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Inflation, Attention and Expectations*

Etienne Briand [†] Massimiliano Marcellino [‡] Dalibor Stevanović [§]

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Abstract

We investigate the role of attention in shaping inflation dynamics. To measure the general public attention, we utilize Google Trends (GT) data for keywords such as "inflation." For professional attention, we construct an indicator based on the standardized count of Wall Street Journal (WSJ) articles with "inflation" in their titles. Through empirical analysis, we show that attention significantly impacts inflation dynamics, even when accounting for traditional inflation-related factors. Macroeconomic theory suggests that expectations formation is a natural mechanism to explain these findings. We find support for this hypothesis by measuring a decrease in professional forecasters' information rigidity during periods of high attention. In contrast to prior research, our findings highlight the critical roles of media communication and public attention in shaping aggregate inflation expectations. We then develop a theoretical model that captures our stylized facts, showing that both inflation dynamics and forecaster expectations are regime-dependent. Finally, we examine the implications of this framework for the effectiveness of monetary policy.

Keywords: Inflation, Expectations, Monetary policy, Google trends, Text analysis

JEL Classification Code: C53, C83, D83, D84, E31, E37.

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1 Introduction

The decisions of economic agents are fundamentally influenced by their expectations of current and future conditions. Understanding how these expectations are formed is a crucial component of understanding macroeconomic dynamics. In this paper, we acknowledge that this process may vary across periods, influenced by agents' desire to learn about the state of the economy which fluctuates with the business cycle, as suggested by Flynn and Sastry (2024). Moreover, as argued by Carroll (2003) and Chahrour et al. (2021), news media play a pivotal role in framing agents' information sets by acting as delegates that gather and synthesize economic information. From this perspective, news (or narratives) generate time-varying dynamics through two primary channels: (i) by amplifying the perceived importance of unusual events via disproportionate coverage, and (ii) by framing editorial decisions that alter economic dynamics independently of underlying conditions. Both phenomena can be interpreted as variations in attention.

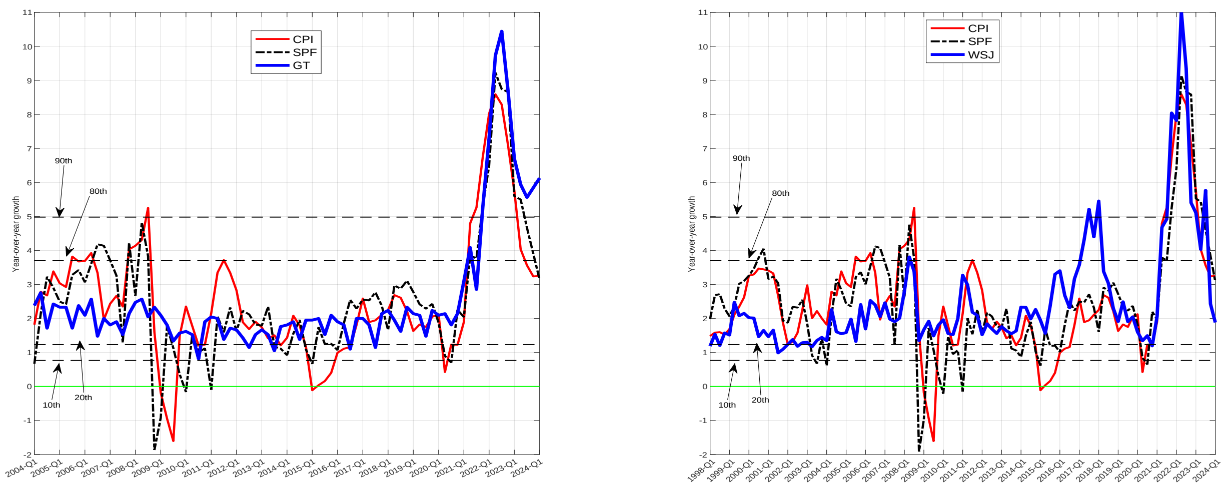
This paper examines how attention shapes inflation dynamics. Through a series of empirical exercises, we show that attention significantly affects inflation dynamics, even after controlling for typical inflation-related factors. Macroeconomic theory points to expectations formation as a natural mechanism that could explain those findings. We find support for this hypothesis by measuring a decrease in professional forecasters' information rigidity during periods of high attention. We then develop a theoretical model that captures our stylized facts, in which inflation dynamics and forecaster expectations depend on the attention regime. Finally, we explore the implications of this framework for the effectiveness of monetary policy.

We construct two broad measures of attention. The first, referred to as the public attention indicator, is derived from Google Trends (GT) data for keywords such as "inflation". The rationale is that when agents are more concerned about inflation, they are likely to seek information, and Google has become a natural source for such inquiries. The second measure serves as a proxy for professional attention, constructed using an indicator based on a (standardized) count of Wall Street Journal (WSJ) online articles with titles containing the term "inflat".[1] A

[1]The use of non-standard data, such as text analysis and internet search volumes, has become increasingly

graphical analysis, presented in Figure 1, suggests that both GT and WSJ attention measures are closely related to inflation trends, particularly during periods of high inflation, such as the beginning of financial crisis and the aftermath of the COVID-19 pandemic.

Figure 1: Inflation, expectations and attention



(a) General attention

(b) Professional attention

Note: The left panel plots the CPI inflation and the Survey of Professional Forecasters mean 1-quarter ahead forecast against the Google Trend. Dashed lines show the 10th, 20th, 80th and the 90th quantiles of the CPI inflation. The right panel opposes the same inflation and expectations measures against the WSJ indicator. GT and WSJ are normalized to the same mean and standard deviation as the CPI.

The transmission of information about inflation to actual inflation developments likely occurs through the formation of inflation expectations (see Coibion et al. (2018a) and Binder and Kamdar (2022) for recent surveys on inflation and inflation expectations). Indeed, an initial examination of Figure 1 suggests a relationship between inflation expectations and our proxies for agents' attention to inflation, particularly when inflation is high. This observation aligns with Bracha and Tang (2022), who find that consumers' attention to inflation increases when inflation is elevated, and with Coibion et al. (2018b), who document that firms allocate fewer resources to collecting and processing inflation information when they perceive it as less relevant to their decisions. Additionally, Weber et al. (2024) show that agents are more attentive to inflation in economies with a history of high inflation compared to countries where inflation has remained low. While documenting these dynamics of attention, inflation, and expectations, we remain agnostic about the triggers behind these fluctuations and the causal relationships

popular in economics. See Choi and Varian (2009) for an early application of Google Trends and Gentzkow et al. (2019) for a review on text analysis.

driving them.

To provide formal evidence of the transmission channel from inflation information to expectations and actual inflation, we conduct three empirical exercises. First, we project standard measures of inflation expectations onto our general and professional attention indicators. The measures of expectations considered include forecasts from the Survey of Professional Forecasters and BlueChip Consensus, as well as consumer and business expectations derived from surveys conducted by the University of Michigan and the New York and Atlanta Federal Reserve Banks, respectively. The results indicate that both GT and WSJ attention indicators exhibit substantial and significant explanatory power for the various measures of inflation expectations. Moreover, quantile regression analyses reveal that the importance of inflation attention is amplified during periods of high inflation. This finding aligns with the predictions of rational inattention models, such as those proposed by Sims (2003) and Mackowiak and Wiederholt (2009), which suggest that during periods of large inflationary changes, failing to update inflation expectations can incur significant costs.

Second, we evaluate whether attention measures can improve forecasts of inflation when added to standard models, such as New Keynesian Phillips Curves and factor-augmented regressions based on large information sets. We find that GT and WSJ have significant additional out-of-sample predictive power for standard inflation measures, such as CPI and PCE, with a particularly strong effect during periods of high inflation.[2] Third, to shed additional light on the effects of inflation attention and its dynamic transmission, we run a structural VAR analysis. Overall, the analysis confirms that attention shocks matter, and their effects are not fully captured by the inclusion of standard inflation factors in the model. This aligns with the previously discussed regression results and likely occurs because both GT and WSJ provide more granular information.

Next, we evaluate the relevance of inflation attention in the context of full information ra-

[2] Kelly et al. (2021) also find, using a different technique, that WSJ articles contain relevant information for forecasting a variety of US economic indicators, including CPI inflation. Bybee et al. (2024) further extend the methodology to identify the most relevant topics in WSJ articles, finding that a selection of these topics is useful for monitoring US business cycle conditions. A related analysis is conducted by Angelico et al. (2022), but using Twitter data, which also turns out to be quite useful for tracking inflation expectations.

tional expectations (FIRE) models, 'a la Coibion and Gorodnichenko (2015). It turns out that both GT and WSJ have substantial and significant explanatory power for the various measures of inflation-implied forecast errors. Thus, the FIRE hypothesis is often rejected, in line with previous evidence reviewed by Coibion et al. (2018a), implying that some informational rigidities exist and are yet to be exploited. However, when attention is high, the estimated degree of information stickiness is lower, suggesting that attention introduces state-dependent information rigidities. This state-dependent behavior of attention is consistent with the attention cycles described by Flynn and Sastry (2024), as well as with Yotzov et al. (2024), who find that firms' speed of adjustment increases when inflation coverage in the media is higher.

To rationalize our findings on the impact of attention on information rigidities, we propose a theoretical model incorporating higher-order beliefs and public information. We hypothesize that forecasters always rely on some common information, which becomes publicly available to firms in the model only during high-attention periods. Under this assumption, measures of forecasters' information rigidity decrease during high-attention periods. This occurs because the model's equilibrium depends on firms' expectations, and when forecasters' information sets overlap with those of firms, it becomes easier for them to predict outcomes. This assumption also influences the model's dynamics. Notably, the real effects of monetary policy shocks are muted during high-attention periods. We further validate the model's predictions empirically by estimating the effects of monetary policy shocks during low- and high-attention periods using a threshold VAR.

The paper is structured as follows. Section 2 presents the data we use. Section 3 evaluates the role of attention in inflation expectations and inflation developments. Section 4 examines the role of attention in the context of full information rational expectations (FIRE) models, while Section 5 proposes a quantitative model that rationalizes our results and tests the implications for monetary policy transmission. Section 6 summarizes our main findings and concludes. The Appendix contains robustness analyses, additional empirical results, and technical details on the theoretical model.

2 Data

Table 1 provides a detailed description of the data used in this paper. In particular, GT data is retrieved from the Google Trends website. Since 2006, Google has granted public access to some of its data dating back to 2004, concerning the number of searches made for a particular keyword. In fact, Google Trends is an index of relative popularity based on the geographical region for which the data is collected. More precisely, the number of searches made for a keyword (e.g., "inflation") is divided by the total number of searches made in the United States on a monthly basis. The results are then normalized on a scale from 0 to 100 according to the proportion of searches for the selected keyword relative to all searches conducted during the given time period.[3]

To construct the WSJ index, we collect the headlines from the online version of the Wall Street Journal, spanning from January 2004 to March 2024. We apply standard text transformations, such as lowercasing, removing common stopwords (e.g., "the"), and applying Porter Stemming. We then count the number of unigrams (single words) and bigrams (two adjacent words) in each headline, aggregating the counts at the monthly level. The WSJ inflation index is constructed by dividing the monthly counts for "inflat" (the stemmed version of "inflation") by the total number of titles in that month.

Note that since the data availability differs across series, the sample used in the analyses reported below also differs (it coincides with that of the variable with the shortest data availability as stated in Table 1). Appendix A presents descriptive statistics and correlation analyses for GT and WSJ.

[3]There are two types of data: real-time data, which is a random sample of searches performed in the last seven days, and non-real-time data, which is a random sample of Google searches that can date back to 2004 and as far as 36 hours before a keyword search. Here, we use the non-real-time data. Thus, the index values may vary depending on when the data were collected. However, neither Chauvet et al. (2016) nor D'Amuri and Marcucci (2017) found substantial differences between data downloaded over multiple days.

Table 1: Data description

Attention measures		
Google Trends		
Benchmark keyword: "inflation“	Monthly	2004M01-2024M03
Wall Street Journal index		
Count of articles’ titles containing the keyword "inflat*"	Monthly	1998M01-2024M03
Inflation measures		
Variable	Frequency	Time span
CPI: All items	Monthly	1998M01-2024M03
PCE: Personal Consumption Expenditures	Monthly	1998M01-2024M03
Inflation expectations measures		
SPF Mean: CPI		
Forecast for the 1 up to 4 quarters ahead	Quarterly	1998Q1 - 2024Q1
BlueChip consensus		
Forecast for the next year up to 12 months ahead	Monthly	1998M01 - 2024M03
Surveys		
Michigan U. Survey of Consumers: Median expected price change next 12 months	Monthly	2004M01-2024M03
New York Fed Survey of Consumer Expectations: Median one-year ahead expected inflation rate	Monthly	2013M08-2024M03
Atlanta Fed Mean Business Inflation Expectations: changes to unit costs over the next 12 months	Monthly	2011M10-2024M03
Cleveland Fed		
Forecast 10 years ahead	Monthly	2004M01-2024M03
Controls		
Regular All Formulations Gas Price	Monthly	1998M01-2024M03
Global Supply Chain Pressure Index (GSCPI)	Monthly	1998M01-2024M03
CPI: Food	Monthly	1998M01-2024M03
Google Trend of keywords "federal reserve system"	Monthly	2004M01-2024M03
FOMC sentiments from (Gardner et al., 2021)	Monthly	2000M02-2023M12

3 The role of inflation attention

Let us define some notation before delving into the technical details of the empirical strategy. $\pi_{t+h,t}$ represents the forecast or expectation of the year-over-year inflation growth h periods ahead, made at time t, while π_{t+h} is the realization. Ω_t denotes the information set available to forecasters at time t. The forecast error is defined as $e_{t+h,t} = \pi_{t+h} - \pi_{t+h,t}$. Finally, Z_t contains the general or professional attention proxy, GT and WSJ, respectively, observable at time t.

3.1 Can attention explain inflation expectations?

To measure the explanatory power of attention, we project the inflation expectations made at period t onto Z_t and the lagged values of expectations to control for their serial dependence. Hence, the models are of the following form:

$$y_t = c + \alpha y_{t-1} + \beta Z_t + u_t \tag{1}$$

where $y_t = \pi_{t+h,t}$ and $y_{t-1} = \pi_{t+h-1,t-1}$ in the case of SPF, Michigan, NYFed and Atlanta Fed surveys, while in the case of BlueChip consensus $y_t = \pi_{t+h,t}$ and $y_{t-1} = \pi_{t+h,t-1}$. In equation (1), we assume that Z_t is available to agents during the month or quarter when the expectations are made. The null hypothesis of interest is $\beta = 0$. If H_0 is rejected, it implies that attention to inflation is informative about the formation of inflation expectations. The expected sign of β is positive.

Results are presented in Table 2. In the case of SPF inflation expectations, both GT and WSJ are significant at the $h = 1$, 2, and 4 quarter horizons, with coefficients that decrease as h increases.[4] A similar finding emerges for the other measure of professional expectations, the BlueChip consensus. Regarding 12-month ahead consumer inflation expectations, for the Michigan survey, both WSJ and GT are significant, while neither is significant for the NY Fed survey. For the 12-month ahead business inflation expectations, as measured by the Atlanta Fed, WSJ is significant but GT is not.

We estimated equation (1) using quantile regression to evaluate the heterogeneity of attention effects in the tails of the distribution. Table 3 presents the results.[5] Both attention measures have a stronger impact in the right tail of the expectations' distributions, suggesting that paying attention during periods of higher inflation could play a role in the formation of expectations.

To assess whether the significance of the attention variables can be due to omitted variables,

[4]Prior to produce standard errors we have tested for heteroskedasticity and serial correlation using Breusch-Pagan, Durbin-Watson and Portmanteau tests. If only heteroskedasticity is detected, we apply the White correction, and when serial correlation is also detected, we use Newey-West procedure.

[5]When a correction for heterskodeastacity and serial correlation is needed, the inference is produced using Powell's kernel estimator.

Table 2: Attention and expectations

	Professional forecasters						
	SPF (quarters)						BlueChip
	h=1	h=2	h=4	h=1	h=2	h=4	h=12
GT	0.31	0.17	0.11				0.09
p-val	0.00	0.00	0.00				0.00
WSJ				0.21	0.13	0.07	0.07
p-val				0.00	0.00	0.00	0.00

	Consumer				Business	
	Michigan		NY Fed		Atlanta Fed	
	h=12					
GT	0.09		-0.02		0.04	
p-val	0.01		0.66		0.15	
WSJ		0.10		0.05		0.04
p-val		0.00		0.13		0.06

Note: This table presents estimates of β_{GT} and β_{WSJ} from the ADL regression in (1). The complete results are available in Appendix B.1. The dependent variable, $\pi_{t+h,t}$, is an inflation expectation measure. All explanatory variables have been standardized prior to estimation. When needed, inference is performed using HAC standard errors.

we have then estimated extended models:

$$y_t = c + \alpha y_{t-1} + \beta Z_t + \gamma X_t + u_t, \tag{2}$$

where the vector X_t contains regressors that may affect both inflation expectations and our attention measures. The most obvious of these is the CPI inflation rate available when agents formulate their expectations. For the SPF, since the survey is conducted at the beginning of the quarter, we assume that forecasters have the previous quarter's CPI inflation in their information set, thus in X_t. Another potentially important signal is the gas price, which we introduce in X_t as the year-over-year growth.[6] We also include the previous quarter's value of the Global Supply Chain Pressure Index (GSCPI) to account for supply-side cost pressures.

In the case of monthly data expectations (BlueChip and Michigan), the vector of control variables, X_t, includes the previous month's CPI inflation rate, gas price, and the food component of the CPI inflation (similar controls to those in Bellemare et al. (2020), who conducted a detailed exercise on NY Fed consumer expectations microdata). We replace the food CPI with

[6] We considered using the current quarter's gas price, as it is available weekly. However, results did not change.

Table 3: Attention and expectations: quantile regression Q=0.9

	Professional forecasters						
	SPF (quarters)						BlueChip
	h=1	h=2	h=4	h=1	h=2	h=4	h=12
GT	0.37	0.23	0.12				0.07
p-val	0.00	0.00	0.00				0.00
WSJ				0.23	0.17	0.09	0.10
p-val				0.00	0.00	0.03	0.00

	Consumer				Business	
	Michigan		NY Fed		Atlanta Fed	
	h=12					
GT	0.15		0.05		0.08	
p-val	0.10		0.56		0.00	
WSJ		0.10		0.11		0.03
p-val		0.00		0.18		0.24

Note: This table presents quantile regression estimates of β_{GT} and β_{WSJ} from the ADL regression in (1), for $q > 90$.

the previous month's GSCPI index for the business expectations survey of the Atlanta Fed.

Additionally, FED communications could also play a role in our regressions, despite the fact that both GT and WSJ may already incorporate them, at least in part. The role of central bank communications is well documented (see Nakamura and Steinsson (2018) and references therein). Regarding inflation expectations and FED communications, Coibion et al. (2022) and Coibion et al. (2020) find that households' and firms' attention to different forms of FED communications is limited, while Fisher et al. (2022) suggests that professional forecasters do take into account the central bank's forward-looking communications about the inflation target. To investigate whether FED communications matter, we add the FOMC monetary and inflation sentiments from Gardner et al. (2021) to the vector of controls (X_t).

Finally, we consider a measure of agents' attention to the Federal Reserve (FED) in the spirit of Jung and Kühl (2021), who use the number of visits to the ECB website. Since we do not have access to this data for the FED website on Google Analytics, we proxy it using Google Trends with keywords such as "Federal Reserve System" or "Fed." The rationale is that people do not necessarily know the exact web address of the FED and may search for it on Google.

Detailed results are presented in Appendix B.1. Overall, while several controls are relevant, the significance of the attention variables is not qualitatively affected.

3.2 Can attention predict inflation?

An even sounder test of the role of attention is whether adding GT and WSJ to the forecasting models improves or not their inflation forecasts. The benchmark is an AR(2) model for inflation:

$$\pi_{t+h} = c + \rho_1 \pi_{t-1} + \rho_2 \pi_{t-2} + u_{t+h}. \tag{3}$$

Then, we consider augmenting the AR model by an attention measure Z_t

$$\pi_{t+h} = c + \rho_1 \pi_{t-1} + \rho_2 \pi_{t-2} + \beta Z_t + u_{t+h}, \tag{4}$$

and then adding a measure of real activity

$$\pi_{t+h} = c + \rho_1 \pi_{t-1} + \rho_2 \pi_{t-2} + \beta Z_t + \delta Real_t + u_{t+h}, \tag{5}$$

where h is the forecasting horizon. We take Initial Claims as the real activity measure, $Claims_t = Real_t$ since it is produced on weekly basis and therefore is available at the end of the month t. Same goes for GT and WSJ, which are available at high frequency. We are interested in predicting the next month's ($h = 1$) values of inflation, but will also examine $h = 0$ and $h = 2$.

Then, we specify a New Keynesian Philips Curve (NKPC) type model by adding to (5) various inflation expectations available at time t:

$$\pi_{t+h} = c + \rho_1 \pi_{t-1} + \rho_2 \pi_{t-2} + \beta Z_t + \delta_1 Claims_t + \delta_2 \pi_{t+12,t} + u_{t+h}. \tag{6}$$

In particular, we include either BlueChip or Michigan 12-month ahead expectations.[7]

We also consider the so-called hybrid (or data-rich) NKPC models by adding the first three factors from McCracken and Ng (2016) FRED-MD dataset to the previous models. The baseline model in this context is the Diffusion Indexes (ARDI) from Stock and Watson (2002), and then ARDI is first augmented by Z_t and then sequentially by expectations and real activity measures.

[7]We consider only those two measures since they are available since the beginning of the sample. Also, we restrict to monthly frequency only to maintain a reasonable amount of observations in the evaluation period.

Table 4: Pseudo-out-of-sample prediction of the next month inflation

	CPI				PCE				CPI Core			
	Z_t = GT		Z_t = WSJ		Z_t = GT		Z_t = WSJ		Z_t = GT		Z_t = WSJ	
Models	Full	>q90	Full	>q90	Full	>q90	Full	>q90	Full	>q90	Full	>q90
AR (RMSE)	0.64	1.07	0.64	1.07	0.44	0.71	0.44	0.71	0.36	0.54	0.36	0.54
Augmented ARs												
AR-Z	0.99	0.94	0.92	0.74*	1	0.96	0.94	0.83	1	1.14	0.96	0.88
AR, CLAIMS	0.96*	0.91	0.96*	0.91	0.96**	0.91	0.96**	0.91	0.96	0.98	0.96	0.98
AR-Z, CLAIMS	0.95	0.86	**0.89****	0.69*	0.96	0.88	0.91**	0.76*	0.96	1.12	0.92	0.88
NKPC-												
MICH, CLAIMS	0.94**	0.86*	0.94**	0.86*	0.97	0.9	0.97	0.9	0.94	**0.95**	0.94	0.95
MICH-Z, CLAIMS	**0.94**	0.82	0.89*	0.65**	0.97	0.87	0.94	0.76*	0.95	1.1	0.92	0.88
BC1YR, CLAIMS	0.95	0.91	0.95	0.91	**0.95**	0.9	0.95	0.9	0.94	0.95	0.94	0.95
BC1YR-Z, CLAIMS	0.95	0.87	0.9	0.69	0.96	0.88	**0.91***	0.75*	**0.93**	1.03	**0.9***	**0.83**
Data-rich NKPC-												
ARDI	1.11**	1.03	1.11**	1.03	1.17**	1.03	1.17**	1.03	1.02	1.06	1.02	1.06
ARDI-Z	1.1	0.9	1.06	0.74*	1.17*	0.94	1.14	0.83*	1.01	1.17	0.98	0.93
ARDI-MICH, CLAIMS	1.1	0.89	1.1	0.89	1.16*	0.92	1.16*	0.92	0.96	1.01	0.96	1.01
ARDI-MICH-Z, CLAIMS	1.1	**0.75**	1.05	**0.63****	1.17	**0.83**	1.14	**0.75****	0.96	1.1	0.94	0.91
ARDI-BC1YR, CLAIMS	1.1	0.95	1.1	0.95	1.16*	0.96	1.16*	0.96	0.98	1.01	0.98	1.01
ARDI-BC1YR-Z, CLAIMS	1.09	0.84	1.06	0.69*	1.16	0.87	1.14	0.78**	0.96	1.07	0.94	0.88

Note: This table shows out-of-sample predictive performance, mean squared errors (MSE) relative to AR, of various models augmented by GT or WSJ. The group of Augmented ARs is given by equation (5) where π_t is the year-over-year CPI inflation. The second group consists of NKPC-type models as in equation (6). The third group is made of "hybrid" NKPC models defined in (7). The full *OOS is 2010M01 - 2024M03, >q90 stands for the 90^{th} quantile of the target variable. Minimum values for each column are in bold, while ***, ** and * stand for 1%, 5% and 10% significance of Diebold- Mariano test.*

The resulting model can be written as:

$$\pi_{t+h} = c + \rho_1 \pi_{t-1} + \rho_2 \pi_{t-2} + \beta Z_t + \delta_1 Claims_t + \delta_2 \pi_{t+12,t} + \omega F_{t-1} + u_{t+h}. \tag{7}$$

Factors are estimated by principal components. The evaluation period is from 2010M01 to 2024M3.[8] We use an expanding window and re-estimate all models recursively.

The results for predicting inflation one month ahead are presented in Table 4. We find that both GT and WSJ exhibit significant out-of-sample predictive power for standard inflation measures such as CPI, PCE, and Core CPI, especially during periods of high inflation. Among the NKPC models of the form (6), those using either BlueChip or Michigan expectations, along with Initial Claims, and augmented by the professional attention measure WSJ, appear to be the most robust specification. These models consistently yield better predictive performance than the baseline models across different inflation measures.

Table 4 also highlights that attention measures are particularly beneficial when inflation is in the 90^{th} percentile. For instance, the hybrid NKPC with Michigan expectations, augmented

[8]We have excluded the Great recession 2007-2009 period since all models produce very large forecast errors that then affect mean squared forecast errors for the entire pseudo out-of-sample. Nevertheless, results from 2007-2024 test sample, presented in Table 28 in Appendix B.2, show that attention still helps predicting inflation.

with professional attention, reduces the mean squared error by as much as 37% and 25% in the case of CPI and PCE respectively. Results for other horizons, presented in Appendix B.2, further illustrate that incorporating attention measures improves forecast accuracy. This emphasizes the value of using media-based attention metrics to enhance inflation predictions in both stable and high-inflation environments.

3.3 The effects of inflation attention shocks

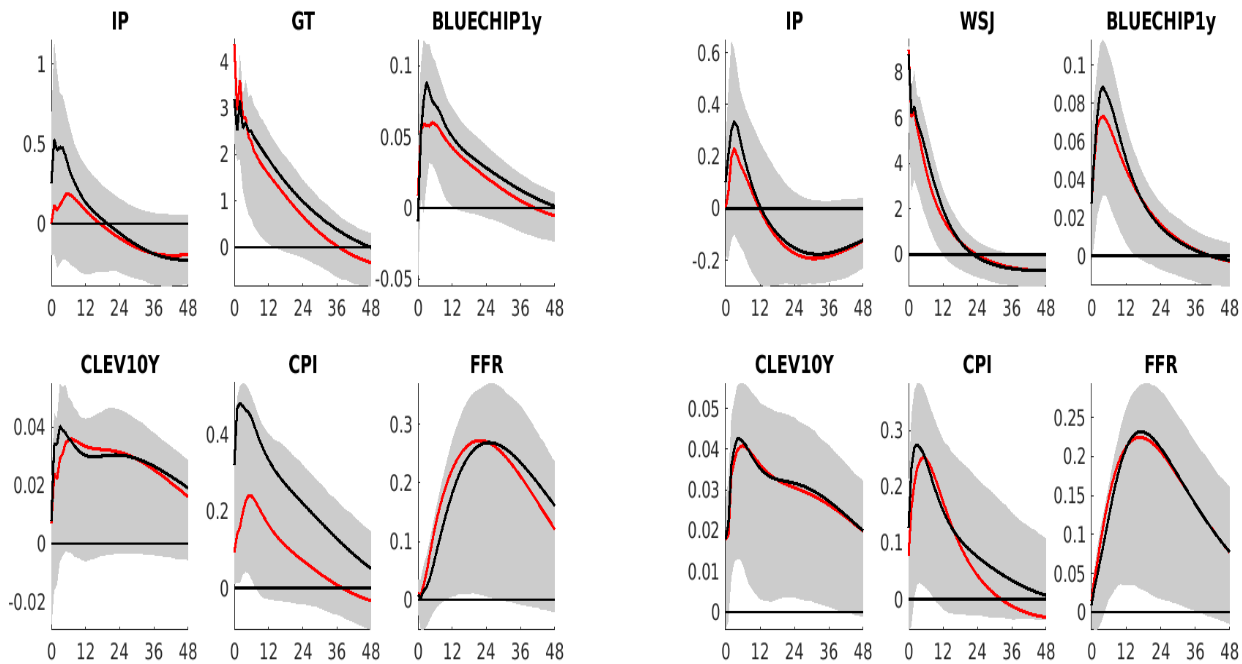
To explore the impact of attention and its dynamic transmission to inflation expectations and actual inflation, we estimate a monthly structural VAR model. The model includes oil inflation (year-on-year growth of the West Texas Intermediate spot crude oil price), industrial production growth (IP), GT or WSJ attention, BlueChip inflation expectations, Cleveland Fed 10-year ahead expectations (CLEV10Y) to measure long-run expectations, CPI inflation, and the Fed Funds Rate (FFR) to control for monetary policy influences. [9]

Identifying an attention shock is not straightforward. While imposing a recursive ordering among the variables listed above is plausible in terms of timing restrictions, it does not account for the long-run effects of attention and may overlook the impact of price increases on attention, which is not captured by standard short-run restrictions, similar to sentiment shocks. Therefore, we identify attention shocks using the following set of restrictions on our benchmark monthly VAR. First, we identify a shock that is the only one to have a long-run impact on inflation. Next, we identify the second shock using the Max Share identification method, as outlined by Barsky and Sims (2011). This innovation, labeled as the attention shock, explains the largest portion of the short-run forecasting variance of the attention measure (up to $h = 2$). [10] We set the number of lags to 3, and the 90% confidence intervals are computed using a block-bootstrap procedure.

Figure 2 presents the impulse response functions to attention shocks. In general, a positive shock to public attention GT (left panels) or a positive shock to professional attention WSJ (right panels) leads to a significant increase in BlueChip short-run inflation expectations, in line with the results in Section 3.1. Additionally, the WSJ shock has a significant, short-lived impact

[9] See Clark and Davig (2008) for an assessment of VAR analyses that include inflation and its expectations.
[10] Maximizing the forecasting variance up to 6 or 12 months ahead did not alter the results.

Figure 2: IRFs to professional attention shocks



(a) Shock to GT

(b) Shock to WSJ

Note: The VAR contains $[Oil_t, IP_t, Z_t, BlueChip_t, CLEV10Y_t, CPI_t, FFR_t]$*. Recursive ordering IRFs are in red. The 90% confidence intervals are obtained using a block-bootstrap procedure.*

on long-run expectations. This, in turn, triggers a significant rise in inflation, followed by a response from monetary policy.

The analysis using recursive identification is presented in Appendix B.3.1. Overall, the results are consistent and robust to various orderings and controls. Additionally, dynamic responses estimated from a quantile VAR are even stronger in the right tail, particularly for short- and long-run inflation expectations, as well as for CPI inflation, reinforcing the findings from previous sections.

In conclusion, this section demonstrates that attention retains significant predictive power for both inflation and inflation expectations, even after controlling for several factors typically associated with inflation, and in particular when inflation is high. This suggests that the dynamics of inflation are state-dependent with respect to attention. The structural VAR analysis further isolates the effects of shocks to our attention measures, which are not fully captured by standard inflation expectations in the model, likely because both GT and WSJ provide more granular information. We find that increased attention leads to higher inflation, which we interpret as evidence that changes in the processing of information can induce real changes in economic dynamics. This finding aligns with Chahrour et al. (2021), who show that media can independently drive business cycle fluctuations, and with the attention cycles documented in Flynn and Sastry (2024).

4 Attention and Full Information Rational Expectations

We now examine the relevance of our professional and general attention measures in the context of full-information rational expectations (FIRE) tests. Let $\pi_{t+h|t} - \pi_{t+h|t-1} = \mathrm{E}(\pi_{t+h}|\Omega_t) - \mathrm{E}(\pi_{t+h}|\Omega_{t-1}) = R_{t+h|t}$ denote the ex-ante mean forecast revision, and recall that $e_{t+h|t} = \pi_{t+h} - \pi_{t+h|t}$ is the ex-post forecast error. Following Coibion and Gorodnichenko (2015), we utilize theory-based relationships between these two objects to link our findings with three categories of models: FIRE models, models of rational expectations featuring information frictions, and alternative models.

Specifically, two frameworks of information rigidities are considered. In the sticky-information model proposed by Mankiw and Reis (2002), agents update their predictions between $t-1$ and t based on the new information set Ω_t with probability $(1-\lambda)$, meaning they fail to revise their forecasts with probability λ, which represents the degree of information rigidity or stickiness. Under FIRE, agents fully incorporate their new information set, implying $\lambda = 0$, so $e_{t+h|t}$ cannot be predicted using information from Ω_t or earlier. Coibion and Gorodnichenko (2015) demonstrate that this sticky-information environment leads to the following relationship:

$$e_{t+h|t} = c + \beta R_{t+h|t} + u_{t+h} \tag{8}$$

from which λ is derived as $\beta/(1+\beta)$.[11] Thus, under the null hypothesis (FIRE), we have $\beta = 0$, while the alternative with $\beta > 0$ is consistent with the sticky-information model. Conversely, a rejection of the null with $\beta < 0$ suggests a deviation from rational expectations for which we have no specific model in mind.[12]

[11] It is important to note that the prediction in terms of 8 holds only when averaging across agents.

[12] See Bordalo et al. (2020) or Kohlhas and Walther (2021) for alternative theories.

Table 5: Implied degrees of information rigidity in standard FIRE testing

	OLS	Quantile reg. eq. 8		
		q=0.5	q=0.8	q=0.9
Inf. stickiness (λ)	0.63	0.67	0.61	0.59
	[0.58,0.69]	[0.57,0.77]	[0.53,0.7]	[0.53,0.65]
Kalman gain (G)	0.37	0.33	0.39	0.41
	[0.31,0.42]	[0.23,0.43]	[0.3,0.47]	[0.35,0.47]

Note: This table presents the implied measures of information stickiness and noise estimated from equation (8) by OLS and by quantile regressions for quantiles 0.5, 0.8 and 0.9. The brackets are the 90th confidence intervals computed using Newey-West procedure. The sample span is 1998Q1-2024Q1.

An alternative set-up is the general noisy-information model, where agents fully update their beliefs based on Ω_t but observe only a noisy representation of the state of the economy. The Kalman gain from the filtering process, denoted as G, reflects the signal-to-noise ratio of the new information. In the absence of noise, the signal perfectly correlates with the true state, resulting in $G = 1$. The model's predictions can again be expressed using equation (8), but now the null hypothesis and its rejection with $\beta > 0$ are interpreted as evidence of noisy information. The Kalman gain is computed as $G = 1/(1 + \beta)$.

The interpretation of a rejection of the null hypothesis with $\beta > 0$ depends on one's preferred view of information frictions. However, regardless of the specific interpretation, expectations remain rational and are compatible with the vast majority of macroeconomic models, including those in which the expectation formation process responds to variations in attention.

4.1 Information rigidity

We start by estimating (8), to run the standard test of the FIRE hypothesis, using measured one-quarter-ahead expectations from the SPF. Additionally, we conduct an equivalent analysis using quantile regression, which enables us to examine whether a systematic relationship exists between the magnitude of forecast errors and their revisions. The estimated information stickiness (λ) and Kalman gain (G), along with 90% confidence intervals, are shown in Table 5.

The degrees of information rigidity implied by equation (8) indicate a rejection of the full-information hypothesis, consistent with models of imperfect information. Moreover, the results from the quantile regressions do not suggest that information is processed at different rates depending on the size of forecast errors — while point estimates of λ vary, their confidence intervals generally overlap. Specifically, if one associates the magnitude of forecast errors with the volatility of the predicted variable (inflation, in this case), it would not be possible to attribute changes in the expectations formation process to these fluctuations.

4.2 Forecasts optimality with respect to attention

So far, we have implicitly treated the expectations formation process as optimal[13] meaning that we assumed forecasts revisions incorporate all the information available to forecasters up to that point in time. However, as discussed in Section 3.3, we found that an increase in attention leads to both higher inflation and inflation expectations.

Our general and professional attention measures are available during the information set update between $t-1$ and t, and are measured as averages over agents. Therefore, they can be used in the previous setups. We first estimate the following regression

$$e_{t+h|t} = c + \delta Z_t + u_{t+h}, \tag{9}$$

where Z_t contains either GT or WSJ. For an optimal forecast to be unbiased, $c = 0$, and forecast errors should not be predictable based on information available at the time the prediction is made, i.e. $\delta = 0$. To link this to information rigidity, the key question is whether Z_t belongs to the informational set Ω_t. In Section 3, we showed that attention significantly explains inflation expectations, suggesting that Z_t is likely included in Ω_t. However, this does not necessarily imply that the information contained in Z_t has been fully incorporated into the revision $R_{t+h|t}$. Thus, we estimate an additional regression

$$e_{t+h|t} = c + \beta R_{t+h|t} + \delta Z_t + u_{t+h} \tag{10}$$

which enables to test for the marginal effect of attention in the presence of forecast revisions

[13] Coibion and Gorodnichenko (2015) demonstrated that few controls are relevant when estimating equation 8, suggesting that information is typically processed optimally by forecasters. However, Kohlhas and Walther (2021) argue that expectations tend to overreact to some macroeconomic variables.

($H_0 : \delta = 0$), to test the forecast optimality with respect to information set spanned by both $R_{t+h|t}$ and Z_t ($H_0 : \beta = \delta = 0$), but also to update the estimates of information rigidities λ and G from those obtained after equation (8). Note that if $H_0 : \delta = 0$ is rejected, it can also indicate that deviations from FIRE may not be compatible with the above information friction models. However, the coefficient β remains informative about how forecasters react to new information.

Rejecting $H_0 : \beta = \delta = 0$, in equation (10) implies that forecasters have not fully absorbed the effects of attention in their beliefs about future inflation. One possible explanation is that forecasters do not observe Z_t as we econometricians do (e.g. they observe Z_t plus a noise). In this case, attention to inflation dynamics contributes to (sticky or noisy) information rigidities, and we expect $\delta > 0$ and β to be smaller than the estimate obtained in equation (8).

Regression (10) captures the average effects of attention on deviations from FIRE and information rigidities. However, as shown in Section 3, attention has a nonlinear impact on expectations. We exploit this heterogeneity by estimating equation (10) with quantile regression:

$$Q_{e_{t+h|t}}(\tau) = c(\tau) + \beta(\tau)R_{t+h|t} + \delta(\tau)Z_t + u_{t+h}(\tau) \tag{11}$$

Equations (8) - (11) are estimated using SPF forecast errors for one-quarter ahead. The estimation results are presented in Table 6. As expected, the estimated β with attention is smaller than without it, implying that forecast errors in the baseline FIRE regression are partially explained by the fact that forecasters do not fully absorb the effects that attention to inflation developments has on actual inflation. This is particularly true in the case of professional attention, as β drops from 1.73 to 0.88. At the same time, the positive and significant coefficients on attention –measured by the parameter δ – confirm our hypothesis that forecast revisions do not fully incorporate the information contained in the public signal Z_t. Additionally, models including attention exhibit more unbiased forecasts, as shown by the lower significance of the constant term, implying that paying attention leads to more accurate predictions of inflation.

Regarding the quantile regression estimates from equation (11), we observe that the impact of attention varies across different segments of the forecast error distribution. As we move to higher quantiles ($q = 0.8$ and $q = 0.9$), β shrinks even further, while the impact of attention

Table 6: Estimation results

	GT attention						WSJ attention					
	OLS			Quantile reg. eq. 11			OLS			Quantile reg. eq. 11		
	eq. 8	eq. 9	eq. 10	q=0.5	q=0.8	q=0.9	eq. 8	eq. 9	eq. 10	q=0.5	q=0.8	q=0.9
c	0.34	-1.16	-0.7	-0.61	-1.02	-1.36	0.32	-0.46	-0.26	-0.3	0.32	0.54
p-val	0.02	0	0.05	0.01	0.06	0.05	0.01	0	0.13	0.26	0.31	0
β	1.76		1.12	1.19	0.94	0.45	1.73		0.88	0.89	0.7	0.01
p-val	0		0	0	0.11	0.55	0		0.01	0.17	0.18	0.99
δ^{GT}		0.06	0.04	0.03	0.08	0.13						
p-val		0	0	0	0	0						
δ^{WSJ}								0.04	0.03	0.02	0.04	0.05
p-val								0	0	0.05	0.01	0
$\beta = \delta = 0$			0	0	0	0			0	0	0	0
R^2	0.24	0.26	0.32	0.81	0.77	0.72	0.23	0.31	0.35	0.85	0.75	0.64

Note: Columns under OLS show estimates of equations 8, 9 and 10, while the last three columns present estimates from the quantile regression 11 for quantiles $q < 0.5$, $q > 0.8$ and $q > 0.9$. The adjusted R^2 is reported for the OLS columns, and the pseudo-R^2 for quantile regressions. Sample span is 2004Q1-2024Q1 in the case of GT (left panel) and 1998Q1-2024Q1 in the case of WSJ (right panel). Inference is performed using Newey-West procedure.

becomes more pronounced. This suggests that measured information rigidity would decrease by a larger extent during periods of high inflation if forecasters would fully absorb the effects of Z_t. The forecast bias is also reduced with the inclusion of attention, as evidenced by the decrease in the significance of the constant term.

In Table 7 we summarize the impact of attention on the implied degrees of information rigidity. The upper panel shows the estimates of information stickiness λ, while the bottom panel reports the Kalman filter gain G. We find that attention plays an important role for information rigidity. On average, adding professional (WSJ) attention reduces information stickiness by 34%, as λ decreases from 0.63 to 0.47 in the right panel, from columns (1) to (2). This implies that forecasters who pay more attention to economic news update their information sets more often, shortening the time between forecast revisions from over 8 months to 5-6 months.

The impact of attention using estimates from the quantile regression (11) is even stronger. The degree of information stickiness decreases to 0.48 (0.41) at the 80^{th} quantile of the forecast error distribution when general (professional) attention is included. At the 90^{th} percentile, the estimates are smaller but not significant, suggesting that FIRE hypothesis is not violated at the far right tail of the distribution.

The Kalman gain (G), which reflects the signal-to-noise ratio of the information received and is the inverse of information stickiness, increases with the inclusion of attention measures.

Table 7: Implied degrees of information rigidity

	No attention				GT attention			
	OLS	Quantile reg. eq. 8			OLS	Quantile reg. eq. 11		
	eq. 8	q=0.5	q=0.8	q=0.9	eq. 10	q=0.5	q=0.8	q=0.9
Stickiness (λ)	0.64	0.68	0.6	0.57	0.53	0.54	0.48	0.31
	[0.58,0.7]	[0.64,0.72]	[0.44,0.76]	[0.48,0.65]	[0.42,0.64]	[0.47,0.61]	[0.28,0.68]	[-0.15,0.77]
Kalman gain (G)	0.36	0.32	0.4	0.43	0.47	0.46	0.52	0.69
	[0.3,0.42]	[0.28,0.36]	[0.24,0.56]	[0.35,0.52]	[0.36,0.58]	[0.39,0.53]	[0.32,0.72]	[0.23,1.15]

	No attention				WSJ attention			
	OLS	Quantile reg. eq. 8			OLS	Quantile reg. eq. 11		
	eq. 8	q=0.5	q=0.8	q=0.9	eq. 10	q=0.5	q=0.8	q=0.9
Inf. stickiness (λ)	0.63	0.67	0.61	0.59	0.47	0.47	0.41	0.01
	[0.58,0.69]	[0.57,0.77]	[0.53,0.7]	[0.53,0.65]	[0.34,0.59]	[0.35,0.59]	[0.19,0.63]	[-0.3,0.3]
Kalman gain (G)	0.37	0.33	0.39	0.41	0.53	0.53	0.59	0.99
	[0.31,0.42]	[0.23,0.43]	[0.3,0.47]	[0.35,0.47]	[0.41,0.66]	[0.41,0.65]	[0.37,0.81]	[0.7,1.3]

Note: Columns (1) and (2) show estimates from equations 8 and 10 respectively, while the column (3) to (5) present estimates obtained from the quantile regression 11 for quantiles ($q < 50$, $q > 80$ and $q > 90$) respectively. The brackets are the 90th confidence bands computed using Newey-West procedure.

This indicates that attention helps forecasters better filter out noise and focus on relevant information when making their predictions. At the right tail of the distribution, the Kalman gain reaches even higher values, further supporting the idea that attention helps forecasters improve their information-processing abilities, especially during periods of heightened uncertainty.

Overall, we find that the FIRE hypothesis is often rejected, suggesting that some informational rigidities exist and can be exploited. Higher attention is associated with lower information stickiness, indicating that attention introduces state-dependent information rigidities, which is consistent with (Flynn and Sastry, 2024). These results are qualitatively robust, as shown in Appendix C, when we include control variables as in Coibion and Gorodnichenko (2015): previous quarter CPI inflation, GSCPI, oil prices, the 3-month T-bill, the unemployment rate, and the VIX, as well as for the 2-quarter ahead forecasts.

5 Model

Our empirical evidence suggests that broad measures of attention affect the information rigidity associated with inflation expectations. In this section, we propose a theoretical model that can explain why professional forecasters' information rigidity decreases with the level of attention, even in the limiting case where they process a constant amount of information.[14]

At the core of the model is the idea that there is information regarding inflation that is publicly available. This information is always used by forecasters, but active economic agents (firms in our model) only use it during high-attention periods to form their expectations. When this occurs, the information sets of forecasters and firms share a common element, which is not the case during low-attention periods. As a result, the firms' (hierarchy of) beliefs become more predictable for the forecasters[15], explaining why their information rigidity decreases. This is also true for a firm's forecast of other firms' forecasts, and it has consequences for the dynamics of real and nominal variables within our model. In particular, the real effects of monetary policy depend on the attention regimes.

5.1 A price-setting model under imperfect information

We consider Woodford (2003) model of monopolistic competition, in which a continuum of firms indexed by $i \in [0,1]$ can freely adjust their prices in every period based on their beliefs regarding the state of the economy. Firm i sets its price according to the following log-linear rule

$$p_t(i) = p_{t|t}(i) + \alpha y_{t|t}(i) \tag{12}$$

where $x_{t+s|t}(i) := E_t[x_{t+s}|\Omega_t(i)]$ denotes firm i's beliefs regarding variable x at horizon $t+s$, given its information set in period t, denoted $\Omega_t(i)$[16] . The parameter α is strictly greater than 0, but we assume that it is also bounded above by 1, such that prices are strategic complements. A lower value of α means that a firm's optimal price depends more on the prices charged by other firms than on real variables. This parameter is often referred to as the degree of real rigidity in the economy, which is a form of price stickiness under imperfect information.

We follow Woodford and assume that the demand side of the economy can be modeled by

[14] Assuming that forecasters process more information during periods of high attention would strengthen our results.

[15] The model's dynamics are driven by the aggregate noise shock which depends on a signal observed by all agents.

[16] What information is contained in $\Omega_t(i)$ will be formally defined later.

an exogenous stochastic process for nominal expenditure, corresponding to a specific monetary policy. We can rewrite firm i's pricing decision as:

$$p_t(i) = \alpha q_{t|t}(i) + (1-\alpha) p_{t|t}(i). \tag{13}$$

Equation 13 states that a firm sets a price that is a linear combination of its expectations of nominal expenditure and the price level. Taking the average across firms, we obtain the following equation for the price level:

$$p_t = \alpha q_{t|t} + (1-\alpha) p_{t|t} \tag{14}$$

where $x_{t|t} := \int x_{t|t}(i) di$ represents the average expectation of x_t. Thus, the price level is a linear combination of the firms' average first-order expectations for both the price level itself and nominal expenditure. Introducing the following notation for higher-order expectations:

$$x_t^{(0)} = x_t \tag{15}$$

$$x_t^{(k)} = x_{t|t}^{(k-1)} \quad \forall k > 0 \tag{16}$$

we can express the price level as a linear combination of higher-order expectations regarding nominal expenditure:

$$p_t = \sum_{k=1}^{+\infty} \alpha (1-\alpha)^k q_t^{(k)}. \tag{17}$$

Clearly, a condition for monetary policy to have real effects is that $q_{t|t}(i) \neq q_t$; otherwise, the price level would perfectly follow nominal expenditure, and output would never deviate. This is what would occur if firms had perfect information. Under imperfect information, firms slowly update their beliefs regarding q_t and are uncertain about the beliefs of others due to dispersed information. The degree of strategic complementarity determines how much each element in a firm's hierarchy of beliefs matters for its pricing decision.

Information sets During periods of low attention, we assume that firms receive a private noisy signal regarding the value of q_t such that

$$s_t(i) = q_t + \epsilon_t(i) \; ; \; \epsilon_t(i) \sim N(0, \sigma_\epsilon^2). \tag{18}$$

Then, firm i's information set is given by

$$\Omega_t(i) = \{s_t(i), s_{t-1}(i), ...\}. \tag{19}$$

In periods of high attention, we introduce the following public signal into the information set of every firm:

$$s_t = q_t + \epsilon_t \; ; \; \epsilon_t \sim N(0, \sigma_\epsilon^2). \tag{20}$$

We do not analyze the transition between these two attention regimes and make the simplifying assumption that "enough" time has passed such that the firms' filtering problem has reached its steady state.[17] Our results do not depend on this assumption. In fact, firms would update their beliefs by a larger amount during the transition period, which would strengthen our findings.

We assume that there is common knowledge of the model's structure and of rationality among firms, which allows them to recursively compute expectations of average higher-order beliefs through Kalman filtering. In particular, we have that, during periods of high attention, the public signal and average higher-order beliefs for $k > 0$ are positively correlated.

The assumption of information sets that are specific to low- and high-attention periods implies that firms adjust their prices at different rates under the different regimes. We will show that, in our model, this feature induces a negative correlation between price stickiness and inflation, replicating the findings documented by Yotzov et al. (2024).

[17]For instance, Korenok et al. (2023) finds that attention activates when inflation reaches a threshold, which is estimated between 2 and 4%.

Forecasters We introduce forecasters who play no active role in the economy but know the structure of the model in each of its states. Therefore, they can form estimates of the firms' average higher-order beliefs regarding nominal expenditure, which they can use to forecast the price level and output. A forecaster's information set is given by

$$\Lambda_t(j) = \{s_t, s_t(j), s_{t-1}, s_t(j), ...\} \tag{21}$$

where s_t is the same public signal that firms have access to in periods of high attention, and $s_t(j)$ is the private signal such that

$$s_t(j) = q_t + \eta(j) \ ; \ \eta(j) \sim N(0, \sigma_\eta^2) \tag{22}$$

5.2 Dynamics

We consider the case where nominal expenditure follows a random walk such that

$$q_t = q_{t-1} + u_t \ ; \ u_t \sim N(0, \sigma_u^2) \tag{23}$$

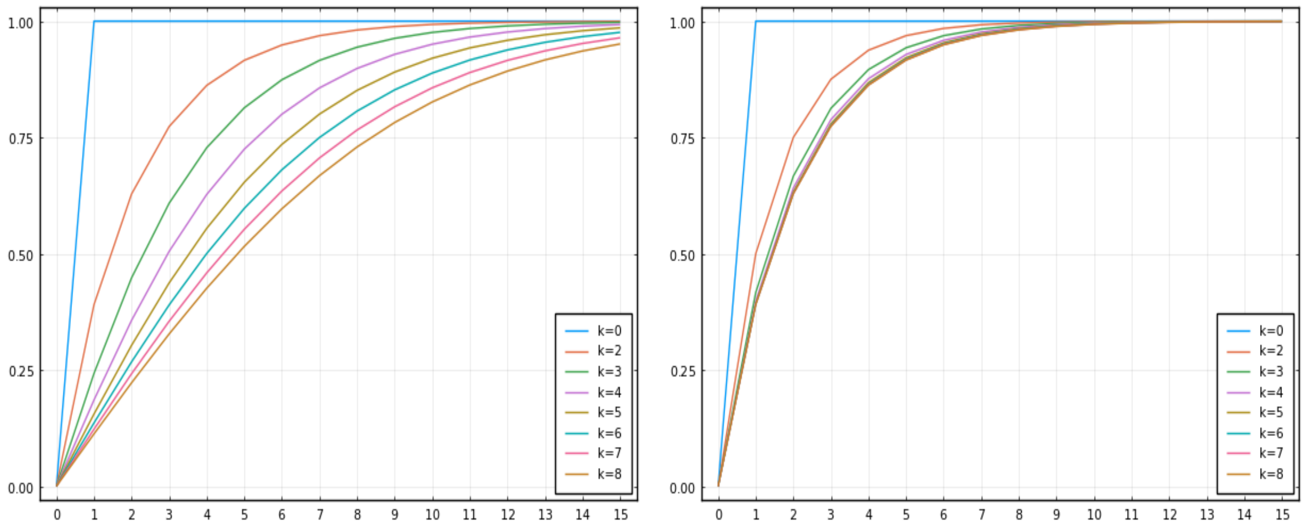
and study the effects of a positive shock equal to one standard deviation at $t = 0$ under both attention regimes. In other words, the same expansionary monetary policy is conducted under the different regimes, with the only difference being that, in high-attention periods, firms have more information and share some of it with the forecasters.

We set the parameters to the following values: $\sigma_u^2 = 1$, $\sigma_\epsilon^2 = 4$,$\sigma_\eta^2 = 4$ and $\alpha = 0.15$. This is essentially the same parametrization proposed by Woodford (2003), except for the variance of the public signal error term, which we select. Given our choice for σ_ϵ^2, the combined forecasters' signals have twice the precision of the firms' private signal[18] during low-attention periods. We consider this a reasonable benchmark.

The procedure used to solve the model in the different regimes is detailed in Appendix D.

[18]Here, precision refers to the inverse of the noise variance in a given signal. The variance of the combined signals can be computed as follows: $(\sigma_\eta^2 \sigma_\epsilon^2)(\sigma_\eta^2 \sigma_\epsilon^2)^{-1}$, which follows from optimal filtering.

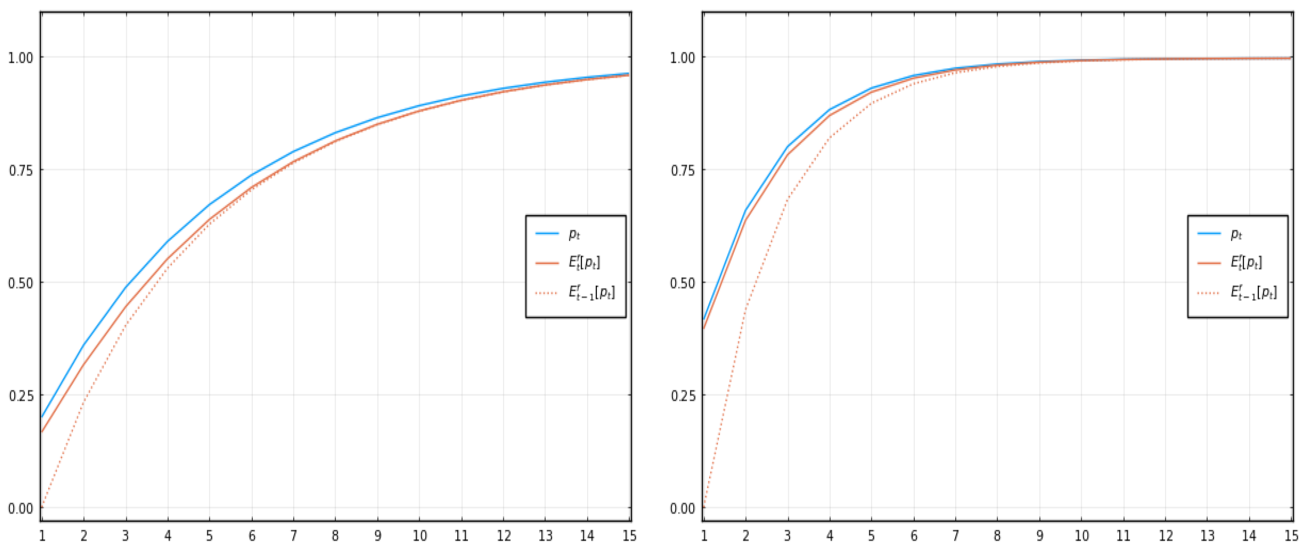
Figure 3: Higher order expectations



(a) Low-attention

(b) High-attention

Figure 4: Impulse responses of the price level and forecasts to a positive shock on q_t



(a) Low-attention

(b) High-attention

5.3 Implication for information rigidity

We begin by examining the model's predictions about information rigidity, focusing first on firms. After the shock, Figure 3 shows that the hierarchy of firms' average beliefs regarding nominal expenditure is closer to the true value of q_t and more concentrated during high-attention periods. The first observation reflects that beliefs update faster when firms receive more information.[19] The second observation relates to a decrease in the uncertainty about the beliefs of others. This is driven by the positive correlation between the public signal and higher-order beliefs (i.e., everyone knows that everyone is using the same signal to form beliefs, which anchors the hierarchy).

Since the public signal is shared between firms and forecasters, this also means that the latter can forecast variables that depend on the hierarchy of firms' beliefs with better accuracy during high-attention periods. In particular, it can be seen in Figure 4 that their forecasts track the price level with more accuracy in high-attention periods. This is synonymous with a decrease in their information rigidity, as documented in Section 4.

We can formally compute the magnitude of this decrease in information rigidity by simulating the model under the different regimes and regressing forecast errors on forecast revisions. For our chosen parametrization, we simulate $T = 10000$ periods for both regimes and estimate the forecasters' Kalman gain for the price level as follows:

$$\underbrace{p_t - E_t^f[p_t]}_{\text{Forecast errors}} = c + \beta \underbrace{\left(E_t^f[p_t] - E_{t-1}^f[p_t]\right)}_{\text{Forecast revisions}} + e_t, \tag{24}$$

where $E_t^f[x_{t+h}] := E_t[x_{t+h}|\Lambda_t]$.

For low-attention periods, we get $G_{\text{low}} = 0.576$, and for high-attention periods, we obtain $G_{\text{high}} = 0.737$. For high-attention periods, where firms have access to an additional private signal, we find that the forecasters' Kalman gain does not change at all, confirming that in our model, sharing information between forecasters and firms is sufficient to decrease the former's information rigidity.

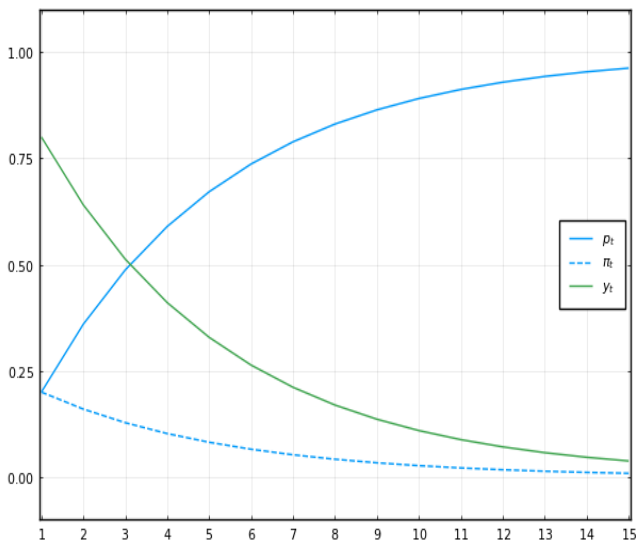
5.4 Implications for monetary policy

We now turn to the model's predictions regarding macroeconomic variables. In our framework, the price level is a function of the firms' hierarchy of beliefs regarding nominal expenditures, and output follows directly from this. We showed that having access to a public signal has

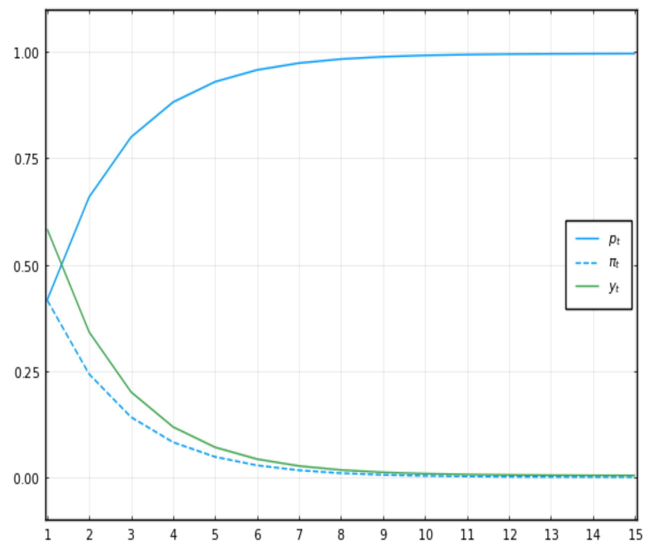
[19] More information is always synonymous with more precise information in this model.

two effects: (i) the accuracy of individual forecasts of q_t increases, and (ii) higher-order beliefs become more concentrated and exhibit less inertia. These two forces push the (real) effects of monetary policy in the same direction. Output deviations are initially smaller and less persistent during periods of high attention, as shown in Figure 5. The converse is true for the price level; it is initially closer to nominal expenditure and converges towards it at a faster rate, in accordance with Yotzov et al. (2024).

Figure 5: Impulse responses of nominal and real variables to a positive shock on q_t



(a) Low-attention



(b) High-attention

Our model is stylized along two dimensions, as noted by Swensson (2003). First, monetary policy places equal weight on the price level and output. Second, the available signals provide information about nominal expenditure. Both concerns could be addressed by adjusting the targeting rule or considering optimal monetary policy, as discussed by Adam (2007), and by allowing for endogenous signals related to the price level, inflation, or real output. While this would affect the unconditional dynamics of the model, the differences between the two regimes we highlight would remain as long as some degree of information rigidity persists.

5.5 Empirical Evaluation

We now test the model's prediction that the real effects of monetary policy are less persistent during high-attention periods, as shown in Figure 5. To do so, we specify a structural VAR following Gertler and Karadi (2015), which includes four variables: the market yield on 1-year constant maturities (GS1), the log of CPI (CPI), the log of industrial production (IP), and the equity-bond premium (EBP) from Gilchrist and Zakrajšek (2012). We also add our measure of professional attention, WSJ. The monetary policy shock is identified using sign restrictions implied by the model. Specifically, we impose that GS1 reacts negatively, while CPI and IP respond positively to an expansionary monetary policy shock. These restrictions are applied for 6 months following the shock, while the responses of EBP and WSJ are unrestricted.

To evaluate the impact of attention on monetary policy transmission, we estimate the VAR in two regimes. The first regime corresponds to periods when the previous month's WSJ attention was below its 70^{th} quantile, while the second regime includes periods when attention was higher. The second regime is thus interpreted as *high attention*, and the first as *low attention*.[20]

The results are presented in Figure 6. Since the model in each regime is linear, we scale the impulse responses so that the monetary policy shock has the same impact on GS1 in both regimes. The results align with the model's prediction regarding the real effects of monetary policy. When attention is low, the contemporaneous impact on output is much larger than in the high-attention regime. Furthermore, the dynamic responses of IP are significantly more muted under high attention. CPI reacts similarly in both regimes initially, but it reaches the new level more quickly in the high-attention regime. Finally, WSJ responds positively and significantly only in the high-attention environment.

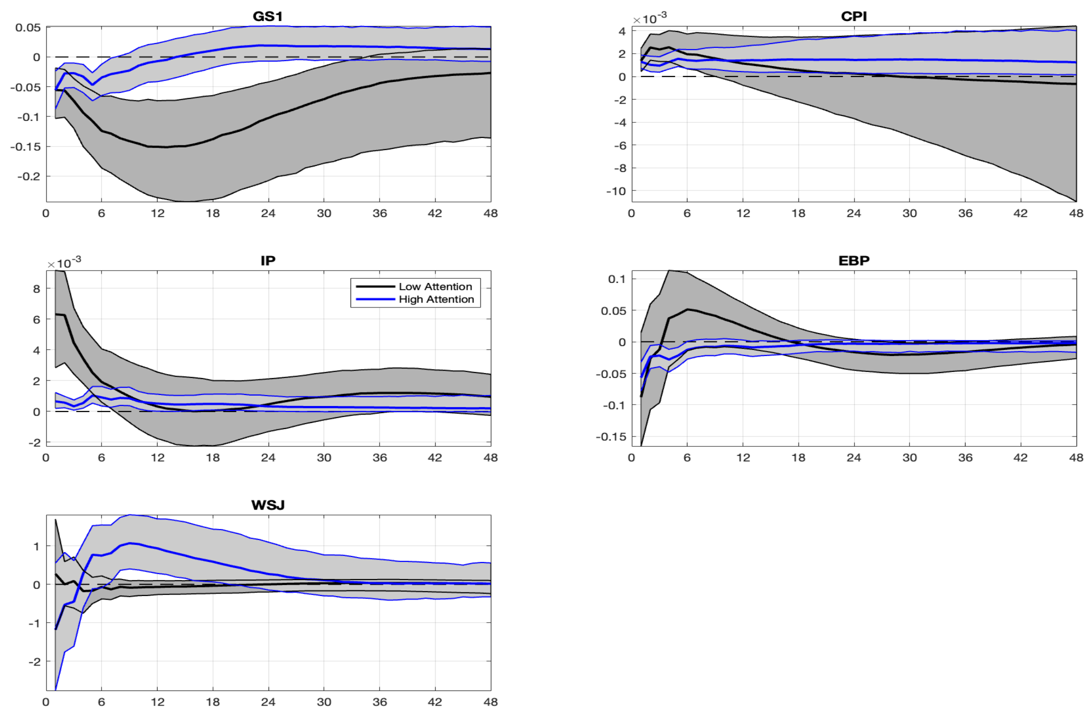
Therefore, we have shown that attention not only plays a crucial role in shaping rational expectations but also tends to diminish the real effects of monetary policy.

[20]This is an approximation of a threshold VAR where the threshold variable is WSJ attention, and the threshold value is known. We choose the 70^{th} quantile to ensure enough observations in the high-attention regime. We also set the number of lags to 4. The results are similar when using an alternative specification with interaction terms of the form:

$$Y_t = B_1(L)Y_{t-1} + B_2(L)D(q)Y_{t-1} + \gamma D(q) + u_t,$$

where $D(q)$ is a dummy variable that takes the value 1 for periods when WSJ_{t-1} exceeds its q^{th} quantile.

Figure 6: Dynamic responses to MP shocks: low versus high attention



Note: This figure compares impulse response functions estimated under low and high attention regimes. 68% confidence intervals are produced by bootstrap.

6 Conclusion

In this paper, we emphasized the pivotal role of attention in shaping inflation dynamics and expectations. Using Google Trends data and Wall Street Journal coverage indicators to capture both general and professional attention, we documented that heightened attention significantly impacts inflation outcomes, even when controlling for traditional inflation-related factors. The full information rational expectation hypothesis has been rejected; however, we found that heightened attention reduces professional forecasters' information rigidity, indicating that media communication and public awareness are critical in framing aggregate inflation expectations.

Building on these insights, we developed a theoretical model that aligns with our empirical results, revealing that both inflation dynamics and forecasters' expectations are contingent on the prevailing attention regime. In particular, the sharing of public information between forecasters and firms during periods of high attention proves sufficient to decrease forecasters' information rigidity.

The implications of this framework extend to monetary policy, suggesting that policymakers need to account for the influence of attention and media communication in designing effective policies. In sum, these findings stress the importance of understanding the dynamic interaction between attention, expectations, and economic outcomes in managing inflation and guiding macroeconomic policy.

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APPENDIX

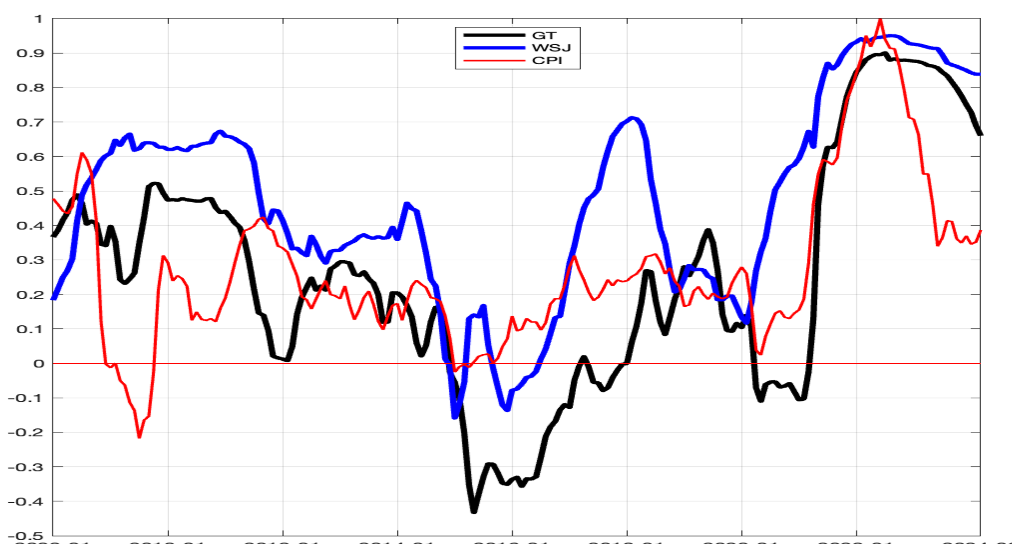
A Data: descriptive statistics of GT and WSJ

Table 8: Correlation between GT / WSJ and CPI inflation and inflation expectations

		GT	WSJ
CPI	Full sample	0.74	0.71
	<q10	0.42	-0.09
	>q90	0.88	0.79
SPF 1y fcst	Full sample	0.78	0.72
	<q10	0.43	-0.56
	>q90	0.95	0.69
BlueChip	Full sample	0.64	0.60
	<q10	-0.15	0.26
	>q90	0.42	0.21
MICH	Full sample	0.64	0.62
	<q10	-0.31	0.35
	>q90	0.35	0.51

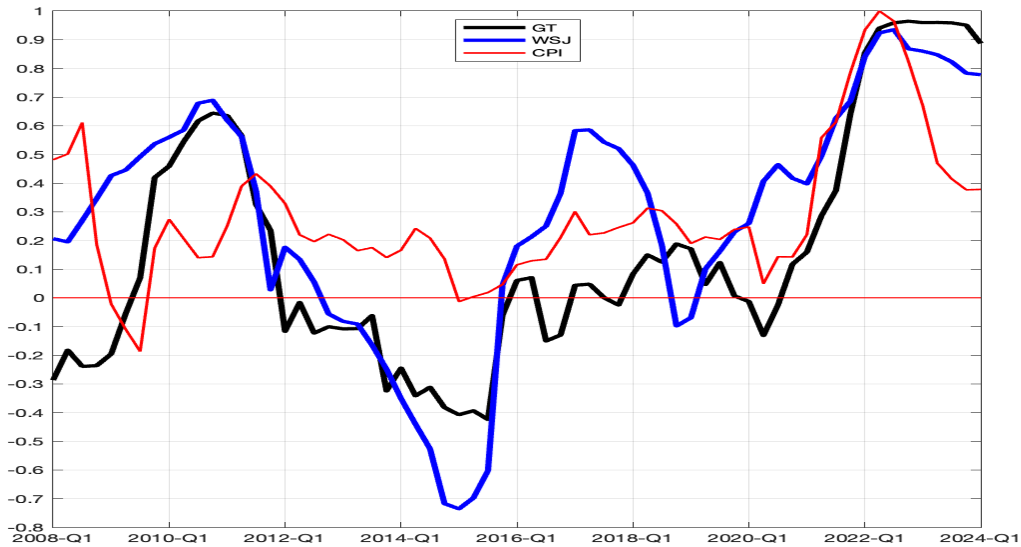
Note: This table presents contemporaneous correlation coefficients between GT or WSJ and CPI inflation, SPF 1-year ahead forecasts, BlueChip forecasts and the Michigan consumer inflation expectations.

Figure 7: Correlation between GT / WSJ and CPI inflation over time



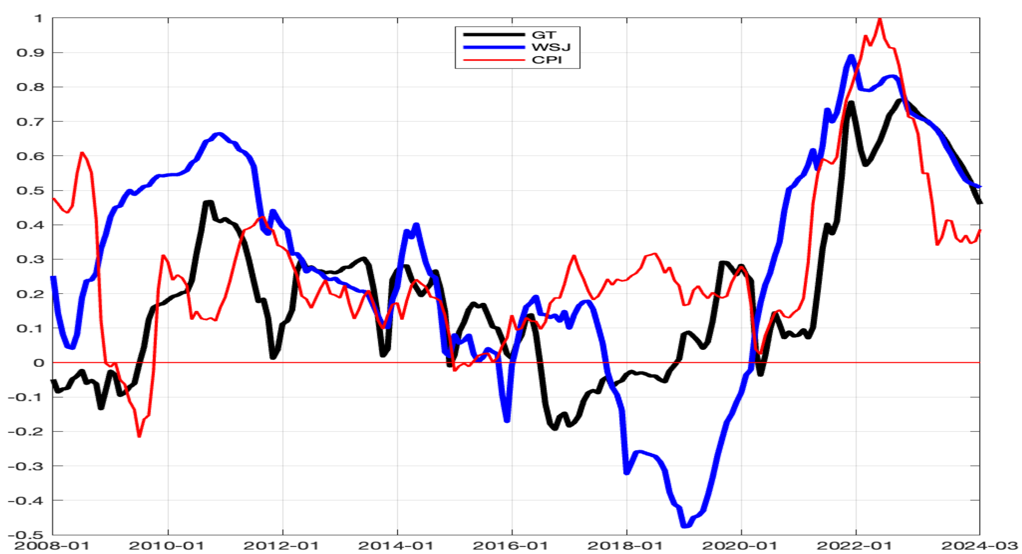
Note: This figure plots the contemporaneous correlation coefficients between GT / WSJ and the year-over-year CPI inflation with a 36-month rolling window. The CPI time series has been normalized.

Figure 8: Correlation between GT / WSJ and SPF 1-year forecasts over time



Note: This figure plots the contemporaneous correlation coefficients between GT / WSJ and the SPF 1-year forecasts with a 12-quarter rolling window. The CPI time series has been normalized.

Figure 9: Correlation between GT / WSJ and BlueChip forecasts over time



Note: This figure plots the contemporaneous correlation coefficients between GT / WSJ and the BlueChip forecasts with a 36-month rolling window. The CPI time series has been normalized.

Figure 11: GT and WSJ quantiles

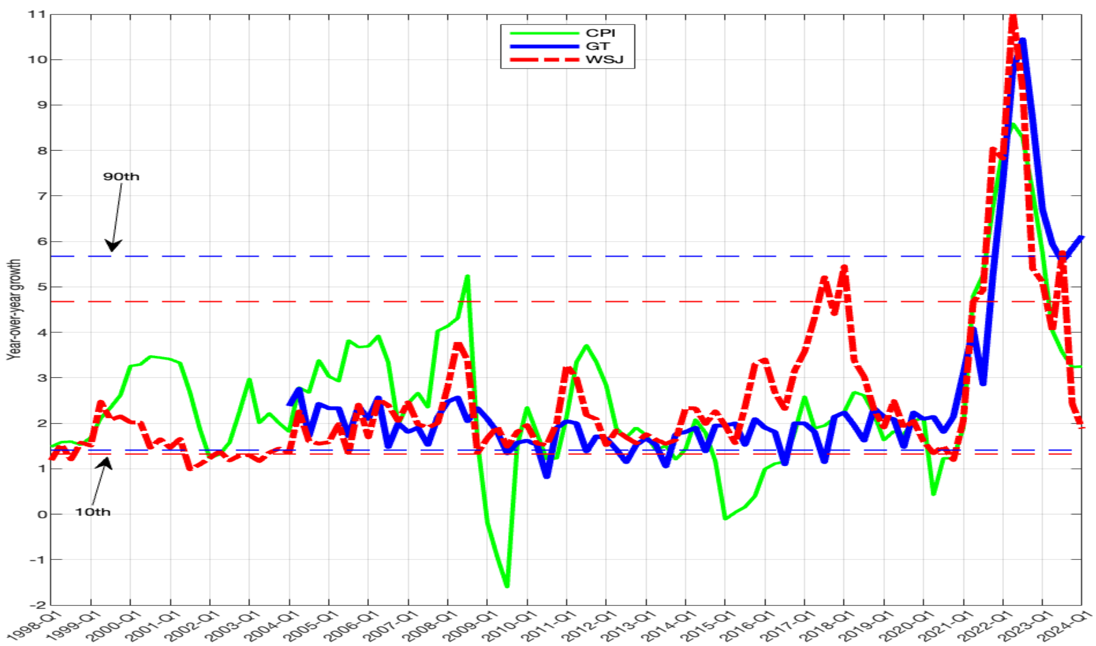
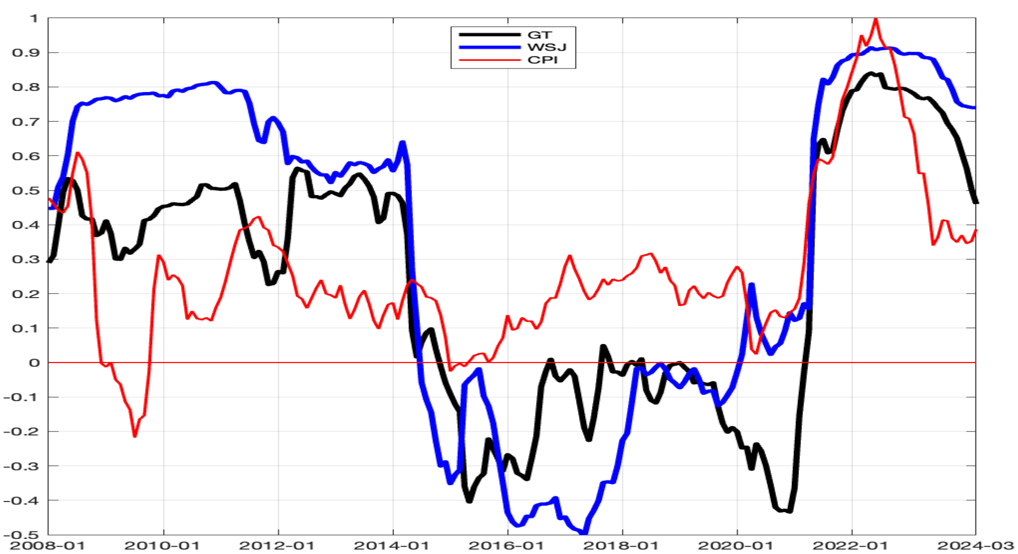


Figure 10: Correlation between GT / WSJ and consumer expectations over time



Note: This figure plots the contemporaneous correlation coefficients between GT / WSJ and the Michigan consumer expectations with a 36-month rolling window. The CPI time series has been normalized.

B Role of inflation attention: additional results

B.1 Additional results from ADL regressions

Table 9: Attention and expectations: quantile regression Q=0.8

	Professional forecasters							
	SPF (quarters)						BlueChip	
	h=1	h=2	h=4	h=1	h=2	h=4	h=12	
GT	0.38	0.15	0.14				0.03	
p-val	0.00	0.00	0.00				0.00	
WSJ				0.26	0.11	0.10		0.08
p-val				0.00	0.00	0.00		0.00

	Consumer				Business	
	Michigan		NY Fed		Atlanta Fed	
	h=12					
GT	0.15		0.07		0.04	
p-val	0.10		0.07		0.28	
WSJ		0.06		0.03		0.05
p-val		0.00		0.44		0.04

Note: This table presents quantile regression estimates of β_{GT} and β_{WSJ} from the ADL equation in (1), for $q > 0.8$.

Table 10: Attention and expectations: quantile regression Q=0.5

	Professional forecasters							
	SPF (quarters)						BlueChip	
	h=1	h=2	h=4	h=1	h=2	h=4	h=12	
GT	0.22	0.18	0.11				0.03	
p-val	0.01	0.00	0.00				0.00	
WSJ				0.13	0.13	0.08		0.02
p-val				0.00	0.00	0.00		0.00

	Consumer				Business	
	Michigan		NY Fed		Atlanta Fed	
	h=12					
GT	0.07		-0.01		0.03	
p-val	0.00		0.78		0.40	
WSJ		0.06		0.03		0.02
p-val		0.00		0.29		0.46

Note: This table presents quantile regression estimates of β_{GT} and β_{WSJ} from the ADL equation in (1), for $q > 0.5$.

Table 11: Attention and SPF expectations with Price controls

	No controls						Price controls																	
	h=1	h=2	h=4	h=1	h=2	h=4	h=1	h=2	h=4	h=1	h=2	h=4	h=1	h=2	h=4	h=1	h=2	h=4	h=1	h=2	h=4	h=1	h=2	h=4
c	2.24	2.24	2.26	2.23	2.24	2.29	2.24	2.24	2.26	2.24	2.24	2.26	2.24	2.24	2.26	2.23	2.24	2.29	2.23	2.24	2.29	2.23	2.24	2.29
p-val	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
α	0.31	0.27	0.14	0.38	0.3	0.19	0.23	0.19	0.08	0.31	0.29	0.16	0.32	0.28	0.15	0.3	0.23	0.15	0.39	0.31	0.2	0.38	0.3	0.19
p-val	0	0	0	0	0	0	0.01	0	0.01	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
GT	0.31	0.17	0.11				0.26	0.11	0.07	0.31	0.16	0.1	0.27	0.14	0.09									
p-val	0	0	0				0	0.01	0.01	0	0	0	0	0	0.01									
WSJ				0.21	0.13	0.07										0.19	0.1	0.04	0.2	0.12	0.06	0.2	0.13	0.06
p-val				0	0	0										0	0	0.02	0	0	0	0	0	0.01
γ_{π}							0.15	0.15	0.12							0.12	0.11	0.07						
p-val							0.07	0	0							0.05	0	0						
γ_{gas}										0.12	0.07	0.06							0.08	0.05	0.05			
p-val										0.01	0.01	0							0.03	0.02	0			
γ_{gscpi}													0.07	0.03	0.03							0.03	0	0.01
p-val													0.16	0.29	0.13							0.56	0.94	0.64
$\bar{R}^2$ ADL	0.71	0.75	0.71	0.71	0.76	0.7	0.72	0.78	0.76	0.73	0.77	0.75	0.71	0.75	0.72	0.72	0.78	0.72	0.72	0.77	0.73	0.71	0.76	0.7
$\bar{R}^2$ AR	0.63	0.7	0.65	0.63	0.69	0.65	0.63	0.7	0.65	0.63	0.7	0.65	0.63	0.7	0.65	0.63	0.69	0.65	0.63	0.69	0.65	0.63	0.69	0.65

Note: This table presents results from the ADL regression in (1). The dependent variable, $\pi_{t+h,t}$, is the SPF mean 1-quarter, 2-quarters and 1-year ahead forecast ($h = 1$, $h = 2$ and $h = 4$) of the year-over-year CPI inflation. All explanatory variables have been standardized prior to estimation. When needed, inference is performed using White or Newey-West standard errors. $\bar{R}^2$ ADL and $\bar{R}^2$ AR stand for the adjusted R^2 from the ADL predictive regressions and the AR(1) model respectively. Regressions with WSJ and price controls are performed on the sample 1998Q1-2024Q1. Note that the right panel regressions are estimated with data ending 2023Q4.

Table 12: Attention and SPF expectations with Communication controls

	No controls						Communication controls																	
	h=1	h=2	h=4	h=1	h=2	h=4	h=1	h=2	h=4	h=1	h=2	h=4	h=1	h=2	h=4	h=1	h=2	h=4	h=1	h=2	h=4	h=1	h=2	h=4
c	2.24	2.24	2.26	2.23	2.24	2.29	2.24	2.24	2.26	2.24	2.24	2.26	2.24	2.24	2.26	2.23	2.23	2.28	2.23	2.23	2.28	2.24	2.24	2.26
p-val	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
α	0.31	0.27	0.14	0.38	0.3	0.19	0.29	0.26	0.13	0.23	0.22	0.1	0.29	0.27	0.14	0.32	0.27	0.18	0.37	0.28	0.18	0.39	0.3	0.17
p-val	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
GT	0.31	0.17	0.11				0.31	0.17	0.12	0.39	0.22	0.16	0.33	0.18	0.11									
p-val	0	0	0				0	0	0	0	0	0	0	0	0									
WSJ				0.21	0.13	0.07										0.2	0.13	0.06	0.24	0.15	0.08	0.27	0.16	0.1
p-val				0	0	0										0	0	0	0	0	0	0	0	0
$\gamma_{fomc^{mon}}$							0.04	0.02	0.02							0.12	0.06	0.03						
p-val							0.62	0.71	0.63							0.04	0.13	0.18						
$\gamma_{fomc^{inf}}$										0.16	0.11	0.07							0.1	0.07	0.05			
p-val										0	0	0							0.01	0	0			
$\gamma_{gt^{frs}}$													-0.05	-0.04	-0.02							0.02	-0.01	0
p-val													0.27	0.12	0.2							0.7	0.74	0.8
$\bar{R}^2$ ADL	0.71	0.75	0.71	0.71	0.76	0.7	0.71	0.76	0.73	0.76	0.81	0.8	0.71	0.76	0.72	0.72	0.76	0.71	0.73	0.78	0.74	0.72	0.78	0.73
$\bar{R}^2$ AR	0.63	0.7	0.65	0.63	0.69	0.65	0.63	0.7	0.66	0.63	0.7	0.66	0.63	0.7	0.65	0.63	0.69	0.65	0.63	0.69	0.65	0.63	0.7	0.65

Note: This table presents results from the ADL regression in (1). The dependent variable, $\pi_{t+h,t}$, is the SPF mean 1-quarter, 2-quarters and 1-year ahead forecast ($h = 1$, $h = 2$ and $h = 4$) of the year-over-year CPI inflation. All explanatory variables have been standardized prior to estimation. When needed, inference is performed using White or Newey-West standard errors. $\bar{R}^2$ ADL and $\bar{R}^2$ AR stand for the adjusted R^2 from the ADL predictive regressions and the AR(1) model respectively. Regressions with WSJ and price controls are performed on the sample 1998Q1-2024Q1. Note that the right panel regressions are estimated with data ending 2023Q4.

Table 13: Attention and SPF expectations with Price controls: quantile regression Q=0.8

	No controls						Price controls																	
	h=1	h=2	h=4	h=1	h=2	h=4	h=1	h=2	h=4	h=1	h=2	h=4	h=1	h=2	h=4	h=1	h=2	h=4	h=1	h=2	h=4	h=1	h=2	h=4
c	2.48	2.39	2.38	2.49	2.39	2.39	2.51	2.4	2.37	2.51	2.39	2.36	2.48	2.39	2.37	2.48	2.38	2.39	2.48	2.39	2.4	2.49	2.4	2.39
p-val	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
α	0.28	0.28	0.13	0.38	0.3	0.2	0.11	0.18	0.09	0.34	0.27	0.15	0.33	0.28	0.14	0.25	0.24	0.15	0.4	0.3	0.2	0.42	0.32	0.19
p-val	0	0	0	0	0	0	0.38	0	0.01	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
GT	0.38	0.15	0.14				0.17	0.11	0.09	0.32	0.16	0.12	0.25	0.13	0.1									
p-val	0	0	0				0.1	0	0.01	0	0	0	0	0	0									
WSJ				0.26	0.11	0.1										0.15	0.06	0.06	0.2	0.11	0.07	0.15	0.07	0.06
p-val				0	0	0										0.02	0.11	0.03	0	0	0.01	0.01	0.1	0.06
γ_{π}							0.35	0.15	0.07							0.25	0.12	0.06						
p-val							0.01	0	0.06							0	0.03	0.07						
γ_{gas}										0.11	0.07	0.06							0.11	0.03	0.04			
p-val										0.02	0	0							0	0.18	0.1			
γ_{gscpi}													0.07	0.01	0.03							0.11	0.03	0.03
p-val													0.23	0.66	0.23							0.03	0.46	0.3
$\tilde{R}^2$ ADL	0.42	0.39	0.46	0.45	0.42	0.52	0.39	0.35	0.43	0.39	0.36	0.43	0.42	0.39	0.45	0.41	0.39	0.5	0.43	0.4	0.5	0.43	0.41	0.51
$\tilde{R}^2$ AR	0.55	0.48	0.53	0.55	0.49	0.57	0.55	0.48	0.53	0.55	0.48	0.53	0.55	0.48	0.53	0.56	0.49	0.57	0.56	0.49	0.57	0.56	0.49	0.57

Note: This table presents results from the ADL quantile regression of equation (1) for $q > 0.8$. The dependent variable, $\pi_{t+h,t}$, is the SPF mean 1-quarter, 2-quarters and 1-year ahead forecast ($h = 1$, $h = 2$ and $h = 4$) of the year-over-year CPI inflation. All explanatory variables have been standardized prior to estimation. When needed, inference is performed using White or Newey-West standard errors. $\tilde{R}^2$ ADL and $\tilde{R}^2$ AR stand for the adjusted pseudo R^2 from the ADL predictive regressions and the AR(1) model respectively. Regressions with WSJ and price controls are performed on the sample 1998Q1-2024Q1. Note that the right panel regressions are estimated with data ending 2023Q4.

Table 14: Attention and SPF expectations with Communication controls: quantile regression Q=0.8

	No controls						Communication controls																	
	h=1	h=2	h=4	h=1	h=2	h=4	h=1	h=2	h=4	h=1	h=2	h=4	h=1	h=2	h=4	h=1	h=2	h=4	h=1	h=2	h=4	h=1	h=2	h=4
c	2.48	2.39	2.38	2.49	2.39	2.39	2.51	2.38	2.37	2.48	2.39	2.37	2.51	2.41	2.38	2.48	2.39	2.38	2.46	2.38	2.38	2.48	2.4	2.37
p-val	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
α	0.28	0.28	0.13	0.38	0.3	0.2	0.29	0.27	0.14	0.19	0.26	0.11	0.31	0.29	0.14	0.33	0.31	0.19	0.35	0.31	0.17	0.37	0.32	0.19
p-val	0	0	0	0	0	0	0	0	0	0.02	0	0.01	0	0	0	0	0	0	0	0	0	0	0	0
GT	0.38	0.15	0.14				0.36	0.15	0.14	0.46	0.19	0.16	0.35	0.15	0.13									
p-val	0	0	0				0	0	0	0	0	0	0	0	0									
WSJ				0.26	0.11	0.1										0.22	0.11	0.1	0.25	0.13	0.1	0.31	0.12	0.11
p-val				0	0	0										0	0	0	0	0	0	0	0	0
$\gamma_{fomc^{mon}}$							0.05	0.02	0							0.12	0.05	0.02						
p-val							0.49	0.66	0.9							0.05	0.17	0.59						
$\gamma_{fomc^{inf}}$										0.13	0.08	0.06							0.09	0.05	0.06			
p-val										0.01	0.02	0.01							0.03	0.01	0			
$\gamma_{gt^{frs}}$													-0.04	0.01	-0.02							0.09	0.01	0
p-val													0.44	0.69	0.4							0	0.68	0.82
$\tilde{R}^2$ ADL	0.42	0.39	0.46	0.45	0.42	0.52	0.41	0.38	0.45	0.37	0.34	0.41	0.42	0.39	0.46	0.43	0.41	0.49	0.42	0.4	0.46	0.41	0.39	0.46
$\tilde{R}^2$ AR	0.55	0.48	0.53	0.55	0.49	0.57	0.55	0.47	0.52	0.55	0.47	0.52	0.55	0.48	0.53	0.55	0.48	0.55	0.55	0.48	0.55	0.55	0.48	0.53

Note: This table presents results from the ADL quantile regression of equation (1) for $q > 0.8$. The dependent variable, $\pi_{t+h,t}$, is the SPF mean 1-quarter, 2-quarters and 1-year ahead forecast ($h = 1$, $h = 2$ and $h = 4$) of the year-over-year CPI inflation. All explanatory variables have been standardized prior to estimation. When needed, inference is performed using White or Newey-West standard errors. $\tilde{R}^2$ ADL and $\tilde{R}^2$ AR stand for the adjusted pseudo R^2 from the ADL predictive regressions and the AR(1) model respectively. Regressions with WSJ and price controls are performed on the sample 1998Q1-2024Q1. Note that the right panel regressions are estimated with data ending 2023Q4.

Table 15: Attention and SPF expectations with Price controls: quantile regression Q=0.9

	No controls						Price controls																	
	h=1	h=2	h=4	h=1	h=2	h=4	h=1	h=2	h=4	h=1	h=2	h=4	h=1	h=2	h=4	h=1	h=2	h=4	h=1	h=2	h=4	h=1	h=2	h=4
c	2.64	2.5	2.45	2.61	2.48	2.47	2.64	2.46	2.44	2.63	2.48	2.43	2.65	2.5	2.44	2.56	2.47	2.46	2.56	2.48	2.47	2.57	2.49	2.48
p-val	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
α	0.3	0.31	0.18	0.4	0.29	0.18	-0.01	0.2	0.12	0.41	0.3	0.16	0.31	0.31	0.19	0.19	0.2	0.15	0.41	0.31	0.19	0.4	0.29	0.18
p-val	0	0	0	0	0	0	0.95	0	0.07	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
GT	0.37	0.22	0.12				0.21	0.14	0.09	0.26	0.2	0.11	0.38	0.18	0.1									
p-val	0	0	0				0.06	0	0.12	0	0	0.01	0	0	0.02									
WSJ				0.23	0.17	0.09										0.15	0.07	0.05	0.17	0.13	0.07	0.15	0.1	0.07
p-val				0	0	0.03										0	0.01	0.22	0	0	0.02	0	0	0.21
γ_{π}							0.43	0.19	0.08							0.28	0.22	0.07						
p-val							0	0	0.22							0	0	0.22						
γ_{gas}										0.2	0.05	0.04							0.13	0.06	0.04			
p-val										0	0	0.12							0	0.08	0.11			
γ_{gscpi}													-0.02	0.05	0.03							0.14	0.11	0.03
p-val													0.81	0.26	0.36							0	0	0.47
$\tilde{R}^2$ ADL	0.36	0.32	0.37	0.38	0.36	0.47	0.32	0.29	0.35	0.32	0.29	0.35	0.36	0.32	0.36	0.33	0.32	0.44	0.37	0.34	0.44	0.36	0.36	0.46
$\tilde{R}^2$ AR	0.51	0.41	0.47	0.52	0.44	0.53	0.51	0.41	0.47	0.51	0.41	0.47	0.51	0.41	0.47	0.52	0.43	0.53	0.52	0.43	0.53	0.52	0.43	0.53

Note: This table presents results from the ADL quantile regression of equation (1) for $q > 0.9$. The dependent variable, $\pi_{t+h,t}$, is the SPF mean 1-quarter, 2-quarters and 1-year ahead forecast ($h = 1$, $h = 2$ and $h = 4$) of the year-over-year CPI inflation. All explanatory variables have been standardized prior to estimation. When needed, inference is performed using White or Newey-West standard errors. $\tilde{R}^2$ ADL and $\tilde{R}^2$ AR stand for the adjusted pseudo R^2 from the ADL predictive regressions and the AR(1) model respectively. Regressions with WSJ and price controls are performed on the sample 1998Q1-2024Q1. Note that the right panel regressions are estimated with data ending 2023Q4.

Table 16: Attention and SPF expectations with Communication controls: quantile regression Q=0.9

	No controls						Communication controls																	
	h=1	h=2	h=4	h=1	h=2	h=4	h=1	h=2	h=4	h=1	h=2	h=4	h=1	h=2	h=4	h=1	h=2	h=4	h=1	h=2	h=4	h=1	h=2	h=4
c	2.64	2.5	2.45	2.61	2.48	2.47	2.6	2.48	2.45	2.6	2.46	2.43	2.64	2.49	2.45	2.6	2.49	2.46	2.6	2.48	2.46	2.66	2.5	2.43
p-val	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
α	0.3	0.31	0.18	0.4	0.29	0.18	0.27	0.3	0.15	0.17	0.23	0.07	0.31	0.3	0.18	0.29	0.31	0.18	0.27	0.24	0.19	0.43	0.28	0.17
p-val	0	0	0	0	0	0	0	0	0	0.07	0	0.11	0.01	0	0	0	0	0	0	0	0	0	0	0
GT	0.37	0.22	0.12				0.33	0.18	0.11	0.45	0.27	0.18	0.37	0.23	0.12									
p-val	0	0	0				0	0	0.01	0	0	0	0	0	0.01									
WSJ				0.23	0.17	0.09										0.21	0.1	0.06	0.31	0.2	0.09	0.23	0.19	0.11
p-val				0	0	0.03										0	0.06	0.17	0	0	0.09	0.07	0.01	0
$\gamma_{fomc^{mon}}$							0.08	0.06	0.03							0.12	0.1	0.05						
p-val							0.34	0.38	0.52							0.1	0.13	0.37						
$\gamma_{fomc^{inf}}$										0.17	0.11	0.09							0.11	0.11	0.06			
p-val										0	0	0							0.08	0	0.25			
$\gamma_{gt^{frs}}$													0.01	0.01	0							0.11	0.04	0.02
p-val													0.9	0.72	0.99							0.28	0.5	0.32
$\tilde{R}^2$ ADL	0.36	0.32	0.37	0.38	0.36	0.47	0.35	0.31	0.35	0.29	0.28	0.32	0.36	0.32	0.37	0.36	0.33	0.43	0.36	0.32	0.42	0.36	0.32	0.37
$\tilde{R}^2$ AR	0.51	0.41	0.47	0.52	0.44	0.53	0.5	0.4	0.46	0.5	0.4	0.46	0.51	0.41	0.47	0.51	0.43	0.51	0.51	0.43	0.51	0.51	0.41	0.47

Note: This table presents results from the ADL quantile regression of equation (1) for $q > 0.9$. The dependent variable, $\pi_{t+h,t}$, is the SPF mean 1-quarter, 2-quarters and 1-year ahead forecast ($h = 1$, $h = 2$ and $h = 4$) of the year-over-year CPI inflation. All explanatory variables have been standardized prior to estimation. When needed, inference is performed using White or Newey-West standard errors. $\tilde{R}^2$ ADL and $\tilde{R}^2$ AR stand for the adjusted pseudo R^2 from the ADL predictive regressions and the AR(1) model respectively. Regressions with WSJ and price controls are performed on the sample 1998Q1-2024Q1. Note that the right panel regressions are estimated with data ending 2023Q4.

Table 17: Attention and BlueChip expectations with controls

	No controls		Price controls						Communication controls					
c	2.26	2.28	2.26	2.26	2.26	2.28	2.28	2.28	2.26	2.26	2.26	2.27	2.27	2.26
p-val	0	0	0	0	0	0	0	0	0	0	0	0	0	0
α	0.34	0.33	0.28	0.31	0.34	0.29	0.32	0.33	0.33	0.32	0.33	0.33	0.33	0.34
p-val	0	0	0	0	0	0	0	0	0	0	0	0	0	0
GT	0.08		0.04	0.09	0.08				0.08	0.1	0.09			
p-val	0		0.04	0	0.02				0	0	0			
WSJ		0.07				0.04	0.06	0.07				0.06	0.08	0.1
p-val		0				0.03	0	0				0	0	0
γ_{π}			0.11			0.07								
p-val			0			0.01								
γ_{gas}				0.07			0.04							
p-val				0			0.01							
γ_{gscpi}					0.02			0						
p-val					0.51			0.94						
$\gamma_{fomc^{mon}}$									0.03			0.03		
p-val									0.36			0.21		
$\gamma_{fomc^{inf}}$										0.04			0.03	
p-val										0.02			0.02	
$\gamma_{gt^{frs}}$											-0.02			0
p-val											0.21			0.75
$\bar{R}^2$ ADL	0.73	0.74	0.74	0.75	0.73	0.75	0.75	0.74	0.73	0.74	0.73	0.74	0.74	0.74
$\bar{R}^2$ AR	0.71	0.72	0.71	0.71	0.71	0.72	0.72	0.72	0.71	0.71	0.71	0.72	0.72	0.71

Note: This table presents results from the ADL regression in (1). The dependent variable, $\pi_{t+h,t}$, is the BlueChip consensus 1-year ahead forecast of the annual CPI inflation. All explanatory variables have been standardized prior to estimation. When needed, inference is performed using White or Newey-West standard errors. $\bar{R}^2$ ADL and $\bar{R}^2$ AR stand for the adjusted R^2 from the ADL predictive regressions and the AR(1) model respectively. Regressions with WSJ and price controls are performed on the sample 1998M01-2024M03. The right panel regressions are estimated with data ending 2023M12.

Table 18: Attention and BlueChip expectations with controls: quantile regression Q=0.8

	No controls		Price controls						Communication controls					
c	2.36	2.37	2.35	2.35	2.36	2.37	2.37	2.36	2.37	2.36	2.36	2.37	2.36	2.36
p-val	0	0	0	0	0	0	0	0	0	0	0	0	0	0
α	0.46	0.39	0.39	0.44	0.47	0.37	0.39	0.41	0.47	0.43	0.47	0.42	0.41	0.44
p-val	0	0	0	0	0	0	0	0	0	0	0	0	0	0
GT	0.03		0.02	0.04	0.02				0.06	0.09	0.03			
p-val	0		0.04	0	0.19				0	0	0			
WSJ		0.08				0.03	0.06	0.05				0.08	0.08	0.08
p-val		0				0	0	0				0	0	0
γ_{π}			0.07			0.06								
p-val			0			0								
γ_{gas}				0.05			0.03							
p-val				0			0							
γ_{gscpi}					0.04			0.03						
p-val					0			0						
$\gamma_{fomc^{mon}}$									-0.01			-0.01		
p-val									0.44			0.5		
$\gamma_{fomc^{inf}}$										0.03			0.02	
p-val										0.02			0.19	
$\gamma_{gt^{frs}}$											0			0.01
p-val											0.25			0.62
$\bar{R}^2$ ADL	0.35	0.36	0.33	0.33	0.34	0.35	0.35	0.35	0.34	0.34	0.35	0.35	0.35	0.34
$\bar{R}^2$ AR	0.36	0.38	0.36	0.36	0.36	0.38	0.38	0.38	0.35	0.35	0.36	0.37	0.37	0.36

Note: This table presents results from the ADL quantile regression of equation (1) for $q > 0.8$. The dependent variable, $\pi_{t+h,t}$, is the BlueChip consensus 1-year ahead forecast of the annual CPI inflation. All explanatory variables have been standardized prior to estimation. When needed, inference is performed using White or Newey-West standard errors. $\bar{R}^2$ ADL and $\bar{R}^2$ AR stand for the adjusted pseudo R^2 from the ADL predictive regressions and the AR(1) model respectively. Regressions with WSJ and price controls are performed on the sample 1998M01-2024M03. The right panel regressions are estimated with data ending 2023M12.

Table 19: Attention and BlueChip expectations with controls: quantile regression Q=0.9

	No controls		Price controls						Communication controls					
c	2.4	2.44	2.42	2.4	2.41	2.42	2.42	2.42	2.4	2.41	2.4	2.43	2.43	2.43
p-val	0	0	0	0	0	0	0	0	0	0	0	0	0	0
α	0.46	0.41	0.37	0.41	0.46	0.36	0.39	0.42	0.49	0.45	0.46	0.43	0.43	0.45
p-val	0	0	0	0	0	0	0	0	0	0	0	0	0	0
GT	0.07		0.03	0.06	0.03				0.07	0.09	0.07			
p-val	0		0.35	0	0.07				0	0	0			
WSJ		0.1				0.07	0.07	0.05				0.1	0.1	0.12
p-val		0				0	0	0				0	0	0
γ_{π}			0.1			0.06								
p-val			0.01			0.02								
γ_{gas}				0.06			0.03							
p-val				0			0.08							
γ_{gscpi}					0.06			0.02						
p-val					0			0.06						
$\gamma_{fomc^{mon}}$									-0.03			0		
p-val									0.03			0.98		
$\gamma_{fomc^{inf}}$										0.02			0	
p-val										0.09			0.87	
$\gamma_{gt^{frs}}$											0			0.01
p-val											0.56			0.59
$\tilde{R}^2$ ADL	0.33	0.34	0.32	0.32	0.31	0.33	0.33	0.33	0.32	0.33	0.33	0.33	0.33	0.31
$\tilde{R}^2$ AR	0.34	0.37	0.34	0.34	0.34	0.37	0.37	0.37	0.34	0.34	0.34	0.37	0.37	0.34

Note: This table presents results from the ADL quantile regression of equation (1) for $q > 0.9$. The dependent variable, $\pi_{t+h,t}$, is the BlueChip consensus 1-year ahead forecast of the annual CPI inflation. All explanatory variables have been standardized prior to estimation. When needed, inference is performed using White or Newey-West standard errors. $\tilde{R}^2$ ADL and $\tilde{R}^2$ AR stand for the adjusted pseudo R^2 from the ADL predictive regressions and the AR(1) model respectively. Regressions with WSJ and price controls are performed on the sample 1998M01-2024M03. The right panel regressions are estimated with data ending 2023M12.

Table 20: Attention and Consumer expectations with controls

	Michigan (Cons)													
c	3.21	3.07	3.21	3.07	3.21	3.07	3.21	3.07	3.21	3.11	3.21	3.11	3.21	3.21
p-val	0	0	0	0	0	0	0	0	0	0	0	0	0	0
α	0.61	0.59	0.54	0.54	0.53	0.55	0.6	0.57	0.59	0.61	0.58	0.6	0.6	0.61
p-val	0	0	0	0	0	0	0	0	0	0	0	0	0	0
GT	0.09		0.05		0.11		0.09		0.17		0.12		0.09	
p-val	0.01		0.18		0		0.03		0		0		0.01	
WSJ		0.1		0.08		0.09		0.1		0.13		0.11		0.1
p-val		0		0		0		0		0		0		0
γ_{π}			0.11	0.07										
p-val			0.02	0.05										
γ_{gas}					0.13	0.1								
p-val					0	0								
γ_{food}							0	0.04						
p-val							0.93	0.3						
$\gamma_{fomc^{mon}}$									-0.1	-0.06				
p-val									0	0.02				
$\gamma_{fomc^{inf}}$											0.04	0.02		
p-val											0.11	0.39		
$\gamma_{gt^{frs}}$													-0.01	0.01
p-val													0.62	0.6
$\bar{R}^2$ ADL	0.8	0.79	0.8	0.79	0.82	0.8	0.79	0.79	0.81	0.79	0.8	0.79	0.8	0.8
$\bar{R}^2$ AR	0.79	0.78	0.79	0.78	0.79	0.78	0.79	0.78	0.79	0.78	0.79	0.78	0.79	0.79

	New York Fed (Cons)													
c	3.38	3.38	3.38	3.38	3.38	3.38	3.38	3.38	3.39	3.39	3.39	3.39	3.38	3.38
p-val	0	0	0	0	0	0	0	0	0	0	0	0	0	0
α	1.1	1.04	1.02	1	1.01	1.03	1.14	1.11	1.11	1.1	1.1	1.05	1.1	1.04
p-val	0	0	0	0	0	0	0	0	0	0	0	0	0	0
GT	-0.02		-0.06		0.01		0.03		0.04		-0.01		-0.02	
p-val	0.66		0.18		0.85		0.57		0.54		0.9		0.74	
WSJ		0.05		0.04		-0.02		0.04		0.06		0.05		0.05
p-val		0.13		0.31		0.59		0.22		0.07		0.15		0.13
γ_{π}			0.12	0.06										
p-val			0.03	0.3										
γ_{gas}					0.11	0.12								
p-val					0	0								
γ_{food}							-0.1	-0.07						
p-val							0.12	0.2						
$\gamma_{fomc^{mon}}$									-0.11	-0.1				
p-val									0.01	0				
$\gamma_{fomc^{inf}}$											0.04	0.04		
p-val											0.12	0.13		
$\gamma_{gt^{frs}}$													-0.01	-0.01
p-val													0.74	0.67
$\bar{R}^2$ ADL	0.96	0.96	0.96	0.96	0.96	0.96	0.96	0.96	0.96	0.96	0.96	0.96	0.96	0.96
$\bar{R}^2$ AR	0.96	0.96	0.96	0.96	0.96	0.96	0.96	0.96	0.96	0.96	0.96	0.96	0.96	0.96

Note: This table presents results from the ADL regression in (1). The dependent variable, $\pi_{t+h,t}$, is the Michigan or New York Fed consumer survey-based 1-year ahead inflation expectation. All explanatory variables have been standardized prior to estimation. When needed, inference is performed using White or Newey-West standard errors. $\bar{R}^2$ ADL and $\bar{R}^2$ AR stand for the adjusted R^2 from the ADL predictive regressions and the AR(1) model respectively. New York Fed data are available since 2013M08. Note that the right panel regressions are estimated with data ending 2023M12.

Table 21: Attention and Consumer expectations with controls: quantile regression Q=0.8

	Michigan (Cons)														New York Fed (Cons)													
c	3.41	3.24	3.42	3.24	3.39	3.23	3.41	3.23	3.41	3.31	3.4	3.31	3.4	3.4	3.51	3.52	3.56	3.54	3.5	3.5	3.51	3.54	3.51	3.51	3.55	3.54	3.53	3.5
p-val	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
α	0.63	0.64	0.62	0.6	0.59	0.6	0.63	0.61	0.6	0.63	0.61	0.61	0.65	0.68	1.11	1.16	1.09	1.07	1.08	1.08	1.11	1.11	1.16	1.15	1.17	1.2	1.13	1.14
p-val	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
GT	0.15		0.15		0.12		0.13		0.26		0.16		0.09		0.07		-0.03		-0.01		0.07		0.1		0.07		0.09	
p-val	0		0		0		0		0		0		0		0.07		0.66		0.8		0.15		0		0.03		0.01	
WSJ		0.06		0.01		0.06		0.03		0.11		0.1		0.04		0.03		0.07		-0.01		0.07		0.09		0.02		0.02
p-val		0.01		0.74		0.02		0.09		0.02		0		0.16		0.44		0.13		0.91		0.18		0.01		0.59		0.52
γ_{π}			0.04	0.12													0.14	0.07										
p-val			0.43	0													0.13	0.31										
γ_{gas}					0.08	0.08													0.1	0.1								
p-val					0	0													0.01	0.02								
γ_{food}							0.04	0.08													0	0.05						
p-val							0.33	0													0.93	0.41						
$\gamma_{fomc^{mon}}$									-0.13	-0.07													-0.11	-0.11				
p-val									0	0.05													0	0				
$\gamma_{fomc^{inf}}$											0.04	0.01													-0.02	-0.02		
p-val											0.19	0.64													0.22	0.3		
$\gamma_{gt^{frs}}$													0.04	0.06													-0.01	0.01
p-val													0.09	0.01													0.71	0.59
$\bar{R}^2$ ADL	0.35	0.39	0.35	0.38	0.34	0.38	0.35	0.38	0.33	0.39	0.35	0.39	0.35	0.36	0.15	0.15	0.15	0.15	0.14	0.14	0.15	0.15	0.14	0.14	0.15	0.15	0.15	0.15
$\bar{R}^2$ AR	0.37	0.39	0.37	0.39	0.37	0.39	0.37	0.39	0.37	0.39	0.37	0.39	0.37	0.37	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15

Note: This table presents results from the ADL quantile regression of equation (1) for $q > 0.8$. The dependent variable, $\pi_{t+h,t}$, is the Michigan or New York Fed consumer survey-based 1-year ahead inflation expectation. All explanatory variables have been standardized prior to estimation. When needed, inference is performed using White or Newey-West standard errors. $\bar{R}^2$ ADL and $\bar{R}^2$ AR stand for the adjusted pseudo R^2 from the ADL predictive regressions and the AR(1) model respectively. New York Fed data are available since 2013M08. Note that the right panel regressions are estimated with data ending 2023M12.

Table 22: Attention and Consumer expectations with controls: quantile regression Q=0.9

	Michigan (Cons)													
c	3.53	3.39	3.53	3.42	3.53	3.39	3.53	3.42	3.57	3.45	3.63	3.47	3.54	3.53
p-val	0	0	0	0	0	0	0	0	0	0	0	0	0	0
α	0.63	0.61	0.63	0.51	0.58	0.53	0.63	0.51	0.62	0.66	0.62	0.59	0.64	0.67
p-val	0	0	0	0	0	0	0	0	0	0	0	0	0	0
GT	0.15		0.14		0.16		0.14		0.35		0.29		0.14	
p-val	0		0.05		0.06		0.01		0		0		0.01	
WSJ		0.1		0.16		0.18		0.17		0.13		0.14		0.09
p-val		0		0		0		0		0		0		0.02
γ_{π}			0.01	0.1										
p-val			0.92	0.07										
γ_{gas}					0.11	0.06								
p-val					0.17	0.04								
γ_{food}							0.01	0.14						
p-val							0.85	0.01						
$\gamma_{fomc^{mon}}$									-0.21	-0.05				
p-val									0	0.1				
$\gamma_{fomc^{inf}}$											0.11	0.08		
p-val											0.06	0		
$\gamma_{gt^{frs}}$													0.03	0.09
p-val													0.44	0.01
$\tilde{R}^2$ ADL	0.38	0.37	0.38	0.36	0.37	0.36	0.38	0.36	0.34	0.38	0.37	0.38	0.38	0.38
$\tilde{R}^2$ AR	0.39	0.37	0.39	0.37	0.39	0.37	0.39	0.37	0.39	0.39	0.39	0.39	0.39	0.39

	New York Fed (Cons)													
c	3.65	3.67	3.63	3.62	3.63	3.65	3.65	3.64	3.62	3.64	3.66	3.67	3.65	3.65
p-val	0	0	0	0	0	0	0	0	0	0	0	0	0	0
α	1.15	1.14	1.05	1.05	1.02	1.12	1.16	1.16	1.1	1.18	1.15	1.16	1.14	1.14
p-val	0	0	0	0	0	0	0	0	0	0	0	0	0	0
GT	0.05		0.03		0.1		0.04		0.16		0.06		0.05	
p-val	0.56		0.27		0.18		0.71		0.15		0.44		0.54	
WSJ		0.11		0.02		0.13		0.04		0.06		0.1		0.12
p-val		0.18		0.12		0.21		0.66		0.38		0.2		0.12
γ_{π}			0.15	0.15										
p-val			0	0										
γ_{gas}					0.12	0.02								
p-val					0.02	0.81								
γ_{food}							0	0.03						
p-val							0.97	0.79						
$\gamma_{fomc^{mon}}$									-0.12	-0.12				
p-val									0.06	0.02				
$\gamma_{fomc^{inf}}$											0.03	0.02		
p-val											0.43	0.73		
$\gamma_{gt^{frs}}$													-0.01	-0.02
p-val													0.88	0.6
$\tilde{R}^2$ ADL	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.15	0.14	0.14
$\tilde{R}^2$ AR	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15

Note: This table presents results from the ADL quantile regression of equation (1) for $q > 0.9$. The dependent variable, $\pi_{t+h,t}$, is the Michigan or New York Fed consumer survey-based 1-year ahead inflation expectation. All explanatory variables have been standardized prior to estimation. When needed, inference is performed using White or Newey-West standard errors. $\tilde{R}^2$ ADL and $\tilde{R}^2$ AR stand for the adjusted pseudo R^2 from the ADL predictive regressions and the AR(1) model respectively. New York Fed data are available since 2013M08. Note that the right panel regressions are estimated with data ending 2023M12.

Table 23: Attention and Business expectations with controls

	No controls		Price controls						Communication controls					
c	2.18	2.18	2.18	2.18	2.18	2.18	2.18	2.18	2.18	2.18	2.18	2.18	2.18	2.18
p-val	0	0	0	0	0	0	0	0	0	0	0	0	0	0
α	0.49	0.49	0.4	0.41	0.46	0.39	0.48	0.48	0.5	0.47	0.5	0.5	0.49	0.49
p-val	0	0	0	0	0	0	0	0	0	0	0	0	0	0
GT	0.04		0.02	0.08	0.04				0.04	0.06	0.03			
p-val	0.15		0.35	0	0.06				0.13	0.04	0.21			
WSJ		0.04				0.03	0.01	0.02				0.04	0.04	0.04
p-val		0.06				0.09	0.51	0.22				0.06	0.05	0.05
γ_{π}			0.11			0.12								
p-val			0			0								
γ_{gas}				0.07			0.06							
p-val				0			0							
γ_{gscpi}					0.05			0.04						
p-val					0			0						
$\gamma_{fomc^{mon}}$									-0.01			0		
p-val									0.52			0.87		
$\gamma_{fomc^{inf}}$										0.03			0.02	
p-val										0.01			0.03	
$\gamma_{gt^{frs}}$											0.01			0.01
p-val											0.65			0.31
$\bar{R}^2$ ADL	0.93	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.93	0.94	0.94	0.94
$\bar{R}^2$ AR	0.93	0.93	0.93	0.93	0.93	0.93	0.93	0.93	0.93	0.93	0.93	0.93	0.93	0.93

Note: This table presents results from the ADL regression in (1). The dependent variable, $\pi_{t+h,t}$, is the Atlanta Fed inflation expectation survey of firms. All explanatory variables have been standardized prior to estimation. When needed, inference is performed using White or Newey-West standard errors. $\bar{R}^2$ ADL and $\bar{R}^2$ AR stand for the adjusted R^2 from the ADL predictive regressions and the AR(1) model respectively. Atlanta Fed since 2011M10. Note that the right panel regressions are estimated with data ending 2023M12.

Table 24: Attention and Business expectations with controls: quantile regression Q=0.8

	No controls		Price controls						Communication controls					
c	2.31	2.3	2.29	2.28	2.28	2.29	2.28	2.28	2.3	2.29	2.3	2.29	2.29	2.3
p-val	0	0	0	0	0	0	0	0	0	0	0	0	0	0
α	0.52	0.51	0.44	0.44	0.45	0.43	0.49	0.48	0.52	0.51	0.53	0.55	0.5	0.51
p-val	0	0	0	0	0	0	0	0	0	0	0	0	0	0
GT	0.04		0.01	0.08	0.04				0.06	0.04	0.03			
p-val	0.28		0.8	0	0.11				0.02	0.25	0.44			
WSJ		0.04				0.02	0.01	0.02				0.01	0.03	0.05
p-val		0.04				0.43	0.71	0.19				0.54	0.27	0.04
γ_{π}			0.11			0.11								
p-val			0.01			0.02								
γ_{gas}				0.07			0.05							
p-val				0			0							
γ_{gscpi}					0.07			0.05						
p-val					0			0						
$\gamma_{fomc^{mon}}$									-0.05			-0.03		
p-val									0			0.05		
$\gamma_{fomc^{inf}}$										0.02			0.03	
p-val										0.12			0.05	
$\gamma_{gt^{frs}}$											0.01			0
p-val											0.69			0.92
$\tilde{R}^2$ ADL	0.18	0.18	0.18	0.17	0.17	0.18	0.17	0.17	0.18	0.18	0.18	0.18	0.18	0.18
$\tilde{R}^2$ AR	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18

Note: This table presents results from the ADL quantile regression of equation (1) for $q > 0.8$. The dependent variable, $\pi_{t+h,t}$, is the Atlanta Fed inflation expectation survey of firms. All explanatory variables have been standardized prior to estimation. When needed, inference is performed using White or Newey-West standard errors. $\tilde{R}^2$ ADL and $\tilde{R}^2$ AR stand for the adjusted pseudo R^2 from the ADL predictive regressions and the AR(1) model respectively. Atlanta Fed since 2011M10. Note that the right panel regressions are estimated with data ending 2023M12.

Table 25: Attention and Business expectations with controls: quantile regression Q=0.9

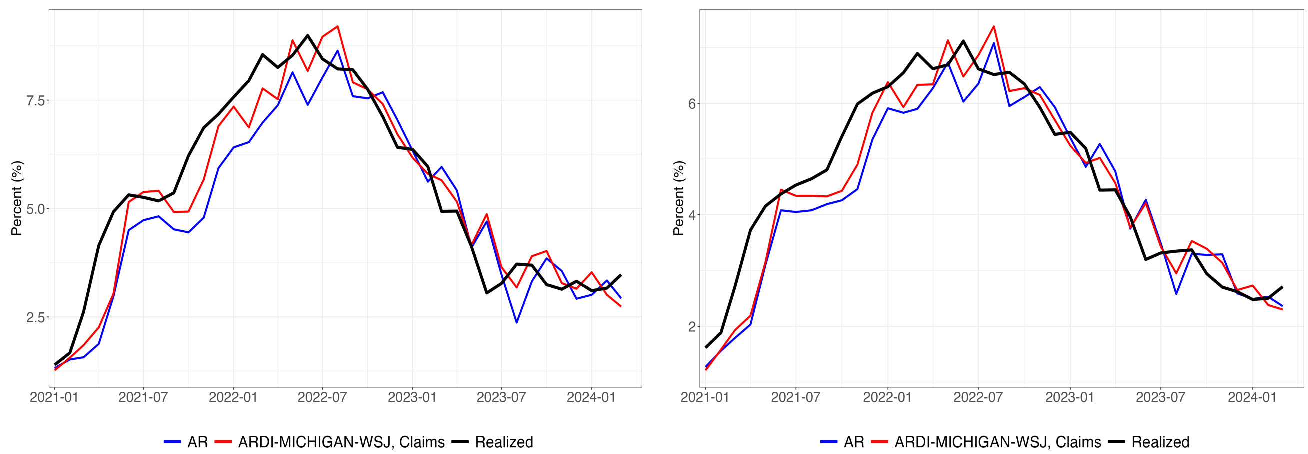
	No controls		Price controls						Communication controls					
c	2.36	2.34	2.35	2.33	2.33	2.33	2.33	2.34	2.35	2.35	2.36	2.34	2.34	2.34
p-val	0	0	0	0	0	0	0	0	0	0	0	0	0	0
α	0.48	0.52	0.44	0.44	0.48	0.46	0.5	0.52	0.48	0.49	0.48	0.52	0.52	0.52
p-val	0	0	0	0	0	0	0	0	0	0	0	0	0	0
GT	0.08		0.07	0.1	0.06				0.09	0.07	0.1			
p-val	0.01		0	0	0.17				0.02	0.05	0.01			
WSJ		0.03				0.03	0.03	0				0.03	0.03	0.02
p-val		0.24				0.13	0.25	0.92				0.4	0.34	0.34
γ_{π}			0.05			0.07								
p-val			0.13			0.04								
γ_{gas}				0.04			0.02							
p-val				0			0.43							
γ_{gscpi}					0.04			0.04						
p-val					0.1			0.2						
$\gamma_{fomc^{mon}}$									-0.02			0		
p-val									0.39			0.95		
$\gamma_{fomc^{inf}}$										0			0.01	
p-val										0.79			0.7	
$\gamma_{gt^{frs}}$											-0.01			0
p-val											0.48			0.86
$\tilde{R}^2$ ADL	0.17	0.17	0.16	0.16	0.16	0.17	0.17	0.16	0.16	0.16	0.16	0.17	0.17	0.17
$\tilde{R}^2$ AR	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17

Note: This table presents results from the ADL quantile regression of equation (1) for $q > 0.9$. The dependent variable, $\pi_{t+h,t}$, is the Atlanta Fed inflation expectation survey of firms. All explanatory variables have been standardized prior to estimation. When needed, inference is performed using White or Newey-West standard errors. $\tilde{R}^2$ ADL and $\tilde{R}^2$ AR stand for the adjusted pseudo R^2 from the ADL predictive regressions and the AR(1) model respectively. Atlanta Fed since 2011M10. Note that the right panel regressions are estimated with data ending 2023M12.

B.2 Additional forecasting analysis

Figure 12 compares the out-of-sample forecasts of CPI and PCE inflation since 2021 of the best model including WSJ professional attention and the reference AR. Model using WSJ tracks very well the recent developments of inflation, especially since the surge in inflation from 2021.

Figure 12: Out-of-sample forecasts



(a) CPI inflation

(b) PCE inflation

Table 26: Pseudo-out-of-sample prediction of inflation: current month ($h = 0$)

	CPI				PCE				CPI Core			
	$Z_t = \text{GT}$		$Z_t = \text{WSJ}$		$Z_t = \text{GT}$		$Z_t = \text{WSJ}$		$Z_t = \text{GT}$		$Z_t = \text{WSJ}$	
Models	Full	>q90	Full	>q90	Full	>q90	Full	>q90	Full	>q90	Full	>q90
AR (RMSE)	0.35	0.51	0.35	0.51	0.25	0.37	0.25	0.37	0.18	0.24	0.18	0.24
Augmented ARs												
AR-Z	0.98	0.91	0.95	0.82	0.99	0.95	0.97	0.9	0.98	1.07	0.98	0.94
AR, CLAIMS	0.95***	0.91	0.95***	0.91	0.95***	0.91*	0.95***	0.91*	0.96	1	0.96	1
AR-Z, CLAIMS	**0.94**	0.83	**0.92****	0.76*	**0.95**	0.86	**0.93****	0.82	0.96	1.06	0.95	0.96
NKPC-												
MICH, CLAIMS	0.95***	0.89*	0.95***	0.89*	0.96**	0.91*	0.96**	0.91*	0.95*	0.98	0.95*	0.98
MICH-Z, CLAIMS	0.94	0.82	0.94*	**0.75***	0.96	0.86	0.96	0.82	0.94	1.05	0.95	0.96
BC1YR, CLAIMS	0.95**	0.9	0.95**	0.9	0.95***	0.9	0.95***	0.9	0.95*	**0.98**	0.95*	0.98
BC1YR-Z, CLAIMS	0.94	0.83	0.92**	0.75*	0.95	0.86	0.93**	**0.82**	**0.93**	0.99	**0.94***	**0.92**
Data-rich NKPC-												
ARDI	1.06**	1.03	1.06**	1.03	1.09*	1.02	1.09*	1.02	1.02	1.07*	1.02	1.07*
ARDI-Z	1.06	0.89	1.03	0.85	1.09	0.94	1.07	0.91	1.01	1.15	1.01	1.03
ARDI-MICH, CLAIMS	1.04	0.92	1.04	0.92	1.06	0.93	1.06	0.93	0.97	1.03	0.97	1.03
ARDI-MICH-Z, CLAIMS	1.03	**0.79**	1.01	0.76*	1.06	**0.85**	1.05	0.82	0.96	1.07	0.96	1
ARDI-BC1YR, CLAIMS	1.03	0.93	1.03	0.93	1.06	0.93	1.06	0.93	0.97	1.02	0.97	1.02
ARDI-BC1YR-Z, CLAIMS	1.03	0.82	1.01	0.76*	1.06	0.85	1.05	0.82	0.95	1.03	0.96	0.97

Note: This table shows out-of-sample predictive performance of various models augmented by GT or WSJ. The group of Augmented ARs is given by equation (5) where π_t is the year-over-year CPI inflation. The second group consists of NKPC-type models as in equation (6). The final group is made of "hybrid" NKPC models defined in (7). The full *out-of-sample period is 2010M01 - 2024M03, >q90 represent periods in the 90^{th} quantile of the target variable. Numbers in the table are the mean squared errors (MSE) relative to AR. Minimum values for each column are in bold, while ***, ** and * stand for 1%, 5% and 10% significance of Diebold- Mariano test.*

Table 27: Pseudo-out-of-sample prediction of inflation: 2-month ahead ($h = 2$)

	CPI				PCE				CPI Core			
	Z_t = GT		Z_t = WSJ		Z_t = GT		Z_t = WSJ		Z_t = GT		Z_t = WSJ	
Models	Full	>q90	Full	>q90	Full	>q90	Full	>q90	Full	>q90	Full	>q90
AR (RMSE)	0.89	1.64	0.89	1.64	0.61	1.06	0.61	1.06	0.53	0.93	0.53	0.93
Augmented ARs												
AR-Z	1.02	1.04	0.92	0.77	1.02	1.03	0.94	0.82	1.05	1.22	0.95	0.89
AR, CLAIMS	0.97	0.93	0.97	0.93	**0.97**	0.92	0.97	0.92	0.96	0.93	0.96	0.93
AR-Z, CLAIMS	0.99	0.96	0.9	0.72	0.99	0.94	**0.92**	0.76	1	1.15	0.91	0.84
NKPC-												
MICH, CLAIMS	**0.94**	0.87	0.94	0.87	0.97	0.9	0.97	0.9	**0.93**	**0.89**	0.93	0.89
MICH-Z, CLAIMS	0.97	0.92	**0.89**	0.67	0.99	0.93	0.94	0.75	0.98	1.12	0.9	0.82
BC1YR, CLAIMS	0.97	0.93	0.97	0.93	0.97	0.91	0.97	0.91	0.94	0.91	0.94	0.91
BC1YR-Z, CLAIMS	1	0.97	0.91	0.71	0.99	0.94	0.92	0.75	0.97	1.09	**0.89**	**0.78**
Data-rich NKPC-												
ARDI	1.18*	1.03	1.18*	1.03	1.26**	1.04	1.26**	1.04	1.04	1.06	1.04	1.06
ARDI-Z	1.2	0.99	1.13	0.75	1.27*	1	1.24*	0.83*	1.07	1.24	0.98	0.93
ARDI-MICH, CLAIMS	1.17	0.9	1.17	0.9	1.27*	0.94	1.27*	0.94	0.97	0.95	0.97	0.95
ARDI-MICH-Z, CLAIMS	1.2	**0.82**	1.12	**0.63***	1.3*	**0.87**	1.25	**0.74***	1	1.11	0.93	0.85
ARDI-BC1YR, CLAIMS	1.17	0.99	1.17	0.99	1.25*	1	1.25*	1	1	0.99	1	0.99
ARDI-BC1YR-Z, CLAIMS	1.19	0.95	1.13	0.72	1.26*	0.94	1.24	0.79*	1.01	1.14	0.94	0.84

Note: This table shows out-of-sample predictive performance of various models augmented by GT or WSJ. The group of Augmented ARs is given by equation (5) where π_t is the year-over-year CPI inflation. The second group consists of NKPC-type models as in equation (6). The final group is made of "hybrid" NKPC models defined in (7). The full *out-of-sample period is 2010M01 - 2024M03, >q90 represent periods in the 90^{th} quantile of the target variable. Numbers in the table are the mean squared errors (MSE) relative to AR. Minimum values for each column are in bold, while ***, ** and * stand for 1%, 5% and 10% significance of Diebold-Mariano test.*

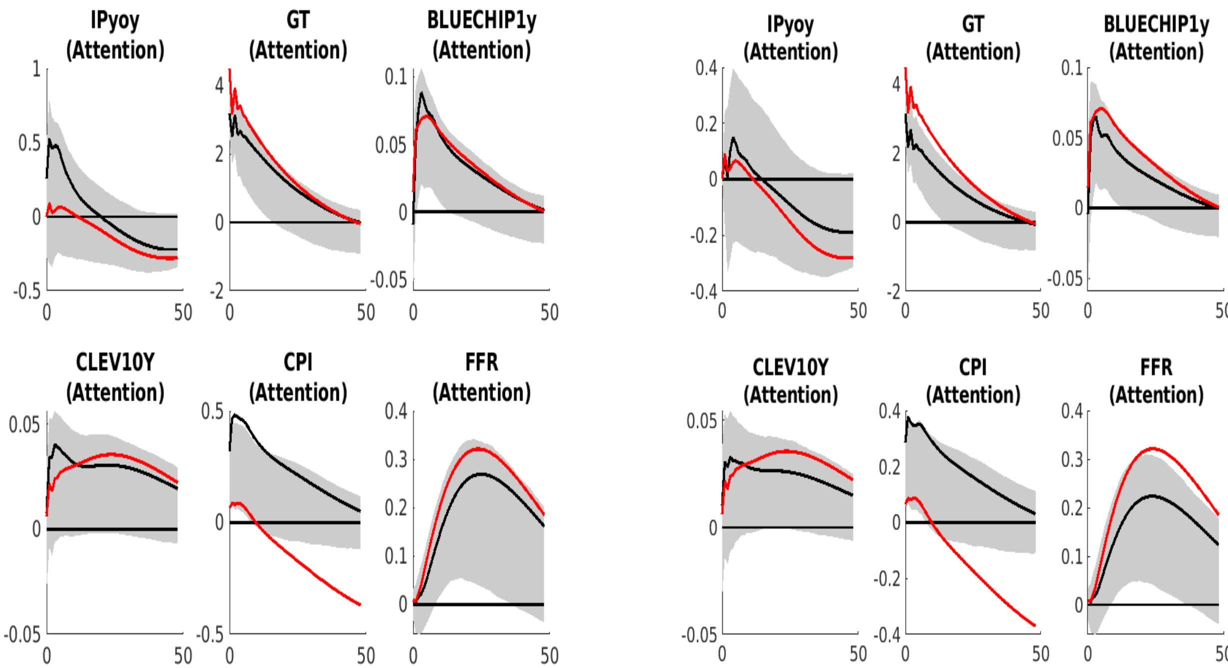
Table 28: Pseudo-out-of-sample prediction of the next month inflation: 2007 - 2024

	CPI				PCE				CPI Core			
	Z_t = GT		Z_t = WSJ		Z_t = GT		Z_t = WSJ		Z_t = GT		Z_t = WSJ	
Models	Full	>q90	Full	>q90	Full	>q90	Full	>q90	Full	>q90	Full	>q90
AR (RMSE)	0.86	1.11	0.86	1.11	0.6	0.68	0.6	0.68	0.34	0.6	0.34	0.6
Augmented ARs												
AR-Z	1	0.94	0.99	0.87	1.01	0.96	1.01	0.82*	1	1.05	0.96	0.87
AR, CLAIMS	0.99	0.9**	0.99	0.9**	**0.99**	0.9*	**0.99**	0.9*	0.96	0.94	0.96	0.94
AR-Z, CLAIMS	1	0.86	0.99	0.81	1.01	0.86	1.01	0.75**	0.97	1	0.93	0.83
NKPC-												
MICH, CLAIMS	1.02	0.89*	1.02	0.89*	1.02	0.89*	1.02	0.89*	0.95	0.9	0.95	0.9
MICH-Z, CLAIMS	1.03	0.87	1.02	**0.78**	1.03	0.86	1.03	0.74**	0.96	0.98	0.92	0.82
BC1YR, CLAIMS	**0.99**	0.9	0.99	0.9	1.01	0.89	1.01	0.89	0.95	**0.9**	0.95	0.9
BC1YR-Z, CLAIMS	1	0.86	**0.98**	0.8	1.03	0.86	1.02	0.74*	**0.94**	0.92	**0.92**	**0.78**
Data-rich NKPC-												
ARDI	1.08	1.01	1.08	1.01	1.07	1.03*	1.07	1.03*	1.02	1.06*	1.02	1.06*
ARDI-Z	1.07	0.9	1.06	0.9	1.07	0.94	1.07	0.83*	1.01	1.08	0.97	0.92
ARDI-MICH, CLAIMS	1.09	0.93	1.09	0.93	1.08	0.92	1.08	0.92	0.97	0.96	0.97	0.96
ARDI-MICH-Z, CLAIMS	1.09	0.84	1.07	0.83	1.09	**0.82**	1.08	**0.73****	0.97	0.99	0.94	0.86
ARDI-BC1YR, CLAIMS	1.09	0.92	1.09	0.92	1.08	0.95	1.08	0.95	0.98	0.96	0.98	0.96
ARDI-BC1YR-Z, CLAIMS	1.1	**0.83**	1.08	0.8	1.08	0.86	1.08	0.76**	0.96	0.96	0.94	0.83

B.3 Additional SVAR results

The first set of restrictions, (LR1), the first shock is the only one to have a long run impact on inflation, and then the second shock, labelled attention shock, is such that it explains the most of the forecasting variance of attention measure up to $h = 2$. In the second strategy (LR2), the first shock is the same as in LR1, and then short-run recursive restrictions are imposed on the first three equations, so the attention shock is ordered fourth in the vector of structural shocks. Figure 13 present dynamic effects of general attention shocks. These are compared to the benchmark IRFs with recursive ordering (in red).

Figure 13: IRFs to GT attention shocks



(a) LR1 identification (b) LR2 identification

Note: The VAR contains $[Oil_t, IP_t, GT_t, BlueChip_t, CLEV10Y_t, CPI_t, FFR_t]$. *Cholesky ordering IRFs are in red.*

B.3.1 Recursive ordering identification of inflation attention shocks

Here we impose the following recursive ordering in the monthly structural VAR: oil price inflation, industrial production growth, GT or WSJ attention, BlueChip inflation expectations, long-run inflation expectations, CPI inflation and the Fed Funds Rate. The recursive structure can be plausible for the following reasons.

First, oil inflation is measured from daily prices, which should not be contemporaneously influenced by the other four variables. Second, GT and WSJ are also measured by aggregating daily data, and hence they should also not be contemporaneously influenced by expected and actual inflation, which are measured at lower frequency and released with some delay. Finally, the BlueChip survey and Cleveland Fed long-run expectations are released prior to the CPI, and the NKPC states that expectations affect current inflation, while ordering the monetary policy instrument last is the common practice.

The impulse response functions are presented in Figure 14. It turns out that in general a positive shock to public attention GT (left panels) or a positive shock to professional attention WSJ (right panels) induces a significant increase in BlueChip short-run inflation expectations, and WSJ shock has also a significant, short-lived, impact on long-run expectations. This, in turn, induces a significant increase of inflation, followed by a response of the monetary policy.

This graphical analysis is confirmed by the variance decomposition presented in Table 29. An exogenous increase to the general and public attention about inflation explains sizeable fractions of the forecast error variance of all inflation series in the system. For instance, a shock to WSJ explains up to 17% of variation in BlueChip expectations, more than a shock to GT that still contributes up to 11% at the 4-year horizon. Professional attention shock is more important for CPI inflation, while the impact on long-run expectations is similar across sources

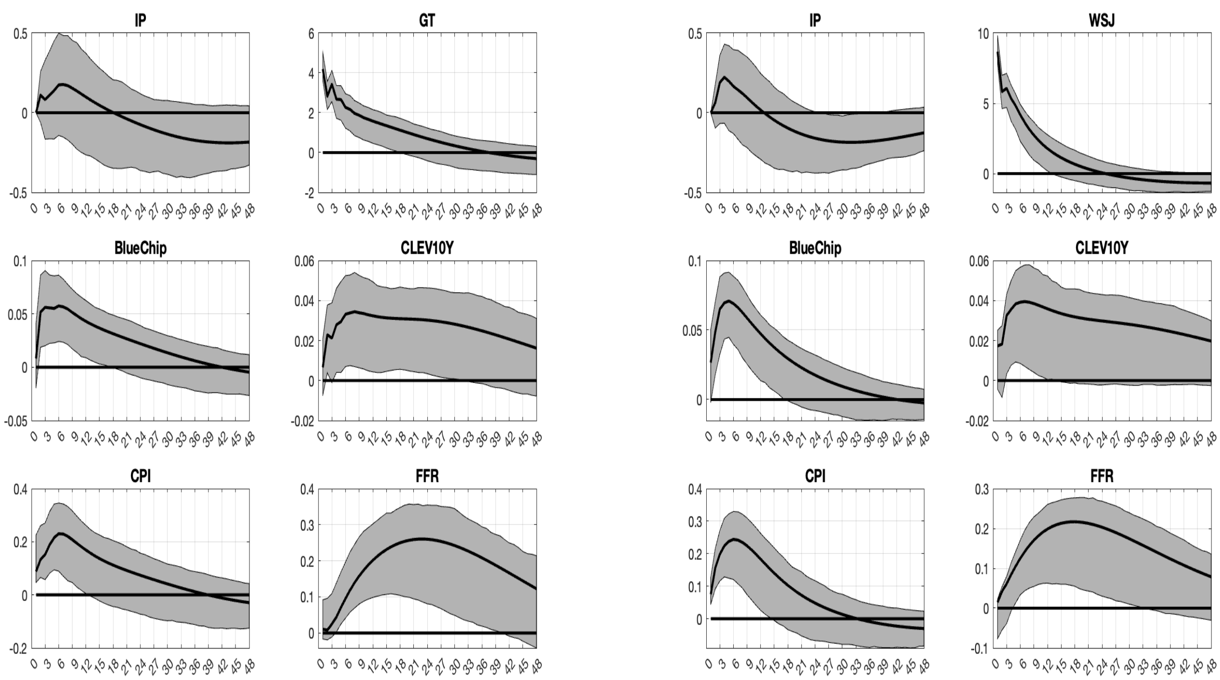
Table 29: Attention shocks: Variance Decomposition

	Shock to GT			Shock to WSJ		
	$h = 3$	$h = 12$	$h = 48$	$h = 3$	$h = 12$	$h = 48$
IP	0.00	0.00	0.00	0.01	0.01	0.01
GT / WSJ	0.90	0.80	0.80	0.90	0.84	0.84
BlueChip	0.08	0.11	0.11	0.14	0.17	0.17
CLEV10Y	0.06	0.12	0.12	0.07	0.12	0.12
CPI	0.09	0.12	0.12	0.14	0.17	0.17
FFR	0.06	0.37	0.37	0.08	0.22	0.22

Note: This table shows variance decomposition 3, 12 and 48 months following general and professional attention shocks in the VAR specified as in Figure 14.

of attention. Lastly, the shock to GT (WSJ) explains up to 37% (23%) of the FFR forecast error.

Figure 14: Dynamic responses to attention shocks



(a) Shock to GT (b) Shock to WSJ

Note: The left panel plots the IRFs after a 1-SD positive shock to GT, and the right panel after a 1-SD positive shock to WSJ. The VAR recursive ordering is specified as follows $[Oil_t, IP_t, Z_t, BlueChip_t, CLEV10Y_t, CPI_t, FFR_t]$. We used 5000 bootstrap replications to construct the 90% confidence intervals.

We assessed the robustness to several modifications. First, we placed BlueChip before the attention to take into account a possible reverse contemporaneous causality between attention and survey expectations. Second, we placed FFR just before attention, to control even more for monetary policy when identifying attention shocks. Third, we placed CPI inflation prior to attention to control the possibility that a shock to inflation might trigger attention. Fourth, we added macro uncertainty measure from Jurado et al. (2015) or a sentiment measure (PMI) and placed it just before attention to control for a possibility that results might partly be driven by uncertainty or sentiment disturbances during our sample period. Fifth, we replaced short-run professional expectation by the Michigan consumer survey. Sixth, we put both measures of attention in VAR by ordering GT before WSJ to reflect the possibility that journalists respond to the general public demand for information about inflation. Finally, we considered a quarterly VAR with GDP and SPF instead of IP and BlueChip. Results are overall robust to changing order among variables, while the attention shock remains important despite the addition of uncertainty or sentiments. When both GT and WSJ included, the shock to professional attention produces stronger results.

B.3.2 Quantile SVAR

Here we construct impulse responses from a Quantile SVAR. Quantile VAR (QVAR) models were originally introduced by White et al. (2015) and were later applied to scenario analysis and structural analysis by Chavleishvili and Manganelli (2021), Montes-Rojas (2021) and Ruzicka (2021). The latter, that we follow to estimate the model and produce impulse responses, introduced the theory for estimation and inference under recursive short-run identification used in this paper. The model takes the following form

$$\begin{bmatrix} \mathbb{Q}_{y_{1,t}}(\tau_1|x_t^{(1)}) \\ \cdots \\ \mathbb{Q}_{y_{K,t}}(\tau_1|x_t^{(K)}) \end{bmatrix} = \begin{bmatrix} 0 & 0 & \dots & 0 \\ a_{0,2,1}(\tau_2) & 0 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ a_{0,K,1}(\tau_K) & a_{0,K,2}(\tau_K) & \dots & 0 \end{bmatrix} \begin{bmatrix} y_{1,t} \\ \cdots \\ y_{K,t} \end{bmatrix} \tag{25}$$
$$+ \sum_{j=1}^{p} \begin{bmatrix} a_{j,1,1}(\tau_1) & \dots & a_{j,1,K}(\tau_1) \\ \vdots & \ddots & \vdots \\ a_{j,K,1}(\tau_K) & \dots & a_{j,K,K}(\tau_K) \end{bmatrix} \begin{bmatrix} y_{1,t-j} \\ \cdots \\ y_{K,t-j} \end{bmatrix} + \begin{bmatrix} \epsilon_1(\tau_1) \\ \vdots \\ \epsilon_K(\tau_K) \end{bmatrix}.$$

This approach generalizes a SVAR by defining each equation as a linear quantile regression model and therefore allowing parameters to vary according to the conditional quantile of the dependent variable one equation at a time. The structural impact matrix $A_0(\tau) := \big(a_{0,k,j}(\tau_k)\big)$ is lower triangular which corresponds to a short-run recursive identification scheme just as in a standard VAR.

To generate quantile impulse responses from this model, we exploit the fact that quantile regression models admit a restricted random coefficient representation which takes the following form

$$y_t = A_0(u_t)y_t + \sum_{j=1}^{p} A_j(u_t)y_{t-j} + \epsilon(u_t).$$

The idea here is that we can sample from the CDF $F(y_{k,t}|x_t^{(k)})$ because we have its inverse $\mathbb{Q}_{y_{k,t}}(.|x_t^{(k)}) = F^{-1}_{y_{k,t}}\left(.|x_t^{(k)}\right)$ and $y \sim F(y_{k,t}|x_t^{(k)})$ and $\tilde{y} = F^{-1}_{y_{k,t}}\left(u|x_t^{(k)}\right)$ for $u \sim U[0,1]$ have the same distribution. At each point in time, we can thus sample a vector of parameters for each equation using K random uniform draws to determine the quantile from which they should be drawn. We can iterate the procedure forward to sample from the distributions of $y_{t+1}, \dots, y_{t+H}$.

The following step, inspired by Koop et al. (1996), is added to obtain quantile impulse responses. Let $\epsilon(u_t)^{(s)}, \dots, \epsilon(u_{t+H})^{(s)}$ for $s \in \{0,1\}$ be two histories of shocks that only differ at time t by a quantity $\delta \neq 0$ for element j, i.e. $\epsilon(u_{t+h})^{(1)} = \epsilon(u_{t+h})^{(0)} + \mathbb{I}\{h = 0\}e_j\delta$ for all horizons h where e_j is the $j-$th column of $K \times K$ identity matrix. Using the sampling procedure described above, histories $\{{y_t}^{(s)}, \dots, {y_{t+H}}^{(s)}\}$ can be simulated for horizons $h = 0, \dots, H$ where the only difference between both histories is that $s = 1$ sustained a shock of size δ to variable j and $s = 0$ did not. Ruzicka (2021) then defines the quantile impulse response at quantile τ of variable k to a shock j at horizon h as

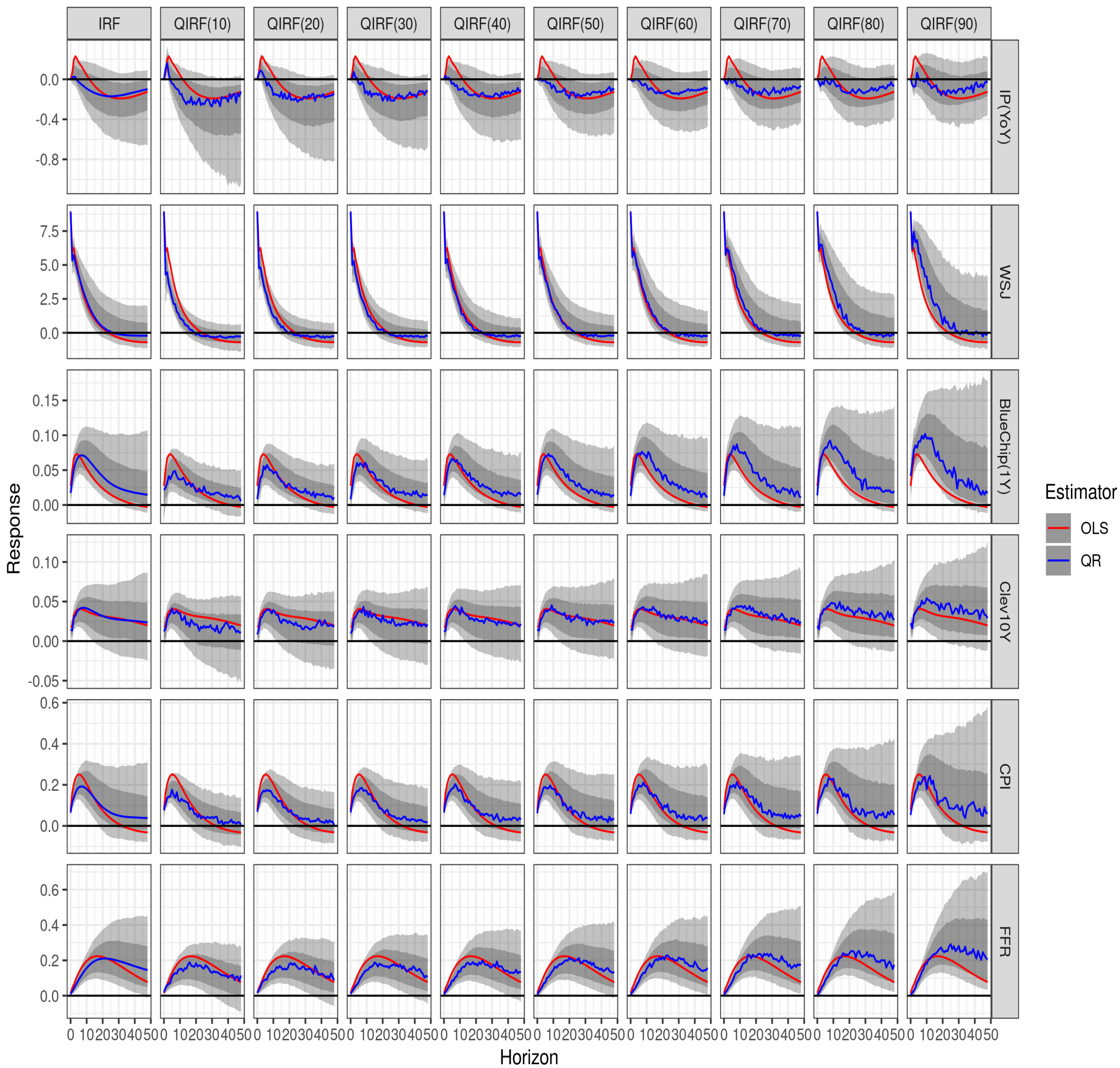
$$QIRF(\tau, k, j, h) := \mathbb{Q}_{y^{(1)}_{k,t+h}}(\tau) - \mathbb{Q}_{y^{(0)}_{k,t+h}}(\tau).$$

In practice, model (25) needs to be estimated at a finite number of quantiles for each equation. We used an equally spaced grid of 200 quantiles $\{0.005, \ldots, 0.995\}$ and generate quantile impulse responses using 1000 Monte Carlo draws of pairs of histories. It also requires, like a SVAR, to specify a lag order. We use 3 lags.

Next, following Ruzicka (2021), the inference is obtained using a weighted bootstrap algorithm. In the present case, model (25) is estimated by weighted linear quantile regressions using exponential random weights for observations and quantile impulse responses are obtained by simulation as before. We use 1000 Monte Carlo draws for the weighted bootstrap. To clarify, we simulate a total 2 000 000 paths of length $H + 1$ for the whole vector of variables to conduct inference on the effect of just one shock (i.e., 1000 pairs of histories for each of the 1000 randomly weighted estimates of the parameters of model (25).

The professional attention shock is identified using the same recursive ordering as in section B.3.1. Results are presented in Figure 15. Clearly, a positive shock to attention about inflation generates stronger effects in the right tail, especially for short and long-run inflation expectations, but also for CPI inflation itself. The monetary policy also reacts accordingly by a stronger response of FFR.

Figure 15: Quantile SVAR: additional impulse responses



C Additional FIRE testing results

Table 30: Attention and FIRE testing: 1-quarter ahead until 2021Q1

	GT attention						WSJ attention					
	OLS			Quantile reg. eq. 11			OLS			Quantile reg. eq. 11		
	eq. 8	eq. 9	eq. 10	q=0.5	q=0.8	q=0.9	eq. 8	eq. 9	eq. 10	q=0.5	q=0.8	q=0.9
c	0.04	-2.02	-1.92	-1.77	-2.86	-2.46	0.07	-0.16	-0.08	-0.08	0.76	0.67
p-val	0.74	0.05	0.06	0.06	0.04	0.19	0.48	0.4	0.68	0.73	0	0.15
β	0.57		0.53	0.53	0.73	0.04	0.59		0.53	0.68	0.77	-0.24
p-val	0.15		0.16	0.13	0.17	0.95	0.08		0.12	0.08	0	0.77
δ^{GT}		0.09	0.09	0.08	0.17	0.17						
p-val		0.05	0.05	0.05	0.01	0.04						
δ^{WSJ}								0.01	0.01	0.01	0	0.05
p-val								0.22	0.35	0.59	0.81	0.05
$\beta = \delta = 0$			0.05	0.04	0.01	0.13			0.14	0.16	0	0.15
R^2	0.02	0.04	0.06	0.93	0.88	0.91	0.02	0.01	0.02	0.97	0.96	0.92

Note: This table presents results from regressions using 1-quarter ahead SPF expectations. Columns under OLS show regression estimates of equations 8, 9 and 10, while the last three columns present estimates from the quantile regression of equation 11 for quantiles $q < 50$, $q > 80$ and $q > 90$. The adjusted R^2 is reported for the OLS columns, while it's the pseudo-R^2 in the case of quantile regressions. Note that sample span is 2004Q1-2021Q1 in the case of GT (left panel) and 1998Q1-2021Q1 in the case of WSJ (right panel).

Table 31: Implied degrees of information rigidity: 1-quarter ahead until 2021Q1

	No attention				GT attention			
	OLS	Quantile reg. eq. 8			eq. 10	Quantile reg. eq. 11		
	eq. 8	q=0.5	q=0.8	q=0.9		q=0.5	q=0.8	q=0.9
Stickiness (λ)	0.36	0.33	0.45	0.45	0.35	0.35	0.42	0.04
	[0.16,0.56]	[0.18,0.49]	[0.21,0.69]	[0.17,0.72]	[0.14,0.55]	[0.16,0.54]	[0.2,0.65]	[-0.79,0.87]
Kalman gain (G)	0.64	0.67	0.55	0.55	0.65	0.65	0.58	0.96
	[0.44,0.84]	[0.51,0.82]	[0.31,0.79]	[0.28,0.83]	[0.45,0.86]	[0.46,0.84]	[0.35,0.8]	[0.13,1.79]
	No attention				WSJ attention			
	OLS	Quantile reg. eq. 8			eq. 10	Quantile reg. eq. 11		
	eq. 8	q=0.5	q=0.8	q=0.9		q=0.5	q=0.8	q=0.9
Inf. stickiness (λ)	0.37	0.45	0.44	0.48	0.35	0.4	0.44	-0.32
	[0.2,0.54]	[0.32,0.57]	[0.36,0.51]	[0.17,0.79]	[0.16,0.53]	[0.23,0.58]	[0.36,0.52]	[-2.12,1.49]
Kalman gain (G)	0.63	0.55	0.56	0.52	0.65	0.6	0.56	1.32
	[0.46,0.8]	[0.43,0.68]	[0.49,0.64]	[0.21,0.83]	[0.47,0.84]	[0.42,0.77]	[0.48,0.64]	[-0.49,3.12]

Note: This table presents the implied measures of information stickiness and noise. Columns (1) and (2) show implied estimates from equations 8 and 10 respectively, while the column (3) to (5) present estimates obtained from the quantile regression 11 for quantiles ($q < 50$, $q > 80$ and $q > 90$) respectively. The numbers in the brackets are the 90th confidence intervals. Note that sample span is 2004Q1-2021Q1 in the case of GT (left panel) and 1998Q1-2021Q1 in the case of WSJ (right panel).

Table 32: Implied degrees of information rigidity: 2-quarter ahead

	No attention				GT attention			
	OLS	Quantile reg. eq. 8			eq. 10	Quantile reg. eq. 11		
	eq. 8	q=0.5	q=0.8	q=0.9		q=0.5	q=0.8	q=0.9
Stickiness (λ)	0.76	0.77	0.74	0.84	0.69	0.62	0.46	0.71
	[0.7,0.82]	[0.73,0.81]	[0.58,0.91]	[0.81,0.87]	[0.59,0.79]	[0.48,0.77]	[-0.04,0.97]	[0.62,0.79]
Kalman gain (G)	0.24	0.23	0.26	0.16	0.31	0.38	0.54	0.29
	[0.18,0.3]	[0.19,0.27]	[0.09,0.42]	[0.13,0.19]	[0.21,0.41]	[0.23,0.52]	[0.03,1.04]	[0.21,0.38]
	No attention				WSJ attention			
	OLS	Quantile reg. eq. 8			eq. 10	Quantile reg. eq. 11		
	eq. 8	q=0.5	q=0.8	q=0.9		q=0.5	q=0.8	q=0.9
Inf. stickiness (λ)	0.75	0.62	0.71	0.83	0.63	0.53	0.46	0.74
	[0.69,0.8]	[0.5,0.74]	[0.63,0.79]	[0.8,0.87]	[0.5,0.76]	[0.24,0.83]	[0.16,0.76]	[0.66,0.82]
Kalman gain (G)	0.25	0.38	0.29	0.17	0.37	0.47	0.54	0.26
	[0.2,0.31]	[0.26,0.5]	[0.21,0.37]	[0.13,0.2]	[0.24,0.5]	[0.17,0.76]	[0.24,0.84]	[0.18,0.34]

Note: This table presents the implied measures of information stickiness and noise. Columns (1) and (2) show implied estimates from equations 8 and 10 respectively, while the column (3) to (5) present estimates obtained from the quantile regression 11 for quantiles ($q < 50$, $q > 80$ and $q > 90$) respectively. The numbers in the brackets are the 90th confidence intervals. Note that sample span is 2004Q1-2024Q1 in the case of GT (left panel) and 1998Q1-2024Q1 in the case of WSJ (right panel).

Table 33: Implied degrees of information rigidity: 2-quarter ahead until 2021Q1

	No attention				GT attention			
	OLS	Quantile reg. eq. 8			eq. 10	Quantile reg. eq. 11		
	eq. 8	q=0.5	q=0.8	q=0.9		q=0.5	q=0.8	q=0.9
Stickiness (λ)	0.57	0.43	0.51	0.34	0.56	0.37	0.11	-1.72
	[0.38,0.76]	[0.12,0.75]	[0.13,0.9]	[-0.71,1.39]	[0.37,0.76]	[-0.06,0.8]	[-1.29,1.51]	[-17.58,14.14]
Kalman gain (G)	0.43	0.57	0.49	0.66	0.44	0.63	0.89	2.72
	[0.24,0.62]	[0.25,0.88]	[0.1,0.87]	[-0.39,1.71]	[0.24,0.63]	[0.2,1.06]	[-0.51,2.29]	[-13.14,18.58]
	No attention				WSJ attention			
	OLS	Quantile reg. eq. 8			eq. 10	Quantile reg. eq. 11		
	eq. 8	q=0.5	q=0.8	q=0.9		q=0.5	q=0.8	q=0.9
Inf. stickiness (λ)	0.55	0.28	0.55	0.32	0.56	0.45	0.54	0.16
	[0.39,0.71]	[-0.26,0.82]	[0.44,0.67]	[-0.72,1.35]	[0.4,0.72]	[0.12,0.78]	[0.43,0.65]	[-1.55,1.87]
Kalman gain (G)	0.45	0.72	0.45	0.68	0.44	0.55	0.46	0.84
	[0.29,0.61]	[0.18,1.26]	[0.33,0.56]	[-0.35,1.72]	[0.28,0.6]	[0.22,0.88]	[0.35,0.57]	[-0.87,2.55]

Note: This table presents the implied measures of information stickiness and noise. Columns (1) and (2) show implied estimates from equations 8 and 10 respectively, while the column (3) to (5) present estimates obtained from the quantile regression 11 for quantiles ($q < 50$, $q > 80$ and $q > 90$) respectively. The numbers in the brackets are the 90th confidence intervals. Note that sample span is 2004Q1-2021Q1 in the case of GT (left panel) and 1998Q1-2021Q1 in the case of WSJ (right panel).

Table 34: Attention and FIRE testing: 2-quarter ahead

	GT attention						WSJ attention					
	OLS			Quantile reg. eq. 11			OLS			Quantile reg. eq. 11		
	eq. 8	eq. 9	eq. 10	q=0.5	q=0.8	q=0.9	eq. 8	eq. 9	eq. 10	q=0.5	q=0.8	q=0.9
c	0.37	-1.09	-0.66	-0.78	-0.96	-0.65	0.38	-0.42	-0.2	-0.15	0.22	1.11
p-val	0.04	0.01	0.12	0.05	0.16	0.11	0.01	0.03	0.36	0.62	0.34	0
β	3.18		2.23	1.65	0.87	2.4	2.95		1.68	1.15	0.85	2.81
p-val	0		0.01	0.04	0.52	0	0		0.02	0.28	0.28	0
δ^{GT}		0.06	0.04	0.03	0.1	0.12						
p-val		0	0.01	0.02	0	0						
δ^{WSJ}								0.03	0.03	0.01	0.05	0.04
p-val								0	0	0.19	0	0
$\beta = \delta = 0$			0	0	0	0			0	0.05	0	0
R^2	0.16	0.17	0.23	0.9	0.83	0.69	0.16	0.21	0.24	0.93	0.83	0.72

Note: This table presents results from regressions using 2-quarter ahead SPF expectations. Columns under OLS show regression estimates of equations 8, 9 and 10, while the last three columns present estimates from the quantile regression of equation 11 for quantiles $q < 50$, $q > 80$ and $q > 90$. The adjusted R^2 is reported for the OLS columns, while it's the pseudo-R^2 in the case of quantile regressions. Note that sample span is 2004Q1-2024Q1 in the case of GT (left panel) and 1998Q1-2024Q1 in the case of WSJ (right panel).

Table 35: Attention and FIRE testing: 2-quarter ahead until 2021Q1

	GT attention						WSJ attention					
	OLS			Quantile reg. eq. 11			OLS			Quantile reg. eq. 11		
	eq. 8	eq. 9	eq. 10	q=0.5	q=0.8	q=0.9	eq. 8	eq. 9	eq. 10	q=0.5	q=0.8	q=0.9
c	-0.03	-0.91	-0.72	-0.3	-0.65	-2.05	0.03	-0.06	0.1	0.1	0.79	0.98
p-val	0.82	0.43	0.53	0.81	0.74	0.4	0.77	0.76	0.66	0.75	0	0.13
β	1.32		1.28	0.6	0.13	-0.63	1.24		1.29	0.83	1.18	0.19
p-val	0.09		0.11	0.48	0.93	0.7	0.05		0.05	0.34	0	0.92
δ^{GT}		0.04	0.03	0.01	0.07	0.16						
p-val		0.47	0.55	0.92	0.44	0.14						
δ^{WSJ}								0	0	-0.01	0	0.03
p-val								0.84	0.74	0.64	0.57	0.38
$\beta = \delta = 0$			0.21	0.77	0.73	0.33			0.14	0.61	0.01	0.64
R^2	0.03	-0.01	0.02	1	0.93	0.93	0.03	-0.01	0.02	0.99	0.96	0.98

Note: This table presents results from regressions using 2-quarter ahead SPF expectations. Columns under OLS show regression estimates of equations 8, 9 and 10, while the last three columns present estimates from the quantile regression of equation 11 for quantiles $q < 50$, $q > 80$ and $q > 90$. The adjusted R^2 is reported for the OLS columns, while it's the pseudo-R^2 in the case of quantile regressions. Note that sample span is 2004Q1-2021Q1 in the case of GT (left panel) and 1998Q1-2021Q1 in the case of WSJ (right panel).

Table 36: Implied degrees of information rigidity: 1-quarter ahead and controls

No controls

	No attention				With attention			
	OLS	Quantile reg. eq.8			OLS	Quantile reg. eq.11		
	eq.8	q=0.5	q=0.8	q=0.9	eq.10	q=0.5	q=0.8	q=0.9
GT attention								
Stickiness (λ)	0.64	0.68	0.6	0.57	0.53	0.54	0.48	0.31
	[0.58,0.7]	[0.64,0.72]	[0.44,0.76]	[0.48,0.65]	[0.42,0.64]	[0.47,0.61]	[0.28,0.68]	[-0.15,0.77]
Kalman gain (G)	0.36	0.32	0.4	0.43	0.47	0.46	0.52	0.69
	[0.3,0.42]	[0.28,0.36]	[0.24,0.56]	[0.35,0.52]	[0.36,0.58]	[0.39,0.53]	[0.32,0.72]	[0.23,1.15]
WSJ attention								
Stickiness (λ)	0.63	0.67	0.61	0.59	0.47	0.47	0.41	0
	[0.58,0.69]	[0.63,0.71]	[0.53,0.7]	[0.44,0.74]	[0.34,0.59]	[0.35,0.59]	[0.19,0.63]	[-0.3,0.3]
Kalman gain (G)	0.37	0.33	0.39	0.41	0.53	0.53	0.59	1
	[0.31,0.42]	[0.29,0.37]	[0.3,0.47]	[0.26,0.56]	[0.41,0.66]	[0.41,0.65]	[0.37,0.81]	[0.7,1.3]

CPI(t-1)

	No attention				With attention			
	OLS	Quantile reg. eq.8			OLS	Quantile reg. eq.11		
	eq.8	q=0.5	q=0.8	q=0.9	eq.10	q=0.5	q=0.8	q=0.9
GT attention								
Stickiness (λ)	0.55	0.54	0.62	0.64	0.54	0.54	0.6	0.21
	[0.47,0.64]	[0.47,0.62]	[0.54,0.7]	[0.45,0.82]	[0.44,0.64]	[0.45,0.64]	[0.45,0.74]	[-0.22,0.64]
Kalman gain (G)	0.45	0.46	0.38	0.36	0.46	0.46	0.4	0.79
	[0.36,0.53]	[0.38,0.53]	[0.3,0.46]	[0.18,0.55]	[0.36,0.56]	[0.36,0.55]	[0.26,0.55]	[0.36,1.22]
WSJ attention								
Stickiness (λ)	0.55	0.49	0.59	0.63	0.47	0.48	0.4	-0.55
	[0.47,0.63]	[0.42,0.56]	[0.48,0.71]	[0.55,0.72]	[0.35,0.59]	[0.39,0.58]	[0.23,0.56]	[-1.93,0.83]
Kalman gain (G)	0.45	0.51	0.41	0.37	0.53	0.52	0.6	1.55
	[0.37,0.53]	[0.44,0.58]	[0.29,0.52]	[0.28,0.45]	[0.41,0.65]	[0.42,0.61]	[0.44,0.77]	[0.17,2.93]

GSPCI(t-1)

	No attention				With attention			
	OLS	Quantile reg. eq.8			OLS	Quantile reg. eq.11		
	eq.8	q=0.5	q=0.8	q=0.9	eq.10	q=0.5	q=0.8	q=0.9
GT attention								
Stickiness (λ)	0.47	0.49	0.5	0.34	0.42	0.52	0.49	0.32
	[0.35,0.6]	[0.36,0.62]	[0.37,0.63]	[0.07,0.62]	[0.26,0.58]	[0.44,0.6]	[0.35,0.63]	[-0.08,0.72]
Kalman gain (G)	0.53	0.51	0.5	0.66	0.58	0.48	0.51	0.68
	[0.4,0.65]	[0.38,0.64]	[0.37,0.63]	[0.38,0.93]	[0.42,0.74]	[0.4,0.56]	[0.37,0.65]	[0.28,1.08]
WSJ attention								
Stickiness (λ)	0.47	0.52	0.5	0.4	0.4	0.49	0.49	0.32
	[0.36,0.59]	[0.42,0.61]	[0.4,0.59]	[0.13,0.66]	[0.25,0.56]	[0.36,0.62]	[0.39,0.59]	[-0.16,0.8]
Kalman gain (G)	0.53	0.48	0.5	0.6	0.6	0.51	0.51	0.68
	[0.41,0.64]	[0.39,0.58]	[0.41,0.6]	[0.34,0.87]	[0.44,0.75]	[0.38,0.64]	[0.41,0.61]	[0.2,1.16]

WTI(t-1)

	No attention				With attention			
	OLS	Quantile reg. eq.8			OLS	Quantile reg. eq.11		
	eq.8	q=0.5	q=0.8	q=0.9	eq.10	q=0.5	q=0.8	q=0.9
GT attention								
Stickiness (λ)	0.62	0.66	0.51	0.51	0.45	0.34	0.43	0.36
	[0.54,0.69]	[0.61,0.71]	[0.33,0.68]	[0.3,0.73]	[0.28,0.61]	[0.14,0.54]	[0.16,0.69]	[-0.04,0.76]
Kalman gain (G)	0.38	0.34	0.49	0.49	0.55	0.66	0.57	0.64
	[0.31,0.46]	[0.29,0.39]	[0.32,0.67]	[0.27,0.7]	[0.39,0.72]	[0.46,0.86]	[0.31,0.84]	[0.24,1.04]
WSJ attention								
Stickiness (λ)	0.61	0.64	0.55	0.54	0.39	0.49	0.15	-0.15
	[0.54,0.68]	[0.59,0.7]	[0.36,0.73]	[0.33,0.76]	[0.22,0.57]	[0.35,0.63]	[-0.37,0.68]	[-0.76,0.46]
Kalman gain (G)	0.39	0.36	0.45	0.46	0.61	0.51	0.85	1.15
	[0.32,0.46]	[0.3,0.41]	[0.27,0.64]	[0.24,0.67]	[0.43,0.78]	[0.37,0.65]	[0.32,1.37]	[0.54,1.76]

3MTBill(t-1)

	No attention				With attention			
	OLS	Quantile reg. eq.8			OLS	Quantile reg. eq.11		
	eq.8	q=0.5	q=0.8	q=0.9	eq.10	q=0.5	q=0.8	q=0.9
GT attention								
Stickiness (λ)	0.64	0.66	0.57	0.58	0.53	0.54	0.48	0.57
	[0.58,0.7]	[0.61,0.71]	[0.4,0.73]	[0.52,0.64]	[0.42,0.64]	[0.46,0.61]	[0.21,0.76]	[0.32,0.81]
Kalman gain (G)	0.36	0.34	0.43	0.42	0.47	0.46	0.52	0.43
	[0.3,0.42]	[0.29,0.39]	[0.27,0.6]	[0.36,0.48]	[0.36,0.58]	[0.39,0.54]	[0.24,0.79]	[0.19,0.68]
WSJ attention								
Stickiness (λ)	0.63	0.66	0.61	0.56	0.46	0.5	0.4	-0.27
	[0.58,0.69]	[0.62,0.7]	[0.56,0.65]	[0.38,0.74]	[0.33,0.59]	[0.38,0.63]	[0.16,0.64]	[-1.38,0.84]
Kalman gain (G)	0.37	0.34	0.39	0.44	0.54	0.5	0.6	1.27
	[0.31,0.42]	[0.3,0.38]	[0.35,0.44]	[0.26,0.62]	[0.41,0.67]	[0.37,0.62]	[0.36,0.84]	[0.16,2.38]

UNRATE(t-1)

	No attention				With attention			
	OLS	Quantile reg. eq.8			OLS	Quantile reg. eq.11		
	eq.8	q=0.5	q=0.8	q=0.9	eq.10	q=0.5	q=0.8	q=0.9
GT attention								
Stickiness (λ)	0.63	0.69	0.61	0.57	0.52	0.54	0.5	0.56
	[0.57,0.7]	[0.65,0.73]	[0.45,0.77]	[0.42,0.72]	[0.41,0.64]	[0.47,0.62]	[0.25,0.75]	[0.38,0.74]
Kalman gain (G)	0.37	0.31	0.39	0.43	0.48	0.46	0.5	0.44
	[0.3,0.43]	[0.27,0.35]	[0.23,0.55]	[0.28,0.58]	[0.36,0.59]	[0.38,0.53]	[0.25,0.75]	[0.26,0.62]
WSJ attention								
Stickiness (λ)	0.63	0.67	0.63	0.6	0.47	0.48	0.41	0.14
	[0.58,0.69]	[0.63,0.71]	[0.56,0.7]	[0.41,0.8]	[0.34,0.59]	[0.36,0.6]	[0.23,0.59]	[-0.14,0.42]
Kalman gain (G)	0.37	0.33	0.37	0.4	0.53	0.52	0.59	0.86
	[0.31,0.42]	[0.29,0.37]	[0.3,0.44]	[0.2,0.59]	[0.41,0.66]	[0.4,0.64]	[0.41,0.77]	[0.58,1.14]

VIX(t-1)

	No attention				With attention			
	OLS	Quantile reg. eq.8			OLS	Quantile reg. eq.11		
	eq.8	q=0.5	q=0.8	q=0.9	eq.10	q=0.5	q=0.8	q=0.9
GT attention								
Stickiness (λ)	0.64	0.68	0.57	0.61	0.51	0.54	0.48	0.49
	[0.58,0.7]	[0.64,0.73]	[0.4,0.74]	[0.47,0.76]	[0.4,0.63]	[0.46,0.62]	[0.22,0.74]	[0.09,0.89]
Kalman gain (G)	0.36	0.32	0.43	0.39	0.49	0.46	0.52	0.51
	[0.3,0.42]	[0.27,0.36]	[0.26,0.6]	[0.24,0.53]	[0.37,0.6]	[0.38,0.54]	[0.26,0.78]	[0.11,0.91]
WSJ attention								
Stickiness (λ)	0.63	0.67	0.61	0.59	0.47	0.45	0.38	-0.09
	[0.58,0.69]	[0.63,0.71]	[0.52,0.71]	[0.42,0.76]	[0.34,0.59]	[0.32,0.57]	[0.24,0.51]	[-0.67,0.49]
Kalman gain (G)	0.37	0.33	0.39	0.41	0.53	0.55	0.62	1.09
	[0.31,0.42]	[0.29,0.37]	[0.29,0.48]	[0.24,0.58]	[0.41,0.66]	[0.43,0.68]	[0.49,0.76]	[0.51,1.67]

Table 37: Implied degrees of information rigidity: 2-quarter ahead and controls

	No controls								**CPI(t-1)**							
	No attention				With attention				No attention				With attention			
	OLS	Quantile reg. eq.8			OLS	Quantile reg. eq.11			OLS	Quantile reg. eq.8			OLS	Quantile reg. eq.11		
	eq.8	q=0.5	q=0.8	q=0.9	eq.10	q=0.5	q=0.8	q=0.9	eq.8	q=0.5	q=0.8	q=0.9	eq.10	q=0.5	q=0.8	q=0.9
GT attention																
Stickiness (λ)	0.76	0.77	0.74	0.84	0.69	0.62	0.46	0.71	0.73	0.71	0.54	0.75	0.69	0.63	0.44	0.71
	[0.7,0.82]	[0.73,0.81]	[0.58,0.91]	[0.81,0.87]	[0.59,0.79]	[0.48,0.77]	[-0.04,0.97]	[0.62,0.79]	[0.64,0.81]	[0.62,0.8]	[0.06,1.03]	[0.59,0.9]	[0.59,0.8]	[0.48,0.77]	[-0.1,0.99]	[0.6,0.83]
Kalman gain (G)	0.24	0.23	0.26	0.16	0.31	0.38	0.54	0.29	0.27	0.29	0.46	0.25	0.31	0.37	0.56	0.29
	[0.18,0.3]	[0.19,0.27]	[0.09,0.42]	[0.13,0.19]	[0.21,0.41]	[0.23,0.52]	[0.03,1.04]	[0.21,0.38]	[0.19,0.36]	[0.2,0.38]	[-0.03,0.94]	[0.1,0.41]	[0.2,0.41]	[0.23,0.52]	[0.01,1.1]	[0.17,0.4]
WSJ attention																
Stickiness (λ)	0.75	0.62	0.71	0.83	0.63	0.53	0.46	0.74	0.71	0.64	0.67	0.81	0.63	0.6	0.42	0.75
	[0.69,0.8]	[0.5,0.74]	[0.63,0.79]	[0.8,0.87]	[0.5,0.76]	[0.24,0.83]	[0.16,0.76]	[0.66,0.82]	[0.64,0.78]	[0.52,0.75]	[0.56,0.78]	[0.73,0.9]	[0.49,0.76]	[0.41,0.78]	[0.12,0.72]	[0.68,0.83]
Kalman gain (G)	0.25	0.38	0.29	0.17	0.37	0.47	0.54	0.26	0.29	0.36	0.33	0.19	0.37	0.4	0.58	0.25
	[0.2,0.31]	[0.26,0.5]	[0.21,0.37]	[0.13,0.2]	[0.24,0.5]	[0.17,0.76]	[0.24,0.84]	[0.18,0.34]	[0.22,0.36]	[0.25,0.48]	[0.22,0.44]	[0.1,0.27]	[0.24,0.51]	[0.22,0.59]	[0.28,0.88]	[0.17,0.32]

	GSPCI(t-1)								**WTI(t-1)**							
	No attention				With attention				No attention				With attention			
	OLS	Quantile reg. eq.8			OLS	Quantile reg. eq.11			OLS	Quantile reg. eq.8			OLS	Quantile reg. eq.11		
	eq.8	q=0.5	q=0.8	q=0.9	eq.10	q=0.5	q=0.8	q=0.9	eq.8	q=0.5	q=0.8	q=0.9	eq.10	q=0.5	q=0.8	q=0.9
GT attention																
Stickiness (λ)	0.61	0.52	0.04	0.53	0.62	0.47	-0.22	0.53	0.7	0.69	0.69	0.78	0.53	0.27	0.64	0.74
	[0.48,0.75]	[0.31,0.74]	[-2,2.07]	[0.22,0.84]	[0.48,0.76]	[0.17,0.77]	[-3.59,3.16]	[0.17,0.89]	[0.61,0.8]	[0.59,0.79]	[0.51,0.88]	[0.69,0.88]	[0.27,0.78]	[-0.23,0.76]	[0.34,0.94]	[0.66,0.81]
Kalman gain (G)	0.39	0.48	0.96	0.47	0.38	0.53	1.22	0.47	0.3	0.31	0.31	0.22	0.47	0.73	0.36	0.26
	[0.25,0.52]	[0.26,0.69]	[-1.07,3]	[0.16,0.78]	[0.24,0.52]	[0.23,0.83]	[-2.16,4.59]	[0.11,0.83]	[0.2,0.39]	[0.21,0.41]	[0.12,0.49]	[0.12,0.31]	[0.22,0.73]	[0.24,1.23]	[0.06,0.66]	[0.19,0.34]
WSJ attention																
Stickiness (λ)	0.58	0.47	0.23	0.58	0.58	0.56	0.42	0.39	0.69	0.61	0.59	0.8	0.48	0.34	0.57	0.71
	[0.44,0.71]	[0.21,0.72]	[-0.41,0.87]	[0.27,0.89]	[0.44,0.73]	[0.34,0.77]	[0.11,0.73]	[-0.46,1.25]	[0.61,0.78]	[0.5,0.73]	[0.45,0.74]	[0.77,0.82]	[0.23,0.74]	[-0.06,0.73]	[0.3,0.83]	[0.59,0.83]
Kalman gain (G)	0.42	0.53	0.77	0.42	0.42	0.44	0.58	0.61	0.31	0.39	0.41	0.2	0.52	0.66	0.43	0.29
	[0.29,0.56]	[0.28,0.79]	[0.13,1.41]	[0.11,0.73]	[0.27,0.56]	[0.23,0.66]	[0.27,0.89]	[-0.25,1.46]	[0.22,0.39]	[0.27,0.5]	[0.26,0.55]	[0.18,0.23]	[0.26,0.77]	[0.27,1.06]	[0.17,0.7]	[0.17,0.41]

	3MTBill(t-1)								**UNRATE(t-1)**							
	No attention				With attention				No attention				With attention			
	OLS	Quantile reg. eq.8			OLS	Quantile reg. eq.11			OLS	Quantile reg. eq.8			OLS	Quantile reg. eq.11		
	eq.8	q=0.5	q=0.8	q=0.9	eq.10	q=0.5	q=0.8	q=0.9	eq.8	q=0.5	q=0.8	q=0.9	eq.10	q=0.5	q=0.8	q=0.9
GT attention																
Stickiness (λ)	0.76	0.78	0.7	0.82	0.69	0.69	0.57	0.71	0.77	0.78	0.79	0.83	0.71	0.58	0.61	0.69
	[0.7,0.82]	[0.74,0.82]	[0.53,0.87]	[0.73,0.9]	[0.58,0.79]	[0.58,0.8]	[0.24,0.9]	[0.57,0.84]	[0.72,0.83]	[0.73,0.83]	[0.68,0.9]	[0.8,0.86]	[0.62,0.8]	[0.43,0.73]	[0.27,0.95]	[0.54,0.83]
Kalman gain (G)	0.24	0.22	0.3	0.18	0.31	0.31	0.43	0.29	0.23	0.22	0.21	0.17	0.29	0.42	0.39	0.31
	[0.18,0.3]	[0.18,0.26]	[0.13,0.47]	[0.1,0.27]	[0.21,0.42]	[0.2,0.42]	[0.1,0.76]	[0.16,0.43]	[0.17,0.28]	[0.17,0.27]	[0.1,0.32]	[0.14,0.2]	[0.2,0.38]	[0.27,0.57]	[0.05,0.73]	[0.17,0.46]
WSJ attention																
Stickiness (λ)	0.75	0.65	0.7	0.84	0.62	0.61	0.42	0.76	0.76	0.65	0.72	0.82	0.64	0.53	0.71	0.77
	[0.69,0.8]	[0.58,0.73]	[0.64,0.77]	[0.76,0.91]	[0.49,0.76]	[0.46,0.77]	[0.1,0.73]	[0.62,0.91]	[0.7,0.81]	[0.53,0.78]	[0.66,0.79]	[0.76,0.88]	[0.53,0.76]	[0.25,0.82]	[0.62,0.79]	[0.68,0.87]
Kalman gain (G)	0.25	0.35	0.3	0.16	0.38	0.39	0.58	0.24	0.24	0.35	0.28	0.18	0.36	0.47	0.29	0.23
	[0.2,0.31]	[0.27,0.42]	[0.23,0.36]	[0.09,0.24]	[0.24,0.51]	[0.23,0.54]	[0.27,0.9]	[0.09,0.38]	[0.19,0.3]	[0.22,0.47]	[0.21,0.34]	[0.12,0.24]	[0.24,0.47]	[0.18,0.75]	[0.21,0.38]	[0.13,0.32]

	VIX(t-1)							
	No attention				With attention			
	OLS	Quantile reg. eq.8			OLS	Quantile reg. eq.11		
	eq.8	q=0.5	q=0.8	q=0.9	eq.10	q=0.5	q=0.8	q=0.9
GT attention								
Stickiness (λ)	0.76	0.77	0.77	0.85	0.68	0.62	0.49	0.7
	[0.7,0.82]	[0.73,0.82]	[0.64,0.91]	[0.82,0.89]	[0.56,0.8]	[0.46,0.78]	[-0.08,1.07]	[0.6,0.8]
Kalman gain (G)	0.24	0.23	0.23	0.15	0.32	0.38	0.51	0.3
	[0.18,0.3]	[0.18,0.27]	[0.09,0.36]	[0.11,0.18]	[0.2,0.44]	[0.22,0.54]	[-0.07,1.08]	[0.2,0.4]
WSJ attention								
Stickiness (λ)	0.75	0.71	0.71	0.82	0.64	0.59	0.19	0.75
	[0.7,0.81]	[0.64,0.78]	[0.61,0.8]	[0.75,0.88]	[0.51,0.76]	[0.4,0.78]	[-0.48,0.85]	[0.68,0.83]
Kalman gain (G)	0.25	0.29	0.29	0.18	0.36	0.41	0.81	0.25
	[0.19,0.3]	[0.22,0.36]	[0.2,0.39]	[0.12,0.25]	[0.24,0.49]	[0.22,0.6]	[0.15,1.48]	[0.17,0.32]

D Model: technical details

The model has a single exogenous state variable, q_t, but its dynamics depend on the infinite length extended state vector containing the complete hierarchy of firms' beliefs. In practice, we must truncate this vector such that it contains a finite number of higher-order beliefs. In this case, it is not a problem as the importance of higher-order beliefs on the model's endogenous variables decreases as we move up the hierarchy, meaning that we can get arbitrary close to the true solution by choosing a truncation length k such that the model's dynamics do not change by more than a certain convergence criterion if we append the $k+1^{th}$ order beliefs to the state.

The model can be solved in two steps. First, recursively find the state-space representation for the firms beliefs up to the k^{th} order. Second, map those beliefs into the model's endogenous variables. The procedure described below is an application of Nimark (2017) algorithm to solve linear dynamic rational expectations in which agents with private information form higher-order expectations.

D.1 Recursive computation of higher order beliefs.

By definition, the 0^{th} order beliefs about q_t is q_t itself, which can be written under the state-space form

$$q_t^{(0)} = M_0 q_{t-1}^{(0)} + N_0 w_t \; ; \; w_t \sim N(0, I) \tag{26}$$

where w_t is the vector of aggregate shocks.

Given the linear structure and Gaussian shocks, firm i's belief about q_t that follows from observing the signal vector $s_t(i)$ can be computed using the Kalman filter. For the sake of generality, consider periods in which the public signal is available such that the signal vector writes

$$s_t(i) = D_0 q_t^{(0)} + R_w w_t + R_\eta \eta_t(i) \; ; \; \eta_t(i) \sim N(0, I) \tag{27}$$

where $D_0 = [1\ 1]'$, $w_t = [\varepsilon_t\ \eta_t]$ and $\eta_t(j)$ is the unidimensional vector of idiosyncratic noise. Then, firm i's optimal prediction are computed according to

$$q_{t|t}(i)^{(0)} = M_0 q_{t|t-1}(i)^{(0)} + K_0[s_t(i) - D_0 M_0 q_{t|t-1}(i)^{(0)}] \tag{28}$$

where K_o is the Kalman gain.

To find the average first-order expectations, use that $\int_0^1 \eta_t(i) = 0$ and combine the resulting expression with Equation 26 to obtain a law of motion for the hierarchy $(0:1)$ of beliefs

$$\begin{bmatrix} q_t^{(0)} \\ q_t^{(1)} \end{bmatrix} = \begin{bmatrix} M_0 & 0 \\ K_0 D_0 M_0 & (I - K_0 D_0 M_0) \end{bmatrix} \begin{bmatrix} q_{t-1}^{(0)} \\ q_{t-1}^{(1)} \end{bmatrix} + \begin{bmatrix} 1 & 0 \\ K_0 D_0 & K_0 \end{bmatrix} \begin{bmatrix} \varepsilon_t \\ \eta_t \end{bmatrix} \tag{29}$$

or more compactly

$$q_t^{(0:1)} = M_1 q_{t-1}^{(0:1)} + N_1 w_t \; ; \; w_t \sim N(0, I) \tag{30}$$

.

The model's does not feature endogenous signals, thus Equation 27 does not need updating. The same steps can be used to incrementally extend $q_{(0:k-1)}$ to $q_{(0:k)}$. Given an equation that describes the dynamics for average beliefs $(0:k-1)$, compute firm i's hierarchy of beliefs up to order $k-1$ using the Kalman filter

$$q_{t|t}(i)^{(0:k-1)} = M_{k-1}q_{t|t-1}(i)^{(0:k-1)} + K_{k-1}[s_t(i) - D_{k-1}M_{k-1}q_{t|t-1}(i)^{(0:k-1)}] \tag{31}$$

integrate over firms to annihilate idiosyncratic noise and append the result to Equation 26 to get

$$q_t^{(0:k)} = M_k q_{t-1}^{(0:k)} + N_k w_t \; ; \; w_t \sim N(0, I) \tag{32}$$

.

D.2 Mapping beliefs to endogenous.

The firms' optimal pricing rule allow us to directly map the vector $q_t^{(0:k)}$ to the price level as follows

$$p_t = g_k H_k q_t^{(0:k)} \tag{33}$$

where

$$g_k = \begin{bmatrix} \alpha & \alpha(1-\alpha) & \ldots & \alpha(1-\alpha)^{k-1} \end{bmatrix} \tag{34}$$

is a vector of coefficients and

$$H_k = \begin{bmatrix} 0_{k\times 1} & I_k \end{bmatrix} \tag{35}$$

is a matrix that annihilates the first element in the hierarchy of beliefs.

This procedure is used to solve the model under the different attention regimes. The endogenous variable p_t is a function of the past and current realizations of the fundamental disturbance $\{\varepsilon_s\}_{s=0}^t$ and the aggregate noise shock $\{\eta_s\}_{s=0}^t$ during high-attention periods.

The Kalman gain. The filtering problem varies with attention and thus also how precisely one can forecast p_t. This can be seen by analyzing the Kalman gain associated with the state-space system Equation 32 and Equation 27 which can be computed using the formulas

$$K_k = (\Sigma_k D_k' + N_k R')(D_k \Sigma_k D_k' + RR')^{-1} \tag{36}$$

$$\Sigma_k = M_k(\Sigma_k - (\Sigma_k D_k' + N_k R')(D_k \Sigma_k D_k' + RR')^{-1}(\Sigma_k D_k' + N_k R')')M_k + N_k N_k' \tag{37}$$

where $R = [R_w \; R_\eta]$ and Σ_k is the posterior covariance matrix.

Notice the presence of the term $N_k R'$ in Equation 36 establishing a relationship between the filtering process and the presence of aggregate noise through the correlation between the noise in the signal vector and the aggregate shocks affecting the hierachy of beliefs.