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

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Abstract

We develop a novel measure of firm-level inflation exposure by applying a deep learning approach 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' market power attenuates the negative market reaction. Consistent with the market reaction, firms with higher inflation exposure have higher future costs of goods sold due to an increase in raw material costs and wages. We also observe a negative drift in the firm's stock return after the earnings call, suggesting that it takes time for investors to fully incorporate firm-level inflation exposure into stock prices.

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1 Introduction

With inflation reaching a four decade high in 2022, inflation and cost pressure are the most pressing concern for firms (The CFO Survey, Q4 2021)[1]. However, firms differ in their exposure to inflation and in their ability to pass through cost increases to consumers. Consequently, it is important to better understand this heterogeneity and how it affects asset prices and corporate decisions. In this paper, we develop a novel text-based measure of firm-level inflation exposure and study its implications for asset prices.

Measuring firm-level exposure to inflation is challenging as we do not directly observe an individual firm's input prices. We overcome this challenge by extracting information on firm level input and output price changes from their earnings conference call transcripts using a deep learning methodology (Vaswani et al. (2017)). This approach has several advantages. First, managers have first-hand information on input prices and can communicate this information to investors during earnings conference calls. Managers also set prices for products and services, potentially passing through some of their inflation exposure to consumers. Second, we can analyze the earnings call transcripts at the sentence level. In particular, we not only identify sentences that discuss price changes, but also differentiate price increases from price decreases, and input prices from output prices.

We collect earnings call transcripts for U.S. firms from January 2007 to July 2021 from SeekingAlpha. After matching transcripts to CRSP and COMPUSTAT and cleaning the data, we have 102,112 transcripts in the final sample. To measure firm-level inflation exposure, the key task is to identify price-change related discussions in earnings call transcripts. It is challenging to accomplish this task using traditional bag-of-words approach. First, discussions on price changes contain diverse vocabularies rather than certain terminologies. Constructing a dictionary of words is hard. If the dictionary is narrow, we could miss a big part of price-change related discussions. Alternatively, we would misclassify a sentence. Second, bag-of-words can only identify words, while identifying price-change related discussion

[1] https://www.wsj.com/articles/us-inflation-consumer-price-index-february-2022-11646857681.

may require a context. For example, "cost" would be a key word to identify price-change related discussions. However, "cost" may be mentioned in the context of inefficiency or mismanagement. Further, cost can either go up or down, which is important to distinguish when measuring inflation exposure. Bag-of-words method is limited in differentiating them. The more recent rule-based models, requiring two sets of words occurring within a fixed number of words, could improve the ability to capture price-change information, but potentially loses some patterns due to the difficulty to define a reasonable word distance.

To overcome these methodological challenges, we deploy state-of-the-art deep learning techniques to analyze earnings call transcripts at the sentence level. Our model can understand the meaning of a given sentence. It can answer the following questions: Does the sentence contain price-change related information? If so, is it about price increases or price decreases? Is it about input prices or output prices? All these questions are essential for constructing a measure of inflation exposure. Our methodology involves three steps: constructing a training sample; training deep learning models; applying the best trained model to all earnings call transcripts and construct measures.

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) covering big categories that are likely to be associated with price-change information.[2] For all earnings calls during January 2021 to June 2021, we select the top 5 earnings call transcripts with the highest overall frequency of target words from each industry to capture the language variation across industries[3]. Extensive human labeling and checking work is conducted where each sentence receives three labels: 1) with price-change information or not; 2) go up or down; 3) about input or output price.

[2]The list include "inflation", "deflation", "price", "cost", "margin", "labor", "wage", "expense", and "payment".

[3]One potential concern about the construction of the training sample is the look-ahead bias, meaning our training sample could mislead the model to focus on the information of the high inflation happening in 2021. However, in Figure 3, the aggregated textual inflation measure constructed based on this training sample successfully captures the up-and-down movements of prices over time, implying 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.

Among the 28,932 sentences we manually check, 1,335 sentences (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. Yet, it is worth noting that 4,710 sentences have a target word. Only 27.18% are labeled as price-change related. Thus we cannot directly construct measures using target words in the spirit of bag-of-words approach. Instead, it is necessary to have extensive manual checking and deploy deep learning techniques to classify sentence level information. Overall, our training sample consists of 4,710 sentences. 1,280 sentences are labeled price-change related.

We train three state-of-the-art deep learning language models using our training sample. Namely, Bidirectional Encoder Representations from Transformers (BERT), Robustly Optimized BERT Pretraining Approach (RoBERTa), and Financial Sentiment Analysis with Pre-trained Language Models (FinBERT). RoBERTa achieves the best performance in predicting whether a sentence is price-change related, with an accuracy of 90.44%. Therefore, we use RoBERTa 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: whether it is price-change related. Similarly, we train two more RoBERTa models to label price change related sentences: (1) the direction of price change (up vs down); (2) the source of price change (input vs 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, adjusted 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 leads 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 inflation exposure spike in 2008, 2011, 2021 when inflation is high. The chemical, non-durable, and manufacturing firms have high average inflation exposure, while firms in the business equipment, telecom, and healthcare industries have low 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 PPI growth is 0.775. The high correlation between our measure and standard inflation measures indicates that our methodology is able to 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 before official data releases.

Next, we study how inflation exposure affects asset prices by investigating how the market react to the textual inflation exposure measured from firms' earnings calls. Ex ante it is unclear how investors react. Higher inflation exposure means higher input prices, which would in theory hurt the firm. However, if firms have market power and are able to pass it through to consumers. They may not be affected. Further, if our measure does not accurately measure inflation exposure or capture additional information on top of fundamental measures, there should be no abnormal stock reaction to our measures.

Event panel regressions show that a one standard deviation increase in *InflationExp* is associated with 23 to 36.3 basis point lower abnormal cumulative returns from one day before the earnings call to one day after the earnings call, CAR[-1,+1]. This result suggests that firms, on average, are unable to pass through the cost pressure.

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 be potentially correlated with firm's under-performance. As such, The negative reaction we estimate could be due to bad performance instead of inflation exposure. To alleviate concerns, 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.

Further, we investigate the role of firms' market power in the price reaction we document. The idea is that if firms have high market power, they are able to increase output prices and pass the input price pressure onto customers. Therefore, these firms should experience less negative price reactions. To test this hypothesis, we construct a unique text-based market power measure. The measure is 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 market power, they would mention that they are able to pass it through to consumers by raising output prices. A higher value indicates more market power and pass through. The analysis using this text-based measure suggests that market power attenuates the negative market reaction.

To understand why the market responds negatively to firm's inflation exposure, we investigate the relationship between inflation exposure and cost of good sold. The regression results show that firms that have higher inflation exposure see the cost of good sold increase in the future. We also find that both raw material costs and wage increase for firms more exposed to inflation.

Lastly, we observe a negative drift after the earnings call. Specifically, an one standard deviation increase in *InflationExp* is associated with 48.6 basis points lower cumulative abnormal returns from 2 days 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.

Our paper contributes to the literature on understanding the impact of inflation on asset prices. Fama & Schwert (1977), Schwert (1981), Stulz (1986), Campbell & Vuolteenaho

(2004), 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), Bhamra et al. (2021), investigate the role of inflation in the cross-section of stock returns. We develop a novel text-based firm-level inflation exposure measure. We study the both the immediate and long-term market reaction to these inflation exposure measures. Further, we directly test the role of market power in the market reaction.

Our paper also contributes to the emerging literature that uses machine learning techniques in finance. Buehlmaier & Whited (2018) predict the probability of a firm being financially constrained based on the textual analysis of firms' annual reports. Li, Mai, Shen & Yan (2021) create a culture dictionary by using the word embedding model to measure the corporate culture. The study by Jha, Liu & Manela (2020) applies the BERT model to measure sentiment towards finance across eight countries, which is adopted in a separate study, Jha, Liu & Manela (2021), to analyze the response of this finance sentiment to natural disasters and its impact on economic outcomes. To our knowledge, our paper is one of the first to apply deep learning language models, RoBERTa, to analyze financial documents in the finance literature. Our methodology is able to analyze text at the sentence level and can be applied in many other settings in finance research.

2 Data and Methodology

2.1 Data sources

Earnings conference calls provide a good institutional setting for analyzing the firm-level discussion about the price-change related content for two important reasons. First, existing literature has documented that earnings conference calls convey critical corporate information to the market (Bowen et al. 2002, Brown et al. 2004). 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 the regulatory filings and are allowed to interact with participants in the Q&A section in a more conversational format. The discussion about the firm's pressure and actions related to the price change is expected to be more flexible in earnings conference call.

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

2.2 Constructing text-based inflation exposure measure

The construction of the text-based inflation exposure measure consists of three steps: training sample construction, training deep learning model, and processing entire earnings call transcripts, as shown in Figure 1. We first describe why we need deep learning models in our context. Then we describe each of the steps in details in this subsection.

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, CEO of Sanderson Farms (SAFM) in the 2021 Q2 earnings conference call was discussing the price increase (in bold) in business as following:

> 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, not limited to certain terminologies. This characteristic makes it hard to build a dictionary of words for "inflation" as the traditional bag-of-words approach does. The bag-of-words approach would also neglect word order information and could result in missing a big part of price-change contents in earnings calls. In addition, the price-change language occurs with flexible syntactic patterns and shows 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, like requiring two sets of words occurring within a fixed number of words, could improve the ability to capture price-change information, but potentially loses some patterns due to the difficulty to define 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 will 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 price-change information.

First, the deep learning model learns the general meaning of words and sentences after pre-trained by very large amount of text (Jurafsky & Martin 2014). For example, RoBERTa is pre-trained with over 160GB of uncompressed text, consisting of BookCorpus + 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 process words sequentially. In addition, based on the contextual information, BERT and its descendant models are able to understand multiple connotations of the *same* phrase depending on how the phrase is used, compared to the 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 Training sample construction

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 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 which 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 necessary the ones related to 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 A1, we count the overall frequency on the earnings call transcripts from January 1, 2021 to June 30, 2021 when lots of discussions on inflation occur. For each industry among the Fama-French 12 industries except for the finance and utilities, we keep the top 5 transcripts with the highest total frequency of target words as our training sample. Our training sample includes 50 earnings call transcripts.

For the selected transcripts, we decompose each earnings call transcript into sentences, and manually label them with the following questions: (1) whether the sentence contains price-change related information; (2) the direction of the price change (up or down); (3) whether it is 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 detailed description of our labeling procedures.

After extensive manual check on the training sample, the number of sentences with different labels are shown in Table A3. Among the 1,335 sentences with price-change information, 1,280 sentences (95.88%) contain target words, which suggests that the target word list performs pretty well on covering the potential price-change information. Because of this finding, we focus only on the sentences with target words in this paper's analysis, which improves the model accuracy and the computational efficiency. On the other hand, 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 Model training & processing 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).[4] Based on BERT, FinBERT model is further pre-trained on financial news and social media texts. We include FinBERT in the horse-race in the hope that it may perform well by capturing the business-specific language usage.

We test the model performance on price-change task with our labeled data. The detailed training procedure is shown in Appendix C. As Table A4 shows, 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 RoBERTa model to make predictions on the entire earnings call data during 2007-2021. For each transcripts, we only feed the sentences with target words into the RoBERTa model as discussed in Section 2.2.2. The model classifies each sentence into price-change related or not. After that, we keep the price-change related sentences, and feed them into the RoBERTa model which is trained with the labeled data with the price-change directions (i.e. move up or down). Similarly, we train two RoBERTa models to identify the source of price change: (1) input price change or not; (2) output price change or not. With these two models, we further identify the change source of each price-change sentence.

2.2.4 Measuring inflation exposure

If a firm is more exposed 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

[4]See Chava, Du & Paradkar (2020), Chava, Du & Malakar (2021) for a detailed discussion of application of these models in finance.

inflation exposure for firm i at time t as,

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

where $\#InputUp$ is the number of sentences about input price up in a transcript, $\#InputDown$ is the number of sentences about input price down in a transcript, and $\#SentencesinTranscript$ is the number of sentences in a transcript. We subtract $\#InputDown$ to take into account of deflationary forces. One assumption of this measures is that how much managers talk about input price pressure is a good proxy for the actual exposure to inflation. However, managers choose what to communicate. If managers decide not to convey any information about prices even they are highly exposed to inflation, we are unable to accurately measure inflation exposure for the firm. Nevertheless, this issue would just add noise to our measure and bias against finding results. In the empirical regressions, we standardize $InflationExp$ for the ease of explanation.

Figure 2 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 have high average inflation exposure, while business equipment, telecom, and healthcare have low average low inflation exposure.

2.3 Summary statistics

In Table 2, we present the descriptive statistics for the 80,024 earnings conference calls occurring between 2007 and 2021 with non-missing financial variables. The construction of all variables is described in Table A6. About the discussion of input price movement, we find that on average, there are 2.740 sentences containing input price-increase information in earnings calls, while the average number of input price-decrease sentences is 0.624. Moreover, the average of the $InflationExp$ measure, which is 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, is 0.506%. As discussed in 2.2.4, we use the standardized $InflationExp$ in our empirical analyses.

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-base 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 3. Panel A uses the quarterly Producer Price Index (PPI) year-over-year growth rate. Panel B uses the quarterly Consumer Price Index (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 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 3, we find that the correlation between the PPI growth rate and text-base 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 official inflation measures gives us confidence that our methodology performs well in capturing inflation related information from earnings conference calls.

3 Results

3.1 Does the stock market react to firms' inflation exposure?

In this section, we study 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 the firm. However, if firms have market power and are able to 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:

$$Y_{i,f,t} = \alpha + \beta InflationExp_{i,f,t} + Controls_{i,f,t} + \delta_{f,t} + \phi_i + \epsilon_{i,f,t} \tag{1}$$

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 cumulative abnormal return (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. $Controls_{i,f,t}$ represents a set of firm-level and earnings call transcript–level characteristics which might influence the immediate price reaction. 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. To alleviate this concern, we control form firms' unexpected earning surprise and pre-event returns, as well the sentiment and uncertainty of earnings call transcripts. All variables are defined in Table A6.

The specification includes firm fixed effects and industry × 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 × 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.

Our findings are presented in Table 3. 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 1% level, which suggests that inflation exposure generate a negative immediate price response.

In Column (2), we further control for firm fixed effects to address the concern like certain firms tend to always or never discuss the price change information. We find that our coefficient estimate is still negative and significant at 1% level. In Column (3), we add year-quarter fixed effects in the regression to control for time-varying macroeconomic changes broadly, like the business cycles influencing the entire stock market. The coefficient estimate is largely unchanged and significant at 1% level.

In Column (4), we control for both the firm fixed effects and the industry × year-quarter fixed effects. We deploy the Fama-French 12 industry as the industry classification. We find that one standard deviation increase in inflation exposure is associated with 32.7 bps stronger immediate price reaction. Overall, the results in Table 3 indicate that investors react negatively to inflation exposure, suggesting that on average firms are unable to completely pass it through to consumers.

3.2 The decomposition of price movement and immediate market reaction

In this section, we decompose the information of price movement in earnings calls, and examine how each component influences the immediate stock market reaction. The discussion of price change could be about the input price headwinds or downward trend from the areas of labor, energy, and raw material costs, as well as the output price increase or falling considering the firm's market 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 source (input vs output) and direction (up vs down) of the price movement.

Table 4 shows the expirical 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 Column (1)-(4), we find that investors have a significantly negative reaction to the discussion of input-price increase and output-price decrease, but have a strongly positive response to the discussion of input-price decrease and the output-price increase in earnings conference calls. These findings imply that investors react positively to the news of potential margin increase, and negatively to the information of potential margin shrinking. The consistent pattern in Table 4 further supports that our deep learning methodology performs well in extracting price-change related information in earnings conference calls.

3.3 Market power and market reaction inflation exposure

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

To measure market power, We define a text-based measure as follows:

$$MP_{i,t} = \frac{\#OutputUp_{i,t}}{\#InputUp_{i,t} + 1} \tag{2}$$

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 market power, they would mention that they are able to pass it through to consumers by raising output prices. We add one in the denominator to address the condition that some earnings calls do not have sentence about input price up. A higher MP indicates more market power and pass through. For each year-quarter, we create a dummy variable $HighMP$ which equals one if a firm's MP is above the median, otherwise 0.

We run the following specification,

$$\begin{aligned} Y_{i,f,t} =& \alpha + \beta_1 InflationExp_{i,f,t} + \beta_2 MP_{i,f,t} + \beta_3 InflationExp_{i,f,t} * MP_{i,f,t} \\ &+ Controls_{i,f,t} + \delta_{f,t} + \phi_i + \epsilon_{i,f,t} \end{aligned} \tag{3}$$

Table 5 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' market power attenuates the negative market reaction as they are able to pass through the inflation exposure to consumers.

3.4 Inflation exposure and future cost of goods sold

In this section, we investigate the channel of the negative market reaction by analyzing whether the inflation exposure is associated with the higher level of the firm's cost of goods sold in the post-earnings call period. We calculate the the cost of goods sold in the next 1-4 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. The results are shown in Appendix Table A7. We find that the coefficient estimates of $InflationExp$ is significantly positive over the future 1-4 quarters, and the magnitude of coefficient decreases as the time horizon gets longer. This finding suggests that the inflation exposure measured from earnings conference calls is positively associated with the firm's cost in the future. This could partly explain the negative market reaction to inflation exposure.

Next, we further distinguish the components of the firm's cost of goods sold into the wages and raw material costs. Since the wages data from Compustat are available annually, we aggregate the inflation exposure from earnings conference calls into yearly level. 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 sentences of the earnings calls. Details about the construction of the firm-year level sample and the definitions of wages and material costs are shown in Appendix Section D and Table A6.

Table 6 shows the results of cost of goods sold and its components when we controlled for the firm fixed effects and industry cross year fixed effects. Consistent with Appendix Table A7, Column (1) shows a positively significant relationship between a firm's textual inflation exposure and its cost of goods sold. In Column (2) and (3), we separately analyze the material cost and labor 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 Long-term abnormal price response

In this section, 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 works 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 the firms with more inflation exposure in earnings calls will continue to perform poorly in the post–earnings call longer period.

Table 7 shows the results of long-run drift. In Column (1), we analyze the price drift over the 30 trading days after the earnings conference calls (CAR[+2,30] (%)). The coefficient estimate on $InflationExp$ is negative. When analyzing the price drifts over the 60 and 90 trading days after the earnings conference 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), an one standard deviation increase in $InflationExp$ is associated with 48.6 bps lower cumulative abnormal returns from 2 days 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.

4 Conclusion

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. Particularly, the strong negative immediate responses to inflation exposure suggest that firms are unable to fully pass through inflation exposure to consumers. This is further supported by the result that firms with more market power experience less reaction. The long-term drift that we document in the paper suggests that it takes time for investors to fully incorporate inflation exposure into stock prices.

Further, 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-move with official inflation measures which are released at low frequency. Our deep learning methodology is flexible and can understand the meaning of sentences, which can be used for many other finance settings.

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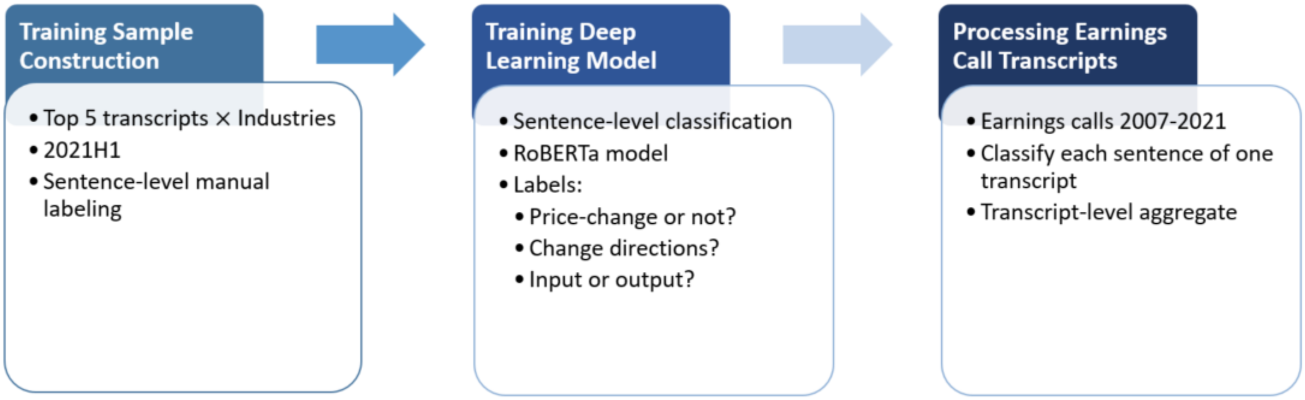


This figure shows the main steps we take with the deep learning techniques to generate the inflation exposure measure for firms' earnings conference call transcripts.

Figure 1: Main steps for constructing inflation exposure measure

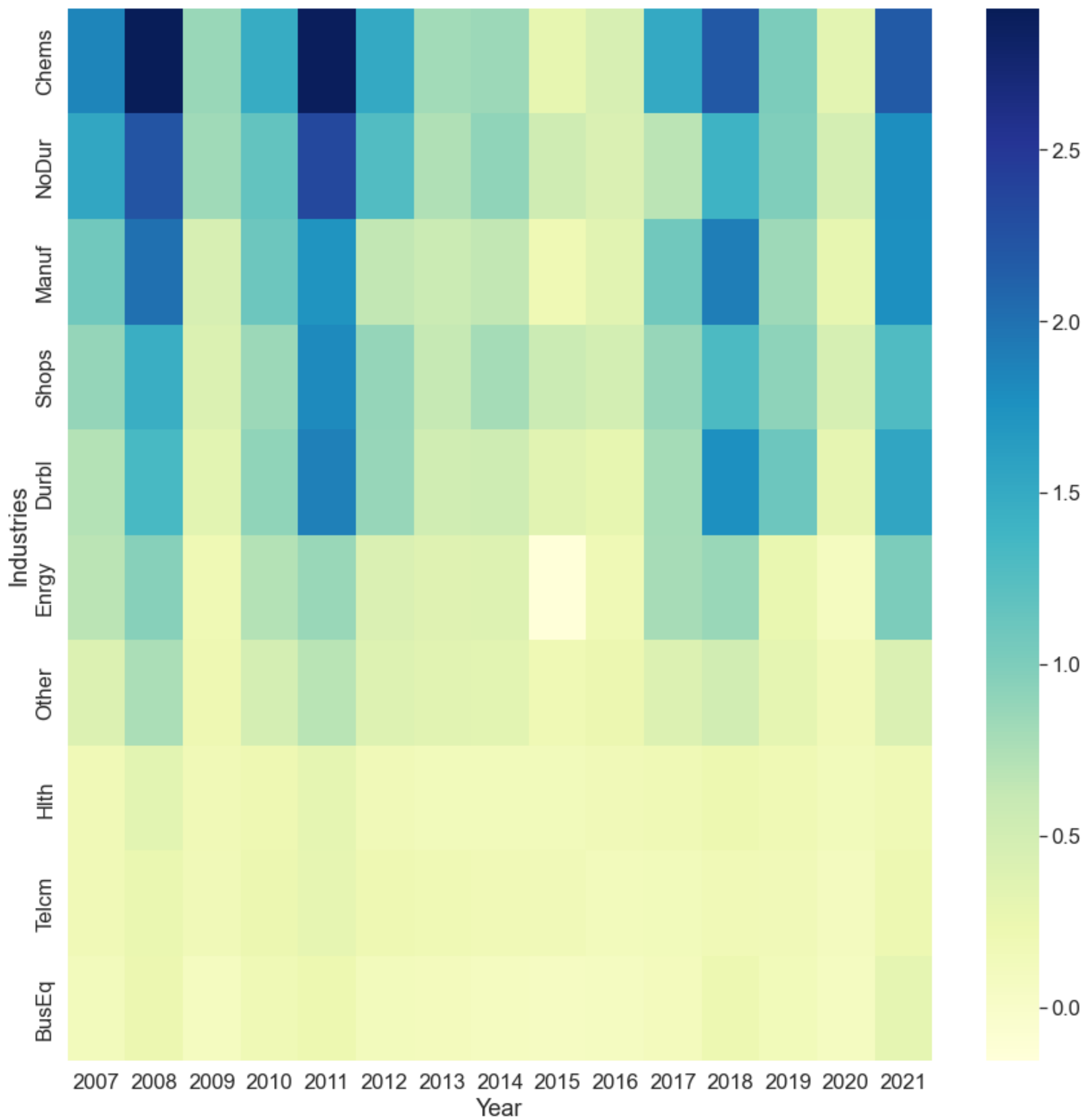
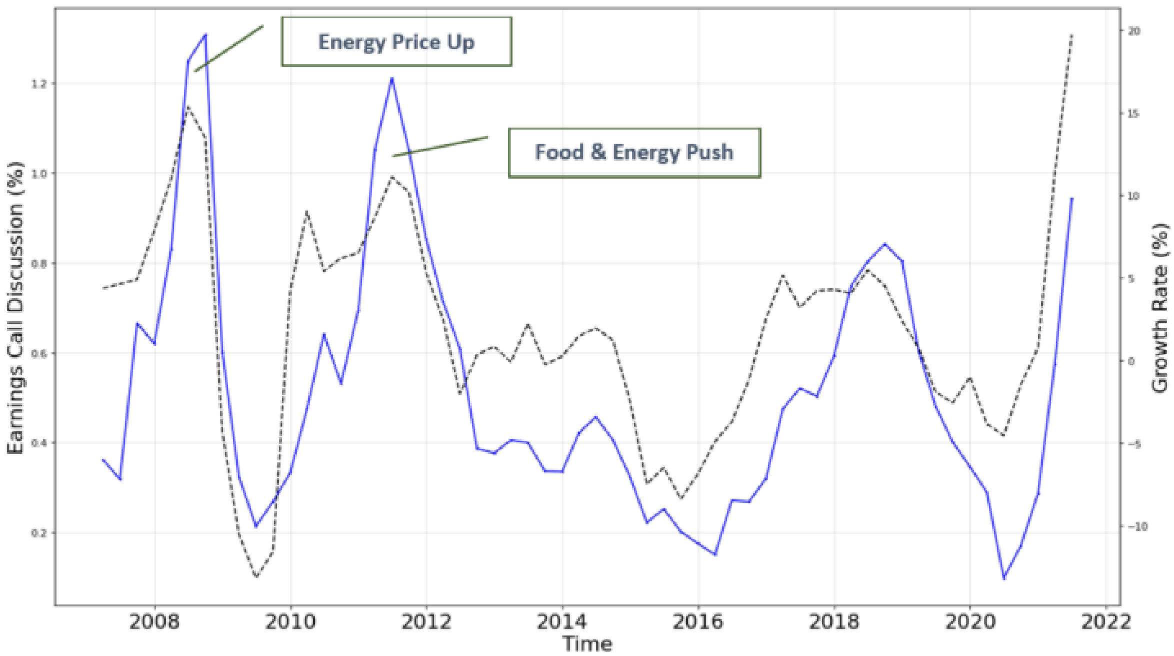
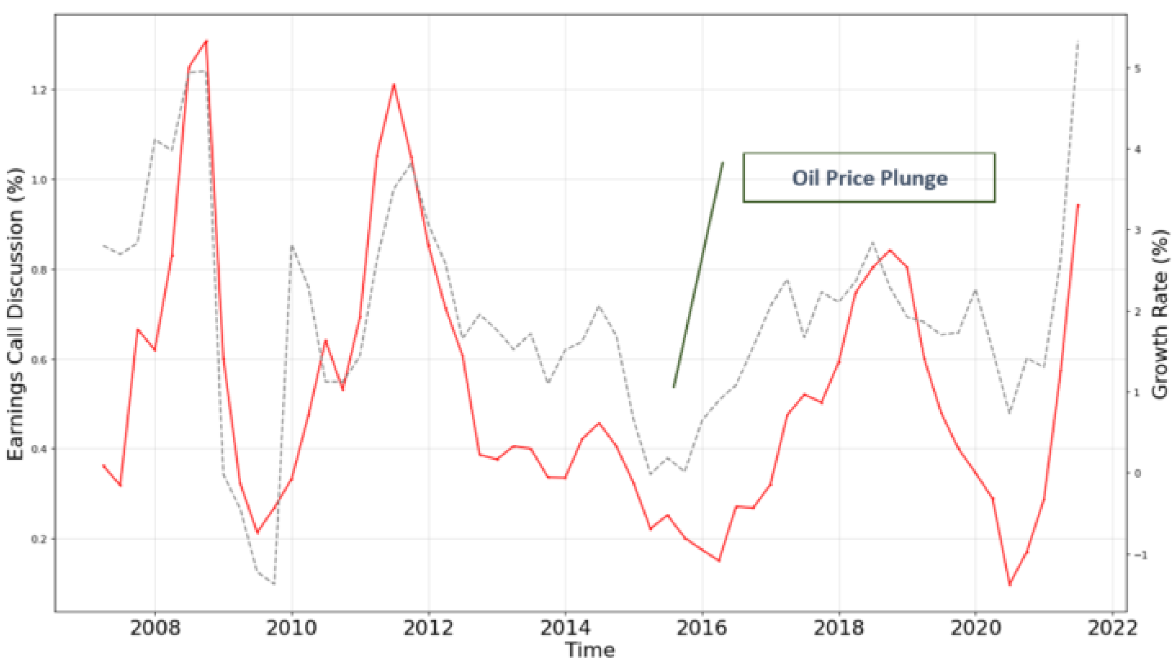


Figure 2: Inflation exposure across industries and time This figure shows the average inflation exposure across Fama-French 12 industries (except for finance and utilities) and years. The darker the color, the higher level of inflation exposure for that industry and year.



Panel A: PPI Growth Rate and Textual Inflation Exposure



Panel B: CPI Growth Rate and Textual Inflation Exposure

Figure 3: 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 black 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 gray 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. Since in our sample there are only 30 transcripts in 2021Q3, we drop the earnings call transcripts for that period to avoid noise.

Table 1: 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 2: 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	2.740	1.000	4.941
#InputDown	0.624	0.000	1.563
InflationExp (Not Std %)	0.506	0.000	1.006
InflationExp (Std)	-0.000	-0.503	1.000
Outcome variables			
CAR[−1,+1] (%)	0.061	0.108	9.397
Control variables			
Size	7.438	7.379	1.810
MTB	2.285	1.709	1.687
Earnings surprise	0.000	0.001	0.014
PreEvent Return	0.000	0.001	0.004
Uncertainty (%)	0.996	0.976	0.238
SentimentOverall (%)	0.688	0.686	0.584
#Sentences in earnings call transcript	395.5	393.0	132.6

Table 3: 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)
InflationExp	-0.230***	-0.363***	-0.354***	-0.327***
	(-3.60)	(-4.99)	(-6.20)	(-6.06)
Size	-0.091***	-2.024***	-1.813***	-1.997***
	(-3.08)	(-13.29)	(-12.55)	(-14.95)
MTB	-0.164***	-0.179***	-0.198***	-0.171***
	(-3.38)	(-2.68)	(-3.19)	(-2.84)
Earnings surprise	131.298***	133.309***	132.064***	132.042***
	(18.36)	(18.46)	(17.78)	(18.02)
PreEvent Return	-30.822	-56.445**	-62.496***	-70.403***
	(-1.35)	(-2.63)	(-4.03)	(-4.34)
Uncertainty	1.215***	0.864***	0.556***	0.595***
	(6.65)	(3.85)	(2.88)	(3.11)
SentimentOverall	2.404***	3.664***	4.057***	4.129***
	(22.65)	(17.84)	(26.95)	(27.19)
Observations	80,024	80,024	80,024	80,024
Adjusted R-squared	0.064	0.100	0.106	0.110
Firm FE		✓	✓	✓
YearQtr FE			✓	
FF12 × YearQtr FE				✓

Table 4: 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	-0.503***	-0.564***	-0.570***	-0.543***
	(-7.05)	(-7.17)	(-9.31)	(-9.48)
InputDown	0.312***	0.202***	0.167**	0.157**
	(4.61)	(2.94)	(2.29)	(2.35)
OutputUp	0.338***	0.193***	0.212***	0.216***
	(5.65)	(2.96)	(3.37)	(3.42)
OutputDown	-0.219***	-0.268***	-0.257***	-0.279***
	(-3.66)	(-3.65)	(-3.65)	(-4.18)
Observations	80,024	80,024	80,024	80,024
Adjusted R-squared	0.064	0.100	0.107	0.111
Controls	✓	✓	✓	✓
Firm FE		✓	✓	✓
YearQtr FE			✓	
FF12 × YearQtr FE				✓

Table 5: Market 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' market 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' market 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 2). $HighMP$ is a dummy variable which equals to one if a firm's text-based market 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	-0.552***	-0.643***	-0.632***
	(-6.51)	(-8.94)	(-9.16)
HighMP	0.368**	0.160	0.131
	(2.03)	(1.56)	(1.33)
InflationExp × HighMP	0.242***	0.371***	0.395***
	(2.71)	(5.20)	(5.78)
Observations	80,024	80,024	80,024
Adjusted R-squared	0.100	0.106	0.110
Controls	✓	✓	✓
Firm FE	✓	✓	✓
YearQtr FE		✓	
FF12 × YearQtr FE			✓

Table 6: Inflation exposure and future 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 in the future. 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 A6. 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**
	(7.38)	(6.73)	(2.42)
Observations	28,394	28,381	28,395
Adjusted R-squared	0.908	0.880	0.843
Controls	✓	✓	✓
Firm FE	✓	✓	✓
FF12 × Year FE	✓	✓	✓

Table 7: 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 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 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	-0.103	-0.199	-0.486***
	(-1.17)	(-1.48)	(-3.36)
Observations	80,023	80,023	80,023
Adjusted R-squared	0.130	0.169	0.209
Controls	✓	✓	✓
Firm FE	✓	✓	✓
FF12 × YearQtr 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.[5] 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

[5]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[6], 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;

[6]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 A4. 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.

Table A1: 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 A2: 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 A3: 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 A4: 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 A5: 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 A6: 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	Cost of goods sold of year t divided by the total assets of year $t-1$.
Wages	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	Cost of goods sold minus depreciation and amortization 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.
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.

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.

Table A7: Future cost of goods sold 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 in the future. The dependent variable in Columns (1)-(4) 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. 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.

	(1)	(2)	(3)	(4)
Depvar:	COGS(q+1)	COGS(q+2)	COGS(q+3)	COGS(q+4)
InflationExp	0.003***	0.003***	0.002***	0.002***
	(5.20)	(4.81)	(3.82)	(4.26)
Size	-0.022***	-0.023***	-0.024***	-0.026***
	(-12.80)	(-12.66)	(-13.01)	(-13.20)
MTB	0.014***	0.016***	0.017***	0.018***
	(17.42)	(17.86)	(18.06)	(17.89)
Earnings surprise	0.044*	0.060**	0.078***	0.105***
	(1.99)	(2.41)	(3.08)	(4.21)
PreEvent Return	0.386***	0.519***	0.782***	0.748***
	(2.94)	(4.29)	(6.12)	(6.71)
Uncertainty	0.002	0.003	0.003	0.006***
	(0.95)	(1.30)	(1.45)	(2.84)
SentimentOverall	0.006***	0.007***	0.007***	0.008***
	(6.89)	(8.41)	(7.94)	(8.25)
Observations	79,584	78,854	77,939	76,975
Adjusted R-squared	0.897	0.883	0.873	0.869
Firm FE	✓	✓	✓	✓
FF12 × YearQtr FE	✓	✓	✓	✓