Measuring Firm-Level Inflation Exposure: A Deep Learning Approach *

Sudheer Chava† Wendi Du‡ Agam Shah§ Linghang Zeng¶

Abstract

We develop a novel measure of firm-level inflation exposure by applying a deep learning model to firms' earnings conference call transcripts. Our methodology not only identifies sentences that discuss price changes but also differentiates price increases from price decreases and input prices from output prices. In the time series, our aggregate inflation exposure measure strongly correlates with official inflation measures. In the cross section, firms that have higher inflation exposure experience a strong negative stock price reaction to earnings calls. Firms' pricing power attenuates the negative market reaction. Consistent with the market reaction, firms with higher inflation exposure have higher future costs of goods sold and lower operating cash flows. Last, high inflation exposure firms perform worse on Consumer Price Index (CPI) release days, in particular when the CPI release is salient and the CPI is higher than the consensus forecast.

*We thank Alex Hsu, Da Li, Jiacui Li, Erik Sirri, Wenting Song, Luke Stein, Jerome Taillard, Jincheng Tong, Michael Weisbach, Nancy Xu, Ivan Shaliastovich, Alejandro Lopez-Lira, Norman Guo, and seminar participants at China International Conference in Finance, Stanford SITE Conference on New Frontiers in Asset Pricing, Swedish House of Finance Conference on AI & Machine Learning in Finance, University of Florida Research Conference on Machine Learning in Finance, UT Dallas 2022 Fall Finance Conference, 2022 FMA Annual Meeting, 2022 Conference on Financial Economics and Accounting, Babson College, Georgia Institute of Technology, and Texas A&M for their helpful comments and suggestions.

†Scheller College of Business, Georgia Institute of Technology, sudheer.chava@scheller.gatech.edu

‡Scheller College of Business, Georgia Institute of Technology, wendi.du@gatech.edu

§College of Computing, Georgia Institute of Technology, ashah482@gatech.edu

¶Babson College, lzeng@babson.edu

1 Introduction

With inflation reaching a four-decade high in 2022, inflation and cost pressures are among the most pressing concerns for firms (The CFO Survey, Q4 2021). Firms differ in their exposure to inflation and in their ability to pass through their cost pressures to consumers, and this differential exposure can affect asset prices and corporate decisions. However, measuring firm-level exposure to inflation is challenging as we do not directly observe an individual firm's input prices.

In this paper, we develop a novel text-based measure of firm-level inflation exposure by applying a deep learning model to firms' earnings conference call transcripts and study its implications for asset prices. Earnings call transcripts contain important information on firm-level input and output price changes. Managers have first-hand information on input prices and can communicate this information to investors during earnings conference calls as they are less constrained than their disclosures through regulatory filings. Managers also set prices for products and services, potentially passing through some of their inflation exposure to consumers. We analyze earnings call transcripts at the sentence level by deploying a state-of-the-art deep learning technique (Vaswani et al. 2017). In particular, our model can help answer the following questions: Does the sentence contain price-change-related information? If so, is it about price increases or price decreases, or is it about input prices or output prices? All these questions are essential for constructing a firm-level measure of inflation exposure.

We analyze 102,112 earnings call transcripts for U.S. firms in the intersection of CRSP and Compustat during January 2007 and July 2021 from SeekingAlpha. We select training sample from earnings call data to capture as much price-change-related information as possible for models to learn. To achieve this goal, we build a list of words (target words)[1] covering categories likely to be associated with price change information. For all earnings calls from January 2021 to June 2021, we select the top five earnings call transcripts with the highest overall frequency of target words from each industry to capture the language variation across

[1] "inflation," "deflation," "price," "cost," "margin," "labor," "wage," "expense," "payment."

industries. We manually label each sentence into three categories: 1) whether it contains price change information, 2) the direction of the price change (up or down), and 3) whether the discussion is about input or output price.

Among the 28,932 sentences we manually check, 1,335 (4.61%) are labeled as price change related. Among the price-change-related sentences, 1,280 (95.88%) contain a target word, suggesting the target word list performs well in capturing potential inflation-related information. Given that the labels are unbalanced and the list of target words performs well in capturing relevant information, we focus on sentences that contain target words in training deep learning models. However, 4,710 sentences have a target word, and only 27.18% are labeled as price change related. Thus we cannot directly construct measures using target words in the spirit of a bag-of-words approach.

We train three state-of-the-art deep learning language models using our training sample, namely Bidirectional Encoder Representations from Transformers (BERT, Devlin et al. 2018), Robustly Optimized BERT Pretraining Approach (RoBERTa, Liu et al. 2019), and Financial Sentiment Analysis with Pre-Trained Language Models (FinBERT, Araci 2019). Since these deep learning models are already pre-trained using a large text corpus, they can understand words that are not included in our price-change-related training sample. In addition, these deep learning models can learn domain knowledge (e.g., how firms describe price changes) through further training with the corresponding labeled sample. In this step, deep learning models can learn which parts of an input sequence are important to make an accurate prediction in the price movement context. Moreover, during the training process, deep learning models absorb the context information by analyzing sequences of multiple lengths with the word order information, which is helpful to better understand the price-change-related language.

Among the three models, RoBERTa achieves the best performance in predicting whether a sentence is price change related, with an accuracy of 90.44%. Therefore, we use it for all the remaining analysis. We apply the fine-tuned RoBERTa model to all sentences with target words in earnings call transcripts from 2007 to 2021. The model generates a label for each sentence, which is whether it is price change related. Similarly, we train (fine-tune) two more RoBERTa models to label price-change-related sentences: (1) the direction of the price change (up versus down) and (2) the source of the price change (input versus output).

For each transcript, we define the firm-level exposure to inflation, *InflationExp*, as the number of sentences labeled as input price increase minus the number of sentences labeled as input price decrease, scaled by the number of sentences in the transcript. The intuition is that if a firm is more exposed to inflation, its input prices, such as raw materials and wages, are more likely to increase. Managers would convey this information to the investors, which could lead to a higher value of *InflationExp*.

There is significant variation in the inflation exposure measure both in the time series and in the cross section. For example, many firms have experienced a spike in inflation exposure in 2008, 2011, and 2021, when overall inflation is high. Chemical, non-durable, and manufacturing firms have higher average inflation exposure, while firms in the business equipment, telecom, and healthcare industries have lower average inflation exposure.

We validate our methodology by examining whether our measure captures inflation in aggregate. Each quarter, we aggregate the firm-level inflation exposure to construct a text-based inflation measure by taking the average of *InflationExp* across all firms. The aggregate *InflationExp* measure strongly correlates with standard inflation measures. For example, the correlation between our measure and year-over-year Producer Price Index (PPI) growth is 0.775. In contrast, a simple measure based on the frequency of target words has a correlation with PPI of 0.01. The high correlation between our measure and standard inflation measures indicates that our methodology can extract relevant information on inflation. While it is not the focus of this paper, it is worth noting that our measure can be constructed in real time and may provide valuable information on inflation even before the official inflation data are released.

Next, we study how inflation exposure affects asset prices by investigating how the stock market reacts to the text-based inflation exposure as measured from firms' earning calls. Ex ante, it is unclear how the reaction should be. Higher inflation exposure means higher input prices, which could impact a firm negatively. However, if firms have pricing power and can pass the higher costs to their consumers, they may not be affected. Further, if our measure does not accurately measure inflation exposure or capture additional price-relevant information relative to standard controls, there should be no abnormal stock reaction based on our measure.

The event panel regressions show that a one standard deviation increase in *InflationExp* is associated with 26.3 to 32.5 basis point lower CARs from one day before to one day after the earnings call, CAR[-1,+1]. This result suggests that, on average, firms cannot completely pass through their cost pressures. The coefficient for *InflationExp* is little changed when we include a dictionary-based measure—the frequency of target words in the earnings call, while the coefficient for the frequency of target words is close to zero. This provides further supporting evidence that our deep learning approach performs better than the dictionary approach in terms of measuring inflation exposure.

One major concern with the immediate market reaction to *InflationExp* that we document is that firms may talk about input price increases to distract investors when they under-perform. Our measure could thus be potentially correlated with firms' under-performance, and the negative reaction we estimate could be then due to bad performance instead of inflation exposure. To alleviate this concern, we control for unexpected earnings surprises. We also include other text-based measures of earnings call transcripts, such as the sentiment and the uncertainty of earnings call transcripts. In general, the concern is that there is some omitted quantitative information released during the earnings call that may be correlated with our textual inflation measure that may be driving the results. We further conduct a causal forest analysis (Wager & Athey 2018, Athey et al. 2019) using a large set of quantitative variables. The results remain similar in all these robustness tests.

We also observe a negative drift after the earnings call. Specifically, a one standard deviation increase in *InflationExp* is associated with 44.2 basis point lower CARs from 2 to 90 days after the earnings call. This result suggests that investors do not fully price in the inflation exposure that our measure captures during the earnings call, which leads to a drift after the earnings call.

Next, we investigate the role of firms' pricing power in explaining the price reaction that we document. If firms have high pricing power, they can increase their output prices and pass the input price pressure onto their customers. Therefore, these firms should experience a less negative price reaction. To test this hypothesis, we construct a text-based pricing power measure defined as the number of sentences with output price increases divided by the number of sentences with input price increases. The intuition is that when firms discuss input price increases, if they have pricing power, then it is more likely that they would also mention that they can pass it through to consumers by raising their output prices. A higher value indicates more pricing power and pass through. The results suggest that a firm's pricing power can attenuate the negative market reaction to its inflation exposure.

Further, we investigate the relationship between a firm's inflation exposure and its future fundamentals that are directly affected by inflation, such as costs of goods sold and operating cash flows. The regression results show that firms that have higher inflation exposure also experience an increase in their future costs of goods sold and a decrease in future operating cash flows. These results could also partly explain the negative stock market reaction to inflation exposure.

Next, we study the heterogeneous stock price response to Consumer Price Index (CPI) releases. We hypothesize that firms with high inflation exposure perform worse on CPI releases, in particular when the CPI release is more salient. Our regression analysis finds supporting evidence for this hypothesis. The results are mainly driven by days when the inflation level is high (i.e., CPI $> 2\%$) and there is a positive inflation shock (i.e., the actual number is higher than the consensus forecast). These results provide further supporting evidence that our measure captures firms' exposure to inflation.

Finally, we analyze whether our text-based inflation exposure is simply proxying for the return-based inflation beta. Conceptually, these two measures are different. Our text-based inflation exposure specifically measures how firms' input prices are exposed to inflation. In contrast, the return-based inflation beta measures how firms' stock returns comove with inflation, and could be driven by the impact of inflation on firms' cash flows, discount rates, and the real value of debt. We construct inflation betas and control for inflation betas in the analysis on the market response to the earnings calls and CPI releases. The coefficient estimates on our inflation exposure remains unchanged after we control for the inflation beta. These results provide further empirical evidence that our text-based inflation exposure measure captures additional information over traditional inflation beta.

This paper contributes to the literature on understanding the impact of inflation on asset prices. Fama & Schwert (1977), Schwert (1981), Stulz (1986), Campbell & Vuolteenaho (2004), and Bekaert & Engstrom (2010) study the relationship between inflation and aggregate stock market returns. More recent literature, such as Ang et al. (2012), Eraker et al. (2016), and Bhamra et al. (2021), investigate the role of inflation in the cross-section of stock returns. Corhay & Tong (2021) focus on the wealth transfer channel of inflation and study its implication for asset prices. We develop a novel text-based firm-level inflation exposure measure to understand the heterogeneous impact of inflation on firms' stock returns. We do this by measuring the exposure of firms' input prices to inflation, which is hard to measure and is different from the return-based inflation beta used in the literature. We also test the heterogeneous responses to earnings calls and CPI releases based on firms' inflation exposure, and we directly test the role of pricing power in the market reaction.

The paper also contributes to the emerging literature that uses textual analysis in finance. Buehlmaier & Whited (2018) predict the probability of a firm being financially constrained based on the textual analysis of firms' annual reports. Li et al. (2021) create a culture dictionary by using a word embedding model to measure corporate culture. Jha et al. (2020) apply the BERT model to measure sentiment toward finance across eight countries, and Jha et al. (2021) analyze the response of this finance sentiment to natural disasters and its impact on economic outcomes. Moreover, Chava et al. (2020) identify emerging technologies using BERT, and Chava et al. (2021) use RoBERTa to construct a comprehensive environmental and social dictionary that incorporates materiality. To our knowledge, our paper is the first to apply a deep learning language model, RoBERTa, to construct a firm-level inflation exposure measure from firms' earnings calls. Our methodology can analyze text at the sentence level and can be applied in many other settings in finance research.

2 Data and Methodology

In this section, we first describe the datasets we use in the paper. Then, we describe the methodology to construct the text-based firm-level inflation exposure measure. Further, we present the summary statistic. Last, we discuss the text-based aggregate inflation exposure measure.

2.1 Data sources

We collect data on the 178,547 earnings conference call transcripts from January 2007 to July 2021 from SeekingAlpha. We then merge the transcripts with CRSP and Compustat based on the identification information of the stock ticker, the company name, the title of the event, and the earnings conference call date. After matching, we are left with 154,463 transcripts. Table A1 shows the matching and filtering steps involved, and Appendix Section A provides the detailed information about the matching process. For the matched earnings calls, we keep 119,978 transcripts by further requiring the company to have a non-missing SIC code, a share code of 10 or 11, and an exchange code of 1, 2, or 3. Finally, we get 102,112 earnings call transcripts after removing finance and utilities companies. We also obtain financial variables from Compustat, I/B/E/S, and CRSP.

2.2 Constructing the text-based inflation exposure measure

We use earnings conference calls to extract information on price changes for two reasons. First, the existing literature has documented that these calls convey critical corporate information to the market (Bowen et al. 2002, Brown et al. 2004). For example, the price-change-related contents, as the critical aspects of the firm's business operations, would be discussed by the chief executives and the analysts. Second, managers in earnings conference calls are less constrained than in their regulatory filings and are allowed to interact with participants in the Q&A section in a more conversational format. Thus the discussion about the firm's pressure and actions related to the price change is expected to be more flexible in earnings conference call.

Constructing the text-based inflation exposure measure involves three steps: constructing the training sample, training the deep learning model and processing all the earnings call transcripts, as shown in Figure 1 shows these steps in more detail. In the rest of this subsection, we first describe why we need deep learning models in our context and then describe each of the steps in detail.

2.2.1 Why do we need deep learning classification?

To measure inflation exposure from earnings conference calls, the key challenge is to identify price-change-related discussions. The language patterns for these discussions are complicated. For example, in the 2021 Q2 earnings conference call, the CEO of Sanderson Farms was discussing the price increase (in bold) in business as follows:

> Sanderson Farms operated very well during the second quarter of fiscal 2021 in all areas of our business. Improved poultry markets more than offset **feed grain costs that were significantly higher** compared to last year's record fiscal quarter, resulting in increased operating margins... In addition to improved domestic demand for chicken, export demand also improved during the quarter as a result of **higher crude oil prices**... **Prices paid for corn and soybean meal increased significantly** during

> the quarter compared to last year... **We have priced all of our soy meal basis** through October **and most of our corn basis** through September.

As this example shows, the price change contents are described by diverse vocabularies and are not limited to certain terminologies. This characteristic makes it hard to build a dictionary of words for "inflation" like the traditional bag-of-words approach does. This approach would also neglect word order information and could result in a big part of the price change contents in earnings calls being missing. In addition, the price change language occurs with flexible syntactic patterns and appears in sentences with various lengths, which is a natural consequence of the price change in business being an intricate issue to describe.

The rule-based model, which requires two sets of words to occur within a fixed number of words, could improve the ability to capture price change information, but it could also potentially lose some patterns due to the difficulty of defining a reasonable word distance. Specifically, speakers often only use "price" as a verb to describe the product price increase, in which case the rule-based approach could even add in noise. It would become more challenging when we further want to identify the source of price changes ("input" or "output").

To address these challenges, we deploy state-of-the-art deep learning techniques to identify sentence-level price change information in earnings conference calls. The deep learning models, like BERT (Devlin et al. 2018) and its descendant RoBERTa (Liu et al. 2019), have been widely used in processing textual information in machine translation, sentiment analysis, and question answering due to their superior performances. There are several advantages when applying this approach in identifying the price change information.

First, the deep learning model learns the general meaning of words and sentences after being pre-trained by a very large amount of text (Jurafsky & Martin 2014). For example, RoBERTa is pre-trained with over 160GB of uncompressed text, consisting of BookCorpus and Wikipedia (16GB), CC-News (76GB), OpenWebText (38GB), and Stories (31GB), which enables it to absorb the general semantic and syntactic knowledge of the English language. When detecting the price change information in the earnings call sentences, the knowledge embodied in the model allows it to extract the word meaning even for the unseen vocabularies in the training sample.

Second, the pre-trained deep learning models can be easily adopted by the price change classification task through further training (called fine-tuning) on the labeled training sample from our earnings call data. In this step, the model further learns which parts are important to detect the price change information to address the concern of flexible syntactic patterns used in this context. Third, the bidirectional architecture of BERT and its descendants allows the models to see entire sentence at a time, which is an upgrade over the unidirectional deep learning models like OpenAI GPT (Radford et al. 2018), which processes words sequentially. In addition, based on the contextual information, BERT and its descendant models can understand multiple connotations of the *same* phrase depending on how the phrase is used, compared to models such as Word2Vec (Mikolov et al. 2013) and Glove (Pennington et al. 2014), which are only capable of understanding one meaning for each unique phrase.

2.2.2 Constructing the training sample

Constructing a high-quality training sample is a key step before training a powerful deep learning model to measure firm-level price-change-related information. We first select a sample of earnings call transcripts and then manually annotate every sentence in those sample transcripts. The intuition for the training sample selection is to pick the transcripts with the most price-change-related information. The more information we get, the more the model can learn. To achieve this goal, we construct a word list that covers the broad topics where price change information may occur, including "inflation," "deflation," "price," "cost," "margin," "labor," "wage," "expense," and "payment." Sentences containing the target words are not necessarily the ones related to the price change. Target words only serve as setting the broad scope for the potential price-change-related contents.

Based on the target words, as shown in Appendix Table A2, we count the overall frequency on the earnings call transcripts from January 1, 2021 to June 30, 2021, when many discussions on inflation occur. For each industry among the Fama-French 12 industries except for finance and utilities, we keep the top 5 transcripts with the highest total frequency of target words as our training sample. We end up with a training sample that includes 50 earnings call transcripts.

One potential concern about the construction of this sample is look-ahead bias, meaning our training sample could mislead the model to focus on the information concerning the high inflation happening in 2021. However, in Figure 2, the aggregated textual inflation measure constructed based on this training sample successfully captures the up-and-down movements of prices over time, implying that our methodology with the training data effectively captures the language patterns of the price change discussion instead of the high inflation information specifically in 2021.

For the selected transcripts, we decompose each transcript into sentences and manually label them with the following: (1) whether the sentence contains price-change-related information, (2) the direction of the price change (up or down), and (3) whether it is an input- or output-related price change. Since the deep learning model is implemented at the sentence level, we label the sentence purely based on the information in the sentence itself and ignore the context. Appendix B provides a detailed description of our labeling procedures.

We then perform extensive manual checks on the training sample, and the number of sentences with different labels are shown in Table A4. Among the 1,335 sentences with price change information, 1,280 (95.88%) contain target words, suggesting that the target word list performs pretty well on covering the potential price change information. Because of this finding, we focus only on sentences with target words in this paper's analysis, which improves the model accuracy and the computational efficiency.

However, the target word method is not accurate enough to detect price change information on its own. For the 4,710 sentences with target words, only 1,280 (27.18%) actually contain price change information. This finding supports the necessity of extensive human checking and further deploying deep learning techniques to classify the sentence-level information. Overall, our training sample consists of 4,710 sentences, with 1,280 price-change-related sentences and 3,430 sentences without price change information.

2.2.3 Training the model and processing the earnings call transcripts

We identify the best deep learning model in classifying the price change information by testing the accuracy of three candidate models: BERT, RoBERTa, and FinBERT (Araci 2019).[2] Based on BERT, the FinBERT model is further pre-trained on financial news and social media text. We include FinBERT in the analysis in the hope that it may perform well by capturing the business-specific language usage.

We next test the model performance on the price change task with our labeled data. Appendix C provides an overview the detailed training procedure. As Table A5 shows, the RoBERTa model achieves the best performance with 90.44% test accuracy. Thus, we select RoBERTa as our deep learning model for all training and measure generation.

We use the RoBERTa model to make predictions on the entire earnings call data during 2007–2021. Since the target word list performs well in capturing potential price change information, we only feed the sentences with target words into the model for computational efficiency. The model classifies each sentence into a price-change-related sentence or not. After that, we keep the price-change-related sentences and feed them into the model, which is trained with the labeled data with the price change directions (i.e., moves up or down). Similarly, we train two RoBERTa models to identify the source of the price change: (1) the input price change or not or (2) the output price change or not. With these two models, we further identify the change source of each price change sentence.

[2] See Chava et al. (2020) and Chava et al. (2021) for a detailed discussion of application of these models in finance.

2.2.4 Measuring inflation exposure

If a firm is more exposed to inflation, its input prices, such as raw materials and wages, are more likely to increase. When managers convey this information to the investors during earnings calls, our methodology can capture this information. The more they discuss input price increases, the more they are exposed to inflation. Based on this intuition, we define inflation exposure for firm i at time t as

$$InflationExp_{i,t} = \frac{\#InputUp_{i,t} - \#InputDown_{i,t}}{\#SentencesinTranscript_{i,t}}, \tag{1}$$

where $\#InputUp$ is the number of sentences about the input price being up in a transcript, $\#InputDown$ is the number of sentences about the input price being down in a transcript, and $\#SentencesinTranscript$ is the number of sentences in a transcript. We subtract $\#InputDown$ to account for deflationary forces. One assumption of this measure is that the frequency with which managers talk about input price pressure is a good proxy for the actual exposure to inflation. However, managers choose what to communicate. If they decide not to convey any information about prices even if they are highly exposed to inflation, we cannot accurately measure inflation exposure for the firm as it would just add noise to our measure. In the empirical regressions, we standardize $InflationExp$ for ease of explanation.

Figure 3 shows that there is significant variation in the inflation exposure measure both in the time series and in the cross-section. For example, many industries have inflation exposure spike in 2008, 2011, and 2021, when inflation is high. Chemical, non-durable, and manufacturing firms have higher average inflation exposure, while business equipment, telecom, and healthcare firms have lower average inflation exposure.

2.3 Summary statistics

Table 1 presents descriptive statistics for the 82,381 earnings conference calls occurring between 2007 and 2021 with non-missing financial variables. Table A7 describes the construction of all variables. Regarding the discussion of the input price movement, we find that, on average, there are 2.793 sentences containing input price increase information in earnings calls, while the average number of input price decrease sentences is 0.609. Moreover, the average of the $InflationExp$ measure is 0.521%, calculated as the difference of the input price-up sentences and the input price-down sentences relative to the total number of sentences of one earnings call transcript.

2.4 Text-based aggregate inflation exposure

To validate our methodology, we examine whether our method captures information for inflation. For each quarter, we construct the text-based aggregate inflation exposure by taking the average of the firm-level inflation exposure. The trends of the text-based aggregate inflation exposure and official inflation measures are shown in Figure 2. Panel A uses the quarterly PPI year-over-year growth rate, and Panel B uses the quarterly CPI year-over-year growth rate.

The figures show that the text-based aggregate inflation exposure co-moves strongly with PPI and CPI and captures the important time periods of high inflation concerns. For example, the text-based inflation exposure increases significantly during the 2008 inflation, which is driven by skyrocketing gas prices, and also during the 2011 inflation with food and energy pushes. In addition, our measure incorporates the information of the price change direction and thus captures the precise downward movement of price-related information. For example, for the 2014–2015 oil price plunge, the text-based aggregate inflation exposure successfully captures the price downward trend.

Based on the sample data for Figure 2, we find that the correlation between the PPI growth rate and text-based aggregate inflation exposure is 0.775, and the correlation between the CPI growth rate and the text-based aggregated inflation exposure measure is 0.735. The high correlation between the text-based inflation measure and the official inflation measures gives us confidence that our methodology performs well in capturing inflation-related information from earnings conference calls. It also mitigates the concern that our measure is driven by idiosyncratic cost pressure because the aggregate idiosyncratic cost pressure would likely have a very low correlation with aggregate inflation.

3 Results

3.1 Inflation exposure and market reaction to earnings conference calls

We start our empirical analysis by studying how the stock market reacts to the inflation exposure around earnings conference calls. Ex ante it is unclear how investors react. Higher inflation exposure means higher input prices, which would in theory hurt firms. However, if firms have pricing power and can pass it through to consumers, they may not be affected. Further, if our measure does not accurately measure inflation exposure or does not capture additional information on top of fundamental measures, there should be no abnormal stock reaction to our measures.

To test these competing hypotheses, we run the following empirical specification:

$$Y_{i,f,t} = \alpha + \beta InflationExp_{i,f,t} + Controls_{i,f,t} + \delta_{f,t} + \phi_i + \epsilon_{i,f,t}, \tag{2}$$

where $Y_{i,f,t}$ represents the stock market's response to the earnings conference call of firm i (operating in industry f) at time t. We analyze the stock market's immediate response to firms' earnings conference calls through the three-day CAR (CAR[−1,+1] (%)), calculated using the market model.

The key independent variable, $InflationExp_{i,f,t}$, represents inflation exposure measured from firm i's earnings conference call at time t. The construction of this variable is discussed in more detail in Section 2.2.4. One major concern is that firms blame input price increases when they under-perform. Consequently, our inflation exposure could be correlated with firms' performance, which affects stock price reaction. This is less likely because the aggregate inflation exposure strongly correlates with actual inflation. Nevertheless, to alleviate this concern, we control for a set of transcript- and firm-level characteristics, which might influence the immediate price reaction. The variables include firms' unexpected earning surprise, the sentiment and uncertainty of earnings call transcripts, firm size, market-to-book ratio, pre-event return, leverage, cost of goods sold, and return on assets. All variables are defined in Table A7.

The specification includes firm fixed effects and industry $\times$ year-quarter fixed effects, with robust t-statistics double clustered at the firm and year-quarter levels. The inclusion of firm fixed effects in the specification helps account for any firm-specific, time-invariant characteristics, such as a firm's general proclivity to always or never discuss price change information in their conference calls or the market's general tendency to consistently over- or under-react to a given firm's earnings conference calls. Moreover, adding the industry $\times$ year-quarter fixed effects helps us account for any time-varying trends within industries that are potentially correlated with the general price change within specific industries.

Table 2 presents the findings. In Column (1), we study the impact of $InflationExp$ on the immediate stock price response to the earnings conference calls. We find that the coefficient estimate on $InflationExp$ is negative and significant at the 1% level, suggesting that inflation exposure generates a negative immediate price response. In Column (2), we further control for firm fixed effects to address the concern that certain firms tend to always or never discuss the price change information. We find that the coefficient estimate is still negative and significant at the 1% level.

In Column (3), we add year-quarter fixed effects in the regression to control for time-varying macroeconomic changes broadly, like business cycles influencing the entire stock market. The coefficient estimate is largely unchanged and significant at the 1% level. In Column (4), we control for both the firm fixed effects and the industry $\times$ year-quarter fixed effects and deploy the Fama-French 12 industry as the industry classification. We find that a one standard deviation increase in inflation exposure is associated with a 32.5 basis point stronger immediate price reaction. Overall, the results in Table 2 indicate that investors react negatively to inflation exposure, suggesting that, on average, firms cannot completely pass it through to consumers.

As discussed in Section 2.2.2, our methodology performs better than the dictionary approach in capturing price change information. We further test this in the baseline result and construct a measure in the spirit of the bag-of-words approach, $Target$, which is defined as the number of targeted words that may be related to inflation by the total number of words in the transcripts. The correlation between $InflationExp$ and $Target$ is 0.529. We include both measures in the baseline regression. As shown in Column (5), the coefficient for $InflationExp$ is –0.304, little changed from Column (4). However, the coefficient for $Target$ is –0.072 and statistically insignificant.

Although we control for several firm-level characteristics, to further examine whether the $InflationExp$ measure provides incremental information above the firm's quantitative characteristics, we conduct a causal forest test on the immediate stock price response and the inflation exposure (Wager & Athey 2018, Athey et al. 2019). This methodology allows us to control for more variables in a non-linear fashion. In addition to the firm- and transcript-level control variables we considered in Table 2, we include 14 additional financial variables as covariates in the test.

Table A8 shows the estimation results by using the generalized random forest (GRF) R-package.[3] Panel A shows the estimation results for the whole sample, where the estimated average treatment effects, i.e., the short-term stock price response to the firms with high inflation exposure, are statistically significant. We further test Panels B and C by tightening

[3]The detailed information about the package is available at `https://grf-labs.github.io/grf/reference/causal_forest.html`.

the treatment condition to address the potential concern that some firms merely and coincidentally discussed price changes with one or two sentences. We find the estimated average treatment effects stay statistically significant, and the magnitudes are stronger than the test on the entire sample. Overall, our findings suggest that the text-based inflation exposure measure captures additional information over the firm-level financial variables.

One may be concerned that the negative market reaction to the inflation exposure is due to firm-specific cost pressure instead of cost increases due to inflation. We address this concern by decomposing the text-based inflation exposure into a systematic component and an idiosyncratic component. For each firm i, we run a time-series regression:

$$InflationExp_{i,t} = \alpha_i + \beta_1 PPI_t + \beta_2 AggInflationExp_t + \beta_3 IndInflationExp_t + \epsilon_{i,t}, \quad (3)$$

where $InflationExp_{i,t}$ is the text-based inflation exposure for firm i at time t and PPI_t is the year-over-year PPI growth at time t. $AggInflationExp_t$ is the average $InflationExp$ of firms reporting at time t, and $IndInflationExp_t$ is the average $InflationExp$ of firms in the same Fama-French 12 industry reporting at time t. We include two text-based measures as independent variables to capture inflation that is not fully measured in PPI.

We define the systematic component, sys, as $\beta \times X$ and define the idiosyncratic component, $idio$, as ϵ. The systematic component is part of $InflationExp$ that is driven by inflation. Even though we include three measures for inflation in the firm-level time-series regression, we may still not fully account for inflation. Further, firms' exposure to inflation could be time-varying. Consequently, the idiosyncratic component could include an unexplained systematic component. We rerun the baseline analysis in Table 2 by replacing $InflationExp$ with sys and $idio$. Table A9 reports the results. After controlling for the idiosyncratic component, a one standard deviation increase in the systematic component is associated with 12.8–36.2 basis point lower returns. This analysis provides further supporting evidence that the result we document is not driven by firm-specific cost pressures.

Further, we examine whether the immediate stock price reaction to inflation exposure is an over- or under-reaction by analyzing the long-run drift after the earnings call date. Existing research documents that immediate mispricing is corrected over the longer horizon (DellaVigna & Pollet 2009, Hirshleifer et al. 2009, Chava & Paradkar 2020). Thus, if the negative immediate price reaction to inflation exposure in earnings calls is an over-reaction, we would expect a relatively better stock performance for firms with higher textual inflation exposure in their earnings calls in the longer horizon. On the other hand, if the market investors do not fully adjust the stock price based on inflation exposure in earnings calls and under-react, we would expect that the firms with more inflation exposure in earnings calls will continue to perform poorly in the post-earnings call for a longer period.

Table A10 shows the results of the long-run drift. In Column (1), we analyze the price drift over the 30 trading days after the earnings conference calls (CAR[+2,30] (%)) and find that the coefficient estimate on $InflationExp$ is negative. When analyzing the price drifts over the 60 and 90 trading days after the calls (CAR[+2,60] (%) and CAR[+2,90] (%)), we find that the inferences of the negative price drifts remain unchanged and the magnitudes get larger. In Column (3), a one standard deviation increase in $InflationExp$ is associated with 44.2 basis point lower CARs from 2 to 90 days after the earnings calls. These findings suggest that the information about inflation exposure discussed in earnings calls is not fully incorporated by the investors immediately.

3.2 Decomposition of the price movement and the market reaction

In this subsection, we decompose the information of the price movement in earnings calls and examine how each component influences the immediate stock market reaction. The discussion of price changes could be about the input price headwinds or downward trend from the areas of labor, energy, and raw material costs as well as about the output price increase or decrease considering the firm's pricing power or the intensified competition environment in its industry. To address this, we decompose the price change discussion in earnings calls into four components based on the price movement's source (input versus output) and direction (up versus down).

Table 3 shows the empirical results. The key dependent variable $InputUp$ ($InputDown$) is calculated as the number of the input-up (input-down) sentences scaled by the total number of sentences in the earnings call transcript. Similarly, the $OutputUp$ ($OutputDown$) is computed as the number of the output-up (output-down) sentences scaled by the total number of sentences in the earnings call. From the results in Columns (1)–(4), we find that investors have a significantly negative reaction to the discussion of input price increases and output price decreases but have a strongly positive response to the discussion of input price decreases and the output price increases in earnings conference calls. These findings imply that investors react positively to the news of a potential margin increase and negatively to the information of potential margin shrinking. The consistent pattern in the table further supports that our deep learning methodology performs well in extracting price-change-related information in earnings conference calls.

3.3 Pricing power and market reaction

Firms with pricing power can pass through the inflation pressure to their customers. Consequently, investors may be less worried about firms with high inflation exposure and high pricing power. In this subsection, we examine how investors react to the inflation exposure in earnings calls by firms' pricing power.

To measure pricing power, we define a text-based measure as follows:

$$PP_{i,t} = \frac{\#OutputUp_{i,t}}{\#InputUp_{i,t} + 1}, \tag{4}$$

where $\#OutputUp$ is the number of sentences labeled as output price up and $\#InputUp$ is the number of sentences labeled as input price up. The intuition is that when firms discuss input price increases, if they have pricing power, they will mention that they can pass it through to consumers by raising output prices. We add 1 in the denominator to address the condition that some earnings calls do not have sentences about the input price being up. A higher PP indicates more pricing power and pass-through. For each year-quarter, we create a dummy variable $HighPP$ that equals one if a firm's PP is larger than or equal to the median and zero otherwise.

We then run the following specification:

$$\begin{aligned} Y_{i,f,t} = & \alpha + \beta_1 InflationExp_{i,f,t} + \beta_2 HighPP_{i,f,t} + \beta_3 InflationExp_{i,f,t} * HighPP_{i,f,t} \\ & + Controls_{i,f,t} + \delta_{f,t} + \phi_i + \epsilon_{i,f,t}. \end{aligned} \tag{5}$$

Table 4 shows the results. Consistent with the baseline result, the coefficient estimate for $InflationExp$ is negative and significant. However, the interaction term is positive and significant, indicating that firms' pricing power attenuates the negative market reaction as they can pass through the inflation exposure to consumers.

3.4 Inflation exposure and future fundamentals

In this subsection, we investigate whether and how the inflation exposure is associated with firms' future fundamentals that are directly affected by inflation, such as cost of goods sold and operating cash flow. We first calculate the cost of goods sold in the next one to four quarters after the earnings conference calls (from $q+1$ to $q+4$) scaled by the total assets of quarter q, and examine the relationship between the inflation exposure and the future cost of goods sold of a company. Table 5, Panel A shows the results. We find that the coefficient estimates of $InflationExp$ are significantly positive over the next one to four quarters. This finding suggests that the inflation exposure measured from earnings conference calls is positively associated with firms' cost in the future.

Following Banker et al. (2017), we then calculate the firm's operating cash flow after the earnings conference call by scaling the operating cash flow in the next one to four quarters with the market value of equity at quarter q. As shown in Panel B of Table 5, we find that the $InflationExp$ measure is negatively associated with the firm's operating cash flow in the next one to two quarters after the earnings call, and this effect disappears when we extend the time horizon to the next three to four quarters. This finding implies that firms with high levels of inflation exposure would have a decrease in operating cash flow in the next one to two quarters. Taken together, these findings indicate that the inflation exposure can predict firms' future fundamentals that are directly affected by inflation. This could also partly explain the negative market reaction to inflation exposure.

Next, we further distinguish the components of the firm's cost of goods sold into wage and raw material costs. Since the wage data from Compustat are available annually, we aggregate the inflation exposure from earnings conference calls into yearly levels. Specifically, for one firm, we sum the numbers of price-change-related sentences of its earnings conference calls happening during the period of its fiscal year and generate the measure $InflationExp$ by using the number of sentences about input price increases minus the number of sentences about input price decreases, scaled by the number of earnings call sentences.

Appendix Section D and Table A7 provides details on the construction of the firm-year-level sample and the definitions of wage and material costs. Table A11 shows the results for cost of goods sold and its components when we control for the firm fixed effects and industry $\times$ year fixed effects. Consistent with Table 5, Column (1) shows a positive and significant relationship between a firm's textual inflation exposure and its cost of goods sold. In Columns (2) and (3), we separately analyze the wage and material cost and find that the positive association between cost of goods sold and the inflation exposure is largely driven by the increase of raw material costs.

3.5 Inflation exposure and market reaction to CPI releases

So far, we have studied how the stock market reacts to the inflation exposure around earnings conference calls and how inflation exposure predicts firms' future fundamentals. In this subsection, we study whether firms' stock price reacts differently to CPI releases based on their inflation exposure. We focus on CPI releases because they are the most followed inflation data by market participants. We hypothesize that firms with high inflation exposure perform worse during CPI releases, particularly when the CPI release is more salient to investors. This hypothesis will not be supported in the data if our measure does not capture firms' exposure to inflation.

To test this hypothesis, we construct an event panel where each CPI release is an event. For each event, we compute CARs for every firm in our sample. We then run the following specification:

$$Y_{i,t} = \alpha + \beta InflationExp_{i,t} + Controls_{i,t} + \theta_t + \epsilon_{i,t}, \tag{6}$$

where $Y_{i,t}$ is CAR of firm i at event t and θ_t is the event fixed effect. The regression includes all controls in the baseline regression and event fixed effects. The standard errors are clustered at the event level, and the events are from May 2012 to October 2021, when there are data available on the inflation shock and the inflation exposure.

Table 6 reports the results. Column (1) shows that on CPI release days, a one standard deviation increase in the inflation exposure measure is associated with a 3 basis point lower CAR. In Column (2), we extend the window for CAR to five days after the CPI release, and the economic magnitude increases to 4.3 basis points. In Columns (3) and (4), we split the events into salient and non-salient days. A salient day is defined as a day where the inflation level is high (CPI $>$ 2%) and there is a positive inflation shock (i.e., the actual inflation number is higher than the consensus forecast). On salient days, a one standard deviation increase in the inflation exposure is associated with 27.4 basis point lower CARs, while the estimate is almost zero in non-salient days.

Overall, these results indicate that firms with high inflation exposure have lower returns on CPI releases, particularly when the release is more salient. They also provide further supporting evidence that our measure captures firms' exposure to inflation.

3.6 Text-based inflation exposure versus return-based inflation beta

Finally, we study whether our text-based inflation exposure measure is different from the return-based inflation beta measure that has been used in the literature. Conceptually, these two measures are different. The text-based inflation exposure measure captures how much firms' input prices are exposed to inflation. In contrast, the return-based inflation beta measures how much firms' stock returns comove with inflation and is agnostic about the specific channels. A non-exhaustive list of resasons for why a firm's return can be affected by inflation are: 1) its input prices/output prices are impacted by inflation and thus its cash flows; 2) a change in monetary policy because of inflation has an impact on a firm's discount rates; 3) inflation influences the real value of debt.

Although theoretically these two measures are different, we provide some empirical support to rule out the concern that our text based measure of inflation is not simply proxying for the return-based inflation beta. We empirically construct a return-based inflation beta and control for inflation beta in our baseline market reaction to earnings call analysis and the CPI event studies. We construct two inflation betas. First, we follow Ang et al. (2012) and regress monthly stock returns on monthly log change in CPI and the three Fama-French factors (Fama & French 1993). We include Fama-French three factors to control for systematic risks that matter for stock returns. We use 60-month rolling window to estimate β_{CPI} and require a minimum 36-month data. Second, we follow Corhay & Tong (2021) and regress monthly stock returns on the monthly change in inflation expectation of the University of Michigan Surveys of Consumers and Fama-French three factors. Similarly, we use 60-month rolling window to estimate β_{Mich} with a minimum 36-month requirement.

We start with the market response to earnings calls. We include the lagged inflation beta in Equation (2) and report results in Table 7 Panel A. We standardize the inflation beta, similar to inflation exposure, for the ease of interpretation. As shown in Column (1) and Column (3), two inflation beta measures β_{CPI} and β_{Mich} are uncorrelated with the market response to earnings calls. This is unsurprising given that the inflation beta is already public information before the calls. In contrast, in Column (2) and (4), the coefficient estimates remain unchanged compared to Table 2 after controlling for inflation betas.

In Panel B, we repeat the analysis of the market response to CPI releases. We focus on salient CPI releases because Table 6 shows that inflation exposure matters only on salient CPI release days. We analyze two return windows, [0,0] and [0,5]. In Column (1) and (2), we control for β_{CPI}. β_{CPI} is insignificant in both regressions, while the coefficient estimates remain unchanged for $InflationExp$. In Column (3) and (4), we control for β_{Mich}. Interestingly, the coefficient on β_{Mich} is negative and significant, suggesting that firms with higher inflation beta as measured by β_{Mich} have lower returns on salient CPI releases. In the meantime, the coefficient estimates for $InflationExp$ remain unchanged. Moreover, the economic magnitudes for $InflationExp$ and β_{Mich} are comparable. Overall, consistent with the conceptual differences, our text-based inflation exposure and return-based inflation beta are different empirically.

4 Conclusion

Measuring firm-level inflation exposure is challenging as we do not directly observe an individual firm's input price. In this paper, we develop a novel text-based firm-level measure of inflation exposure by applying state-of-the-art deep learning techniques to earnings conference calls. Our analysis advances the understanding of inflation exposure and the cross-section of stock returns. In particular, the strong negative market reaction to earnings calls and CPI releases for high inflation exposure firms suggest that firms seem unable to fully pass through their cost pressure to their consumers. In line with this hypothesis, firms with more pricing power experience less negative market reaction. The stock return drift subsequent to the earnings calls suggests that it takes time for investors to fully incorporate firms' inflation exposure into stock prices. Consistent with the market reaction, the inflation exposure measure predicts higher costs of goods sold and lower operating cash flows in the future.

Earning calls allow us to extract information on inflation from managers who have first-hand knowledge on input prices and set prices for products and services and future price actions. Our firm-level inflation exposure measure can be used to better understand aggregate inflation as it can be constructed in real time and strongly co-moves with the official inflation measures.

References

Ang, A., Brière, M. & Signori, O. (2012), 'Inflation and individual equities', *Financial Analysts Journal* **68**(4), 36–55.

Araci, D. (2019), 'Finbert: Financial sentiment analysis with pre-trained language models', *arXiv preprint arXiv:1908.10063* .

Athey, S., Tibshirani, J. & Wager, S. (2019), 'Generalized random forests', *The Annals of Statistics* **47**(2), 1148–1178.

Banker, R. D., Basu, S. & Byzalov, D. (2017), 'Implications of impairment decisions and assets' cash-flow horizons for conservatism research', *The Accounting Review* **92**(2), 41–67.

Bekaert, G. & Engstrom, E. (2010), 'Inflation and the stock market: Understanding the "fed model"', *Journal of Monetary Economics* **57**(3), 278–294.

Bhamra, H. S., Dorion, C., Jeanneret, A. & Weber, M. (2021), 'High inflation: Low default risk and low equity valuations', *Chicago Booth Research Paper* (18-12).

Bochkay, K., Hales, J. & Chava, S. (2020), 'Hyperbole or reality? investor response to extreme language in earnings conference calls', *The Accounting Review* **95**(2), 31–60.

Bowen, R. M., Davis, A. K. & Matsumoto, D. A. (2002), 'Do conference calls affect analysts' forecasts?', *The Accounting Review* **77**(2), 285–316.

Brown, S., Hillegeist, S. A. & Lo, K. (2004), 'Conference calls and information asymmetry', *Journal of Accounting and Economics* **37**(3), 343–366.

Buehlmaier, M. M. & Whited, T. M. (2018), 'Are financial constraints priced? evidence from textual analysis', *The Review of Financial Studies* **31**(7), 2693–2728.

Campbell, J. Y. & Vuolteenaho, T. (2004), 'Inflation illusion and stock prices', *American Economic Review* **94**(2), 19–23.

Chava, S., Du, W. & Malakar, B. (2021), 'Do managers walk the talk on environmental and social issues?', *Available at SSRN 3900814* .

Chava, S., Du, W. & Paradkar, N. (2020), 'Buzzwords?', *Available at SSRN 3862645* .

Chava, S. & Paradkar, N. (2020), 'December doldrums, investor distraction, and stock market reaction to unscheduled news events'.

Corhay, A. & Tong, J. (2021), 'Inflation risk and the finance-growth nexus', *Rotman School of Management Working Paper* (3795679).

DellaVigna, S. & Pollet, J. M. (2009), 'Investor inattention and friday earnings announcements', *The Journal of Finance* **64**(2), 709–749.

Devlin, J., Chang, M.-W., Lee, K. & Toutanova, K. (2018), 'Bert: Pre-training of deep bidirectional transformers for language understanding', *arXiv preprint arXiv:1810.04805* .

Eraker, B., Shaliastovich, I. & Wang, W. (2016), 'Durable goods, inflation risk, and equilibrium asset prices', *The Review of Financial Studies* **29**(1), 193–231.

Fama, E. F. & French, K. R. (1993), 'Common risk factors in the returns on stocks and bonds', *Journal of* .

Fama, E. F. & Schwert, G. W. (1977), 'Asset returns and inflation', *Journal of financial economics* **5**(2), 115–146.

Hirshleifer, D., Lim, S. S. & Teoh, S. H. (2009), 'Driven to distraction: Extraneous events and underreaction to earnings news', *The Journal of Finance* **64**(5), 2289–2325.

Jha, M., Liu, H. & Manela, A. (2020), 'Does finance benefit society? a language embedding approach', *A Language Embedding Approach (July 18, 2020)* .

Jha, M., Liu, H. & Manela, A. (2021), 'Natural disaster effects on popular sentiment toward finance', *Available at SSRN 3833110* .

Jurafsky, D. & Martin, J. H. (2014), 'Speech and language processing. vol. 3'.

Li, K., Mai, F., Shen, R. & Yan, X. (2021), 'Measuring corporate culture using machine learning', *The Review of Financial Studies* **34**(7), 3265–3315.

Liu, Y., Ott, M., Goyal, N., Du, J., Joshi, M., Chen, D., Levy, O., Lewis, M., Zettlemoyer, L. & Stoyanov, V. (2019), 'Roberta: A robustly optimized bert pretraining approach', *arXiv preprint arXiv:1907.11692* .

Loughran, T. & McDonald, B. (2011), 'When is a liability not a liability? textual analysis, dictionaries, and 10-ks', *The Journal of finance* **66**(1), 35–65.

Mikolov, T., Sutskever, I., Chen, K., Corrado, G. S. & Dean, J. (2013), Distributed representations of words and phrases and their compositionality, *in* 'Advances in neural information processing systems', pp. 3111–3119.

Pennington, J., Socher, R. & Manning, C. D. (2014), Glove: Global vectors for word representation, *in* 'Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP)', pp. 1532–1543.

Peters, R. H. & Taylor, L. A. (2017), 'Intangible capital and the investment-q relation', *Journal of Financial Economics* **123**(2), 251–272.

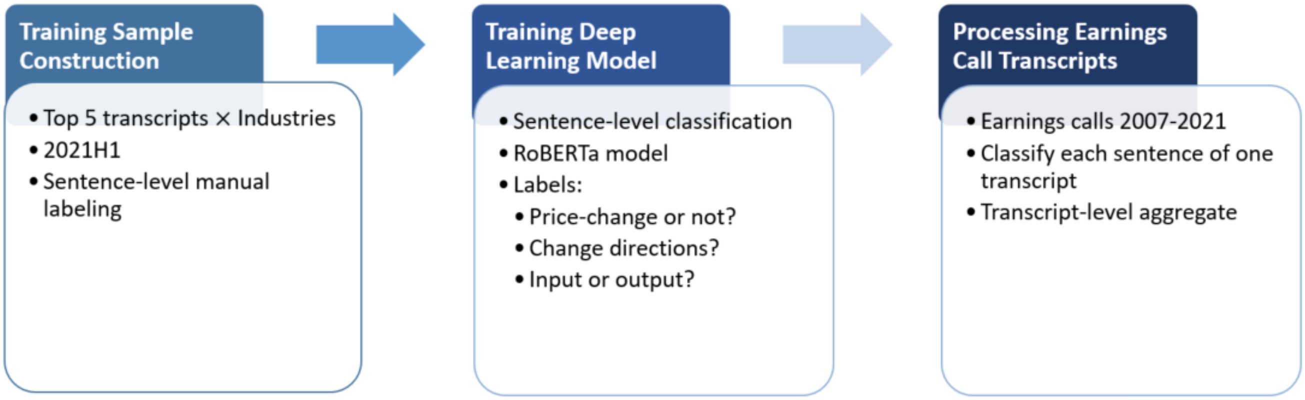
Radford, A., Narasimhan, K., Salimans, T. & Sutskever, I. (2018), 'Improving language understanding with unsupervised learning', *Technical report, OpenAI* .

Schwert, G. W. (1981), 'The adjustment of stock prices to information about inflation', *The Journal of Finance* **36**(1), 15–29.

Stulz, R. M. (1986), 'Asset pricing and expected inflation', *The Journal of Finance* **41**(1), 209–223.

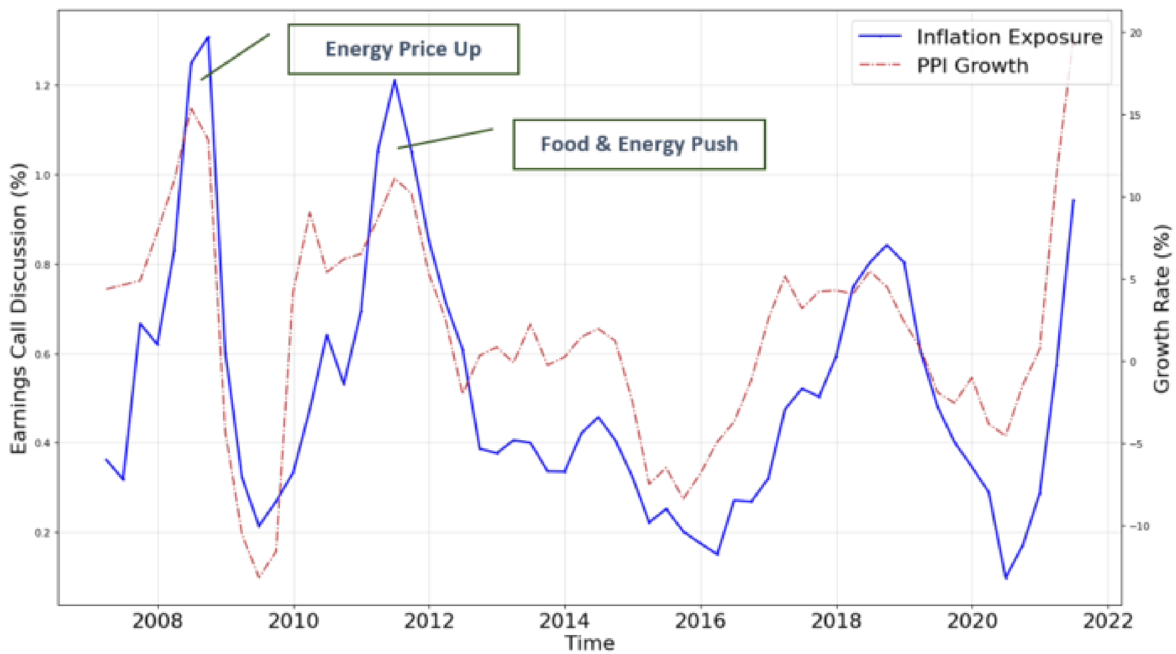
Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, Ł. & Polosukhin, I. (2017), Attention is all you need, *in* 'Advances in neural information processing systems', pp. 5998–6008.

Wager, S. & Athey, S. (2018), 'Estimation and inference of heterogeneous treatment effects using random forests', *Journal of the American Statistical Association* **113**(523), 1228–1242.

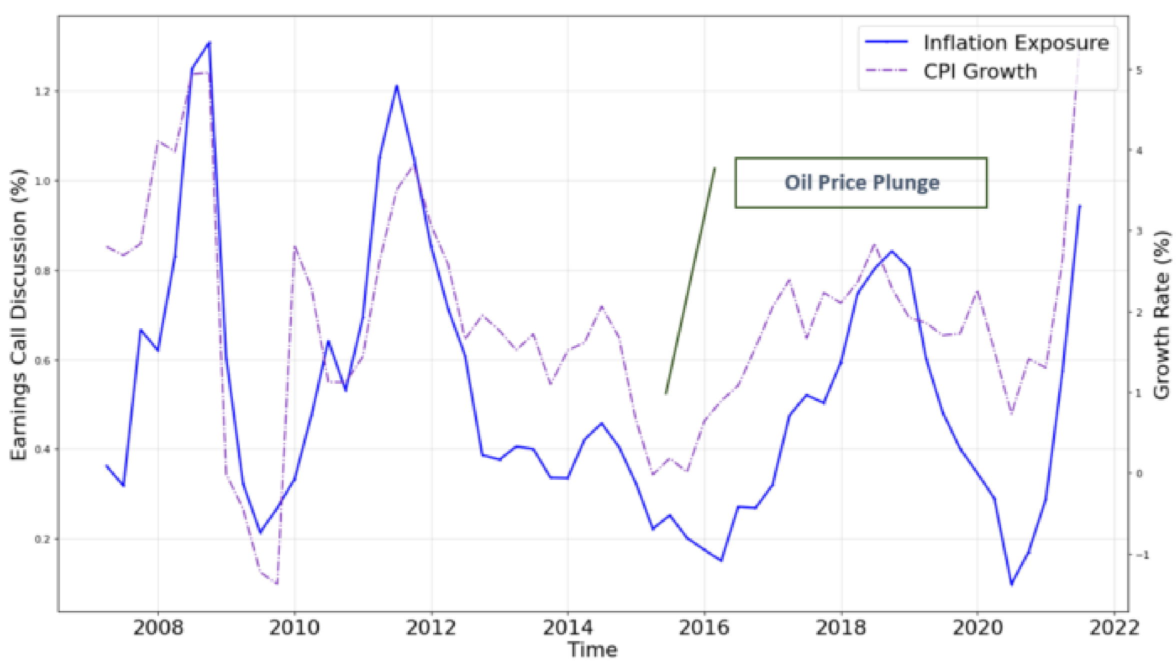


This figure shows the main steps we take with the deep learning techniques to generate the inflation exposure measure for firms' earnings conference call transcripts.

Figure 1: Main steps for constructing inflation exposure measure



Panel A: PPI Growth Rate and Textual Inflation Exposure



Panel B: CPI Growth Rate and Textual Inflation Exposure

Figure 2: Trend of inflation indexes and text-based aggregate inflation exposure
This figure shows the trend of official inflation indexes and the text-based aggregate inflation exposure we construct. In Panel A and B, the solid line represents the text-based aggregate inflation exposure, which is the average of *InflationExp* across all earnings call transcripts in each quarter. In Panel A, the dashed red line represents the quarterly (end of period) measure of the percent change from year ago for the Producer Price Index (PPI) by commodity: all commodities. In Panel B, the dashed purple line represents the quarterly (end of period) measure of the percent change from year ago for the Consumer Price Index (CPI) for all urban consumers: all items in U.S. city average. Both price indexes are downloaded from `https://fred.stlouisfed.org/`. The text-based inflation measure is generated without any winsorization or standardization. The sample for this figure is the 102,112 earnings call transcripts for U.S. firms during January 2007 to July 2021 from SeekingAlpha. Since in our sample there are only 30 transcripts in 2021Q3, we drop the earnings call transcripts for that period to avoid noise.

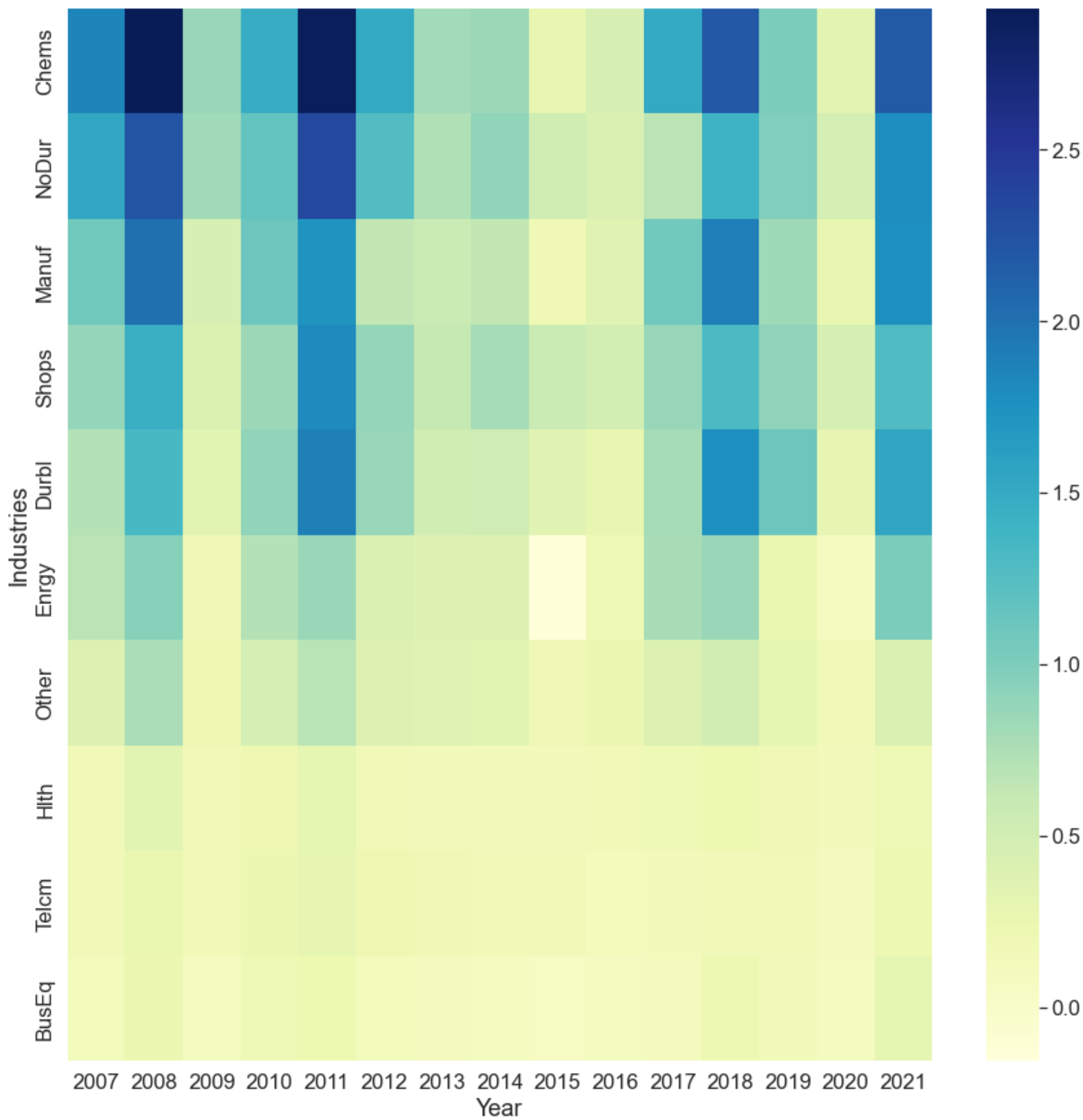


Figure 3: Inflation exposure across industries and time This figure shows the average inflation exposure across Fama-French 12 industries (except for finance and utilities) and years. The darker the color, the higher level of inflation exposure for that industry and year.

Table 1: Descriptive statistics

This table presents the descriptive statistics of the characteristics of earnings conference calls and the characteristics of the firms participating in these earnings calls. All continuous variables are winsorized at the 1% and 99% levels.

	Mean	Median	Std. Dev.
Input Price-Change Discussion in Earnings Calls			
#InputUp	2.793	1.000	4.996
#InputDown	0.609	0.000	1.537
InflationExp (Not Std %)	0.521	0.000	1.021
InflationExp (Std)	0.000	-0.510	1.000
Outcome variables			
CAR[−1,+1] (%)	0.046	0.084	9.366
Control variables			
Size	7.459	7.401	1.818
MTB	2.310	1.717	1.740
Earnings surprise (%)	0.041	0.065	1.405
PreEvent Return	0.001	0.001	0.004
Leverage	0.240	0.209	0.217
COGS	0.155	0.113	0.148
ROA	-0.004	0.009	0.055
Uncertainty (%)	0.995	0.975	0.238
SentimentOverall (%)	0.698	0.696	0.585
#Sentences in earnings call transcript	396.8	394.0	133.0

Table 2: Immediate stock price response to inflation exposure

This table presents results for the immediate stock price response to the inflation exposure measured from firms' earnings conference calls. The dependent variable across all columns is CAR[−1,+1] (%), calculated using the market model. The key independent variable is $InflationExp$, which is computed as the difference between the number of sentences about input price up and the number of sentences about input price down in an earnings conference call scaled by the number of sentences in the earnings call. All control variables are described in the Appendix. Robust T-statistics, double clustered at the firm and year-quarter levels, are presented in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Depvar: CAR[−1,+1] (%)	(1)	(2)	(3)	(4)	(5)
InflationExp	-0.263***	-0.371***	-0.340***	-0.325***	-0.304***
	(-4.20)	(-5.42)	(-5.72)	(-6.17)	(-5.39)
Target					-0.072
					(-1.26)
Earnings surprise (%)	1.223***	1.230***	1.215***	1.214***	1.214***
	(17.90)	(18.13)	(17.18)	(17.50)	(17.51)
Uncertainty (%)	1.270***	0.838***	0.590***	0.608***	0.607***
	(7.08)	(3.69)	(3.08)	(3.22)	(3.22)
SentimentOverall (%)	2.295***	3.549***	3.900***	3.969***	3.967***
	(21.89)	(17.06)	(26.40)	(26.51)	(26.49)
Size	-0.208***	-2.173***	-2.045***	-2.196***	-2.203***
	(-6.23)	(-15.20)	(-14.34)	(-16.35)	(-16.44)
MTB	-0.141***	-0.200***	-0.206***	-0.174***	-0.175***
	(-2.91)	(-3.17)	(-3.36)	(-2.89)	(-2.90)
PreEvent Return	-28.708	-46.907**	-51.973***	-62.968***	-62.91***
	(-1.32)	(-2.19)	(-3.53)	(-4.22)	(-4.22)
Leverage	0.354	-0.529	-0.767*	-0.835*	-0.828*
	(1.24)	(-0.82)	(-1.68)	(-1.91)	(-1.90)
COGS	0.131	2.481**	2.852***	2.531***	2.553***
	(0.44)	(2.42)	(3.30)	(2.95)	(2.97)
ROA	8.780***	10.789***	11.128***	11.331***	11.318***
	(8.27)	(8.42)	(8.58)	(8.78)	(8.78)
Observations	82,381	82,381	82,381	82,381	82,381
Adjusted R-squared	0.064	0.101	0.107	0.111	0.111
Firm FE		✓	✓	✓	✓
YearQtr FE			✓		
FF12 × YearQtr FE				✓	✓

Table 3: Immediate stock price response to the decomposition of price change

This table presents results for the immediate stock price response to the source and direction of price changes measured from firms' earnings conference calls. The dependent variable across all columns is CAR[−1,+1], calculated using the market model. The key independent variable, *InputUp* (*InputDown*) is computed as the number of sentences about input price up (input price down) scaled by the number of sentences in the earnings call. *OutputUp* (*OutputDown*) is computed as the number of sentences about output price up (output price down) scaled by the number of sentences in the earnings call. All control variables are described in the Appendix. Robust T-statistics, double clustered at the firm and year-quarter levels, are presented in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Depvar: CAR[−1,+1] (%)	(1)	(2)	(3)	(4)
InputUp	-0.561***	-0.587***	-0.576***	-0.556***
	(-8.22)	(-7.70)	(-8.60)	(-9.32)
InputDown	0.297***	0.181**	0.145**	0.141**
	(4.47)	(2.66)	(2.03)	(2.15)
OutputUp	0.373***	0.207***	0.242***	0.241***
	(5.71)	(3.09)	(3.76)	(3.76)
OutputDown	-0.214***	-0.257***	-0.245***	-0.267***
	(-3.69)	(-3.72)	(-3.70)	(-4.23)
Observations	82,381	82,381	82,381	82,381
Adjusted R-squared	0.065	0.101	0.107	0.112
Controls	✓	✓	✓	✓
Firm FE		✓	✓	✓
YearQtr FE			✓	
FF12 × YearQtr FE				✓

Table 4: Pricing power and immediate stock price response to inflation exposure

This table presents results for the heterogeneous immediate stock price response to inflation exposure measured from firms' earnings conference calls based on firms' pricing power. The dependent variable across all columns is CAR[−1,+1] (%), calculated using the market model. The independent variable $InflationExp$ is computed as the difference between the number of sentences about input price up and the number of sentences about input price down in an earnings conference call scaled by the number of sentences in the earnings call. Each year-quarter, firms' pricing power is calculated as the number of sentences about output price up divided by the number of sentences about input price up sentences plus 1 (as defined in Equation 4). $HighPP$ is a dummy variable which equals to one if a firm's text-based pricing power is above the median, 0 otherwise. All control variables are described in the Appendix. Robust T-statistics, double clustered at the firm and year-quarter levels, are presented in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Depvar: CAR[−1,+1] (%)	(1)	(2)	(3)
InflationExp	-0.576***	-0.647***	-0.637***
	(-6.71)	(-8.56)	(-8.99)
HighPP	0.462**	0.219**	0.179*
	(2.47)	(2.06)	(1.78)
InflationExp × HighPP	0.257***	0.390***	0.403***
	(2.73)	(5.27)	(5.65)
Observations	82,381	82,381	82,381
Adjusted R-squared	0.101	0.107	0.111
Firm FE	✓	✓	✓
Controls	✓	✓	✓
YearQtr FE		✓	
FF12 × YearQtr FE			✓

Table 5: Future fundamental variables and the inflation exposure

This table presents results testing whether the discussion of input price-increase information in firms' earnings conference calls is associated with the firm's cost of goods sold and operating cash flow in the future. The dependent variable in Columns (1)-(4) of Panel A is the cost of goods sold in the next 1-4 quarters (from $q+1$ to $q+4$) scaled by the total assets of quarter q. In Panel B, we calculate the dependent variable following Banker et al. (2017) as the operating cash flow in the next 1-4 quarters scaled by the market value of equity of quarter q. The key independent variable is $InflationExp$, which is computed as the difference between the number of input price-up sentences and the number of input price-down sentences in an earnings conference call scaled by the total number of sentences in this earnings call. All control variables are described in the Appendix. Robust T-statistics, double clustered at the firm and year-quarter levels, are presented in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Cost of Goods Sold

	(1)	(2)	(3)	(4)
Depvar:	COGS(q+1)	COGS(q+2)	COGS(q+3)	COGS(q+4)
InflationExp	0.002***	0.002***	0.001**	0.001**
	(4.50)	(3.72)	(2.36)	(2.41)
Observations	81,947	81,219	80,285	79,319
Adjusted R-squared	0.943	0.917	0.905	0.909
Controls	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
FF12 × YearQtr FE	✓	✓	✓	✓

Panel B: Operating Cash Flow

	(1)	(2)	(3)	(4)
Depvar:	OCF(q+1)	OCF(q+2)	OCF(q+3)	OCF(q+4)
InflationExp	-0.001***	-0.001*	0.000	0.000
	(-3.29)	(-1.73)	(0.00)	(0.34)
Observations	81,994	81,263	80,326	79,330
Adjusted R-squared	0.314	0.315	0.309	0.317
Controls	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
FF12 × YearQtr FE	✓	✓	✓	✓

Table 6: Inflation exposure and immediate stock price response to CPI releases

This table presents results for the heterogeneous immediate stock price response to CPI releases based on firms' inflation exposure. The dependent variables are cumulative abnormal returns calculated using the market model. The independent variable $InflationExp$ is computed as the difference between the number of sentences about input price up and the number of sentences about input price down in an earnings conference call scaled by the number of sentences in the earnings call. Salient days are CPI release days when CPI is above 2% and the actual number is higher the consensus forecast. All control variables are described in the Appendix. Robust T-statistics clustered at the event levels are presented in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Depvar: (%)	CAR[0,0]	CAR[0,5]	CAR[0,5] Salient	CAR[0,5] Non-salient
InflationExp	-0.030**	-0.043	-0.274**	-0.004
	(-2.39)	(-1.05)	(-2.23)	(-0.11)
Observations	180,372	180,372	17,746	162,626
Adjusted R-squared	0.036	0.036	0.056	0.033
Controls	✓	✓	✓	✓
Event FE	✓	✓	✓	✓

Table 7: Comparison of textual inflation exposure and inflation beta

This table presents results comparing our text-based inflation exposure with inflation beta. In Panel A, the dependent variable are the 3-day cumulative abnormal returns to the firms' earnings conference calls. The dependent variable in Panel B are the cumulative abnormal returns around the salient CPI release days, which we consider as the CPI release days when CPI is above 2% and the actual number is higher the consensus forecast. The independent variable $InflationExp$ is computed as the difference between the number of sentences about input price up and the number of sentences about input price down in an earnings conference call scaled by the number of sentences in the earnings call. β_{CPI} is the inflation beta constructed following Ang et al. (2012), and β_{Mich} is the one based on Corhay & Tong (2021). All control variables are described in the Appendix. Robust T-statistics, double clustered at the firm and year-quarter levels, are presented in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Market Response to Earnings Calls

Depvar:	CAR[−1,+1] (%)			
	(1)	(2)	(3)	(4)
InflationExp		-0.337***		-0.336***
		(-6.72)		(-6.74)
β_{CPI}	0.064	0.070		
	(0.75)	(0.82)		
β_{Mich}			-0.061	-0.092
			(-0.81)	(-0.83)
Observations	72,852	72,852	72,852	72,852
Adj. R^2	0.113	0.114	0.113	0.114
Controls	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
FF12 × YQ FE	✓	✓	✓	✓

Panel B: Market Response to Salient CPI Releases

	(1)	(2)	(3)	(4)
Depvar:	CAR[0,0]	CAR[0,5]	CAR[0,0]	CAR[0,5]
InflationExp	-0.089**	-0.266*	-0.090**	-0.267*
	(-2.22)	(-2.14)	(-2.22)	(-2.14)
β_{CPI}	-0.048	0.057		
	(-0.95)	(0.59)		
β_{Mich}			-0.134**	-0.281**
			(-2.28)	(-2.20)
Observations	16,099	16,099	16,099	16,099
Adjusted R-squared	0.046	0.056	0.048	0.057
Controls	✓	✓	✓	✓
Event FE	✓	✓	✓	✓

Appendix

A Matching Earnings Conference Calls to GVKEY

We downloaded 200,587 transcripts in HTML format from SeekingAlpha from Jan. 2007 to Jul. 2021. Each transcript contains identification information of title, stock ticker, event date, and the date when the transcript is posted on the website. We identify the 178,547 earnings conference call transcripts based on their title containing "earning", fiscal quarter information, but without "webcast".

We notice that the stock ticker from SeekingAlpha suffers from the "backfill" problem as discussed by Li et al. (2021) for the earnings call transcripts from Thomson Reuters' StreetEvents (SE) database. That is when one company changes its ticker, for example due to name change or being acquired, the SeekingAlpha backfills with the new company's stock ticker or the ticker of the acquirer's ticker. Fortunately, the SeekingAlpha earnings call transcripts store the historical stock tickers, in addition to the historical company names, in the title and the first sentence of each transcript. Thus, our matching process starts from matching with the historical tickers, and then we do company name matching for the remaining transcripts.

We use python code to extract the historical ticker in the title, in the first sentence, and the potentially backfilled ticker of the transcript. To make sure the historical tickers are accurate, we get the final historical ticker by setting up three rules:

1. If the historical tickers in the title and the first sentence are non-missing and same;
2. Else, if the historical ticker in the title and the potentially backfilled ticker are non-missing and same;
3. Else, if the historical ticker in the first sentence and the potentially backfilled ticker are non-missing and same.

The basic idea is we have three tickers, we pick the one which at least two of three agree on it. This step helps us to tackle some coding error from SeekingAlpha website. The later two cases imply that for those transcripts, there is no backfilling problem.

For the 178,547 earnings conference call transcripts, we get the accurate historical ticker from case 1 for 118,460 transcripts (66.35%), from case 2 for 314 transcripts (0.18%), from Case 3 for 51,896 transcripts (29.07%). There are 7,877 transcripts (4.41%) satisfying none of the cases.

A.1 Matching to CRSP PERMNO

We download CRSP *dsenames* data, which stores the link between the historical ticker and PERMNO of a stock.[4] By using the historical ticker and the event date of the earnings call, we match each transcript with the corresponding PERMNO. If multiple PERMNOs satisfy

[4]The *dsenames* data we downloaded with the *nameendt* max at 2020-12-31. We assume the *nameendt* will extend to the Jul. 26, 2021, the date after the latest data collection date Jul. 19, 2021.

the requirement (around 0.5% of transcripts), which is often the case that one company has multiple shares traded in the market, we sort the records by share classes and starting date of the record, and select the top one record.

Using CRSP *dsenames* data, we have 152,656 transcripts matched to PERMNO, which is 85.5% of earnings call and 89.4% of transcripts with accurate historical ticker. There are 18,014 transcripts with accurate historical ticker, but not matched to PERMNO.

For the remaining 25,891 transcripts without the matched PERMNO, including those with and without the accurate historical tickers, we continue with the name matching method. We extract the historical company name from each transcript's title, and standardize the historical company names in earnings call transcripts and the CRSP *desnames* data. For each standardized company name of earnings call transcript, we find the closest matched CRSP company name by using Python package of *fuzzywuzzy*. Then, for the matched names selected by *fuzzywuzzy*, we further request the first 25 characters (without space) of the two names should be same. With the matched company name and the event date of earnings call, we get another 6,891 transcripts matched with PERMNO after manual checking.

In total, we get 159,547 transcripts matched with PERMNO. We drop 599 duplicated transcripts with same PERMNO and event date, caused by multiple versions of the same earnings call transcript. Overall, we get 158,948 transcripts matched with CRSP PERMNO.

A.2 Matching to Compustat GVKEY

By using CRSP-Compustat link table, we get 157,751 transcripts (99.2%) matched with GVKEY. Then, for each earnings call transcript, we find the closest prior earnings announcement date (*rdq*) from Compustat Quarterly data since 2006. There are 157,705 transcripts after removing the ones with missing *rdq*. Based on Bochkay et al. (2020), the earnings call date is within one week after the earnings announcement date. Thus, we keep 154,570 (98.01%) transcripts which satisfy this requirement. Then, we drop 107 transcripts duplicated at GVKEY-earnings announcement date (rdq) level[5], and get 154,463 earnings call transcripts.

B Training Sample Labeling

We have the following rules when labeling the sentences of the earnings conference calls in the training sample:

1. Sentences along have to be self-contained. No contextual information is required for the related labels;

2. If one sentence contains the information of both input and output or the entire market, we give 2 for input_output variable;

3. If we are not sure about one question, we keep it blank;

[5]For each GVKEY-rdq pair, we keep the transcripts with the earliest event date and highest share class.

4. We do not treat the sentences related to demand and supply of the market as the price-change-related ones, since the change in demand or supply side do not necessary result in price changes;

5. If the sentence is about the price increase of competitors' products, we label the sentence as output-related price-change information.

6. Sentences about the general costs are not treated as price-change related. For example, the general cost decreases for one firm could be due to the improved efficiency, instead of the decline of input costs;

7. Business-strategy sentences are not considered as price-change related;

8. "Price action" or "pricing action" is viewed as information of product price increase.

C Performance of ML Models

We consider three models (BERT, RoBERTa and FinBERT) as candidates. To fine-tune these models, we keep the weights of initial layers of the model unchanged and further train (find weights) higher layers specifically for our task. To identify the best model with best hyper parameters (batch size and learning rate), we run all three models for three different seeds (5768, 78516 and 944601) with three different batch sizes (2, 4 and 8) and three different learning rates (1e-5, 1e-6, and 1e-7).

In the fine-tuning step, we use *Transformers* library available on huggingface. We run our experiments on NVIDIA V100 GPU. Annotated dataset is split into three parts of 70-10-20 for training-validation-testing. We use AdamW optimizer in our training. We train our model for maximum of 100 epochs. To avoid overfitting, at each epoch of training we calculate accuracy on cross-validation set. If cross-validation accuracy doesn't improve by more than 10^{-2} for 7 consecutive epochs, training will be stopped early to avoid overfitting of the model.

To select model, we measure performance of model based on test accuracy and F-1 score on a task to identify whether sentences has price-change-related information or not. The best result (over all hyper parameters) for all three models is listed in the Table A5. We also list the best hyper parameters found for the model in the same. Based on the results, we select RoBERTa as our model for all supervised training and prediction.

D Annual Sample Construction

We download annual data from Compustat during 2000-2022, and connect it with our sample of 119,978 earnings call transcripts. For a firm's one fiscal year, we collect its earnings calls happening during this time period and summarize the information as below:

- Sum the number of price-change related sentences in those transcripts

- Sum the total number of sentences in those transcripts

- Average the percentage levels of sentiment and uncertainty of those transcripts as control variables in the firm-year level test

We calculate the annual cost of goods sold, material cost, wages, and lagged financial control variables from Compustat, and keep the observations with the year of *datadate* equal to or later than 2007. We also drop the firm-year observations with no earnings call transcripts happening, and further require to have positive total assets. Then, to get industry information, we drop the observations with missing SICH code, and remove firms in banking and utilities industries.

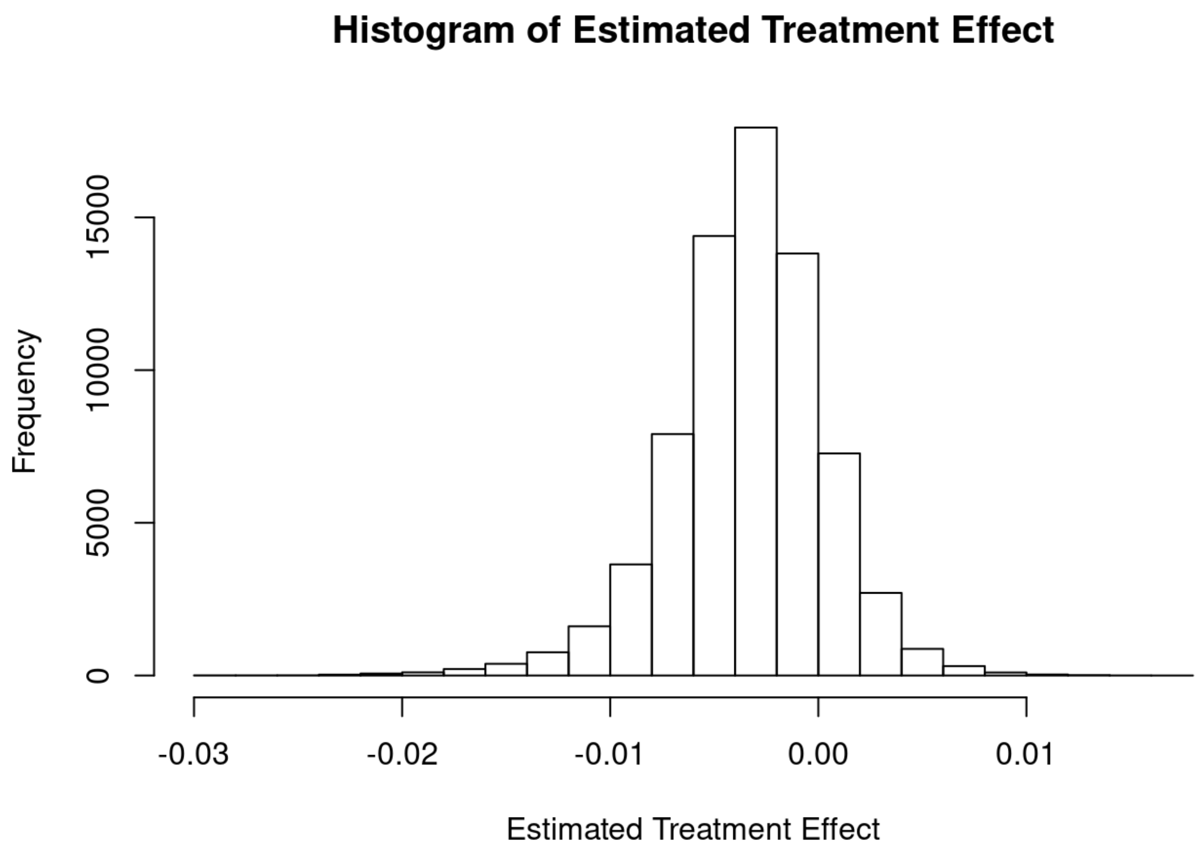


Figure A1: Histogram of Estimated Treatment Effect This figure shows the treatment effect distribution for Panel A (with fraction of target words) experiment explained in Table A8. Out of 72,178 datapoints, estimated treatment effect value is negative for 60,875 (more than 80%) sample. It implies that the results are not driven by few outliers.

Table A1: Earnings Conference Call Sample Creation

This table reports the impact of various data filters and matching on earnings conference call transcripts. *rdq* represents the firm's earnings announcement date from Compustat.

Steps	**Sample Size**	**#Removed**
Transcripts from SeekingAlpha	200,587	
Earnings call transcripts	178,547	
Transcripts matched with PERMNO	158,948	
Including		
Match with PERMNO with historical ticker	152,656	
Match with PERMNO with historical company name	6,891	
Drop duplicates at PERMNO-date level		599
Transcripts matched with GVKEY	154,463	
Processing		
Match with GVKEY with link table	157,751	
Keep transcripts with matched *rdq*	157,705	46
Keep transcripts within one week after *rdq*	154,570	3,135
Drop duplicates at GVKEY-*rdq* level		107
Non-missing SIC code	154,295	168
Share code of 10 or 11	120,052	34,243
Exchange code of 1, 2, or 3	119,978	74
Drop Financial and Utilities Industries	102,112	17,866

Table A2: Target Word List

This table provides a detailed words we include in the target word list we used for training sample selection.

Topic	**Target Words**
Inflation	inflation, inflationary, inflate, inflable, inflated, inflates, inflating, inflator, inflators
Deflation	deflation, deflationary, deflate, deflable, deflated, deflates, deflating, deflator, deflators
Price	price, priced, pricing, prices, pricey, pricy
Cost	cost, costs, costing, costed, costly
Margin	margin, margins, margining, margined
Labor	labor, labors, laboring, labored, laborer, laborers, labour, labours, labourer, labourers, laboured, labouring
Wage	wage, wages, waging, waged
Expense	expense, expenses, expensing, expensed, expensive, expensively, expensiveness, expendable, expenditure, expenditures, expend, expends, expending, expended
Payment	pay, pays, paid, paying, payment, payments, payable, payables, payload, payloads, paycheck, paychecks

Table A3: Labeling Variable Definitions

This table provides a detailed description of the labeling variables in our training sample.

Labeling Variable	Question	Definition
prince_change	Whether the sentence contains the price-change-related information?	Dummy variable which equals to 1 if the sentence contains price-change information; 0 otherwise.
change_direction	Which direction of price change (up or down)?	Dummy variable equals to 1 if it is about price increase; 0 if about price decrease.
input_output	Is it input- or output-related price change?	Categorical variable equals to 0 if the price-change sentence is about output side; 1 if about input side; 2 if about both sides or the general market.

Table A4: Number of Sentences in Labeled Training Sample

This table reports the number of sentences under each category in the labeled training sample, which consists of 50 earnings call transcripts.

	Target Words	**No Target Words**	Sum
Price Change	1,280 (95.88%)	55 (4.12%)	1,335 (100%)
No Price Change	3,430 (12.43%)	24,167 (87.57%)	27,597 (100%)
Total			28,932

Table A5: Accuracy Analysis of Three Candidate Models

This table shows the model performance on detecting the price-change information and the best set of hyper parameters for each model. All the values are average over three different seeds.

Model	**Learning Rate**	**Batch Size**	**Test Accuracy**	**Test F-1 Score**
BERT-base	1e-5	8	89.60%	0.8963
FinBERT-base	1e-6	4	89.81%	0.8995
RoBERTa-base	1e-5	8	**90.44%**	**0.9055**

Table A6: Test Accuracy for All Four Classification Tasks

This table shows the RoBERTa model's performance on the 4 classification tasks related to price change. The number of observations of each task is also included in the table.

Model Task	Dataset Size			**Test Accuracy**
	Train	**Valid**	**Test**	
Price-change or not	3,297	471	942	90.44%
Direction of price change	896	128	256	96.09%
Input price change or not	896	127	255	92.94%
Output price change or not	896	127	255	95.69%

Table A7: Variable Definitions

This table provides a detailed description of the construction of the variables used in all the regression specifications in the paper. All continuous variables are winsorized at the 1% and 99% levels.

Dependent variables	
CAR[−1,+1]	Three-day cumulative abnormal return centered on the earnings conference call date, calculated using the market model.
CAR[+2,+x]	Cumulative abnormal return over the [+2,+x] window in terms of trading days relative to the earnings call date, calculated using the market model.
COGS($q+k$)	Cost of goods sold (*cogsq*) in the next k quarter (k = 1-4) after earnings conference calls scaled by the total assets at quarter q.
OCF($q+k$)	Operating cash flow in the next k quarter (k = 1-4) after earnings conference calls scaled by the market value of equity at quarter q. We calculate quarterly operating cash flow by subtract the year-to-date variable $oancfy$ by its value in the previous quarter for the 2-4 fiscal quarters, and taking the first fiscal quarter's $oancfy$ as the corresponding quarter's operating cash flow.
COGS	Annual cost of goods sold of year t divided by the total assets of year $t-1$.
Wages	Annual total wages of year t divided by the total assets of year $t-1$, where total wages equal to xlr, for which the missing ones are replaced with $xsga$. Following Peters & Taylor (2017), we replace $xsga$ with zero if missing.
Materials	Annual cost of goods sold minus depreciation and amortization (dp) and minus the total wages of year t, scaled by the total assets of year $t-1$.
Key independent variables	
InflationExp	The difference between the number of sentences about input price up and the number of sentences about input price down in an earnings conference call scaled by the number of sentences in the earnings call.
InputUp	The number of sentences about input price up in an earnings conference call scaled by the number of sentences in the earnings call.
InputDown	The number of sentences about input price down in an earnings conference call scaled by the number of sentences in the earnings call.
OutputUp	The number of sentences about output price up in an earnings conference call scaled by the number of sentences in the earnings call.
OutputDown	The number of sentences about output price down in an earnings conference call scaled by the number of sentences in the earnings call.
Target	The number of target words in an earnings conference call scaled by the number of words in the earnings call.

Firm-level control variables	
Earnings surprise	Actual earnings per share (EPS) from IBES minus the consensus (median) of EPS forecasts issued or reviewed in 90 days before the earnings announcement date. The difference is scaled by the stock price at the end of the quarter.
Pre-event return	Average stock return in window [−71,−11] in terms of trading days relative to the earnings conference call date.
Size	Natural logarithm of the market cap at the end of the quarter.
MTB	Market cap plus book value of liabilities scaled by total assets at the end of the quarter.
Leverage	Long-term debt divided by total assets.
COGS	Cost of goods sold divided by total assets.
ROA	Income before extraordinary items divided by total assets.
β_{CPI}	Inflation beta constructed by regressing monthly stock returns on monthly log change in CPI and Fama-French three factors, following Ang et al. (2012) and using 60-month (minimum 36-month) rolling window.
β_{Mich}	Inflation beta constructed by regressing monthly stock returns on the monthly change in inflation expectation of the University of Michigan Surveys of Consumers, following Corhay & Tong (2021) and using 60-month (minimum 36-month) rolling window.
Earnings conference call–level control variables	
Uncertainty	Percentage of uncertain words in the earnings call transcript based on Loughran & McDonald (2011) dictionary and the code from Bill McDonald's website.
Sentiment	Percentage of positive words minus the percentage of negative words in the earnings call transcript based on Loughran & McDonald (2011) dictionary and the code from Bill McDonald's website.
#Sentences	Total number of sentences in the transcript of the earnings conference call.
Annual–level fundamental analysis control variables	
Revenue	Sales of year $t-1$ divided by the total assets of year $t-1$.
Size	Natural logarithm of the market cap ($csho \times prcc\_f$) of year $t-1$.
Leverage	Long-term debt ($dltt$) of year $t-1$ divided by the total assets of year $t-1$.
MTB	Market cap ($csho \times prcc\_f$) plus book value of liabilities (lt) of year $t-1$ scaled by total assets of year $t-1$.

Table A8: Causal Forest Estimates

This table presents results testing the short-term stock price response to the inflation exposure by using causal forest analysis. We use GRF (2.2.0) package with 2000 trees, 0.5 honesty fraction, and 0.5 sample fraction. The dependent variable is CAR[−1,+1]. The covariates in this test are the firm-level and transcript-level control variables in the baseline regression, the year-quarter, the Fama French 12 industry the firm belongs to, and a group of additional firm-level financial variables, including Net Income/Assets, Liabilities/Assets, NWC/Assets, Retained Earnings/Assets, Market Equity/Debt, Sales/Assets, P/E ratio, Net Income/Equity, Book Leverage, Gross Profit/Sales, (SGA + COGS)/Assets, (Cash and Short Term Investments)/Assets, Net PPE/Assets, and Operating Cost/Assets. Further, in each panel we separately examine results with and without the fraction of target words in the earnings call, to validate robustness of our result and examine the performance of the deep-learning-based approach compared to the bag-of-words method in capturing the firm-level inflation exposure. Panel A presents the estimation results for the whole sample, where the treated group contains the observations with the positive $InflationExp$ (Not Std) and the control group consists of the ones with non-positive values. In Panel B (Panel C), we keep the control group same as Panel A and tighten the treated group with the additional condition of having more than 2 sentences about the price-change (input-price-change) related discussion. We report the average treatment effect (ATE), the average treatment effect on the treated (ATT), the average treatment effect on the controls (ATC), and the overlap-weighted average treatment effect (ATO).

	Panel A					
	w/o fraction of target words		with fraction of target words			
	Estimate	Standard Error	Estimate	Standard Error	N (Treated)	N (Control)
ATE	-0.3243%	0.0742%	-0.3397%	0.0766%	36,434	35,744
ATT	-0.3111%	0.0745%	-0.3219%	0.0787%	36,434	35,744
ATC	-0.3354%	0.0960%	-0.3559%	0.1011%	36,434	35,744
ATO	-0.3354%	0.0811%	-0.3460%	0.0822%	36,434	35,744
	Panel B					
	Estimate	Standard Error	Estimate	Standard Error	N (Treated)	N (Control)
ATE	-0.4974%	0.0885%	-0.5248%	0.0951%	27,784	35,744
ATT	-0.3672%	0.0819%	-0.3940%	0.0898%	27,784	35,744
ATC	-0.6093%	0.1354%	-0.6384%	0.1543%	27,784	35,744
ATO	-0.4553%	0.0918%	-0.4728%	0.0943%	27,784	35,744
	Panel C					
	Estimate	Standard Error	Estimate	Standard Error	N (Treated)	N (Control)
ATE	-0.5250%	0.1049%	-0.5158%	0.1094%	22,352	35,744
ATT	-0.4075%	0.0895%	-0.3984%	0.0997%	22,352	35,744
ATC	-0.6055%	0.1809%	-0.5843%	0.1948%	22,352	35,744
ATO	-0.4980%	0.1002%	-0.5167%	0.1037%	22,352	35,744

Table A9: Immediate stock price response to the systematic and idiosyncratic component of the inflation exposure

This table presents results for the immediate stock price response to the systematic and idiosyncratic component of the inflation exposure. The dependent variable across all columns is CAR[−1,+1], calculated using the market model. The key independent variable, *Sys* and *Idio*, are obtained by running firm-level regressions using Equation 3. All control variables are described in the Appendix. Robust T-statistics, double clustered at the firm and year-quarter levels, are presented in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Depvar: CAR[−1,+1] (%)	(1)	(2)	(3)	(4)
Sys	-0.128***	-0.362***	-0.274***	-0.223**
	(-2.87)	(-3.03)	(-2.68)	(-2.63)
Idio	-0.229***	-0.206***	-0.210***	-0.206***
	(-7.10)	(-6.67)	(-6.80)	(-6.76)
Observations	81,509	81,509	81,509	81,509
Adjusted R-squared	0.065	0.100	0.106	0.110
Controls	✓	✓	✓	✓
Firm FE		✓	✓	✓
YearQtr FE			✓	
FF12 × YearQtr FE				✓

Table A10: Long-run abnormal stock price response

This table documents the long-run abnormal stock price response to inflation exposure measured from earnings conference calls. The dependent variables in Columns (1)–(3) report results for progressively longer horizons after the earnings calls. The key independent variable is $InflationExp$, which is computed as the difference between the total number of price-up sentences and the total number of price-down sentences in an earnings conference call scaled by the total number of sentences in the earnings call. All control variables are defined in the Appendix. Robust T-statistics, double clustered at the firm and year-quarter levels, are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

	(1)	(2)	(3)
Depvar:	CAR[+2,+30] (%)	CAR[+2,+60] (%)	CAR[+2,+90] (%)
InflationExp	-0.127	-0.174	-0.442***
	(-1.31)	(-1.28)	(-2.96)
Observations	82,380	82,380	82,380
Adjusted R-squared	0.131	0.172	0.212
Controls	✓	✓	✓
Firm FE	✓	✓	✓
FF12 × YearQtr FE	✓	✓	✓

Table A11: Inflation exposure and annual cost of goods sold

This table presents results testing whether inflation exposure measured from firms' earnings conference calls is associated with the firm's cost of goods sold, materials cost, and wages. The dependent variable in Columns (1) is the cost of goods sold scaled by the total assets of previous year. Definitions of $Materials$ and $Wages$ can be found in Appendix Table A7. The key independent variable is $InflationExp$, which is computed as the difference between the number of sentences about input price up and the number of sentences about input price down in an earnings conference call scaled by the number of sentences in the earnings call. All control variables are described in the Appendix. Robust T-statistics, double clustered at the firm and year-quarter levels, are presented in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
Depvar:	COGS	Materials	Wages
InflationExp	0.022***	0.018***	0.003**
	(7.37)	(6.66)	(2.51)
Observations	28,445	28,432	28,446
Adjusted R-squared	0.908	0.880	0.843
Firm FE	✓	✓	✓
FF12 × Year FE	✓	✓	✓