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Monetary Policy’s Impact on Firms Under Inflationary Pressure: A Natural Language Processing Approach to Firms’ Earnings Calls

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Abstract

Using Natural Language Processing, I quantify the inflationary pressure that firms experience based on their quarterly earnings call transcripts. Then, using an event-study method, I find that stocks under inflationary pressure are priced more moderately in response to monetary policy shocks, declining less after contractionary shocks and rising less after expansionary shocks. This finding suggests that monetary policy influences the investors' beliefs about future inflation. Additionally, it offers a new explanation for the price puzzle of monetary policy. Furthermore, a regime-dependent analysis reveals that conventional policy rate changes influence inflationary-pressured stocks only when inflation expectations exceed the 2% target, and while forward guidance is consistently effective, it becomes roughly twice as effective when expectations fall below the target. Finally, using Jordà's local projections, I show that contractionary (expansionary) monetary policy has a favorable (unfavorable) impact on the cash flow, investment, and size of firms under inflationary pressure.

JEL Classification: C55, E31, E44, E52, G14

Keywords: Monetary policy, Inflation, Earnings calls, Natural Language Processing

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1 Introduction

Firms do not experience inflation homogenously. Even within the same industry, firms differ in their inputs, supply chains, contractual rigidities, operations, and their ability to pass costs onto customers. Such differences can put uneven pressure on the margins of different firms during periods of high inflation. Consequently, a monetary policy decision aimed at stabilizing aggregate prices transmits unevenly across firms; a contractionary decision may relieve the margin compression for firms facing high cost-push pressure, while constraining the revenues of firms for whom inflation has been demand-pull. This paper quantifies this heterogeneity to study the impact of monetary policy on firms with heterogenous levels of inflationary pressure and provides evidence that has important implications for monetary policy's impact on inflation expectations, the price puzzle of monetary policy, and the effectiveness of different policy tools in different inflationary regimes.

I start by quantifying the level of inflationary pressure that a firm experiences by applying Natural Language Processing to its earnings call transcripts. Earnings calls are quarterly events held by publicly traded firms where they discuss their results, disclose forward-looking information, and answer questions from investors. Afterward, I use an event-study method to measure how stock market participants price stocks under different inflationary pressures in response to the unexpected component of monetary policy announcements. Both in theory and practice, tighter monetary policy results in a negative stock price reaction, while looser monetary policy results in a positive reaction. This paper finds that stocks of firms experiencing higher levels of inflationary pressure react less negatively to contractionary monetary shocks and less positively to expansionary monetary shocks. Moreover, using Jordà's local projections, I find that contractionary (expansionary) monetary policy leads to increases (decreases) in cash flow, investment, and market capitalization for firms under inflationary pressure in the subsequent quarters.

The evidence provided by this paper contributes to four important strands of literature. First, this paper identifies a new channel for the impact of monetary policy on stock markets. Existing studies find that monetary policy affects stock prices through different transmission channels, and the size of this impact varies among firms depending on their characteristics (Ehrmann and Fratzscher, 2004). For example, they show that stock prices of firms with stricter financial constraints (Ozdagli, 2018; Chava and Hsu, 2020) and larger shares of intangible capital (Döttling and Ratnovski, 2023) are more responsive to monetary policy, indirectly implying the impact of monetary policy on credit conditions. Additionally, other papers show that firms operating in sectors producing durable goods (Peersman and Smets, 2005; Dedola and Lippi, 2005; Choi et al., 2024) and firms with larger shares of floating rate debt (Ippolito et al., 2018; Gürkaynak et al., 2022) are more responsive to monetary policy, providing evidence for the interest rate channel and the floating rate debt channel, respectively. Controlling for all other firm characteristics, this paper shows that monetary policy's impact on stocks varies along the level of cost-push inflationary pressure that the firm experiences.

Secondly, this paper provides indirect evidence for the role of monetary policy in shaping inflation expectations among stock market participants. Existing literature relies on surveys to measure inflation expectations of firms, households, and professional forecasters (Savignac et al., 2024; Candia, Gorodnichenko, and Coibion, 2024). Surveys, while informative, typically involve relatively small and potentially inconsistent samples of respondents over time, and they are conducted quarterly or monthly, making causal identification more challenging. Moreover, no survey addresses the inflation expectations held by stock market participants. Stock markets are forward-looking, meaning stock prices reflect investors' beliefs about firms' future performance and macroeconomic conditions. Assuming no other systematic news is routinely announced on event days and that all confounding factors have been accounted for, my results show that market participants interpret contractionary shocks as positive news for firms under inflationary pressure, suggesting a downward revision in their inflation expectations in response to the policy surprise. Conversely, expansionary shocks (such as lower-than-expected contractionary decisions) are interpreted as negative news for stocks under inflationary pressure, signaling an increase in market participants' inflation expectations. These results complement existing evidence through an event study as a powerful tool of causal inference that addresses the endogenous nature of monetary policy (Nakamura and Steinsson, 2018a).

Third, this paper offers a new explanation for the well-known price puzzle in monetary policy. While standard theory predicts a negative relationship between monetary policy shocks and stock returns, in practice, some contractionary shocks are followed by a positive stock market reaction, and some expansionary shocks are followed by a negative reaction. The prevailing explanation for this phenomenon is the central bank information effect: monetary policy decisions may convey the central bank's private assessment of the economic outlook, prompting market participants to update their growth expectations (Nakamura and Steinsson, 2018b; Jarociński and Karadi, 2020). For instance, if the central bank unexpectedly holds rates steady despite market expectations of a cut, investors may infer that economic conditions are stronger than anticipated and revise their outlook accordingly.

Using the "pure" monetary policy shocks provided by Jarociński and Karadi (2020) and Jarociński (2024)—which are purged of the information effect—this paper shows that even these isolated contractionary (expansionary) shocks can lead to a lower-than expected negative (positive) or even a positive (negative) stock price reaction by inflationary pressured firms. This occurs because investors revise their expectations about firm's inflationary pressure: a contractionary shock is perceived as reducing future cost pressures and may thus be welcomed for firms under inflation pressure, while an expansionary shock may raise expected input costs and weigh negatively on those same firms.

In addition to the firm-level results, I use macro-level high-frequency data to show that the S&P 500 index's response to various measures of pure monetary policy shocks is significantly muted when 1-, 2-, and 5-year inflation expectations—sourced from the Federal Reserve Economic Data (FRED)—are elevated. A time series regression reveals that an average pure expansionary shock results in a 0.28% basis point rally by S&P 500 index when 5-year inflation expectations are at first quantile (1.8%) and the same shock results only in a 0.16% basis point rally when expectations are at third quantile (3.2%).

Finally, this paper contributes to the literature on the effectiveness of different monetary policy tools (Gürkaynak, Sack, and Swanson, 2005; Bernanke, 2020; Swanson, 2021). More specifically, I introduce a second regime using a dummy variable for periods when the 2-year ahead inflation expectations provided by the FRED exceed the 2% target. Then, using the four-factor monetary policy shocks provided by Jarociński (2024), where each factor captured information on a specific aspect of monetary policy, I show that conventional rate cuts significantly influence stock prices of inflationary pressured firms only when the 2-year inflation expectations are above the target. In contrast, when expectations fall below 2%, rate cuts lose much of their effectiveness. Forward guidance, by comparison, remains effective in both regimes and becomes roughly twice as influential when inflation expectations fall below target, highlighting its crucial role in low-inflation expectations environments.

To conduct my analysis, I start by measuring firm-level inflationary pressure from the full text of earnings call transcripts. These quarterly calls are key corporate events where senior management communicates directly with investors, analysts, and the press, often revealing significant forward-looking information not disclosed in regulatory filings such as 10-Ks (Loughran and McDonald, 2011). With advances in Natural Language Processing (hereafter NLP), a growing literature has used these transcripts to quantify firm-level exposures to climate risk (Li et al., 2024), political risk (Hassan et al., 2019, 2024), corporate strategy (Jha et al., 2024), and uncertainty (Allee et al., 2021). These conference calls are conducted by all publicly traded firms on a quarterly basis, making their coverage larger and more consistent compared to firm-level surveys. This study uses 64,055 unique earnings call transcripts for 2,176 unique publicly traded U.S. firms from 2012 to 2024.

To quantify firm-level inflationary pressures, I begin by identifying relevant sentences from earnings call transcripts using a custom lexicon. To create this lexicon, I start by selecting a subset of transcripts that contain the highest frequency of the word "inflation", stratified across time and 4-digit NAICS industries to ensure linguistic and sectoral representation. Then, I process the text in these selected 6,208 unique transcripts by removing entity names, non-alphabetic tokens, and stop words, as well as reducing terms to their stems. Next, I generate bigrams using the Phraser algorithm and apply a word embedding model trained to recognize synonyms and related expressions of inflation, such as rising input prices, expensive raw materials, rising costs, and higher wages. Finally, I manually select the most relevant terms for my inflation lexicon and expand the list of bigrams in this lexicon through permutation to capture additional variations in phrasing.

Next, in my quantification process, I measure the sentiment of the selected inflation-related sentences to create my measure for firms' inflationary pressure, following the approach of Hassan et al. (2019, 2023, 2024). I assume that a selected sentence that discusses inflation reflects adverse pressure if its sentiment is negative. The sentiment of a sentence is determined using sets of positive and negative unigrams and bigrams from García, Hu, and Rohrer (2023; hereafter GHR). They developed their dictionary based on stock price reactions to the textual content of earnings calls using a machine learning framework. They show that their method outperforms traditional dictionaries, such as Loughran and McDonald (2011; hereafter LM). I validate the accuracy of the GHR-based measure of inflationary pressure by: 1) showing that this measure is positively correlated with macroeconomic inflation, as well as both survey-based and market-based measures of inflation expectations, and 2) showing that firms experiencing higher inflationary pressure exhibit higher cost of goods sold in subsequent quarters, even when controlling for a comprehensive set of firm-level control variables. These findings suggest that the GHR-based measure developed in this paper captures incremental information about firms' current and future inflationary pressure that is not reflected in standard firm-level fundamentals, such as Cost of Goods Sold or EBITDA.

For the event study, I use exogenous monetary policy shocks provided by Jarociński (2024). These shocks consist of four factors. The first three factors, namely 1) conventional policy rate changes, 2) forward guidance, and 3) asset purchases, capture pure monetary policy shocks. The fourth factor, namely the central bank information effect, reflects changes in the private sector's perception of the economic outlook based on signals revealed by the central bank's decisions. The results indicate that a one standard deviation increase in a firm's inflationary pressure is associated with roughly a 1-basis point reduction in sensitivity to an average pure monetary policy shock, as measured by the first three shock factors. At the same time, this increase in inflationary pressure leads to a 1-basis point rise in sensitivity to an average central bank information shock. These findings are fully consistent with this paper's initial hypothesis, showcasing monetary policy's impact on inflationary pressures and reflecting market participants' revisions to their inflation expectations following central bank decisions.

A potential issue is that when inflation and inflation expectations are low, discussions about inflationary pressures may be replaced by conversations about weak demand and a poor macroeconomic outlook. This shift is evident from the high correlation between the average proportion of transcripts dedicated to inflationary discussions and macroeconomic inflation expectations (85%, 70%, 71%, and 69% in Table 7). Analyzing periods of low inflation, such as the periods before the COVID pandemic where interest rates were limited by the zero lower bound, is equally important. To address this, I developed a second measure that quantifies insufficient inflation through weak macroeconomic demand. I refer to this measure as demand distress, and I expect monetary policy shocks will have a greater impact on firms experiencing higher demand distress. However, results are mixed. The findings show that stock prices of firms discussing macroeconomic demand during their earnings calls are more responsive to monetary policy shocks; however, when controlling for this variable, stocks with negative sentiment in macroeconomic-related statements (indicating higher demand distress) are less responsive to monetary shocks. This latter finding does not align with the initial hypothesis of this paper.

To understand the real impact of monetary policy on firm-level outcomes, I analyze the response of slow-moving balance sheet and income statement variables to monetary policy shocks across firms with different levels of inflationary pressure. Following an approach by similar studies that assess heterogeneous responses to monetary policy across firms based on default risk (Ottonello and Winberry, 2020), firm age, or dividend policy (Cloyne et al., 2023), I aggregate monetary policy shocks to the quarterly level and use Jordà's (2005) local projections method. The results show that contractionary (expansionary) shocks are associated with increases (decreases) in cash flow, investment, and market capitalization among firms experiencing high inflationary pressure. Additionally, these same shocks are linked to decreases (increases) in Cost of Goods Sold for these firms.

Two existing papers have measured inflationary pressure (or exposure) from earnings calls. Chava et al. (2025) develop a firm-level measure of input and output price changes from earnings calls, document stylized facts about price changes, and analyze stock price reactions to price information disclosed during earnings calls. They do not conduct any analysis of monetary policy. Albrizio, Dizioli, and Simon (2023) develop a bag of words to identify sentences on "inflation expectations" in transcripts and use the prevalence of these sentences, without measuring sentiment or uncertainty, as a measure for firms' inflation expectations. They apply Jordà's local projections to study how firms' inflation expectations respond to monetary policy changes on a quarterly basis. This paper differs from their work in both methodology and objectives because it focuses on monetary policy's impact on stock prices, balance sheets, and income statements of inflationary pressured firms.

I explain the data in Section 2 and explain the creation of my inflation pressure and demand distress indices in Sections 2.1 and 2.2. I verify the validity of my distress measures in Section 2.5. I explain the methodology in Section 3 and provide my event study findings in Section 4. Section 5 provides high frequency macro-level evidence for the role of inflationary pressure in the price puzzle. Section 6 provides the results for real outcomes based on local projections. Section 7 concludes the paper.

2 Data

This paper uses stock market and financial data from S&P Market Intelligence. I start with the universe of public firms in the U.S. Then, I merge this stock market and financial data with earnings call transcripts obtained from "Financial Modelling Prep" API service based on company tickers. I verify this merge by checking for the company's name, as provided by S&P Market Intelligence, in the operator's welcome message (detailed in Appendix A). Following a procedure that is common to financial literature, I exclude Utilities (NAICS: 22), Financials (NAICS: 52, 53), and Governmental (NAICS: 92) industries. I exclude firm-event observations with stock price below 1$, book assets below 10$ million, market cap below 10$ million, or a transcript with less than 1000 characters. I remove any firm-event observation with missing data for financial or transcript variables. Finally, I winsorize all control variables and stock returns by 1%. For stock returns, winsorization is done on a per-event basis. I winsorize variables extracted from transcripts by 2.5%. In Appendix B, I discuss the distribution for the main transcript-level variables and show that results are robust to changes in the winsorization. This process yields 2,171 unique firms for the 2012Q2-2024Q3 period, with an average of 1,326 unique firms per FOMC meeting. The main factor limiting the number of observations in this study, especially over time, is the availability of earnings call transcripts in the Financial Modelling Prep database.

Firm financial variables that are used as control variables include log book assets, log age, leverage, Tobin's q, cash holding, cash flow, dividend payout dummy, capital tangibility, and cost of goods sold. General transcript level control variables refer to the sentiment and uncertainty of the transcripts entire text. Each transcript-based measure is constructed from a properly processed transcript text as detailed at Appendix C. Table 1 provides the definitions of variables and their sources.

2.1 Measuring a firm's inflationary pressure

This section explains the process for measuring the inflationary pressure that firms experience using their earnings call transcripts. The measurement of demand distress follows a similar process; however, for simplicity, I explain it separately in Section 2.2. I test the validity of my measures in Section 2.5.

I begin by selecting sentences from transcripts that address inflation and inflation-related topics, such as rising input costs, raw material prices, wages, and more, using a set of unigrams, bigrams, and general inflation-related terms. To create this lexicon, I use a Word Embedding method. This approach in natural language processing represents words as numerical vectors that reflect their contextual similarities within the text. Words that frequently appear in similar textual contexts share closer embeddings, which enable the identification of semantically related unigrams and bigrams. To begin, I select a representative subset of earnings call transcripts that exhibit the highest frequency of the term "inflation," stratified by quarter-year and four-digit NAICS industry classifications. This yields a total of 6,208 unique transcripts. Afterwards, I process the text by removing entity names, non-alphabetic tokens, single-character words, and standard stop words, with exceptions for potentially inflation-relevant terms such as up, down, bottom, top, less, more, under, above, least, most, and below. Finally, tokens are converted to lowercase and stemmed using the Porter Stemmer. Next, I create bigrams using Phraser. I set a very loose criteria for the creation of bigrams to produce as many bigrams as possible. I implement a Word Embedding with a vector size of 300, 25 epochs, and a window size of 15. I repeat the creation of bigrams and Word Embedding with different parameters to ensure I capture all relevant unigrams and bigrams. Lastly, I review each output, examining the top 1,000 potential synonyms of inflation, and manually choose a lexicon of relevant unigrams and bigrams. I provide further details on sample selection, bigram creation, and Word Embedding in Appendix D.

After developing the initial lexicon, I expand it by generating new bigrams through permuting existing bigrams. For instance, the initial lexicon includes the bigram "increas cost", which I expand by substituting synonyms for "increase", creating more bigrams such as "escal cost", "elev cost", "climb cost", and others. As a second example, the initial lexicon includes "cost suppli," which I expand by incorporating the reordered form "suppli cost" into the lexicon. The final lexicon can be categorized into three types of keywords as shown in Table 2: 1) unigrams and general inflation-related terms, such as "inflat" and "cpi", 2) passive bigrams such as "input cost", and 3) active bigrams, such as "increas cost". I select all sentences containing these unigrams and bigrams from transcripts as sentences that contain information on firm's inflationary environment. Moreover, I add sentences where the active bigrams occur within a one-word distance. For example, the current selection skips a sentence that mentions "costs are significantly increasing" due to the word "significantly" while allowing for this one-word distance between the terms of the active bigram "cost increas" resolves such instances. I verify the robustness of my main findings against the size of this distance at Appendix E.

From these selected sentences, I exclude questions indicated by a question mark. I exclude sentences that refer to other countries or continents without directly mentioning the U.S. because our focus is on the U.S. domestic inflation rate. I also exclude sentences mentioning exchange rate costs and other currencies, as well as sentences mentioning bigrams about costs related to interest rates (detailed in Appendix D). This is because our focus is on the input cost inflation, and exchange rate and interest costs create a different dynamic. For example, contractionary monetary policy increases the interest costs of a firm with higher debt, which is different from the positive impact of contractionary monetary policy on stocks experiencing higher raw material costs associated with inflation. This selection process yields 467,185 unique sentences from my universe of transcripts.

Inspired by of Hassan et al. (2019, 2023, 2024), the inflation pressure is calculated as the net sentiment of the inflation-related sentences —defined as the difference between the number of positive and negative words— and standardized by transcript size. This measure is multiplied by (-1) to ensure that higher values correspond to greater inflationary pressure, as indicated by increasingly negative sentiment. Transcript size refers to word counts from processed transcripts as detailed in Appendix C. I use the dictionary provided by García, Hu, and Rohrer (2023) and their text processing technique for measuring the sentiment of inflation-related sentences. They construct their dictionary using the reaction of stock markets to the earnings call discussions, assigning unigrams and bigrams in earnings calls to either the positive or negative sentiment lexicons based on the consequent stock price reaction. Their list is recently developed, focuses on the relationship between earnings calls and stock markets, and is shown to outperform other dictionaries out of sample. Moreover, I show that the inflation pressure obtained from their measure outperforms the widely used Loughran and McDonald (2011) dictionary in Section 2.5 and Appendix F. The mathematical representation of inflation pressure is:

$$\Pi_{it} = \left(\frac{\sum_{s=1}^{S_{it}} \mathbf{1}\{s \cap L_{\text{inf}} \neq \emptyset\} \left(\sum_{w \in s} \mathbf{1}\{w \in P_{GHR}\} - \sum_{w \in s} \mathbf{1}\{w \in N_{GHR}\} \right)}{T_{i,t}} \right) \times (-1) \tag{1}$$

Where Π_{it} is inflationary pressure for the transcript of firm i in quarter t, s represents the sentences in that transcript, $S_{i,t}$ is total number of sentences in the transcript, L_{inf} is my constructed lexicon for inflation, w represents the words and word combinations (unigrams and bigrams), P_{GHR} represents the positive terms from GHR dictionary, N_{GHR} represents the negative terms, and $T_{i,t}$ is the transcript size.

A challenge is the fact that a zero inflationary pressure can come from a transcript that does not refer to inflation at all or a transcript that refers to inflation but with an equally positive and negative sentiment, yielding a net neutral sentiment. These two cases are very different. To address this, I control for the extent of inflation-related discussions in earnings calls by accounting for the number of sentences that contain at least one term from the inflation lexicon. The inflation sentence count is mathematically defined as:

$$\Pi\text{count}_{it} = \frac{1}{S_{it}} \sum_{s=1}^{S_{it}} \mathbf{1}\{s \cap L_{\text{inf}} \neq \emptyset\} \tag{2}$$

Where Πcount_{it} represents inflation sentence count in transcript for firm i and quarter t, S_{it} is the total count of sentences in the transcript, s represents sentences, L_{inf} presents the constructed inflation lexicon. This can be used as a measure of inflationary pressure in itself because a larger proportion of earnings call dedicated to inflation discussions signals a firm's heightened concern about rising input prices. This is evident in Table 7, which shows a moderate to strong positive correlation between discussions of inflation and inflation rate, as well as expectations of inflation rate.

Finally, a measure for uncertainty associated with inflation is constructed based on Loughran and McDonald dictionary with following specification:

$$\Pi\text{uncertainty}_{it} = \left(\frac{\sum_{s=1}^{S_{it}} \mathbf{1}\{s \cap L \neq \emptyset\} \left(\sum_{w \in s} \mathbf{1}\{w \in U_{LM}\} \right)}{T_{i,t}} \right) \tag{3}$$

Where $\Pi\text{uncertainty}_{it}$ represents the uncertainty associated with inflation in transcript for firm i and quarter t and U_{LM} represents LM dictionary's list for uncertainty words. Other terms are similar to Equation 1.

A final important step is implemented before aggregating sentence-level sentiment to the transcript level in Equation 1. Specifically, I exclude sentences with sentiment values below the 0.01st percentile or above the 99.99th percentile. I then winsorize the remaining sentence-level sentiment values at the 1st and 99th percentiles. Only after this adjustment, I aggregate sentiment to the transcript level. A similar winsorization procedure is applied to the uncertainty measure in Equation 3.

2.2 Measuring a firm's demand distress

Measuring demand distress follows a procedure that is very similar to measuring inflationary pressure explained in Section 2.1. As the process is detailed in that section and Appendix D, I only briefly explain the construction of demand distress. I begin with selecting transcripts with the most frequent mentions of "recession" while stratifying across quarter-year and 4-digit NAICS industries to ensure representativeness. This yields 4,271 unique transcripts. I create bigrams and implement Word Embedding on the processed transcripts. I repeat this step with different parameters to generate comprehensive lists of stemmed unigrams and bigrams that are synonyms of recession. Finally, I manually select relevant unigrams and bigrams and expand my lexicon by permutation as previously explained.

This process yields 10 unique unigrams and 1115 unique bigrams. Again, the final list can be divided into 1) unigrams, such as "downturn" or "slowdown", 2) passive bigrams, such as "consum sentiment" or "market outlook", and 3) active bigrams, such as "slow econom" or "demand sluggish". I allow for the distance of one word between bigrams in the third case, similar to the previous section. The list of these unigrams and bigrams is provided in Table 3.

I select relevant sentences using these unigrams and bigrams and then exclude questions and sentences that contain the names of countries, continents, or nationalities other than the U.S. I also exclude other cases of wrong sentence selections, such as welcome messages or general messages. These are explained in Appendix D with more detail. Contrary to the previous section, I do not drop sentences discussing exchange rates or interest expenses, as there is no reason to do so for this measure. I count the number of GHR-positive words minus the GHR-negative words in the selected relevant sentence. I standardize this number by the transcript size and multiply by (-1) similar to Equation 1 so that larger values correspond to a higher distress level. This yields my measure for a firm's demand distress.

Moreover, I include the count of macroeconomic demand-related lexicon, constructed similar to Equation 2, to control for the differences between neutral demand sentiment transcripts (equal number of GHR-positive and GHR-negative words in macroeconomic demand-related sentences) and transcripts that do not discuss macroeconomic demand altogether. This count is standardized by transcript size. I also control for demand uncertainty using uncertainty terms from LM dictionary similar to Equation 3.

2.3 Monetary policy shocks

In order to capture the causal impact of monetary policy, its changes have to be unexpected. This is challenging because markets formulate expectations about the central bank announcements and these expectations are incorporated in interest rates and stock prices before the actual announcement. For example, markets could expect a significant tightening of monetary stance due to an inflationary episode, and stock prices would decrease prior to the actual announcement. A lower-than-expected increase in interest rates would translate into an expansionary monetary policy shock where markets would respond with a rally. Hence, we need an exogenous measure of unexpected changes in monetary policy.

Recent literature offers several measures of monetary policy shocks that summarize all policy changes into one or several factors. The general idea is to measure the high-frequency changes in outcome variables such as interest rates in a narrow window around the central banks' announcements. My preferred measure of monetary shocks is provided by Jarociński (2024). Jarociński expresses the surprises (i.e., the high-frequency reactions to FOMC announcements) in the near-term fed funds futures, 2- and 10-year Treasury yield and the S&P500 stock index as linear combinations of four Student-t distributed shocks. The first shock (MP-J1) raises the near-term fed funds futures, with a diminishing effect on longer maturities, and depresses the stock prices. It can be naturally labeled as the standard monetary policy shock. The second shock (MP-J2) increases the 2-year Treasury yield the most and depresses the stock prices. It can be naturally labeled as the (Odyssean) forward guidance shock. The third shock (MP-J3) increases the 10-year Treasury yield the most and plays a large role in some of the most important asset purchase announcements. It can be naturally labeled as the asset purchase shock. The fourth shock (MP-J4) has a similar impact on the yield curve as the Odyssean forward guidance shock, but triggers an increase, rather than a decrease, in the stock prices. This fourth shock can be interpreted as central bank information effect. Table 4 provides descriptive statistics and correlations for monetary policy shocks.

I use alternative policy shocks to test the robustness of my results. I use Gürkaynak, Sack, and Swanson (2005) because they also differentiate between changes in current policy rate and forward guidance that impacts rates with longer maturities. Their measure is two-dimensional: the first dimension, referred to as the target factor (MP-GSS-TARGET), captures the unexpected changes in the current month's Federal Funds Futures contracts similar to Kuttner (2001), while the second dimension, referred to as the path factor (MP-GSS-PATH), summarizes the revisions to the expectations of the future interest rates up to a year. The path factor is orthogonal to the target factor, and it captures unconventional monetary policies such as forward guidance. As a single factor monetary policy shock, I use series provided by Jarociński and Karadi (2020) which is the first principal component of the surprises in interest rate derivatives with maturities from 1 month to 1 year (MP1, FF4, ED2, ED3, ED4). This single factor shock series (MP-JK) summarizes information from all monetary policy tools and allows for a unified analysis of monetary policy (specifically useful in Figure 6). Moreover, Jarociński and Karadi differentiate between pure monetary policy shocks and those driven by central bank information effects by imposing sign restrictions on the relationship between unexpected changes in monetary policy and stock market responses. Specifically, they require these variables to move in opposite directions in the case of a pure monetary policy shock.

2.4 Descriptive statistics

This section provides descriptive statistics, with a particular focus on inflationary pressure and demand distress indices. Table 5 provides the descriptive statistics for balance sheet and transcript variables. It is important to note that this study presents inflationary pressure and demand distress by multiple variables, namely, the count of relevant sentences that shows the prevalence of inflation and macroeconomic discussions in a transcript, the sentiment of these sentences that measures the attitude towards these topics, and uncertainty of these sentences.

Table 6 provides correlations across transcript variables. This table shows that the correlation between GHR and LM-based sentiments for inflation pressure and demand distress (respectively 9% and 50%) are not optimal, specifically for inflation. This signals the need for careful evaluation and identification of the better-suited dictionary for our purposes. I discuss this more in Section 2.5. The correlation between inflation pressure and inflation sentence count, as well as inflation uncertainty, are moderate at 60% and 44% respectively. While, the correlation between demand distress and demand sentence count, as well as demand uncertainty, are very low at 20% and 15% respectively. This shows that discussions of inflation and rising input costs are much more likely to be associated with a negative sentiment, while discussions of macroeconomic outlook, even though the focus of my demand distress lexicon is biased towards sluggish macroeconomic outcomes, can be associated with both positive and negative sentiment.

2.5 Validation tests of inflationary pressure and demand distress indices

This section tests the validity of the the inflationary pressure and demand distress indices. It shows that these measures are correlated with macroeconomic indices and also can predict the firms' future costs and revenues. Moreover, it compares the measure obtained based on GHR dictionary with LM dictionary and shows GHR-based measure is the accurate measure to be used.

The first verification examines the correlation between our measures, averaged across firms at a quarterly frequency, and macroeconomic variables. Panel A in Table 7 shows the correlation between inflation pressure and macroeconomic inflation indices from FRED. The key column is the first column in this table. Aggregated inflationary pressure has no correlation (13%) with inflation sentiment LM. Next, inflationary pressure has correlations of 87% and 89% with inflation count and inflation uncertainty, which is much better compared to LM's correlations at -18% and -21%. This shows that periods with more discussions of inflation in transcripts (measured by inflation count) and higher inflation uncertainty are associated with larger inflationary pressure. Looking at correlations with CPI inflation, PPI inflation, and manufacturing PPI inflation, the correlations of inflationary pressure stand higher at 54%, 17%, and 20%.

These correlations are better compared to correlations of LM with macroeconomic inflation indices (-4%, 10%, 7%). However, they are not convincing for PPI inflation. A reason for this lower-than-expected correlation between inflationary pressure and macroeconomic inflation indices can be seen in Figure 2's Plot A. This figure plots the PPI inflation and average firm inflationary pressure. Looking at this figure, we see that the 2021-22 surge in producer prices (highlighted red) is associated with a continuous increase in inflation pressure. However, inflation pressure continues to remain high and recovers very slowly even as PPI inflation drops to negative in Q4 of 2022 (highlighted green). In other words, sentiment has a much higher autocorrelation compared to the actual macroeconomic indicator. A similar pattern is visible in Figure 2 Plot B, where simultaneously with COVID's impact on the GDP growth rate in 2020Q2 and 2020Q3, the demand distress surged significantly and recovered slowly in 2020Q4 to 2021Q2 even as GDP growth returned to a very high level at 2020Q4 (+8.8%). This shows that macroeconomic shocks have a persistent impact on earnings calls sentiments, and these sentiments gradually recover even if the macroeconomic shock has ended. This explains the lower-than-expected correlation between extracted sentiment and macroeconomic indicators.

Inflation pressure has a moderate to strong correlation with survey based and market based measures of inflation expectations. Its correlation with consumer inflation expectations from the University of Michigan surveys is 85%, and it shows a 58% correlation with the 5-year breakeven inflation rate, which more accurately represents the long-term inflation expectations of the markets. These results support the validity of the inflationary pressure index created by this study.

Panel B on Table 7 shows the correlation between aggregated demand distress measures and macroeconomic indicators. First, the correlation between GHR and LM sentiment for demand distress is high at 94%. Second, the correlation between demand distress and demand sentence count and uncertainty is also high at 87% and higher compared to LM's correlations of 71%. However, the correlation of demand distress with the GDP growth rate and change in the unemployment rate (-38% and 49%) is lower compared to the correlations of demand distress LM (-48% and 56%). The direction of correlation is correct, as increasing demand distress is correlated with lower GDP growth and a higher unemployment rate. Even though demand distress based on LM dictionary outperforms GHR-based demand distress in correlation with macroeconomic indicators, the next test shows that GHR still outperforms LM on the firm level outcomes.

The second and more comprehensive verification test involves analyzing the change in relevant balance sheet items, namely the cost of goods sold for inflation pressure and asset turnover for demand distress, following the changes in these distress measures. This verification uses Jorda's (2005) local projections method and involves h regressions with the following specifications:

$$CoGS_{i,t+h} = \alpha + \lambda_{1,h}, \times \Pi_{i,t-1} + \lambda_{2,h} \times \mathrm{T}_{i,t-1} + \lambda_{3,h} \times X_{i,t-1} + \phi_{\text{NAICS, t}} + \mu_i + \epsilon'_{i,t} \tag{4}$$

$$ATR_{i,t+h} = \alpha + \eta_{1,h} \times \mathrm{D}_{i,t-1} + \eta_{2,h} \times \mathrm{T}_{i,t-1} + \eta_{3,h} \times X_{i,t-1} + \phi_{\text{NAICS, t}} + \mu_i + \epsilon''_{i,t} \tag{5}$$

where h = {0,1,2,...,8} indicates estimation horizon in terms of quarters, $CoGS_{i,t}$ denotes the ratio of cost of goods sold to operating revenue for firm i at quarter t, $ATR_{i,t}$ denotes asset turnover ratio, $\Pi_{i,t-1}$ denotes lagged inflation pressure, namely inflation pressure based on GHR, sentence count and uncertainty, $D_{i,t-1}$ denotes lagged demand distress, namely demand distress based on GHR, sentence count, and uncertainty, $T_{i,t-1}$ denotes lagged transcript's general sentiment, namely general GHR sentiment, LM sentiment, and LM uncertainty, $X_{i,t-1}$ denotes a vector of lagged control variables for firm financials such as, size, age, leverage, Tobin's q, cash holding, cash flow, dividend dummy, capital tangibility, and CoGS, $\phi_{\text{NAICS, t}}$ denotes industry-time fixed effects, and μ_i denotes firm fixed effects. Our interest here is the evolution of $\lambda_{1,h}$ and $\eta_{1,h}$ across h. I report these coefficients for inflation pressure in Figure 3 and demand distress in Figure 4 with 95% confidence intervals that are clustered both on firm and time levels. I report coefficients using LM-based inflationary pressure and demand distress in Appendix E.

The idea behind this verification is that if the measured inflation pressure is accurate, then a higher inflationary pressure in a firm's transcript should predict an increasing ratio of CoGS in future quarters, even when controlling for the firm's financial variables, due to the call participants' incremental information about their businesses. Similarly for demand distress, if the created measure is valid, then a greater demand distress should lead to lower asset turnover in the future quarters.

Plot A in Figure 3 shows that indeed a higher inflation pressure is associated with a higher cost of goods sold to operating revenue ratio. This predictive power diminishes over longer time horizons. Furthermore, Plot B shows that, even when accounting for the complete set of transcript and balance sheet variables, inflation pressure maintains statistically significant predictive power, particularly for the second and third quarters ahead. Plot A in Figure 4 shows similar findings regarding demand distress. The results indicate that an increase in firm's demand distress in the transcript is linked to a decline in the asset turnover ratio in the following quarters.

These results show that using the GHR dictionary to measure sentiments in inflation and demand-related sentences as a proxy for a firm's inflationary pressure and demand distress is effective and provides extra information, compared to balance sheet items, regarding the firm's future performance in terms of costs and revenue. Consequently, these measures are valid indicators of inflation pressure and macroeconomic distress for firms. Furthermore, by comparing GHR results with LM results detailed in Appendix F, we see that LM-based sentiments fail to deliver statistically significant information when accounting for the complete set of firm-level variables. These findings demonstrate that GHR-based distress measures outperform LM-based measures. As a result, I use GHR-based measures hereafter.

3 Methodology

The primary methodology employed in this paper is an event study, which examines how investors price stocks with different levels of inflationary pressure and demand distress in response to the unanticipated component of monetary policy announcements on FOMC meeting days. This approach assumes that, on FOMC meeting days, no other news systematically affects stock prices expect for the monetary policy announcement. The model specification is as follows:

$$R_{i,t} = \alpha + \beta_1 \times \Delta MP_t \times \Pi^{\text{EWMA}}_{i,t-1} + \beta_2 \times \Delta MP_t \times \text{D}^{\text{EWMA}}_{i,t-1} + \beta_3 \times \Delta MP_t \times T_{i,t-1} + \beta_4 \times \Delta MP_t \times X_{i,t-1} + \phi_{NAICS,t} + \mu_i + \epsilon_{i,t} \tag{6}$$

where $R_{i,t}$ is the stock return for firm i on FOMC meeting day t, ΔMP_t is a vector containing MP-J monetary policy shocks of Jarociński (2024), $\Pi^{\text{EWMA}}_{i,t-1}$ and $D^{\text{EWMA}}_{i,t-1}$ denote the exponentially weighted moving average inflationary pressure and demand distress of firm i in the latest quarter prior to the announcement date t, $T_{i,t-1}$ denotes a vector of other lagged transcript-level control variables, and $X_{i,t-1}$ denotes a vector of lagged balance sheet-level control variables. For brevity, the model specification shows only the interaction terms and omits the non-interacted terms. The transcript-level control variables include inflation sentence count, inflation uncertainty, demand sentence count, demand uncertainty, general transcript sentiment GHR, general transcript sentiment LM, and general transcript uncertainty. The balance sheet control variables include log book assets, log age, leverage, Tobin's q, cash holding, cash flow, dividend payment dummy, capital tangibility, and cost of goods sold. μ_i and $\phi_{NAICS,t}$ denote firm fixed effects and *4-digit NAICS* × *time* fixed effects respectively.

In this model specification, I use Exponentially Weighted Moving Average (EWMA) of inflationary pressure and demand distress. This method is used to smooth time series by giving more weight to recent observations while still considering past data, but with exponentially decreasing weights. This model is appropriate because investors can consider past information at any given quarter along the most recent information disclosed during an earnings call. $\Pi^{\text{EWMA}}_{i,t}$ and $D^{\text{EWMA}}_{i,t}$ are defined as:

$$\begin{aligned}\Pi_{i,t}^{\text{EWMA}} &= \lambda \times \Pi_{i,t} + (1-\lambda) \times \Pi_{i,t-1}^{\text{EWMA}} \\ D_{i,t}^{\text{EWMA}} &= \lambda \times D_{i,t} + (1-\lambda) \times D_{i,t-1}^{\text{EWMA}}\end{aligned} \tag{7}$$

where λ is set equal to 0.75, emphasizing the importance of most recent earnings call. The creation of EWMA is on quarterly basis as t denotes quarters in Equation 7. The use of none-EWMA inflationary pressure and demand distress does not change findings of this paper..

Our coefficients of interest are given in the vectors β_1 and β_2. The positive and statistically significant coefficients on the interactions between inflationary pressure and MP-J1, MP-J2, and MP-J3 indicate that investors price stocks under inflationary pressure more favorably (unfavorably) following contractionary (expansionary) monetary policy shocks. Regarding demand distress, negative and statistically significant coefficients on its interactions with MP-J1, MP-J2, and MP-J3 would indicate that expansionary (contractionary) monetary policy shocks are perceived as favorable (unfavorable) news for firms experiencing greater macroeconomic demand distress. Given the fact that stock markets are forward looking, these findings would imply that monetary policy is impacting inflation expectations and growth expectations of stock market participants.

4 Results

Table 8 presents the main findings of this paper. Following Equation 6, all regressions in this table include firm fixed effects, *4-digit NAICS* × *time fixed effects*, and the complete set of balance sheet control variables. Regression 1 shows that inflationary pressured stocks are less sensitive to changes in conventional policy rates (MP-J1) and asset purchase programs (MP-J3). This aligns with our hypothesis that investors price inflationary pressured stocks less negatively in the face of contractionary monetary policy shocks and less positively in face of expansionary monetary policy shocks. Although Regression 1 shows a statistically insignificant coefficient for the interaction of inflation pressure and forward guidance shocks (MP-J2), the results in Table 13 in Appendix B, which replicate Table 8 with higher winsorizations, as well as the results from Regressions 2 to 5 in Table 8, show that forward guidance has a significant impact on inflation expectations. Results are largely unchanged across Regressions 2 to 5, which control for general transcript variables, inflation sentence count, and inflation uncertainty. Moreover, inflationary pressured firms are more sensitive to central bank information shocks (MP-J4) since contractionary information shocks can indicate that the central bank perceives the economy is heating up and inflation is likely to increase (or stay high), while expansionary central bank information shocks signal that the central bank believes economic activity is slowing down and inflation is falling below the target.

The results indicate that a one standard deviation increase in a firm's inflationary pressure is associated with approximately a 1-basis point reduction in sensitivity to an average monetary policy shock, as captured by MP-J1, MP-J2, and MP-J3, over the 2012–2024 period, while simultaneously leading to a 1-basis point increase in sensitivity to an average central bank information shock.

Focusing more on demand distress, Regression 1 shows no impact of monetary policy on firms based on their demand distress. However, controlling for demand sentence count and demand uncertainty, Regressions 3 to 5 show that stocks with higher demand distress are less sensitive to conventional policy rate changes and forward guidance (MP-J1 and MP-J2). This lower sensitivity does not reconcile with this paper's initial hypothesis that monetary policy should have a larger impact in stimulating the demand for firms that face weak demand and poor macroeconomic outlook. These regressions also show that firms that devote a larger proportion of their discussions to macroeconomic topics are more reactive to monetary policy shocks. This is more in line with this paper's initial hypothesis. However, the latter finding is not sufficient to conclude that monetary policy affects growth expectations when inflation is low and, conversely, demand distress is very high.

These results, specifically for inflationary pressure, are robust to changes in the construction of inflation pressure and demand distress measures. They are also robust to the use of alternative monetary policy shock series. Table 11 shows results using monetary policy shocks provided by Gürkaynak, Sack, and Swanson (2005). These results are largely similar to the main results on Table 8. Table 12 shows that the results are driven exclusively by pure monetary policy shocks. This table also shows that central bank information might have some effect on inflation expectations. For example, a sudden stop to expansionary monetary policy that registers as a contractionary shock might signal that the Fed believes the economy is heating up and inflation might overshoot. Consequently, inflationary pressured stocks will react unfavorably to such contractionary monetary shock that is dominated by central bank information. This is seen in the consistently positive sign for the interaction of inflation pressure with MP-J4 in Table 8 and with MP-JK-CBI in Table 12. However, the latter Table shows insignificant results, and the former Table has weakly significant results. The findings of this paper are also robust to changes in winsorization of transcript-level variables, as they become statistically more significant in Appendix B.

4.1 Marginal effects

In this section, I implement a two-step regression framework to graphically show the marginal effect of monetary policy on inflationary pressured stocks and to study the effectiveness of different policy tools in different regimes of inflation expectations. In the first step, I run t-number of weighted regressions for each monetary policy announcement date $t \in \{1, 2, \dots, T\}$ with following model specification:

$$R_{i,t} = \alpha_t + \Gamma_{1,t} \times \Pi^{\text{EWMA}}_{i,t-1} + \Gamma_{2,t} \times \text{D}^{\text{EWMA}}_{i,t-1} + \Gamma_{3,t} \times \text{T}_{i,t-1} + \Gamma_{4,t} \times \text{X}_{i,t-1} + \phi_{\text{NAICS}} + \epsilon_{i,t}, \quad \forall i, \tag{8}$$

where $R_{i,t}$ denotes the stock return of firm i on event date t, $\Pi^{\text{EWMA}}_{i,t-1}$ is lagged inflationary pressure, $\text{D}^{\text{EWMA}}_{i,t-1}$ is lagged macroeconomic demand distress, $\text{T}_{i,t-1}$ is a vector of lagged transcript control variables, $\text{X}_{i,t-1}$ is a vector of lagged financial control variables, and ϕ_{NAICS} represents 4 digit NAICS industry fixed effects. The regressions are weighted by log market cap in the day prior to monetary announcement. A positive estimated $\Gamma_{1,t}$ suggests that inflationary pressured firms were better off on a given policy announcement day, signaling a decrease in stock market's inflation expectations. Conversely, a negative estimated $\Gamma_{1,t}$ indicates that these firms were worse off, signaling an increase in stock market's inflation expectations.

In the second step, I regress the estimated coefficients $\Gamma_{1,t}$ on monetary policy shocks with following model specification:

$$\Gamma_{1,t} = \alpha' + \Lambda \times \Delta MP_t + \epsilon'_t, \quad \forall t, \tag{9}$$

where ΔMP_t denotes a vector of monetary policy shocks on event date t. A positive slope (Λ) suggests that an expansionary monetary shock is associated with a favorable stock price reaction by inflationary pressured firms and a contractionary monetary shock is associated with an unfavorable stock price reaction by the same firms. Hence, this positive slope suggests that monetary policy affects inflation expectations.

As a useful graphical representation, Figure 6 plots the single-factor MP-JK pure monetary policy shocks provided by Jarociński and Karadi (2020), along with the estimated coefficients $\Gamma_{1,t}$ from Equation 8. This figure shows a statistically significant positive slope, demonstrating a favorable reaction by stocks under inflationary pressure during contractionary policy shocks and an unfavorable reaction during expansionary shocks. Central banks can use this figure to plot the latest monetary shock and the estimated coefficient $\Gamma_{1,t}$ to assess the impact of the unanticipated component of their decision on inflation expectations based on historical data. To illustrate this, let's analyze the two FOMC meeting dates of November 2, 2022, and December 14, 2022. The 2-year inflation expectation on both dates is the highest value observed in the 2012-2024 period, standing at 3.18%. At the same time, MP-JK captures two of the largest monetary policy shocks, the former being expansionary and the latter being contractionary. These shocks are marked with a red triangle in Figure 6's Plot A. The shock in November, although a contractionary decision[2], was registered as an expansionary monetary policy shock by MP-JK because the markets anticipated an even stronger contractionary decision. This led to a negative reaction among inflationary pressured stocks, as indicated by the negative estimated $\Gamma_{1,t=\textit{2022-11-02}}$. The shock in December was registered as a stronger-than-expected contractionary monetary policy decision[3] by MP-JK, resulting in a favorable reaction from inflationary pressured stocks, as indicated by positive estimated $\Gamma_{1,t=\textit{2022-12-14}}$.

Comparing these two shocks to the regression line derived from other data, the expansionary (less than expected contractionary) monetary decision of November 2022 had a disproportionately large impact on stock market participants' inflation expectations, as shown by the significant negative reaction of stock prices under inflationary pressure. Meanwhile, the substantial contractionary decision in the following December, which was much larger in size compared to November's shock, had a smaller impact on inflation expectations relative to historical data. This indicates that during periods of high inflation expectations, delivering a contractionary decision that is lower than anticipated can lead to disproportionately adverse effects on inflation expectations that a contractionary decision

[2] https://www.federalreserve.gov/monetarypolicy/files/monetary20221102a1.pdf
[3] https://www.federalreserve.gov/monetarypolicy/files/monetary20221214a1.pdf

of the same size cannot offset.

Regression 1 on Table 9 reports the results for the second step following the Equation 9. In this regression, MP-J monetary shocks of Jarociński (2024) are used. The results show that pure monetary policy shocks, such as conventional rate changes, forward guidance, and asset purchases, are effective on stock market inflation expectations. Regressions 3 and 5 replicate the results using alternative monetary policy shocks and show similar results. The results show that a one standard deviation increase in monetary shock in terms of MP-J1, MP-J2, and MP-J3 corresponds to a positive reaction of 0.95 basis points, 1.45 basis points, and 0.8 basis points, respectively, by a firm experiencing average inflationary pressure.

In regression 2, 4, and 6, I introduce a dummy variable for periods where 2-year inflation expectations were above the 2% central bank target with following model specification:

$$\Gamma_{1,t} = \alpha'' + \Lambda' \times H_t \times \Delta MP_t + \epsilon''_t \tag{10}$$

where H_t denotes the dummy variable for periods with inflation expectations above 2%. Regression 2 on Table 9 shows that different monetary policy tools have varying effectiveness in times of high and low inflation expectations. Conventional policy rate changes are only effective when inflation expectations are sufficiently high and become ineffective at inflation expectations below the target. While, forward guidance looks effective in both regimes, but becomes more effective when inflation expectations are low. The direction of the coefficients in Regression 4 point to a similar pattern, but coefficients are not statistically significant. This lack of significance could be because of larger standard errors that results from small number of observations. As a solution, I run a limited form of Equation 10:

$$\Gamma_{1,t} = \alpha''' + \Lambda' \times H_t \times \Delta MP - J1_t + \Lambda'' \times L_t \times \Delta MP - J2_t + \epsilon'''_t \tag{11}$$

which only focuses on conventional policy rate changes during periods with 2-year inflation expectations above 2% (denoted H_t) and forward guidance during periods with inflation expectations below 2% (denoted L_t).The results presented in Column 7 of Table 9 confirm that forward guidance is effective in both high and low inflation expectation regimes. It becomes particularly effective when inflation expectations fall below the 2% target, while conventional policy rate changes are only effective in high inflation expectation environments.

5 Macroeconomic evidence on inflationary pressures role in the price puzzle

Although standard theory predicts that monetary policy shocks should trigger stock market reactions of the opposite sign—contractionary shocks lowering stock prices and expansionary shocks raising them—empirical evidence often reveals the opposite, a phenomenon referred to as the price puzzle. The main explanation for this puzzle is the central bank information effect: monetary announcements may reveal the central bank's private assessment of the macroeconomic growth outlook, prompting the private sector to revise its growth expectations accordingly. As a result, stock prices may move in the same direction as the policy shock. However, the event-study results in the previous section show that pure monetary policy shocks, which are shocks that exclude central bank information effect, can cause a same-signed reaction among stocks of firms under inflationary pressure because of contractionary (expansionary) monetary policy's decreasing (increasing) impact on inflationary pressure.

In this section, I extend the firm-level event-study evidence by conducting a macro-level high-frequency examination of stock market responses to monetary policy. Using data from Jarociński and Karadi (2020), I analyze the S&P 500 index's reaction within a 30-minute window around policy announcements to monetary policy shocks across different inflation expectations regime. I use 5-year inflation expectations from FRED. The objective is to assess how the immediate market response to monetary policy shocks differs depending on the inflation expectation environment. The analysis uses the following model specification.

$$R_t^{\mathrm{SP500}} = \alpha + \beta \times \Delta MP_t \times \Pi_{t-1}^{exp} + \epsilon_{i,t} \tag{12}$$

where the R_t^{SP500} denotes the high frequency return for S&P 500 index in a 30-minute window around the policy announcement t, $DeltaMP_t$ is a vector of monetary policy shocks, and Π_{t-1}^{exp} is 5-year inflation expectations from FRED. Π_{t-1}^{exp} is lagged to the latest month prior to the event to prevent endogeneity issues.

The results, reported on Table 10, show that elevated inflation expectations are associated with a very muted stock market response to monetary shocks because of the monetary policy's link with future inflation pressure and inflation expectations. For example, Regression 4 shows that an average pure expansionary shock results in a 28 basis point rally by S&P 500 index when 5-year inflation expectations are at first quantile (1.8%) and the same shock results only in a 16 basis point rally when expectations are at third quantile (3.2%). Comparing Regressions 2 and 4 with Regressions 1 and 3 respectively, we observe that monetary shocks would have much larger opposite-singed impact on stock markets at a given fixed inflation expectations. Moreover, Regression 4 shows the same effect for the shocks dominated by the central bank information effect, where an average contractionary shock that is dominated by information effect results in a 8 basis point rally when 5-year inflation expectations are at first quantile and only a 4 basis point rally when expectations are at third quantile. The overall results show that the dominant explanation for the price puzzle remains to be the central bank information effect, but identifies a second important mechanism that leads to a much muted stock market reaction to monetary shocks. Eventhough S&P 500 index might not show a same-sign reaction because of the inflationary pressures, but individual stocks that are under significant inflationary pressure can certainly move in the same direction as monetary policy.

The results, presented in Table 10, indicate that elevated inflation expectations are associated with a significantly muted stock market response to monetary policy shocks because of the monetary policy's link with future inflation pressure and inflation expectations. For instance, Regression 4 shows that an average pure expansionary monetary shock leads to a 0.28% increase in the S&P 500 index when 5-year inflation expectations are at the first quartile

(1.8%), but only a 0.16% increase when expectations are at the third quartile (3.2%). A comparison of Regressions 2 and 4 with Regressions 1 and 3, respectively, reveals that when inflation expectations are held constant, monetary policy shocks have much larger and oppositely signed effects on stock returns.

Moreover, Regression 4 provides evidence for a similar pattern in the case of shocks dominated by the central bank information effect: an average contractionary shock of this type leads to an 0.08% increase in the S&P 500 index when inflation expectations are at first quantile, but only a 0.04% increase when expectations are at third quantile

Taken together, these findings reaffirm the central bank information effect as the leading explanation for the price puzzle, but also highlight a second distinct mechanism, which can substantially dampen the stock market's reaction to monetary shocks. While the aggregate S&P 500 index may not display a same-sign response due to offsetting effects from inflationary pressures, individual firms under significant inflationary pressure can respond in the same direction as the policy shock.

6 Real effects of monetary policy on inflationary pressured firms

In this section, I show that contractionary monetary policy results in favorable real outcomes for firms facing inflationary pressure compared to other firms, while expansionary monetary policy results in unfavorable outcomes for the same firms. To conduct this analysis, I use Jordà's local projections, which is widely used in similar literature (Ottonello and Winberry, 2020; Gürkaynak et al., 2022; Cloyne et al., 2023; Dôttling and Ratnovski, 2023). The model specification is based on the following equation:

$$y_{i,t+h} - y_{i,t-1} = \beta_1^h \times \Delta MP_t \times \Pi_{i,t-1} + \beta_2^h \times \Delta MP_t \times T_{i,t-1} + \beta_3^h \times \Delta MP_t \times X_{i,t-1} + \beta_4^h \times \Delta MP_t \times Y_{i,t-1} + \alpha_i^h + \phi_{NAICS,t}^h + \epsilon_{i,t}^h \tag{13}$$

where $h = \{1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16\}$ denotes the estimation horizon, $y_{i,t+h}$ is the outcome variable for firm i at quarter $t+h$, and $y_{i,t-1}$ is the outcome variable at one quarter before the monetary shock. The term $y_{i,t+h} - y_{i,t-1}$ is the cumulative change of the outcome variable between $t+h$ and $t-1$ by firm i. The outcome variables used are; 1) the log ratio of CoGS to operating revenue (Plot A), 2) cash flow (Plot B), 3) log of asset turnover (Plot C), 4) log of investment, defined as capex to lagged booked assets (Plot D), 5) log of tangible capital, defined as NPPE to lagged book assets (Plot E), 6) log of total book assets (Plot F), and 7) log of market cap (Plot G). The regressions include firm fixed effects α_i^h, 4-digit NAICS × event date fixed effects $\phi_{NAICS,t}^h$, the single factor pure monetary policy shocks ΔMP_t of Jarociński and Karadi (2020) that are summed up to quarter level, lagged firm-level inflationary pressure $\Pi_{i,t-1}$, a vector of complete firm-level control variables $X_{i,t-1}$, $T_{i,t-1}$ general transcript sentiment, and $Y_{i,t-1}$ the lagged level of outcome variable (not log-transformed).

The estimated coefficients of interest β_1^h are reported in Figure 7 with 90% and 95% confidence intervals constructed based on firm-level and time-level clustered standard errors. Plot (A) shows that contractionary monetary policy results in a consistently lower CoGS ratio for firms under inflationary pressure. Plot (B) shows a short-lived increase in cash flow that disappears after 4 quarters. Plot (C) shows no difference in asset turnover between inflationary pressured firms and others. Plot (D) shows that investment reacts positively after 4 quarters and remains elevated in long-term. Plot (E) shows tangible asset ratio experiences a short-lived statistically insignificant increase and Plot (F) shows that total book assets experience an increase. Finally, Plot (G) shows that market cap increases in the initial quarters, decreases, and increases again in the long-term.

The direction of the estimated coefficients for all outcome variables point to the favorable impact of contractionary monetary policy on inflationary pressured firms and the unfavorable impact of expansionary monetary policy, showing the consistency of the results and complemeting the event-study findings. However, the estimated coefficients are often insignificant on 95%. This relates to the power problem in studies of monetary policy (Nakamura and Steinsson, 2018a), where the size of the identified high frequency exogenous monetary policy shock is very small, making the detection of its impact over long-horizons even more difficult. Moreover, the reported confidence intervals are very strict, constructed based on standard errors that clustered on firm-level and quarter-level. Hence, the lower ratio of signal-to-noise in this type of studies can result in lack of statistical power.

The estimated coefficients for all outcome variables consistently indicate that contractionary monetary policy has a favorable impact on firms under inflationary pressure, while expansionary policy has an unfavorable effect. The consistency in the direction of the estimated coefficients complements the event-study findings. However, many of the coefficients are not statistically significant at the 95% level. This reflects the power problem, which is a well-known limitation in monetary policy research (Nakamura and Steinsson, 2018a). The exogenous monetary policy shocks identified at high frequency tend to be small in size, making it challenging to identify their effects over longer horizons. Additionally, the reported confidence intervals are very strict, constructed based on robust standard errors clustered at both the firm-level and quarter-level. As a result, the inherently low signal-to-noise ratio in this type of method reduces statistical power, even when the economic effects are directionally clear.

7 Conclusions

This paper introduces a firm-level measure of inflationary pressure using textual analysis of earnings call transcripts. This measure serves as a forward-looking proxy for the cost-push inflation that firms experience. It complements balance sheet indicators, macroeconomic indicators, and survey-based information by providing granular firm-specific insights into how inflation affects corporate fundamentals in real time. Using this measure, I find that monetary policy shocks are priced differently depending on a firm's inflation pressure. Stocks of firms facing greater inflationary pressure respond less negatively to contractionary shocks and less positively to expansionary shocks. This finding holds across a range of empirical specifications and robustness tests, aligning with the interpretation that market participants revise their inflation expectations in response to policy surprises. Contractionary policy is viewed as reducing future cost pressures for inflation-pressured firms, leading to more favorable pricing, while expansionary policy raises future cost expectations and dampens the positive reaction typically associated with looser policy stance.

These findings provide a novel explanation for the well-documented price puzzle, where stock prices rise following contractionary monetary shocks and fall after expansionary shocks contrary to what theory predicts. The leading explanation attributes the puzzle to the central bank information effect, where markets revise their expectations for future economic growth based on the signal in the central bank's policy decision, which reflects its private assessment of the economic outlook. However, using "pure" monetary policy shocks that are purged of the information effect, I show that muted or counterintuitive stock price reactions persist for firms facing high inflationary pressure. This suggests a complementary mechanism: firms exposed to cost-push inflation interpret tighter policy as a sign of future cost relief, producing a same-signed stock price response even in the absence of an information channel.

Further supporting this mechanism, I find that contractionary monetary policy shocks are followed by improvements in real firm-level outcomes for firms with elevated inflationary pressure, specifically, increases in cash flow, investment, and size, as well as reductions in the cost of goods sold. These results highlight that the policy's effect on inflation expectations is not limited to financial markets but also extends to firms' actual operating performance. While statistical significance is sometimes limited due to the very small size of high-frequency monetary shocks, the consistency across both price and quantity responses reinforces the interpretation that inflationary pressure is a key axis along which monetary policy operates.

On a macro level and with a significantly longer study interval, I document that the high-frequency reaction of the S&P 500 index to pure monetary shocks diminishes when general inflation expectations are high. This muted reaction further corroborates the paper's central hypothesis: when markets expect inflation to remain elevated, monetary policy news is interpreted primarily through its implications for future inflation rather than growth. Additionally, the paper shows that the effectiveness of conventional rate policy is regime-dependent, stronger when inflation expectations are high, while forward guidance remains consistently effective and becomes even more influential in low-inflation environments.

In sum, these findings underscore the importance of accounting for firm-level heterogeneity in inflation pressure when evaluating the effects of monetary policy on financial markets and the real economy, and highlight the fact that monetary policy news is interpreted through its implications for future inflation rather than growth when inflation expectations are elevated.

8 References

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9 Tables and figures

Table 1: Variable Definitions

Variable	Definition	Source
Inflation sentence count	The number of sentences discussing input inflation related topics standardized by the number of sentences in the transcript	Calculated by the author
Inflation pressure*	The number of GHR-positive words minus the GHR-negative words in the sentences discussing input inflation topics standardized by transcript size and multiplied by (-1)	Calculated by the author
Inflation pressure LM*	The number of LM-positive words minus the LM-negative words in the sentences discussing input inflation topics standardized by transcript size and multiplied by (-1)	Calculated by the author
Inflation uncertainty	The number of words signaling uncertainty based on LM dictionary in the sentences discussing input inflation standardized by transcript size	Calculated by the author
Demand sentence count	The number of sentences discussing macroeconomic environment and economic outlook standardized by the number of sentences in the transcript	Calculated by the author
Demand distress*	The number of GHR-positive words minus the GHR-negative words in the sentences discussing macroeconomic environment and economic outlook topics standardized by transcript size and multiplied by (-1)	Calculated by the author
Demand distress LM*	The number of LM-positive words minus the LM-negative words in the sentences discussing macroeconomic environment and economic outlook topics standardized by transcript size and multiplied by (-1)	Calculated by the author
Demand uncertainty	The number of words signaling uncertainty based on LM dictionary in the sentences discussing macroeconomic environment and economic outlook standardized by transcript size	Calculated by the author
Transcript size	The number of words in transcript after exclusion of none-alphabetic terms, stop words, entity names, and one character terms, and removal of welcome messages	Calculated by author
General Sentiment GHR	The ratio between the number of GHR-positive words minus the GHR-negative words for the entirety of transcript and transcript size	Calculated by author
General Sentiment LM	The ratio between the number of LM-positive words minus the LM-negative words for the entirety of transcript and transcript size	Calculated by author
General Uncertainty LM	The ratio between the number of LM-uncertainty words for the entirety of transcript and transcript size	Calculated by author
Log asset	Log of balance sheet total assets deflated by Consumer Price Index for the U.S. firms and Harmonized Index of Consumer Prices for the Euro firms	Capital IQ & FRED
Log age	Log of quarters since the earliest year observed among firm's establishment year, incorporation year, IPO year, and first year of observation in Compustat	Capital IQ, Compustat
Leverage	Ratio of total debt to total assets	Capital IQ
Tobin's q	((Market capitalization) + Total assets + Total common equity) / Total assets	Capital IQ
Cash holding	The ratio of cash and cash equivalents to total assets	Capital IQ
Cash flow	Four quarter rolling sum of EBITDA divided by lagged total assets	Capital IQ
Dividend dummy	Binary variable indicating if a firm paid out dividend in a fiscal year	Capital IQ
Capital tangibility	The ratio of NPPE to the sum of NPPE and total intangible capital à la Peters and Taylor	Capital IQ
CoGS	The ratio of cost of goods sold to operating revenue	Capital IQ
RoA	The ratio of operating revenue to total assets in the previous quarter	Capital IQ
Stock return	Log of event day's closing stock price minus log of the closing price from the day before	Capital IQ
MP-J	MP-J1 to MP-J4 are shocks provided by Jarociński (2024) where MP-J1 represents standard monetary policy shocks, MP-J2 represents forward guidance shocks, MP-J3 represents asset purchase shocks, and MP-J4 represents central bank information shocks.	Marek Jarociński's personal website
MP-GSS-Target & MP-GSS-Path	Two factor Monetary shocks of Gürkaynak, Sack, and Swanson (2005) where target factor contains unexpected changes to current federal funds rate and path factor contains revisions to the expectations of future rates up to 1 year	Miguel Acosta's personal website
MP-JK	Monetary shocks of Jarociński and Karadi (2020) that is the first principal component of interest rates up to 1 year for U.S. and Euro area	Marek Jarociński's personal website

The variables marked with an asterisk (*), namely Inflation pressure, Inflation pressure LM, Demand distress, Demand distress LM, are multiplied by a (-1) to ensure that, across all measures, larger values point to a higher inflationary pressure or a higher demand distress.

Table 2: Inflation Lexicon

Unigrams and general terms	['inflat', 'inflationari', 'hyperinfl', 'stagflat', 'cog', 'cpi', 'consum price index', 'ppi', 'produc price index', 'price cost', 'pricecost', 'cost price', 'costprice', 'cost good sold']
Passive bigrams	['cost input', 'cost raw materi', 'cost supplier', 'cost suppli', 'cost suppli chain', 'cost labor', 'cost materi', 'cost energi', 'cost fuel', 'cost operat', 'cost commod', 'cost freight', 'cost produc', 'cost manufactur', 'cost compon', 'cost ingredi', 'cost procur', 'cost inventori', 'cost logist', 'cost transport', 'cost wage', 'cost salari', 'cost hire', 'cost recruit', 'cost employ', 'cost workforc', 'cost oper', 'cost factori', 'cost plant', 'cost equip', 'cost product', 'cost lifo', 'cost raw', 'cost raw mat', 'expens raw materi', 'expens input', 'expens supplier', 'expens suppli', 'expens suppli chain', 'expens labor', 'expens materi', 'expens energi', 'expens fuel', 'expens operat', 'expens commod', 'expens freight', 'expens produc', 'expens manufactur', 'expens compon', 'expens ingredi', 'expens procur', 'expens inventori', 'expens logist', 'expens transport', 'expens wage', 'expens salari', 'expens hire', 'expens recruit', 'expens employ', 'expens workforc', 'expens oper', 'expens factori', 'expens plant', 'expens equip', 'expens product', 'expens lifo', 'expens raw', 'expens raw mat', 'expenditur raw materi', 'expenditur input', 'expenditur supplier', 'expenditur suppli', 'expenditur suppli chain', 'expenditur labor', 'expenditur materi', 'expenditur energi', 'expenditur fuel', 'expenditur operat', 'expenditur commod', 'expenditur freight', 'expenditur produc', 'expenditur manufactur', 'expenditur compon', 'expenditur ingredi', 'expenditur procur', 'expenditur inventori', 'expenditur logist', 'expenditur transport', 'expenditur wage', 'expenditur salari', 'expenditur hire', 'expenditur recruit', 'expenditur employ', 'expenditur workforc', 'expenditur oper', 'expenditur factori', 'expenditur plant', 'expenditur equip', 'expenditur product', 'expenditur lifo', 'expenditur raw', 'expenditur raw mat', 'price raw materi', 'price input', 'price supplier', 'price suppli', 'price suppli chain', 'price materi', 'price energy', 'price raw', 'price raw mat']
Active bigrams*	['cost', 'wage'] ['increas', 'rise', 'rais', 'high', 'higher', 'highest', 'skyrock', 'grow', 'escal', 'surg', 'mount', 'climb', 'soar', 'elev', 'spike', 'escal', 'upward', 'excess', 'creep', 'balloon', 'amplifi', 'inflat', 'acceler', 'surpass', 'outpac', 'pace', 'addit', 'jump', 'elev', 'peak', 'explod', 'outgrow', 'exacerb', 'upshoot', 'exceed', 'up', 'more', 'abov', 'pressur', 'burden', 'headwind', 'challeng', 'unpreced', 'shock', 'backdrop', 'impact', 'unfavor', 'volatil', 'problem']

This table presents a summary of the list of unigrams, bigrams, and a few general terms used for identifying inflation-related sentences from firms' transcripts. Note that all terms are stemmed using the Porter Stemmer and the selection process has been applied to properly processed transcripts as described in Section 2.1 and Appendix D. The unigrams, such as "inflationari", and general terms, such as "cost good sold" and "cog", are reported on the top row. The passive and active bigrams are presented on the next two rows without permutation for brevity. For example, the second row presents 'cost input' as a passive bigrams and this means 'input cost' is also used to select target sentences. Another example is 'cost increas' as an active bigram on the final row which means 'increas cost' is also used. For passive bigrams, I select a sentence as inflation-related when a given passive bigram is present in the processed version of that sentence. As for active bigrams, presented on the final row, I select sentences where a unigram from one of the two lists appears not further than 2 words away from any unigram from the other list. The developments of these bigrams are explained in Section 2.1. and detailed in Appendix D.

Table 3: Macroeconomic Demand Distress Lexicon

Unigrams and general terms	['recess', 'unemploy', 'layoff', 'gdp', 'downturn', 'slowdown', 'macro', 'macroeconom', 'macroeconomi', 'economist']
Passive bigrams	['crisi bank', 'crisi financi', 'crisi debt', 'crisi econom', 'crisi economi', 'crisi demand', 'crisi market', 'consum confid', 'consum demand', 'consum spend', 'consum sentiment', 'consum uncertain', 'consum uncertainti', 'consum cautiou', 'consum stress', 'consum discretionari', 'consum cautious', 'market confid', 'market demand', 'market spend', 'market sentiment', 'market uncertain', 'market uncertainti', 'market cautiou', 'market stress', 'market discretionari', 'market cautious', 'econom activ', 'economi activ', 'market activ', 'cycl busi', 'cycl market', 'cycl demand', 'cycl econom', 'cycl economi', 'cyclic busi', 'cyclic market', 'cyclic demand', 'cyclic econom', 'cyclic economi', 'time bad', 'time difficult', 'time tough', 'time tougher', 'time challeng', 'year bad', 'year difficult', 'year tough', 'year tougher', 'year challeng', 'quarter bad', 'quarter difficult', 'quarter tough', 'quarter tougher', 'quarter challeng', 'demand broader', 'demand broad', 'demand overal', 'demand global', 'demand outlook', 'demand environ', 'demand condit', 'demand situat', 'demand trend', 'market broader', 'market broad', 'market overal', 'market global', 'market outlook', 'market environ', 'market condit', 'market situat', 'market trend', 'environ broader', 'environ broad', 'environ overal', 'environ global', 'environ outlook', 'environ environ', 'environ condit', 'environ situat', 'environ trend', 'econom broader', 'econom broad', 'econom overal', 'econom global', 'econom outlook', 'econom environ', 'econom condit', 'econom situat', 'econom trend', 'economi broader', 'economi broad', 'economi overal', 'economi global', 'economi outlook', 'economi environ', 'economi condit', 'economi situat', 'economi trend', 'cycl broader', 'cycl broad', 'cycl overal', 'cycl global', 'cycl outlook', 'cycl environ', 'cycl condit', 'cycl situat', 'cycl trend']
Active bigrams	['demand', 'market', 'environ', 'econom', 'economi', 'cycl'] ['weak', 'weaker', 'weakest', 'slow', 'slower', 'slowest', 'wors', 'worsen', 'worst', 'low', 'lower', 'lowest', 'soft', 'softer', 'soften', 'tough', 'tougher', 'reduc', 'decreas', 'diminish', 'sluggish', 'shutdown', 'down', 'hit', 'collaps', 'fail', 'fall', 'drop', 'dip', 'bust', 'declin', 'neg', 'bust', 'below', 'come down', 'downsid', 'crash', 'doubl dip', 'dampen', 'modest', 'hunker down', 'drop down', 'shrink', 'contract', 'stagnate', 'cutback', 'slump', 'risk', 'uncertain', 'uncertainti', 'unsure', 'unknown', 'stress', 'pessimist', 'difficult', 'difficulti', 'challeng', 'headwind', 'suffer', 'pressur', 'volatil', 'unstabl','instabl', 'alarm', 'poor', 'depress', 'distress', 'troubl', 'impact', 'problem', 'shallow', 'unfortun', 'unfavor', 'crisi', 'backdrop', 'shock', 'unpreced', 'contract', 'turmoil', 'unusu']

This table presents a summary of the unigrams and bigrams used for identifying macro-demand-related sentences from firms' transcripts. Note that all terms are stemmed using the Porter Stemmer and the selection process has been applied to properly processed transcripts as described in Section 2.2 and Appendix D. The unigrams, such as "recess", and general terms, such as "gdp", are reported on the top row. The passive and active bigrams are presented on the next two rows without permutation for brevity. For example, the second row presents "crisi bank" as a passive bigrams and this means "bank crisi" is also used to select target sentences. Another example is "demand weak" as an active bigram on the final row which means "weak demand" is also used. For passive bigrams, I select a sentence as macro-demand-related when this bigram is present in the processed version of that sentence. As for active bigrams, presented on the final row, I select sentences where a unigram from one of the two lists appears not further than 2 words away from any unigram from the other list. The developments of these bigrams are detailed in Appendix D.

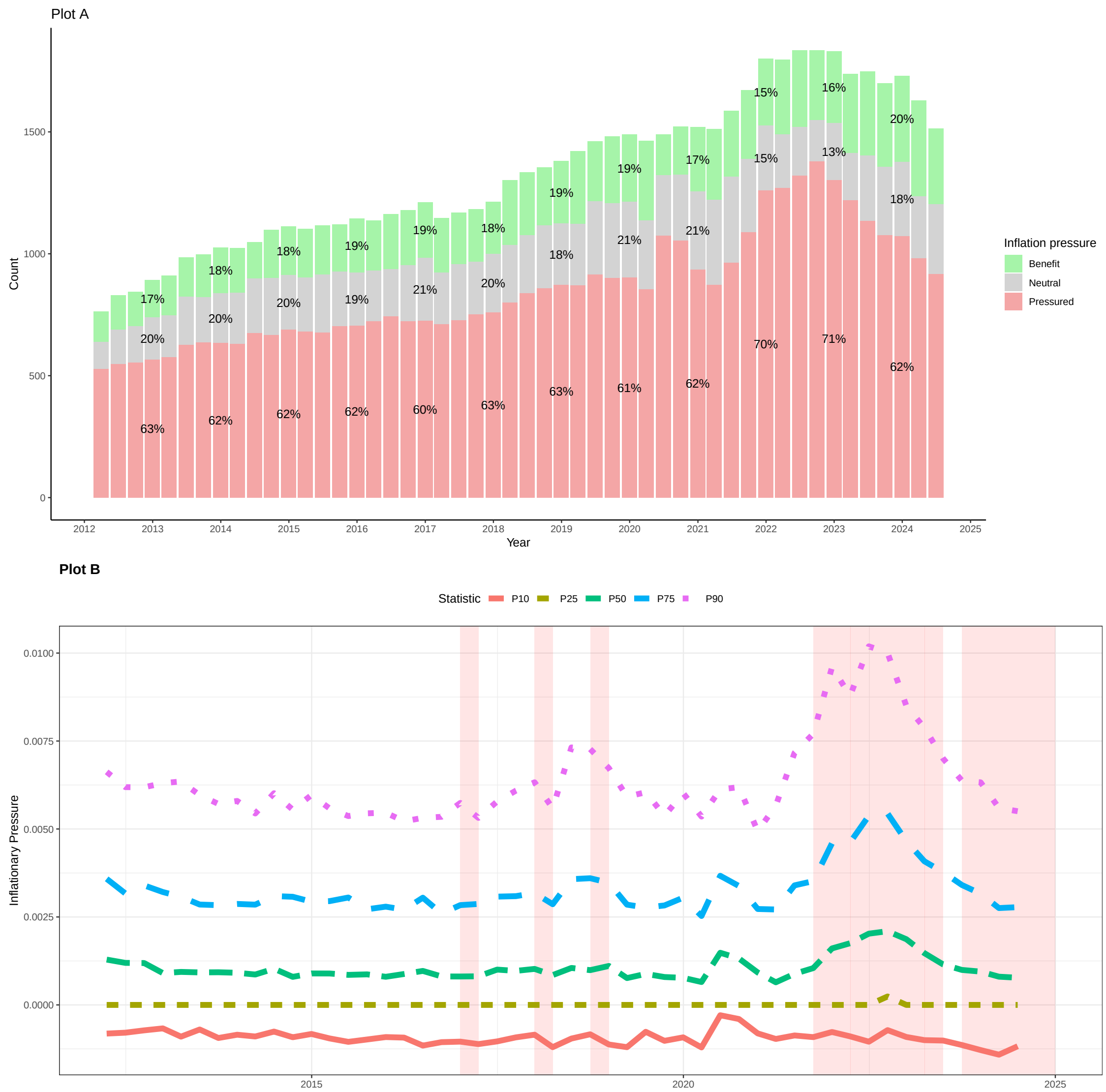

Figure 1: The count and distribution of firms experiencing inflationary pressure over time

Plot A in this figure shows the count of the firms with positive, neutral, and negative inflationary pressure over time. Positive inflationary pressure indicates that the firm is negatively impacted by rising input costs. The percentages on Plot A show the share of firms based on their inflationary pressure.

Plot B shows the distribution of inflationary pressure over time. Specifically, it shows the 10th, 25th, 50th, 75th, and 90th percentiles. The red shaded areas are periods where 2-year inflation expectations provided by FRED is above 2%.

Table 4: Descriptive Statistics: Fed's Monetary Policy Shocks

	N	Mean	Median	SD	Min	1st Q	3rd Q	Max	MP-J2	MP-J3	MP-J4	MP-JK	MP-GSS-TARGET	MP-GSS-PATH
MP-J1	99	-0.088	0.008	1.961	-11.86	-0.390	0.171	6.189	-0.12	0.04	0.10	0.33	0.92	-0.25
MP-J2	99	-0.327	-0.206	4.297	-12.81	-2.003	1.075	14.15		0.03	-0.21	0.83	-0.25	0.96
MP-J3	99	-0.053	-0.199	1.808	-10.98	-0.730	0.639	4.607			0.11	0.04	0.11	0.02
MP-J4	99	0.173	0.190	1.038	-3.168	-0.305	0.679	3.293				-0.01	0.08	-0.04
MP-JK	99	-0.068	0.104	3.447	-13.40	-0.870	1.457	9.762					0.11	0.89
MP-GSS-Target	96	0.280	0.267	1.585	-5.699	-0.281	0.648	5.930						-0.29
MP-GSS-Path	96	0.780	1.006	8.725	-24.88	-1.195	3.107	30.38						

This table reports the descriptive statistics and Pearson's correlation coefficients for the Fed's monetary policy shocks. MP-J1 to MP-J4 are shocks provided by Jarociński (2024) where MP-J1 represents standard monetary policy shocks, MP-J2 represents forward guidance shocks, MP-J3 represents asset purchase shocks, and MP-J4 represents central bank information shocks. MP-JK is shock series provided by Jarociński and Karadi (2020) which provides a summary of overall monetary policy shock in a single factor. These shocks cover the scheduled FOMC meetings between 2012Q2 and 2024Q3. MP-GSS-Target and MP-GSS-Path are the Target factor and Path factor of Gürkaynak, Sack, and Swanson (2005). These shocks cover the scheduled FOMC meetings between 2012Q2 and 2024Q2.

Table 5: Summary Statistics

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 50	Pctl. 75	Max
Inflation pressure	66562	0.002	0.0029	-0.0021	0.0001	0.0012	0.0032	0.011
Inflation pressure LM	66562	-0.0003	0.0007	-0.0025	-0.0006	-0.0001	0	0.0012
Inflation sentence count	66562	0.0143	0.0125	0.0001	0.0051	0.0109	0.0198	0.0528
Inflation uncertainty	66562	0.0004	0.0005	0	0	0.0002	0.0006	0.002
Demand distress	66562	0.0009	0.0022	-0.0032	-0.0003	0.0004	0.0018	0.0076
Demand distress LM	66562	0	0.0009	-0.0023	-0.0005	0	0.0004	0.0025
Demand sentence count	66562	0.014	0.0118	0	0.005	0.0108	0.0199	0.0476
Demand uncertainty	66562	0.0005	0.0006	0	0	0.0003	0.0008	0.0024
Sentiment GHR	66562	0.027	0.0392	-0.0509	-0.0014	0.0263	0.0549	0.1084
Sentiment LM	66562	0.0208	0.0121	-0.004	0.0122	0.0206	0.0292	0.0461
Uncertainty LM	66562	0.0216	0.0054	0.0117	0.0177	0.0212	0.0251	0.0341
Log asset	66562	14.11	1.99	7.08	12.82	14.12	15.44	20.34
Log age	66562	4.96	0.87	0.69	4.38	4.93	5.61	6.91
Leverage	66562	0.29	0.23	0	0.1	0.26	0.42	1.09
Tobin's q	66562	2.52	2.04	0.69	1.28	1.8	2.92	12.35
Cash holding	66562	0.15	0.17	0	0.04	0.1	0.2	0.79
Cash flow	66562	0.06	0.2	-0.83	0.04	0.1	0.16	0.4
Dividend dummy	66562	0.43	0.49	0	0	0	1	1
Capital tangibility	66562	0.29	0.28	0	0.08	0.18	0.43	0.98
CoGS	66562	0.75	1.03	0.09	0.43	0.63	0.78	9.25
Asset turnover ratio	66562	0.24	0.17	0	0.12	0.19	0.31	0.9

The definitions of variables are provided on Table 1.

Table 6: Correlations for Transcript-level Variables

	Inflation Pressure	Inflation sentence count	Inflation uncertainty	Inflation Pressure LM	Demand distress	Demand sentence count	Demand uncertainty	Demand distress LM	General sentiment GHR	General sentiment LM
Inflation sentence count	0.6									
Inflation uncertainty	0.44	0.68								
Inflation Pressure LM	0.09	-0.3	-0.16							
Demand distress	0.2	0.09	0.08	0.05						
Demand sentence count	0.15	0.2	0.15	-0.07	0.43					
Demand uncertainty	0.11	0.14	0.15	-0.04	0.4	0.74				
Demand distress LM	0.07	-0.01	0	0.12	0.5	0.11	0.14			
General sentiment GHR	-0.34	-0.09	-0.09	-0.16	-0.38	-0.02	-0.05	-0.27		
General sentiment LM	-0.17	0.02	-0.03	-0.27	-0.28	-0.03	-0.07	-0.36	0.67	
General uncertainty LM	0.05	-0.04	0.16	0.07	0.11	-0.01	0.16	0.11	-0.33	-0.33

This table reports the pearson's correlations between measures obtained from earning call transcripts. The data comes from 66,562 unique earnings call transcripts. Variable definitions are provided on Table 1.

Table 7: Correlations for Macro-level Variables

Panel A: Macro-level correlations for inflation distress measures

	Inflation pressure	Inflation pressure LM	Inflation sentence count	Inflation uncertainty LM	CPI inflation	PPI inflation	PPI Inf. Manufacturing	Inf. exp. Michigan	Inf. exp. 1year	Inf. exp. 2year
Inflation pressure LM	0.13									
Inflation sentence count	0.89	-0.21								
Inflation uncertainty LM	0.91	-0.12	0.98							
CPI inflation	0.54	-0.04	0.59	0.59						
PPI inflation	0.17	0.1	0.19	0.22	0.77					
PPI Inf. Manufacturing	0.2	0.07	0.26	0.28	0.78	0.97				
Inf. exp. Michigan	0.85	0.08	0.85	0.87	0.67	0.38	0.4			
Inf. exp. 1year	0.61	-0.25	0.7	0.66	0.5	0.13	0.14	0.6		
Inf. exp. 2year	0.56	-0.41	0.71	0.65	0.43	0.06	0.08	0.52	0.96	
Inf break even 5year	0.58	-0.17	0.69	0.67	0.76	0.58	0.6	0.74	0.54	0.52

Panel B: Macro-level correlations for macro-demand distress measures

	Demand distress	Demand distress LM	Demand sentence count	Demand uncertainty LM	GDP growth	Unemployment rate	Consumer sentiment	Industrial production	Manufacturing new order
Demand distress LM	0.94								
Demand sentence count	0.87	0.71							
Demand uncertainty LM	0.87	0.71	0.99						
GDP growth	-0.38	-0.48	-0.19	-0.18					
Unemployment rate	0.49	0.56	0.36	0.34	-0.92				
Consumer sentiment	0.02	-0.02	0.08	0.1	0.19	-0.24			
Industrial production	-0.38	-0.43	-0.26	-0.25	0.78	-0.75	0.18		
Manufacturing new order	-0.08	-0.11	0.02	0.02	0.52	-0.4	0.05	0.54	
Business confidence	0.3	0.28	0.13	0.13	0.14	-0.07	0.15	0.22	0.39

Panel A reports pearson's correlation between macroeconomic inflation indicators obtained from FRED and the transcript-based measures for inflation pressure that are averaged across firms to quarterly level. Panel B reports the correlations of GDP growth rate and the change in unemployment rate with the macroeconomic demand distress measures. This table covers 50 quarters from 2012Q2 to 2024Q3.

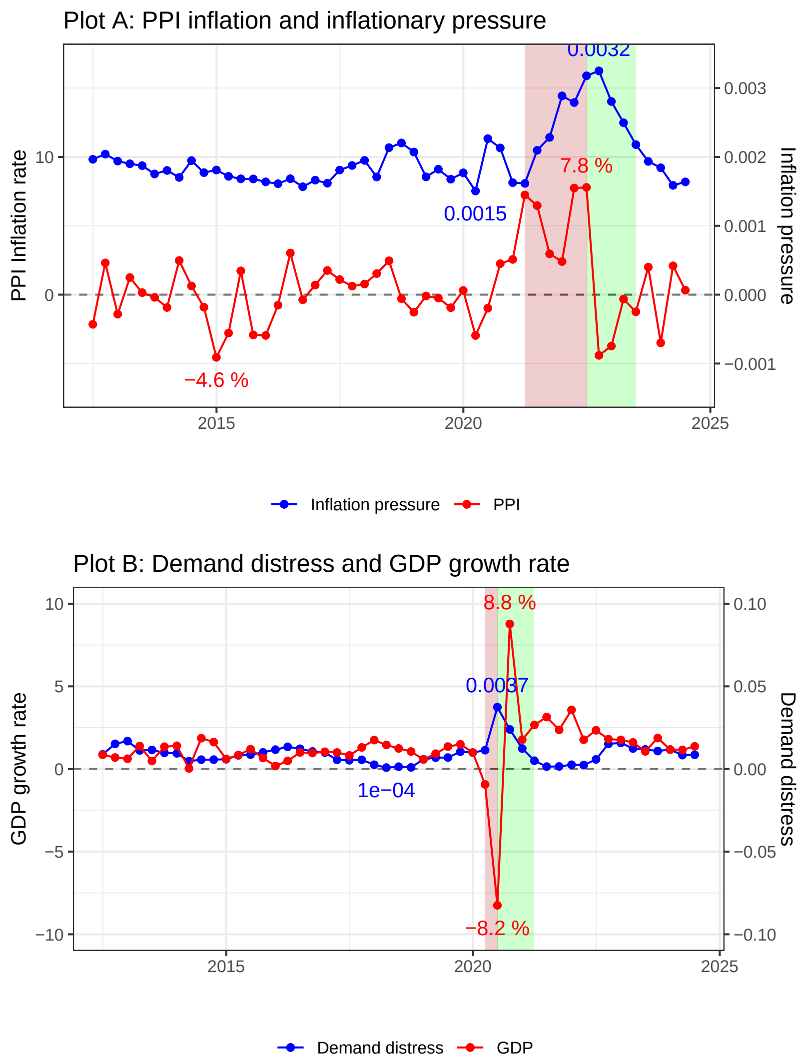

Figure 2: Macroeconomic Variables and Transcript-Extracted Variables

Plot A in this figure shows the Producer Price Index (PPI) inflation rate and inflationary pressure averaged across firms to a time series. The red shaded area in this plot shows the surge in PPI followed by a significant drop to negative rates in the green shaded area. However, inflationary pressure from transcripts shows a higher autocorrelation and recovers slowly after the 2022-23 inflationary period.

Plot B shows the GDP growth rate and demand distress averaged across firms to a time series. The red shaded area shows the large economic contraction at the start of the COVID shock, followed by a sharp recovery in the following period shaded green. However, demand distress shows a higher autocorrelation and recovers only gradually even when the economy recovered in 2021.

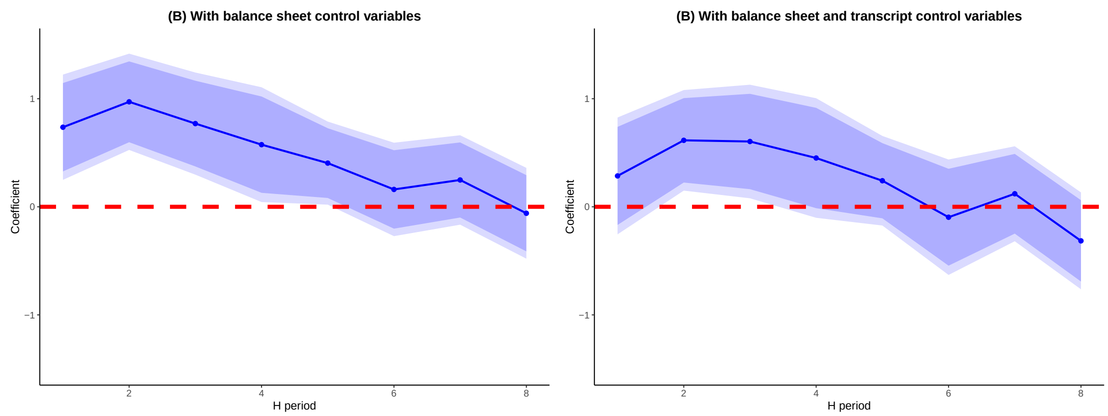

Figure 3: Firm's cost of goods sold and its inflationary pressure

This figures plots the estimated coefficients $\lambda_{1,h}$ and their 95% confidence intervals from 8 separate regressions based on Equation 4 for each h in h=1,2,3,4,5,6,7,8. These coefficients show the reaction in the ratio between cost of goods sold and operating revenue for firm i in quarter (t+h) to changes of my measure for firm's inflationary pressure, measured by GHR sentiment of inflation-relevant setences in the transcript, in quarter t-1. The positive and statistically significant coefficients show that higher inflationary pressure is associated with increasing cost of good sold at future quarters. This assures the validity of inflation sentiment calculated based on GHR dictionary as a measure for inflationary pressure of the firm. All regressions have firm fixed effects and industry × time fixed effects where industries are 4 digit NAICS codes. Plot A controls for the full set of firm's balance sheet information, and Plot B controls for both balance sheet and transcript-level control variables. Confidence intervals are constructed based on standard errors clustered at firm-level and time-level.

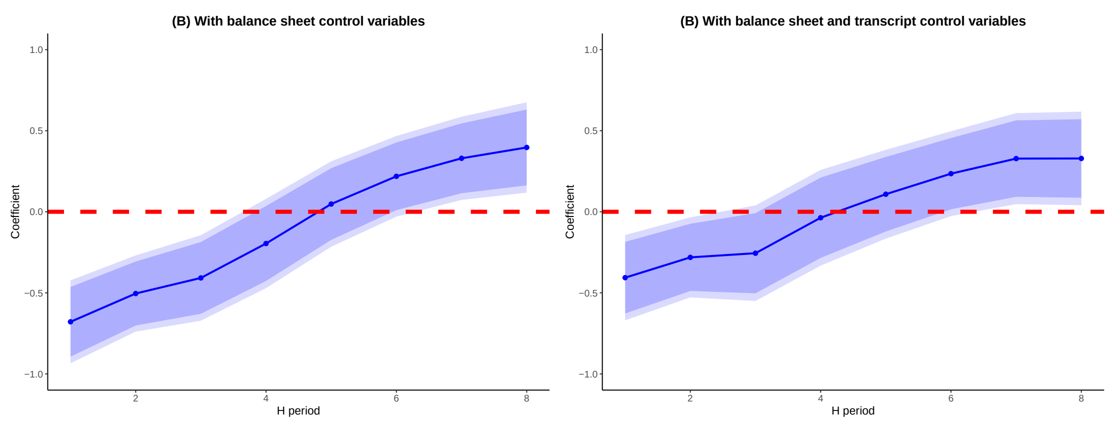

Figure 4: Firm's revenue and macroeconomic demand distress

This figures plots the estimated coefficients $\eta_{1,h}$ and their 95% confidence intervals from 8 separate regressions based on Equation 5 for each h in h=1,2,3,4,5,6,7,8. These coefficients show the reaction in the ratio between operating revenue and lagged book assets for firm i in quarter (t+h) to changes of demand distress,measured by the sentiment of macroeconomic demand related sentences in the transcript, in quarter t-1. The illustrated negative and statistically significant coefficients show that a higher demand distress is associated with decreasing revenue at the short-term future quarters. This assures the validity of demand sentiment calculated based on GHR dictionary as a measure for demand distress of the firm. All regressions have firm fixed effects and industry × time fixed effects where industries are 4 digit NAICS codes. Plot A controls for the full set of firm's balance sheet information, and Plot B controls for both balance sheet and transcript-level control variables. Confidence intervals are constructed based on standard errors clustered at firm-level and time-level.

NULL

Figure 5: Industry average inflationary pressure and demand distress

This figure plots the industries' average inflationary pressure (Plot A) and demand distress (Plot B) across different years. Values are time-demeaned to eliminate the effect of the economy-wide trends. Industries are sorted based on lowest sentiment from the top to bottom on the y-axis. Red signifies higher pressure (distress) while green signals lower pressure (distress). Due to large number of categories in 4 digit NAICS industries, I use IQ Group industries provided by Capital IQ.

Table 8: Main results: The impact of monetary policy on inflation expectations

	Dependent variable:				
	Stock returns on FOMC meeting day				
	(1)	(2)	(3)	(4)	(5)
Inflationary pressure : MP-J1	3.58***	3.94***	3.45***	4.33***	3.55***
	(1.24)	(1.35)	(1.03)	(1.29)	(1.03)
Inflationary pressure : MP-J2	0.77	1.30**	1.34**	1.27*	1.36**
	(0.57)	(0.63)	(0.64)	(0.65)	(0.63)
Inflationary pressure : MP-J3	2.31**	2.22*	2.41	2.73**	2.52*
	(1.12)	(1.13)	(1.46)	(1.22)	(1.45)
Inflationary pressure : MP-J4	−3.82	−4.64*	−4.87*	−4.97*	−4.82*
	(2.39)	(2.62)	(2.52)	(2.88)	(2.56)
Demand distress : MP-J1	1.59	2.24	4.45**	3.31*	4.41**
	(1.82)	(1.74)	(1.91)	(1.86)	(1.90)
Demand distress : MP-J2	1.41	2.17*	2.40**	1.89*	2.21**
	(1.14)	(1.18)	(1.05)	(1.01)	(1.00)
Demand distress : MP-J3	−0.49	−0.69	−0.71	−1.06	−0.83
	(1.64)	(1.66)	(1.57)	(1.65)	(1.57)
Demand distress : MP-J4	0.19	−0.63	−0.84	−0.37	−0.45
	(4.44)	(4.69)	(4.17)	(4.21)	(4.11)
Inflation sentence count : MP-J1			0.30		0.55
			(0.40)		(0.48)
Inflation sentence count : MP-J2			−0.001		−0.04
			(0.20)		(0.26)
Inflation sentence count : MP-J3			−0.09		0.16
			(0.51)		(0.65)
Inflation sentence count : MP-J4			0.08		−0.09
			(0.79)		(1.00)
Demand sentence count : MP-J1			−1.43***		−1.51***
			(0.48)		(0.52)
Demand sentence count : MP-J2			−0.15		−0.44*
			(0.21)		(0.25)
Demand sentence count : MP-J3			0.03		−0.17
			(0.42)		(0.53)
Demand sentence count : MP-J4			0.15		0.44
			(1.21)		(1.36)
Inflation uncertainty : MP-J1				−5.00	−10.06
				(8.63)	(10.20)
Inflation uncertainty : MP-J2				0.45	1.16
				(2.63)	(3.60)
Inflation uncertainty : MP-J3				−7.87	−9.75
				(8.21)	(10.91)
Inflation uncertainty : MP-J4				5.47	6.27
				(15.45)	(19.83)
Demand uncertainty : MP-J1				−14.54**	2.46
				(6.13)	(5.21)
Demand uncertainty : MP-J2				2.96	8.02**
				(3.31)	(3.77)
Demand uncertainty : MP-J3				4.17	5.70
				(6.93)	(8.89)
Demand uncertainty : MP-J4				−3.60	−8.23
				(14.99)	(14.29)
CoGS : MP-J1	−0.01**	−0.01*	−0.01**	−0.01*	−0.01*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
CoGS : MP-J2	−0.005*	−0.005	−0.005*	−0.005	−0.005*
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
CoGS : MP-J3	−0.01	−0.01	−0.01	−0.01	−0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
CoGS : MP-J4	0.02*	0.02*	0.02*	0.02*	0.02*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Transcript general controls		Yes	Yes	Yes	Yes
Industry.Time FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes	Yes
Observations	131,344	131,344	131,344	131,344	131,344
Adjusted R^2	0.34	0.34	0.34	0.34	0.34

This table reports the main results for the impact of the unanticipated changes in monetary policy on the stock prices of firms with different levels of inflation pressure and macro-demand distress. All regressions are based on Equation 6. All regressions include firm fixed effects, *4-digit NAICS* × *time fixed effects*, and full set of firm-level balance sheet control variables. Variable definitions are provided on Table 1. MP-J1 to MP-J4 are monetary policy shocks provided by Jarociński (2024) where MP-J1 represents standard monetary policy shocks, MP-J2 represents forward guidance shocks, MP-J3 represents asset purchase shocks, and MP-J4 represents central bank information shocks. Regressions include 99 FOMC meetings between April 2012 and September 2024. All firm-level and transcript-level independent variables are lagged by 1 quarter to account for endogeneity. The balance sheet variables are winsorized at 1

Table 9: Monetary policy and inflation expectations in different regimes

	Dependent variable:						
	$\Gamma_{1,t}$ coefficients from Eq. 8						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MP-J1	2.42^{***}	0.57					0.72
	(0.77)	(1.28)					(1.23)
MP-J2	1.70^{***}	2.57^{**}					1.29^{***}
	(0.54)	(1.07)					(0.49)
MP-J3	2.33^{*}	2.10					
	(1.34)	(1.53)					
MP-J4	−3.77	−4.02					
	(2.59)	(4.01)					
MP-J1 : high inflation regime		3.16^{**}					2.84^{*}
		(1.55)					(1.55)
MP-J2 : high inflation regime		−1.35					
		(1.20)					
MP-J3 : high inflation regime		−0.33					
		(3.83)					
MP-J4 : high inflation regime		0.21					
		(4.99)					
MP-GSS-TARGET			2.94^{**}	1.84			
			(1.37)	(1.75)			
MP-GSS-PATH			0.86^{***}	1.27^{***}			
			(0.27)	(0.49)			
MP-GSS-TARGET : high inflation regime				2.27			
				(2.74)			
MP-GSS-PATH : high inflation regime				−0.59			
				(0.56)			
MP-JK Pure					2.53^{***}	3.57^{***}	
					(0.71)	(1.20)	
MP-JK CBI					−0.53	−0.46	
					(1.42)	(2.18)	
MP-JK Pure : high inflation regime						−1.71	
						(1.43)	
MP-JK CBI : high inflation regime						0.56	
						(2.89)	
MP-J2 : low inflation regime							1.76^{*}
							(1.06)
low inflation regime							
high inflation regime		−1.75		−0.55		−3.62	−0.05
		(5.14)		(4.96)		(5.12)	(5.07)
Observations	99	99	96	96	99	99	99
Adjusted R^2	0.10	0.08	0.05	0.04	0.11	0.10	0.09

This table presents the relationship between monetary policy shocks and stock returns of inflationary pressured firms on event days. Regressions 1, 3, and 5 are based on Equation 9 using MP-J, MP-GSS, and MP-JK shocks respectively. These results show that monetary policy impacts the stock market inflation expectations. Regressions 2, 4, and 6 are based on Equation 10 using MP-J, MP-GSS, and MP-JK shocks respectively, while allowing for a second regime; High inflation regime, introduced as a dummy variable, which represents periods where 2-year inflation expectations were above 2%. These results show that conventional policy rate changes are more effective when inflation expectations are high, while forward guidance is more effective when inflation expectations are low. These results are further confirmed by Regression 7, which focuses on MP-J1 and MP-J2 based on Equation 11, and introduces a low inflation regime for periods with 2-year inflation expectations below 2%. The results for Regression 7 further clarifies the findings from Regression 2 that forward guidance is more effective when inflation expectations are well anchored, or falling below the target, and conventional rate cuts are only effective when inflation expectations are above target. The study period covers 99 FOMC meetings between 2012 and 2024 for MP-J and MP-JK and 96 for MP-GSS shocks. Dependent variable is $\Gamma_{1,t}$ from Equation 8. Robust (HC1) standard errors are used. $*, **, and ***$ indicate significance on 0.1, 0.05, and 0.01.

[1] 0.009483256 [1] 0.01459784 [1] 0.008416997 [1] 0.002233659 [1] -0.0115924

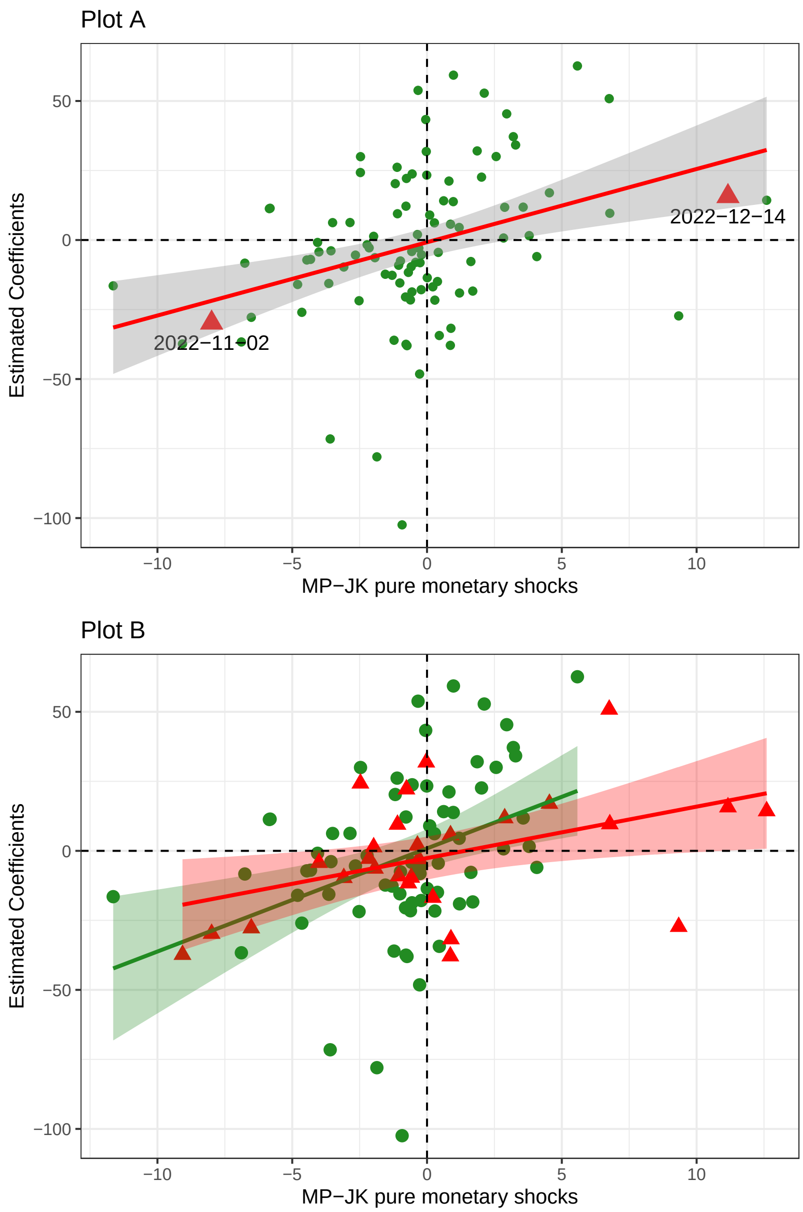

Figure 6: MP-JK pure monetary policy shocks and stock returns of firms under inflationary pressure

Both plots in this figure show the MP-JK pure monetary shocks on the X axis and estimated $\Gamma_{1,t}$ coefficients from Equation 8 on Y axis. Plot (A) shows a linear regression line following Equation 9 with a slope Λ and shaded 95% prediction interval. This plot shows contractionary monetary shocks are associated with a positive stock price reaction by inflationary pressured firms.

Plot (B) categorizes each event point to either a 'High inflation expectation' period where 2-year inflation expectations were above 2% or 'Low inflation expectation' period with expectations below 2% target. This plot demonstrates regression line following Equation 9 for each category. The slope of the green regression line that depicts low inflation expectation environment is larger than the red line that depicts high inflation expectations environment, suggesting a higher effectiveness of monetary policy in controlling expectations when expectations are well-anchored.

Table 10: The price puzzle: Macro-level evidence

	Dependent variable:					
	S&P 500 index					
	(1)	(2)	(3)	(4)	(5)	(6)
MP-JK	-4.20^{***}	-8.40^{***}				
	(0.69)	(1.91)				
MP-JK : Π_{t-1}^{exp}		1.40^{**}				
		(0.60)				
MP-JK Pure			-5.04^{***}	-12.61^{***}		
			(0.76)	(2.32)		
MP-JK Pure : Π_{t-1}^{exp}				2.53^{***}		
				(0.70)		
MP-JK CBI			8.12^{***}	18.64^{***}		
			(1.18)	(3.83)		
MP-JK CBI : Π_{t-1}^{exp}				-4.09^{***}		
				(1.18)		
MP-J1					-0.02^{**}	-0.06^{***}
					(0.01)	(0.02)
MP-J1 : Π_{t-1}^{exp}						0.01^{*}
						(0.01)
MP-J2					-0.06^{***}	-0.08^{***}
					(0.005)	(0.02)
MP-J2 : Π_{t-1}^{exp}						0.01^{*}
						(0.01)
MP-J3					-0.06^{***}	-0.07^{***}
					(0.01)	(0.02)
MP-J3 : Π_{t-1}^{exp}						0.002
						(0.01)
MP-J4					0.13^{**}	0.32
					(0.05)	(0.20)
MP-J4 : Π_{t-1}^{exp}						−0.07
						(0.10)
Π_{t-1}^{exp}		-0.06^{***}		-0.05^{***}		0.02
		(0.02)		(0.02)		(0.02)
Observations	345	345	345	345	345	345
Adjusted R^2	0.25	0.27	0.40	0.46	0.46	0.47

This table reports the high frequency macro-level results for the role of monetary policy's impact on inflationary expectations in explaining the price puzzle. The regressions are time series with a model specification based on Equation 13 and cover 345 scheduled monetary policy announcements between January 1991 and September 2024. The dependent variable is return on the S&P index in a 30-minute narrow window around the policy announcement. MP-JK are monetary policy shocks provided by Jarociński, Karadi (2020) and MP-J are shocks provided by Jarociński (2024), and Π_{t-1}^{exp} denotes 5-year inflation expectations from FRED which are lagged to the month prior to the announcement. Standard errors are robust HC3. $*, **, and ***$ indicate significance on 0.1, 0.05, and 0.01.

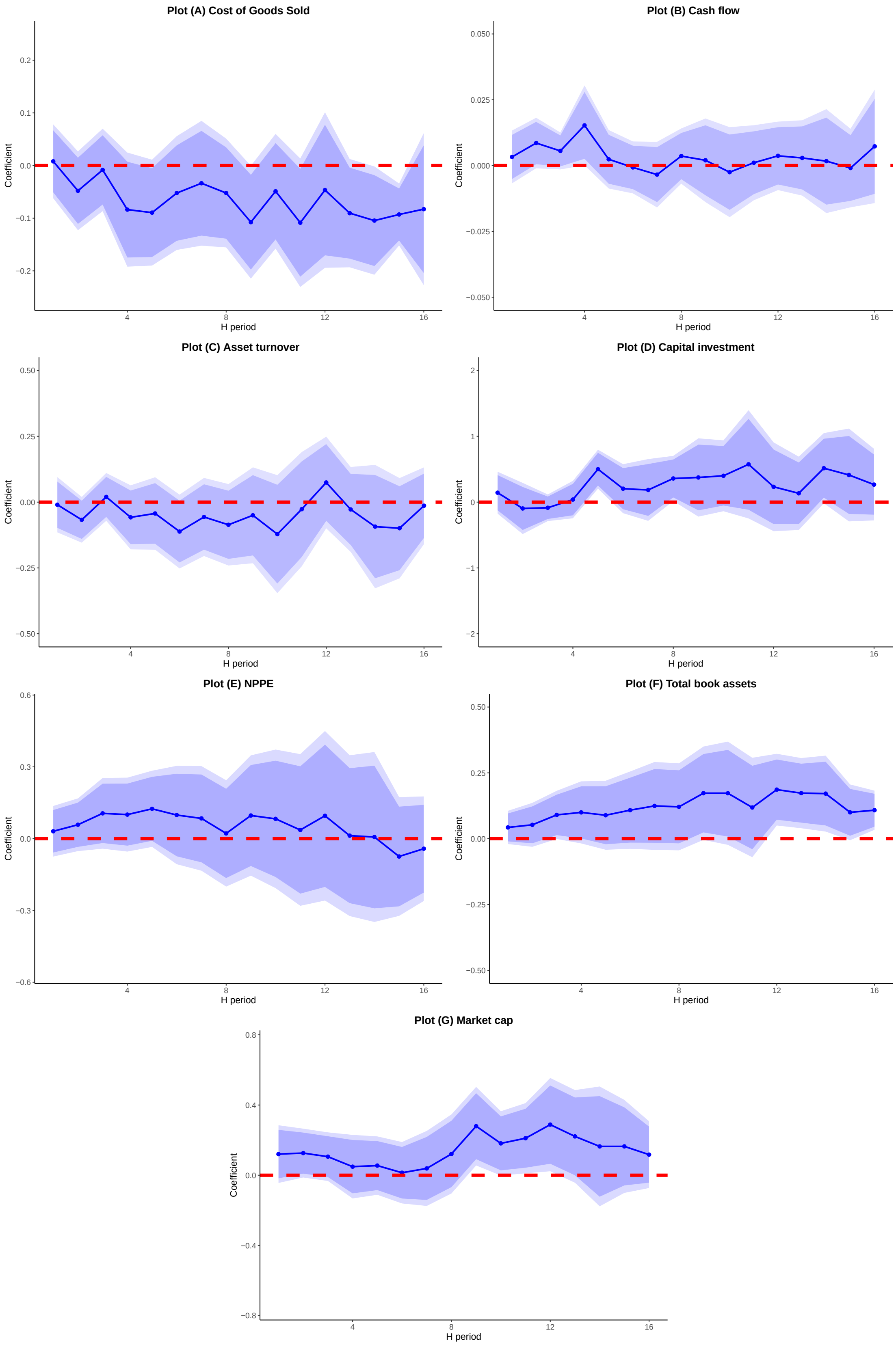

Figure 7: Monetary policy's impact on firm-level real outcomes for inflationary pressured firms

10 Robustness tests

Table 11: Robustness test: Alternative measure of monetary policy

	Dependent variable:				
	Stock returns on FOMC meeting day				
	(1)	(2)	(3)	(4)	(5)
MP-Target : Inflation pressure	4.33^{**}	4.27^{*}	4.08^{**}	5.55^{***}	4.42^{***}
	(1.77)	(2.18)	(1.57)	(2.03)	(1.57)
MP-Path : Inflation pressure	0.50	0.73^{**}	0.77^{**}	0.76^{**}	0.79^{**}
	(0.32)	(0.36)	(0.36)	(0.36)	(0.35)
MP-Target : Demand distress	2.92	2.96	5.91^{**}	4.20	5.74^{**}
	(3.12)	(3.07)	(2.53)	(2.83)	(2.55)
MP-Path : Demand distress	0.80	1.13^{*}	1.34^{**}	1.01^{*}	1.22^{**}
	(0.58)	(0.63)	(0.55)	(0.55)	(0.53)
MP-Target : Inflation sentence count			0.21		0.90
			(0.63)		(0.81)
MP-Path : Inflation sentence count			−0.003		0.01
			(0.11)		(0.14)
MP-Target : Demand sentence count			-1.80^{**}		-2.04^{***}
			(0.69)		(0.68)
MP-Path : Demand sentence count			−0.13		-0.30^{**}
			(0.11)		(0.12)
MP-Target : Inflation uncertainty				-18.12^{**}	-27.10^{**}
				(9.08)	(12.46)
MP-Path : Inflation uncertainty				−0.51	−0.39
				(1.26)	(2.02)
MP-Target : Demand uncertainty				−14.88	6.97
				(11.42)	(10.56)
MP-Path : Demand uncertainty				1.31	4.59^{**}
				(1.94)	(2.16)
MP-Target : Sentiment-LM		0.19	0.18	0.20	0.19
		(0.53)	(0.55)	(0.53)	(0.55)
MP-Path : Sentiment-LM		−0.08	−0.08	−0.08	−0.08
		(0.12)	(0.12)	(0.12)	(0.12)
MP-Target : Uncertainty-LM		−0.27	−0.32	0.36	0.09
		(1.03)	(1.05)	(1.03)	(1.15)
MP-Path : Uncertainty-LM		−0.26	−0.27	−0.29	−0.37
		(0.20)	(0.20)	(0.21)	(0.22)
MP-Target : Sentiment-GHR		−0.06	−0.01	−0.01	0.0002
		(0.21)	(0.21)	(0.20)	(0.21)
MP-Path : Sentiment-GHR		0.08^{*}	0.08^{*}	0.07	0.08^{*}
		(0.04)	(0.04)	(0.04)	(0.04)
MP-Target : COGS	-0.02^{**}	-0.02^{**}	-0.02^{**}	-0.02^{**}	-0.02^{**}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
MP-Path : COGS	-0.003^{**}	-0.003^{**}	-0.003^{**}	-0.003^{**}	-0.003^{**}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Industry.Time FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes	Yes
Observations	126,712	126,712	126,712	126,712	126,712
Adjusted R^2	0.34	0.34	0.34	0.34	0.34

This table replicates the main results of this paper as reported on Table 8 using alternative measures for monetary policy shocks. It uses monetary policy shocks provided by Gürkaynak, Sack, and Swanson (2005) where MP-Target captures changes to current policy rates and MP-Path captures revisions to policy expectations with maturity up to a year. Regressions include 96 FOMC meetings between April 2012 and May 2024. Variable definitions are provided on Table 1. All regressions are based on Equation 6. All regressions include firm fixed effects, *4-digit NAICS × time fixed effects*, and full set of firm-level balance sheet control variables. All firm-level and transcript-level independent variables are lagged by 1 quarter to account for endogeneity. The balance sheet variables are winsorized at 1

Table 12: Robustness test: Pure monetary policy shocks and central bank information

	Dependent variable:				
	Stock returns on FOMC meeting day				
	(1)	(2)	(3)	(4)	(5)
MP-JK-PM : Inflation pressure	1.31	1.85^{*}	1.99^{**}	1.91^{*}	2.01^{**}
	(0.91)	(0.94)	(0.92)	(0.96)	(0.91)
MP-JK-CBI : Inflation pressure	−0.46	−0.88	−0.69	−0.84	−0.70
	(1.73)	(1.81)	(1.74)	(1.83)	(1.73)
MP-JK-PM : Demand distress	2.11	2.90^{*}	3.39^{**}	2.60^{*}	3.10^{**}
	(1.35)	(1.52)	(1.43)	(1.34)	(1.36)
MP-JK-CBI : Demand distress	2.36	2.24	3.10	2.52	3.08
	(2.39)	(2.50)	(2.40)	(2.34)	(2.37)
MP-JK-PM : Inflation sentence count			−0.03		−0.02
			(0.23)		(0.30)
MP-JK-CBI : Inflation sentence count			−0.04		−0.06
			(0.49)		(0.61)
MP-JK-PM : Demand sentence count			−0.33		-0.77^{***}
			(0.24)		(0.27)
MP-JK-CBI : Demand sentence count			−0.57		−0.77
			(0.79)		(0.88)
MP-JK-PM : Inflation uncertainty				−0.86	−0.10
				(3.28)	(4.83)
MP-JK-CBI : Inflation uncertainty				−0.30	1.00
				(8.97)	(11.62)
MP-JK-PM : Demand uncertainty				3.67	12.31^{**}
				(4.44)	(5.12)
MP-JK-CBI : Demand uncertainty				−3.00	5.89
				(10.01)	(9.41)
MP-JK-PM : Sentiment-LM		−0.08	−0.08	−0.08	−0.08
		(0.24)	(0.25)	(0.24)	(0.25)
MP-JK-CBI : Sentiment-LM		0.78^{*}	0.80^{*}	0.79^{*}	0.80^{*}
		(0.47)	(0.47)	(0.47)	(0.47)
MP-JK-PM : Uncertainty-LM		−0.59	−0.60	−0.64	−0.86
		(0.49)	(0.49)	(0.52)	(0.55)
MP-JK-CBI : Uncertainty-LM		−1.03	−1.05	−0.99	−1.20
		(0.87)	(0.88)	(0.89)	(0.99)
MP-JK-PM : Sentiment-GHR		0.16^{*}	0.17^{**}	0.16^{*}	0.16^{*}
		(0.09)	(0.08)	(0.09)	(0.09)
MP-JK-CBI : Sentiment-GHR		−0.25	−0.24	−0.25	−0.25
		(0.16)	(0.16)	(0.16)	(0.16)
MP-JK-PM : COGS	-0.01^{**}	-0.01^{**}	-0.01^{**}	-0.01^{*}	-0.01^{*}
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
MP-JK-CBI : COGS	0.01	0.01	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Industry.Time FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes	Yes
Observations	131,344	131,344	131,344	131,344	131,344
Adjusted R^2	0.34	0.34	0.34	0.34	0.34

This table replicates the main results of this paper as reported on Table 8 using alternative measures for monetary policy shocks. Specifically, it tests the results against central bank information effects. It uses monetary policy shocks provided by Jarociński and Karadi (2020) where MP-JK-PM captures pure monetary policy shocks and MP-JK-CBI captures central bank information effects. Regressions include 99 FOMC meetings between April 2012 and September 2024. Variable definitions are provided on Table 1. All regressions are based on Equation 6. All regressions include firm fixed effects, *4-digit NAICS× time fixed effects*, and full set of firm-level balance sheet control variables. All firm-level and transcript-level independent variables are lagged by 1 quarter to account for endogeneity. The balance sheet variables are winsorized at 1

11 Appendix

11.1 Appendix A: Verification of the match between financial and transcript data

This appendix explains how I verify the match between earnings call transcripts from Discounting Cash Flow and financial data from S&P Market Intelligence. I merge transcripts with financial data using company tickers. Next, I ensure that the company name from S&P Market Intelligence [SP_COMPANY_NAME] is repeated in the operator's welcome message in the transcript. Earning calls are usually moderated by an operator who reads a welcome message at the beginning of the call, and the company's name is always repeated in this message.

There are two key challenges to this approach. The first challenge is the fact that the company name from S&P might not perfectly match the name repeated by the operator. For example, the company name "Rocky Mountain Chocolate Factory, Inc." could be simply referred to in the form of "Welcome to Rocky Mountain's earnings call!" during the operator's message. Moreover, S&P company names usually end with {inc., corp., corporation, company, incorporated, limited, and so on}. As a remedy, I remove the following words from the end of S&P company names {",", ".", " inc.", " inc "," ltd", ' plc', 'incorporated', 'limited', 'co.', 'corp', 'corp.', 'l.p.', 'llc'}. Next, I remove non-alphabetic characters and spaces. Then I remove 3 characters from the end of S&P company names with more than 10 characters, I remove 1 character from company names with 5 to 10 characters, and keep company names with less than 5 characters as is. I export this list and manually compare the company names keys that I created with their original S&P company name to 1) ensure that the adjusted name is representative of the original name, 2) the adjusted name is not generic, and 3) verify if adjusted names with less than 5 characters are unique enough. After these final adjustments, I verify if the created company name key exists in the first 2000 characters of the earnings call transcript (where the welcome message is usually situated). Before this verification, I also processed the earnings call transcript by removing non-alphabetic characters and spaces.

The second problem is the change in company names. An example is "Facebook" changing its name to "Meta" in 2021. Company names from S&P only report the latest company name without a time dimension. As a solution, I validate ticker matches for which the created company name keyword is present in at least one of the transcripts for that ticker. For Meta's case, the created company name key ("Meta") based on S&P company names would match the welcome message of transcripts that took place after 2021.

11.2 Appendix B: The distribution of inflation and demand distress and robustness of main results to changes in winsorization

Figure 8 depicts the distribution for inflation pressure and demand distress in this paper. Inflation pressure has a longer right tail. This is logical because discussions of inflation and rising input costs should be associated with a more negative sentiment. This negative sentiment creates the larger and longer right tail in my inflation pressure measure because I multiply GHR sentiment by a (-1) to create a pressure metric that increases as inflation pressure increases (or as inflation sentiment deteriorates). Similarly, demand-distress has a longer and a larger right tail, but to a lesser extent compared to inflation pressure.

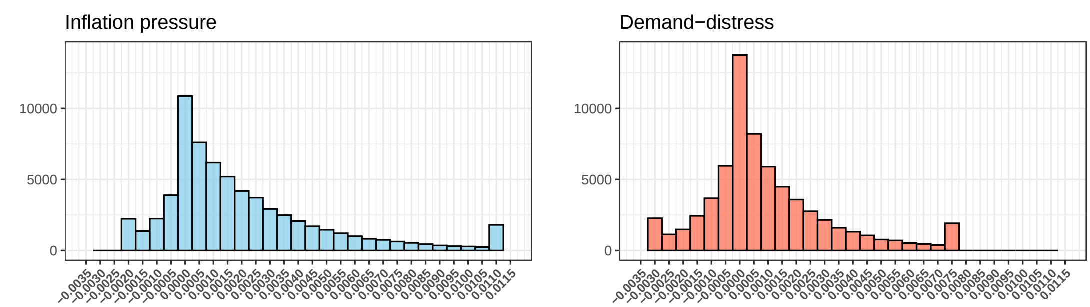

Figure 8: Distributions of inflation pressure and demand-distress based on GHR sentiment

Table 13: Robustness test: Change in winsorization of transcript level variables

	Dependent variable:				
	Stock returns on FOMC meeting day				
Panel A: Winsorizing transcript variables by 5%					
	(1)	(2)	(3)	(4)	(5)
Inflationary pressure : MP-J1	4.18***	4.55***	3.89***	5.00***	4.02***
	(1.37)	(1.50)	(1.20)	(1.45)	(1.22)
Inflationary pressure : MP-J2	1.10*	1.66**	1.77**	1.61**	1.78***
	(0.62)	(0.68)	(0.68)	(0.71)	(0.68)
Inflationary pressure : MP-J3	2.45**	2.34*	2.39	2.93**	2.52
	(1.23)	(1.24)	(1.60)	(1.35)	(1.59)
Inflationary pressure : MP-J4	−4.51*	−5.54*	−5.73**	−6.16**	−5.75**
	(2.60)	(2.85)	(2.77)	(3.01)	(2.79)
Demand distress : MP-J1	1.65	2.34	4.74**	3.55*	4.74**
	(1.99)	(1.92)	(2.21)	(2.11)	(2.20)
Demand distress : MP-J2	1.28	2.08	2.26*	1.77	2.06*
	(1.27)	(1.31)	(1.20)	(1.15)	(1.15)
Demand distress : MP-J3	−0.85	−1.07	−1.08	−1.49	−1.23
	(1.81)	(1.83)	(1.81)	(1.90)	(1.82)
Demand distress : MP-J4	0.06	−1.03	−1.72	−0.83	−1.23
	(4.78)	(5.05)	(4.62)	(4.62)	(4.55)
Demand sentence count : MP-J1			−1.51***		−1.55***
			(0.52)		(0.56)
Sentence count controls			Yes		Yes
Uncertainty controls				Yes	Yes
Transcript general controls		Yes	Yes	Yes	Yes
Industry.Time FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes	Yes
Observations	131,344	131,344	131,344	131,344	131,344
Adjusted R^2	0.34	0.34	0.34	0.34	0.34
Panel B: Winsorizing transcript variables by 10%					
	(1)	(2)	(3)	(4)	(5)
Inflationary pressure : MP-J1	5.07***	5.47***	4.53***	5.95***	4.68***
	(1.66)	(1.82)	(1.61)	(1.88)	(1.66)
Inflationary pressure : MP-J2	1.51**	2.04**	2.18***	1.93**	2.17***
	(0.72)	(0.80)	(0.81)	(0.84)	(0.81)
Inflationary pressure : MP-J3	2.95**	2.87*	2.95	3.64**	3.11
	(1.46)	(1.52)	(1.93)	(1.67)	(1.93)
Inflationary pressure : MP-J4	−5.62*	−6.93*	−7.04*	−7.88**	−7.18**
	(3.28)	(3.58)	(3.55)	(3.65)	(3.56)
Demand distress : MP-J1	2.11	2.88	5.84**	4.50*	5.91**
	(2.33)	(2.26)	(2.68)	(2.53)	(2.69)
Demand distress : MP-J2	1.23	2.04	2.14	1.65	1.93
	(1.49)	(1.51)	(1.44)	(1.33)	(1.38)
Demand distress : MP-J3	−1.93	−2.07	−2.41	−2.60	−2.56
	(2.25)	(2.30)	(2.32)	(2.41)	(2.35)
Demand distress : MP-J4	0.08	−1.47	−2.63	−0.97	−1.85
	(5.63)	(5.90)	(5.56)	(5.48)	(5.48)
Demand sentence count : MP-J1			−1.76***		−1.68***
			(0.58)		(0.59)
Sentence count controls			Yes		Yes
Uncertainty controls				Yes	Yes
Transcript general controls		Yes	Yes	Yes	Yes
Industry.Time FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes	Yes
Observations	131,344	131,344	131,344	131,344	131,344
Adjusted R^2	0.34	0.34	0.34	0.34	0.34

This table replicates the main results of this paper as presented on Table 8 while testing for the robustness of these results with winsorization of all transcript level variables, including the inflationary pressure and demand distress, by 5% in Panel A and by 10% in Panebl B. The model specification and regressions are the same as in Table 8.

11.3 Appendix C: The general processing of the transcripts and creation of general sentiment and uncertainty measures

This appendix details the text processing procedure for transcripts. First, I exclude the operator welcome messages. Then, the process continues by using spaCy model to exclude stopwords, entity names, tokens with none-alphabetic characters, and tokens with only one character. Then all remaining text is lower cased. Finally, all text is stemmed using Porter Stemmer. The number of words in these processed transcripts are taken as transcript size.

In the next step, for LM based sentiment measures, I correct for suffixes. For example, LM dictionary includes "bailout" and "breakdown" as a negative sentiment word. There are instances of "bail out" and "break down" in transcripts. I remove the space between these instances so LM sentiment accounts for them. Then, I account for negation. This is done by replacing the negative sentiment words with "good" and positive sentiment words with "bad" when these words occur after a negation. This negation accounts for double negation and also stops at punctuation or when conjunction is encountered. Next, I measure the general sentiment of the transcript using the LM dictionary.

For the GHR based general sentiment measure, I remove non-ASCII characters, tokenize the text, position tag each token, remove proper nouns (NNP, NNPS) and determiners (DT), remove single-character words, remove numbers, punctuation, and non-alphanumeric characters, and remove stopwords (except "no" and "not"). These steps are in line with the text processing implemented by García, Hu, and Rohrer (2023). Finally, I measure the general sentiment of the transcript using GHR dictionary.

11.4 Appendix D

This appendix explains the details for selection of transcripts for Word Embedding, creation of bigrams, and Word Embedding process. The complete transcript corpus is too large for a Word Embedding. Hence, I select a representative large sample. I start by counting the occurrences of "inflation" and "recession" per transcript. For inflation, I ensure that I am not counting occurrences of the "inflation reduction act". This count includes words that contain the terms "inflation" or "recession" within them, such as inflationary, hyperinflation, recessionary, and similar variants. Next, I only keep transcripts that mention inflation more than once and recession at least once. This is to reduce the number of transcripts in my Word Embedding corpus. Next, I create two ratios, one ratio is the ratio of occurrences of inflation to transcript size, and the second is the ratio of occurrences of recession to transcript size. Transcript size is equal to the number of words in each processed transcript where the processing procedure removes entity names, stop words and none-alphabetic characters, and welcome messages. Then for inflation, I select transcripts with inflation occurrence ratio above 80th percentile per quarter and per 4 digit NAICS industries. There can be combinations of quarter-year and 4 digit NAICS industries with less than 5 transcripts, yielding an empty set. As a remedy, I select transcripts with the highest inflation occurrence ratios for these cases. I conduct a similar procedure to select recession sample using recession occurrence ratio. This process yields 6208 unique transcripts for inflation's Word Embedding sample and 4271 unique transcripts for recession's.

In the next step, I create bigrams based on processed transcript texts. I process the text for these transcripts by removing entity names, stop words, and non-alphabetic characters. Then, the text is stemmed using the Porter Stemmer. Then, I create bigrams using Phraser from the gensim.models.phrases. This python function uses the ratio of co-occurrence of two unigrams to their separate occurrences in the corpus to determine whether two unigrams form a bigram. The formula is:

$$\text{score}(w_i, w_j) = \frac{\text{count}(w_i, w_j) - \delta}{\text{count}(w_i) \cdot \text{count}(w_j)} \cdot N \tag{14}$$

where w_i and w_j are two consecutive words, count(w_i) is the count of the occurrence of i, count(w_j) is the count of the occurrence of j, count(w_i, w_j) is the count of their co-occurrence, δ is the minimum co-occurrence required for count(w_i, w_j) to be taken into account, and N is the size of corpus. Using this formula, I can select two consecutive words with score(w_i, w_j) above a certain thresholds as bigrams.

A challenge in selecting the threshold is that the individual words within the targeted bigrams occur frequently on their own throughout the transcripts. For example, "increas cost" (in stemmed format) is an important synonym for inflation. However, "increas" and "cost" frequently occur as stand alone words or in combination with other words. I need to capture as much as bigrams as possible. Hence, I select a near-zero treshold for the formation of my bigrams. To ensure I capture all relevant bigrams, I create three separate corpuses with bigrams that are created based on 1) δ equal to 25 and threshold set at $10^{(-20)}$, 2) δ equal to 15 and threshold set at $10^{(-20)}$, and 3) δ equal to 25 and threshold set at $10^{(-15)}$.

Finally, I implement Word Embedding. Word embedding is a Natural Language Processing method that represents words as large numerical vectors in a continuous vector space, capturing semantic and syntactic relationships between words based on their contextual co-occurrence. I use Word2Vec from gensim.models with following specification (vector_size=300, window=15, min_count=25, workers=8, sg=1, seed = 50, epochs = 25, negative = 10, hs = 0). Using different a vector size, window, and min count does not significantly alter the resulting list of words. Next, I select the top 1000 words (bigrams) with highest similarity score to "inflate" for inflation and "recess" for recession.

To create my list of unigrams and bigrams that allow me to identify inflation related and macroeconomic related sentences, I review the resulting 1000 words per inflation and recession and manually select key unigrams and bigrams. After manual selection of most relevant unigrams and bigrams, I expand my list by using synonyms of bigrams (where necessary) and allowing for the reversal of the order of bigrams. As for the first method, I introduce synonyms where necessary. For example, "increas cost" is identified by the Word Embedding. I introduce synonyms of "increas" and create new bigrams, such as "surg cost", "elev cost", "soar cost", "escal cost", "spike cost", "climb cost" and so on. As for the second method, I reverse the order of bigrams and add them to my list. For example, "increas cost" can be "cost increas" and added to the list. This is done for the bigrams constructed based on synonyms.

After completing my bigrams, I order keywords in my inflation keywords and recession keywords into 3 categories. These categories are available on Table 2 and 3. The first category is unigrams and general terms that directly related to inflation or recession. For example, cog (as in CoGS which is short for Cost of Goods Sold), cpi (consumer price index), ppi (producer price index), and other keywords in this category are directly related to inflation. The second category is passive bigrams. These bigrams do not convey a direction of movement for prices or costs and they are neutral, such as "input cost", "raw materi", "suppli chain", and so on. The third and last category is active bigrams that convey a direction for "cost" and "wage". The word "Price" is not included in this category because prices alone can both point to input or output prices, and I only focus on input prices. In selection of sentences using active bigrams, I allow for a distance of 1 word between the two words in the list. For example, the processed sentence "cost significantli higher" is selected in this method because active bigrams (here "cost higher") can occur with a distance of one word between each other. A similar method is applied for "recession" to identify sentences discussing macroeconomic demand conditions and outlook, for which the unigrams and bigrams are reproted on Table 3.

After this selection process, there are still cases that systematically introduce noise into our measures of inflation pressure and demand distress. One common issue involves welcome messages and general statements typically made by operators at the start of earnings calls. These statements often inform listeners that the call includes forward-looking comments about inflation and the economic environment. To address this, I carefully examine these sentences and identify common patterns to exclude irrelevant cases. Specifically, I remove sentences that mention phrases like "forward looking statement," "analysts:", "operator:", or "During this call". Additionally, I exclude sentences containing combinations from specific lists. These include:

- {“presentation”, “call”, “recording”, “copy”, “release”} and {“website”, “webpage”, “.com”}
- {“results”, “factors”} and {“differs”, “differ”, “materially”}
- {“reconciliation”} and {“GAAP”}
- {“forward-looking”} and {“statement”}

Moreover, for both measures, I exclude sentences mentioning names of other countries, regions, continents, and foreign currencies (as well as terms like “foreign”, “currenc”, or “exchange rat”) unless they specifically mention the U.S. Sentences referring to foreign regions along with phrases like “outside of U.S.” are also excluded. Finally, I remove sentences shorter than three characters.

For the inflation pressure measure specifically, I further exclude sentences mentioning interest expenses. This involves excluding sentences containing one of the following terms: “interest expense,” “expense interest,” “interest expenditure,” “expenditure interest,” “interest pay,” “pay interest,” “interest cost,” “cost interest,” “debt expense,” “expense debt,” “debt cost,” “cost debt,” “borrow cost,” “cost borrow,” “loan cost,” and “cost loan.” Additionally, sentences mentioning inflation in the context of the Inflation Reduction Act are removed. For the demand distress measure specifically, I remove sentences containing terms commonly found in speaker titles: “Markets:”, “Markets,”, “Markets.”, “Market Development:”, “LLC”, “LLP”, “Inc.”, “Co.”, “Cor.”, “Research Division”, “Co,”, and “Capital Markets”.

11.5 Appendix E: Robustness test for the distance of active bigrams in selectin of relevant sentences

[To be added]

11.6 Appendix F: Failure of LM based distress measures in firm-level validation test

This appendix reports the second verification results for inflationary pressure and demand distress measures obtained from the LM dictionary. It uses the model specification from equations 1 and 2 and follows a similar approach as explained in Section 2.5 and shown in Figures 3 and 4. These results show that the LM-based measures provide no additional information on firms’ future CoGS or asset turnover when controlling for the complete set of firm-level financial variables and transcript-level variables.

This figures plots the estimated coefficients $\lambda_{1,h}$ and their 95% confidence intervals from 8 separate regressions based on equation 1 for each h in h=1,2,3,4,5,6,7,8. These coefficients show the reaction in the ratio between cost of goods sold and operating revenue for firm i in quarter (t+h) to changes of inflationary pressure, constructed using LM dictionary, in quarter t-1. All regressions have firm fixed effects and industry × time fixed effects where industries are 4 digit NAICS codes. Plot A controls for the full set of firm’s balance sheet information, and Plot B controls for both balance sheet and transcript-level control variables. Confidence intervals are constructed based on standard errors clustered at firm-level and time-level. The results show that the LM based inflationary pressure contains no additional information on firms’ future CoGS.

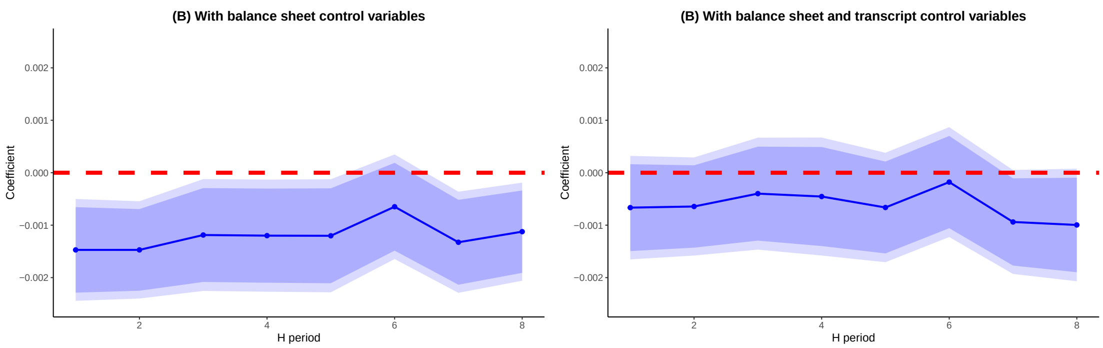

Figure 9: Firm's cost of goods sold and LM based inflationary pressure

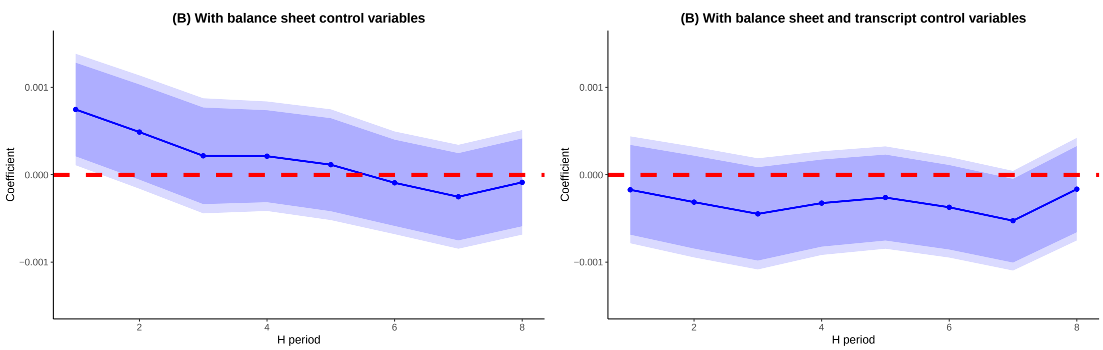

Figure 10: Firm's revenue and LM based demand distress

This figures plots the estimated coefficients $\eta_{1,h}$ and their 95% confidence intervals from 8 separate regressions based on equation 2 for each h in h=1,2,3,4,5,6,7,8. These coefficients show the reaction in the ratio between operating revenue and lagged book assets for firm i in quarter (t+h) to changes in LM based demand distress in quarter t-1. All regressions have firm fixed effects and industry × time fixed effects where industries are 4 digit NAICS codes. Plot A controls for the full set of firm's balance sheet information, and Plot B controls for both balance sheet and transcript-level control variables. Confidence intervals are constructed based on standard errors clustered at firm-level and time-level. The results show that the LM based demand distress contains no additional information on firms' future asset turnover.