Mining the gap:
Extracting firms' inflation expectations from earnings calls.

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Abstract

Using a novel approach involving natural language processing (NLP) algorithms, we construct a new cross-country index of firms' inflation expectations from earnings calls transcripts. Our index has a high correlation with existing survey-based measures of firms' inflation expectations, it is robust to external validation tests and is built using a new method that outperforms other NLP algorithms. In an application of our index to United States, we uncover relevant facts characterizing firm's inflation expectations and show that higher expected inflation translates into future inflation. Delving into the firm-level dimension of our index, we demonstrate deviations from the rational framework in firms' inflation expectations and show that firms' attention to the central bank enhances monetary policy effectiveness.

Keywords: Firms' inflation expectations, Natural Language processing, GPT3.5, Firms' earnings calls transcripts, Monetary policy
JEL Codes: D22, D84, E31, C00.

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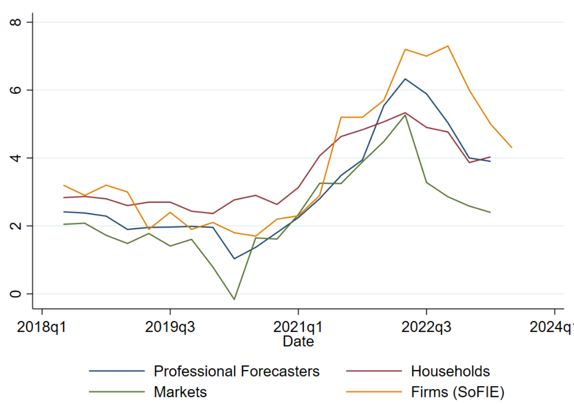
Introduction

In 2022, inflation reached decades-high levels and core inflation was more persistent than expected. In this context, there have been many discussions on the role that inflation expectations played in shaping inflation dynamics. More specifically, households and firms' inflation expectations are critical, since these economic agents are primary price and wage setters, and their consumption and investment decision partly reflect their expectations about future inflation. Households anticipating higher inflation may demand higher wages and firms may increase their prices in anticipation of future generalized price increases, thereby potentially intensifying inflationary pressures. Households' and firms' inflation expectations may differ from market participants' and professional forecasters' expectations since their information set is very likely to be more limited, and they may suffer from different biases (Reis and others (2020)). For instance, Figure 1 shows the recent pattern of cross-agent inflation expectations for the United States. Although they share a common pattern, they differ in terms of timing and magnitude. For instance, households' inflation expectations increased slightly in 2020Q2, while the other agents expected a drop in near-term inflation. Firms' expectations increased more than those of professional and market participants and started declining much later. Thus, discrepancies in terms of turning points and magnitudes can shape current inflation and the real economy differently from what policymakers might forecast only based on the largely available professional forecasters' inflation expectations.[1]

Figure 1: Different agents' inflation expectations



Notes: The figure shows US professional forecasters, market-based, SoFIE survey-based firms and households' 12-month ahead inflation expectations.
Source: Bloomberg, Haver Analytics, Cleveland Fed and authors' calculation.

While there is a wide availability of household surveys, there is much less information on firms' inflation expectations (Candia, Coibion, and Gorodnichenko (2023)). That scarcity of information limits the analysis of how firms' inflation expectations impact inflation dynamics and how monetary policy could influence it. The COVID-19 pandemic prompted a new effort by central banks to collect firms' inflation expectations, but surveys remain costly, time-consuming to implement, and with limited firm coverage.

[1]Market participants' expectations are generally extracted from swaps and index bonds. Since their availability is conditional on market demand and supply, discussing their availability and usefulness if out of the scope of this paper.

This paper addresses the scarcity of quantitative measures of inflation expectations among firms by leveraging text-mining and machine learning techniques applied to earnings calls transcripts. Firms' earnings calls provide real time information on firms' views on future inflation on a large geographical scale. In fact, these are quarterly calls between the management of a public company and its stakeholders to discuss the company's financial results and views on the company's outlook. We build on the recent literature that applies natural language processing algorithms on earnings calls transcripts (Hassan and others (2019), Hassan and others (2021a) and Hassan and others (2021b)), and construct an Earnings Calls-based Firm's Inflation Expectations (ECFIE) index to proxy firms inflation expectations based on the intensity of firms discussion about inflation.

After building the index, we show that our index has predictive power of future inflation and proceed with a series of validation exercises to make sure our index is properly capturing firms' inflation expectations. First and foremost, the ECFIE index is highly correlated with survey data on firm's inflation expectations. Given the more complete data availability, most of the analysis in the paper is conducted for the United States. However, some of the validation exercises are also extended for a larger sample of both advanced and emerging market countries.

Furthermore, we characterize the firm's inflation expectations formation process. Importantly, we document several violation of the full-information rational expectations (FIRE) assumption. By matching firms' inflation expectations with balance sheet data, we find that firm level growth sentiment and firm's characteristics, such as leverage, might influence firms' economy-wide inflation expectations and their perception of the effect of monetary policy on inflation. Among other findings, high sales growth firms are more optimistic about disinflation after a monetary policy shock. This result suggests that the inflation expectations channel might be impaired in a period of negative confidence shocks. Moreover, highly leveraged firms decrease their inflation expectations relatively less following a monetary policy shock, indicating that firms might extrapolate their own perceived inflation when formulating expectations for aggregate inflation. This result suggests that the inflation expectations channel of monetary policy could be weaker in economies with higher private debt.

Zooming into the inflation expectations channel of monetary policy, we further analyze the transmission conditional on the firm's attention to the central bank. For this purpose, we construct the Earnings Calls-based Attention to the Central Bank index. Using the same methodology as for the ECFIE index, earnings calls transcripts are especially suitable for constructing an attention index since the intensity of the discussion captures attention by construction. Results suggest that firms' attention to the central bank amplifies the impact of monetary policy shocks on inflation expectations by 10 percent. This result suggests that monetary policy effectiveness can be enhanced by strategies that improve agents' attention and understanding of the transmission mechanism of central bank actions. However, this amplification mechanism seems to fail in a period of high disagreement when the prediction power of all firms decreases and the forecasting error increases. This could hint towards shortcomings of the Central Bank's communication strategy during high uncertainty, uncovering some room for policy improvement.

The rest of this paper is organized as follows. Section I discusses existing firms' inflation expectations surveys, focusing on the case of the US and their shortcomings, and reviews the literature. Section II presents the data. Section III discusses the natural language processing methodology used to extract a firm's inflation from earnings calls transcripts. Section IV shows the properties of our new index and conducts some external validation tests. Sections V and VI present the empirical analysis of the expectation channel of monetary policy and the role of the firm's attention to the central bank.

Section VII concludes.

1 Comparing with existing surveys and related literature

1.1 Existing surveys of firms' inflation expectations

Firms' inflation expectations surveys are scarce (Coibion and others (2020)), and the available surveys remain time-consuming to implement and with limited time and firms' coverage. For the United States, three firms' inflation expectations surveys are available. The surveys are the Livingston Survey conducted by the Federal Reserve Bank of Philadelphia, the Business Inflation Expectations (BIE) conducted by the Federal Reserve Bank of Atlanta, and the Survey of Firms' Inflation Expectations (SoFIE) conducted by the Federal Reserve Bank of Cleveland. All three have limitations that our newly developed firms' expectations index addresses effectively.

As highlighted by Candia, Coibion, and Gorodnichenko (2021), for a firm survey to be valuable for research or policymaking purposes, it is essential that it meets certain criteria. The survey should be conducted at a high frequency, such as monthly or quarterly, enabling timely and relevant data collection. Unfortunately, some surveys are biannual, like the Livingston survey, or annual. Another critical factor is the sample size, which should be sufficiently large to yield reliable results. In this context, a desirable threshold would be an average of more than 350 responses. Appendix B.1 shows the number of US companies used to construct our inflation expectation index over time. Our sample consists of more than one thousand firms since 2002 and more than two thousand firms since 2004. Furthermore, a firm survey should comprehensively encompass a wide range of industries and firm sizes to ensure its representation of the overall economy. However, many surveys tend to focus on specific sectors or geographic areas, limiting their ability to accurately capture the broader distribution of firms. For example, BIE is a quarterly survey that only collects inflation expectations of the Sixth District firms. Our new firm inflation expectation index encompasses 96.3% of the US market capitalization.[2] Also, it is crucial that the survey does not influence or "prime" the answers in specific directions. This means that the formulation of questions and the information provided to the firms should not bias or steer the responses. Although SoFIE possesses all the desired features mentioned earlier, it has a drawback regarding limited time coverage. The limited time coverage can pose challenges for researchers and policymakers. In contrast, our index addresses this limitation as it started in 2002, solving the time coverage problem.

Other countries' policymakers have recognized the importance of understanding the agents' expectations process and conduct regular surveys (for instance, the Bank of England's Decision Maker Panel, the Bank of Italy's Survey on Inflation and Growth Expectations, among others). However, the number of central banks is relatively small[3] and most of the surveys suffer form the same limitations mentioned above.

In addition, unlike traditional firm surveys, which might present varying questions related to expectations, leading to difficulties in direct comparisons,[4] our index overcomes this issue through a

[2] In the case of other countries, the ECFIE index is based on a smaller number of firms, but with an acceptable market capitalization threshold. Moreover, in countries where most of the firms are non-listed small-medium enterprises, like Italy, the ECFIE index has a very high correlation with survey-based firms' inflation expectations as presented in Appendix A.1.

[3] See Candia, Coibion, and Gorodnichenko (2023) for a comprehensive review of cross-country firms' surveys available.

[4] As shown in Armantier and others (2013) differences in the wording of questions matter.

consistent methodology for extracting firms' inflation expectations across time and countries. Our method is easy to implement and allows the generation of an aggregate index and the ability to analyze sector and firm level data. This advantage stems from the fact that earnings calls transcripts are publicly available. Therefore, anyone with access to the transcripts can replicate our approach. This is particularly valuable because existing survey microdata are often confidential and not accessible to the public. Moreover, our index facilitates the alignment of firms' inflation expectations with their balance sheets via Compustat data. This aspect is crucial as it significantly expands the scope of analysis and enhances the depth of insights that can be gained from the data.

1.2 Related literature

This paper contributes to the growing literature applying language processing to extract data from text (Gentzkow, Kelly, and Taddy (2019)). Traditional sources of text utilized for data extraction include newspapers (Ferreira and others (2019), Baker, Davis, and Levy (2022) and Caldara and Iacoviello (2022)), central bank statements (Hansen and McMahon (2016) and Handlan (2020)), tweets (Baker and others (2021)) and earnings calls transcripts.

We follow recent papers that have leveraged companies' earnings calls transcripts to extract firm level data. For instance, researchers have used these transcripts to measure firm level offshore sale of output (Hoberg and Moon (2017)), political and non-political risk (Hassan and others (2019)), attention to monetary policy (Song and Stern (2020)), exposure to epidemic diseases (Hassan and others (2021a)), and tax policy expectations (Gallemore and others (2021)). The closest studies to ours are Konchitchki and Xie (2023), which applied human labeling to US firms' 10-K filings to measure inflation risk, and Chava and others (2022), which used text-based analysis on earnings calls transcripts to construct a measure on how firms are exposed to inflation. To the best of our knowledge, our study represents the first attempt to construct a cross-country and firm level inflation expectations index using advanced text mining techniques.

In the context of literature studying expectations, there has been a growing focus on exploring how agents develop their expectations and tests whether agents conform with the full-information rational expectations assumption (FIRE). Coibion and Gorodnichenko (2015) tested and rejected the FIRE hypothesis using professional forecasters' expectations. Weber, Gorodnichenko, and Coibion (2023) and Kamdar and others (2018) documented that households' expectations of unemployment and inflation are strongly positively correlated. Specifically about firms, Andrade and others (2022) found that firms' aggregate expectations respond to industry shocks that have no aggregate effects, violating FIRE. Song and Stern (2020) documents that the heterogeneity of firms paying more attention to macroeconomic variables results in asymmetric responses concerning market value and firm performance when faced with monetary policy changes. Our contribution is threefold. First, We show that firms' expectations do non perform according to the FIRE assumption, since firms' characteristics and sentiment impact how firms adjust their expectations after a monetary policy shock. In fact, firms extrapolate their own costs when formulating inflation expectations for the aggregate economy. Financially constrained firms, which are more exposed to an increase in interest rate since they rely more on external finance, increase their inflation expectations relatively more than unconstrained firms after a monetary policy shock. Firms with more positive "sentiment", expressed through the non-political sentiment indicator developed by Hassan and others (2019), tend to be relatively more optimistic about disinflation following a contractionary monetary policy shock. Additionally and differently from Song and Stern

(2020), we built a firm level attention to monetary policy index with a higher frequency. We use this index to show that the inflation expectations channel of monetary policy is larger in firms that pay more attention to monetary policy. This result suggests that more awareness and better information can improve monetary policy transmission, giving the central banks room to leverage this channel.

Finally, this paper also contributes to the literature on disagreement among economic agents and their role in monetary policy transmission. Several papers documented stylized facts from different sources, such as firms, professional forecasters, and households' disagreement on inflation expectations, and that disagreement shows substantial variation through time (e.g., Mankiw, Reis, and Wolfers (2003), Dovern, Fritsche, and Slacalek (2012) and Andrade and others (2016), Reis and others (2020)). Following studies showed that disagreement is a crucial element of macroeconomic dynamics. For example, Falck, Hoffmann, and Hürtgen (2021) and Esady (2022) empirically found that the transmission of monetary policy varies with the disagreement regime.[5] We contribute to this literature in several ways. First, we developed a new measure of firms' inflation expectation disagreement with our novel index. Second, using micro level data, we corroborate the results found in Falck, Hoffmann, and Hürtgen (2021) that when disagreement is high, monetary policy leads to a rise in inflation expectations. Third, when disagreement is high, monetary policy loses its additional effectiveness via the expectations channel, on firms paying more attention to the central bank relative to other firms. In other words, when uncertainty exists on the future inflation path, disagreement among agents increases, and firms' attention to the central bank is insufficient to guide their expectations. This suggests that, in periods of high disagreement, instead of just increasing interest rates, the central bank communication should focus on reducing disagreement to mitigate output losses from disinflation (see Esady (2022)).

2 Data

The index is developed in two stages. First, we collect from the S&P Capital IQ 13,407 US companies earnings calls transcripts released in 2022 to build our training sample. In the second step, the index is computed using more than 200,000 transcripts of publicly listed companies over 39 countries, of which 26 are advanced economies and 13 emerging markets[6]. Most of the firms held at least one earning call per quarter, which gives us approximately four observations per year at the firm level. The actual computation is done using NL Analytics.

Additional data used in the analysis consists of:

Firm Level balance sheet data: Since our firm inflation expectation index is constructed with publicly listed firms, we can merge our firm level index with the corresponding balance sheet data from quarterly Compustat. Including firm specific characteristics allows us to control for potential confounding factors that could influence the relationship between inflation expectations and the explanatory variables we are interested in. We control for total assets, sales growth, current assets as a share of total assets, employment, and leverage, consistently with previous literature.

[5]A broader body of research investigates the state-dependence effects of monetary shocks. For example, Tenreyro and Thwaites (2016) shows that monetary policy is less powerful in recessions. Eichenbaum, Rebelo, and Wong (2022) found that monetary policy efficacy depends on the distribution of savings from refinancing mortgages.

[6]The list of countries with more than 500 transcripts available are: Argentina, Australia, Austria, Belgium, Bermuda, Brazil, Canada, Chile, China, Colombia, Denmark, Finland, France, Germany, Greece, Hong Kong, India, Ireland, Israel, Italy, Japan, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Russia, Singapore, South Africa, South Korea, Spain, Sweden, Switzerland, Thailand, Turkey, United Kingdom, United States.

Firms Non-Political Sentiment: We use Hassan and others (2019) firm level non-political sentiment dataset to asses how firms' sentiments impact monetary policy transmission.

Monetary Policy Shocks: We adopt two measures of monetary policy shocks that rely on high frequency identification constructed by Gürkaynak, Sack, and Swanson (2005) and Nakamura and Steinsson (2018).[7] The shocks are measured as changes in the fed funds futures rate during a specific one-hour period surrounding FOMC announcements. Since this time window is narrow, any rate changes can be attributed to unanticipated shifts in monetary policy, as it is unlikely that other shocks occurred during this brief period. To merge the high-frequency shocks with our data, we convert them to a quarterly frequency through time aggregation following Ottonello and Winberry (2020). This process involves constructing a moving average of the raw shocks, where each shock is weighted by the number of days in the quarter after it occurs. This strategy allows us to weigh shocks by how long firms have had to react to them. In the main analysis, we use the monetary policy shock proposed by Gürkaynak, Sack, and Swanson (2005), and in the Appendix B.3, we use the shock proposed by Nakamura and Steinsson (2018) as a robustness test.

3 Building the index: Using natural language process methods to unveil firm's expectations

Earnings Calls-based Firm's Inflation Expectations Index (ECFIE). One of the main contributions of this paper is on methodology and relates to the emerging literature that uses natural language processing models for economic analysis. In the literature, a large number of papers have used the so-called "bag of words method". With some variations, this method first involves the construction of a list of keywords related to a topic of interest, "the dictionary". Then the method counts the frequency in which these words are used in the entire text.[8] More recently, some papers have employed deep learning sentence-level classification methods to improve on the traditional bag-of-words approach. These methods' main advantage is using sentence context to refine the indicators that would better reflect the topic of interest.. Among these methods, the deep learning models, like BERT (Devlin and others (2018)) and it's descendant Liu and others (2019)), have been widely used in sentiment analysis.

We built on these previous methodologies and extract a novel index of firm's inflation expectations proxied by firms' intensity of discussion about future inflation from earnings conference calls. The underpinning idea is that the more the managers talk about future inflation, the more they are concern about it, which is a sign of rising expected inflation. We use a novel approach to choose the words that make up our dictionary and extract our index (represented in Figure 2). In particular, the choice of words is guided by the interaction of the Generative Pre-trained Transformers (GPT) model and human judgment. This approach involves two main steps:

1. To build the training sample, we selected the top 100 transcripts with the highest frequency of two set of words "inflation" and "expectation" among all the 2022 earnings calls transcripts in the USA. Using these transcripts, we randomly selected 4000 sentences to be our training sample.

[7] The monetary policy shocks series were extended until 2022.Q3 by Acosta (2022) and can be found in the author's website.

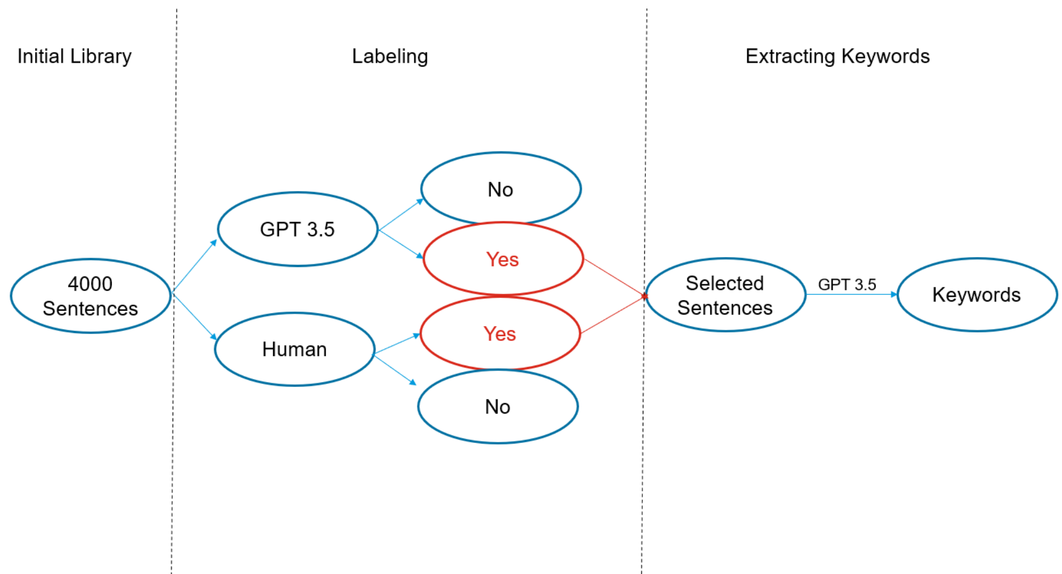
[8] Some papers count the frequency of the sentences in which these words appeared.

2. We used human judgment[9] to classify the sentences into the ones that were referring to inflation expectations or not. We then fed the GPT model with these same sentences and conducted a machine classification. If the human judgment and machine agreed that a sentence was referring to inflation expectations, we followed-up and asked GPT which words were key for this classification. The resulting list of words make up our dictionary that we feed to NL Analytics to build our ECFIE index.The index is calculated as the number of sentences with two set of words "inflation" and "expectation" in our dictionary divided by the total number of sentences in the transcript (the index is re-scaled for presentation purposes):

$$\text{ECFIE Index}_{it} = 1000 \times \frac{\sum \text{ Sentences with Inflation} \bigcap \text{ Expectations}_{it}}{\sum \text{Sentences}_{it}}$$

Finally, we processed the same method to all transcripts in the US and other countries and built a cross-country time series index.

Figure 2: Selecting the Keywords



Notes: This figure show steps to extract the inflation and expectations keywords to construct the ECFIE index.

We developed this method for word selection in an attempt to improve from a simple arbitrary human word selection. In fact, the data presented in Table 1 indicates that our method is far superior than our initial "naive" approach. Our method exhibits a much higher correlation with both the Livingston Survey, a proxy for inflation expectations, and CPI, with increases of approximately 0.09 and 0.14, respectively. This enhanced correlation also extends to the SoFIE indicator, where it is evident in both actual expectations and the disagreement among firm inflation expectations, as illustrated in more detail in Appendix A.

Earnings Calls-based Firm's Attention to the Central Bank Index (ECFACB). Using a similar methodology, we construct an index of firm level attention to the central bank. We adapt the methodology by Song and Stern (2020) to build an index identifying the intensity of firm's discussion about the central bank and monetary policy. We diverge from Song and Stern (2020) methodology in

[9]Two people classified these sentences and they had to agree on the common classification.

Table 1: The method to select the keywords matters

Correlations	ECFIE Index	Naive Search
Livingston Survey	0.8415	0.7545
CPI	0.8096	0.6707

Source: S&P Capital IQ, NL Analytic, Livingston Survey and authors' calculation.

three dimensions. First, we apply this index to firms' earnings calls in US at a quarterly frequency instead of US firms' 10-K filings at a yearly frequency. Second, we use an extended dictionary to better capture the attention to the Federal Reserve and monetary policy.[10]. Third, we use it at the sentence level instead of the word level.

$$\text{Attention to the FED Index}_{it} = 1000 \times \frac{\sum \text{ Sentences with Central Bank words}_{it}}{\sum \text{Sentences}_{it}}.$$

Thus, our attention index reflects the frequency of sentences discussing monetary policy in earnings calls transcripts, which provides firm level information on attention to the central bank.[11] In the sub-section 4, we discuss the validation of our attention index and in Section 6, we use it to study how attention to the central bank can change monetary policy effectiveness.

4 External validation tests of our indexes: firm's inflation expectations and attention to the central bank

For most of the validation exercises, we focus on the case of the US where more information is available. In the appendix, we extend some of these exercises to other countries.

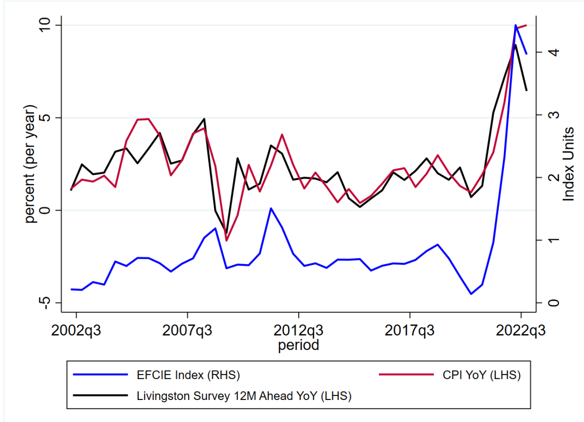
The first external validation exercise looks at the correlation of our index with aggregate inflation and existing survey-based measures of firm's inflation expectations. We use the Livingstone Survey (non-financial businesses) for inflation expectations. In Figure 3, we also plot the Consumer Price Index for All Urban Consumers (CPI-U) for inflation. Our ECFIE index is strongly correlated with these measures: 0.84 and 0.8 correlation with survey-based inflation expectations and inflation, respectively. The Appendix A.1 provides compelling evidence of the robustness of our index. It demonstrates strong positive correlations between our index and the firms' surveys for both advanced economies and emerging market economies.

Since our index does not have an obvious time dimension, we calculate the sample cross-correlation function (CCF) with the inflation expectations from the Livingston Survey at different horizons. Earnings calls are mostly targeted at discussing the near-term, so it is not surprising that the highest correlation of our indicator is with short-term inflation (see Table 3).

[10]The dictionary used to construct the index contains the following words: Fed, Fed Funds, monetary policy, central bank, FOMC, monetary policy, quantitative easing, quantitative tightening, monetary easing, monetary tightening, Federal Reserve.

[11]In the Section 4 We validate our index of firms' attention to the Federal Reserve by applying the same keywords in the Google Trends platform - which reflect searches by a larger portion of agents, not only firms. The correlation between both measures is 0.557, which suggests that we are reasonably capturing firms' attention to the central bank and monetary policy. Moreover, Figure 9 illustrates that the measures of attention are not perfectly collinear. These sorts of variations in the series highlight the differences in attention to the Central Bank between agents.

Figure 3: ECFIE index, firms' inflation expectations and inflation



Notes: The figure shows US firms' inflation expectations index according to the information content extracted from the earnings calls (LHS) and the Livingston Survey, as well as US headline CPI inflation (RHS). The firms inflation expectations index is calculated from a text analysis over 235,361 transcripts of US-based companies. It is based on the intensity of discussion of inflation expectations over the near term.
Source: S&P Capital IQ, NL Analytic, Livingston Survey, Haver Analytics and authors' calculation.

Table 2: Correlation of our indicator firms inflation expectations index with inflation measures

Correlations	Livingston Survey	CPI
ECFIE index	0.84	0.81
Livingston Survey	1	0.83

Source: S&P Capital IQ, NL Analytic, Livingston Survey, Haver Analytics and authors' calculation.

Table 3: Correlation between firm inflation expectations index and Livingston Survey for different horizon

Horizon	**Correl with Firms Index**
Next 1M (end of the period)	0.8296
Next 6M (end of the period)	0.8339
Next 12M (end of the period)	0.8250
Following 1Y (average)	0.8415
Next 10Y (average)	0.1383

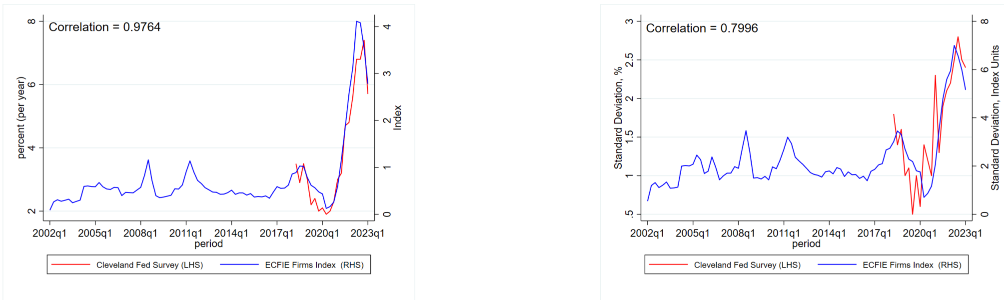
Notes: This table shows the correlation between the ECFIE index and different inflation expectations at different horizons sourced from the Livingston Survey.
Source: NL Analytic, Livingston Survey and authors' calculation.

When comparing our index with SoFIE in Figure 4, we observe an exceptionally high correlation between the two series ($\rho = 0.9764$). This correlation persists even when considering the disagreement in both expectation measures ($\rho = 0.7996$) since the survey's inception.

Our second validation exercise goes underneath the aggregate effects and uses sectors' heterogeneity. The idea is to use the forward looking behavior of stock market pricing - since they capture the next

Figure 4: Correlations between our novel firms' inflation expectation index and Cleveland Fed Survey

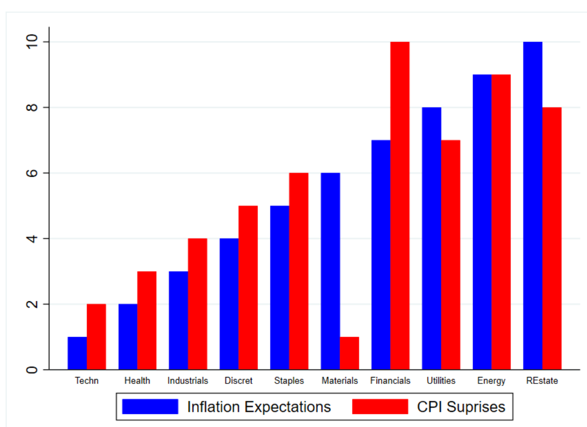
(a) Expectations **(b)** Disagreement



Notes: The figure shows our novel firms' inflation expectation index in blue (RHS) and the Cleveland Fed Survey in red (LHS) for the United States. Figure (a) show the expectations and expectations index. Figure (b) shows the disagreement in the firms' expectations and expectations index. The correlations are displayed at the figure's top left.
Source: S&P Capital IQ, NL Analytic, Cleveland Bank and authors' calculations.

present values of expected future dividends - to evaluate if our index is properly capturing inflation expectations. We first establish which sectors are more exposed to an inflation surprise by comparing sectoral returns after an inflation release. We then evaluate which sectors are most exposed to changes in our inflation expectation index. The validation exercise is to check that the sectors more exposed to inflation surprises are also the sectors more affected by changes in our index. The almost perfect relationship shown in Figure 5 suggests that the index is properly capturing the inflation outlook at the sectoral level.

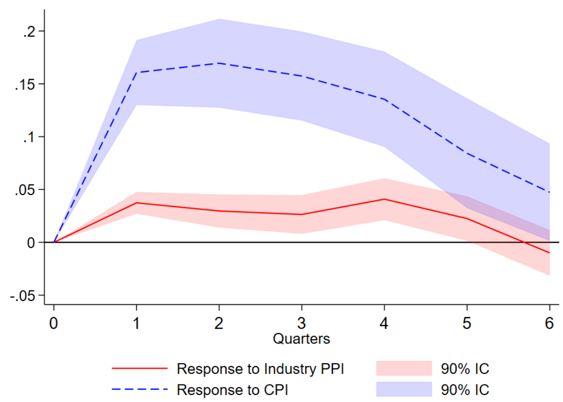
Figure 5: Sectors exposed to inflation surprises are also the ones affected by our inflation expectation index.



Notes: The figure shows the ranking of the sensitivity of stock returns by sector to the firms inflation expectations index (blue) and inflation surprises (red), for the US case.
Source: NL Analytic, Bloomberg, Haver Analytics and authors' calculation.

Our third validation exercise digs deeper at the firm level and is motivated by the work of Andrade and others (2022). They show that firms adjust their aggregate inflation expectation measure in reaction to industry-level shocks that have no aggregate effects[12]. If our indicator is indeed representing firm's expectations, then our indicator should also reflect this "irrational" behavior in response to industry shocks. We use a local projections specification that jointly estimates the dynamic response of our ECFIE indicator to variations in industry and aggregate conditions. The latter two are measured using aggregate inflation and industry inflation. Similar to Andrade and others (2022), in response to industry-level shocks that have no aggregate effects, firms' aggregate inflation expectations respond persistently (as seeing in the red line in Figure 6).

Figure 6: Our indicator of aggregate inflation expectations also responds to industry level conditions.



Notes: This figure show the Impulse Response Function (IRF) for US firms' inflation expectations index according to the information content extracted from the earnings calls on innovations in aggregate inflation (blue line) vs. changes in industry inflation (red line). The confidence interval are set at 90%. The horizontal axis shows the impulse-response horizon measured in quarter.
Source: NL Analytic, Haver Analytics and authors' calculation.

In our fourth validation test, we recompile 1 including the ECFIE index instead of the SoFIE in the comparison of inflation expectations across different agents. In Figure 7, we show how our new index compares with other sources of publicly available inflation expectations. All expectations indicators by agent-type are transformed into z-scores for comparability. The four agents' expectations measures captured a decrease during the financial crisis and an increase in 2021. However, there are some differences in intensity; for example, our firm index decreased considerably less than professional forecasters, market-based expectations in 2008, while it increased at the peak of 2022. There is no reason to assume that different agents would have exactly the same expectations, and these sorts of variations show that this index could potentially bring relevant information for policymakers when deciding monetary policy stance.

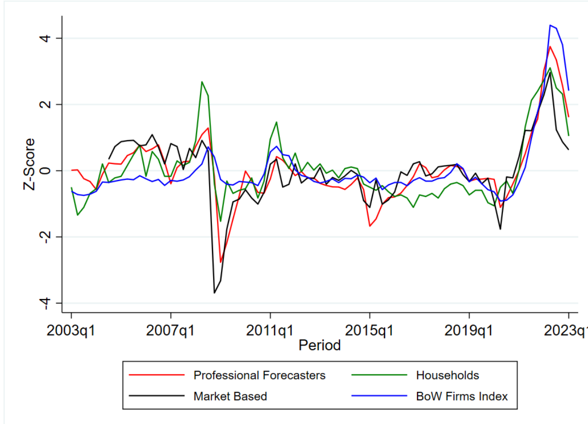
Finally, our index would only be valuable if it is able to predict future inflation.

Given the high correlation with the one-year ahead inflation, we assess the dynamic influence of our indicator to inflation using a local projection analysis. In particular, we estimate the following equation for each quarter ahead h:

$$\pi_{t+h} = \alpha^h + \beta^H \pi_t^e + \xi^H X_t + \epsilon_{t+h}, \tag{1}$$

[12] This is consistent with "island" models in which firms use the local prices they observe to make inferences about broader aggregate conditions.

Figure 7: There is a high correlation of our index with other sources of inflation expectations.

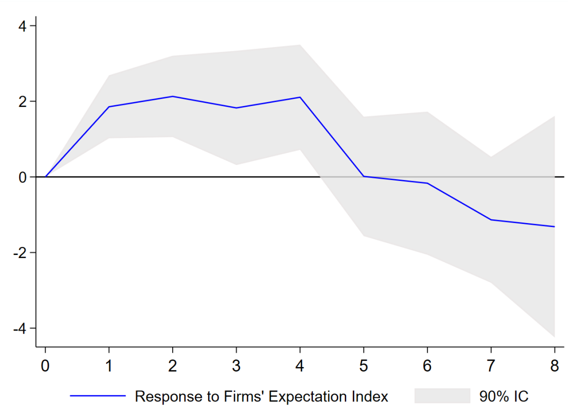


Notes: The figure shows the standard deviation from the mean of 2002.Q1 to 2023.Q1 of different agents.
Source: S&P Capital IQ, NL Analytic, Haver, and authors' calculations.

where the dependent variable is the year-on-year CPI inflation, π^e is our firm's inflation expectations index, X_t are controls and include four lags of CPI, GDP growth and unemployment rate.

The parameters of interest, β^H, are plotted in Figure 8. They show that an one-unit increase in our index of firms' inflation expectations is associated with an increase in two percent inflation in the US in the first four quarters. That is, higher expected inflation feeds into future inflation. In other words, our firm's indicator has predictive power for future inflation.

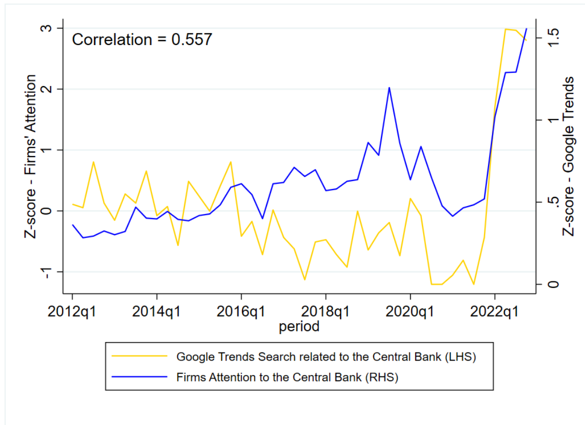
Figure 8: An increase in our index predicts future inflation.



Notes: This figure show the Impulse Response Function (IRF) for US headline inflation year-over-year after an one unit increase our in our firm inflation expectation index. The confidence interval are set at 90%. The reported standard errors are Newey-West standard errors. The horizontal axis shows the impulse-response horizon measured in quarter.
Source: NL Analytic, Haver Analytics and authors' calculation.

Turning to the ECFACB index, we use Google trends as validation. The attention to the central bank index is much simpler than the inflation expectations index since it measures how much firms are talking about the central bank, by construction. In this sense, there is no direct measure of validation such as to compare to an inflation outcome. However, we fed the Google Trends platform with the same keywords that we used to construct our attention to the central bank index as a form to validate our index. In principle, it is very likely that "the general public", represented by google searches, pays attention to the central bank at the same time that firms do. In fact, the correlation between both measures is 0.557, which suggests that we are correctly capturing attention to the central bank and monetary policy, but as Figure 9 illustrates, these measures of attention are not perfectly collinear.

Figure 9: Firms vs general public attention to central bank



Source: S&P Capital IQ, NL Analytic, Google Trends and authors' calculations.

5 Stylized facts of our index of inflation expectations

5.1 Expectations by firms' size and leverage

Moving on to firms' characteristics, Figure 10 displays the breakdown of the inflation expectations index based on firms' size and leverage. For this analysis, firms are categorized into percentiles, namely the 33rd percentile, the range between the 33rd and 67th percentiles, and the 67th to 100th percentiles.

The figure demonstrates insights regarding the relationship between firms' size and inflation expectations. Specifically, larger firms, as measured by their total assets, discuss more about inflation expectations than smaller firms. This could be indicating that large firms might have more capacity to discuss macroeconomic shocks. However, despite the level difference, there is a high correlation between the series, indicating that firms of different sizes agree about the change in inflation.

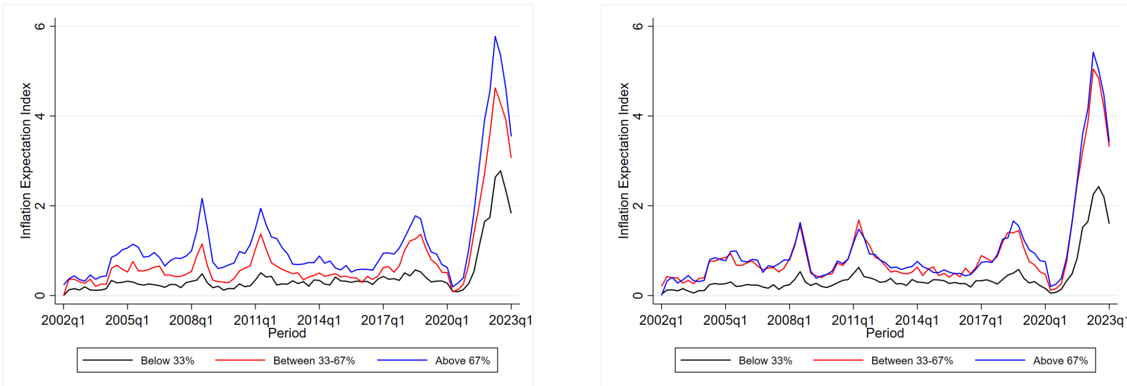
Moving to firms' leverage, we find that firms with higher leverage tend to discuss more about inflation expectations. This could just be suggesting that inflation outcomes are more important for firms with higher debt. Similarly, despite level differences, the series also features a high correlation.

5.2 Deviation from FIRE assumption

In the previous sections, we showed that our aggregated inflation expectations index has predictive power for future inflation and correlates well with other inflation expectations surveys and available disagreement measures. We also show that our index features other characteristics analyzed in studies of firm level inflation expectations. Given that this index features these properties, we can be more confident in using it to understand better the inflation expectations channel of monetary policy. With

Figure 10: Firms' characteristics and inflation expectations

(a) Size **(b)** Leverage



Notes: The evolution of the inflation expectation by (a) firms' size and (b) firms leverage. The black line shows the firms in the 33rd percentile, the red line show the firms in the range between the 33rd and 67th percentiles, and the blue line shows the firms above the 67th percentiles of the distribution by period.
Source: S&P Capital IQ, NL Analytic, Compustat and authors' calculations.

a better understanding of this channel, the central bank can better target communications to help the public understand the monetary policy stance and the economic outlook.

We show several deviations from the full-information rational expectations model. First, we show that inflation expectations depend on sector specific shocks. Narrowing to study the inflation expectations channel of monetary policy, we show that firms extrapolate their own costs when analyzing the impact of monetary policy and that more optimistic firms tend to believe that monetary policy is more effective.

Firms' sectoral conditions matter for aggregate inflation expectations

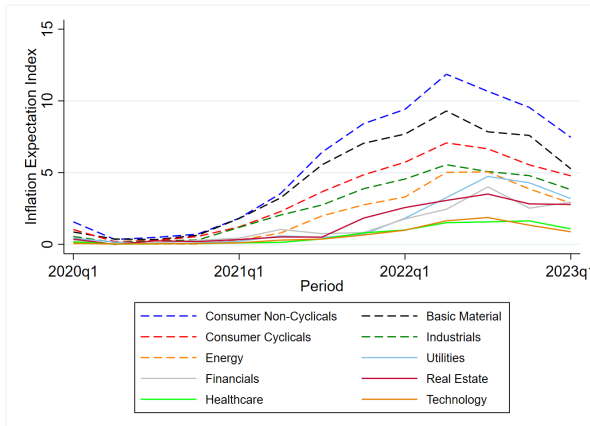
In this section, we provide a detailed analysis of inflation expectations, focusing on how they vary across different firms' characteristics. Specifically, we aim to compare and contrast inflation expectations among firms based on their sector of operation, size, and leverage. By examining these distinct dimensions, we can gain valuable insights into how various factors influence and shape firms' perceptions of future inflation.

Figure 11 provides a detailed breakdown of inflation expectations by sector of the recent inflationary episode that saw multi-decade highs in the middle of 2022.[13] The heterogeneity in inflation expectations across sectors is present in the magnitudes and the diverse behavioral patterns exhibited by different sectors, with the sectors' inflation expectations peaking at different times. We observe that sectors represented by dashed lines (Consumer Non-Cyclical, Consumer Cyclical, Basic Materials, Industrials and Energy) not only had higher inflation expectations during the specified period but also reached their peak expectations in 2022Q2. In contrast, the sectors characterized by solid lines (Utilities, Financials, Real Estate, Healthcare and Technology) had lower inflation expectations and experienced their peaks either in 2022Q3 or 2022Q4. When normalizing by the sector average and standard deviation in Figure B.4, the magnitude of the recent increase in inflation expectations was similar across sectors but the timing differ. It took a lot longer for the inflation expectations index to pick

[13] In the Appendix Figure B.3 replicates the same exercise for the entire sample from 2002.Q1 until 2023.Q1.

up and peak in sectors that usually don't pay attention to inflation, such as the health sector. This suggests heterogeneity in how firm's incorporate recent information. While this is not a casual evidence, it goes in line with the Andrade and others (2022) and our validation exercise in Section 4 that firms adjust their aggregate inflation expectation measure in reaction to industry-level shocks.

Figure 11: The evolution of the inflation expectation by economic sector



Notes: The figure shows the evolution of the inflation expectation by economic sector from 2020.Q1 until 2023.Q1
Source: S&P Capital IQ, NL Analytic, and authors' calculations.

Firms' characteristics affect the monetary policy transmission

Turning to the policy implications, our index of firm's expectations allows us to test for the expectation channel of monetary policy at the firm level. Since previous literature found that firms mostly disregard macro signals and act as islands (Andrade and others (2022)), those firms might ignore monetary policy shocks when exposure is low. The time and cross-section dimension provided by the match between firm's expectations and balance-sheet data allows us to improve our understanding of firms' inattention to monetary policy and can provide clues for better central bank communication (Candia, Coibion, and Gorodnichenko (2021), Bottone and Rosolia (2019)).

If firms formed expectations according to the standard full information rational expectations model, we would expect that they would have similar views about how monetary policy impacts inflation, regardless of their own outlook. If this assumption is not confirmed by the data, then we could learn more about how firms form inflation expectations after a monetary policy shock by looking at the micro level data.

Financial constraint and monetary policy effectiveness

Using household data, Kamdar and others (2018) and Weber, Gorodnichenko, and Coibion (2023) argue that households often seem to take a "supply-side" view of inflation as perceived inflation at the household level may be moved by idiosyncratic shocks (e.g., a respondent happens to buy something expensive and concludes that aggregate inflation is high). Using the same logic, we want to test if firms extrapolate from their own costs when forming inflation expectations for the economy. In particular, we look at the interaction of monetary policy and financial constraint measured by long-term debt maturing within one year. We estimate the equation below:

$$\pi^e_{j,t+h} = \alpha_j + \alpha_t + \delta^H_{t+h} FinancialConstraint_{j,t-1} \times MP_t + \beta_{t+h} X_{j,t-1} + \epsilon_{j,t} \tag{2}$$

we use the same set of controls for each firm j. The only difference in the specification here compared to

Equation 5 is the iteration term of monetary policy and $FinancialConstraint_j$. Similarly to Equation 5, firm's financial constraint is standardized at the sectoral level for each period. Therefore, a value of $FinancialConstraint_{j,t}$ equal one, means that the firm j one standard deviation more financially constrainted than the average firm in the sector period t. Note also that the introduction of time fixed effects controls for the average effect of monetary policy on inflation expectations.

Firms that have a higher proportion of long-term debt due within a year are more vulnerable to the impact of a monetary policy shock, given their heightened sensitivity to changes in interest rates, which affects their debt service costs. As shown in Figure 12, there appears to be a positive correlation between financial constraint and the response to monetary policy shocks, implying that firms might rely on their own perceived inflation, in this case, a relatively higher increase in debt service costs, when forming expectations for aggregate inflation.

In particular, we observe that firms facing higher financial constraints compared to their peers in the sector tend to increase their inflation expectations by approximately 0.15 units more, measured by our index. However, it's important to note that the average impact of a monetary policy shock results in a decrease of 0.4 units in the expectation index. Therefore, the total effect of the shock on a firm one standard deviation more financial constraint than the sector average right before the shock is weakened by 37%. These findings suggest that the inflation expectations channel of monetary policy might be notably weaker for firms with a larger portion of debt maturing within a year. The increased exposure to monetary policy shocks due to their financial position could potentially hinder the transmission of monetary policy through expectations for these firms.

Figure 12: Firms extrapolate their own costs when forming aggregate inflation expectations.

Notes: This figure show the dynamics of interaction coefficient between the financial constraint measure and monetary shocks over time on our US's firms' inflation expectation index. The confidence interval is set at 68% and 90%, respectively. The reported standard errors are two-way clustered by firms and time. The horizontal axis shows the impulse-response horizon measured in quarter.

Sentiment and monetary policy effectiveness

Similarly, Kamdar and others (2018) shows that sentiment is important for consumers' inflation expectations, with "optimistic" consumers expecting an expansion also predicting disinflation. This is not only an extrapolation of own idiosyncratic shocks, but also at odds with a negatively slopped Phillips Curve. Using the same logic for firms, we want to test if sentiment is an important factor when firms form inflation expectations for the economy. In particular, we look at the interaction between monetary policy and firms' sentiment related to non-political aspects developed by Hassan and others (2019) to estimate the equation below:

$$\pi^e_{j,t+h} = \alpha_j + \alpha_t + \delta^H_{t+h} NPSentiment_{j,t-1} \times MP_t + \beta_{t+h} X_{j,t-1} + \epsilon_{j,t} \quad (3)$$

where we once again use the same set of controls for each firm j. The only difference here with respect to Equation 5 is the iteration term of monetary policy and $NPSentiment_j$. We also standardized firm's sentiment at the sectoral level for each period. Therefore, a value of $NPSentiment_{j,t}$ equal one, means that the firm j one standard deviation more optimistic than the average firm in the sector at period t.

Similar to the literature result for households, Figure 13 suggests that sentiment is indeed important for inflation expectations formation. Firms with a more positive outlook than their sector are more responsive to the shock and decrease their inflation expectations by about 0.13 units which represents an amplification of the monetary policy shock equal to 33%. Our findings indicate that firms with a better outlook believe that monetary policy will be more effective in lowering inflation. In other words, those firms are more optimistic about disinflation after a monetary policy shock. This result suggests another source of possible non-linearity for the transmission of monetary policy shocks. The central bank might have a harder time in lowering inflation in periods the economy is hit by negative confidence shocks. This result aligns with Tenreyro and Thwaites (2016) findings that monetary policy shocks are less effective in recession than in expansions since recessionary periods are usually characterized by pessimism among agents.

Figure 13: Firms sentiment is important when forming aggregate inflation expectations.

Notes: This figure show the dynamics of interaction coefficient between the non-political sentiment measure and monetary shocks over time on our US's firms' inflation expectation index. The confidence interval is set at 68% and 90%, respectively. The reported standard errors are two-way clustered by firms and time. The horizontal axis shows the impulse-response horizon measured in quarter.

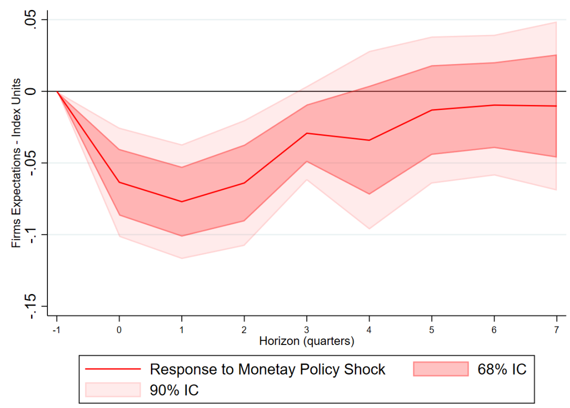
Size and monetary policy effectiveness

We also test if larger firms react more to monetary policy shocks. In particular, we look at the interaction between monetary policy and firms' total assets to estimate the equation below:

$$\pi^e_{j,t+h} = \alpha_j + \alpha_t + \delta^H_{t+h} Size_{j,t-1} \times MP_t + \beta_{t+h} X_{j,t-1} + \epsilon_{j,t} \tag{4}$$

where we once again use the same set of controls for each firm j. The only difference here with respect to Equation 5 is the iteration term of monetary policy and $Size_j$. We also standardized firm's size measured by total assets at the sectoral level for each period. Therefore, a value of $Size_{j,t}$ equal one, means that the firm j one standard deviation more assets than the average firm in the sector at period t.

Figure 14: Firms' size s plays a role in the transmission on monetary policy to inflation expectations.



Notes: This figure show the dynamics of interaction coefficient between the firm's size measured by total assets and monetary shocks over time on our US's firms' inflation expectation index. The confidence interval is set at 68% and 90%, respectively. The reported standard errors are two-way clustered by firms and time. The horizontal axis shows the impulse-response horizon measured in quarter.

Figure 14 suggests that larger firms decrease more their inflation expectations after an contractionary monetary policy shock by about 0.07 units which represents an amplification of the monetary policy shock equal to 17%. Even though we don't formally test this, a possible explanation for this is that large firms have more resources to devote attention to macroeconomic shocks and then can understand better how monetary policy gets transmitted to the economy.

6 Attention and monetary policy effectiveness

Attention to central bank policies is likely to be associated with better knowledge of monetary policy objectives and transmission, potentially enhancing the inflation expectations channel of monetary policy. This subsection tests this hypothesis with a novel central bank attention index.

6.1 Features of the attention index

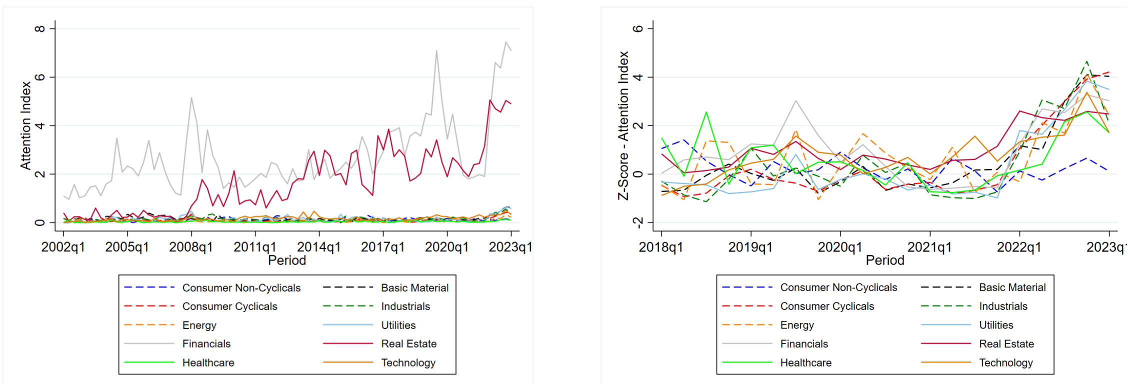
This subsection discusses some stylized facts of our attention to the central bank index. Figure 15 shows a large heterogeneity in attention per sector. Naturally, the financial sector pays more attention to the central bank. Interestingly, the real estate sector started paying much more attention to the central bank after the Global Financial Crisis. All the other sectors pay much less attention to the central bank, but attention has quickly increased in all sectors in the recent tightening cycle.

While explaining attention to the central bank is beyond the scope of this paper, we assess some relationships with other macroeconomic variables. One might think that agents only pay attention to the central bank in high inflation periods. Figure 16a shows that this is only partially true. Attention to the central bank was low between 2009 and 2012 when the inflation was slightly above the Federal Reserve target of 2% and it grew even in the low inflation period in 2019. In fact, the correlation between the two series is equal to 0.577.

Another hypothesis is that agents only pay attention to the central bank when interest rates are high enough to affect their decisions, especially during tightening cycles. Figure 16b shows that this hypothesis is also partially true. The correlation between our index of firms' attention and the Fed Fund Rates is strong, standing at 0.792.

Figure 15: The evolution of the attention to the Federal Reserve by economic sector

(a) Attention Index **(b)** Z-Score Attention Index



Notes: This figure shows (a) the central bank index by economic sector and (b) the central bank index standardize to mean zero and standard deviation equal to one from 2018.Q1 until 2023.Q1
Source: S&P Capital IQ, NL Analytic, and authors' calculations.

6.2 Attention and Monetary policy

This subsection explores the hypothesis that companies that pay more attention to the central bank tend to be more well-informed about the transmission of the monetary policy to the economy. To investigate this link, we consider factors like the impact of a monetary policy shock, the company's attention to the central bank, some firm controls, as well as fixed effects related to specific companies and time periods.

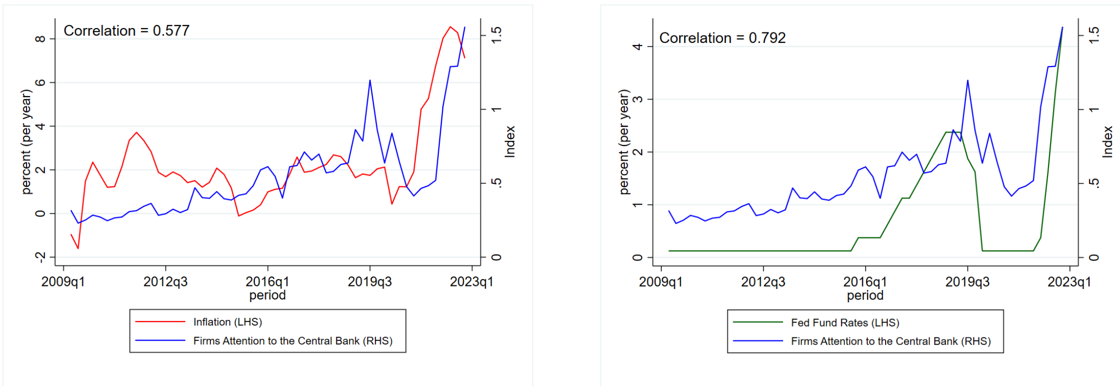
We once again employ a local projection analysis pioneered by Jordà (2005) to test our hypothesis. In particular, we test how different companies' inflation expectations respond to a monetary policy shock. We focus on different quarters, ranging from the immediate impact (quarter 0) to subsequent periods (quarters 1 to 7). The equation we estimate for each quarter ($h = 0, ..., 7$) is as follows:

$$\pi^e_{j,t+h} = \alpha_j + \alpha_t + \delta^H_{t+h} Attention_{j,t-1} \times MP_t + \beta_{t+h} X_{j,t-1} + \epsilon_{j,t} \tag{5}$$

The specification includes time fixed effects which capture any aggregate time varying confounding factor. firm level controls resemble Ottonello and Winberry (2020), for each firm j we include the

Figure 16: Attention to the central bank has information that is not capture just by the level of inflation

(a) Actual Inflation **(b)** Interest Rates



Notes: This figure show the the central bank index in blue (RHS) against (a) actual inflation in red (LHS) and (b) the Fed Funds Rate (LHS). The correlations are displayed at the figure's top left.
Source: S&P Capital IQ, NL Analytic, Haver, and authors' calculations.

standard variables that matter for a firm's optimization problem: sales growth, leverage, employment, total assets, liquidity ratio and the ratio of the long-term debt maturing within one year. Standard errors are two-way clustered by firms and time. Since differences in attention are likely correlated with structural sectoral exposures to monetary policy, firm's attention is standardized at the sectoral level for each period.[14] Therefore, a value of $Attention_{j,t}$ equal one, means that the firm j is paying one standard deviation more to the central bank than the average sector attention at period t. By de-meaning at the sector level and adding time fixed effect, the interaction between monetary policy shock and attention to the central bank reflects the marginal impact on firms' inflation expectations for being more attentive to the central than the sector's average right before the monetary policy shock.

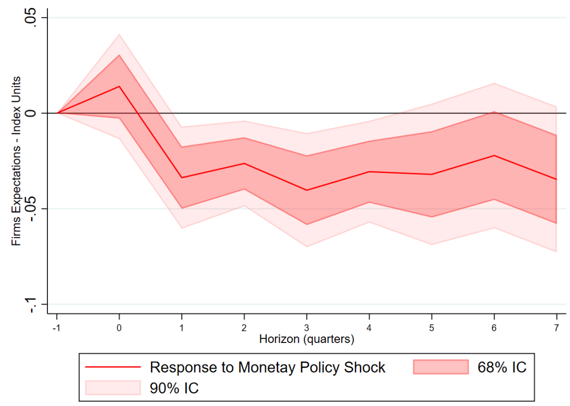
Figure 17 shows the relationship between firms' attentiveness and their response to a contractionary monetary policy shock. Firms that exhibit higher levels of attentiveness tend to decrease their inflation expectations by about 0.04 units of our index more than the sector average, amplifying the monetary policy shock. To better understand how large is the amplification effect, Appendix B.2 estimates the dynamic version of the specification without the time fixed effect. A contractionary monetary policy's average impact on firms' expectations shows that the average firm's response is persistent, peaking at 0.4 units of our index four quarters after the shock. Therefore, the amplification effect of paying one standard deviation more attention than the sector to the central bank is around 10%. As a robustness test, Appendix B.4 controls for the information effect of monetary policy announcements, while Appendix B.5 shows the impulse response function controlling for the interaction between firms' level characteristics and the monetary policy. The idea is to ensure that we also disentangle firm level exposure to monetary policy from attention. The results are robust to this specification as well.

Firms' disagreement and monetary policy effectiveness

In the validation section, we showed that our inflation expectation index matched publicly available aggregate firms' inflation expectations indexes and that our index does a good job of tracking firms'

[14] We divide the sector at the NAICS 2-digit level.

Figure 17: Monetary policy works better when firm's are paying attention.



Notes: This figure show the dynamics of interaction coefficient between attention and monetary shocks over time on our US firms' inflation expectation index. The confidence interval is set at 68% and 90%, respectively. The reported standard errors are two-way clustered by firms and time. The horizontal axis shows the impulse-response horizon measured in quarter.

disagreement. Using aggregate data, Falck, Hoffmann, and Hürtgen (2021) found that a monetary policy tightening increases inflation when disagreement is high. We test here if this result is robust when using micro-level data.

Similar to Falck, Hoffmann, and Hürtgen (2021), our empirical strategy is to estimate the responses of firms' inflation expectations, $\pi^e_{j,t+h}$, to a monetary policy shock MP_t depending on the probability of being in the high- or low-disagreement regime. We employed a local projection estimate for every quarter ($h = 0, ..., 7$). This estimate assesses the effect on the inflation expectation of firm j at time $t + h$.

$$\pi^e_{j,t+h} = \alpha_j + \left(\alpha^H_h + \beta^H_h MP_t + \gamma^H_h x_{j,t-1}\right) F\left(z_{s,t-1}\right) + \left(\alpha^L_h + \beta^L_h MP_t + \gamma^L_h x_{j,t-1}\right)\left(1 - F\left(z_{s,t-1}\right)\right) + \epsilon_{j,t+h} \tag{6}$$

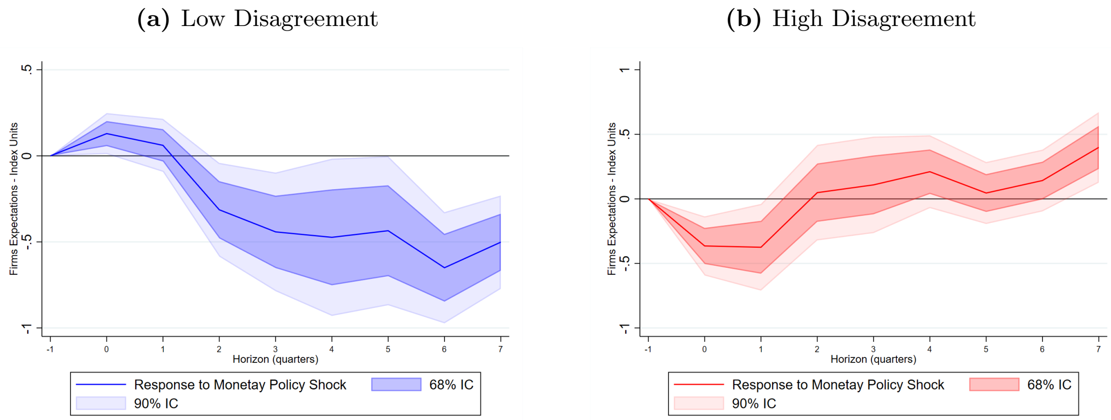
where α_j is the firm fixed effect. We include regime-specific constants, α^S_h, regime-dependent effects of the monetary policy shock, β^S_h, and a set of regime-specific coefficients for the vector of control variables x_{t-1}.[15] $S = H, L$ refers to the high (H) and low (L) disagreement regime, respectively. The regression residual is denoted by $\epsilon_{j,t+h}$. The function $F\left(z_{s,t-1}\right) \in [0, 1]$ is a smooth transition function that reflects the probability of the sector to be in a high-disagreement regime at time $t-1$. Through the interaction of these coefficients with $F\left(z_{s,t-1}\right)$, the effects of monetary policy shocks are conditioned on the probability to the sector be in a high or low-disagreement regime. The regimes are identified with the regime-indicating variable $z_{s,t-1}$, reflecting the level of disagreement about firms' inflation expectations index at the sector level.[16] To prevent potential endogeneity bias, the regime-indicating variable is lagged by one period.

Following the regime-switching literature, we employ the continuous function $F\left(z_{s,t-1}\right)$ has a lo-

[15]The firm level controls are the same used in the Equation 5. Since we are not using time fixed effects, we also included four lags of the GDP growth, the annual inflation rate and the Fed Funds Rate.

[16]In the Appendix B.6, we see the disagreement regime at the aggregate level, and the results are robust.

Figure 18: Firms' disagreement about inflation expectations and monetary policy effectiveness



Notes: This figure show the Impulse Response Function (IRF) for our US's firms' inflation expectation index after an one standard deviation contractionary monetary shocks over time conditional on the sector disagreement regime. Figure (a) shows US firms' inflation expectation index under a low disagreement regime in the sector. Figure (b) shows US firms' inflation expectation index under a high disagreement regime in the sector. The confidence interval is set at 68% and 90%, respectively. The reported standard errors are two-way clustered by firms and time. The horizontal axis shows the impulse-response horizon measured in quarter.

gistic shape[17]:

$$F\left(z_{s,t-1}\right) = \frac{\exp(\theta z_{s,t-1})}{1 + \exp(\theta z_{s,t-1})}$$

where the variable z is an index normalized to have unit variance of the disagreement. This method allows a smooth transition between the states of high and low disagreement rather than assuming distinct regimes. We calibrate the parameter value to $\theta = 3$, as in Tenreyro and Thwaites (2016).[18]

Figure 18 illustrates the impact of monetary policy shocks on inflation expectations within sectors. When in a low disagreement regime in expectations, firms tend to lower their inflation expectations by around 0.5 index units after a contractionary monetary policy shock. On the other hand, during periods characterized by high disagreement, the influence of monetary policy on firms' inflation expectations is less pronounced. In this scenario, inflation expectations initially decrease but then rebound. These findings corroborate those presented by Falck, Hoffmann, and Hürtgen (2021) at the aggregate level. Notably, our study, conducted using firm level data, yields similar outcomes supporting the literature findings that monetary policy is state dependent on the disagreement regime. Falck, Hoffmann, and Hürtgen (2021) motivate the aggregate empirical findings with a signalling model where, in the high-disagreement regime, firms use the central bank's interest rate decisions as a signal of supply and demand conditions. Thus, an unexpected increase in interest rates is perceived as a signal that demand is increasing and firms raise their prices.

Firms' attention, disagreement and monetary policy effectiveness

In Subsection 6.2, we show that firms paying more attention than their peers to the central bank right before the monetary policy shock decrease their inflation expectation by 10% more than the

[17] Check for example, Granger, Terasvirta and others (1993), Auerbach and Gorodnichenko (2012), Tenreyro and Thwaites (2016) and Falck, Hoffmann, and Hürtgen (2021).

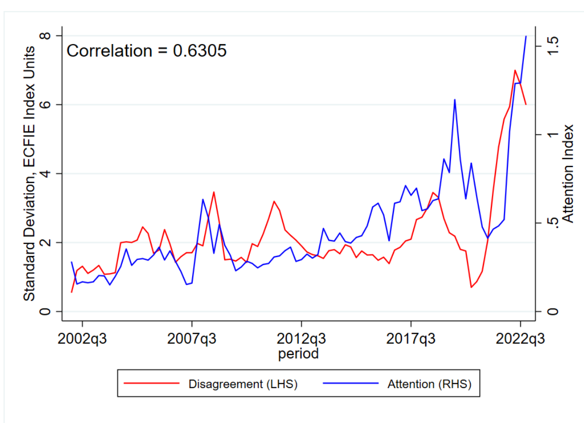
[18] Appendix B.6 show that the results are robust to θ value.

average firm in the sector, enhancing the effectiveness of monetary policy.

However, an open question in the empirical literature is whether this same enhancing mechanism also works in periods of substantial disagreement and uncertainty. Maćkowiak and Wiederholt (2009) propose a rational inattention model, suggesting that firms primarily focus on idiosyncratic shocks, paying limited attention to overall conditions and reacting slowly to monetary policy shocks. This approach aids in explaining the persistence of price levels. However, when the variability of aggregate demand rises, firms shift their attention from individual to overall conditions. In high variability scenarios, firms allocate more attention to overall conditions, leading to diminished real effects following nominal macroeconomic shocks, such as a monetary policy shock. Likewise, Zhang (2017) incorporates volatility uncertainty and endogenous information processing in the rational inattention model. This model indicates that when agents perceive heightened uncertainty, they are motivated to enhance their information capacity and allocate more resources to understanding overall conditions, especially if the perceived increase in aggregate volatility significantly outweighs the increase in individual volatility. Increased attention facilitates more precise information acquisition. Therefore, firms are able to detect aggregate shocks more quickly, respond to them more accurately, and be less afraid of making large adjustments.

If the distribution of attention within the sector shift to the right and becomes more centered, we might not observe this amplification effect in periods of high disagreement because the levels of attention in the sector is already elevated. In other words, when firms' attention is already relatively focused on the central bank, the expectations channel of monetary policy is enhanced for the average firm, as much as for the highly attentive firm, and the differential effect is null. To test for this hypothesis, we first look at the correlation of firms' inflation expectation disagreement and firms' attention to the central bank. In Figure 19 We can observe a high correlation ($\rho = 0.63$) between both series, suggesting that on a period of disagreement about aggregate inflation, firms' increase their information capacity and allocate more resources to monitor the central bank and its monetary policy actions.

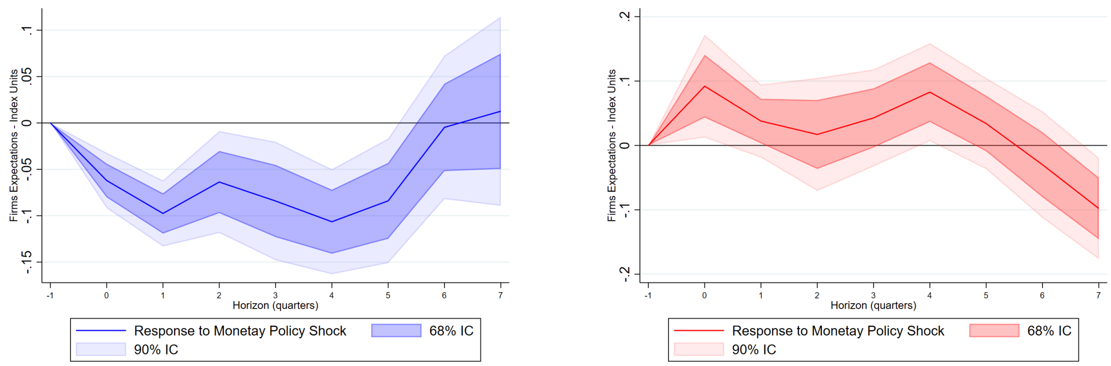
Figure 19: Firms attention to the central bank is highly correlated with inflation expectations disagreement.



Notes: This figure show the inflation expectation disagreement in red (LHS) and firms' attention to the central bank index in blue (RHS). The correlations are displayed at the figure's top left.
Source: S&P Capital IQ, NL Analytic, Haver, and authors' calculations.

Figure 20: State-dependent effect of a firm more attentive to central bank

(a) Low Disagreement **(b)** High Disagreement



Notes: This figure show the Impulse Response Function (IRF) for our US's firms' inflation expectation index after an one standard deviation contractionary monetary shocks over time conditional on the sector disagreement regime and firms' attention to the central bank. Figure (a) shows US firms' inflation expectation index under a low disagreement regime in the sector for a firm paying one standard deviation more attention to the central bank. Figure (b) shows US firms' inflation expectation index under a high disagreement regime in the sector for a firm paying one standard deviation more attention to the central bank. The confidence interval is set at 68% and 90%, respectively. The reported standard errors are two-way clustered by firms and time. The horizontal axis shows the impulse-response horizon measured in quarter.

Second, we empirically assess whether the amplification effect on the inflation expectations channel of monetary policy caused by attentiveness to the central bank is state-dependent. For that, we estimate the following local projection:

$$\begin{aligned}\pi^e_{j,t+h} =& \alpha_j + \alpha_t + \left(\alpha^H_h + \beta^H_h \text{Attention}_{j,t-1} \times \text{MP}_t + \gamma^H_h x_{j,t-1}\right) F\left(z_{t-1}\right) \\ &+ \left(\alpha^L_h + \beta^L_h \text{Attention}_{j,t-1} \times \text{MP}_t + \gamma^L_h x_{j,t-1}\right)\left(1 - F\left(z_{t-1}\right)\right) + \epsilon_{j,t+h},\end{aligned} \tag{7}$$

where α_j is the firm fixed effect and α_t is the time fixed effect. Regime-specific constants are represented by α^S_h, regime-dependent effects of the monetary policy shock, β^S_h, and a set of regime-specific coefficients for the vector of control variables x_{t-1}.[19] $S = H, L$ refers to the high (H) and low (L) disagreement regime, respectively. The regression residual is denoted by $\epsilon_{j,t+h}$. The function $F\left(z_{s,t-1}\right) \in [0,1]$ reflects the probability of the sector to be in a high-disagreement regime at time $t-1$. The coefficients that we are interested are β^L_h and β^H_h, through the interaction of these coefficients with $F\left(z_{s,t-1}\right)$, the effects of how monetary policy shocks impact the inflation expectations of firms that are particularly attentive to the central bank, just before the shock conditional on the probability to the sector be in a low or high-disagreement regime, respectively.

Figure 20 shows that firms that are one standard deviation more attentive to the central bank than the average firm in the sector one period before the shock lower their inflation expectations more than other firms within the sector during times of low disagreement. However, when disagreement is high, this effect becomes insignificant across almost all time periods.

The above results hint towards the tested mechanism, in line with rational inattention model with endogenous information choice (e.g., Maćkowiak and Wiederholt (2009), Zhang (2017) and Esady

[19]The controls are the same used in the Equation 5.

(2022)) where a period of high inflation expectations disagreement increase agents' incentive to pay more attention to the central bank actions impacting not yielding additional benefits from increased attention, given the heightened focus on the central bank. We are the first paper to provide empirical evidence of these common hypotheses behind irrational inattention models with endogenous information choice.

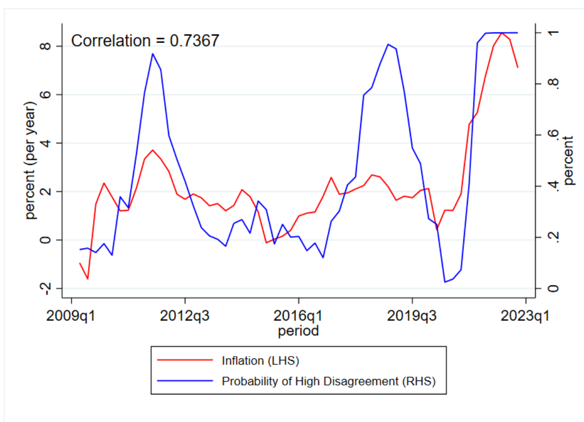
However, there could also be another story where information quality deteriorates during periods of high disagreement, either because economic signals become too volatile or the central bank's guidance and communication might become less transparent or clear. If this hypothesis is true, then lower information quality could be another explanation for the weakened differential effect of attention to the central bank during periods of high disagreement.

One way to test this is to assess the inflation predictive power of our inflation expectations index in two different environments: 1) low disagreement and low inflation; 2) high disagreement and low inflation. The choice of these two different environments seeks to isolate differences coming from disagreement from those coming from high levels of inflation and uncertainty.

In particular, we investigate whether the inflation expectations index from firms that generally pay more attention than the median of their sectors have better forecasting power in both regimes.

In particular, we regress for each firm future inflation one year ahead on firms' inflation expectations up until the fourth quarter of 2014 and the second quarter of 2017. As Figure 21 shows, from 2015Q1 until 2017Q2 we have low inflation and low disagreement and from 2017Q3 until 2019Q4 we have low inflation and high disagreement.

Figure 21: Actual Inflation and Disagreement Regimes



Notes: This figure show the actual inflation in red (LHS) and probability of being in the high-disagreement regime in blue (RHS). The correlations are displayed at the figure's top left.
Source: S&P Capital IQ, NL Analytic, Haver, and authors' calculations.

Given this context, when we maintain the "constant" factor of inflation, we capture the ability of more attentive firms to forecast inflation across two distinct situations: low disagreement and high disagreement.

To quantify the precision of these forecasts, we calculate the mean squared errors ten periods ahead for each sector separately, considering both time periods and both groups of firms (those with high and low attention within the sector). For each sector and disagreement regime, we calculated the ratio ofthe average mean square error of the firms with low attention to firms with high attention. Finally, we calculate the simple median of these ratios across sectors.

We find that the median mean square error of less attentive firms is 3.9% higher than that of more attentive firms during periods of low disagreement. However, during periods of high disagreement, this difference diminishes to approximately zero. Overall, this result suggests that attention to the central bank improves overall information in normal times but is ineffective during periods of high disagreement. This suggests that the information quality deteriorates during these periods. These are suggestive explanations for the null result of attention during a high disagreement scenario. Future research can focus on narrowing these hypotheses down in the context of a theoretical model.

7 Conclusion

This paper addresses the scarcity of quantitative measures of inflation expectations among firms by leveraging text-mining techniques applied to earnings calls transcripts. Firms' earnings calls provide real time information on firms' views on future inflation. We use machine learning algorithms to build and validate our index with multiple tests.

In an application for the United States, we show that our final index well captures firms' inflation expectations and has predictive power for future inflation. Leveraging the firm dimension of the inflation expectation index, we match it with balance sheet data and document several violations of the full-information rational expectations (FIRE) assumption. When looking at the expectations channel of monetary policy transmission, our results suggest that the inflation expectations channel of monetary policy could be weaker in economies with higher private debt and in periods of negative confidence shocks. On the contrary, we find that monetary policy is more effective is shaping expectations when firms are more attentive to the central bank. This result suggests that monetary policy effectiveness can be enhanced by strategies that improve agents' attention and understanding of the mechanism of transmission of central bank actions. Finally, the inflation expectations channel appear to be impaired during a period of high inflation expectations disagreement, with potential implications for central bank communication strategy in a period of uncertainty.

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Appendix

Appendix A Additional Validation

Appendix Table A.1: The method to select the keywords matters - SoFIE

Correlations	ECFIE Index	Naive Search
SoFIE	0.9764	0.9570

Source: S&P Capital IQ, NL Analytic, Cleveland Bank, and authors' calculation.

Appendix Table A.2: The method to select the keywords matters - SoFIE Disagreement

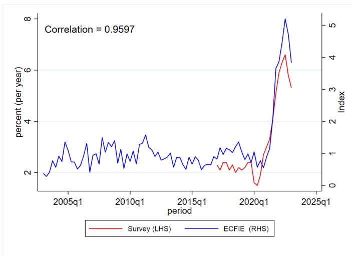
Correlations Disagreement	ECFIE Index	Naive Search
SoFIE	0.7996	0.7574

Source: S&P Capital IQ, NL Analytic, Cleveland Bank, and authors' calculation.

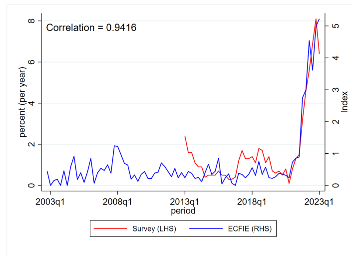
Appendix A.1 Validation Cross-Country

Appendix Figure A.1: Correlations between our novel firms' inflation expectation index and existing firms surveys

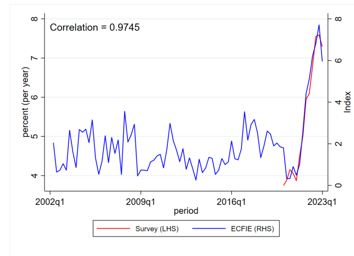
(a) United Kingdom



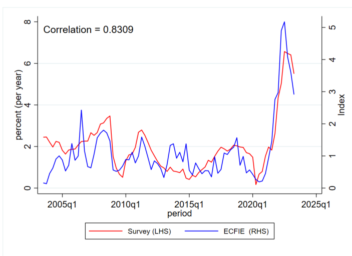
(b) Italy



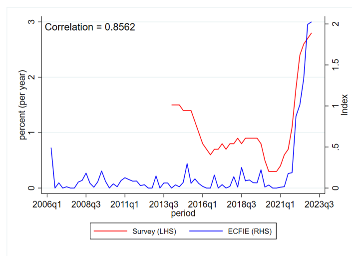
(c) Mexico



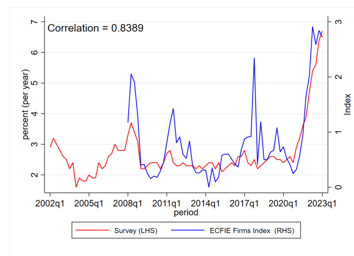
(d) Sweden



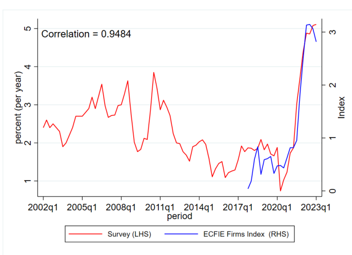
(e) Japan



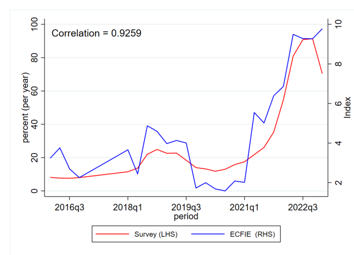
(f) Norway



(g) New Zealand



(h) Turkey

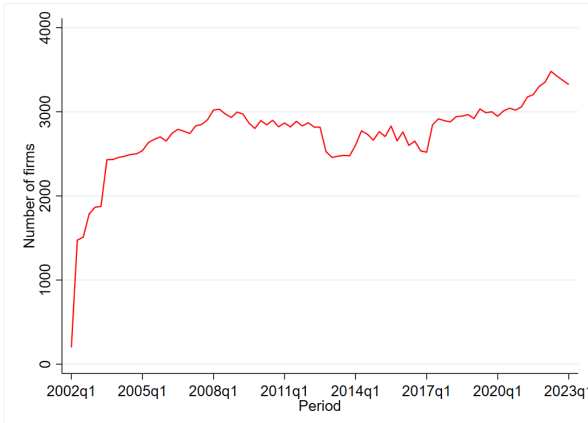


Notes: The figure shows our novel firms' inflation expectation index in blue (RHS) and existing firms surveys in red (LHS) for the United Kingdom, Italy, Mexico, Sweden, Japan, Norway New Zealand, and Turkey, respectively. The correlations are displayed at the figure's top left.
Source: S&P Capital IQ, NL Analytic, Bank of England, Italy Central Bank, Mexico Central Bank, Sweden Central Bank, Japan Central Bank, Norges Bank, Reserve Bank of New Zealand, Turkey Central Bank, and authors' calculations.

Appendix B Additional Empirical Results

Appendix B.1 US statistics

Appendix Figure B.2: Number of US companies used to construct the inflation expectation index over time.



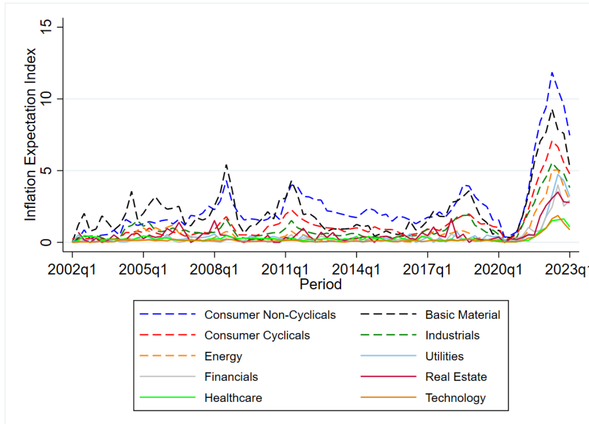
Notes: The figure show the number of transcripts available for US-based companies per quarter.
Source: S&P Capital IQ, NL Analytic and authors' calculations.

Appendix Table B.3: Summary statistics of firms' inflation expectations and firms' characteristics

	Obs	Mean	SD	Median
All Firms				
Inflation Expectation Index	178479	0.88	2.98	0.00
Total Assets (US$ million)	178479	1865.52	6822.54	344.98
Leverage	173691	0.27	0.34	0.23
High Inflation Expectations				
Inflation Expectation Index	89220	1.66	4.01	0.00
Total Assets (US$ million)	89220	2176.54	6183.01	544.33
Leverage	87399	0.29	0.24	0.27
Low Inflation Expectations				
Inflation Expectation Index	89259	0.10	0.65	0.00
Total Assets (US$ million)	89259	1554.63	7393.78	207.96
Leverage	86292	0.24	0.41	0.16

Notes: This table reports summary statistics for the inflation expectations index, total assets and leverage (ratio of total debt to total assets). The firms are divided in firms that on average have inflation expectation above the sample median (high inflation expectations) and firms that have inflation expectations below the sample median (low inflation expectations).

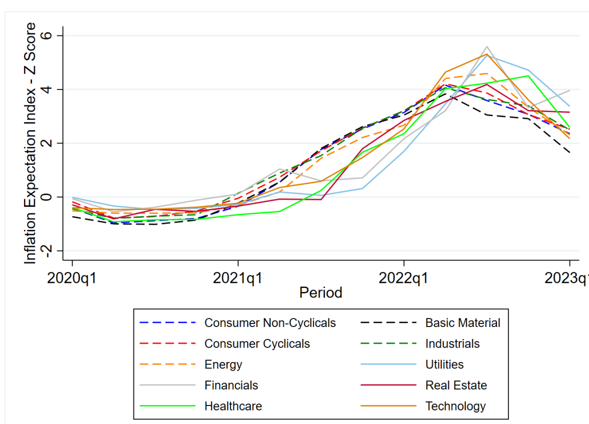
Appendix Figure B.3: The evolution of the inflation expectation by economic sector - all sample.



Notes: The figure shows the evolution of the inflation expectation by economic sector for the entire sample from 2002.Q1 until 2023.Q1.

Source: S&P Capital IQ, NL Analytic, and authors' calculations.

Appendix Figure B.4: The evolution of the inflation expectation by economic sector - z-scores.



Notes: The figure shows the evolution of the inflation expectation by economic sector standardize to mean zero and standard deviation equal to one from 2020.Q1 until 2023.Q.1

Source: S&P Capital IQ, NL Analytic, and authors' calculations.

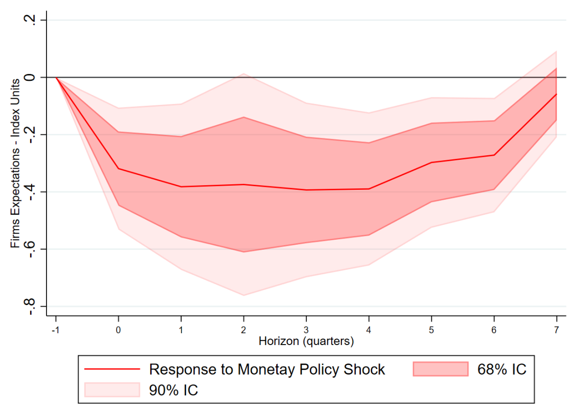
Appendix B.2 The Average Effect of Monetary Policy

We estimate the equation below to quantify the average effect of monetary policy shocks on firms' inflation expectations:

$$\pi^e_{j,t+h} = \alpha_j + \gamma^H_{t+h} MP_t + \delta^H_{t+h} Attention_{j,t-1} \times MP_t + \beta_{t+h} X_{j,t-1} + \eta_{t+h} Y_{j,t-1} + \epsilon_{j,t} \tag{B.1}$$

Where, $Y_{j,t}$ is a vector with four lags of GDP growth, the inflation rate, and the Fed Fund Rates and $X_{j,t}$ is a vector of firm level controls (same used in Equation 5). Figure B.5 shows that the average response to monetary policy, γ^H. The average effect peaked after four quarters reducing our inflation expectation index by approximately 0.4 units after an one standard deviation contractionary monetary policy shock.

Appendix Figure B.5: The average effect of a monetary policy on firms inflation expectations.



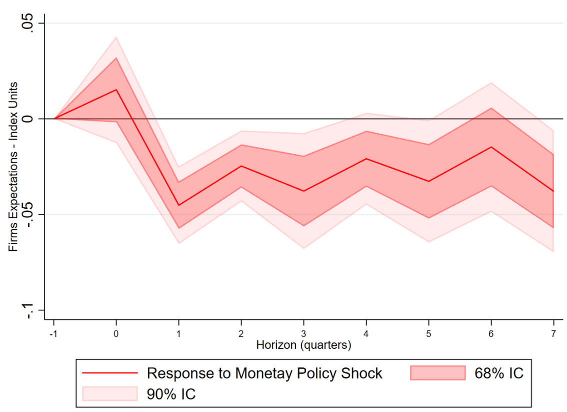
Notes: This figure show the average effect of a monetary policy on firms inflation expectations over time on our US's firms' inflation expectation index using the Equation B.1. The confidence interval is set at 68% and 90%, respectively. The reported standard errors are two-way clustered by firms and time. The horizontal axis shows the impulse-response horizon measured in quarter.

Appendix B.3 Additional Results with an Alternative Monetary Policy Shock

In this section we re estimate the Equations 5, 2, 3; 4 with the monetary policy shock constructed by Nakamura and Steinsson (2018). Figure B.6 shows that the results are robust to the monetary policy shock considered.

Appendix Figure B.6: Robustness to the monetary policy shock

(a) Attention



(b) Financial Constraint

(c) Non-Political Sentiment

(d) Size

Notes: This figure show the dynamics of interaction coefficient between the monetary shocks over time and firms' (a) attention, (b) financial constraint, (c) non-political sentiment and (d) size over time on our US's firms' inflation expectation index. The specification is the Equation as Equations 5, 2, 3; 4 but it uses the monetary policy shock constructed by Nakamura and Steinsson (2018) instead of the shock developed by Gürkaynak, Sack, and Swanson (2005). The confidence interval is set at 68% and 90%, respectively. The reported standard errors are two-way clustered by firms and time. The horizontal axis shows the impulse-response horizon measured in quarter.

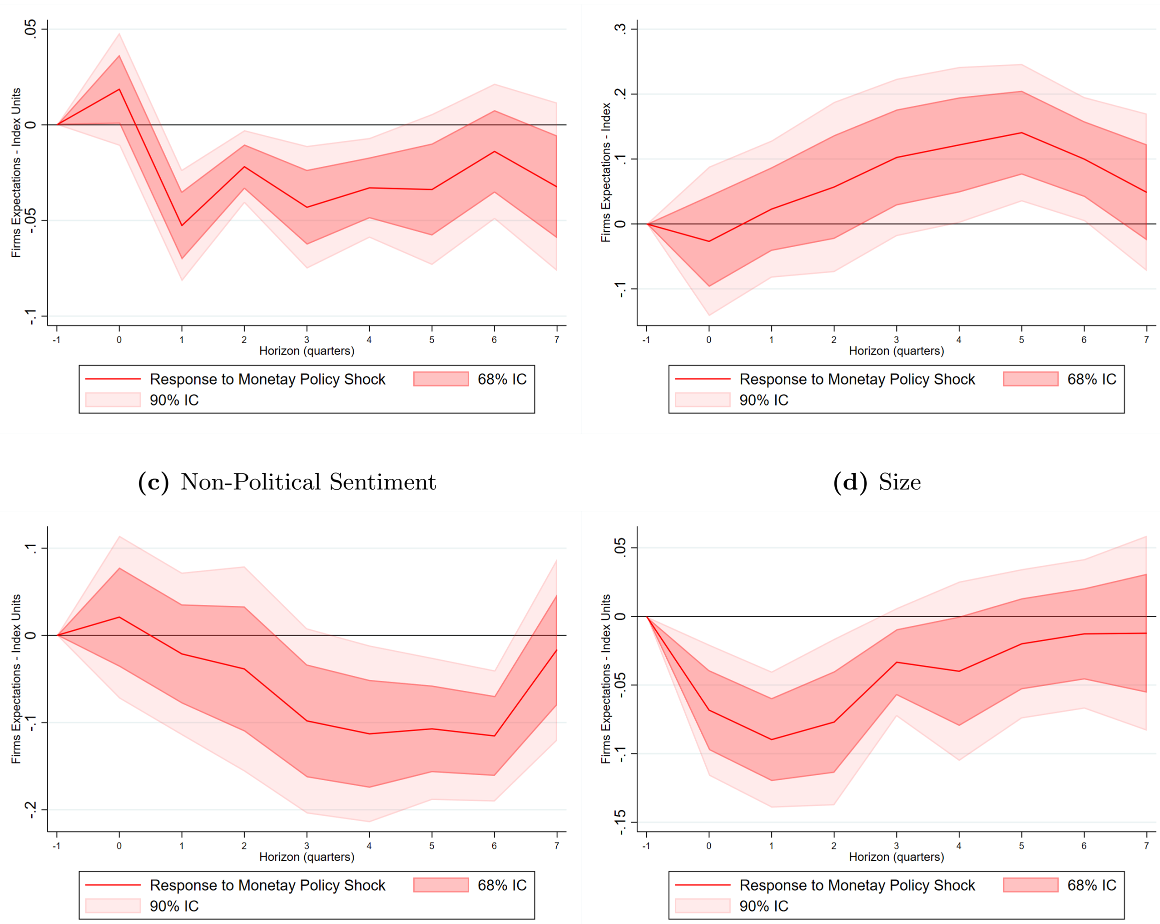
Appendix B.4 Robustness check for the information channel of monetary policy

A potential issue with our monetary policy shocks MPS_t is that the FOMC announcements, which form the basis for these shocks, also contain insights about the future trajectory of economic activity. To address this concern, we estimate the Equations 5, 2, 3, 4 and including as controls in the interaction between our variable of interest ($Attention_{j,t-1}$, $FinancialConstraint_{j,t-1}$, $NPSentiment_{j,t-1}$ and $Size_{j,t-1}$) and the information effect measure by the "future path of policy" factor calculated by Gürkaynak, Sack, and Swanson (2005) that corresponds to changes in futures rates out to horizons of one year that are independent of changes in the current funds rate target. Figure B.7 shows that the results are robust to the information channel of monetary policy.

Appendix Figure B.7: Robustness to the monetary policy shock

(a) Attention **(b)** Financial Constraint

(c) Non-Political Sentiment **(d)** Size



Notes: This figure show the dynamics of interaction coefficient between the monetary shocks over time and firms' (a) attention, (b) financial constraint, (c) non-political sentiment and (d) size over time on our US's firms' inflation expectation index. The specification is the Equation as Equations 5, 2, 3, 4 but controlling for the interaction between our variable of interest ($Attention_{j,t-1}$, $FinancialConstraint_{j,t-1}$, $NPSentiment_{j,t-1}$ and $Size_{j,t-1}$) and the information effect. The confidence interval is set at 68% and 90%, respectively. The reported standard errors are two-way clustered by firms and time. The horizontal axis shows the impulse-response horizon measured in quarter.

Appendix B.5 Robustness check for firm level exposure to monetary policy shock

This section ensures we also disentangle firm level exposure to monetary policy from attention. Therefore, we control for the interaction between firms' level characteristics and the monetary policy shock as the specification below:

$$\pi^e_{j,t+h} = \alpha_j + \alpha_t + \delta^H_{t+h} Attention_{j,t-1} \times MP_t + \beta_{t+h} X_{j,t-1} + \theta_{t+h} X_{j,t-1} \times MP_t + \epsilon_{j,t} \quad \text{(B.2)}$$

Appendix Figure B.8: Robustness interacting MP with all firms level controls

Notes: This figure show the dynamics of interaction coefficient between attention and monetary shocks over time on our US firms' inflation expectation index. The confidence interval is set at 68% and 90%, respectively. The reported standard errors are two-way clustered by firms and time. The horizontal axis shows the impulse-response horizon measured in quarter.

Appendix B.6 Robustness check for disagreement regime

Appendix B.6.1 Sector level

One concern is that our results on firms' disagreement and monetary policy effectiveness are sensitive to the value of the parameter θ that determines how abruptly the economy switches from low disagreement to a high disagreement regime. In this section, we estimate the coefficients β^L_h and β^H_h in Equation 6 for values of $\theta = 1$ and 5. Figure B.9 shows that the results are robust to the value of the parameter θ.

Appendix Figure B.9: Robustness: Firms' disagreement about inflation expectations at the sector level and monetary policy effectiveness

(a) Low Disagreement $\theta = 5$

(b) High Disagreement $\theta = 5$

(c) Low Disagreement $\theta = 1$

(d) High Disagreement $\theta = 1$

Notes: This figure show the Impulse Response Function (IRF) for our US's firms' inflation expectation index after an one standard deviation contractionary monetary shocks over time conditional on the sector disagreement regime. Figures on the left (blue) shows US firms' inflation expectation index under a low disagreement regime in the sector for different values of the parameter θ. Figure on the right (in red) shows US firms' inflation expectation index under a high disagreement regime in the sector for different values of the parameter θ. The confidence interval is set at 68% and 90%, respectively. The reported standard errors are two-way clustered by firms and time. The horizontal axis shows the impulse-response horizon measured in quarter.

Appendix B.6.2 Aggregate level

$$\pi^e_{j,t+h} = \alpha_j + \left(\alpha^H_h + \beta^H_h MP_t + \gamma^H_h x_{j,t-1}\right) F\left(z_{t-1}\right) + \left(\alpha^L_h + \beta^L_h MP_t + \gamma^L_h x_{j,t-1}\right)\left(1 - F\left(z_{t-1}\right)\right) + \epsilon_{j,t+h} \tag{B.3}$$

We include regime-specific constants, α^S_h, regime-dependent effects of the monetary policy shock, β^S_h, and a set of regime-specific coefficients for the vector of control variables x_{t-1}. Where $S = H, L$ refers to the high (H) and low (L) disagreement regime, respectively. The firm fixed effect is represented by α_j. The regression residual is denoted by $\epsilon_{j,t+h}$. The function $F\left(z_{t-1}\right) \in [0,1]$ reflects the probability of the economy to be in a high-disagreement regime at time $t-1$. Through the interaction of these coefficients with $F\left(z_{t-1}\right)$, the effects of monetary policy shocks are conditioned on the probability to the economy be in a high or low-disagreement regime. The regimes are identified with the regime-indicating variable z_{t-1}, reflecting the level of disagreement about firms' inflation expectations index.

The probabilities of being in a high-disagreement regime is calculate as following:

$$F\left(z_{t-1}\right) = \frac{\exp(\theta z_{t-1})}{1 + \exp(\theta z_{t-1})}$$

where the variable z is an index normalized to have unit variance of the disagreement. The Figure B.10 plots the β^S_h for different values of the parameter θ and show that the results are robust to its value.

Appendix Figure B.10: Robustness: Firms' aggregate disagreement about inflation expectations and monetary policy effectiveness

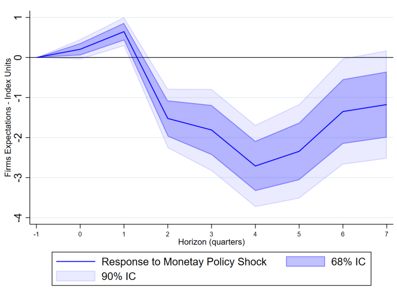
(a) Low Disagreement $\theta = 5$

(b) High Disagreement $\theta = 5$

(c) Low Disagreement $\theta = 3$

(d) High Disagreement $\theta = 3$

(e) Low Disagreement $\theta = 1$



(f) High Disagreement $\theta = 1$

Notes: This figure show the Impulse Response Function (IRF) for our US's firms' inflation expectation index after an one standard deviation contractionary monetary shocks over time conditional on the aggregate disagreement regime. Figures on the left (blue) shows US firms' inflation expectation index under a low disagreement regime for different values of the parameter θ. Figure on the right (in red) shows US firms' inflation expectation index under a high disagreement regime for different values of the parameter θ. The confidence interval is set at 68% and 90%, respectively. The reported standard errors are two-way clustered by firms and time. The horizontal axis shows the impulse-response horizon measured in quarter.