	0.041
		(0.049)	(0.049)	(0.053)	(0.054)
Earnings Surprise $_{q-1}$		0.024***	0.026***	0.026***	0.025***
		(0.008)	(0.007)	(0.007)	(0.007)
Industry FE	No	No	No	Yes	No
Year-Quarter FE	No	No	Yes	Yes	No
Industry-Year-Quarter FE	No	No	No	No	Yes
Obs.	100,588	100,588	100,588	100,588	100,588
Adj. R2	0.000	0.152	0.176	0.176	0.182

Table 5. Implications of Firm-level Labor-shortage Exposure: Cross-sectional Stock Returns and Operating Performance

This table reports the regression results that investigate the implications of firm-level labor-shortage exposure on one-year-ahead cross-sectional stock returns and operating performance. The dependent variable *Stock Return* is measured as a firm's one-year-ahead buy-and-hold stock return. *ROA* is measured as a firm's one-year-ahead income before extraordinary items divided by its total value of assets. *OCF* is measured as a firm's one-year-ahead operating cash flow divided by its total value of assets. The independent variable *LS Exposure* is a firm's labor-shortage exposure in a year. All specifications except Column 1 include firm characteristics controls. Columns 1-2 do not include any fixed effect. Column 3 includes year fixed effects. Column 4 includes both year fixed effects and industry fixed effects. Columns 5-7 include industry-by-year fixed effects. Table A1 in Appendix A provides detailed variable definitions. Robust standard errors clustered at the firm level are provided in parentheses. All financial variables are winsorized at the 1st and 99th percentiles. ***, **, and * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES			Stock Return $_{t+1}$			ROA $_{t+1}$	OCF $_{t+1}$
LS Exposure	**-0.031****	**-0.037****	**-0.060*****	**-0.058*****	**-0.063*****	**-0.013****	**-0.009****
	(0.016)	**(0.017)**	**(0.015)**	**(0.015)**	**(0.016)**	**(0.006)**	**(0.004)**
ROA		0.314***	0.247***	0.246***	0.240***		0.402***
		(0.027)	(0.026)	(0.026)	(0.026)		(0.018)
Book Leverage		-0.010	0.001	-0.006	-0.005	-0.047***	0.001
		(0.011)	(0.010)	(0.011)	(0.011)	(0.007)	(0.005)
Stock Return		0.169***	0.184***	0.177***	0.191***	0.078***	0.006*
		(0.010)	(0.010)	(0.010)	(0.010)	(0.004)	(0.003)
CAPEX		-1.165***	-0.678***	-0.609***	-0.466***	0.064	0.313***
		(0.081)	(0.073)	(0.082)	(0.078)	(0.043)	(0.032)
MTB		0.008***	0.006***	0.006***	0.005***	0.001***	0.001***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Sales Growth		-0.119***	-0.044***	-0.041***	-0.025*	0.000	-0.016***
		(0.014)	(0.013)	(0.013)	(0.013)	(0.007)	(0.006)
Firm Size		0.019***	0.013***	0.014***	0.012***	0.028***	0.012***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Cash		0.097***	0.043*	0.055**	0.062**	-0.053**	-0.082***
		(0.027)	(0.025)	(0.025)	(0.025)	(0.022)	(0.014)
Asset Tangibility		0.129***	0.054***	0.099***	0.072***	-0.017	0.014*
		(0.019)	(0.016)	(0.023)	(0.022)	(0.011)	(0.008)
Stock Volatility		2.524***	1.659***	1.744***	1.614***	-0.545***	-0.123***
		(0.093)	(0.095)	(0.099)	(0.095)	(0.035)	(0.024)
R&D		0.032	0.079*	0.091*	0.075	-0.690***	-0.189***
		(0.048)	(0.046)	(0.049)	(0.049)	(0.040)	(0.030)
Employees/AT		-0.676	0.905**	0.383	0.268	0.608*	0.515**
		(0.453)	(0.404)	(0.529)	(0.524)	(0.313)	(0.226)
Industry FE	No	No	No	Yes	No	No	No
Year FE	No	No	Yes	Yes	No	No	No
Industry-Year FE	No	No	No	No	Yes	Yes	Yes
Obs.	25,551	25,551	25,551	25,551	25,551	25,551	25,551
Adj. R2	0.000	0.147	0.280	0.284	0.333	0.435	0.578

Table 6. Implications of Firm-level Labor-shortage Exposure: Corporate Investment

This table reports the regression results that investigate the implications of firm-level labor-shortage exposure on one-year-ahead corporate investment. The dependent variable *CAPEX* is measured as a firm's capital expenditures divided by its total value of assets. *R&D* is measured as a firm's research and development expenses divided by its total value of assets. △*Employees/AT* is measured as the change in a firm's number of employees divided by its total value of assets from year *t* to year *t+1*. The independent variable *LS Exposure* is a firm's labor-shortage exposure in a year. All specifications include firm characteristics controls, firm fixed effects, and year (or industry-by-year) fixed effects. Table A1 in Appendix A provides detailed variable definitions. Robust standard errors clustered at the firm level are provided in parentheses. All financial variables are winsorized at the 1st and 99th percentiles. ***, **, and * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	CAPEX $_{t+1}$		R&D $_{t+1}$		△Employees/AT $_{t+1}$	
LS Exposure	**0.005*** **	**0.002***	**0.002***	**0.001**	**-0.0003*** **	**-0.0003*** **
	(0.001)	**(0.001)**	**(0.001)**	**(0.001)**	**(0.0001)**	**(0.0001)**
ROA	0.015***	0.010***	-0.040***	-0.039***	0.000	0.000
	(0.002)	(0.002)	(0.007)	(0.007)	(0.000)	(0.000)
Book Leverage	-0.008***	-0.006***	-0.005	-0.005	0.000	0.000*
	(0.001)	(0.001)	(0.004)	(0.004)	(0.000)	(0.000)
Stock Return	0.006***	0.005***	-0.003*	-0.003**	-0.000***	-0.000**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
CAPEX			0.020*	0.029**	-0.001***	-0.002**
			(0.012)	(0.013)	(0.00)	(0.00)
MTB	0.000***	0.000***	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sales Growth	0.006***	0.005***	0.004	0.003	0.000	0.000
	(0.001)	(0.001)	(0.003)	(0.003)	(0.000)	(0.000)
Firm Size	-0.001	-0.002**	-0.007***	-0.005**	-0.000	-0.000
	(0.001)	(0.001)	(0.002)	(0.003)	(0.000)	(0.000)
Cash	0.008***	0.011***	0.016*	0.016*	0.000***	0.001***
	(0.002)	(0.002)	(0.009)	(0.009)	(0.000)	(0.000)
Asset Tangibility	-0.007	0.002	0.013	0.001	-0.001***	-0.001***
	(0.007)	(0.007)	(0.011)	(0.012)	(0.000)	(0.000)
Stock Volatility	-0.049***	-0.029***	-0.026**	-0.025**	0.000	0.000
	(0.005)	(0.005)	(0.011)	(0.012)	(0.000)	(0.000)
R&D	0.025***	0.017***			-0.002***	-0.002***
	(0.005)	(0.004)			(0.000)	(0.000)
Employees/AT	1.023***	0.749***	0.926***	1.453***		
	(0.175)	(0.163)	(0.224)	(0.275)		
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No	Yes	No
Industry-Year FE	No	Yes	No	Yes	No	Yes
Obs.	25,541	25,541	25,541	25,541	25,495	25,495
Adj. R2	0.718	0.749	0.836	0.836	0.071	0.150

Table 7. Implications of Firm-level Labor-shortage Exposure: Process Patent Outputs

This table reports the regression results that investigate the implications of firm-level labor-shortage exposure on process (non-process) patent outputs from year *t+1* to *t+3*. The dependent variable *Process Claims Share* is measured as the number of process claims divided by the number of total claims for all patents a firm has applied in a year; *# CW Process Patents/AT* is measured as the citation weighted number of process patents a firm has applied (and later granted) scaled by the total assets of the firm; *# CW Non-Process Patents/AT* is measured as the citation weighted number of non-process patents a firm has applied (and later granted) scaled by the total assets of the firm. The independent variable *LS Exposure* is a firm's labor-shortage exposure in a year. All specifications include firm characteristics controls, firm fixed effects, and year (industry-by-year) fixed effects. Table A1 in Appendix A provides detailed variable definitions. Robust standard errors clustered at the firm level are provided in parentheses. All financial variables are winsorized at the 1st and 99th percentiles. ***, **, and * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

VARIABLES	(1) Process Claims Share $_{t+1,t+3}$	(2)	(3) # CW Process Patents/AT $_{t+1,t+3}$	(4)	(5) # CW Non-Process Patents/AT $_{t+1,t+3}$	(6)
LS Exposure	**0.042*** **	**0.026*** **	**0.006*** **	**0.004** **	**0.003**	**0.001**
	(0.010)	**(0.010)**	**(0.002)**	**(0.002)**	**(0.002)**	**(0.003)**
ROA	0.024*	0.016	0.020	0.020	0.038***	0.039***
	(0.013)	(0.014)	(0.017)	(0.018)	(0.013)	(0.014)
Book Leverage	-0.009	-0.006	0.008	0.010	0.003	0.004
	(0.010)	(0.010)	(0.006)	(0.007)	(0.005)	(0.005)
Stock Return	-0.005	-0.001	-0.000	0.002	0.002	0.004
	(0.003)	(0.004)	(0.002)	(0.002)	(0.003)	(0.003)
CAPEX	0.028	0.056	-0.005	-0.003	-0.011	-0.002
	(0.061)	(0.064)	(0.022)	(0.025)	(0.027)	(0.031)
MTB	0.000	0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sales Growth	0.019***	0.011*	0.003	0.002	0.011**	0.010**
	(0.006)	(0.006)	(0.004)	(0.005)	(0.005)	(0.005)
Firm Size	-0.015***	-0.005	-0.008**	-0.007**	-0.017***	-0.016***
	(0.005)	(0.005)	(0.003)	(0.003)	(0.004)	(0.004)
Cash	0.029	0.016	-0.004	-0.006	0.006	0.007
	(0.020)	(0.020)	(0.024)	(0.025)	(0.027)	(0.028)
Asset Tangibility	0.044	0.006	-0.016	-0.020	-0.029	-0.038*
	(0.037)	(0.039)	(0.013)	(0.015)	(0.019)	(0.021)
Stock Volatility	0.043	0.042	-0.008	-0.015	0.040	0.041
	(0.031)	(0.030)	(0.019)	(0.023)	(0.029)	(0.032)
R&D	0.066	0.030	0.121***	0.127***	0.160***	0.162***
	(0.042)	(0.044)	(0.028)	(0.029)	(0.052)	(0.056)
Employees/AT	-5.574***	-5.247***	-0.017	-0.077	-0.765	-0.710
	(1.301)	(1.418)	(0.423)	(0.491)	(1.305)	(1.543)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No	Yes	No
Industry-Year FE	No	Yes	No	Yes	No	Yes
Observations	16,231	16,116	16,231	16,116	16,231	16,116
Adjusted R-squared	0.678	0.692	0.607	0.590	0.565	0.546

Table 8. Corporate Policy Responses to Labor-shortage Exposure and Future Stock Returns

This table reports the regression results that investigate whether corporate policy responses to labor-shortage exposure help improve future stock performance. The dependent variable *Stock Return* is a firm's one-year-ahead buy-and-hold stock return. The independent variable *LS Exposure* is a firm's labor-shortage exposure in a year; $\triangle$*CAPEX* is measured as the change in a firm's capital expenditure from year *t-1* to year *t*, divided by the firm's capital expenditure in year *t-1*; $\triangle$*R&D* is measured as the change in a firm's R&D expenses from year *t-2* to year *t-1*, divided by the firm's R&D expenses in year *t-2*; $\triangle$*CW Process Patent* is measured as the change in a firm's number of citation-weighted process patents from year *t-2* to year *t-1*, divided by the firm's number of citation-weighted process patents in year *t-2*. All specifications include firm characteristics controls and industry-by-year fixed effects. Table A1 in Appendix A provides detailed variable definitions. Robust standard errors clustered at the firm level are provided in parentheses. All financial variables are winsorized at the 1st and 99th percentiles. ***, **, and * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)
VARIABLES		Stock Return $_{t+1}$	
LS Exposure	-0.066***	-0.064***	-0.090***
	(0.016)	(0.016)	(0.022)
$\triangle$CAPEX	-0.001***		
	(0.000)		
$\triangle$R&D $_{t-1}$		-0.002	
		(0.004)	
$\triangle$CW Process Patent $_{t-1}$			-0.000*
			(0.000)
LS Exposure × $\triangle$CAPEX	**0.012****		
	(0.005)		
LS Exposure × $\triangle$R&D $_{t-1}$		**0.021**	
		(0.045)	
LS Exposure × $\triangle$CW Process Patent $_{t-1}$			**0.010*****
			(0.004)
Firm Controls	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes
Obs.	25,274	25,448	14,060
Adj. R2	0.327	0.327	0.304

Table 9. Industry Labor-shortage Exposure and Firms' Operating Performance and Policy Responses

The table compares stock and operating performance and firm policy responses based on their industry-year-level labor-shortage exposure. We construct an indicator, $I\ (LS^{ind\text{-}top20\%})$, that equals one if a firm's industry (2-digit SIC) falls within the top quintile of industry-average *LS Exposure* across all industries in a given year and zero otherwise. Firm controls are included in each panel (consistent with the main results) but are omitted from reporting for brevity. Table A1 in Appendix A provides detailed variable definitions. Robust standard errors clustered at the firm level are provided in parentheses. All financial variables are winsorized at the 1st and 99th percentiles. ***, **, and * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
VARIABLES	Stock Return $_{t+1}$		ROA $_{t+1}$		OCF $_{t+1}$		CAPEX $_{t+1}$	R&D $_{t+1}$	$\triangle$Employee/AT $_{t+1}$	Process Claim Share $_{t+1,t+3}$	# CW Process Patents/AT $_{t+1,t+3}$
I ($LS^{ind\text{-}top20\%}$)	-0.036***	-0.043**	-0.010***	-0.000	-0.009***	-0.006***	0.003***	0.001*	0.000	0.017***	0.003***
	(0.006)	(0.010)	(0.003)	(0.003)	(0.002)	(0.002)	(0.001)	(0.000)	(0.000)	(0.004)	(0.001)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes	No	Yes	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	25,551	25,551	25,551	25,551	25,551	25,551	25,539	25,539	25,495	16,231	16,231
Adj. R2	0.281	0.284	0.417	0.426	0.561	0.578	0.719	0.836	0.129	0.678	0.607

Table 10. Addressing Endogeneity Concerns: Bartik Shift-Share Instrumental-variable Analyses

The table reports the results from Bartik shift-share instrumental-variable Analyses. In Panel A, we construct an instrument *Bartik IV1*$_{i,t}$ by summing the products of *LS Exposure*$_{j,t}^{\text{Ind-Avg}}$ and *Segment Share*$_{s,i,t\text{-}1}$ for each firm i and year t. *LS Exposure*$_{j,t}^{\text{Ind-Avg}}$ is the average labor-shortage exposure for industry j (to which the segment s of firm i belongs) in year t. We only use the labor-shortage exposures of single-segment firms in industry j to calculate industry j's labor-shortage exposure. *Segment Share*$_{s,i,t\text{-}1}$ is the predetermined sales share of segment s in firm i in year *t-1*. In Panel B, *Bartik IV2* is the product of *LS Exposure*$_{j,t}^{M}$, the average labor-shortage exposure for *LS-mentioning firms* in industry j and year t, and *LS Exposure*$_{j,t\text{-}1}^{Fraction}$, the fraction of firms exposed to labor shortages in industry j and year *t-1*. Firm controls are included in each panel but are omitted from reporting for brevity. A1 in Appendix A provides detailed variable definitions. Robust standard errors clustered at the firm level are provided in parentheses. ***, **, and * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A. Industry-Year Labor Shortage Exposures Weighted by Preexisting Firm Segment Sales Shares

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	LS Exposure $_t$		Stock Return $_{t+1}$	ROA $_{t+1}$	OCF $_{t+1}$	CAPEX $_{t+1}$	R&D $_{t+1}$	△Employee/AT $_{t+1}$	Process Claim Share $_{t+1,t+3}$	CW Process Patents/AT $_{t+1,t+3}$
	First Stage		*Second Stage*							
Bartik IV1	**0.462*** (0.043)**	**0.311*** (0.041)**								
$\widehat{\text{LS Exposure}}$			**-0.600*** (0.184)**	**-0.109** (0.053)**	**0.014 (0.051)**	**0.006 (0.025)**	**0.109*** (0.030)**	**-0.004*** (0.001)**	**0.894*** (0.232)**	**0.146*** (0.053)**
Cragg-Donald Wald F Stat	422.95	229.17								
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	No	Yes	Yes	Yes	No	No	No	No	No
Firm FE	No	Yes	No	No	No	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	23,682	23,557	23,682	23,682	23,682	23,557	23,557	23,517	15,328	15,328
Adjusted R-squared	0.183	0.376	0.069	0.451	0.489	0.047	-0.038	-0.103	-0.431	-0.035

Panel B. Industry-Year Labor-shortage Exposure (LS-mentioning Firms) Multiplied by Preexisting Fraction of LS-mentioning Firms in Industry

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	LS Exposure $_t$		Stock Return $_{t+1}$	ROA $_{t+1}$	OCF $_{t+1}$	CAPEX $_{t+1}$	R&D $_{t+1}$	△Employees/ AT $_{t+1}$	Process Claim Share $_{t+1,t+3}$	CW Process Patents/AT $_{t+1,t+3}$
	First Stage		*Second Stage*							
Bartik IV2	**0.309*** (0.052)**	**0.372*** (0.051)**								
$\widehat{\text{LS Exposure}}$			**-0.560** (0.285)**	**0.113 (0.076)**	**0.078 (0.066)**	**0.039* (0.021)**	**0.070*** (0.023)**	**-0.003** (0.001)**	**1.759*** (0.597)**	**0.330** (0.151)**
Cragg-Donald Wald F Stat	149.36	296.66								
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	No	Yes	Yes	Yes	No	No	No	No	No
Firm FE	No	Yes	No	No	No	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,975	20,718	20,975	20,975	20,975	20,718	20,718	20,681	12,850	12,850
Adjusted R-squared	0.188	0.404	0.082	0.459	0.493	0.034	-0.002	-0.034	-1.696	-0.218

Table 11. Heterogeneous Effect of COVID-19 on Ex-ante Labor-Shortage-Exposed Firms versus Non-Exposed Firms

This table examines the Heterogeneous effects of the COVID-19 shock on ex-ante labor-shortage-exposed firms versus non-exposed firms. Panel A reports the results of the difference-in-differences (DiD) regressions of the COVID-19 shock on firm performance between the ex-ante labor-shortage-exposed versus non-exposed firms. The dependent variable *ROA* is measured as a firm's earnings before extraordinary items divided by its total value of assets; *OCF* is measured as a firm's net operating cash flow divided by its total value of assets. The independent variable $LS^{ex\text{-}ante}$ is an indicator variable that equals one if the firm mentioned about labor-shortage issues in its conference earnings call transcripts in the two years immediately before the COVID-19 crisis (i.e., 2018 and 2019), and equals zero if the firm did not mention about labor shortages during the entire 2005-2021 sample period. *Post COVID* is an indicator variable that equals one if the year is 2020 or after and equals zero otherwise. Panel B reports the results of dynamic DiD regressions of the COVID-19 shock on firm performance, investigating whether there is any pretrend in firm performance for the labor-shortage-exposed firms relative to the non-exposed firms. $Year_j$ is an indicator variable that equals one if the year is the jth year relative to the event year (i.e., 2020) and equals zero otherwise. Table A1 in Appendix A provides detailed variable definitions. All specifications include firm fixed effects and year (industry-year) fixed effects. We also include lag firm characteristics controls in all specifications. Robust standard errors clustered at the firm level are provided in parentheses. All financial variables are winsorized at the 1st and 99th percentiles. ***, **, and * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A. Heterogeneous Effects of COVID-19 on Labor-shortage-exposed and Non-exposed Firms

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Stock Return		ROA		OCF	
$LS^{ex\text{-}ante}$×Post COVID	**-0.055****	**-0.066****	**-0.024*****	**-0.020*****	**-0.015*****	**-0.009***
	(0.027)	**(0.027)**	**(0.008)**	**(0.007)**	**(0.006)**	**(0.005)**
ROA $_{t-1}$	0.130	0.182			0.072*	0.067
	(0.114)	(0.112)			(0.040)	(0.042)
Book Leverage $_{t-1}$	0.171***	0.183***	0.093***	0.095***	0.033	0.033
	(0.062)	(0.064)	(0.024)	(0.025)	(0.020)	(0.021)
Stock Return $_{t-1}$	-0.092***	-0.075**	0.019***	0.020**	0.000	0.003
	(0.034)	(0.033)	(0.007)	(0.008)	(0.007)	(0.007)
CAPEX $_{t-1}$	-3.079***	-2.660***	0.094	0.142	-0.006	-0.039
	(0.437)	(0.439)	(0.133)	(0.144)	(0.083)	(0.083)
MTB $_{t-1}$	0.004***	0.004**	0.000	0.000	-0.000	-0.000
	(0.002)	(0.002)	(0.001)	(0.001)	(0.000)	(0.001)
Sales Growth $_{t-1}$	0.104**	0.076*	0.013	0.007	-0.012	-0.010
	(0.042)	(0.042)	(0.015)	(0.016)	(0.014)	(0.015)
Firm Size $_{t-1}$	-0.210***	-0.175***	0.025*	0.031*	0.020*	0.019
	(0.039)	(0.039)	(0.015)	(0.016)	(0.011)	(0.012)
Cash $_{t-1}$	0.251**	0.239**	0.026	0.036	-0.057	-0.051
	(0.119)	(0.118)	(0.048)	(0.048)	(0.040)	(0.042)
Asset Tangibility $_{t-1}$	0.334	0.218	0.040	0.064	0.063	0.100**
	(0.238)	(0.258)	(0.056)	(0.061)	(0.045)	(0.049)
Stock Volatility $_{t-1}$	3.139***	2.851***	0.252***	0.217***	0.084*	0.071
	(0.279)	(0.286)	(0.056)	(0.060)	(0.044)	(0.049)
R&D $_{t-1}$	-0.005	-0.004	0.061	0.056	-0.034	-0.031
	(0.260)	(0.256)	(0.105)	(0.106)	(0.079)	(0.081)
Employees/AT $_{t-1}$	15.844**	9.743	4.172**	3.087	3.683**	1.797
	(6.661)	(8.060)	(1.926)	(2.620)	(1.809)	(2.596)

Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No	Yes	No
Industry-Year FE	No	Yes	No	Yes	No	Yes
Obs.	6,724	6,724	6,816	6,816	6,816	6,816
Adj. R2	0.341	0.383	0.697	0.703	0.739	0.738

Panel B. Dynamic Difference-in-Differences Tests

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Stock Return		ROA		OCF	
$LS^{\text{ex-ante}} \times Year_{-1}$	0.014	0.012	-0.009	-0.010	0.001	-0.003
	(0.022)	(0.022)	(0.008)	(0.007)	(0.007)	(0.006)
$\mathbf{LS^{ex\text{-}ante} \times Year_{0}}$	**-0.038**	**-0.016**	**-0.040*** **	**-0.032*** **	**-0.015** **	**-0.012***
	(0.029)	**(0.029)**	**(0.010)**	**(0.009)**	**(0.007)**	**(0.006)**
$\mathbf{LS^{ex\text{-}ante} \times Year_{1}}$	**-0.060**	**-0.113** **	**-0.016**	**-0.016***	**-0.013**	**-0.010**
	(0.045)	**(0.047)**	**(0.010)**	**(0.010)**	**(0.008)**	**(0.007)**
Lagged Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No	Yes	No
Industry-Year FE	No	Yes	No	Yes	No	Yes
Obs.	6,724	6,724	6,816	6,816	6,816	6,816
Adj. R2	0.341	0.384	0.698	0.703	0.739	0.738

Appendix A

Table A1. Variable Definitions

Variables	Definition
Dependent Variables	
Unemployment Rate	A state's total number of people unemployed divided by the state's total labor force in a year. **Source:** U.S. Bureau of Labor Statistics (BLS).
Wage Growth	A state's total wage in year t minus the state's total wage in year t-1, further divided by the state's total wage in year t-1. **Source:** U.S. Bureau of Labor Statistics (BLS).
Log($\frac{\#Job\ Openings}{\#Unemployed}$)	Natural logarithm of a state's number of job openings divided by the state's number of people unemployed in a year. **Source:** U.S. Bureau of Labor Statistics (BLS).
Growth in Per-Employee Staff Expenses	The difference in the natural logarithm of a firm's per-employee staff expenses between year *t* and year *t-1*. **Source:** Compustat.
CAR(0, 2)	Cumulative abnormal stock returns within a three-day event window of (0, 2) following the earnings conference calls. **Source:** CRSP
Stock Return	Buy-and-hold stock return of a firm. **Source:** CRSP
ROA	A firm's earnings before extraordinary items divided by the book value of assets. **Source:** Compustat.
Operating Cash Flow	A firm's operating cash flow divided by the book value of assets. **Source:** Compustat.
CAPEX	A firm's capital expenditures divided by the book value of assets. **Source:** Compustat.
R&D	A firm's research and development expenses divided by the book value of total assets. **Source:** Compustat.
$\triangle$Employees/AT	The change in a firm's number of employees (in thousand) divided by the book value of assets. **Source:** Compustat.
Process Claims Share	The number of process claims divided by the number of total claims for all patents a firm has applied for (and later granted) in year t. **Source:** Bena et al. (2021) process patent classification dataset.
# CW Process Patents/AT	The citation weighted number of process patents a firm has applied (and later granted), further scaled by the total assets of the firm at the beginning of the year. **Source:** Bena et al. (2021) process patent classification dataset.
# CW Non-Process Patents/AT	The citation weighted number of non-process patents a firm has applied (and later granted), further scaled by the total assets of the firm at the beginning of the year. **Source:** Bena et al. (2021) process patent classification dataset.
Independent Variables	

LS $\text{Exposure}^{\text{state}}$	The average labor-shortage exposure of all public firms headquartered in that state in a year. **Source:** S&P Capital IQ and our fine-tuned machine learning model.
LS Exposure	The average number of labor-shortage-related sentences divided by the average number of total sentences of earnings call transcripts of a firm in a year. **Source:** S&P Capital IQ and our fine-tuned machine learning model.
I ($\text{LS}^{\text{ind-top20\%}}$)	An indicator that equals one if a firm's industry (2-digit SIC) is in the top quintile of industry-average *LS Exposure* across all industries in a given year and equals zero otherwise. **Source:** S&P Capital IQ and our fine-tuned machine learning model.
Log(GDP)	Natural logarithm of annual GDP of a state in a year. **Source:** Bureau of Economic Analysis (BEA)
Log(Population)	Natural logarithm of total population of a state in a year. **Source:** Bureau of Economic Analysis (BEA)
Log(Per Cap Income)	Natural logarithm of per capital income of a state in a year. **Source:** Bureau of Economic Analysis (BEA)
COVID $\text{Stringency}^{\text{state}}$	A state-level index that records the strictness of "lockdown style" policies that primarily restrict people's behavior. **Source:** COVID-19 Government Response Tracker.
Book Leverage	The sum of a firm's current liabilities and long-term debt divided by the sum of the firm's current liabilities, long-term debt, and book value of equity. **Source:** Compustat.
MTB	A firm's market value of assets divided by quarterly book value of total assets. **Source:** Compustat.
Sales Growth	A firm's value of sales in year t minus the firm's value of sales in year t-1, further divided by the value of sales in year t-1. **Source:** Compustat.
Firm Size	Natural logarithm of the sales of a firm in a year. **Source:** Compustat.
Cash	A firm's cash holdings divided by the book value of assets. **Source:** Compustat.
Asset Tangibility	A firm's property, plants, and equipment (PPE) divided by the book value of assets. **Source:** Compustat.
Stock Volatility	Square root of the sum of squared monthly returns of a year. **Source:** CRSP.
Earnings Surprise	Actual quarterly earnings per share (EPS) announced in a quarter minus median analyst forecasted EPS made before the EPS announcement quarter, scaled by absolute stock price at the end of the quarter before the EPS announcement quarter. **Source:** I/B/E/S and CRSP

Table A2. Keyword List from *Word2Vec*

Panel A. Labor-related keyword list

Seed words	labor, manpower, staff, personnel, people, worker, human, employee, workforce
Expanded words from Word2Vec	wage, hourly, salary, overhead, overtime, nurse, nursing, technician, headcount, payroll, salaried, part-time, furlough, therapist, engineer, sick, crew, rehire, team, member, frontline, absenteeism, full-time, training, pay, layoff, hire, hiring, workmen, job, roster, driver, contractor, skilled, work, trainee, leave, talent, blue-collar, head count, recruit

Panel B. Labor-shortage-related keyword list

Seed words	labor shortage, manpower shortage, worker shortage, staff shortage, labor constraint, labor crisis, labor scarcity, labor market constraint, understaffing
Expanded words from Word2Vec	tight labor market, labor availability, shortage labor, labor challenge, driver shortage, absenteeism, labor market shortage, talent crunch, labor availability issue, tightening labor market, worker availability, labor market challenge, labor bottleneck, shortage skilled, labor shortage issue, nursing shortage, truck driver shortage, tightness labor market, staffing challenge, labor availability challenge, staff burnout, shortage skilled labor, construction labor shortage, employee absenteeism, labor tightness, workforce availability, employee shortage, labor market pressure, workforce disruption, supply and labor constraint, workforce constraint, staffing shortage, driver challenge, skill shortage, aging workforce, talent shortage, salary inflation and labor shortage, labor capacity constraint, staffing issue, hiring challenge, immigration restriction, labor supply issue, staffing availability, recruiting labor, full-employment, contractor shortage, staffing inefficiency, driver staffing, labor market disruption, overtime issue, employment challenge, absentee rate, hiring driver, manpower availability, personnel challenge, labor slowdown, , labor market tighten, driver availability, crew shortage, nurse attrition, employee absence, staff availability, recruitment issue, hiring issue, labor shortfall, short-staffed, labor recruitment, tightening job market, manpower restriction

Table A3. Prediction Performance in Classifying Labor-Shortage-related Sentences

This table presents the prediction performance in classifying labor-shortage-related sentences in the testing sample using the fine-tuned *FinBert*. The testing sample contains 500 sentences, of which 314 are non-labor-shortage-related (negative) and 186 are labor-shortage-related (positive). The 500 testing sentences are randomly selected from the full sample of 5,000 sentences and are manually labeled by the authors. For each sentence category, we compare three dimensions of prediction performance, which are precision, recall, and f1-score, respectively. For the total testing sentence sample, we also report the overall accuracy, macro average, and weighted average. The overall accuracy is measured as the number of correctly classified sentences divided by the total number of sentences in the testing sample. The macro average represents the unweighted mean value for each category and does not take label imbalance into account. The weighted average represents the weighted mean value for each category and take into account the label imbalance. The precision is calculated as *true positives/(true positives + false postives)*. The recall is calculated as *true positives/(true positives + false negatives)*. The f1-score represents a harmonic mean of the precision and recall, which is measured as $2 \times$ *(precision* $\times$ *recall)/(precision + recall)*.

	Precision	**Recall**	**F1-score**	**# Sentence**
Negative	0.97	0.95	0.96	314
Positive	0.91	0.95	0.93	186
Overall Accuracy			**0.95**	500
Macro Average	0.94	0.95	0.94	500
Weighted Average	0.95	0.95	0.95	500

Table A4. Labor-Shortage-related Sample Sentences from Conference Call Transcripts

This table reports 20 randomly selected labor-shortage-related sentences that are predicted by the fine-tuned *FinBert* model.

Examples of Labor-shortage-related Sentence	Company	Year-Quarter
1. We are experiencing some inflationary pressures that are more annualized but – in our cost of equipment and cost of parts, and we're definitely going to see some cost pressure in compensation and labor as the market tightens, and the labor market especially is getting tightened at a few of the growth plays.	ARCHROCK INC	2017Q4
2. And the product – the lack of improved efficiency year-over-year in the factory, in large part, is driven by the labor scarcity.	LENNOX INTERNATIONAL INC	2019Q4
3. We've launched remediation plans to be back on track, but unfortunately, staffing issues limited some of the positive momentum of our results in this quarter.	SCHOOL SPECIALTY INC	2018Q3
4. Business leaders have also noted that one of their emerging concerns for the region is tightening labor supply company by upward pressure on wages.	COLUMBIA BANKING SYSTEM INC	2017Q2
5. The root cause is largely domestic, heavily tied to the labor availability staffing challenges that in all businesses are essentially facing today.	DEL TACO RESTAURANTS INC	2021Q3
6. Many of the productivity improvement initiatives and some of the near-term issues pass as a result of the productivity issues, like some of the labor constraint issues that we faced.	WABASH NATIONAL CORP	2017Q4
7. The Mayodan guys are running full out, a lot of overtime, and we're working hard to increase production there.	STURM RUGER & CO INC	2015Q3
8. The difficulty recruiting and retaining qualified drivers continues to be a challenge, and we have not been paid commensurately for the services we provide.	COVENANT LOGISTICS GROUP INC	2012Q2
9. I would like to have gotten there sooner, but I think we're finding the hiring environment is pretty intense out there.	ARIBA INC	2010Q3
10. And just last question on the labor piece, and I understand there's pressures now and you're anxious to get people hired.	DENNYS CORP	2021Q2
11. High U.S. employment levels created wage pressure and made it increasingly difficult to attract and retain employees.	BRINKS CO	2020Q1
12. The increase in compensation and benefits as a percentage of company-owned store sales reflected the increased shift of the portfolio to markets with lower sales volumes and continued labor inefficiencies associated with new store openings.	PAPA MURPHY'S HOLDINGS INC	2017Q3
13. And so we had a personnel issue where that was not getting done as timely as it was in the past and we made changes there, redirected resources and got that caught up.	AIR METHODS CORP	2012Q4
14. This catch up of new equipment, combined with the challenging driver recruiting market, were the key contributing factors to our unseated tractor percentage.	USA TRUCK INC	2019Q1
15. But as highlighted in last quarter's call, labor shortages are limiting growth.	BAKER HUGHES INC	2012Q1
16. As you navigate your way through that, we obviously will have a potential labor headwind.	JETBLUE AIRWAYS CORP	2017Q4

17. Well, I mean listen, labor was tight before we got into this pandemic.	OMEGA HEALTHCARE INVS INC	2020Q2
18. With the continued tightness in the labor markets, we are focused on investments in manufacturing automation, continuous improvement initiatives and Lean Six Sigma implementation throughout our organization.	CORNERSTNE BULDNG BRNDS INC	2019Q4
19. We currently expect year-over-year F&E revenue improvement versus this year's softness related to COVID absenteeism and inspection delays, which occurred primarily in the second and third fiscal quarters.	REV GROUP INC	2021Q1
20. The other issue that we definitely continue to face out on the job site – really plays into our strengths – is the labor shortage.	BUILDERS FIRSTSOURCE	2015Q3

Table A5. Correlation Matrix of Firm-level Labor-Shortage Exposure

This table reports the correlation matrix of *LS Exposure* and its lags (panel A) and the correlation matrix of *I (LS)* and its lags (panel B). *LS Exposure* is a firm's labor-shortage exposure in year *t*. *I (LS)* is an indicator variable that equals one if the *LS Exposure* of a firm in that year is larger than zero, and equals zero otherwise.

Panel A. LS Exposure

VARIABLES	LS Exposure	LS Exposure $_{t-1}$	LS Exposure $_{t-2}$	LS Exposure $_{t-3}$	LS Exposure $_{t-4}$
LS Exposure	1.000				
LS Exposure $_{t-1}$	0.566	1.000			
LS Exposure $_{t-2}$	0.409	0.581	1.000		
LS Exposure $_{t-3}$	0.361	0.408	0.548	1.000	
LS Exposure $_{t-4}$	0.302	0.335	0.414	0.554	1.000

Panel B. LS Indicator

VARIABLES	**I (LS)**	I (LS) $_{t-1}$	I (LS) $_{t-2}$	I (LS) $_{t-3}$	I (LS) $_{t-4}$
I (LS)	1.000				
I (LS) $_{t-1}$	0.336	1.000			
I (LS) $_{t-2}$	0.277	0.326	1.000		
I (LS) $_{t-3}$	0.240	0.261	0.310	1.000	
I (LS) $_{t-4}$	0.222	0.237	0.240	0.297	1.000

Table A6. Firm Characteristics and Labor-Shortage Exposure

This table reports the regression results that investigate the relations between various firm characteristics and labor-shortage exposure. The dependent variable *LS Exposure* is a firm's labor-shortage exposure in year *t*. *I (LS)* is an indicator variable that equals one if the *LS Exposure* of a firm in that year is larger than zero, and equals zero otherwise. Columns 1-4 (5-8) investigate the relations between various firm characteristics and *LS Exposure* (*I (LS)*) of a firm in the same year. Columns 1 and 5 do not include any fixed effects. Columns 2 and 6 include year fixed effects. Columns 3 and 7 include both year fixed effects and industry fixed effects. Columns 4 and 8 include industry-by-year fixed effects. Table A1 in Appendix A provides detailed variable definitions. Robust standard errors clustered at the firm level are provided in parentheses. All financial variables are winsorized at the 1st and 99th percentiles. ***, **, and * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES		LS Exposure				I (LS)		
ROA	-0.019***	-0.014**	-0.011	-0.020***	-0.068***	-0.076***	-0.079***	-0.099***
	(0.007)	(0.007)	(0.007)	(0.008)	(0.021)	(0.021)	(0.020)	(0.020)
Book Leverage	-0.012**	-0.021***	-0.017***	-0.020***	-0.037***	-0.053***	-0.033***	-0.038***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.013)	(0.013)	(0.011)	(0.011)
Stock Return	0.000	0.001	0.002	-0.000	0.007	0.004	0.006	0.005
	(0.002)	(0.003)	(0.003)	(0.003)	(0.007)	(0.008)	(0.007)	(0.008)
CAPEX	-0.072**	0.005	-0.016	-0.083*	-0.076	0.177*	0.142	-0.026
	(0.034)	(0.035)	(0.042)	(0.046)	(0.101)	(0.103)	(0.097)	(0.101)
MTB	0.000	-0.000**	-0.000	-0.000	0.003***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Sales Growth	0.013***	0.011***	0.011***	0.007***	0.011	0.016	0.023**	0.015
	(0.003)	(0.003)	(0.003)	(0.003)	(0.010)	(0.010)	(0.009)	(0.010)
Firm Size	0.004***	0.005***	0.004***	0.004***	0.033***	0.031***	0.027***	0.028***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)	(0.003)
Cash	-0.022**	-0.024**	-0.021**	-0.014	-0.015	-0.029	-0.025	-0.017
	(0.010)	(0.010)	(0.010)	(0.010)	(0.026)	(0.026)	(0.025)	(0.025)
Asset Tangibility	0.034***	0.026**	0.023*	0.034**	0.126***	0.093***	0.079***	0.107***
	(0.011)	(0.012)	(0.013)	(0.013)	(0.028)	(0.028)	(0.030)	(0.031)
Stock Volatility	0.018***	0.014*	0.001	0.007	0.052***	-0.012	-0.053***	-0.047***
	(0.007)	(0.008)	(0.008)	(0.008)	(0.014)	(0.018)	(0.016)	(0.016)
R&D	-0.127***	-0.120***	-0.080***	-0.090***	-0.435***	-0.410***	-0.269***	-0.282***
	(0.014)	(0.014)	(0.015)	(0.015)	(0.039)	(0.039)	(0.039)	(0.040)
Employees/AT	4.802***	5.130***	6.357***	6.982***	9.933***	10.883***	10.273***	10.993***
	(0.671)	(0.676)	(0.980)	(1.019)	(0.808)	(0.796)	(0.985)	(0.991)
Year FE	No	Yes	Yes	No	No	Yes	Yes	No
Industry FE	No	No	Yes	No	No	No	Yes	No
Industry-Year FE	No	No	No	Yes	No	No	No	Yes
Obs.	25,551	25,551	25,551	25,551	25,551	25,551	25,551	25,551
Adj. R2	0.051	0.070	0.138	0.183	0.069	0.090	0.147	0.162

Table A7. Bottom-10 Industries by Average Labor-Shortage Exposure

This table reports the bottom-10 industries by average labor-shortage exposure.

2-Digit SIC	Industry	LS Exposure
02	Agricultural Production - Livestock	0.000
08	Forestry	0.000
09	Fishing, Hunting and Trapping	0.000
76	Miscellaneous Repair Services	0.000
86	Membership Organizations	0.000
89	Miscellaneous Services	0.000
21	Tobacco Products	0.009
28	Chemicals and Allied Products	0.017
48	Communications	0.017
99	Non-classifiable Establishments	0.023

Table A8. Excluding the COVID-19 Period

This table examines the robustness of the results by excluding the COVID-19 period (2020 and 2021) from the empirical analyses. Panel A investigates a state's labor-shortage exposure on the state's one-year-ahead unemployment rate, wage growth, and labor market tightness. Panel B examines firm-level labor-shortage exposure on one-year-ahead growth in per-employee staff expenses. Panel C examines the stock price reactions to firm-level labor-shortage exposure and the implications of firm-level labor-shortage exposure on future stock and operating performance. Panel D examines the corporate policy responses to firm-level labor-shortage exposures. The state/firm controls are included in each panel (consistent with the main results) but are omitted from reporting for brevity. Table A1 in Appendix A provides detailed variable definitions. Robust standard errors clustered at the state/firm level (consistent with the main results) are provided in parentheses. All financial variables are winsorized at the 1st and 99th percentiles. ***, **, and * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A. Validation: State-level Labor-Shortage Exposure, Unemployment Rate, and Wages

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Unemployment Rate $_{t+1}$		Wage Growth $_{t+1}$		$\text{Log}(\frac{\#Job\ Openings}{\#Unemployed})_{t+1}$	
LS Exposure$^{\mathbf{state}}$	**-0.039***** **(0.013)**	**-0.016*** **(0.008)**	**0.031**** **(0.015)**	**0.027*** **(0.016)**	**0.826***** **(0.262)**	**0.346**** **(0.152)**
State Controls	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	676	676	676	676	655	655
Adj. R2	0.645	0.856	0.588	0.642	0.842	0.934

Panel B. Validation: Firm-level Labor-Shortage Exposure and Staff Expenses

	(1)	(2)	(3)	(4)
VARIABLES	Growth in Per-employee Staff Expenses $_{t+1}$			
LS Exposure	**0.010*** **(0.006)**	**0.016***** **(0.006)**	**0.011** **(0.007)**	**0.014*** **(0.008)**
Firm Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	No	No	No
Year FE	Yes	No	Yes	No
Industry-Year FE	No	Yes	No	Yes
Firm FE	No	No	Yes	Yes
Obs.	3,727	3,564	3,706	3,534
Adj. R2	0.023	0.057	-0.008	0.024

Panel C. Stock Price Reactions to Labor-Shortage Exposure and Implications on Firm Performance

VARIABLES	(1) CAR (0, 2)	(2) Stock Return $_{t+1}$	(3) ROA $_{t+1}$	(4) OCF $_{t+1}$
LS Exposure	**-0.007***** **(0.001)**	**-0.053***** **(0.014)**	**-0.012**** **(0.006)**	**-0.007*** **(0.004)**
Firm Controls	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Obs.	86,218	23,851	23,851	23,851
Adj. R2	0.210	0.280	0.440	0.576

Panel D. Corporate Policy Responses to Labor-Shortage

VARIABLES	(1) CAPEX $_{t+1}$	(2) R&D $_{t+1}$	(3) $\triangle$Employees/AT $_{t+1}$	(4) Process Claims Share $_{t+1,\ t+3}$	(5) # CW Process Patents/AT $_{t+1,t+3}$
LS Exposure	**0.005***** **(0.001)**	**0.002*** **(0.001)**	**-0.0003***** **(0.0001)**	**0.039***** **(0.009)**	**0.005***** **(0.002)**
Firm Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Obs.	23,729	23,729	23,686	15,153	15,153
Adj. R2	0.725	0.840	0.074	0.699	0.660

Table A9. Extensive Margin vs. Intensive Margin

The table compares the extensive margin and intensive margin of the effects of firm-level labor-shortage exposure on stock price reactions, future stock returns and operating performance, and corporate policy responses. We conduct the extensive margin analyses by replacing the continuous labor-shortage exposure measure with an indicator *I (LS)* that equals one if *LS Exposure* is larger than zero, and equals zero otherwise. We conduct the intensive margin analyses by restricting to the sample of firms that are exposed to labor shortages (i.e., *LS Exposure* is larger than zero in a firm-year). Panel A (B) examines the extensive (intensive) margin of the effects of firm-level labor-shortage exposure on stock price reactions and future stock returns and operating performance. Panel C (D) examines the extensive (intensive) margin of the effects of firm-level labor-shortage exposure on corporate policy responses. Firm controls are included in each panel (consistent with the main results) but are omitted for brevity. Table A1 in Appendix A provides detailed variable definitions. Robust standard errors clustered at the firm level are provided in parentheses. All financial variables are winsorized at the 1st and 99th percentiles. ***, **, and * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A. Extensive Margin Analysis: Stock Price Reactions to Labor-Shortage Exposure and Implications on Future Stock Returns and Operating Performance

	(1)	(2)	(3)	(4)
VARIABLES	CAR (0, 2)	Stock Return $_{t+1}$	ROA $_{t+1}$	OCF $_{t+1}$
I (LS)	**-0.004*** **	**-0.023*** **	**-0.008*** **	**-0.004*** **
	(0.001)	**(0.006)**	**(0.002)**	**(0.002)**
Firm Controls	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Obs.	100,588	25,551	25,551	25,551
Adj. R2	0.189	0.326	0.442	0.579

Panel B. Intensive Margin Analysis: Stock Price Reactions to Labor-Shortage Exposure and Implications on Future Stock Returns and Operating Performance

	(1)	(2)	(3)	(4)
VARIABLES	CAR (0, 2)	Stock Return $_{t+1}$	ROA $_{t+1}$	OCF $_{t+1}$
LS Exposure	**-0.006*** **	**-0.044** **	**-0.000**	**-0.004**
	(0.002)	**(0.018)**	**(0.005)**	**(0.004)**
Firm Controls	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Obs.	13,519	7,832	7,832	7,832
Adj. R2	0.200	0.365	0.332	0.526

Panel C. Extensive Margin Analysis: Corporate Policy Responses to Labor-Shortage Exposure

VARIABLES	(1) CAPEX $_{t+1}$	(2) R&D $_{t+1}$	(3) $\triangle$Employees/AT $_{t+1}$	(4) Process Claims Share $_{t+1,\ t+3}$	(5) # CW Process Patents/AT $_{t+1,t+3}$
I (LS)	**0.002***** **(0.000)**	**-0.000** **(0.001)**	**-0.000** **(0.000)**	**0.006**** **(0.003)**	**0.000** **(0.001)**
Firm Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Obs.	25,541	25,541	25,495	16,231	16,231
Adj. R2	0.719	0.836	0.070	0.677	0.607

Panel D. Intensive Margin Analysis: Corporate Policy Responses to Labor-Shortage Exposure

VARIABLES	(1) CAPEX $_{t+1}$	(2) R&D $_{t+1}$	(3) $\triangle$Employees/AT $_{t+1}$	(4) Process Claims Share $_{t+1,\ t+3}$	(5) # CW Process Patents/AT $_{t+1,t+3}$
LS Exposure	**0.002** **(0.001)**	**0.001** **(0.001)**	**-0.0003***** **(0.0001)**	**0.021**** **(0.009)**	**0.004** **(0.003)**
Firm Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Obs.	7,266	7,266	7,256	4,171	4,171
Adj. R2	0.725	0.878	0.090	0.692	0.402

Table A10. Management Presentation Section vs. Q&A Section

The table examines the robustness of the results using firm-level labor-shortage exposure constructed from the management presentation section or the Q&A section of the earnings conference call transcripts. Panel A investigates the stock price reactions to firm-level labor-shortage exposure and the implications of firm-level labor-shortage exposure on future stock returns and operating performance. Panel B examines the corporate policy responses to firm-level labor-shortage exposure. *LS Exposure*^{Mgm} is a firm's labor-shortage exposure measured using the management presentation section of the earnings conference call transcripts in a year (except the results on *CAR (0,2)*, where we measure a firm's labor-shortage exposure in the management presentation section of the earnings conference call transcript in a year-quarter). *LS Exposure*$^{Q\&A}$ is a firm's labor-shortage exposure measured using the Q&A section of the earnings conference call transcripts in a year (or year-quarter for the results on *CAR (0,2)*). Firm controls are included in each panel (consistent with the main results) but are omitted from reporting for brevity. Table A1 in Appendix A provides detailed variable definitions. Robust standard errors clustered at the firm level are provided in parentheses. All financial variables are winsorized at the 1st and 99th percentiles. ***, **, and * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A. Stock Price Reactions to Labor-Shortage Exposure and Implications on Future Stock Returns and Operating Performance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES		CAR (0, 2)			Stock Return $_{t+1}$			ROA $_{t+1}$			OCF $_{t+1}$	
LS Exposure^{Mgmt}	-0.002***		-0.002***	-0.015**		-0.002	-0.005**		-0.004**	-0.003*		-0.001
	(0.000)		(0.000)	(0.007)		(0.006)	(0.002)		(0.002)	(0.001)		(0.001)
LS Exposure$^{Q\&A}$		-0.003***	-0.002*		-0.075***	-0.073***		-0.007*	-0.003		-0.009**	-0.007**
		(0.001)	(0.001)		(0.015)	(0.016)		(0.005)	(0.005)		(0.004)	(0.004)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	100,588	100,588	100,588	25,551	25,551	25,551	25,551	25,551	25,551	25,551	25,551	25,551
Adj. R2	0.189	0.189	0.189	0.326	0.327	0.327	0.442	0.441	0.442	0.578	0.578	0.578

Panel B. Corporate Policy Responses to Labor-Shortage Exposure with Firm and Year Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
VARIABLES		CAPEX$_{t+1}$			R&D$_{t+1}$			$\triangle$Employees/AT$_{t+1}$			Process Claims Share$_{t+1,t+3}$			#CW Process Patents/AT$_{t+1,t+3}$	
LS Exposure^{Mgmt}	0.002***		0.002**	0.001**		0.000	-0.0002***		-0.0002***	0.021***		0.018***	0.003***		0.003*
	(0.001)		(0.001)	(0.000)		(0.000)	(0.0000)		(0.0000)	(0.004)		(0.004)	(0.001)		(0.002)
LS Exposure$^{Q\&A}$		0.005***	0.004***		0.002***	0.002**		-0.0003***	-0.0001		0.030***	0.017*		0.001	-0.002
		(0.001)	(0.001)		(0.001)	(0.001)		(0.0001)	(0.0001)		(0.009)	(0.009)		(0.005)	(0.006)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	25,541	25,541	25,541	25,541	25,541	25,541	25,495	25,495	25,495	16,231	16,231	16,231	16,231	16,231	16,231
Adj. R2	0.718	0.718	0.718	0.836	0.836	0.836	0.074	0.071	0.074	0.678	0.678	0.678	0.607	0.607	0.607

Table A11. Implications of Firm-level Labor-shortage Exposure: Fama-French Three (Five)-Factor-adjusted Stock Returns

This table reports the regression results that investigate the implications of firm-level labor-shortage exposure on one-year-ahead cross-sectional stock returns. In Panel A, the dependent variable *FF3F-adjusted Stock Return* is the Fama-French three-factor-adjusted stock returns. In Panel B, the dependent variable *FF5F-adjusted Stock Return* is the Fama-French five-factor-adjusted stock returns. The independent variable *LS Exposure* is a firm's labor-shortage exposure in a year. For each stock, we use the past year's daily returns to estimate the stock's three-factor (five-factor) exposures by running time-series regressions. We next calculate the factor-adjusted daily returns over the next year using the estimated factor loadings and the realized factor returns (factor-adjusted daily returns are calculated as the difference between the realized excess returns of the stock and the expected excess returns from the Fama-French three-factor or five-factor model). We then compound the daily adjusted returns into annual adjusted returns. In both panels, all specifications except column 1 include firm characteristics controls and consistent with the main texts but omitted for brevity. Columns 1-2 do not include any fixed effect. Column 3 includes year fixed effects. Column 4 includes both year fixed effects and industry fixed effects. Column 5 includes industry-by-year fixed effects. Table A1 in Appendix A provides detailed variable definitions. Robust standard errors clustered at the firm level are provided in parentheses. All financial variables are winsorized at the 1st and 99th percentiles. ***, **, and * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A. Fama-French Three-Factor-adjusted Stock Returns

	(1)	(2)	(3)	(4)	(5)
VARIABLES			FF3F-adjusted Stock Return $_{t+1}$		
LS Exposure	**-0.037****	**-0.064*****	**-0.050*****	**-0.046*****	**-0.050*****
	(0.017)	**(0.018)**	**(0.018)**	**(0.018)**	**(0.018)**
Firm Controls	No	Yes	Yes	Yes	Yes
Industry FE	No	No	No	Yes	No
Year FE	No	No	Yes	Yes	No
Industry-Year FE	No	No	No	No	Yes
Obs.	25,461	25,461	25,461	25,461	25,461
Adj. R2	0.000	0.013	0.038	0.044	0.080

Panel B. Fama-French Five-Factor-adjusted Stock Returns

	(1)	(2)	(3)	(4)	(5)
VARIABLES			FF5F-adjusted Stock Return $_{t+1}$		
LS Exposure	**-0.057*****	**-0.071*****	**-0.061*****	**-0.058*****	**-0.057*****
	(0.017)	**(0.018)**	**(0.018)**	**(0.018)**	**(0.018)**
Firm Controls	No	Yes	Yes	Yes	Yes
Industry FE	No	No	No	Yes	No
Year FE	No	No	Yes	Yes	No
Industry-Year FE	No	No	No	No	Yes
Obs.	25,461	25,461	25,461	25,461	25,461
Adj. R2	0.000	0.016	0.037	0.041	0.077

Table A12. Firm-level Labor-shortage Exposure, Geographic Dispersion, and Future Stock Returns and Operating Performance

This table reports the regression results that investigate whether geographic dispersion can help mitigate the negative effects of firm-level labor-shortage exposure on future stock returns and operating performance. We measure a firm's one-year-ahead stock returns using raw stock returns (*Stock Return*), Fama-French three-factor-adjusted stock returns (*FF3F-adjusted Stock Return*), or Fama-French five-factor-adjusted stock returns (*FF5F-adjusted Stock Return*). We measure a firm's one-year-ahead operating performance using *ROA* or *OCF*. *LS Exposure* is a firm's labor-shortage exposure in a year. In Panel A, *GeoDis* is measured as the natural logarithm of the number of unique states mentioned in a firm's 10-K filing in a year. In Panel B, $GeoDis^{decile\ rank}$ is measured as the decile rank of the number of unique states mentioned in a firm's 10-K filing in a year. Firm controls are included in each panel (consistent with the main results) but are omitted from reporting for brevity. Table A1 in Appendix A provides detailed variable definitions. Robust standard errors clustered at the firm level are provided in parentheses. All financial variables are winsorized at the 1st and 99th percentiles. ***, **, and * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A. The Role of Geographic Dispersion (Raw Value)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Stock Return $_{t+1}$	FF3F-adjusted Stock Return $_{t+1}$	FF5F-adjusted Stock Return $_{t+1}$	ROA $_{t+1}$	OCF $_{t+1}$
LS Exposure	-0.087*	-0.137**	-0.146***	-0.050**	-0.035**
	(0.052)	(0.054)	(0.053)	(0.022)	(0.016)
GeoDis	-0.003	-0.015***	-0.016***	-0.026***	-0.012***
	(0.005)	(0.006)	(0.006)	(0.003)	(0.002)
LS Exposure×GeoDis	**0.011**	**0.042***	**0.043***	**0.019****	**0.012***
	(0.022)	**(0.024)**	**(0.024)**	**(0.009)**	**(0.007)**
Firm Controls	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes
Obs.	25,120	25,120	25,120	25,120	25,120
Adj. R2	0.327	0.079	0.076	0.443	0.577

Panel B. The Role of Geographic Dispersion (Decile Rank)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Stock Return $_{t+1}$	FF3F-adjusted Stock Return $_{t+1}$	FF5F-adjusted Stock Return $_{t+1}$	ROA $_{t+1}$	OCF $_{t+1}$
LS Exposure	-0.095***	-0.110***	-0.121***	-0.033**	-0.025**
	(0.034)	(0.035)	(0.034)	(0.014)	(0.010)
$GeoDis^{decile\ rank}$	-0.001	-0.003***	-0.003***	-0.005***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
LS Exposure×$GeoDis^{decile\ rank}$	**0.005**	**0.011****	**0.012****	**0.004****	**0.003***
	(0.005)	**(0.005)**	**(0.005)**	**(0.002)**	**(0.001)**
Firm Controls	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes
Obs.	25,120	25,120	25,120	25,120	25,120
Adj. R2	0.327	0.079	0.076	0.444	0.577

Table A13. First-time Labor-shortage Exposure versus Repeated Labor-shortage Exposure

This table reports the regression results that investigate the implications of first-time versus repeated labor-shortage exposure on one-year-ahead cross-sectional stock returns and operating performance (panel A), and future firm policy responses (Panels B). *First-time LS* is an indicator variable that equals one if the firm discussed labor-shortage-related issues for the first time in the earnings conference calls of the year (and did not discuss labor-shortage-related issues in any of the years before the current year), and equals zero otherwise. Firm controls are included in each panel and consistent with the main results but omitted for brevity. Table A1 in Appendix A provides detailed variable definitions. Robust standard errors clustered at the firm level are provided in parentheses. All financial variables are winsorized at the 1st and 99th percentiles. ***, **, and * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A. Future Stock Return and Operating Performance

VARIABLES	(1) Stock Return $_{t+1}$	(2) ROA $_{t+1}$	(3) OCF $_{t+1}$
LS Exposure	-0.070***	-0.014**	-0.010**
	(0.017)	(0.006)	(0.004)
First-time LS	-0.002	-0.006	-0.001
	(0.012)	(0.004)	(0.003)
LS Exposure×First-time LS	**0.045**	**0.028**	**0.005**
	(0.052)	**(0.017)**	**(0.013)**
Firm Controls	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes
Obs.	25,551	25,551	25,551
Adj. R2	0.326	0.442	0.578

Panel B. Firm Policy Responses

VARIABLES	(1) CAPEX $_{t+1}$	(2) R&D $_{t+1}$	(3) △Employees/AT $_{t+1}$	(4) Process Claims Share $_{t+1,t+3}$	(5) # CW Process Patents/AT $_{t+1,t+3}$
LS Exposure	0.005***	0.003***	-0.0004***	0.057***	0.007***
	(0.001)	(0.001)	(0.0001)	(0.010)	(0.000)
First-time LS	0.002*	-0.001	-0.0000	-0.004	0.000
	(0.001)	(0.001)	(0.0000)	(0.004)	(0.002)
LS Exposure×First-time LS	**-0.004**	**-0.007****	**0.0004****	**-0.079*****	**-0.008****
	(0.004)	**(0.003)**	**(0.0002)**	**(0.019)**	**(0.004)**
Firm Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Obs.	25,541	25,541	25,495	16,231	16,231
Adj. R2	0.718	0.836	0.072	0.678	0.607

Table A14. Controlling for CEO Fixed Effects

This table examines the corporate policy responses to labor-shortage exposure after controlling for CEO fixed effects. Panel A (B) tabulates the regression results where CEO identities are obtained from Execucomp (earnings conference call transcripts). Firm controls are included in each panel (consistent with the main results) but are omitted from reporting for brevity. For both panels, we also control for firm and year fixed effects. Table A1 in Appendix A provides detailed variable definitions. Robust standard errors clustered at the state/firm level (consistent with the main results) are provided in parentheses. All financial variables are winsorized at the 1st and 99th percentiles. ***, **, and * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A. CEO Identidy Information from Execucomp

VARIABLES	(1) CAPEX $_{t+1}$	(2) R&D $_{t+1}$	(3) $\triangle$Employee/AT $_{t+1}$	(4) Process Claim Share $_{t+1,t+3}$	(5) # CW Process Patents/AT $_{t+1,t+3}$
LS Exposure	**0.001**	**0.002***	**-0.0003*****	**0.023****	**0.001***
	(0.001)	**(0.001)**	**(0.0001)**	**(0.010)**	**(0.001)**
Firm Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
CEO FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Obs.	15,816	15,816	15,795	11,474	11,474
Adj. R2	0.723	0.846	0.081	0.725	0.650

Panel B. CEO Identidy Information from Earnings Conference Call Transcripts

VARIABLES	(1) CAPEX $_{t+1}$	(2) R&D $_{t+1}$	(3) $\triangle$Employee/AT $_{t+1}$	(4) Process Claim Share $_{t+1,t+3}$	(5) # CW Process Patents/AT $_{t+1,t+3}$
LS Exposure	**0.004****	**0.001**	**-0.0003****	**0.030*****	**0.006***
	(0.002)	**(0.001)**	**(0.0001)**	**(0.011)**	**(0.004)**
Firm Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
CEO FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Obs.	23,655	23,655	23,611	15,065	15,065
Adj. R2	0.716	0.840	0.060	0.745	0.607

Table A15. AI Investment

This table reports the regression results that investigate the implications of firm-level labor-shortage exposure on AI investment. The dependent variable $\triangle$*AI Employee Share* is measured as the change in a firm's AI employee share from year *t* to year *t+1*. *#CW AI Patents/AT* is measured as the citation-weighted number of AI-related patents a firm has applied (and later granted) scaled by the total assets of the firm. The independent variable *LS Exposure* is a firm's labor-shortage exposure in a year. All specifications include firm characteristics controls, firm fixed effects, and year (or industry-by-year) fixed effects. Table A1 in Appendix A provides detailed variable definitions. Robust standard errors clustered at the firm level are provided in parentheses. All financial variables are winsorized at the 1st and 99th percentiles. ***, **, and * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)
VARIABLES	$\triangle$AI Employee Share $_{t+1}$		#CW AI Patents/AT $_{t+1,t+3}$	
LS Exposure	**0.0001***** **(0.0000)**	**0.0001**** **(0.0000)**	**0.0004***** **(0.0001)**	**0.0003*** **(0.0002)**
Firm Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
Industry-Year FE	No	Yes	No	Yes
Observations	21,543	21,543	16,231	16,116
Adjusted R-squared	0.002	-0.016	0.651	0.637

Table A16. Corporate Policy Responses and the Likelihood of Experiencing Labor Shortages in the Future

This table reports the regression results that investigate whether corporate policy responses help reduce the likelihood of a firm experiencing labor shortages in the future. The dependent variable, *I (LS)*, is an indicator that equals one if the value of *LS Exposure* is larger than zero in the next year, the next two years, or the next three years, and equals zero otherwise. The independent variable, $\triangle$*CAPEX*, is the change in a firm's capital expenditure from year *t-1* to year *t*, divided by the firm's capital expenditure in year *t-1*; $\triangle$*R&D* is the change in a firm's R&D expenses from year *t-1* to year *t*, divided by the firm's R&D expenses in year *t-1*; $\triangle$*CW Process Patent* is the change in a firm's number of citation-weighted process patents from year *t-1* to year *t*, divided by the firm's number of citation-weighted process patents in year *t-1*. All specifications include firm controls. Table A1 in Appendix A provides detailed variable definitions. Robust standard errors clustered at the firm level are provided in parentheses. All financial variables are winsorized at the 1st and 99th percentiles. ***, **, and * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

VARIABLES	(1) I (LS) t+1	(2) I (LS) t+1,t+2	(3) I (LS) t+1,t+3	(4) I (LS) t+1	(5) I (LS) t+1,t+2	(6) I (LS) t+1,t+3	(7) I (LS) t+1	(8) I (LS) t+1,t+2	(9) I (LS) t+1,t+3	(10) I (LS) t+1	(11) I (LS) t+1,t+2	(12) I (LS) t+1,t+3
△CAPEX	**-0.004***	**-0.005****	**-0.005****							**-0.004****	**-0.005****	**-0.005****
	(0.002)	**(0.002)**	**(0.002)**							**(0.002)**	**(0.002)**	**(0.002)**
△R&D				**0.015**	**-0.004**	**-0.017**				**0.015**	**-0.003**	**-0.015**
				(0.012)	**(0.012)**	**(0.012)**				**(0.012)**	**(0.012)**	**(0.012)**
△CW Process Patents							**-0.009**	**0.003**	**0.000**	**-0.010**	**0.002**	**-0.001**
							(0.008)	**(0.007)**	**(0.006)**	**(0.008)**	**(0.007)**	**(0.006)**
ROA	-0.018	0.003	0.012	-0.019	-0.000	0.005	-0.022	0.000	0.008	-0.017	-0.001	0.002
	(0.024)	(0.027)	(0.028)	(0.024)	(0.026)	(0.027)	(0.023)	(0.026)	(0.027)	(0.024)	(0.027)	(0.028)
Book Leverage	-0.021	-0.041**	-0.052***	-0.021	-0.041**	-0.053***	-0.021	-0.041**	-0.052***	-0.021	-0.041**	-0.053***
	(0.015)	(0.018)	(0.018)	(0.015)	(0.018)	(0.018)	(0.015)	(0.018)	(0.018)	(0.015)	(0.018)	(0.018)
Stock Return	0.005	0.011	0.013*	0.005	0.010	0.011*	0.006	0.014*	0.020***	0.007	0.015*	0.021***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)	(0.008)	(0.008)	(0.007)	(0.008)	(0.008)	(0.008)
CAPEX	0.320***	0.565***	0.668***	0.263**	0.497***	0.598***	0.261**	0.488***	0.591***	0.324***	0.572***	0.667***
	(0.113)	(0.125)	(0.127)	(0.109)	(0.121)	(0.122)	(0.109)	(0.121)	(0.122)	(0.113)	(0.125)	(0.126)
MTB	0.001	0.001**	0.002**	0.001	0.001**	0.002**	0.001	0.001**	0.001**	0.001	0.001**	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Sales Growth	0.035***	0.036***	0.046***	0.035***	0.035***	0.044***	0.034***	0.035***	0.042***	0.035***	0.035***	0.044***
	(0.010)	(0.012)	(0.012)	(0.010)	(0.011)	(0.012)	(0.010)	(0.011)	(0.012)	(0.011)	(0.012)	(0.012)
Firm Size	-0.005	-0.014	-0.022**	-0.005	-0.013	-0.020**	-0.004	-0.013	-0.020**	-0.005	-0.013	-0.020**
	(0.007)	(0.009)	(0.010)	(0.007)	(0.009)	(0.010)	(0.007)	(0.009)	(0.010)	(0.007)	(0.009)	(0.010)
Cash	0.048	0.006	0.001	0.052*	0.014	0.002	0.048	0.013	0.003	0.049	0.004	-0.004
	(0.031)	(0.038)	(0.039)	(0.031)	(0.037)	(0.039)	(0.031)	(0.037)	(0.039)	(0.031)	(0.038)	(0.040)
Asset Tangibility	-0.053	-0.074	-0.137**	-0.053	-0.074	-0.138**	-0.044	-0.065	-0.129*	-0.057	-0.078	-0.138**
	(0.056)	(0.064)	(0.068)	(0.056)	(0.064)	(0.068)	(0.056)	(0.064)	(0.068)	(0.056)	(0.064)	(0.068)
Stock Volatility	-0.047**	-0.051**	-0.037*	-0.046**	-0.045**	-0.032	-0.048**	-0.046**	-0.030	-0.044**	-0.048**	-0.036*
	(0.019)	(0.021)	(0.021)	(0.019)	(0.021)	(0.020)	(0.019)	(0.020)	(0.020)	(0.019)	(0.021)	(0.021)
R&D	-0.005	-0.055	-0.065	-0.047	-0.065	-0.050	-0.022	-0.070	-0.075	-0.031	-0.051	-0.043
	(0.054)	(0.067)	(0.076)	(0.056)	(0.070)	(0.079)	(0.054)	(0.066)	(0.074)	(0.056)	(0.070)	(0.080)

Employees/AT	-2.220	-3.890*	-4.274**	-2.227	-4.021**	-4.471**	-2.182	-3.836*	-4.320**	-2.343	-4.101**	-4.468**
	(1.719)	(2.039)	(2.093)	(1.685)	(1.990)	(2.056)	(1.711)	(2.030)	(2.086)	(1.694)	(1.999)	(2.062)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	25,193	25,193	25,193	25,438	25,438	25,438	25,539	25,539	25,539	25,097	25,097	25,097
Adj. R2	0.267	0.348	0.417	0.268	0.351	0.421	0.267	0.350	0.420	0.267	0.349	0.418

Appendix B Additional Validation Tests

In Appendix B, we provide two additional validation tests for our firm-level labor-shortage exposure. The first test utilises the 2017 Trump Immigration Policy Reforms as a negative shock to the U.S. labor supply that could intensify the labor-shortage exposure of firms. The second test leverages the variation in U.S. state-level restrictions on human mobility during the COVID-19 pandemic.

B1.1 U.S. Immigration Policy Reforms

In this section, we exploit the immigration policy reforms proposed by the former U.S. president Donald Trump in 2017 as a quasi-natural experiment to examine the validity of the firm-level measure of labor-shortage exposure.

After his inauguration in 2017, Donald Trump actively reformed the immigration policies in the U.S. following his campaign slogan “Buy American, Hire American”, aiming at enhancing the restrictions on immigrants and protecting American workers (Pierce et al., 2018). A series of executive orders and actions were implemented by the Trump administration, which include but are not limited to i) enhancing immigration enforcements and border security by building a US-Mexico border wall and increasing the construction of detention facilities to stem the flow of illegal entrants; ii) suspending refugee admissions from certain Muslim-majority countries (i.e., Iran, Iraq, Sudan, Syria, Libya, Somalia, and Yemen) and reducing the number of refugees to be admitted to the U.S. from 110,000 to 50,000 in FY2017; iii) increasing vetting and processing time for legal immigration; iv) tightening H-1B visa approvals to high-skilled foreign labors; and v) limiting family-based immigration (or chain migration) to those who are immediate family members (spouses and minor children) of the U.S citizens or green card holders. In essence, these immigration policy reforms seek to protect domestic workers by reducing the number of legal or illegal immigrants.

However, immigrants are an essential component of the U.S. labor force. According to the U.S. Bureau of Labor Statistics (BLS), there are 27 million foreign-born workers in 2016, which account for 16.9 percentage points of total labor force.[1] Therefore, the significantly tightened immigration policies reduced total foreign labor supply in the U.S. We thus use the 2017 immigration policy reforms as a quasi-natural experiment to validate the firm-level measure of labor-shortage exposure. We conjecture that the immigration policy reforms should lead to greater firm-level labor-shortage exposure for labor-intensive firms relative to other firms.

We partition our sample firms into labor-intensive and capital-intensive groups for our difference-in-differences (DiD) analysis. According to the 2016 BLS Foreign-born Workers report, foreign-born workers are more likely to work in labor-intensive occupations, while native-born workers are more likely to be employed in high-skilled occupations.[2] Our DiD regression framework thus compares the changes in labor-shortage exposure of labor-intensive firms with the changes in labor-shortage exposure of capital-intensive firms three years before and after 2017 (i.e., from 2014 to 2019; we avoid the COVID-19 crisis for this analysis). Because labor-

[1] See https://www.bls.gov/news.release/archives/forbrn05182017.pdf.

[2] See https://www.bls.gov/news.release/archives/forbrn_05182017.pdf. For example, a higher portion of foreign-born workers are employed in *service, production*, *transportation and material moving*, *natural resources*, *construction*, and *maintenance* occupations than native-born workers, while native-born workers are more likely to work in *management*, *professional and related*, and *sales and office* occupations.

intensive firms are more dependent on the foreign labor supply than capital-intensive firms, they should be more affected by the 2017 immigration policy reforms. The DiD regression specification is as follows:

$$Y_{i,t} = \beta_1 IMMI\ Post_t \times Labor\ Intensive_{s,i} + \beta_2 Controls_{i,t-1} + \omega_i + \mu_t + \epsilon_{i,t} \tag{1}$$

We further use the following dynamic DiD regression framework to identify the exact timing of the effect:

$$Y_{i,t} = \sum_{j=-2}^{2} \beta_j Labor\ Intensive_{s,i} \times Year_j + \beta_{j+1} Controls_{i,t-1} + \omega_i + \mu_t + \epsilon_{i,t} \tag{2}$$

In Equation 1, Y denotes the labor-shortage exposure of firm i in year t, *IMMI Post* is an indicator that equals one if year t is 2017 or after, and equals zero otherwise. Following prior literature (see, e.g., Dewenter and Malatesta, 2001; Lai et al., 2020; Chino, 2021), we use the labor-capital ratio to capture the relative amount of labor and capital used in a firm's production process. A high (low) labor-capital ratio indicates that the firm relies more heavily on labor inputs (capital inputs) in its production process. The labor-capital ratio is calculated as the number of employees divided by the value of fixed assets. We classify firm i as labor intensive if the firm's labor-capital ratio is above the median value of the firms in the same 2-digit SIC industry s in year 2016. The indicator, *Labor Intensive*, equals one for such labor intensive firms and equals zero otherwise.[3] The coefficient of interest, β_1, captures the differential effect of the immigration policy reforms on firm-level labor-shortage exposure between labor-intensive firms and capital-intensive firms in the same industry. We further control for a variety of lagged firm characteristics as well as firm fixed effects ω_i and year fixed effects μ_t. We expect β_1 to be significantly positive if our measure reflects firm-level labor-shortage exposure. Equation 2 is similar to Equation 1 except that we replace the post indicator (*IMMI Post*) with a series of year indicators to allow for the differential effect to vary across the sample years, with year 2014 being the reference year in the dynamic DiD regressions. The results are reported in Table B1.

[Please insert Table B1 about here]

Columns 1, 3, and 5 control for firm and year fixed effects, while columns 2, 4, and 6 further replace year fixed effects with industry-by-year fixed effects to account for time-varying industry characteristics. All specifications control for one-year-lagged firm characteristics. Columns 1 and 2 show that the coefficient estimates on the DiD term, *IMMI Post* $\times$ *Labor Intensive*, is positive and statistically significant at the 5% level. The economic magnitude is sizeable. For example, column 1 shows that compared with the control firms, the treated firms experience an average increase in labor-shortage exposure of 0.020 post-IMMI, which is equivalent to one third of the sample mean of 0.062. Thus, consistent with our expectation, the results suggest that after the enactment of the immigration policy reforms, relative to the control firms (capital-intensive firms), the treated firms (labor-intensive firms) experience a significant increase in labor-shortage exposure.

[3] Since we develop a firm-level labor-shortage measure, partitioning firms into labor-intensive and capital-intensive groups by each industry helps mitigate the concern that some industry-level confounding factors may drive the differential effect of the immigration policy reforms on labor-intensive firms relative to capital-intensive firms.

Next, we explore the heterogeneity in the positive effect of tightened immigration policies on corporate labor-shortage exposure. Specifically, for each industry, instead of partitioning firms into high- and low-labor-capital-ratio groups, we divide the sample firms into quartiles based on a firm's labor-capital ratio in 2016. We then use a regression specification similar to Equation 1 to test which quartile exhibits largest effect. We expect that firms with the highest labor intensity quartile should be most exposed to labor-shortage issues after the immigration policy reforms. Columns 3-4 report the results. We find that relative to capital-intensive firms in the lowest labor-capital-ratio quartile, the tightened immigration policies have insignificant effect on labor-shortage exposure of firms in quartiles 2-3, while firms in quartile 4 experience a sizable and statistically significant (at the 1% level) increase in corporate labor-shortage exposure. These results are consistent with our expectation that the positive effect of the immigration policy reforms on labor-shortage exposure mainly concentrates in firms with high labor intensity within an industry.

Finally, we investigate whether potential nonparallel trends exist before the reforms. Columns 5-6 report the results of estimating Equation 2. We find that the coefficient estimates of the interaction terms are all insignificantly different from zero for the years before the event year ($Year_0$) across the regression specifications in both columns. The positive effect on corporate labor-shortage exposure can only be observed in or after the event year, with the largest effect occurring in the year immediately after the event year. These findings suggest that the increase in firm-level labor-shortage exposure for the labor-intensive firms relative to the control firms is unlikely to be driven by pre-event nonparallel trends in labor-shortage exposure but is most likely caused by the tightened immigration policies that reduce foreign labor supply.

To summarize, the results based on the 2017 immigration policy reforms further confirm the validity of the measure of firm-level labor-shortage exposure. The U.S. immigration reforms in 2017 shrink foreign labor supply, which directly affects labor-intensive firms because such firms rely heavily on foreign-born workers. Thus, we observe a significant increase in labor-shortage exposure for such firms after the reforms.

B1.2 State COVID-19 Lockdown Policy Stringency

In this section, We use the restrictions on human mobility imposed by U.S. state governments during the COVID-19 pandemic to further validate our measure of firm-level labor-shortage exposure. Since the beginning of the COVID-19 pandemic, state governments across the U.S. have implemented a range of restrictive measures in response to the crisis, including policies such as school closures, suspension of public transportation, gathering restrictions, and stay-at-home orders designed to limit human mobility. While some companies, such as high-tech firms, can allow their employees to work remotely, most businesses, especially those in the service and hospitality industries, face severe labor shortages due to the enforcement of "lockdown-style" policies. Therefore, if our measure of firm-level labor-shortage exposure accurately captures what it is intended to capture, we expect to observe a positive relationship between a state's lockdown policy stringency and the labor-shortage exposure of local firms.

To measure state-level COVID-19 lockdown policy stringency, we utilize the state-level daily COVID-19 policy response index data from the Oxford COVID-19 Government Response Tracker (Hale et al., 2021).[4] Specifically, we use the state-level stringency index at the end of

[4] The data can be accessed via: https://www.bsg.ox.ac.uk/research/covid-19-government-response-tracker.

each quarter, which records the strictness of a state's "lockdown-style" policies that primarily restrict people's behavior, to reflect the COVID-19 lockdown restriction stringency in each state-quarter. We then match the state-level stringency index with the firm-level labor-shortage exposure and estimate the following regression equation to investigate the effect of a state's COVID-19 lockdown stringency on local firms' labor-shortage exposure:

$$LS\ Exposure_{i,q+1} = \beta_1 COVID\ Stringency^{state}_{s,q} + \beta_2 Controls_{i,q} + \omega_i + \mu_q + \epsilon_{i,q} \tag{3}$$

In Equation 3, the dependent variable, *LS Exposure*, represents the labor-shortage exposure of firm i in year-quarter $q+1$. The independent variable, $COVID\ Stringency^{state}$, is the end-of-quarter COVID-19 lockdown stringency index of state s in year-quarter q. We further control for the firm characteristics variables as in Equation 3 as well as firm fixed effects ω_i and year-quarter fixed effects μ_q. The sample period for this analysis is 2020-2021. If our measure indeed captures firm-level labor-shortage exposure, we expect β_1 to be significantly positive. This is because an increase in a state's COVID-19 lockdown stringency should lead to a higher level of labor-shortage exposure for local firms. The results are reported in Table B2.

[Please insert Table B2 about here]

Columns 1 and 3 control for firm and year-quarter fixed effects, while columns 2 and 4 further replace year-quarter fixed effects with industry-by-year-quarter fixed effects. Columns 1 and 2 show that the coefficient estimates on $COVID\ Stringency^{state}$ are positive and statistically significant at least at 5% level. Moreover, the estimated effect is economically meaningful. For example, column 1 shows that a one-standard-deviation increase in a state's COVID-19 lockdown stringency index leads to an average increase in labor-shortage exposure of 0.043 (= 14.312*0.003) in one-quarter-ahead labor-shortage exposure of local firms, which is equivalent to 69.355% of the sample mean of annual firm-level labor-shortage exposure.

In Columns 3 and 4, we further explore the dynamic effects of state COVID lockdown stringency on local firms' labor-shortage exposure by introducing the one-quarter lag, two-quarter lag, one-quarter lead, and two-quarter lead of $COVID\ Stringency^{state}$ in the regression models. The results from both columns clearly indicate that it is the current COVID-19 restriction stringency of a state, rather than its past or future levels, that has a significant impact on local firms' labor-shortage exposure.

In summary, the results in this section show that a state's COVID-19 lockdown stringency has a significant positive effect on local firms' labor-shortage exposure. These validation-test results provide further evidence for the reliability of our measure of firm-level labor-shortage exposure.

Table B1. Validation: The Effect of the 2017 Tightened U.S. Immigration Policy on Firms' Labor-Shortage Exposure

This table presents a validation test of our firm-level labor-shortage exposure measure. Columns 1-4 report the difference-in-differences (DiD) regression results using the 2017 tightened U.S. immigration policy as an exogenous shock on local firms' labor-shortage exposure. *IMMI Post* is an indicator variable that equals one if the year is 2017 or after and equals zero otherwise. *Labor Intensive* is an indicator variable that equals one if a firm's labor capital ratio (emp/ppent) based on the 2016 value is higher than (2-digit SIC) industry median and equals zero otherwise. *Labor Intensive Q2(Q3/Q4)* is an indicator variable that equals one if a firm's labor-capital ratio (emp/ppent) based on the 2016 value is in the second-quartile (third-quartile/fourth-quartile) in its (2-digit SIC) industry and equals zero otherwise. Columns 5-6 report the dynamic DiD regression results that investigate the timing of the effect of the tightened immigration policy on firms' labor-shortage exposure. $Year_j$ is an indicator variable that equals one if the year is the jth year relative to the event year (year zero, which is 2017) and equals zero otherwise. All specifications include firm fixed effects and year (industry-year) fixed effects. We also include lag firm control variables in all specifications. Table A1 in Appendix A provides detailed variable definitions. Robust standard errors clustered at the firm level are provided in parentheses. All financial variables are winsorized at the 1st and 99th percentiles. ***, **, and * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES			LS Exposure			
IMMI Post × Labor Intensive	**0.020****	**0.019****				
	(0.008)	**(0.008)**				
IMMI Post × Labor Intensive Q2			-0.003	-0.004		
			(0.009)	(0.009)		
IMMI Post × Labor Intensive Q3			-0.001	-0.003		
			(0.009)	(0.009)		
IMMI Post × Labor Intensive Q4			**0.046*****	**0.045*****		
			(0.016)	**(0.016)**		
Labor Intensive × Year $_{-2}$					-0.002	-0.002
					(0.007)	(0.007)
Labor Intensive × Year $_{-1}$					0.010	0.011
					(0.008)	(0.007)
Labor Intensive × Year $_{0}$					**0.018**	**0.018***
					(0.011)	**(0.011)**
Labor Intensive × Year $_{+1}$					**0.036*****	**0.035*****
					(0.013)	**(0.013)**
Labor Intensive × Year $_{+2}$					**0.014**	**0.014**
					(0.012)	**(0.012)**
ROA $_{t-1}$	-0.008	-0.009	-0.006	-0.008	-0.008	-0.010
	(0.011)	(0.011)	(0.011)	(0.012)	(0.011)	(0.012)
Book Leverage $_{t-1}$	-0.007	-0.008	-0.007	-0.008	-0.007	-0.008
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Stock Return $_{t-1}$	-0.008	-0.006	-0.007	-0.006	-0.007	-0.006
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
CAPEX $_{t-1}$	0.007	0.043	0.002	0.034	0.002	0.037
	(0.075)	(0.077)	(0.075)	(0.077)	(0.075)	(0.077)
MTB $_{t-1}$	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sales Growth $_{t-1}$	0.011*	0.006	0.011*	0.006	0.011*	0.006

	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)
Firm Size $_{t-1}$	-0.001	0.002	-0.001	0.002	-0.002	0.002
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Cash $_{t-1}$	0.006	0.016	0.005	0.016	0.006	0.017
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Asset Tangibility $_{t-1}$	-0.032	-0.041	-0.032	-0.042	-0.028	-0.037
	(0.040)	(0.039)	(0.040)	(0.039)	(0.041)	(0.039)
Stock Volatility $_{t-1}$	0.077	0.075	0.071	0.071	0.073	0.072
	(0.064)	(0.067)	(0.063)	(0.066)	(0.064)	(0.066)
R&D $_{t-1}$	-0.033*	-0.040**	-0.030	-0.037*	-0.034*	-0.041**
	(0.020)	(0.020)	(0.020)	(0.021)	(0.020)	(0.020)
Employees/AT $_{t-1}$	-1.711	0.062	-1.797	-0.061	-1.760	0.007
	(2.552)	(2.880)	(2.560)	(2.902)	(2.561)	(2.889)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No	Yes	No
Industry-Year FE	No	Yes	No	Yes	No	Yes
Obs.	11,916	11,916	11,916	11,916	11,916	11,916
Adj. R2	0.422	0.443	0.424	0.444	0.422	0.443

Table B2. Validation: State COVID-19 Lockdown Policy Stringency and Firm-level Labor-Shortage Exposure

The table presents the regression results that investigate the effects of a state's COVID-19 lockdown policy stringency on local firms' labor-shortage exposure. The dependent variable, *LS Exposure*, is a firm's one-quarter-ahead labor-shortage exposure. The independent variable, *COVID Stringency*^{state}, is a state's COVID-19 lockdown stringency index at the end of a year-quarter. Columns 3 and 4 also include the one-quarter lag, two-quarter lag, one-quarter lead and two-quarter lead of *COVID Stringency*^{state} in the regression specifications. All specifications include firm controls. Columns 1 and 3 control for year and firm fixed effects. Columns 2 and 4 control for industry-by-year-quarter and firm fixed effects. Table A1 in Appendix A provides detailed variable definitions. Robust standard errors clustered at the firm level are provided in parentheses. All financial variables are winsorized at the 1st and 99th percentiles. ***, **, and * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)
VARIABLES		LS Exposure$_{q+1}$		
COVID Stringency$^{state}{}_{q-2}$			-0.000	-0.000
			(0.001)	(0.001)
COVID Stringency$^{state}{}_{q-1}$			0.002	0.001
			(0.002)	(0.001)
COVID Stringency$^{state}{}_{q}$	**0.003***	**0.002**	**0.005***	**0.003**
	(0.001)	**(0.001)**	**(0.001)**	**(0.001)**
COVID Stringency$^{state}{}_{q+1}$			0.003*	0.001
			(0.001)	(0.001)
COVID Stringency$^{state}{}_{q+2}$			0.000	-0.000
			(0.001)	(0.001)
ROA	0.210*	0.125	0.325	0.107
	(0.119)	(0.098)	(0.202)	(0.154)
Book Leverage	-0.033	-0.012	-0.045	-0.037
	(0.034)	(0.030)	(0.045)	(0.040)
Stock Return	0.011	0.006	0.005	0.011
	(0.009)	(0.010)	(0.013)	(0.015)
CAPEX	-0.215	-0.181	0.010	0.028
	(0.345)	(0.349)	(0.463)	(0.474)
MTB	0.001	-0.000	0.002	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Sales Growth	0.012*	0.013	0.009	0.021*
	(0.007)	(0.008)	(0.011)	(0.012)
Firm Size	-0.018	-0.031**	-0.010	-0.034
	(0.011)	(0.013)	(0.022)	(0.024)
Cash	-0.112**	-0.067	-0.211***	-0.176**
	(0.052)	(0.052)	(0.075)	(0.075)
Asset Tangibility	0.019	0.146	-0.112	0.066
	(0.226)	(0.201)	(0.369)	(0.332)
Stock Volatility	-0.034	-0.015	-0.007	0.023
	(0.034)	(0.033)	(0.055)	(0.052)
R&D	0.382	0.033	-0.063	-0.365
	(0.307)	(0.267)	(0.455)	(0.396)
Employees/AT	27.522**	17.059	29.990**	16.632
	(13.265)	(11.341)	(15.037)	(12.955)

Firm FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	No	Yes	No
Industry-Year-Quarter FE	No	Yes	No	Yes
Obs.	11,841	11,821	7,881	7,867
Adj. R2	0.350	0.400	0.408	0.447