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THE DEMAND AND SUPPLY OF INFORMATION ABOUT INFLATION

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The demand and supply of information about inflation[*]

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Abstract/Résumé

In this article we study how the demand and supply of information about inflation affect inflation developments. As a proxy for the demand of information, we extract Google Trends (GT) for keywords such as "inflation", "inflation rate", or "price increase". The rationale is that when agents are more interested about inflation, they should search for information about it, and Google is by now a natural source. As a proxy for the supply of information about inflation, we instead use an indicator based on a (standardized) count of the Wall Street Journal (WSJ) articles containing the word "inflat" in their title. We find that measures of demand (GT) and supply (WSJ) of inflation information have a relevant role to understand and predict actual inflation developments, with the more granular information improving expectation formation, especially so during periods when inflation is very high or low. In particular, the full information rational expectation hypothesis is rejected, suggesting that some informational rigidities exist and are waiting to be exploited. Contrary to the existing evidence, we conclude that the media communication and agents attention do play an important role for aggregate inflation expectations, and this remains valid also when controlling for FED communications.

Dans cet article, nous étudions comment la demande et l'offre d'informations sur l'inflation affectent l'évolution de l'inflation. Comme indicateur de la demande d'informations, nous extrayons les tendances de Google (GT) pour des mots clés tels que "inflation", "taux d'inflation" ou "augmentation des prix". Le raisonnement est le suivant : lorsque les agents sont plus intéressés par l'inflation, ils doivent rechercher des informations à ce sujet, et Google est désormais une source naturelle. Comme indicateur de l'offre d'informations sur l'inflation, nous utilisons un indicateur basé sur un comptage (standardisé) des articles du Wall Street Journal (WSJ) contenant le mot "inflat" dans leur titre. Nous constatons que les mesures de la demande (GT) et de l'offre (WSJ) d'informations sur l'inflation jouent un rôle important dans la compréhension et la prévision de l'évolution réelle de l'inflation, les informations les plus granulaires améliorant la formation des attentes, en particulier pendant les périodes où l'inflation est très élevée ou très faible. En particulier, l'hypothèse de l'espérance rationnelle à information complète est rejetée, ce qui suggère que certaines rigidités informationnelles existent et attendent d'être exploitées. Contrairement à l'évidence établie, nous concluons que la communication des médias et l'attention des agents jouent un rôle important dans les attentes d'inflation agrégées, et ceci reste valable même en contrôlant les communications de la FED.

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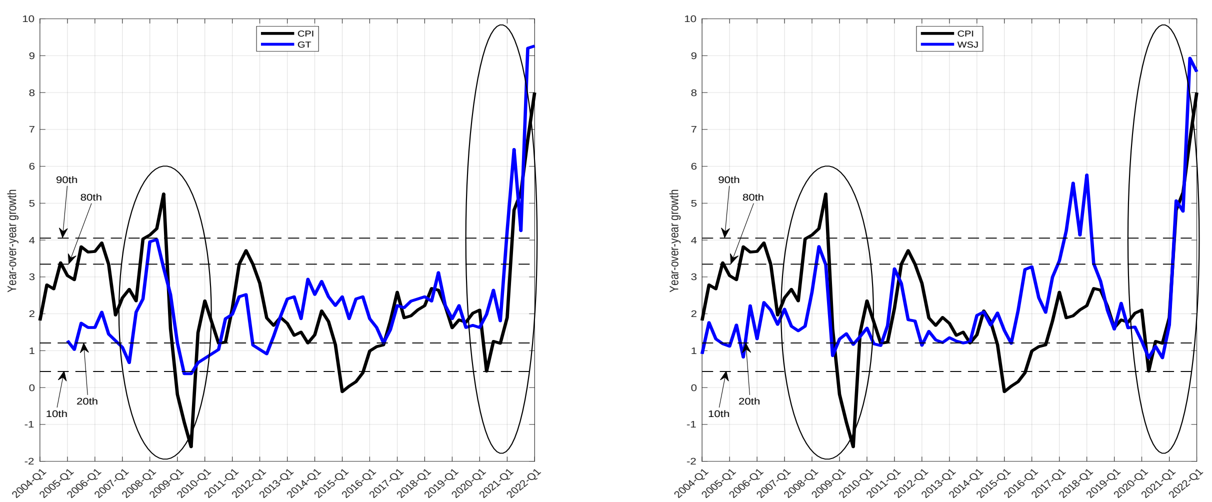
1 Introduction

In this article we study how the demand and supply of information about inflation affect inflation developments. As a proxy for the demand of information about inflation, we extract Google Trends (GT) for keywords such as "inflation", "inflation rate", or "price increase". The rationale is that when agents are more interested about inflation, they should search for information about it, and Google is by now a natural source. As a proxy for the supply of information about inflation, we instead use an indicator based on a (standardized) count of the Wall Street Journal (WSJ) online articles containing the word "inflat*" in their title.[1] A graphical analysis presented in Figure 1 suggests that GT and WSJ are indeed related with inflation developments, with correlation coefficients of 0.74 and 0.68 respectively, particularly so when inflation is very low or very high, such as during the Great Recession and the Covid pandemic episodes.

Figure 1: CPI inflation versus demand and supply of inflation information



(a) CPI and GT

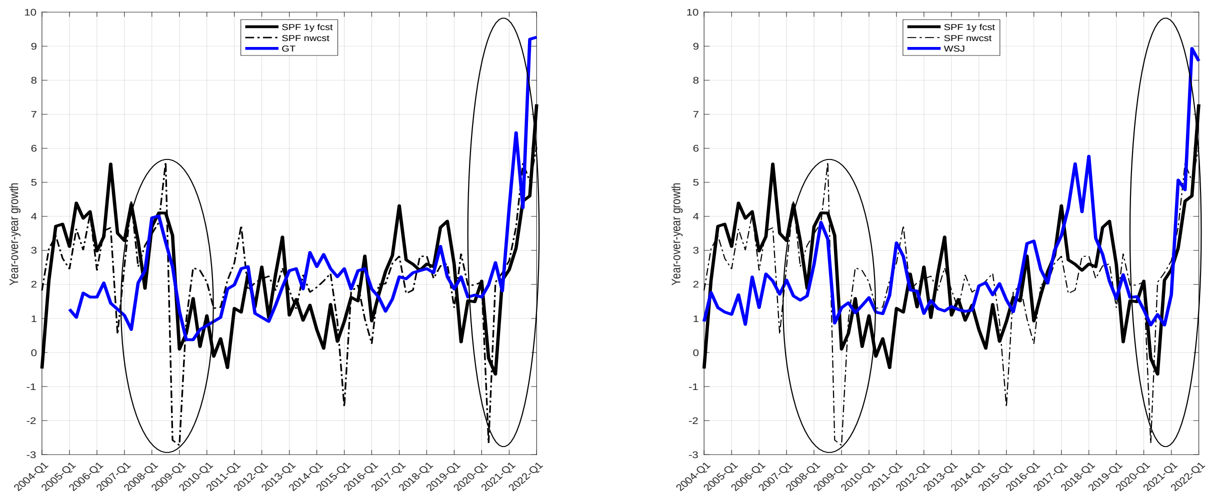
(b) CPI and WSJ

Note: The left panel plots the actual CPI inflation year-over-year growth rate against the Google Trend time series of the keyword "inflation". Dashed horizontal lines show the 10th, 20th, 80th and the 90th quantiles of the CPI inflation during the period 2004Q1-2022Q1. The right panel opposes the same inflation measure against the WSJ indicator. GT and WSJ have been normalized to the same mean and standard deviation as the CPI inflation.

The transmission from information about inflation to inflation developments likely passes

[1] The use of non-standard data such as text and internet volume search is more and more popular in economics. See for example Choi and Varian (2009) for an early application of Google Trends and Gentzkow et al. (2019) for a review on text analysis.

Figure 2: Inflation expectations versus demand and supply of inflation information



(a) SPF and GT (b) SPF and WSJ

Note: The left panel plots the Survey of Professional Forecasters mean nowcast and 1-year ahead forecast against the Google Trend time series of the keyword "inflation". The right panel opposes the same expectation measures against the WSJ indicator. SPF, GT and WSJ have been normalized to the same mean and standard deviation as the CPI inflation.

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, eyeballing Figure 2 suggests a relationships between inflation expectations and our proxies for demand and supply of inflation information, particularly evident when expectations are high. This finding is in line with the analysis in Bracha and Tang (2022), who find that consumers' attention to inflation is higher when inflation is high, and in Coibion et al. (2018b), who document that firms' spend few resources to collecting and processing information about inflation when they think it is not so relevant for their decisions.

To provide formal evidence about this transmission channel from inflation information to expectations and actual inflation, we first project standard measures of inflation expectations onto our demand (GT) and supply (WSJ) information indicators. The measures of expectations considered are forecasts from the Survey of Professional Forecasters and from the Cleveland Fed, and consumer and business expectations from the Michigan, New York and Atlanta Feds respectively. The results show that GT and WSJ have indeed substantial and significant explanatory power for the various measures of inflation expectations. Interestingly, GT matters more than WSJ for consumer and business surveys, while WSJ matters more than GT for SPF.

This is in line with results and explanations in Carroll (2003), in the sense that not all people and firms necessarily read the WSJ or pay attention to inflation articles published in it, but if they search for inflation in Google it means that they are indeed interested in it and more likely to use the acquired information to update their inflation expectations. Instead, for SPF WSJ is in general more significant than GT, which is in line with the idea that professional forecasters pay more attention to WSJ due to their job qualifications and requirements. Moreover, regression analysis confirms that the importance of GT and WSJ is amplified during episodes of high and low inflation, and since the start of the Covid pandemic, in line with the predictions of rational inattention models such as Sims (2003) and Mackowiak and Wiederholt (2009), since in these periods of large changes in inflation not updating inflation expectations can be very costly.

A related analysis is conducted by Angelico et al. (2022) but using Twitter data, which also turn out to be quite useful to track inflation expectations, while Guzman (2011) propose to measure inflation expectations by Google Trends. Korenok et al. (2022) investigate the relationship between the level of inflation and the attention across countries using internet search volumes and Twitter data, and find evidence on attention thresholds. Jung and Kühl (2021) proxy the public's information demand about inflation using the number of visits to the ECB website respectively, as measured by Google Analytics, and show that it influences euro area inflation expectations. Using similar data for the FED, Tillmann (2020) finds that the demand for information about monetary policy has an impact on high-frequency interest rates responses to macroeconomic news. Ellen et al. (2022) construct narrative monetary policy surprises from Norwegian textual data and find that media play an important role in the monetary policy transmission.

Next, we explore the relevance of our measures of demand and supply of inflation information in the context of full information rational expectations (FIRE) models, à la Coibion and Gorodnichenko (2015), and through Mincer and Zarnowitz (1969) optimality regressions. It turns out that GT and WSJ have indeed 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), suggesting that some informational rigidities exist and are waiting to be exploited. At the same time, and contrary to the existing evidence (see, e.g., Weber et al. (2022)), we find that the media communication and agents attention do play an important role for inflation expectations.

WSJ and GT can be considered as providers of private information, as opposed to the public information provided by institutions, central banks in particular in the case of inflation. Shin and Amato (2003) have shown that the latter may have a larger impact on market expectations than the former. More generally, the importance of public communication by central banks for the stabilization of inflation expectations around the inflation target has been long recognized, (e.g., Issing (2005), see also the survey in Binder (2017)). However, WSJ and GT could be also a way to get, indirectly, information about the central banks' communication, so that it is not obvious that the latter would have additional explanatory power for inflation expectations, and for actual inflation developments. Actually, Carroll (2003) demonstrated that more news coverage on inflation affects households' inflation expectations, making them closer to those of professional forecasters. To assess whether central bank communication plays its own role in addition to those of WSJ and GT in affecting inflation expectations we have considered the role of the FOMC sentiment indicator developed by Gardner et al. (2021) and of Google trends for searches related to the FED (mimicking the analysis for the euro area by Jung and Kühl (2021)). It turns out that both indicators are sometimes relevant for some measures of inflation expectations. But their inclusion in the analysis does not change qualitatively the relevance of our main WSJ and GT indicators of information about inflation.

Then, to shed additional light on the effects of the demand and supply of information, we run a simple structural VAR analysis (with the caveat that identification is complex, as detailed later on). Overall, the analysis confirms that both structural information demand and supply shocks matter, and their effects are not fully captured by the inclusion of standard inflation expectations in the model, in line with the previously discussed regression results, and likely since both GT and WSJ are based on (and provide) more granular information. The VAR model can be also used to provide inflation forecasts conditional on specific paths of GT and WSJ indicators. It turns out that both indicators should drop substantially from current levels to bring inflation forecasts back to the around 2% level.

Finally, to provide an even sounder and more direct test of the role of the GT and WSJ measures to anticipate inflation developments, we evaluate whether they 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 do find that GT and WSJ have significant out-of-sample predictive power for standard inflation measures such as CPI and PCE, and especially so in periods of high and low inflation. 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. (2021) further extend the methodology to identify the most relevant topics in the WSJ articles, finding that a selection of the resulting topics is useful to monitor the US business cycle conditions (and a variety of other economic, social and financial phenomena).

The paper is structured as follows. Section 2 presents the projections of inflation expectations onto our demand (GT) and supply (WSJ) information indicators, and studies their role in the context of full information rational expectations (FIRE) models, à la Coibion and Gorodnichenko (2015), and through Mincer-Zarnowitz regressions. Sections 3 and 4 discuss the structural VAR analysis and develop the forecast evaluation. Section 5 summarizes our main findings and concludes. The Appendix contains robustness analysis and additional results.

2 The role of information for inflation developments

Let us define some notation before going to technical details of the empirical strategy. $\pi_{t+h,t}$ is 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 is the informational 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 demand and supply of information proxies, GT and WSJ, observable at time t.

2.1 Data

Table 1 provides the detailed description of data used in this paper. In particular, GT is retrieved from the Google Trend website. Since 2006, Google granted public access to some of its data dating from 2004 and concerning the number of searches made for a particular keyword. In fact, Google Trend is an index of relative popularity according to the geographical region for which we want to collect the data. 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 at the monthly frequency. The results are then normalized on a scale of 0 to 100 according to the proportion of the selected keyword to all searches conducted for a given time period.[2]

To produce WSJ we collect the headlines of the online version of the Wall Street Journal, from January 1998 to April 2022. We apply standard text transformations, such as removing case, common stopwords (e.g. "the") and Porter Stemming. We later count the number of monograms (one word) and bigrams (two adjacent words) in each title, aggregating the counts at the weekly or monthly level. We construct the WSJ inflation index by dividing the monthly counts for "inflat", i.e. the stemmed version of "inflation", by the total number of titles in that week or 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.1 presents descriptive statistics and correlation analyses for GT and WSJ.

2.2 Can GT and WSJ predict inflation expectations?

To measure the explanatory (and predictive) power of GT and WSJ, we include them in Z_t and we project the inflation expectations made at period t onto Z_t. We also add the lagged values of expectations to control for their serial dependance. Hence, the models are of the autoregressive

[2] 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 go back as far as 2004 and as far as 36 hours before a keyword search. Here, we will 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

Variable	Frequency	Time span
Inflation measures		
CPI: All items	Monthly	2004M01-2022M03
Core CPI: CPI less food and energy	Monthly	2004M01-2022M03
PCE: Personal Consumption Expenditures	Monthly	2004M01-2022M03
Google Trends		
Benchmark keyword: "inflation“	Monthly	2004M01-2022M03
Other keywords: "inflation rate“, "price increase“, "cpi“, "price“	Monthly	2004M01-2022M03
Wall Street Journal index		
Count of articles’ titles containing the keyword "inflat*"	Monthly	2004M01-2022M03
Inflation expectations measures		
SPF Mean / Median: CPI		
Forecast for the current quarter up to 4 quarters ahead	Quarterly	2004Q1 - 2022Q1
Cleveland Fed		
Nowcast	Monthly	2013M08-2022M03
Forecast 1 year ahead	Monthly	2004M01-2022M03
Surveys		
Michigan U. Survey of Consumers: Median expected price change next 12 months	Monthly	2004M01-2022M03
New York Fed Survey of Consumer Expectations: Median one-year ahead expected inflation rate	Monthly	2013M08-2022M03
Atlanta Fed Mean Business Inflation Expectations: changes to unit costs over the next 12 months	Monthly	2011M10-2022M03
Other controls		
OIL: Spot Crude Oil Price (WTI)	Monthly	2004M01-2022M03
Regular All Formulations Gas Price	Monthly	2004M01-2022M03
Global Supply Chain Pressure Index (GSCPI)	Monthly	2004M01-2022M03
CPI: Food	Monthly	2004M01-2022M03
Google Trend of keywords "federal reserve system" or "fed"	Monthly	2004M01-2022M03
FOMC inflation sentiments from (Gardner et al., 2021)	Monthly	2004M01-2022M03

(AR) distributed lag (DL) type:

$$\pi_{t+h,t} = c + \alpha\pi_{t+h,t-1} + \beta Z_t + u_t \tag{1}$$

$$\pi_{t+h,t} = c + \alpha\pi_{t+h,t-1} + \beta Z_{t-1} + u_t \tag{2}$$

In equation (1) we assume that Z_t is available to agents during the month or the quarter when the expectations are made. In equation (2) we measure the ability of Z_t to predict the next period expectations.

The null of interest is $\beta = 0$. If H_0 is rejected, demand or supply are informative about the formation of inflation expectations. In order to explore the effect of information during specific important periods of inflation developments we also consider the following augmented specification:

$$\pi_{t+h,t} = c + \alpha\pi_{t+h,t-1} + \beta Z_t + \gamma Z_t \times D_t + \delta D_t + u_t. \tag{3}$$

The dummy variable D_t takes value 1 for periods where CPI inflation is below its 10th quantile, above the 90th quantile or since the Covid pandemic when inflation was first very low and then very high, respectively. We are interested in the marginal effect of Z_t, so the null hypothesis is given by $H_0 : \beta + \gamma = 0$.

The results from regression (1) are presented in Tables 2, 3 and 4, while Table 20 in Appendix report results with monthly surveys with Z_t containing either GT or WSJ. From Table 2 for SPF, over the full sample results show that for SPF, over the full sample WSJ is significant at the 10% level for h=0 (nowcasts) and 4 (one year ahead). GT is not significant, but becomes so for specific periods and horizons, e.g. in either tail for the nowcasts of inflation. Moreover, there are also substantial gains in terms of R2 with respect to the AR benchmark, ranging from about 40% for nowcasts, to 20% for 1 quarter ahead forecasts, to 10-15% for one year ahead forecasts. Another perhaps interesting issue is the sign of the measures of information about inflation. When statistically significant, the sign is positive over the full period, often negative when inflation is low and again positive when it is high (and positive during Covid when periods with very high inflation dominate). This last outcome suggests that increased demand and supply of information about inflation can further increase it when it is high, and decrease it when it is low, due to the positive correlation of the SPF with actual inflation.

Since some of the findings we have reported could be affected by the correlation of GT and WSJ, in Table 3 we have repeated the regression analysis using either GT or WSJ as regressors rather than both of them. Now GT is also generally significant over the full sample, the gains in terms of explanatory power remain, as well as the fact that the coefficients are positive over the full sample, often negative in the left tail and positive in the right tail.

From Table 4, for the Michigan, Atlanta FED and New York FED surveys, over the full sample GT is always significant at the 10% level, but WSJ is never significant, in general not even in the tails or during Covid period. Moreover, the gains in terms of R2 shrink, mainly because the AR benchmark already has very high explanatory power for these target variables, but possibly also because the Professional Forecasters have stronger incentives to pay attention to media coverage about inflation and/or to monitor the related Google Trends. In addition, it is confirmed that the sign is positive over the full sample, but generally negative (when significant) in the left tail. Table 20 confirms these findings when using either GT or WSJ as regressors rather than both of them.[3] The fact that for these surveys GT matters much more than WSJ seems in line with the results and explanations in Carroll (2003), in the sense that not all people and firms necessarily read the WSJ or pay attention to inflation articles published in it, but if they search for inflation in Google it means that they are indeed interested in it and more likely to use the acquired information to update their inflation expectations. Instead, for SPF WSJ is in general more significant than GT, which is in line with the idea that professional forecasters pay more attention to WSJ due to their job qualifications and requirements.

Appendix A.3 contains additional predictive analysis. Tables 21 and 22 report results from the Granger-type regression 2. Tables 23 and 24 show results when the target variable is the Cleveland Fed nowcast (or 1-year ahead forecast) of the CPI year-over-year inflation (Knotek II and Zaman, 2017). Finally, Tables 25 and 26 report the predictive power of the common component extracted from five GT keywords: "inflation", "inflation rate", "price increase", "cpi" and "price". Results are in line with those presented above, in the sense that either GT or WSJ or both seem to matter also when inserted in equation (2), more so for the quarterly SPF than for the monthly surveys, and the gains from using a combination of related Google trends are generally minor.

[3] All results, available upon request, are also very similar in regressions on GT and the residuals of a projection of WSJ on GT, which is by construction orthogonal to GT and could be interpreted as a "cleaned" measure of supply of information about inflation.

Table 2: Predictive regressions with SPF

With GT / WSJ	Nowcast				1-quarter forecast				1-year forecast			
	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid
c	0,79	1,18	0,89	0,87	0,86	0,90	0,95	0,87	0,83	0,85	0,87	0,86
p-val	0,04	0,00	0,04	0,11	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
α	0,24	0,12	0,20	0,24	0,49	0,48	0,46	0,50	0,59	0,59	0,58	0,59
p-val	0,02	0,36	0,09	0,05	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
β_{GT}	0,001	0,010	-0,046	-0,020	0,006	0,007	-0,012	-0,004	0,003	0,003	-0,002	0,003
p-val	0,977				0,519				0,236			
γ_{GT}		-0,137	-0,085	-0,012		-0,033	0,009	0,010		-0,004	0,005	-0,009
$\beta_{GT}+\gamma_{GT}$		-0,126	-0,131	-0,032		-0,026	-0,003	0,006		-0,001	0,003	-0,006
$p(\beta_{GT}+\gamma_{GT})$		0,094	0,000	0,561		0,065	0,916	0,431		0,862	0,721	0,065
β_{WSJ}	0,039	0,036	0,031	0,034	0,010	0,009	0,007	0,008	0,003	0,002	0,002	0,002
p-val	0,055				0,145				0,036			
γ_{WSJ}		0,032	0,057	0,027		-0,002	0,009	0,003		0,008	-0,001	0,006
$\beta_{WSJ}+\gamma_{WSJ}$		0,068	0,088	0,060		0,008	0,016	0,011		0,010	0,001	0,008
$p(\beta_{WSJ}+\gamma_{WSJ})$		0,235	0,000	0,013		0,565	0,384	0,027		0,044	0,873	0,001
$\bar{R}^2$ ADL	0,26	0,29	0,32	0,23	0,46	0,45	0,47	0,45	0,50	0,48	0,50	0,48
$\bar{R}^2$ AR	0,13	0,13	0,13	0,13	0,36	0,36	0,36	0,36	0,43	0,43	0,43	0,43

Note: This table presents results from the ADL regression in (1). The dependant variable, $\pi_{t+h,t}$, is the SPF mean nowcast ($h = 0$), the 1-quarter and 1-year ahead forecast ($h = 1$ and $h = 4$) of the year-over-year CPI inflation. Column Full stands for the full sample analysis. Columns <q10, >q90 and Covid contain results from the specification with a dummy variable as in (3). Inference is performed using 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.

2.2.1 Controlling for other price measures

In this section we verify the robustness of previous results by adding control variables, X_t, that might also affect both inflation expectations and our demand and supply information measures:

$$\pi_{t+h,t} = c + \alpha \pi_{t+h,t-1} + \beta Z_t + \lambda X_t + u_t \tag{4}$$

The most obvious one is the CPI inflation rate available at the time agents formulate their expectations. In the case of SPF, since data are quarterly and CPI is released with a one week lag, we assume that forecasters observe the first two months of the quarter. Hence, we include the average of the first two months of each quarter in X_t. Another potentially important signal is the gas price. We use the year-over-year gas price inflation which is available on weekly basis. Hence, we include the average over three months in X_t. We also consider the Global Supply Chain Pressure Index (gscpi) to take into account the cost pressure on the supply side. These are monthly data released with a one week lag, so we consider the first two months as in the

Table 3: Predictive regressions with SPF: GT and WSJ separately

With GT	Nowcast				1-quarter forecast				1-year forecast			
	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid
c	1,44	1,40	1,43	1,45	0,97	0,99	0,89	0,97	0,81	0,82	0,89	0,84
p-val	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
α	0,26	0,27	0,26	0,26	0,52	0,52	0,57	0,52	0,63	0,62	0,59	0,62
p-val	0,01	0,01	0,01	0,03	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
β	0,052	0,056	0,021	0,011	0,018	0,019	0,007	0,003	0,006	0,006	0,003	0,005
p-val	0,000				0,001				0,000			
γ		-0,138	0,065	0,066		-0,027	0,034	0,023		0,000	0,003	0,003
$\beta+\gamma$		-0,081	0,086	0,077		-0,009	0,041	0,026		0,006	0,006	0,008
$p(\beta+\gamma)$		0,001	0,050	0,002		0,522	0,001	0,000		0,214	0,001	0,002
$\bar{R}^2$ ADL	0,20	0,20	0,20	0,20	0,43	0,43	0,48	0,44	0,49	0,47	0,49	0,48
$\bar{R}^2$ AR	0,13	0,13	0,13	0,13	0,36	0,36	0,36	0,36	0,43	0,43	0,43	0,43
With WSJ	Nowcast				1-quarter forecast				1-year forecast			
	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid
c	0,84	1,18	1,08	1,05	0,90	0,88	1,03	0,98	0,85	0,88	0,92	0,90
p-val	0,00	0,00	0,00	0,02	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
α	0,26	0,13	0,21	0,24	0,56	0,57	0,48	0,52	0,59	0,57	0,57	0,57
p-val	0,01	0,35	0,04	0,02	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
β	0,036	0,038	0,023	0,027	0,008	0,009	0,000	0,002	0,004	0,003	0,002	0,002
p-val	0,002				0,023				0,001			
γ		-0,029	-0,009	0,018		-0,018	0,012	0,011		0,006	0,001	0,003
$\beta+\gamma$		0,010	0,014	0,044		-0,010	0,013	0,013		0,010	0,003	0,005
$p(\beta+\gamma)$		0,823	0,047	0,000		0,029	0,000	0,000		0,004	0,023	0,000
$\bar{R}^2$ ADL	0,26	0,29	0,30	0,25	0,43	0,43	0,47	0,45	0,48	0,47	0,49	0,47
$\bar{R}^2$ AR	0,14	0,14	0,14	0,14	0,36	0,36	0,36	0,36	0,41	0,41	0,41	0,41

Note: This table presents results from the ADL regression in (1). The dependant variable, $\pi_{t+h,t}$, is the SPF mean nowcast ($h = 0$), the 1-quarter and 1-year ahead forecast ($h = 1$ and $h = 4$) of the year-over-year CPI inflation. The top panel shows results where Z contains the GT of the keyword "inflation" observable at time t. In the bottom panel Z_t is given by the text analysis indicator WSJ, also available at time t. Column Full stands for the full sample analysis. Columns <q10, >q90 and Covid contain results from the specification with a dummy variable as in (3). Inference is performed using 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.

Table 4: Predictive regressions with monthly surveys

With GT / WSJ	Michigan				Atlanta Fed				New York Fed			
	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid
c	0,59	0,64	0,70	0,58	0,32	0,36	0,60	0,47	0,20	0,22	0,56	0,43
p-val	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,14	0,11	0,00	0,04
α	0,80	0,79	0,76	0,80	0,83	0,81	0,68	0,75	0,92	0,92	0,80	0,85
p-val	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
β_{GT}	0,012	0,014	0,006	0,009	0,008	0,009	0,005	0,002	0,012	0,013	0,007	0,005
p-val	0,005				0,000				0,002			
γ_{GT}		-0,037	0,016	0,006		-0,032	0,000	0,006		-0,053	0,003	0,000
$\beta_{GT}+\gamma_{GT}$		-0,022	0,022	0,015		-0,023	0,005	0,007		-0,040	0,010	0,005
$p(\beta_{GT}+\gamma_{GT})$		0,113	0,038	0,103		0,000	0,121	0,102		0,000	0,163	0,457
β_{WSJ}	0,001	0,000	0,001	0,001	0,000	0,000	0,000	0,000	0,000	0,000	-0,001	0,000
p-val	0,709				0,872				0,901			
γ_{WSJ}		0,016	-0,010	-0,001		-0,005	0,001	0,002		-0,001	0,001	0,006
$\beta_{WSJ}+\gamma_{WSJ}$		0,016	-0,009	-0,001		-0,005	0,001	0,002		-0,001	-0,001	0,006
$p(\beta_{WSJ}+\gamma_{WSJ})$		0,494	0,140	0,877		0,056	0,619	0,326		0,857	0,938	0,313
$\bar{R}^2$ ADL	0,78	0,79	0,79	0,78	0,90	0,90	0,91	0,90	0,97	0,97	0,97	0,97
$\bar{R}^2$ AR	0,77	0,77	0,77	0,77	0,89	0,89	0,89	0,89	0,96	0,96	0,96	0,96

Note: This table presents results from the ADL regression as in Table 2. The dependant variable is either Michigan 1-year ahead consumer *inflation expectation, Atlanta Fed 1-year ahead* business *inflation expectation or the New York Fed 1-year ahead* consumer *inflation expectation. Data are in monthly frequency. In the case of Atlanta Fed, full sample starts in 2011M10 while the New York Fed data are available from 2013M08.*

case of inflation.

Results are presented in Table 5. In the left panel, X_t contains currently available CPI inflation, the gas inflation is added to X_t in the middle panel, while in the right panel we replace gas inflation by the gscpi index. We remark that coefficients on WSJ remain significant, which confirms their relevance for the formation of expectations above and beyond the information contained in standard measures of the price pressure. Regarding the control variables, current quarter inflation has a positive and significant impact on expectations' formation, but the size vanishes with the horizon. Gas matters especially for the nowcast, in line with the results for the Cleveland FED nowcasts by Knotek II and Zaman (2017), while the global supply chain pressure index does not bring any significant explanatory power.

In the case of monthly consumer surveys (Michigan and New York Fed), the vector of control variables, X_t, contains the CPI inflation rate from the previous month, the gas price of the current month and the previous month food component of the CPI inflation (similar controls as in Bellemare et al. (2020) who conducted a detailed exercise on NYF consumer expectations micro data). We replace the food CPI by the previous month gscpi index in the case of business

Table 5: Predictive regressions with SPF: adding controls

	$X_t = [\pi_t]$			$X_t = [\pi_t\ gas_t]$			$X_t = [\pi_t\ gscpi_t]$		
	Nowcast	1-quarter	1-year	Nowcast	1-quarter	1-year	Nowcast	1-quarter	1-year
c	0,35	1,02	1,10	1,18	1,02	1,16	0,35	1,01	1,15
p-val	0,35	0,00	0,00	0,00	0,00	0,00	0,35	0,00	0,00
α	-0,14	0,30	0,43	-0,17	0,29	0,37	-0,15	0,31	0,40
p-val	0,30	0,09	0,00	0,13	0,02	0,00	0,36	0,06	0,00
β_{GT}	-0,037	-0,003	-0,002	-0,020	-0,004	-0,003	-0,036	-0,006	0,000
p-val	0,121	0,706	0,544	0,256	0,605	0,250	0,293	0,613	0,946
β_{WSJ}	0,025	0,008	0,002	0,019	0,008	0,003	0,026	0,007	0,002
p-val	0,082	0,190	0,015	0,090	0,122	0,007	0,073	0,165	0,008
λ_{pi}	0,70	0,13	0,05	0,31	0,14	0,08	0,70	0,13	0,05
p-val	0,00	0,00	0,00	0,18	0,09	0,00	0,00	0,00	0,00
λ_{gas}				0,03	0,00	0,00			
p-val				0,06	0,94	0,07			
λ_{gscpi}							-0,02	0,04	-0,03
p-val							0,95	0,57	0,15
$\bar{R}^2$ ADL	0,49	0,53	0,58	0,54	0,52	0,59	0,48	0,53	0,58
$\bar{R}^2$ AR	0,13	0,36	0,43	0,13	0,36	0,43	0,13	0,36	0,43

Note: This table presents results from the ADL regression in (4) augmented with the current quarter inflation (constructed as the average of the first two months) and either the average gas price (average of three months, left panel) or the global supply chain pressure index (average of two months, right panel). The dependant variable, $\pi_{t+h,t}$, is the SPF mean nowcast ($h = 0$), the 1-quarter and 1-year ahead forecast ($h = 1$ and $h = 4$) of the year-over-year CPI inflation. Inference is performed using 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.

expectations survey of the Atlanta Fed. The results are summarized in Table 6. Though gains in terms of explanatory power with respect to the benchmark AR model remain small, coefficients on GT are significant in all cases, which confirms the relevance of the information about inflation. The coefficient on CPI inflation is positive and significant for all three surveys, but loses its importance when the actual gas price variations are included. The food part of the CPI is a relevant signal for Michigan survey expectations.

2.3 Full information rational expectations

We now explore the relevance of our measures of demand and supply of inflation information in the context of full information rational expectations (FIRE) models, à la Coibion and Gorodnichenko (2015), and through Mincer-Zarnowitz optimality regressions.

We first add our information supply and demand proxies to the Mincer-Zarnowitz (MZ) regression:

$$\pi_{t+h} = c + \alpha\pi_{t+h,t} + \beta Z_t + u_{t+h}. \tag{5}$$

Table 6: Predictive regressions with monthly surveys: adding controls

	Michigan			Atlanta Fed			New York Fed		
c	0,72	0,82	0,91	0,64	0,69	0,64	0,33	0,32	0,30
p-val	0,00	0,00	0,00	0,00	0,00	0,00	0,02	0,01	0,00
α	0,73	0,74	0,66	0,61	0,62	0,61	0,86	0,88	0,89
p-val	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
β_{GT}	0,011	0,011	0,008	0,009	0,009	0,009	0,012	0,012	0,010
p-val	0,010	0,001	0,029	0,000	0,000	0,000	0,000	0,001	0,012
β_{WSJ}	0,000	-0,001	0,000	0,000	-0,001	0,000	-0,002	-0,002	-0,001
p-val	0,985	0,658	0,933	0,724	0,460	0,764	0,078	0,061	0,314
λ_{pi}	0,05	-0,02		0,06	0,03	0,06	0,05	0,04	
p-val	0,02	0,45		0,00	0,12	0,00	0,01	0,18	
λ_{gas}		0,01	0,01		0,00			0,00	0,00
p-val		0,01	0,00		0,03			0,45	0,01
λ_{food}			0,04			0,00			0,02
p-val			0,03			0,90			0,35
$\bar{R}^2$ ADL	0,79	0,80	0,81	0,91	0,91	0,91	0,97	0,97	0,97
$\bar{R}^2$ AR	0,77	0,77	0,77	0,89	0,89	0,89	0,96	0,96	0,96

Note: This table presents results from the ADL regression in (4) augmented with the previous month CPI inflation and either the current month gas price (or the previous month global supply chain pressure index in the case of Atlanta Fed business survey) and the previous month Food CPI inflation. The dependant variable is either Michigan 1-year ahead consumer *inflation expectation, Atlanta Fed 1-year ahead* business *inflation expectation or the New York Fed 1-year ahead* consumer *inflation expectation. Data are in monthly frequency. In the case of Atlanta Fed, full sample starts in 2011M10 while the New York Fed data are available from 2013M08. Inference is performed using 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.*

Ideally, predictions should be unbiased, $c = 0$, and optimal with respect to the information set Ω_t when the forecast have been made, $\alpha = 1$. But the null of interest in our case is $\beta = 0$. As in the previous section, we also condition the regression on low and high inflation periods[4], as well as since the COVID pandemic:

$$\pi_{t+h} = c + \alpha\pi_{t+h,t} + \beta Z_t + \gamma Z_t \times D(t) + \delta D(t) + u_{t+h}. \tag{6}$$

The second strategy is inspired by Coibion and Gorodnichenko (2015), (CG) hereafter. Assume $\alpha = 1$ in MZ setup. Then,

$$\pi_{t+h} - \pi_{t+h,t} = c + \beta Z_t + u_{t+h}. \tag{7}$$

The null hypothesis of interest is $\beta = 0$. As with MZ, we condition on low, high and COVID

[4]Since in (6) inflation is the dependent variable, another method to consider periods of low and high inflation is to run quantile regressions, focusing for compatibility with the dummies on the 10% and 90% percentiles.

inflation dynamics by specifying the following regression

$$\pi_{t+h} - \pi_{t+h,t} = c + \beta Z_t + \gamma Z_t * D(t) + \delta D(t) + u_{t+h}. \tag{8}$$

To see what rejecting the null means, let us recall the original CG setup. Their main regression is given by

$$\pi_{t+3} - F_t\pi_{t+3,t} = c + \beta(F_t\pi_{t+3,t} - F_{t-1}\pi_{t+3,t}) + error_{t+3} \tag{9}$$

where $\pi_{t+3} - F_t\pi_{t+3,t}$ is the ex-post mean forecast error across agents and $(F_t\pi_{t+3,t} - F_{t-1}\pi_{t+3,t})$ is the ex-ante mean forecast revision. If the null, $H_0 : \beta = 0$, is rejected, it suggests information rigidities. In particular, using the mean SPF as a proxy for $F_t\pi_{t+3,t}$, CG provide evidence in favor of sticky-information or noisy-information models. Note that our information demand/supply proxies Z_t are also measured as an average over agents.

Clearly, the key here is the informational set Ω_t, which is unknown to us since we test predictions made by agents provided in various surveys.[5] Let assume that the ex-ante mean forecast revision is in Ω_t. The question is whether the demand and supply of information, measured by GT and WSJ, are also available in Ω_t when the predictions are made. If $Z_t \in \Omega_t$, which is the most likely possibility since both GT and WSJ articles' titles are publicly available, rejecting the null in (5) or (7) provides evidence against FIRE. If, in addition, Z_t was available to professional forecasters, i.e. $Z_t \in (F_t\pi_{t+3,t} - F_{t-1}\pi_{t+3,t})$, then rejecting the null also signals that the demand and supply of information about inflation dynamics play a role for (sticky / noisy) information rigidities. This would then be in contrast with the existing evidence on the role of media for inflation expectations, which is rather limited, as documented in Weber et al. (2022).

The results from Mincer-Zarnowitz and CG regressions are presented in Tables 7-10.[6] We

[5]Even the Cleveland Fed forecasts are calculated with a model containing mainly financial variables, that in turn are formed on expected inflation development made from an unknown informational set.

[6]In the tables there are some missing values for Atlanta and New York FEDs because there is no data when inflation is higher than the 90th percentile. In fact, the Atlanta (New York) FED data starts only in 2011M10 (2013M08), and in MZ and CG regressions it ends on 2021M03, so all observations are below the 90th percentile when it is calculated over the 2004M01- 2022M03 period.

only present the case where Z_t contains both GT and WSJ, while the results from specifications with only GT and only WSJ are in Appendix A.4. They show that GT and WSJ have indeed substantial and significant explanatory power for the various measures of inflation implied forecast errors. More specifically, in the MZ regressions for the SPF survey, the adjusted R2 is larger at the nowcast than at the 1-quarter horizon, and close to zero at the 1-year horizon, suggesting that forecasts could be improved more at the shorter horizons. The GT and WSJ indicators are particularly significant in the tails of inflation or during the Covid period, and they often have different signs. They lead to marked increases in the adjusted R2, also during the full period for nowcast and 1-quarter horizon, only in the right tail and during the Covid period for the 1-year horizon. Instead, in the MZ regressions for consumers' and firms' expectations, the values of the adjusted R2 are lower than for SPF, but the differences in explanatory power with and without the GT and WSJ indicators remain, particularly so when inflation is high or low, or during the Covid period. Also in this case the two indicators have often a different sign and, in general, the results suggest that they could contribute to improve the forecasts. These results are broadly confirmed in quantile regressions, see Table 30 in the Appendix A.4.

Moving to the CG regressions, when SPF is the dependent variable the GT indicator seems overall more relevant than WSJ for nowcast and 1-quarter horizon, while at the 1-year horizon both indicators are significant for low and high inflation and during Covid, in all cases with different signs (in the CG framework, when $\beta < 0$ ($\beta > 0$) it suggests agents over-react (under-react)). The GT and WSJ measures seem also particularly relevant in the CG regression with the Michigan survey as dependent variable, with GT significant also for the Atlanta FED and the New York FED surveys.

The results are fairly robust when the MZ and CG regressions include price controls such as the currently available CPI inflation, the gas inflation and the gscpi index in the case of SPF expectations, or the food component of the CPI inflation in the case of monthly surveys. Results are presented in Tables 34 -37 in the Appendix A.4.

In summary, the FIRE hypothesis is often rejected, in line with previous evidence reviewed in Coibion et al. (2018a), suggesting that some informational rigidities exist and are waiting to be exploited. At the same time, and contrary to the existing evidence, we find that the media communication and agents attention do play an important role for inflation expectations, with WSJ inflation coverage particularly relevant for SPF and GT for firms' and consumers' surveys. The significance of the information measures is amplified during episodes of high and low inflation, and since the start of the Covid pandemic in line with the predictions of rational inattention models such as Sims (2003) and Mackowiak and Wiederholt (2009), since in these periods of large changes in inflation not updating inflation expectations can be very costly..

2.4 Controlling for FED communications

The role of central bank communications is well documented, see Nakamura and Steinsson (2018) and references therein. In the context of inflation expectations and communications by the FED, Coibion et al. (2022) and Coibion et al. (2020) find that households and firms' attention to different forms of FED communications is rather limited, while Fisher et al. (2022) suggest that professional forecasters do take into account the central bank forward-looking communications about the inflation target. Therefore, a natural question is whether the role of FED communications was ignored in our regressions, despite the fact that both GT and WSJ could already incorporate, at least partly, the monetary policy communications.

To investigate this conjecture, we add the FOMC inflation sentiments from Gardner et al. (2021) (X_t) to the ADL regressions (1) and (3):

$$\pi_{t+h,t} = c + \alpha\pi_{t+h,t-1} + \beta Z_t + \lambda X_t + u_t, \tag{10}$$

$$\pi_{t+h,t} = c + \alpha\pi_{t+h,t-1} + \beta Z_t + \gamma Z_t \times D_t + \delta D_t + \lambda X_t + u_t. \tag{11}$$

We also include as a second variable in X_t a measure of agents' attention to the Federal Reserve (FED) in the spirit of Jung and Kühl (2021) who consider the number of visits to the ECB website. Since we do not have access to those data for the FED website on Google Analytics, we proxy it by Google Trends using 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 Google it. Results are presented in Tables 14 and 15 in Appendix A.2. We then do the same robustness check for MZ and CG regressions by adding X_t to (5)-(6) and (7)-(8) respectively:

$$\pi_{t+h} = c + \alpha\pi_{t+h,t} + \beta Z_t + \lambda X_t + u_{t+h}, \tag{12}$$

$$\pi_{t+h} = c + \alpha\pi_{t+h,t} + \beta Z_t + \gamma Z_t \times D(t) + \delta D(t) + \lambda X_t + u_{t+h}; \tag{13}$$

and

$$\pi_{t+h} - \pi_{t+h,t} = c + \beta Z_t + \lambda X_t + u_{t+h}, \tag{14}$$

$$\pi_{t+h} - \pi_{t+h,t} = c + \beta Z_t + \gamma Z_t * D(t) + \delta D(t) + \lambda X_t + u_{t+h}. \tag{15}$$

Results are presented in Tables 16-17 and 18-19, respectively, in Appendix A.2.

Overall, the benchmark results on the importance of demand and supply of information for inflation are robust to the inclusion of those proxies for the FED communications. Regarding the relevance of those indicators for various measures of inflation expectations, we find that FOMC sentiments have significant impact when predicting SPF forecasts and Atlanta FED business expectations. In the case of CG regressions, the intensity of Google searches related to the FED have significant effects for SPF forecast errors, while FOMC sentiments have significant explanatory power for the forecast errors from monthly expectations surveys. In the next sections we further evaluate the importance of information for inflation dynamics through the lenses of a structural VAR and a pseudo-out-of-sample forecasting exercise.

3 VAR analysis

The analysis so far is based on the GT and WSJ as measures of, respectively, the demand and supply of information about inflation. For more structural analysis, one would instead be interested in the demand shock and supply shock of information, and their dynamic transmission to inflation expectations and actual inflation. For this reason, we consider a monthly structural VAR that includes oil inflation (year on year growth of the West Texas Intermediate spot

Table 7: Mincer-Zarnowitz regressions with SPF

With GT / WSJ	Nowcast				1-quarter forecast				1-year forecast			
	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid
c	0,86	1,20	0,96	1,08	-1,14	-0,25	-0,88	-1,06	0,91	1,79	-1,08	-2,70
p-val	0,01	0,00	0,00	0,01	0,15	0,71	0,27	0,18	0,78	0,59	0,73	0,20
α	0,58	0,45	0,52	0,56	1,48	1,20	1,37	1,45	0,83	0,49	1,79	2,00
p($\alpha = 1$)	0,00	0,00	0,00	0,00	0,21	0,49	0,35	0,22	0,90	0,72	0,56	0,31
β_{GT}	0,081	0,071	0,046	0,095	0,086	0,067	0,057	0,043	-0,042	-0,055	0,031	-0,178
p-val	0,002				0,000				0,699			
γ_{GT}		0,090	-0,003	-0,114		-0,167	-0,008	0,053		-0,004	0,208	0,775
$\beta_{GT}+\gamma_{GT}$		0,162	0,043	-0,019		-0,100	0,049	0,096		-0,059	0,239	0,597
p($\beta_{GT}+\gamma_{GT}$)		0,000	0,094	0,409		0,244	0,774	0,333		0,018	0,000	0,000
β_{WSJ}	0,001	0,007	-0,002	-0,008	0,010	0,020	0,005	0,006	-0,031	-0,034	-0,028	0,011
p-val	0,926				0,477				0,370			
γ_{WSJ}		-0,032	0,018	0,069		0,052	0,029	0,008		0,066	-0,049	-0,706
$\beta_{WSJ}+\gamma_{WSJ}$		-0,026	0,016	0,061		0,073	0,034	0,014		0,032	-0,077	-0,696
p($\beta_{WSJ}+\gamma_{WSJ}$)		0,215	0,280	0,000		0,016	0,693	0,760		0,063	0,000	0,000
$\bar{R}^2$	0,66	0,76	0,67	0,67	0,53	0,61	0,52	0,53	0,02	0,01	0,15	0,61
$\bar{R}^2$ restr	0,51	0,51	0,51	0,51	0,37	0,37	0,37	0,37	-0,02	-0,02	-0,02	-0,02

Note: This table presents results from the Mincer-Zarnowitz regression in (5). The dependant variable, π_{t+h}, is the year-over-year CPI inflation and $\pi_{t+h,t}$ is its SPF mean nowcast ($h = 0$) and 1-year ahead forecast ($h = 4$). Z contains the GT of the keyword "inflation" and the text analysis indicator WSJ, also available at time t. Column Full stands for the full sample analysis. Columns <q10, >q80 and Covid contain results from the specification with a dummy variable as in (6). The line p($\alpha = 1$) shows the p-value for $H_0 : \alpha = 1$, that is the optimality of the forecast with respect to the informational set. Inference is performed using Newey-West standard errors. $\bar{R}^2$ is the adjusted R^2 from the full model, while $\bar{R}^2$ restr shows its value without Z.

Table 8: Mincer-Zarnowitz regressions with monthly surveys

With GT / WSJ	Michigan				Atlanta Fed				New York Fed			
	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid
c	3,70	4,38	2,48	2,65	-0,16	0,89		-0,65	-1,65	-1,55		-0,85
p-val	0,02	0,01	0,16	0,00	0,97	0,02		0,83	0,71	0,73		0,77
α	-0,74	-0,90	-0,41	-0,30	-0,41	-1,06		0,86	0,10	0,09		0,57
p($\alpha = 1$)	0,00	0,00	0,00	0,00	0,42	1,00		0,55	0,46	0,47		0,65
β_{GT}	0,037	0,037	0,042	-0,126	0,089	0,097		-0,079	0,099	0,102		-0,118
p-val	0,312				0,045				0,052			
γ_{GT}		0,010	-0,059	0,402		-0,062		0,320		-0,052		0,482
$\beta_{GT}+\gamma_{GT}$		0,046	-0,017	0,276		0,036		0,241		0,049		0,363
p($\beta_{GT}+\gamma_{GT}$)		0,138	0,892	0,067		0,272		0,133		0,133		0,000
β_{WSJ}	-0,034	-0,039	-0,028	0,008	-0,016	-0,018		0,029	-0,016	-0,019		0,041
p-val	0,033				0,513				0,527			
γ_{WSJ}		0,005	-0,037	-0,116		-0,014		-0,140		-0,010		-0,360
$\beta_{WSJ}+\gamma_{WSJ}$		-0,033	-0,065	-0,108		-0,032		-0,111		-0,029		-0,319
p($\beta_{WSJ}+\gamma_{WSJ}$)		0,435	0,029	0,457		0,580		0,441		0,641		0,000
$\bar{R}^2$	0,12	0,16	0,15	0,52	0,13	0,13		0,78	0,13	0,12		0,73
$\bar{R}^2$ restr	0,07	0,07	0,07	0,07	-0,01	-0,01		-0,01	-0,01	-0,01		-0,01

Note: This table presents results from the Mincer-Zarnowitz regression as in Table 7. The dependant variable is either Michigan 1-year ahead consumer *inflation expectation, Atlanta Fed 1-year ahead* business *inflation expectation or New York Fed 1-year ahead* consumer *inflation expectation. Data are in monthly frequency. In the case of Atlanta Fed, full sample starts in 2011M10, while the New York Fed data starts in 2013M08.*

Table 9: Coibion-Gorodnichenko regressions with SPF

With GT / WSJ	Nowcast				1-quarter forecast				1-year forecast			
	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid
c	0,35	0,42	0,37	0,48	-0,27	-0,05	-0,20	-0,22	0,55	0,72	-2,17	-0,58
p-val	0,32	0,22	0,28	0,23	0,43	0,88	0,53	0,58	0,52	0,41	0,23	0,04
β_{GT}	0,075	0,063	0,063	0,093	0,090	0,085	0,054	0,046	-0,043	-0,055	0,079	-0,174
p-val	0,005				0,000				0,695			
γ_{GT}		0,161	0,050	-0,091		-0,044	-0,013	0,046		-0,004	0,063	0,755
$\beta_{GT}+\gamma_{GT}$		0,223	0,113	0,002		0,041	0,041	0,092		-0,059	0,143	0,581
$p(\beta_{GT}+\gamma_{GT})$		0,009	0,000	0,970		0,442	0,802	0,351		0,020	0,000	0,000
β_{WSJ}	-0,016	-0,014	-0,017	-0,022	0,015	0,013	0,009	0,011	-0,032	-0,036	-0,031	0,014
p-val	0,281				0,228				0,383			
γ_{WSJ}		-0,056	-0,015	0,047		0,010	0,034	0,014		0,063	-0,048	-0,666
$\beta_{WSJ}+\gamma_{WSJ}$		-0,070	-0,033	0,026		0,023	0,043	0,025		0,027	-0,079	-0,651
$p(\beta_{WSJ}+\gamma_{WSJ})$		0,170	0,000	0,221		0,445	0,592	0,581		0,064	0,000	0,000
$\bar{R}^2$	0,15	0,21	0,11	0,13	0,34	0,43	0,33	0,34	0,04	0,03	0,25	0,60

Note: This table presents results from CG type regression in (7). The dependant variable, $\pi_{t+h} - \pi_{t+h,t}$, is the forecast error when the year-over-year CPI inflation is predicted by the SPF mean nowcast ($h = 0$), 1-quarter ahead forecast ($h = 1$) or the 1-year ahead forecast ($h = 4$). Z contains the GT of the keyword "inflation" and the text analysis indicator WSJ, also available at time t. Column Full stands for the full sample analysis. Columns <q10, >q80 and Covid contain results from the specification with a dummy variable in (8). Inference is performed using Newey-West standard errors. $\bar{R}^2$ is the adjusted R^2 from the full model.

Table 10: Coibion-Gorodnichenko regressions with monthly surveys

With GT / WSJ	Michigan				Atlanta Fed				New York Fed			
	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid
c	-1,31	-1,13	-0,68	-1,39	-2,53	-2,52		-0,93	-4,30	-4,20		-2,17
p-val	0,34	0,44	0,01	0,00	0,04	0,06		0,60	0,01	0,02		0,77
β_{GT}	0,035	0,032	-0,044	-0,186	0,082	0,084		-0,080	0,099	0,101		-0,132
p-val	0,393				0,074				0,044			
γ_{GT}		0,037	-0,183	0,416		-0,023		0,316		-0,046		0,479
$\beta_{GT}+\gamma_{GT}$		0,069	-0,226	0,230		0,061		0,237		0,056		0,347
$p(\beta_{GT}+\gamma_{GT})$		0,045	0,012	0,095		0,069		0,108		0,064		0,000
β_{WSJ}	-0,044	-0,045	-0,006	0,013	-0,019	-0,021		0,029	-0,010	-0,014		0,046
p-val	0,098				0,427				0,698			
γ_{WSJ}		-0,021	-0,056	-0,121		-0,007		-0,140		-0,007		-0,356
$\beta_{WSJ}+\gamma_{WSJ}$		-0,066	-0,062	-0,108		-0,028		-0,111		-0,021		-0,310
$p(\beta_{WSJ}+\gamma_{WSJ})$		0,158	0,013	0,437		0,672		0,444		0,725		0,000
$\bar{R}^2$	0,06	0,06	0,19	0,50	0,12	0,11		0,79	0,13	0,12		0,73

Note: This table presents results from the regressions as in Table 9. The dependant variable is either Michigan 1-year ahead consumer *inflation expectation, Atlanta Fed 1-year ahead* business *inflation expectation or New York Fed 1-year ahead* consumer *inflation expectation. Data are in monthly frequency. In the case of Atlanta Fed, full sample starts in 2011M10, while New York Fed data starts in 2013M08.*

crude oil price), GT, WSJ, inflation expectations (measured by the Michigan survey of consumer expectations), and actual inflation (year on year growth of the CPI). We use a Choleski identification, with the variables ordered as above, for the following reasons.

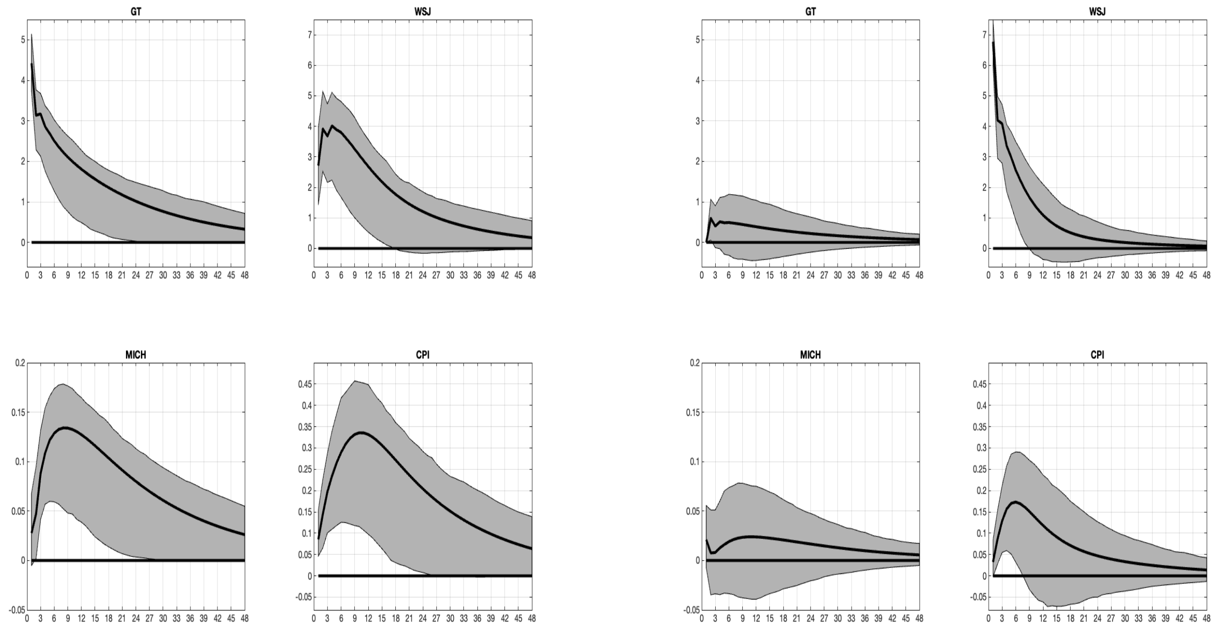
First, oil inflation is measured starting from daily prices, which should not be contemporaneously influenced by the other four variables. Second, GT and WSJ are also measured by aggregating daily data, and hence they should also not be contemporaneously influenced by expected and actual inflation, which are measured at lower frequency and released with some delay. Third, WSJ could be driven by both demand and supply information shocks, in the sense that WSJ journalists can be expected to write more about inflation when there is higher interest in this topic (as measured by GT). In fact, Mullainathan and Shleifer (2005) suggest that the information contained in news media is an equilibrium outcome from the market determined by consumer preferences and production technology. Finally, the Michigan survey is released prior to the CPI, and the NKPC (discussed in more details in the next section) states that expectations affect current inflation.

The impulse response functions are presented in Figure 3. It turns out that in general a positive shock to GT (left panels), that we interpret as a demand for information shock, induces a significant increase in WSJ, Michigan survey, and CPI inflation. A positive shock to WSJ, or the supply of information shock, also generates an increase in expectations and in inflation, but smaller than for the demand shock and significant only for inflation.

This graphical analysis is confirmed by the variance decomposition presented in Table 11. An exogenous increase to the demand of information about inflation explains 11% of the forecast error variance in CPI inflation at the 3-month horizon, increasing to 21% at the one-and four-year-ahead horizons. The corresponding values for the Michigan survey are in the range 10-18%. A shock to WSJ has substantially less impact.

To assess the robustness of the results we have obtained, we consider the effects of three modifications. First, we switch the order of GT and WSJ, on the ground that articles in the WSJ could stimulate Google searches for inflation (even though WSJ readers would likely use other sources to get additional details about inflation).Second, we replace oil with either gas or

Figure 3: Dynamic responses to GT and WSJ shocks



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

Note: The left panel plots the IRFs after a one-standard deviation positive shock to GT, and the right panel after a one-standard deviation positive shock to WSJ. The VAR recursive ordering is specified as follows $[Oil_t, GT_t, WSJ_t, MICH_t, CPI_t]$*. We used 5000 bootstrap replications to construct the 90% confidence intervals.*

food prices, as both variables could matter to explain inflation developments, especially from the household perspective. Finally, we consider a quarterly VAR with oil inflation, GT, WSJ, the SPF one-year ahead expectations, and CPI inflation. The results are reported in Figures 10 to 13 in the Appendix A.5. It turns out that the findings in the baseline model are pretty robust. In particular, ordering WSJ before GT still leads to smaller responses to WSJ than to GT, in particular for expectations. Replacing oil with either gas or food inflation does not change the responses, only those to the WSJ shock are reduced a little bit. And replacing the Michigan survey with the SPF and running the VAR with quarterly data also leads only to a minor further decrease in the effects of the WSJ shock.

Overall, the structural VAR analysis confirms that both information demand and supply shocks matter, with the former more relevant than the latter, and their effects are not fully captured by the inclusion of standard inflation expectations in the model, likely since both GT and WSJ are based on (and provide) more granular information.

In addition to impulse analysis, we construct conditional forecasts from the VAR as in Wag-

Table 11: SVAR Variance Decomposition with Monthly Consumer Expectations

GT is predetermined to WSJ						
	Shock to GT			Shock to WSJ		
	$h = 3$	$h = 12$	$h = 48$	$h = 3$	$h = 12$	$h = 48$
GT	0,85	0,83	0,83	0,01	0,02	0,02
WSJ	0,32	0,37	0,37	0,56	0,51	0,51
MICH	0,10	0,18	0,18	0,00	0,01	0,01
CPI	0,11	0,21	0,21	0,04	0,05	0,05

Note: This table shows variance decomposition 3, 12 and 48 months following shocks to GT and WSJ in the VAR specified as in Figure 3.

goner and Zha (1999). Two sets of scenarios are considered. Under the high attention scenario, we fix either WSJ or GT or both to their March 2022 values for the next 48 months. In the low attention case, those variables are kept at their pre-pandemic averages. The results are presented in Figure 4. If the supply and demand for information about inflation remain high, the implied inflation expectations (MICH) and the CPI inflation persist high as well. On the other hand, if the attention drops to its pre-pandemic value, inflation (expectations) rapidly regain their sample mean. For instance, CPI inflation achieves 2% by the end of 2023 if both WSJ and GT decrease.

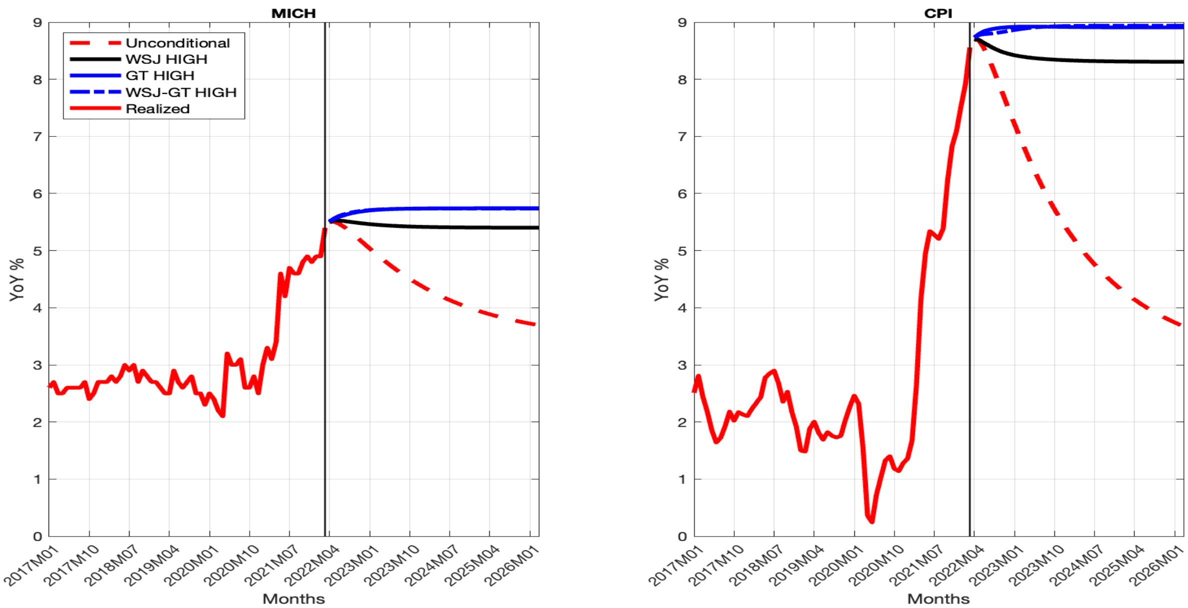
4 Forecasting exercise

The results of the SVAR analysis are suggestive, but an even sounder test of the role of the GT and WSJ is related to whether they can improve forecasts of inflation when added to standard forecasting models. We first consider an augmented AR model

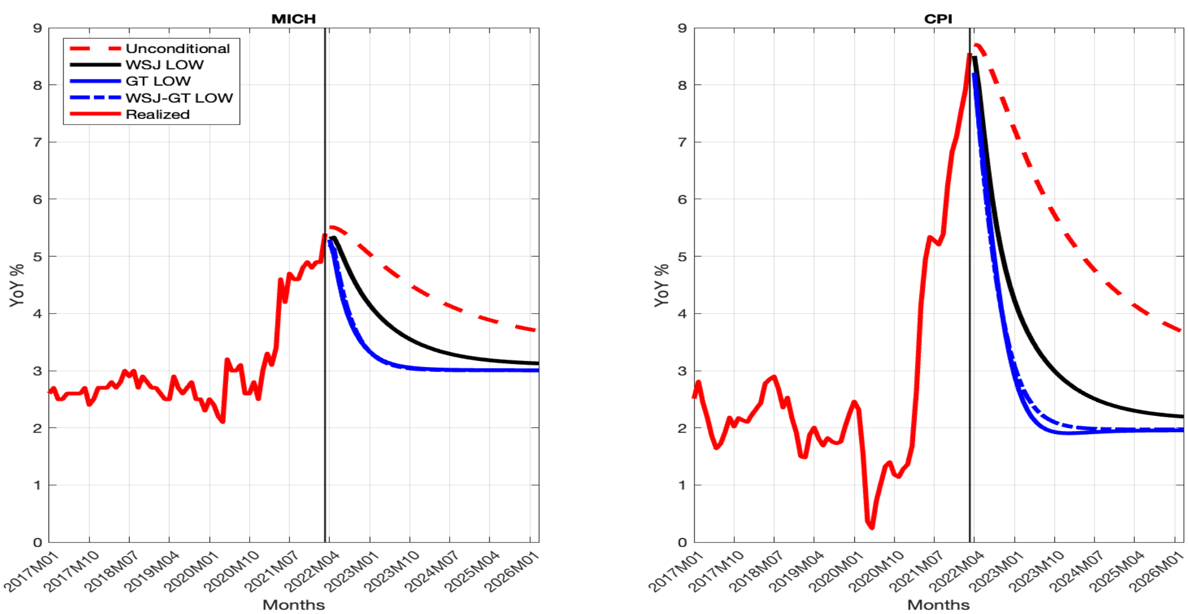
$$\pi_{t+h} = c + \rho_1 \pi_{t-1} + \rho_2 \pi_{t-2} + \beta Z_t + \delta RA_t + u_{t+h}, \quad (16)$$

where RA_t is a measure of real activity available at time t, and h is the forecasting horizon. For instance, RA_t is either Initial Claims that are produced on weekly basis and hence available at the end of the month t ($Claims_t$) or the Help-Wanted Index over unemployment that is available with a one-month lag (HWI_{t-1}). We are interested in predicting the current ($h = 0$) and the 3-

Figure 4: Conditional VAR forecasts



(a) High attention scenarios



(b) Low attention scenarios

Note: The top panel plots the conditional forecasts under high attention scenarios. Under WSJ (GT) HIGH only the WSJ (GT) index is kept at the end of sample value for next 48 months, while under WSJ-GT HIGH both supply and demand attention proxies future paths are fixed to their March 2022 values. The Unconditional *stands for the standard VAR forecast. The bottom panel shows the conditional forecasts for low attention scenarios. In those cases, WSJ and GT paths are fixed to their pre-pandemic averages (2004-2020M02).*

month ahead ($h = 3$) values of the inflation.[7]

Then, we specify a New Keynesian Philips Curve (NKPC) type model by adding to (16) various inflation expectations available at time t, $\pi_{t+h,t}$:

$$\pi_{t+h} = c + \rho_1 \pi_{t-1} + \rho_2 \pi_{t-2} + \beta Z_t + \delta RA_t + \gamma \pi_{t+12,t} + u_{t+h}. \tag{17}$$

In particular, we include either Cleveland Fed or Michigan 1-year ahead expectations. We consider only those two measures since they are available since 2004. Also, we restrict to monthly frequency only (and do not consider SPF which is quarterly) in order to maintain a reasonable amount of observations in the evaluation period (GT is available from 2004).

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. The resulting model can be written as:

$$\pi_{t+h} = c + \rho_1 \pi_{t-1} + \rho_2 \pi_{t-2} + \beta Z_t + \delta RA_t + \gamma \pi_{t+12,t} + \delta F_{t-1} + u_{t+h}. \tag{18}$$

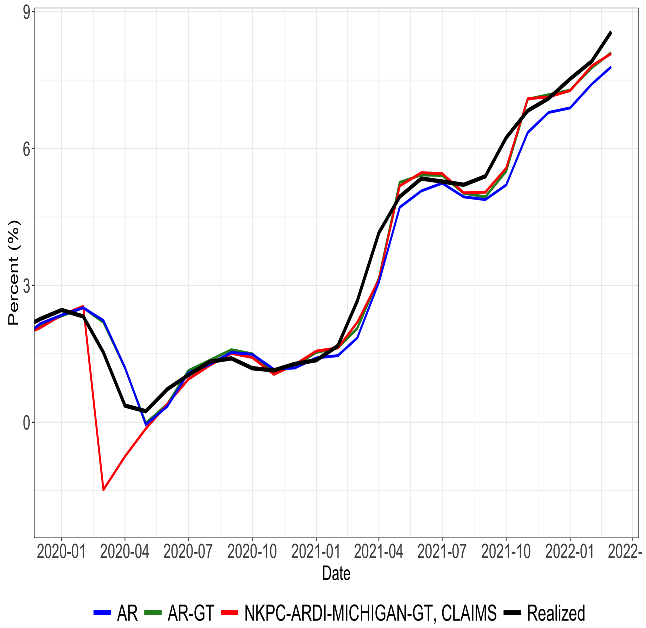
Factors are estimated by principal components.

As stated in (16), we aim to forecast the inflation during the actual month. Since GT and WSJ can be constructed on a daily basis, this is feasible in real-time. The evaluation period is from 2007M06 to 2022M3. We use an expanding window and re-estimate all models recursively. The reference model is an AR(2).

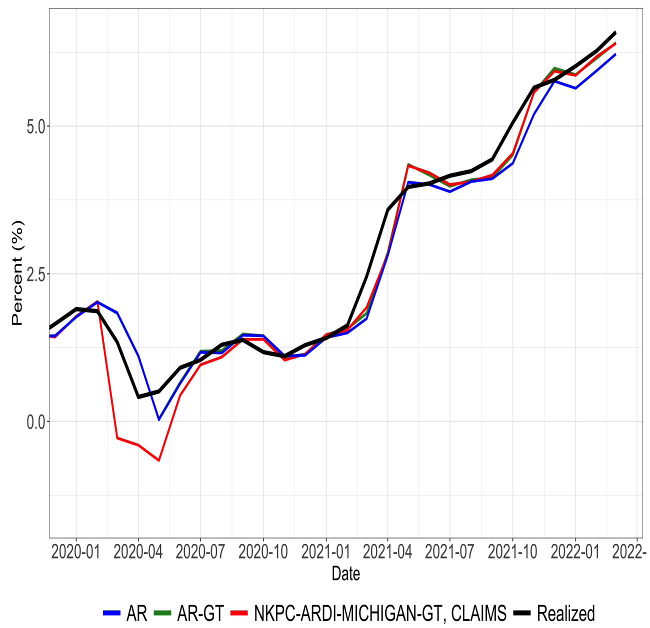
Detailed results are presented in Tables 38 and 40 in Appendix A.6, with a summary in Table 12. We do find that GT and WSJ have significant out-of-sample predictive power for standard inflation measures such as CPI and PCE in periods of high inflation and since 2020. Over the full sample the gains with respect to the benchmark are minor or non existent, but that is in line with previous studies such as Kotchoni et al. (2019) who find that beating autoregressive forecasts

[7] Note that in this particular case the objective is to predict the actual values of inflation, which can be seen as a nowcasting problem, but without using high-frequency predictors.

Figure 5: Out-of-sample forecasts



(a) CPI inflation



(b) PCE inflation

for inflation is difficult even when using large datasets, except during recession periods.

A more interesting evaluation is whether adding GT and WSJ to the forecasting models improves or not their forecasts. We have 14 different models, each with or without GT and WSJ, and Table 12 reports the percentage of cases, and the absolute number of models, where adding the inflation information measures is indeed helpful. Most percentages are above 50%, with the exception of GT for CPI inflation when the latter is in the left tail, with values as high as 100% for both CPI and PCE inflation in the right tail.

Detailed forecasting results for 3 months ahead predictions are available in Appendix A.6. Both GT and WSJ conserve their significant out-of-sample predictive power and the percentages of cases when they improve the accuracy is largely above 50%. We also considered the same forecasting exercise with the Core CPI inflation and we found similar results.

Figure 5 compares the out-of-sample forecasts of CPI and PCE inflation since 2020 of two models including GT and the reference AR. We observe that models using GT track very well the recent developments of inflation, especially since the substantial increase from early 2021.

Table 12: Summary of pseudo-out-of-sample prediction results

	Z = GT				Z = WSJ				Z = GT / WSJ			
Models	Full	>2020	<q10	>q90	Full	>2020	<q10	>q90	Full	>2020	<q10	>q90
	Predicting the current month of the CPI inflation											
↓MSE with Z: %	79	100	0	100	93	100	100	100	71	100	7	100
↓MSE with Z: #	11	14	0	14	13	14	14	14	10	14	1	14
	Predicting the current month of the PCE inflation											
↓MSE with Z: %	57	100	0	100	93	100	86	100	64	100	57	100
↓MSE with Z: #	8	14	0	14	13	14	12	14	9	14	8	14
	Predicting the current month of the Core CPI inflation											
↓MSE with Z: %	100	100	50	100	100	100	29	100	100	100	7	100
↓MSE with Z: #	14	14	7	14	14	14	4	14	14	14	1	14
	Predicting the CPI inflation 3 months ahead											
↓MSE with Z: %	100	93	79	100	93	100	7	93	93	100	71	100
↓MSE with Z: #	14	13	11	14	13	14	1	13	13	14	10	14
	Predicting the PCE inflation 3 months ahead											
↓MSE with Z: %	79	86	71	100	71	100	7	100	79	93	71	100
↓MSE with Z: #	11	12	10	14	10	14	1	14	11	13	10	14
	Predicting the Core CPI inflation 3 months ahead											
↓MSE with Z: %	100	100	79	100	100	100	14	100	100	100	0	100
↓MSE with Z: #	14	14	11	14	14	14	2	14	14	14	0	14

Note: This table summarizes the pseudo-out-of-sample predictive performance of various models augmented by GT and WSJ by reporting the percentage of cases (and their total number out of the 14 competing models) when adding an information measure improves the forecasts from the corresponding model without it. Detailed results are available in Appendix A.6.

5 Conclusion

In this paper we have assessed the role of the demand and supply of information about inflation, with the former proxied by Google Trends and the latter by the number of related Wall Street Journal articles.

We have found that both the GT and the WSJ measures play a relevant role to understand and predict actual inflation developments, with the more granular information improving expectation formation, even more so during periods when inflation is particularly high or low, in line with the predictions of rational inattention models.

Specifically, the full information rational expectation hypothesis was rejected, suggesting that some informational rigidities exist and are waiting to be exploited. Moreover, contrary to most existing evidence, we have concluded that the media communication and agents attention do play an important role for inflation expectation formation, even when controlling for FED communications. In turn, when GT and WSJ are added to standard forecasting models, already including measures of inflation expectations, they lead to further forecast improvements, again even more so when inflation is particularly high or low.

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A APPENDIX

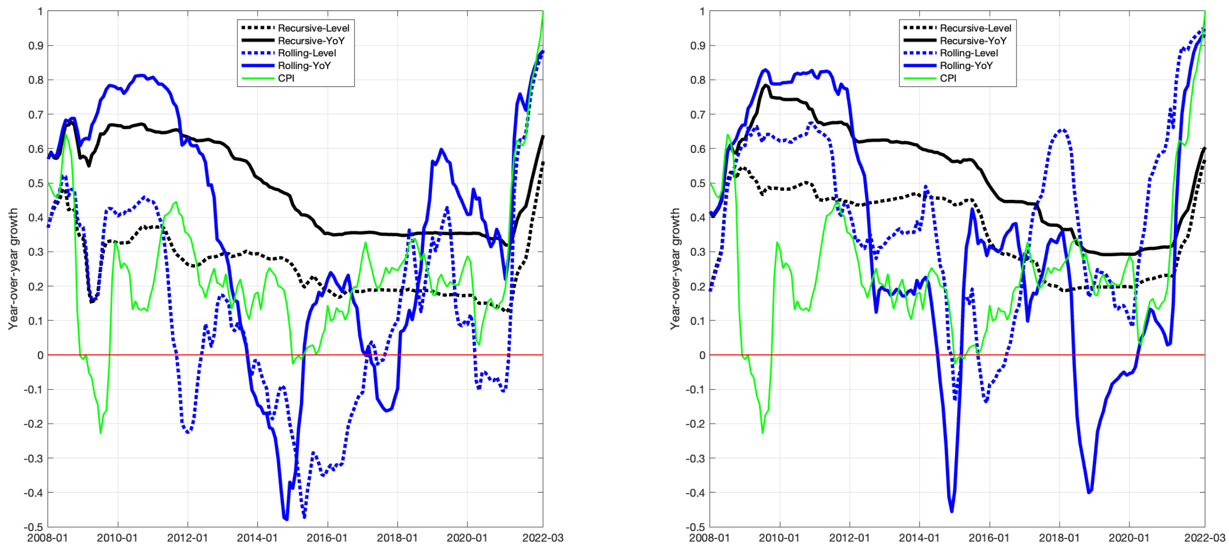
A.1 Data: descriptive statistics of GT and WSJ

Table 13: Correlation between GT / WSJ and CPI inflation and its expectations

		GT		WSJ	
		Level	YoY	Level	YoY
CPI	2004-2022	0,56	0,64	0,55	0,60
	<q10	0,32	0,73	-0,01	0,64
	>q90	0,76	0,76	0,89	0,87
	Covid	0,89	0,88	0,94	0,94
SPF nwcst	2004-2022	0,35	0,42	0,48	0,49
	<q10	-0,83	0,41	0,58	-0,13
	>q90	0,43	0,73	0,76	0,79
	Covid	0,68	0,71	0,76	0,80
SPF 1y fcst	2004-2022	0,44	0,44	0,48	0,39
	<q10	0,15	-0,38	-0,54	-0,01
	>q90	0,44	0,51	0,73	0,64
	Covid	0,86	0,80	0,85	0,84
MICH	2004-2022	0,47	0,61	0,48	0,56
	<q10	-0,33	-0,01	0,35	0,02
	>q90	0,40	0,48	0,67	0,66
	Covid	0,81	0,86	0,90	0,90

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

Figure 6: Correlation between GT / WSJ and CPI inflation over time

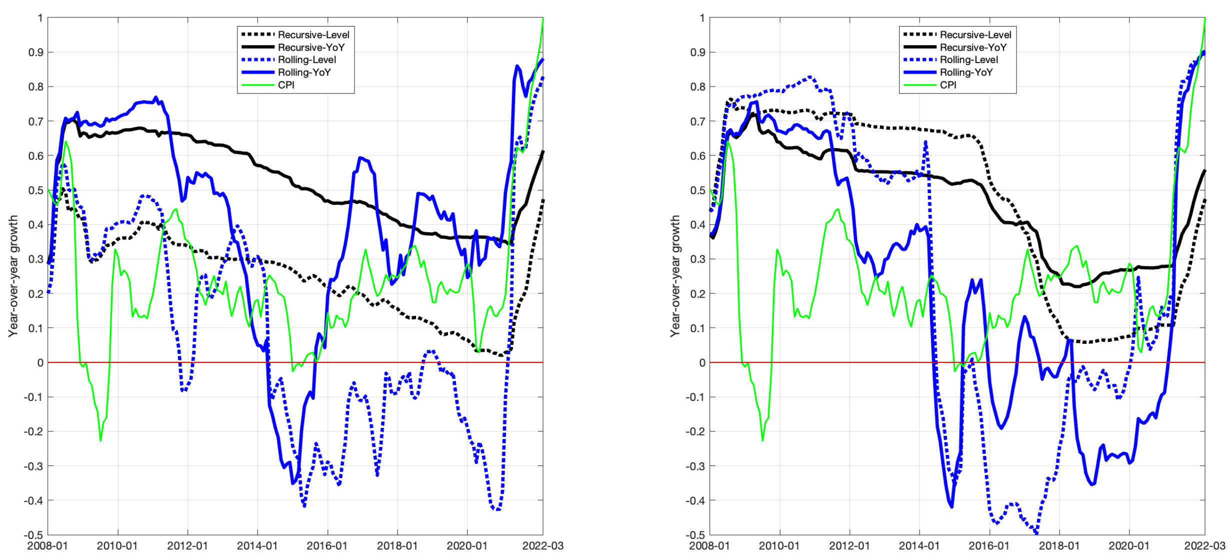


(a) GT

(b) WSJ

Note: Figures plot the contemporaneous correlation coefficients between GT (WSJ) and the year-over-year CPI inflation recursively and with a 36-month rolling window. The CPI time series has been normalized.

Figure 7: Correlation between GT / WSJ and consumer expectations over time

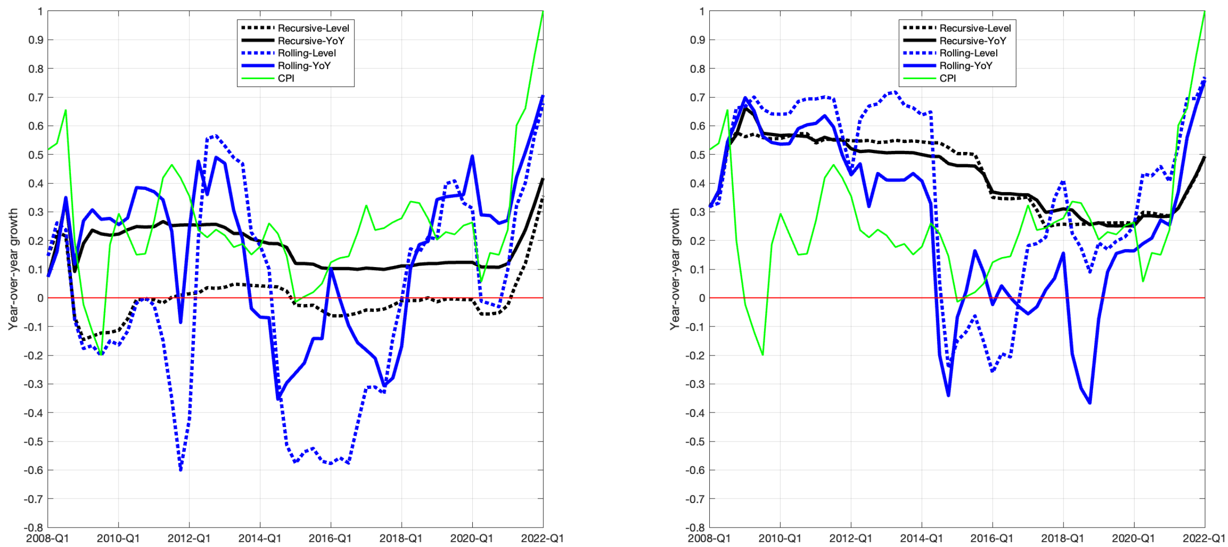


(a) GT

(b) WSJ

Note: Figures plot the contemporaneous correlation coefficients between GT (WSJ) and the Michigan consumer expectations recursively and with a 36-month rolling window. The CPI time series has been normalized.

Figure 8: Correlation between GT / WSJ and SPF nowcasts over time

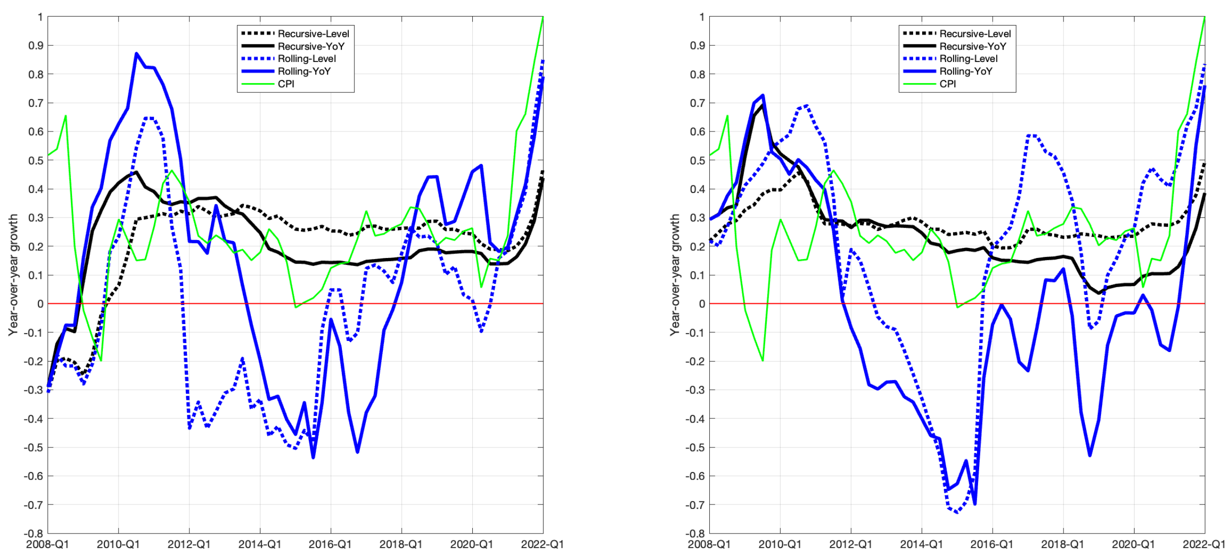


(a) GT

(b) WSJ

Note: Figures plot the contemporaneous correlation coefficients between GT (WSJ) and the SPF nowcasts recursively and with a 12-quarter rolling window. The CPI time series has been normalized.

Figure 9: Correlation between GT / WSJ and SPF 1-year forecasts over time



(a) GT

(b) WSJ

Note: Figures plot the contemporaneous correlation coefficients between GT (WSJ) and the SPF 1-year forecasts recursively and with a 12-quarter rolling window. The CPI time series has been normalized.

A.2 Robustness of results to FED communications

Table 14: Predictive regressions with SPF including FED's communication proxies

GT-FRS	Nowcast				1-quarter forecast				1-year forecast			
	Full	$<$q10	$> q90$	Covid	Full	$<$q10	$> q90$	Covid	Full	$<$q10	$> q90$	Covid
c	1,68	1,88	2,15	1,74	1,37	1,39	1,59	1,43	1,38	1,40	1,45	1,44
p-val	0,01	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
α	0,13	0,02	0,14	0,14	0,32	0,32	0,31	0,29	0,30	0,29	0,28	0,27
p-val	0,28	0,89	0,33	0,34	0,02	0,04	0,02	0,03	0,00	0,00	0,00	0,00
β_{GT}	0,007	0,016	-0,059	-0,049	0,008	0,009	-0,016	-0,013	0,002	0,002	-0,002	-0,003
p-val	0,785				0,321				0,287			
γ_{GT}		-0,122	0,028	0,004		-0,027	0,044	0,013		0,004	0,003	-0,003
$\beta_{GT}+\gamma_{GT}$		-0,106	-0,031	-0,045		-0,018	0,027	0,000		0,006	0,001	-0,006
$p(\beta_{GT}+\gamma_{GT})$		0,259	0,757	0,182		0,310	0,193	0,997		0,338	0,930	0,037
β_{WSJ}	0,024	0,022	0,013	0,017	0,006	0,006	0,001	0,004	0,002	0,002	0,001	0,002
p-val	0,103				0,246				0,063			
γ_{WSJ}		0,062	0,022	0,035		0,006	0,000	0,007		0,006	0,003	0,005
$\beta_{WSJ}+\gamma_{WSJ}$		0,085	0,035	0,051		0,011	0,001	0,010		0,008	0,005	0,007
$p(\beta_{WSJ}+\gamma_{WSJ})$		0,167	0,585	0,012		0,511	0,960	0,100		0,088	0,480	0,001
λ_{FOMC}	4,97	4,64	4,74	5,80	1,54	1,50	1,80	1,88	0,64	0,66	0,71	0,75
p-val	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
λ_{GT-FRS}	-0,02	-0,02	-0,03	-0,02	-0,01	-0,01	-0,01	-0,01	0,00	0,00	0,00	0,00
p-val	0,32	0,41	0,22	0,27	0,31	0,32	0,18	0,26	0,28	0,30	0,41	0,30
$\bar{R}^2$ ADL	0,38	0,39	0,42	0,40	0,55	0,53	0,58	0,57	0,63	0,62	0,62	0,64
$\bar{R}^2$ AR	0,13	0,13	0,13	0,13	0,36	0,36	0,36	0,36	0,43	0,43	0,43	0,43

GT-FED	Nowcast				1-quarter forecast				1-year forecast			
	Full	$<$q10	$> q90$	Covid	Full	$<$q10	$> q90$	Covid	Full	$<$q10	$> q90$	Covid
c	1,77	1,83	2,64	1,46	1,69	1,75	1,99	1,63	1,50	1,51	1,59	1,54
p-val	0,05	0,01	0,03	0,12	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
α	0,12	0,00	0,12	0,12	0,28	0,28	0,25	0,26	0,32	0,32	0,30	0,29
p-val	0,34	0,99	0,37	0,43	0,05	0,10	0,06	0,04	0,00	0,00	0,00	0,00
β_{GT}	0,005	0,013	-0,053	-0,046	0,007	0,009	-0,016	-0,011	0,002	0,003	-0,003	-0,003
p-val	0,859				0,351				0,240			
γ_{GT}		-0,110	-0,032	0,001		-0,029	0,028	0,010		-0,001	0,010	-0,004
$\beta_{GT}+\gamma_{GT}$		-0,097	-0,084	-0,045		-0,021	0,013	-0,001		0,002	0,006	-0,007
$p(\beta_{GT}+\gamma_{GT})$		0,313	0,115	0,324		0,272	0,264	0,922		0,728	0,652	0,070
β_{WSJ}	0,026	0,025	0,017	0,021	0,006	0,006	0,002	0,004	0,002	0,001	0,001	0,001
p-val	0,099				0,266				0,169			
γ_{WSJ}		0,051	0,045	0,033		0,004	0,005	0,007		0,009	0,000	0,006
$\beta_{WSJ}+\gamma_{WSJ}$		0,076	0,062	0,054		0,010	0,007	0,011		0,010	0,001	0,007
$p(\beta_{WSJ}+\gamma_{WSJ})$		0,184	0,101	0,019		0,529	0,407	0,019		0,016	0,942	0,005
λ_{FOMC}	4,53	4,23	4,08	5,12	1,57	1,53	1,72	1,81	0,73	0,74	0,77	0,81
p-val	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
λ_{GT-FED}	-0,01	-0,01	-0,03	-0,01	-0,01	-0,01	-0,01	-0,01	0,00	0,00	0,00	0,00
p-val	0,40	0,53	0,27	0,60	0,13	0,13	0,14	0,25	0,11	0,11	0,02	0,32
$\bar{R}^2$ ADL	0,37	0,38	0,40	0,37	0,55	0,54	0,58	0,57	0,63	0,62	0,63	0,64
$\bar{R}^2$ AR	0,13	0,13	0,13	0,13	0,36	0,36	0,36	0,36	0,43	0,43	0,43	0,43

Note: This table presents results from the ADL regressions in (10) and (11). The dependant variable, $\pi_{t+h,t}$, is the SPF mean nowcast ($h = 0$), the 1-quarter and 1-year ahead forecast ($h = 1$ and $h = 4$) of the year-over-year CPI inflation. Z_t contains both GT and WSJ, while x_t contains the FOMC inflation sentiment and Google Trend of the keyword "federal reserve system" (top panel, GT-FRS) or "fed" (bottom panel, GT-FED). Column Full stands for the full sample analysis. Columns <q10, >q90 and Covid contain results from the specification with a dummy variable as in (3). Inference is performed using 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.

Table 15: Predictive regressions with monthly surveys including FED's communication proxies

GT-FRS	Michigan				Atlanta Fed				New York Fed			
	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid
c	0,67	0,73	0,81	0,67	0,37	0,39	0,75	0,64	0,26	0,27	0,71	0,66
p-val	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,08	0,07	0,00	0,00
α	0,78	0,77	0,74	0,78	0,79	0,78	0,59	0,66	0,92	0,91	0,77	0,79
p-val	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
β_{GT}	0,012	0,015	0,006	0,009	0,009	0,009	0,005	0,000	0,013	0,013	0,006	0,004
p-val	0,002				0,000				0,001			
γ_{GT}		-0,037	0,017	0,005		-0,032	-0,002	0,006		-0,052	0,002	-0,001
$\beta_{GT}+\gamma_{GT}$		-0,022	0,023	0,014		-0,023	0,003	0,006		-0,039	0,008	0,002
$p(\beta_{GT}+\gamma_{GT})$		0,122	0,027	0,113		0,000	0,243	0,178		0,000	0,167	0,674
β_{WSJ}	0,000	-0,001	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	-0,002	-0,001
p-val	0,822				0,974				0,825			
γ_{WSJ}		0,017	-0,009	0,000		-0,005	0,003	0,004		-0,001	0,003	0,010
$\beta_{WSJ}+\gamma_{WSJ}$		0,016	-0,009	0,000		-0,005	0,003	0,004		-0,001	0,001	0,008
$p(\beta_{WSJ}+\gamma_{WSJ})$		0,481	0,102	0,963		0,059	0,083	0,108		0,903	0,816	0,126
λ_{FOMC}	0,27	0,27	0,26	0,30	0,29	0,27	0,43	0,47	0,10	0,11	0,29	0,47
p-val	0,21	0,21	0,25	0,20	0,02	0,02	0,00	0,00	0,65	0,63	0,17	0,05
λ_{GT-FRS}	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
p-val	0,79	0,64	0,46	0,82	0,40	0,20	0,29	0,64	0,38	0,50	0,10	0,03
$\bar{R}^2$ ADL	0,78	0,79	0,79	0,78	0,90	0,91	0,91	0,91	0,97	0,97	0,97	0,97
$\bar{R}^2$ AR	0,77	0,77	0,77	0,77	0,89	0,89	0,89	0,89	0,96	0,96	0,96	0,96

GT-FED	Michigan				Atlanta Fed				New York Fed			
	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid
c	0,56	0,63	0,69	0,53	0,42	0,41	0,78	0,68	0,50	0,47	0,77	0,75
p-val	0,01	0,00	0,02	0,02	0,00	0,00	0,00	0,00	0,02	0,02	0,00	0,00
α	0,77	0,76	0,73	0,76	0,79	0,78	0,59	0,66	0,92	0,91	0,78	0,80
p-val	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
β_{GT}	0,013	0,015	0,007	0,008	0,009	0,009	0,005	0,000	0,012	0,013	0,007	0,005
p-val	0,002				0,000				0,001			
γ_{GT}		-0,035	0,014	0,006		-0,031	-0,001	0,006		-0,049	0,001	-0,003
$\beta_{GT}+\gamma_{GT}$		-0,020	0,021	0,014		-0,022	0,003	0,006		-0,036	0,008	0,002
$p(\beta_{GT}+\gamma_{GT})$		0,160	0,052	0,121		0,000	0,210	0,171		0,001	0,175	0,664
β_{WSJ}	0,001	0,000	0,000	0,001	0,000	0,000	0,000	0,000	0,000	0,000	-0,002	-0,001
p-val	0,716				0,977				0,712			
γ_{WSJ}		0,017	-0,008	-0,001		-0,005	0,003	0,004		-0,001	0,003	0,009
$\beta_{WSJ}+\gamma_{WSJ}$		0,016	-0,008	0,000		-0,005	0,003	0,004		-0,001	0,001	0,008
$p(\beta_{WSJ}+\gamma_{WSJ})$		0,484	0,225	0,984		0,091	0,091	0,098		0,903	0,827	0,127
λ_{FOMC}	0,24	0,23	0,19	0,27	0,30	0,28	0,44	0,48	0,14	0,15	0,29	0,45
p-val	0,23	0,25	0,35	0,19	0,01	0,02	0,00	0,00	0,50	0,49	0,16	0,06
λ_{GT-FED}	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	-0,01	0,00	0,00	0,00
p-val	0,50	0,61	0,58	0,34	0,66	1,00	0,91	0,51	0,09	0,16	0,21	0,14
$\bar{R}^2$ ADL	0,78	0,79	0,79	0,78	0,90	0,91	0,91	0,91	0,97	0,97	0,97	0,97
$\bar{R}^2$ AR	0,77	0,77	0,77	0,77	0,89	0,89	0,89	0,89	0,96	0,96	0,96	0,96

Note: This table presents results from the ADL regression as in Table 14. The dependant variable is either Michigan 1-year ahead consumer *inflation expectation, Atlanta Fed 1-year ahead* business *inflation expectation or the New York Fed 1-year ahead* consumer *inflation expectation. Data are in monthly frequency. In the case of Atlanta Fed, full sample starts in 2011M10 while the New York Fed data are available from 2013M08.*

Table 16: Mincer-Zarnowitz regressions with SPF including FED's communication proxies

GT-FRS	Nowcast				1-quarter forecast				1-year forecast			
	Full	$<$q10	$> q90$	Covid	Full	$<$q10	$> q90$	Covid	Full	$<$q10	$> q90$	Covid
c	0,07	-0,05	0,26	0,33	-2,04	-1,70	-1,82	-1,65	-3,93	-3,54	-3,87	-4,22
p-val	0,86	0,91	0,50	0,44	0,08	0,12	0,17	0,20	0,28	0,38	0,35	0,06
α	0,45	0,35	0,41	0,41	1,46	1,21	1,36	1,22	3,35	3,18	2,86	2,60
p($\alpha = 1$)	0,00	0,00	0,00	0,00	0,33	0,65	0,53	0,69	0,21	0,30	0,34	0,14
β_{GT}	0,076	0,062	0,053	0,061	0,085	0,080	0,070	0,027	-0,024	-0,024	0,041	-0,170
p-val	0,000				0,000				0,821			
γ_{GT}		0,146	-0,051	-0,088		0,000	-0,067	0,077		-0,079	0,045	0,798
$\beta_{GT}+ \gamma_{GT}$		0,207	0,002	-0,026		0,079	0,002	0,104		-0,103	0,086	0,627
p($\beta_{GT} + \gamma_{GT}$)		0,000	0,943	0,000		0,136	0,988	0,364		0,101	0,524	0,000
β_{WSJ}	0,003	0,012	-0,003	-0,005	0,015	0,019	0,010	0,012	-0,028	-0,029	-0,022	0,014
p-val	0,782				0,230				0,382			
γ_{WSJ}		-0,064	0,057	0,065		-0,026	0,063	0,002		0,048	0,009	-0,747
$\beta_{WSJ}+ \gamma_{WSJ}$		-0,052	0,054	0,060		-0,007	0,073	0,014		0,019	-0,013	-0,733
p($\beta_{WSJ} + \gamma_{WSJ}$)		0,000	0,000	0,000		0,814	0,311	0,790		0,499	0,837	0,000
λ_{FOMC}	2,52	1,84	2,77	3,07	-0,43	-1,06	-0,23	0,83	-4,48	-4,95	-3,01	-1,66
p-val	0,00	0,00	0,00	0,00	0,79	0,53	0,90	0,69	0,13	0,14	0,33	0,29
λ_{GT-FRS}	0,02	0,04	0,02	0,02	0,03	0,03	0,03	0,03	-0,01	-0,01	0,02	0,01
p-val	0,00	0,00	0,02	0,01	0,14	0,05	0,15	0,18	0,67	0,79	0,51	0,48
$\bar{R}^2$	0,74	0,85	0,73	0,74	0,54	0,61	0,52	0,55	0,06	0,05	0,15	0,60
$\bar{R}^2$ restr	0,51	0,51	0,51	0,51	0,37	0,37	0,37	0,37	-0,02	-0,02	-0,02	-0,02

GT-FED	Nowcast				1-quarter forecast				1-year forecast			
	Full	$<$q10	$> q90$	Covid	Full	$<$q10	$> q90$	Covid	Full	$<$q10	$> q90$	Covid
c	-0,59	-1,20	-0,39	-0,56	-3,21	-3,10	-3,03	-3,30	-1,02	-0,90	-2,74	-3,78
p-val	0,59	0,15	0,71	0,65	0,00	0,00	0,03	0,00	0,82	0,85	0,59	0,14
α	0,44	0,33	0,40	0,39	1,54	1,31	1,44	1,30	2,89	2,88	2,90	2,66
p($\alpha = 1$)	0,00	0,00	0,00	0,00	0,15	0,40	0,35	0,52	0,31	0,36	0,36	0,13
β_{GT}	0,080	0,066	0,052	0,053	0,085	0,079	0,072	0,017	-0,022	-0,016	0,029	-0,168
p-val	0,000				0,000				0,826			
γ_{GT}		0,155	-0,021	-0,078		0,017	-0,041	0,089		-0,126	0,162	0,771
$\beta_{GT}+ \gamma_{GT}$		0,221	0,030	-0,025		0,096	0,030	0,106		-0,141	0,192	0,603
p($\beta_{GT} + \gamma_{GT}$)		0,000	0,335	0,024		0,069	0,850	0,316		0,040	0,096	0,000
β_{WSJ}	0,002	0,011	-0,005	-0,004	0,013	0,017	0,008	0,013	-0,031	-0,033	-0,027	0,010
p-val	0,865				0,294				0,291			
γ_{WSJ}		-0,048	0,048	0,064		-0,013	0,053	-0,002		0,063	-0,036	-0,717
$\beta_{WSJ}+ \gamma_{WSJ}$		-0,038	0,043	0,060		0,004	0,061	0,010		0,030	-0,063	-0,707
p($\beta_{WSJ} + \gamma_{WSJ}$)		0,003	0,017	0,000		0,897	0,409	0,829		0,278	0,074	0,000
λ_{FOMC}	2,86	2,28	3,17	3,46	-0,42	-0,94	-0,05	0,88	-3,52	-4,04	-2,39	-1,31
p-val	0,01	0,00	0,00	0,00	0,79	0,55	0,98	0,64	0,19	0,19	0,43	0,40
λ_{GT-FED}	0,02	0,04	0,02	0,03	0,03	0,04	0,03	0,04	-0,04	-0,04	-0,01	0,00
p-val	0,13	0,00	0,17	0,17	0,05	0,00	0,09	0,04	0,18	0,24	0,70	0,82
$\bar{R}^2$	0,74	0,85	0,74	0,75	0,54	0,61	0,53	0,57	0,10	0,09	0,14	0,60
$\bar{R}^2$ restr	0,51	0,51	0,51	0,51	0,37	0,37	0,37	0,37	-0,02	-0,02	-0,02	-0,02

Note: This table presents results from the Mincer-Zarnowitz regressions in (12) - (13). The dependant variable, π_{t+h}, is the year-over-year CPI inflation and $\pi_{t+h,t}$ is its SPF mean nowcast ($h = 0$) and 1-year ahead forecast ($h = 4$). Z_t contains both GT and WSJ, while x_t contains the FOMC inflation sentiment and Google Trend of the keyword "federal reserve system" (top panel, GT-FRS) or "fed" (bottom panel, GT-FED). Column Full stands for the full sample analysis. Columns $<$q10, $>$q80 and Covid contain results from the specification with a dummy variable as in (6). The line p($\alpha = 1$) shows the p-value for $H_0 : \alpha = 1$, that is the optimality of the forecast with respect to the informational set. Inference is performed using Newey-West standard errors. $\bar{R}^2$ is the adjusted R^2 from the full model, while $\bar{R}^2$ restr shows its value without Z.

Table 17: Mincer-Zarnowitz regressions with monthly surveys including FED's communication proxies

GT-FRS	Michigan				Atlanta Fed				New York Fed			
	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid
c	3,70	4,34	2,48	2,58	-1,43	-0,37		-0,92	-3,45	-3,71		0,12
p-val	0,02	0,01	0,15	0,00	0,72	0,92		0,47	0,45	0,43		0,95
α	-0,73	-0,88	-0,43	-0,43	0,52	-0,08		1,14	0,77	0,93		0,29
p($\alpha = 1$)	0,00	0,00	0,00	0,00	0,80	0,55		0,86	0,86	0,96		0,30
β_{GT}	0,038	0,038	0,040	-0,129	0,089	0,096		-0,076	0,103	0,103		-0,108
p-val	0,441				0,052				0,050			
γ_{GT}		0,010	-0,061	0,421		-0,034		0,301		-0,039		0,360
$\beta_{GT}+\gamma_{GT}$		0,047	-0,021	0,292		0,062		0,225		0,064		0,253
p($\beta_{GT}+\gamma_{GT}$)		0,206	0,879	0,075		0,146		0,152		0,079		0,081
β_{WSJ}	-0,034	-0,039	-0,028	0,009	-0,011	-0,013		0,030	-0,002	-0,005		0,039
p-val	0,073				0,602				0,925			
γ_{WSJ}		0,005	-0,035	-0,121		0,004		-0,138		0,001		-0,146
$\beta_{WSJ}+\gamma_{WSJ}$		-0,034	-0,063	-0,112		-0,010		-0,108		-0,004		-0,107
p($\beta_{WSJ}+\gamma_{WSJ}$)		0,438	0,070	0,449		0,899		0,451		0,954		0,445
λ_{FOMC}	0,00	-0,14	0,06	1,07	-4,69	-4,76		-1,08	-5,70	-6,61		-0,08
p-val	1,00	0,89	0,96	0,20	0,09	0,09		0,35	0,07	0,05		0,95
λ_{GT-FRS}	0,00	0,00	0,00	0,01	-0,02	-0,02		-0,01	-0,01	-0,01		-0,01
p-val	0,92	0,96	0,91	0,30	0,45	0,43		0,44	0,54	0,57		0,61
$\bar{R}^2$	0,11	0,15	0,14	0,53	0,16	0,16		0,79	0,16	0,17		0,79
$\bar{R}^2$ restr	0,07	0,07	0,07	0,07	-0,01	-0,01		-0,01	-0,01	-0,01		-0,01

GT-FED	Michigan				Atlanta Fed				New York Fed			
	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid
c	4,95	5,14	3,72	3,07	0,21	1,11		-0,15	0,26	-0,28		1,83
p-val	0,00	0,00	0,04	0,01	0,96	0,78		0,90	0,96	0,95		0,39
α	-0,57	-0,75	-0,30	-0,40	0,63	0,06		1,09	0,97	1,08		0,33
p($\alpha = 1$)	0,00	0,00	0,00	0,00	0,85	0,61		0,90	0,98	0,95		0,35
β_{GT}	0,034	0,035	0,039	-0,127	0,079	0,085		-0,078	0,100	0,101		-0,093
p-val	0,32				0,03				0,02			
γ_{GT}		0,013	-0,005	0,402		-0,033		0,310		-0,038		0,340
$\beta_{GT}+\gamma_{GT}$		0,047	0,034	0,275		0,052		0,231		0,063		0,246
p($\beta_{GT}+\gamma_{GT}$)		0,138	0,757	0,078		0,153		0,130		0,064		0,068
β_{WSJ}	-0,03	-0,038	-0,030	0,006	-0,01	-0,014		0,029	0,00	-0,005		0,037
p-val	0,02				0,56				0,90			
γ_{WSJ}		-0,006	-0,043	-0,118		-0,001		-0,141		0,013		-0,152
$\beta_{WSJ}+\gamma_{WSJ}$		-0,045	-0,072	-0,112		-0,015		-0,112		0,008		-0,115
p($\beta_{WSJ}+\gamma_{WSJ}$)		0,345	0,004	0,456		0,830		0,425		0,917		0,401
λ_{FOMC}	0,20	0,01	0,41	1,44	-4,61	-4,68		-1,01	-5,08	-5,88		0,10
p-val	0,86	1,00	0,74	0,09	0,09	0,09		0,38	0,08	0,06		0,94
λ_{GT-FED}	-0,03	-0,02	-0,02	0,00	-0,03	-0,03		-0,02	-0,08	-0,07		-0,03
p-val	0,14	0,29	0,19	0,86	0,26	0,26		0,24	0,14	0,16		0,14
$\bar{R}^2$	0,14	0,17	0,16	0,52	0,17	0,17		0,79	0,22	0,21		0,80
$\bar{R}^2$ restr	0,07	0,07	0,07	0,07	-0,01	-0,01		-0,01	-0,01	-0,01		-0,01

Note: This table presents results from the Mincer-Zarnowitz regression as in Table 16. The dependant variable is either Michigan 1-year ahead consumer *inflation expectation, Atlanta Fed 1-year ahead* business *inflation expectation or New York Fed 1-year ahead* consumer *inflation expectation. Data are in monthly frequency. In the case of Atlanta Fed, full sample starts in 2011M10, while the New York Fed data starts in 2013M08.*

Table 18: Coibion-Gorodnichenko regressions with SPF including FED's communication proxies

GT-FRS	Nowcast				1-quarter forecast				1-year forecast			
	Full	$<$q10	$> q90$	Covid	Full	$<$q10	$> q90$	Covid	Full	$<$q10	$> q90$	Covid
c	-0,92	-1,28	-1,96	-0,81	-1,13	-1,28	-1,88	-1,21	0,76	0,83	1,56	-1,05
p-val	0,03	0,01	0,01	0,06	0,11	0,04	0,20	0,07	0,64	0,63	0,51	0,06
β_{GT}	0,069	0,051	0,078	0,083	0,088	0,081	0,065	0,025	-0,030	-0,036	0,022	-0,177
p-val	0,002				0,000				0,784			
γ_{GT}		0,223	0,007	-0,078		-0,003	-0,031	0,077		-0,045	0,243	0,790
$\beta_{GT}+\gamma_{GT}$		0,275	0,086	0,006		0,079	0,034	0,102		-0,082	0,265	0,612
$p(\beta_{GT}+\gamma_{GT})$		0,001	0,000	0,823		0,131	0,838	0,363		0,094	0,001	0,000
β_{WSJ}	-0,011	-0,003	-0,015	-0,014	0,017	0,020	0,009	0,013	-0,024	-0,026	-0,025	0,017
p-val	0,352				0,147				0,465			
γ_{WSJ}		-0,105	0,015	0,038		-0,025	0,056	0,005		0,060	-0,058	-0,707
$\beta_{WSJ}+\gamma_{WSJ}$		-0,109	0,000	0,024		-0,005	0,065	0,017		0,034	-0,083	-0,690
$p(\beta_{WSJ}+\gamma_{WSJ})$		0,033	0,982	0,115		0,868	0,381	0,727		0,211	0,003	0,000
λ_{FOMC}	-0,39	-1,20	0,53	-0,53	0,51	-0,65	0,89	1,36	-2,41	-2,97	-0,40	-0,20
p-val	0,62	0,06	0,51	0,56	0,68	0,58	0,54	0,34	0,29	0,21	0,84	0,90
λ_{GT-FRS}	0,03	0,05	0,04	0,03	0,02	0,03	0,03	0,02	-0,01	0,00	-0,02	0,01
p-val	0,01	0,00	0,00	0,01	0,22	0,06	0,24	0,22	0,85	0,95	0,56	0,37
$\bar{R}^2$	0,21	0,32	0,17	0,18	0,36	0,46	0,35	0,38	0,05	0,05	0,14	0,60

GT-FED	Nowcast				1-quarter forecast				1-year forecast			
	Full	$<$q10	$> q90$	Covid	Full	$<$q10	$> q90$	Covid	Full	$<$q10	$> q90$	Covid
c	-1,62	-2,43	-1,96	-1,54	-1,95	-2,38	-1,88	-2,64	3,14	3,18	1,56	-0,15
p-val	0,08	0,00	0,01	0,15	0,13	0,03	0,20	0,05	0,20	0,24	0,51	0,89
β_{GT}	0,073	0,057	0,078	0,076	0,089	0,081	0,065	0,015	-0,026	-0,025	0,022	-0,174
p-val	0,003				0,000				0,793			
γ_{GT}		0,229	0,007	-0,069		0,012	-0,031	0,088		-0,105	0,243	0,750
$\beta_{GT}+\gamma_{GT}$		0,286	0,086	0,007		0,093	0,034	0,103		-0,130	0,265	0,576
$p(\beta_{GT}+\gamma_{GT})$		0,001	0,000	0,846		0,067	0,838	0,317		0,036	0,001	0,000
β_{WSJ}	-0,013	-0,006	-0,015	-0,017	0,016	0,019	0,009	0,014	-0,029	-0,032	-0,025	0,012
p-val	0,353				0,190				0,333			
γ_{WSJ}		-0,082	0,015	0,038		-0,011	0,056	0,001		0,080	-0,058	-0,662
$\beta_{WSJ}+\gamma_{WSJ}$		-0,089	0,000	0,022		0,008	0,065	0,015		0,048	-0,083	-0,650
$p(\beta_{WSJ}+\gamma_{WSJ})$		0,071	0,982	0,238		0,780	0,381	0,742		0,052	0,003	0,000
λ_{FOMC}	0,12	-0,55	0,53	0,15	0,70	-0,33	0,89	1,56	-1,60	-2,10	-0,40	0,40
p-val	0,90	0,45	0,51	0,85	0,64	0,81	0,54	0,28	0,45	0,32	0,84	0,79
λ_{GT-FED}	0,03	0,04	0,04	0,03	0,03	0,04	0,03	0,03	-0,04	-0,04	-0,02	-0,01
p-val	0,03	0,00	0,00	0,05	0,18	0,02	0,24	0,09	0,16	0,23	0,56	0,71
$\bar{R}^2$	0,19	0,29	0,17	0,16	0,36	0,47	0,35	0,40	0,10	0,09	0,14	0,59

Note: This table presents results from CG type regression in (14)-(15). The dependant variable, $\pi_{t+h} - \pi_{t+h,t}$, is the forecast error when the year-over-year CPI inflation is predicted by the SPF mean nowcast ($h = 0$), 1-quarter ahead forecast ($h = 1$) or the 1-year ahead forecast ($h = 4$). Z_t contains both GT and WSJ, while x_t contains the FOMC inflation sentiment and Google Trend of the keyword "federal reserve system" (top panel, GT-FRS) or "fed" (bottom panel, GT-FED). Column Full stands for the full sample analysis. Columns $<$q10, $>$q80 and Covid contain results from the specification with a dummy variable in (8). Inference is performed using Newey-West standard errors. $\bar{R}^2$ is the adjusted R^2 from the full model.

Table 19: Coibion-Gorodnichenko regressions with monthly surveys including FED's communication proxies

GT-FRS	Michigan				Atlanta Fed				New York Fed			
	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid
c	-1,25	-1,05	-0,97	-1,61	-2,24	-2,18		-0,67	-4,14	-3,93		-2,08
p-val	0,31	0,43	0,15	0,00	0,03	0,04		0,09	0,00	0,01		0,00
β_{GT}	0,045	0,042	-0,039	-0,185	0,086	0,089		-0,076	0,102	0,102		-0,130
p-val	0,340				0,087				0,056			
γ_{GT}		0,037	-0,208	0,424		-0,014		0,305		-0,038		0,372
$\beta_{GT}+\gamma_{GT}$		0,079	-0,246	0,240		0,074		0,229		0,064		0,242
$p(\beta_{GT}+\gamma_{GT})$		0,072	0,023	0,087		0,055		0,109		0,073		0,076
β_{WSJ}	-0,040	-0,041	-0,006	0,016	-0,012	-0,014		0,030	0,000	-0,004		0,045
p-val	0,127				0,585				0,997			
γ_{WSJ}		-0,028	-0,037	-0,121		0,006		-0,138		0,000		-0,150
$\beta_{WSJ}+\gamma_{WSJ}$		-0,069	-0,043	-0,106		-0,008		-0,108		-0,004		-0,105
$p(\beta_{WSJ}+\gamma_{WSJ})$		0,197	0,119	0,429		0,923		0,453		0,958		0,413
λ_{FOMC}	-2,86	-3,09	-1,90	-1,04	-5,12	-5,65		-0,98	-6,01	-6,72		-0,88
p-val	0,08	0,05	0,16	0,41	0,03	0,02		0,33	0,03	0,02		0,48
λ_{GT-FRS}	-0,01	-0,01	0,01	0,01	-0,02	-0,02		-0,01	-0,01	-0,01		0,00
p-val	0,66	0,68	0,51	0,56	0,48	0,47		0,42	0,60	0,60		0,88
$\bar{R}^2$	0,10	0,10	0,20	0,50	0,17	0,17		0,79	0,18	0,18		0,79

GT-FED	Michigan				Atlanta Fed				New York Fed			
	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid
c	2,06	2,15	1,58	0,24	-0,42	-0,43		0,02	0,18	-0,05		-0,21
p-val	0,29	0,29	0,32	0,83	0,80	0,79		0,98	0,95	0,99		0,88
β_{GT}	0,033	0,029	-0,044	-0,173	0,077	0,079		-0,078	0,100	0,101		-0,116
p-val	0,353				0,069				0,026			
γ_{GT}		0,040	-0,103	0,396		-0,015		0,312		-0,038		0,348
$\beta_{GT}+\gamma_{GT}$		0,069	-0,147	0,223		0,064		0,234		0,063		0,232
$p(\beta_{GT}+\gamma_{GT})$		0,129	0,244	0,083		0,078		0,095		0,055		0,064
β_{WSJ}	-0,038	-0,038	-0,005	0,011	-0,012	-0,014		0,029	-0,002	-0,006		0,044
p-val	0,052				0,544				0,917			
γ_{WSJ}		-0,055	-0,069	-0,122		0,002		-0,141		0,013		-0,156
$\beta_{WSJ}+\gamma_{WSJ}$		-0,092	-0,074	-0,112		-0,013		-0,112		0,007		-0,112
$p(\beta_{WSJ}+\gamma_{WSJ})$		0,146	0,018	0,413		0,865		0,427		0,924		0,376
λ_{FOMC}	-2,09	-2,26	-1,08	-0,41	-4,95	-5,46		-0,94	-5,12	-5,76		-0,64
p-val	0,16	0,12	0,41	0,73	0,03	0,02		0,35	0,04	0,02		0,63
λ_{GT-FED}	-0,05	-0,05	-0,04	-0,02	-0,03	-0,03		-0,02	-0,08	-0,07		-0,03
p-val	0,02	0,03	0,14	0,17	0,26	0,25		0,23	0,14	0,16		0,16
$\bar{R}^2$	0,17	0,17	0,22	0,51	0,18	0,18		0,79	0,23	0,23		0,80

Note: This table presents results from the regressions as in Table 18. The dependant variable is either Michigan 1-year ahead consumer *inflation expectation, Atlanta Fed 1-year ahead* business *inflation expectation or New York Fed 1-year ahead* consumer *inflation expectation. Data are in monthly frequency. In the case of Atlanta Fed, full sample starts in 2011M10, while New York Fed data starts in 2013M08.*

A.3 Additional predictive analysis

Table 20: Predictive regressions with monthly surveys

With GT	Michigan				Atlanta Fed				New York Fed			
	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid
c	0,61	0,63	0,77	0,60	0,32	0,36	0,59	0,41	0,20	0,22	0,52	0,27
p-val	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,14	0,11	0,00	0,02
α	0,80	0,79	0,74	0,80	0,83	0,81	0,69	0,78	0,92	0,92	0,81	0,90
p-val	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
β	0,013	0,014	0,007	0,009	0,008	0,009	0,005	0,001	0,012	0,013	0,006	0,002
p-val	0,000				0,000				0,002			
γ		-0,032	0,001	0,004		-0,037	0,001	0,009		-0,054	0,002	0,010
β+ γ		-0,018	0,009	0,014		-0,028	0,006	0,010		-0,041	0,009	0,012
p($\beta + \gamma$)		0,071	0,087	0,001		0,000	0,000	0,003		0,001	0,008	0,002
$\bar{R}^2$ ADL	0,78	0,79	0,79	0,78	0,90	0,91	0,91	0,91	0,97	0,97	0,97	0,97
$\bar{R}^2$ AR	0,77	0,77	0,77	0,77	0,89	0,89	0,89	0,89	0,96	0,96	0,96	0,96
With WSJ	Michigan				Atlanta Fed				New York Fed			
	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid
c	0,53	0,54	0,76	0,57	0,07	0,07	0,53	0,51	-0,04	-0,04	0,44	0,34
p-val	0,00	0,00	0,00	0,00	0,44	0,41	0,00	0,00	0,62	0,68	0,00	0,07
α	0,83	0,83	0,74	0,81	0,97	0,97	0,72	0,73	1,02	1,02	0,84	0,88
p-val	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
β	0,005	0,005	0,002	0,003	0,001	0,001	-0,001	-0,001	0,002	0,002	0,000	0,000
pval	0,004				0,118				0,097			
γ		-0,003	0,002	0,003		-0,008	0,003	0,007		-0,010	0,003	0,006
β+ γ		0,001	0,004	0,006		-0,006	0,003	0,006		-0,008	0,003	0,007
p($\beta + \gamma$)		0,819	0,153	0,011		0,001	0,001	0,004		0,317	0,477	0,032
$\bar{R}^2$ ADL	0,78	0,78	0,79	0,78	0,89	0,89	0,91	0,91	0,96	0,96	0,97	0,97
$\bar{R}^2$ AR	0,77	0,77	0,77	0,77	0,89	0,89	0,89	0,89	0,96	0,96	0,96	0,96

Note: This table presents results from the ADL regression as in Table 2. The dependant variable is either Michigan 1-year ahead consumer *inflation expectation, Atlanta Fed 1-year ahead* business *inflation expectation or the New York Fed 1-year ahead* consumer *inflation expectation. Data are in monthly frequency. In the case of Atlanta Fed, full sample starts in 2011M10 while the New York Fed data are available from 2013M08.*

Table 21: Predictive regressions with SPF

With GT	Nowcast				1-quarter forecast				1-year forecast			
	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid
c	1,44	1,40	1,43	1,45	0,97	0,99	0,89	0,97	0,81	0,82	0,89	0,84
p-val	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
α	0,26	0,27	0,26	0,26	0,52	0,52	0,57	0,52	0,63	0,62	0,59	0,62
p-val	0,01	0,01	0,01	0,03	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
β	0,052	0,056	0,021	0,011	0,018	0,019	0,007	0,003	0,006	0,006	0,003	0,005
p-val	0,000				0,00				0,000			
γ		-0,138	0,065	0,066		-0,027	0,034	0,023		0,000	0,003	0,003
$\beta+\gamma$		-0,081	0,086	0,077		-0,009	0,041	0,026		0,006	0,006	0,008
$p(\beta+\gamma)$		0,001	0,050	0,002		0,522	0,001	0,000		0,214	0,001	0,002
$\bar{R}^2$ ADL	0,20	0,20	0,20	0,20	0,43	0,43	0,48	0,44	0,49	0,47	0,49	0,48
$\bar{R}^2$ AR	0,13	0,13	0,13	0,13	0,36	0,36	0,36	0,36	0,43	0,43	0,43	0,43

With WSJ	Nowcast				1-quarter forecast				1-year forecast			
	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid
c	0,84	1,18	1,08	1,05	0,90	0,88	1,03	0,98	0,85	0,88	0,92	0,90
p-val	0,00	0,00	0,00	0,02	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
α	0,26	0,13	0,21	0,24	0,56	0,57	0,48	0,52	0,59	0,57	0,57	0,57
p-val	0,01	0,35	0,04	0,02	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
β	0,036	0,038	0,023	0,027	0,008	0,009	0,000	0,002	0,004	0,003	0,002	0,002
p-val	0,002				0,02				0,001			
γ		-0,029	-0,009	0,018		-0,018	0,012	0,011		0,006	0,001	0,003
$\beta+\gamma$		0,010	0,014	0,044		-0,010	0,013	0,013		0,010	0,003	0,005
$p(\beta+\gamma)$		0,823	0,047	0,000		0,029	0,000	0,000		0,004	0,023	0,000
$\bar{R}^2$ ADL	0,26	0,29	0,30	0,25	0,43	0,43	0,47	0,45	0,48	0,47	0,49	0,47
$\bar{R}^2$ AR	0,14	0,14	0,14	0,14	0,36	0,36	0,36	0,36	0,41	0,41	0,41	0,41

With GT / WSJ	Nowcast				1-quarter forecast				1-year forecast			
	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid
c	0,79	1,18	0,89	0,87	0,86	0,90	0,95	0,87	0,83	0,85	0,87	0,86
p-val	0,04	0,00	0,04	0,11	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
α	0,24	0,12	0,20	0,24	0,49	0,48	0,46	0,50	0,59	0,59	0,58	0,59
p-val	0,02	0,36	0,09	0,05	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
β_{GT}	0,001	0,010	-0,046	-0,020	0,006	0,007	-0,012	-0,004	0,003	0,003	-0,002	0,003
p-val	0,977				0,52				0,236			
γ_{GT}		-0,137	-0,085	-0,012		-0,033	0,009	0,010		-0,004	0,005	-0,009
$\beta_{GT}+\gamma_{GT}$		-0,126	-0,131	-0,032		-0,026	-0,003	0,006		-0,001	0,003	-0,006
$p(\beta_{GT}+\gamma_{GT})$		0,094	0,000	0,561		0,065	0,916	0,431		0,862	0,721	0,065
β_{WSJ}	0,039	0,036	0,031	0,034	0,01	0,009	0,007	0,008	0,003	0,002	0,002	0,002
p-val	0,055				0,15				0,036			
γ_{WSJ}		0,032	0,057	0,027		-0,002	0,009	0,003		0,008	-0,001	0,006
$\beta_{WSJ}+\gamma_{WSJ}$		0,068	0,088	0,060		0,008	0,016	0,011		0,010	0,001	0,008
$p(\beta_{WSJ}+\gamma_{WSJ})$		0,235	0,000	0,013		0,565	0,384	0,027		0,044	0,873	0,001
$\bar{R}^2$ ADL	0,26	0,29	0,32	0,23	0,46	0,45	0,47	0,45	0,50	0,48	0,50	0,48
$\bar{R}^2$ AR	0,13	0,13	0,13	0,13	0,36	0,36	0,36	0,36	0,43	0,43	0,43	0,43

Note: This table presents results from the ADL regression in (2). The dependant variable, $\pi_{t+h,t}$, is the SPF mean nowcast ($h = 0$), the 1-quarter and 1-year ahead forecast ($h = 1$ and $h = 4$) of the year-over-year CPI inflation. The top panel shows results where Z contains the GT of the keyword "inflation" observable at time t. In the middle panel Z_t is given by the text analysis indicator WSJ, also available at time t. The bottom panel shows results when both GT and WSJ are included. Column Full stands for the full sample analysis. Columns <q10, >q90 and Covid contain results from the specification with a dummy variable as in (3). Inference is performed using 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.

Table 22: Predictive regressions with monthly surveys

With GT	Michigan				Atlanta Fed				New York Fed			
	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid
c	0,53	0,54	0,65	0,51	0,30	0,32	0,59	0,34	0,01	0,01	0,57	0,14
p-val	0,00	0,00	0,00	0,00	0,02	0,02	0,00	0,02	0,93	0,95	0,00	0,38
α	0,83	0,83	0,78	0,83	0,84	0,83	0,69	0,82	1,00	1,00	0,79	0,95
p-val	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
β	0,009	0,009	0,006	0,007	0,008	0,009	0,010	0,005	0,006	0,006	0,004	-0,005
p-val	0,000				0,001				0,299			
γ		0,000	0,001	0,000		-0,021	-0,006	0,003		0,013	-0,002	0,013
$\beta + \gamma$		0,009	0,007	0,007		-0,012	0,004	0,008		0,019	0,002	0,007
$p(\beta+\gamma)$		0,103	0,185	0,106		0,114	0,048	0,045		0,191	0,572	0,228
$\bar{R}^2$ ADL	0,77	0,77	0,78	0,77	0,90	0,90	0,91	0,90	0,96	0,96	0,97	0,97
$\bar{R}^2$ AR	0,77	0,77	0,77	0,77	0,89	0,89	0,89	0,89	0,96	0,96	0,96	0,96
With WSJ	**Michigan**				**Atlanta Fed**				**New York Fed**			
	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid
c	0,43	0,44	0,61	0,48	0,06	0,06	0,47	0,40	-0,09	-0,08	0,46	0,26
p-val	0,00	0,00	0,00	0,00	0,42	0,45	0,00	0,01	0,10	0,15	0,00	0,24
α	0,86	0,86	0,80	0,84	0,97	0,98	0,75	0,79	1,04	1,04	0,84	0,90
p-val	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
β	0,002	0,003	0,000	0,000	0,001	0,001	0,000	0,000	0,001	0,001	0,000	0,000
p-val	0,079				0,019				0,158			
γ		-0,003	0,002	0,003		-0,011	0,001	0,005		-0,002	-0,001	0,005
$\beta + \gamma$		0,000	0,003	0,004		-0,009	0,001	0,004		0,000	-0,001	0,005
$p(\beta+\gamma)$		0,985	0,335	0,071		0,005	0,487	0,032		0,965	0,504	0,184
$\bar{R}^2$ ADL	0,77	0,77	0,77	0,77	0,89	0,89	0,90	0,90	0,96	0,96	0,97	0,97
$\bar{R}^2$ AR	0,77	0,77	0,77	0,77	0,89	0,89	0,89	0,89	0,96	0,96	0,96	0,96
With GT / WSJ	**Michigan**				**Atlanta Fed**				**New York Fed**			
	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid
c	0,55	0,55	0,67	0,55	0,30	0,32	0,59	0,32	0,01	0,01	0,33	0,01
p-val	0,00	0,00	0,00	0,00	0,03	0,03	0,00	0,03	0,95	0,94	0,02	0,94
α	0,83	0,83	0,79	0,83	0,84	0,83	0,68	0,83	1,00	1,00	0,86	1,00
p-val	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
β_{GT}	0,010	0,010	0,007	0,010	0,008	0,009	0,009	0,009	0,006	0,006	0,002	0,006
p-val	0,010				0,000				0,376			
γ_{GT}		0,000	0,006	0,000		-0,014	-0,006	-0,014		0,024	0,015	0,024
$\beta_{GT} + \gamma_{GT}$		0,010	0,013	0,010		-0,006	0,004	-0,006		0,029	0,017	0,029
$p(\beta_{GT}+\gamma_{GT})$		0,048	0,386	0,048		0,419	0,031	0,419		0,042	0,000	0,042
β_{WSJ}	-0,001	-0,001	-0,001	-0,001	0,000	0,000	0,000	0,000	0,000	0,000	-0,001	0,000
p-val	0,765				0,976				0,884			
γ_{WSJ}		-0,003	-0,002	-0,003		-0,006	0,000	-0,006		-0,009	-0,011	-0,009
$\beta_{WSJ} + \gamma_{WSJ}$		-0,004	-0,004	-0,004		-0,006	0,000	-0,006		-0,009	-0,012	-0,009
$p(\beta_{WSJ}+\gamma_{WSJ})$		0,505	0,667	0,505		0,149	0,992	0,149		0,166	0,000	0,166
$\bar{R}^2$ ADL	0,77	0,77	0,77	0,77	0,90	0,90	0,91	0,90	0,96	0,96	0,98	0,96
$\bar{R}^2$ AR	0,77	0,77	0,77	0,77	0,89	0,89	0,89	0,89	0,96	0,96	0,96	0,96

Note: This table presents results from the ADL regression as in Table 21. The dependant variable is either Michigan 1-year ahead consumer *inflation expectation, Atlanta Fed 1-year ahead* business *inflation expectation or the New York Fed 1-year ahead* consumer *inflation expectation. Data are in monthly frequency. In the case of Atlanta Fed, full sample starts in 2011M10 while New York Fed data are available from 2013M08.*

Table 23: Predictive regressions with Cleveland Fed expectations

With GT	Nowcast				1-year forecast			
	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid
c	0,08	0,18	0,14	0,14	0,41	0,48	0,44	0,44
p-val	0,17	0,00	0,04	0,01	0,00	0,00	0,00	0,00
α	0,94	0,89	0,89	0,92	0,77	0,74	0,74	0,76
p-val	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
β	0,022	0,027	0,017	-0,005	0,004	0,004	-0,008	-0,005
p-val	0,000				0,141			
γ		-0,109	-0,004	0,031		-0,038	0,009	0,016
$\beta+\gamma$		-0,082	0,013	0,026		-0,034	0,000	0,011
$p(\beta+\gamma)$		0,001	0,001	0,000		0,126	0,889	0,011
$\bar{R}^2$ ADL	0,97	0,97	0,97	0,97	0,60	0,61	0,61	0,61
$\bar{R}^2$ AR	0,96	0,96	0,96	0,96	0,60	0,60	0,60	0,60

With WSJ	Nowcast				1-year forecast			
	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid
c	0,03	0,07	0,14	0,15	0,44	0,48	0,46	0,47
p-val	0,58	0,33	0,04	0,06	0,00	0,00	0,00	0,00
α	1,00	0,99	0,91	0,91	0,76	0,74	0,73	0,74
p-val	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
β	0,006	0,006	0,003	0,001	0,003	0,003	0,002	0,003
p-val	0,001				0,001			
γ		0,004	0,001	0,011		-0,013	-0,002	0,003
$\beta+\gamma$		0,010	0,003	0,012		-0,009	0,000	0,005
$p(\beta+\gamma)$		0,178	0,413	0,002		0,159	0,744	0,013
$\bar{R}^2$ ADL	0,96	0,96	0,97	0,97	0,61	0,62	0,61	0,61
$\bar{R}^2$ AR	0,96	0,96	0,96	0,96	0,60	0,60	0,60	0,60

With GT / WSJ	Michigan				Atlanta Fed			
	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid
c	0,04	0,14	0,04	0,03	0,33	0,39	0,37	0,34
p-val	0,60	0,02	0,57	0,72	0,00	0,00	0,00	0,01
α	0,92	0,87	0,89	0,93	0,75	0,74	0,73	0,75
p-val	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
β_{GT}	0,019	0,024	0,015	-0,009	-0,005	-0,004	-0,012	-0,011
p-val	0,001				0,253			
γ_{GT}		-0,124	0,014	0,044		-0,028	0,004	0,020
$\beta_{GT}+\gamma_{GT}$		-0,100	0,029	0,035		-0,032	-0,008	0,009
$p(\beta_{GT}+\gamma_{GT})$		0,000	0,000	0,000		0,186	0,307	0,323
β_{WSJ}	0,003	0,003	0,005	0,005	0,007	0,006	0,006	0,006
p-val	0,216				0,016			
γ_{WSJ}		0,013	-0,016	-0,010		-0,015	0,000	-0,005
$\beta_{WSJ}+\gamma_{WSJ}$		0,017	-0,011	-0,006		-0,009	0,006	0,001
$p(\beta_{WSJ}+\gamma_{WSJ})$		0,009	0,049	0,235		0,716	0,206	0,740
$\bar{R}^2$ ADL	0,97	0,97	0,97	0,97	0,61	0,62	0,62	0,61
$\bar{R}^2$ AR	0,96	0,96	0,96	0,96	0,60	0,60	0,60	0,60

Note: This table presents results from the ADL regression in (1). The dependant variable, $\pi_{t+h,t}$, is the Cleveland Fed nowcast ($h = 0$) and the 1-year ahead forecast ($h = 4$) of the year-over-year CPI inflation. The top panel shows results where Z contains the GT of the keyword "inflation" observable at time t. In the middle panel Z_t is given by the text analysis indicator WSJ, also available at time t. The bottom panel shows results when both GT and WSJ are included. Column Full stands for the full sample analysis. Columns <q10, >q90 and Covid contain results from the specification with a dummy variable as in (3). Inference is performed using 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.

Table 24: Predictive regressions with Cleveland Fed expectations

With GT	Nowcast				1-year forecast			
	Full	<q10	$>q90$	Covid	Full	<q10	$>q90$	Covid
c	0,06	0,06	0,08	0,08	0,42	0,43	0,43	0,46
p-val	0,31	0,48	0,23	0,26	0,00	0,00	0,00	0,00
α	0,96	0,96	0,92	0,95	0,77	0,76	0,75	0,75
p-val	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
β	0,018	0,018	0,030	0,006	0,006	0,007	0,002	0,002
p-val	0,002				0,003			
γ		-0,007	-0,027	0,012		-0,020	0,004	0,011
β+ γ		0,011	0,003	0,018		-0,013	0,006	0,013
p($\beta+\gamma$)		0,492	0,657	0,035		0,245	0,148	0,003
$\bar{R}^2$ ADL	0,96	0,96	0,97	0,96	0,61	0,60	0,60	0,61
$\bar{R}^2$ AR	0,96	0,96	0,96	0,96	0,60	0,60	0,60	0,60
With WSJ	Nowcast				1-year forecast			
	Full	<q10	$>q90$	Covid	Full	<q10	$>q90$	Covid
c	-0,01	-0,04	0,10	0,09	0,43	0,43	0,44	0,46
p-val	0,92	0,58	0,10	0,19	0,00	0,00	0,00	0,00
α	1,03	1,04	0,95	0,95	0,76	0,76	0,75	0,75
p-val	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
β	0,003	0,003	0,001	0,000	0,003	0,003	0,001	0,001
p-val	0,050				0,012			
γ		-0,015	-0,001	0,009		-0,011	0,004	0,004
β+ γ		-0,012	0,000	0,008		-0,007	0,004	0,005
p($\beta+\gamma$)		0,080	0,967	0,034		0,073	0,124	0,006
$\bar{R}^2$ ADL	0,96	0,96	0,96	0,96	0,60	0,60	0,61	0,61
$\bar{R}^2$ AR	0,96	0,96	0,96	0,96	0,60	0,60	0,60	0,60
With GT / WSJ	Nowcast				1-year forecast			
	Full	<q10	$>q90$	Covid	Full	<q10	$>q90$	Covid
c	0,05	0,06	0,08	0,06	0,38	0,40	0,40	0,40
p-val	0,43	0,50	0,28	0,50	0,00	0,00	0,00	0,00
α	0,96	0,96	0,93	0,96	0,75	0,75	0,74	0,75
p-val	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
β_{GT}	0,018	0,018	0,030	0,018	0,002	0,003	0,000	0,003
p-val	0,002				0,544			
γ_{GT}		0,008	-0,022	0,008		-0,016	0,001	-0,016
β_{GT}+ γ_{GT}		0,026	0,008	0,026		-0,013	0,001	-0,013
p($\beta_{GT}+\gamma_{GT}$)		0,006	0,159	0,006		0,161	0,953	0,161
β_{WSJ}	0,000	0,000	0,000	0,000	0,003	0,003	0,003	0,003
p-val	0,943				0,162			
γ_{WSJ}		-0,015	-0,003	-0,015		-0,003	0,000	-0,003
β_{WSJ}+ γ_{WSJ}		-0,015	-0,004	-0,015		-0,001	0,003	-0,001
p($\beta_{WSJ}+\gamma_{WSJ}$)		0,014	0,410	0,014		0,969	0,660	0,969
$\bar{R}^2$ ADL	0,96	0,96	0,97	0,96	0,61	0,60	0,60	0,60
$\bar{R}^2$ AR	0,96	0,96	0,96	0,96	0,60	0,60	0,60	0,60

Note: This table presents results from the ADL regression in (2). The dependant variable, $\pi_{t+h,t}$, is the Cleveland Fed nowcast ($h=0$) and the 1-year ahead forecast ($h=4$) of the year-over-year CPI inflation. The top panel shows results where Z contains the GT of the keyword "inflation" observable at time t. In the middle panel Z_t is given by the text analysis indicator WSJ, also available at time t. The bottom panel shows results when both GT and WSJ are included. Column Full stands for the full sample analysis. Columns <q10, >q90 and Covid contain results from the specification with a dummy variable as in (3). Inference is performed using 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.

Table 25: Predictive regressions with SPF and the common GT factor

With DF1	Nowcast				1-quarter forecast				1-year forecast			
	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid
c	1,56	1,89	1,49	1,57	0,85	0,88	0,88	0,83	0,68	0,72	0,71	0,67
p-val	0,00	0,00	0,00	0,00	0,00	0,01	0,00	0,00	0,00	0,00	0,00	0,00
α	0,20	0,09	0,16	0,20	0,59	0,58	0,56	0,60	0,69	0,67	0,67	0,69
p-val	0,05	0,47	0,16	0,11	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
β	0,034	0,038	-0,013	0,012	0,011	0,011	-0,002	0,003	0,002	0,002	0,000	0,001
p-val	0,000				0,000				0,021			
γ		-0,072	0,017	0,037		-0,018	0,014	0,012		0,004	0,000	0,000
$\beta+\gamma$		-0,034	0,005	0,049		-0,007	0,012	0,016		0,006	0,000	0,002
$p(\beta+\gamma)$		0,476	0,569	0,002		0,334	0,000	0,000		0,019	0,888	0,057
$\bar{R}^2$ ADL	0,17	0,21	0,25	0,16	0,50	0,49	0,52	0,50	0,51	0,51	0,52	0,50
$\bar{R}^2$ AR	0,09	0,09	0,09	0,09	0,42	0,42	0,42	0,42	0,50	0,50	0,50	0,50
With DF1 / WSJ	Nowcast				1-quarter forecast				1-year forecast			
	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid
c	0,78	1,11	0,99	0,90	0,79	0,83	0,98	0,81	0,81	0,83	0,89	0,85
p-val	0,01	0,00	0,01	0,10	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
α	0,24	0,12	0,18	0,24	0,51	0,49	0,45	0,51	0,60	0,59	0,57	0,59
p-val	0,02	0,38	0,10	0,04	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
β_{GT}	0,000	0,000	0,002	0,003	0,001	0,000	0,002	0,003	0,000	0,000	0,000	0,000
p-val	0,981				0,688				0,487			
γ_{GT}		0,014	0,022	-0,004		0,005	0,000	-0,005		0,001	0,001	0,001
$\beta_{GT}+\gamma_{GT}$		0,014	0,024	-0,002		0,005	0,002	-0,002		0,000	0,001	0,000
$p(\beta_{GT}+\gamma_{GT})$		0,493	0,000	0,817		0,140	0,759	0,004		0,834	0,481	0,662
β_{WSJ}	0,039	0,040	0,028	0,033	0,013	0,013	0,007	0,011	0,003	0,003	0,002	0,002
p-val	0,013				0,028				0,005			
γ_{WSJ}		0,013	0,028	0,009		-0,001	0,010	0,000		0,007	0,002	0,003
$\beta_{WSJ}+\gamma_{WSJ}$		0,053	0,057	0,042		0,011	0,018	0,011		0,011	0,005	0,005
$p(\beta_{WSJ}+\gamma_{WSJ})$		0,473	0,000	0,000		0,509	0,173	0,000		0,076	0,161	0,003
$\bar{R}^2$ ADL	0,26	0,28	0,30	0,23	0,46	0,44	0,48	0,47	0,49	0,48	0,50	0,48
$\bar{R}^2$ AR	0,13	0,13	0,13	0,13	0,36	0,36	0,36	0,36	0,43	0,43	0,43	0,43

Note: This table presents results from the ADL regression in (1). The dependant variable, $\pi_{t+h,t}$, is the SPF mean nowcast ($h = 0$), the 1-quarter and 1-year ahead forecast ($h = 1$ and $h = 4$) of the year-over-year CPI inflation. The top panel shows results where Z contains the first common factor (DF1) extracted from five GT keywords: "inflation", "inflation rate", "price increase", "cpi" and "price". The top panel shows results where Z contains the GT of the keyword "inflation" observable at time t. The bottom panel shows results when both DF1 and WSJ are included. Column Full stands for the full sample analysis. Columns <q10, >q90 and Covid contain results from the specification with a dummy variable as in (3). Inference is performed using 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.

Table 26: Predictive regressions with monthly surveys and the common GT factor

With DF1	Michigan				Atlanta Fed				New York Fed			
	Full	$<$q10	$> q90$	Covid	Full	$<$q10	$> q90$	Covid	Full	$<$q10	$> q90$	Covid
c	0,61	0,63	0,77	0,60	0,32	0,36	0,59	0,41	0,20	0,22	0,52	0,27
p-val	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,14	0,11	0,00	0,02
α	0,80	0,79	0,74	0,80	0,83	0,81	0,69	0,78	0,92	0,92	0,81	0,90
p-val	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
β	0,008	0,009	0,004	0,006	0,01	0,005	0,003	0,001	0,01	0,008	0,004	0,001
p-val	0,000				0,000				0,002			
γ		-0,020	0,001	0,003		-0,023	0,001	0,005		-0,033	0,001	0,006
$\beta+\gamma$		-0,011	0,005	0,008		-0,017	0,004	0,006		-0,025	0,005	0,007
p($\beta+\gamma$)		0,071	0,087	0,001		0,000	0,000	0,003		0,001	0,008	0,002
$\bar{R}^2$ ADL	0,78	0,79	0,79	0,78	0,90	0,91	0,91	0,91	0,97	0,97	0,97	0,97
$\bar{R}^2$ AR	0,77	0,77	0,77	0,77	0,89	0,89	0,89	0,89	0,96	0,96	0,96	0,96
With DF1 / WSJ	Michigan				Atlanta Fed				New York Fed			
	Full	$<$q10	$> q90$	Covid	Full	$<$q10	$> q90$	Covid	Full	$<$q10	$> q90$	Covid
c	0,48	0,49	0,67	0,53	0,14	0,15	0,56	0,47	0,03	0,03	0,52	0,42
p-val	0,00	0,00	0,01	0,01	0,07	0,06	0,00	0,00	0,71	0,69	0,00	0,02
α	0,82	0,82	0,77	0,82	0,92	0,91	0,71	0,75	0,98	0,97	0,82	0,85
p-val	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
β_{GT}	-0,002	-0,002	-0,001	-0,001	-0,001	-0,001	0,000	0,000	-0,002	-0,002	-0,001	-0,001
p-val	0,022				0,016				0,000			
γ_{GT}		0,003	-0,005	-0,003		0,001	-0,001	-0,003		0,000	-0,001	0,000
$\beta_{GT}+\gamma_{GT}$		0,001	-0,006	-0,004		0,000	-0,001	-0,002		-0,003	-0,002	-0,002
p($\beta_{GT}+\gamma_{GT}$)		0,879	0,011	0,008		0,730	0,059	0,001		0,503	0,117	0,156
β_{WSJ}	0,002	0,002	0,001	0,001	0,001	0,001	0,000	0,000	0,000	0,001	-0,002	-0,001
p-val	0,205				0,503				0,668			
γ_{WSJ}		0,007	-0,007	0,000		-0,012	0,001	0,003		-0,013	0,003	0,007
$\beta_{WSJ}+\gamma_{WSJ}$		0,009	-0,006	0,001		-0,011	0,002	0,003		-0,012	0,001	0,006
p($\beta_{WSJ}+\gamma_{WSJ}$)		0,746	0,144	0,777		0,000	0,204	0,031		0,261	0,799	0,135
$\bar{R}^2$ ADL	0,78	0,78	0,79	0,78	0,89	0,90	0,91	0,91	0,97	0,97	0,97	0,97
$\bar{R}^2$ AR	0,77	0,77	0,77	0,77	0,89	0,89	0,89	0,89	0,96	0,96	0,96	0,96

Note: This table presents results from the ADL regression as in Table 25. The dependant variable is either Michigan 1-year ahead consumer *inflation expectation, Atlanta Fed 1-year ahead* business *inflation expectation or the New York Fed 1-year ahead* consumer *inflation expectation. Data are in monthly frequency. In the case of Atlanta Fed, full sample starts in 2011M10 while New York Fed data are available from 2013M08.*

A.4 Additional FIRE testing results

Table 27: Mincer-Zarnowitz regressions with SPF

With GT	Nowcast				1-quarter forecast				1-year forecast			
	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid
c	0,87	1,29	0,93	0,91	-1,09	-0,36	-0,88	-1,03	1,28	2,02	-0,75	-2,08
p-val	0,00	0,00	0,00	0,00	0,19	0,64	0,28	0,21	0,72	0,57	0,82	0,31
α	0,58	0,46	0,52	0,57	1,54	1,26	1,42	1,49	0,40	0,11	1,41	1,81
p($\alpha = 1$)	0,00	0,00	0,00	0,00	0,13	0,43	0,24	0,16	0,71	0,58	0,78	0,39
β	0,08	0,080	0,045	0,087	0,10	0,096	0,061	0,049	-0,06	-0,080	0,011	-0,166
p-val	0,00				0,00				0,50			
γ		0,062	0,025	0,004		-0,036	0,043	0,071		0,050	0,235	0,427
$\beta+\gamma$		0,142	0,070	0,091		0,060	0,104	0,120		-0,030	0,246	0,261
p($\beta+\gamma$)		0,000	0,000	0,000		0,191	0,003	0,000		0,243	0,000	0,002
$\bar{R}^2$	0,67	0,76	0,68	0,66	0,53	0,59	0,53	0,54	0,00	0,00	0,15	0,56
$\bar{R}^2$ restr	0,51	0,51	0,51	0,51	0,37	0,37	0,37	0,37	-0,02	-0,02	-0,02	-0,02
With WSJ	**Nowcast**				**1-quarter forecast**				**1-year forecast**			
	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid
c	0,93	1,34	1,00	0,97	-1,22	-0,60	-0,78	-0,99	1,55	2,35	-0,79	-0,54
p-val	0,00	0,00	0,00	0,00	0,10	0,36	0,26	0,17	0,66	0,53	0,81	0,88
α	0,58	0,46	0,48	0,54	1,62	1,39	1,37	1,47	0,27	-0,05	1,43	1,11
p($\alpha = 1$)	0,00	0,00	0,00	0,00	0,06	0,19	0,22	0,13	0,65	0,53	0,77	0,95
β	0,03	0,032	0,013	0,018	0,04	0,038	0,026	0,025	-0,02	-0,022	-0,001	-0,010
p-val	0,01				0,00				0,35			
γ		0,017	0,023	0,029		-0,005	0,024	0,030		0,018	-0,066	0,095
$\beta+\gamma$		0,049	0,035	0,047		0,034	0,050	0,054		-0,004	-0,067	0,085
p($\beta+\gamma$)		0,026	0,000	0,000		0,034	0,000	0,000		0,741	0,000	0,314
$\bar{R}^2$	0,62	0,70	0,67	0,63	0,53	0,57	0,54	0,56	-0,02	-0,02	0,15	0,32
$\bar{R}^2$ restr	0,51	0,51	0,51	0,51	0,37	0,37	0,37	0,37	-0,02	-0,02	-0,02	-0,02

Note: This table presents results from the Mincer-Zarnowitz regression in (5). The dependant variable, π_{t+h}, is the year-over-year CPI inflation and $\pi_{t+h,t}$ is its SPF mean nowcast ($h = 0$), 1-quarter and 1-year ahead forecasts ($h = 1$, $h = 4$). The top panel shows results where Z contains the GT of the keyword "inflation". In the bottom panel Z_t is given by the text analysis indicator WSJ, also available at time t. Column Full stands for the full sample analysis. Columns <q10, >q80 and Covid contain results from the specification with a dummy variable as in (6). The line p($\alpha = 1$) shows the p-value for $H_0 : \alpha = 1$, that is the optimality of the forecast with respect to the informational set. Inference is performed using Newey-West standard errors. $\bar{R}^2$ is the adjusted R^2 from the full model, while $\bar{R}^2$ restr shows its value without Z.

Table 28: Mincer-Zarnowitz regressions with monthly surveys

With GT	Michigan				Atlanta Fed				New York Fed			
	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid
c	4,27	4,69	3,47	2,84	0,11	1,10		-0,57	-2,68	-2,82		0,55
t-stat	0,00	0,00	0,00	0,00	0,98	0,02		0,43	0,57	0,55		0,88
α	-0,69	-0,79	-0,40	-0,31	-0,66	-1,28		1,11	0,35	0,40		0,41
p($\alpha = 1$)	0,00	0,00	0,00	0,00	0,34	0,77		0,33	0,60	0,64		0,64
β	-0,033	-0,048	-0,015	-0,118	0,086	0,094		-0,054	0,099	0,102		-0,097
p-val	0,591				0,042				0,051			
γ		0,034	-0,209	0,332		-0,053		0,223		-0,043		0,381
β+ γ		-0,014	-0,224	0,214		0,041		0,168		0,058		0,284
p($\beta + \gamma$)		0,631	0,000	0,002		0,309		0,035		0,210		0,000
$\bar{R}^2$	0,07	0,10	0,11	0,52	0,12	0,13		0,74	0,13	0,12		0,44
$\bar{R}^2$ restr	0,07	0,07	0,07	0,07	-0,01	-0,01		-0,01	-0,01	-0,01		-0,01
With WSJ	**Michigan**				**Atlanta Fed**				**New York Fed**			
	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid
c	4,47	4,94	3,56	3,77	1,47	1,97		-1,28	1,26	2,31		-5,74
t-stat	0,00	0,00	0,00	0,00	0,76	0,59		0,78	0,75	0,54		0,28
α	-0,76	-0,88	-0,43	-0,62	0,29	0,06		1,22	0,30	0,11		2,10
p($\alpha = 1$)	0,00	0,00	0,00	0,00	0,78	0,15		0,51	0,65	0,54		0,53
β	-0,005	-0,009	-0,002	-0,002	-0,002	-0,001		0,023	-0,004	-0,019		0,053
p-val	0,586				0,893				0,783			
γ		-0,007	-0,039	0,115		-0,067		0,109		-0,025		-0,261
β+ γ		-0,016	-0,041	0,113		-0,068		0,132		-0,045		-0,207
p($\beta + \gamma$)		0,217	0,102	0,001		0,286		0,053		0,540		0,043
$\bar{R}^2$	0,06	0,09	0,09	0,39	-0,02	-0,02		0,73	-0,02	-0,01		0,45
$\bar{R}^2$ restr	0,07	0,07	0,07	0,07	-0,01	-0,01		-0,01	-0,01	-0,01		-0,01

Note: This table presents results from the Mincer-Zarnowitz regression as in Table 27. The dependant variable is either Michigan 1-year ahead consumer *inflation expectation, Atlanta Fed 1-year ahead* business *inflation expectation or New York Fed 1-year ahead* consumer *inflation expectation. Data are in monthly frequency. In the case of Atlanta Fed, full sample starts in 2011M10, while New York Fed data starts in 2013M08.*

Table 29: Mincer-Zarnowitz regressions with Cleveland Fed expectations

With GT	Nowcast				1-year forecast			
	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid
c	0,01	0,03	0,05	0,02	2,47	2,91	2,16	1,40
t-stat	0,67	0,49	0,18	0,43	0,00	0,00	0,00	0,00
α	0,99	0,98	0,96	0,98	-0,16	-0,34	0,07	0,27
p($\alpha = 1$)	0,51	0,38	0,07	0,33	0,00	0,00	0,00	0,00
β	0,008	0,008	0,006	0,002	-0,058	-0,079	-0,025	-0,134
p-val	0,001				0,355			
γ		-0,007	-0,002	0,006		0,062	-0,222	0,326
β+ γ		0,002	0,004	0,008		-0,017	-0,247	0,192
p($\beta + \gamma$)		0,871	0,491	0,003		0,529	0,000	0,004
$\bar{R}^2$	0,99	0,99	0,99	0,99	0,03	0,06	0,10	0,52
$\bar{R}^2$ restr	0,99	0,99	0,99	0,99	0,00	0,00	0,00	0,00
With WSJ	**Nowcast**				**1-year forecast**			
	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid
c	-0,01	-0,02	0,05	0,03	2,40	2,79	2,09	1,50
t-stat	0,70	0,59	0,18	0,30	0,00	0,00	0,00	0,01
α	1,02	1,02	0,97	0,98	-0,13	-0,29	0,11	0,22
p($\alpha = 1$)	0,16	0,15	0,10	0,22	0,00	0,00	0,01	0,02
β	0,002	0,001	0,000	0,000	-0,012	-0,016	-0,005	-0,010
p-val	0,019				0,311			
γ		0,002	0,000	0,004		0,003	-0,057	0,102
β+ γ		0,004	0,000	0,004		-0,013	-0,062	0,092
p($\beta + \gamma$)		0,371	0,951	0,006		0,362	0,001	0,016
$\bar{R}^2$	0,99	0,99	0,99	0,99	0,00	0,02	0,08	0,35
$\bar{R}^2$ restr	0,99	0,99	0,99	0,99	0,00	0,00	0,00	0,00
With GT / WSJ	**Nowcast**				**1-year forecast**			
	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid
c	0,01	0,03	0,05	0,01	1,56	2,01	0,82	1,29
p-val	0,65	0,46	0,19	0,83	0,22	0,12	0,49	0,00
α	0,99	0,98	0,96	0,99	0,00	-0,16	0,24	0,25
p($\alpha = 1$)	0,61	0,47	0,07	0,55	0,00	0,00	0,01	0,00
β_{GT}	0,008	0,009	0,005	0,001	0,036	0,036	0,044	-0,141
p-val	0,00				0,341			
γ_{GT}		-0,014	0,005	0,010		0,009	-0,029	0,401
β_{GT}+ γ_{GT}		-0,006	0,011	0,011		0,045	0,015	0,260
p($\beta_{GT} + \gamma_{GT}$)		0,459	0,086	0,014		0,217	0,913	0,084
β_{WSJ}	0,00	0,000	0,000	0,000	-0,038	-0,041	-0,030	0,007
p-val	0,87				0,053			
γ_{WSJ}		0,007	-0,005	-0,002		-0,004	-0,057	-0,124
β_{WSJ}+ γ_{WSJ}		0,007	-0,005	-0,002		-0,045	-0,087	-0,117
p($\beta_{WSJ} + \gamma_{WSJ}$)		0,045	0,199	0,429		0,252	0,000	0,433
$\bar{R}^2$	0,99	0,99	0,99	0,99	0,06	0,08	0,14	0,52
$\bar{R}^2$ restr	0,99	0,99	0,99	0,99	0,00	0,00	0,00	0,00

Note: This table presents results from the CG regressions as in Table 27. The dependant variable is either Cleveland Fed nowcast / 1-year ahead forecast of the year-over-year CPI inflation. Data are in monthly frequency. Nowcast data starts in 2013M08.

Table 30: Mincer-Zarnowitz quantile regressions

	SPF					
	Nowcast		1-quarter forecast		1-year forecast	
	<q10	$> q90$	<q10	$> q90$	<q10	$> q90$
c	-0,94	2,70	-0,72	1,56	-1,02	3,04
p-val	0,11	0,00	0,18	0,01	0,24	0,00
α	0,92	0,56	0,70	0,62	0,79	0,77
p($\alpha = 1$)	0,76	0,00	0,21	0,00	0,59	0,08
β_{GT}	0,062	0,131	0,066	0,047	-0,139	0,108
p-val	0,008	0,000	0,049	0,361	0,022	0,074
β_{WSJ}	0,011	-0,039	0,016	0,038	0,028	-0,047
p-val	0,374	0,034	0,274	0,308	0,164	0,027
R^1	0,36	0,61	0,33	0,55	0,35	0,47
	Monthly surveys					
	Michigan		Atlanta Fed		New York Fed	
	<q10	$> q90$	<q10	$> q90$	<q10	$> q90$
c	3,15	2,18	1,97	-4,86	3,01	-13,95
p-val	0,01	0,33	0,43	0,12	0,20	0,00
α	-1,10	-0,28	-1,30	2,61	-1,04	6,32
p($\alpha = 1$)	0,00	0,09	0,07	0,28	0,00	0,00
β_{GT}	0,012	0,088	0,014	0,175	-0,001	0,071
p-val	0,560	0,012	0,472	0,000	0,953	0,159
β_{WSJ}	0,013	-0,031	0,035	-0,073	0,032	-0,081
p-val	0,148	0,017	0,000	0,001	0,000	0,001
R^1	0,26	0,04	0,11	0,19	0,15	0,31

Note: This table presents results from the Mincer-Zarnowitz quantile regression in (5) focusing on the 10% and 90% percentiles. The dependant variable, π_{t+h}, is the year-over-year CPI inflation and $\pi_{t+h,t}$ is its SPF mean nowcast ($h = 0$), 1-quarter and 1-year ahead forecasts ($h = 1$, $h = 4$) in the top panel, while in the bottom panel $\pi_{t+h,t}$ is either Michigan 1-year ahead consumer *inflation expectation, Atlanta Fed 1-year ahead* business *inflation expectation or New York Fed 1-year ahead* consumer *inflation expectation. R^1 is the goodness-of-fit criterion from Koenker and Machado (1999).*

Table 31: Coibion-Gorodnichenko regressions with SPF

With GT	Nowcast				1-quarter forecast				1-year forecast			
	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid
c	0,06	0,18	0,07	0,08	0,00	0,18	-0,05	-0,02	-0,01	0,08	0,14	-0,31
p-val	0,62	0,13	0,62	0,58	0,99	0,36	0,81	0,92	0,96	0,80	0,68	0,10
β	0,05	0,044	0,051	0,071	0,11	0,102	0,060	0,057	-0,07	-0,084	0,011	-0,160
p-val	0,00				0,00				0,47			
γ		0,124	0,009	-0,023		-0,042	0,051	0,080		0,045	0,233	0,426
$\beta+\gamma$		0,168	0,059	0,048		0,059	0,111	0,137		-0,038	0,244	0,266
p$(\beta+\gamma)$		0,029	0,000	0,002		0,196	0,002	0,000		0,059	0,000	0,001
$\bar{R}^2$	0,15	0,21	0,12	0,12	0,34	0,44	0,35	0,35	0,02	0,01	0,17	0,56
With WSJ	**Nowcast**				**1-quarter forecast**				**1-year forecast**			
	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid
c	0,11	0,23	0,06	0,07	0,05	0,22	-0,05	-0,03	-0,03	0,06	0,13	-0,31
p-val	0,42	0,07	0,67	0,62	0,80	0,20	0,81	0,88	0,93	0,87	0,67	0,22
β	0,02	0,012	0,001	0,007	0,05	0,042	0,026	0,026	-0,02	-0,022	-0,001	-0,010
p-val	0,03				0,00				0,36			
γ		0,037	0,025	0,015		-0,008	0,028	0,036		0,012	-0,065	0,096
$\beta+\gamma$		0,049	0,026	0,022		0,034	0,053	0,062		-0,010	-0,066	0,086
p$(\beta+\gamma)$		0,194	0,000	0,009		0,034	0,000	0,000		0,165	0,000	0,289
$\bar{R}^2$	0,06	0,11	0,08	0,06	0,32	0,40	0,37	0,38	0,00	-0,01	0,17	0,34

Note: This table presents results from CG type regression in (7). The dependant variable, $\pi_{t+h} - \pi_{t+h,t}$, is the forecast error when the year-over-year CPI inflation is predicted by the SPF mean nowcast ($h = 0$), 1-quarter ahead forecast ($h = 1$) or the 1-year ahead forecast ($h = 4$). The top panel shows results where Z contains the GT of the keyword "inflation". In the bottom panel Z_t is given by the text analysis indicator WSJ, also available at time t. Column Full stands for the full sample analysis. Columns <q10, >q80 and Covid contain results from the specification with a dummy variable in (8). Inference is performed using Newey-West standard errors. $\bar{R}^2$ is the adjusted R^2 from the full model.

Table 32: Coibion-Gorodnichenko regressions with monthly surveys

With GT	Michigan				Atlanta Fed				New York Fed			
	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid
c	-0,83	-1,47	-0,68	-1,15	-2,73	-2,71		-0,36	-4,51	-4,51		-1,16
p-val	0,00	0,34	0,01	0,00	0,06	0,07		0,01	0,01	0,02		0,00
β	-0,10	0,020	-0,048	-0,174	0,08	0,078		-0,054	0,099	0,101		-0,105
p-val	0,19				0,07				0,044			
γ		0,056	-0,254	0,341		-0,009		0,225		-0,040		0,284
β+ γ		0,076	-0,302	0,167		0,069		0,172		0,061		0,179
p($\beta + \gamma$)		0,027	0,000	0,006		0,169		0,007		0,169		0,003
$\bar{R}^2$	0,06	0,00	0,19	0,50	0,11	0,10		0,75	0,13	0,13		0,71

With WSJ	Michigan				Atlanta Fed				New York Fed			
	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid
c	-0,09	-0,01	-0,21	-1,13	0,35	0,16		-0,87	-0,48	1,23		-2,20
p-val	0,85	0,98	0,61	0,00	0,59	0,64		0,00	0,57	0,01		0,00
β	-0,04	-0,042	-0,024	-0,019	-0,01	0,000		0,023	-0,010	-0,046		0,039
p-val	0,11				0,54				0,677			
γ		-0,035	-0,099	0,106		-0,074		0,116		-0,047		0,110
β+ γ		-0,076	-0,123	0,087		-0,074		0,139		-0,093		0,149
p($\beta + \gamma$)		0,129	0,000	0,002		0,309		0,021		0,164		0,027
$\bar{R}^2$	0,05	0,05	0,19	0,32	0,00	-0,01		0,73	-0,01	0,07		0,71

Note: This table presents results from the CG regressions as in Table 31. The dependant variable is either Michigan 1-year ahead consumer *inflation expectation, Atlanta Fed 1-year ahead* business *inflation expectation or New York Fed 1-year ahead* consumer *inflation expectation implied forecast errors. Data are in monthly frequency. In the case of Atlanta Fed, full sample starts in 2011M10, while New York Fed data starts in 2013M08.*

Table 33: Coibion-Gorodnichenko regressions with Cleveland Fed expectations

With GT	Nowcast				1-year forecast			
	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid
c	0,00	0,00	0,00	0,00	0,38	0,40	0,53	0,05
p-val	0,92	0,96	0,80	0,96	0,11	0,09	0,03	0,76
β	0,006	0,006	0,004	0,001	-0,07	-0,080	-0,020	-0,142
p-val	0,000				0,33			
γ		-0,004	-0,003	0,005		0,093	-0,226	0,304
$\beta+\gamma$		0,002	0,001	0,006		0,013	-0,246	0,162
$p(\beta+\gamma)$		0,820	0,814	0,002		0,820	0,000	0,005
$\bar{R}^2$	0,20	0,19	0,23	0,20	0,03	0,03	0,15	0,54
With WSJ	Nowcast				1-year forecast			
	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid
c	0,02	0,02	0,00	0,00	1,21	1,23	1,12	0,63
p-val	0,30	0,31	0,79	0,87	0,01	0,01	0,01	0,05
β	0,002	0,002	0,000	0,000	-0,05	-0,046	-0,033	-0,028
p-val	0,000				0,04			
γ		0,001	-0,001	0,003		-0,047	-0,061	0,145
$\beta+\gamma$		0,004	-0,001	0,003		-0,093	-0,094	0,117
$p(\beta+\gamma)$		0,358	0,827	0,003		0,164	0,000	0,116
$\bar{R}^2$	0,13	0,11	0,22	0,19	0,08	0,07	0,19	0,40
With GT / WSJ	Nowcast				1-year forecast			
	Full	<q10	$> q90$	Covid	Full	<q10	$> q90$	Covid
c	0,01	0,01	-0,01	0,00	0,01	0,33	1,07	1,53
p-val	0,81	0,71	0,77	0,83	0,99	0,81	0,05	0,01
β_{GT}	0,007	0,007	0,004	0,001	0,034	0,026	0,000	-0,026
p-val	0,002				0,397			
γ_{GT}		-0,012	0,012	0,010		0,106	-0,172	0,132
$\beta_{GT}+\gamma_{GT}$		-0,005	0,016	0,011		0,132	-0,172	0,105
$p(\beta_{GT}+\gamma_{GT})$		0,515	0,040	0,016		0,010	0,026	0,042
β_{WSJ}	0,000	-0,001	0,000	0,000	-0,049	-0,049	-0,031	-0,025
p-val	0,656				0,042			
γ_{WSJ}		0,007	-0,010	-0,003		-0,025	-0,014	0,021
$\beta_{WSJ}+\gamma_{WSJ}$		0,007	-0,010	-0,003		-0,074	-0,045	-0,004
$p(\beta_{WSJ}+\gamma_{WSJ})$		0,053	0,040	0,220		0,220	0,072	0,961
$\bar{R}^2$	0,20	0,18	0,28	0,20	0,09	0,09	0,18	0,40

Note: This table presents results from the CG regressions as in Table 31. The dependant variable is either Cleveland Fed nowcast / 1-year ahead forecast errors. Data are in monthly frequency. Nowcast data starts in 2013M08.

A.4.1 MZ and CG regressions with price controls

Table 34: MZ regressions with SPF: adding controls

	$X_t = [\pi_t]$			$X_t = [\pi_t\ gas_t]$			$X_t = [\pi_t\ gscpi_t]$		
	Nowcast	1-quarter	1-year	Nowcast	1-quarter	1-year	Nowcast	1-quarter	1-year
c	0,04	-0,55	-0,77	0,25	0,44	-1,13	0,04	-0,48	-3,51
p-val	0,52	0,44	0,81	0,00	0,27	0,71	0,32	0,45	0,13
α	0,07	0,72	1,83	0,04	0,86	2,36	0,07	0,71	3,27
p($\alpha = 1$)	0,00	0,52	0,59	0,00	0,45	0,40	0,00	0,45	0,10
β_{GT}	0,011	0,053	-0,026	0,014	0,069	-0,014	0,009	0,039	-0,076
p-val	0,000	0,041	0,812	0,000	0,002	0,896	0,010	0,103	0,258
β_{WSJ}	0,000	0,008	-0,031	-0,001	-0,004	-0,039	0,000	0,005	-0,042
p-val	0,869	0,457	0,349	0,733	0,705	0,259	0,946	0,564	0,100
λ_π	0,91	0,49	-0,26	0,83	-0,11	-0,62	0,91	0,50	-0,32
p-val	0,00	0,00	0,34	0,00	0,55	0,18	0,00	0,00	0,14
λ_{GAS}				0,01	0,05	0,03			
p-val				0,00	0,00	0,21			
λ_{GSCPI}							0,03	0,20	1,24
p-val							0,12	0,22	0,00
$\bar{R}^2$	0,98	0,63	0,03	0,99	0,71	0,04	0,98	0,63	0,30
$\bar{R}^2$ restr	0,51	0,37	-0,02	0,51	0,37	-0,02	0,51	0,37	-0,02

Note: This table presents results from the MZ regression in (5) augmented with the current quarter inflation (constructed as the average of the first two months) and either the average gas price (average of three months, left panel) or the global supply chain pressure index (average of two months, right panel). The dependant variable, π_{t+h}, is the year-over-year CPI inflation and $\pi_{t+h,t}$ is its SPF mean nowcast ($h = 0$), 1-quarter and 1-year ahead forecasts ($h = 1$, $h = 4$). Inference is performed using Newey-West standard errors. $\bar{R}^2$ is the adjusted R^2 from the full model, while $\bar{R}^2$ restr shows its value without Z.

Table 35: MZ regressions with monthly surveys: adding controls

	Michigan			Atlanta Fed*			New York Fed		
c	3,89	4,30	4,12	-0,46	0,35	-0,02	-1,80	-1,09	-0,86
p-val	0,02	0,01	0,02	0,91	0,92	1,00	0,68	0,77	0,83
α	-0,83	-0,89	-0,95	-0,10	-0,36	1,35	0,21	0,11	-0,42
p($\alpha = 1$)	0,00	0,00	0,00	0,57	0,43	0,82	0,51	0,43	0,21
β_{GT}	0,036	0,037	0,030	0,086	0,087	0,005	0,102	0,101	0,072
p-val	0,340	0,310	0,392	0,035	0,034	0,843	0,045	0,035	0,082
β_{WSJ}	-0,035	-0,037	-0,030	-0,015	-0,018	-0,009	-0,010	-0,014	0,011
p-val	0,024	0,015	0,038	0,520	0,474	0,570	0,658	0,573	0,556
λ_π	0,07	-0,09	0,04	-0,13	-0,28	-0,36	-0,25	-0,41	-0,04
p-val	0,67	0,71	0,82	0,63	0,52	0,10	0,43	0,45	0,90
λ_{GAS}		0,01			0,01			0,01	
p-val		0,27			0,62			0,72	
λ_{FOOD}			0,12			1,45			0,71
p-val			0,43			0,00			0,07
$\bar{R}^2$	0,12	0,13	0,13	0,12	0,12	0,50	0,13	0,12	0,25
$\bar{R}^2$ restr	0,07	0,07	0,07	-0,01	-0,01	-0,01	-0,01	-0,01	-0,01

Note: This table presents results from the MZ regression in (34) augmented with the previous month CPI inflation and either the current month gas price (or the previous month global supply chain pressure index in the case of Atlanta Fed business survey) and the previous month Food CPI inflation. The dependant variable is either Michigan 1-year ahead consumer *inflation expectation, Atlanta Fed 1-year ahead* business *inflation expectation or New York Fed 1-year ahead* consumer *inflation expectation. Data are in monthly frequency. In the case of Atlanta Fed, full sample starts in 2011M10 while the New York Fed data are available from 2013M08.*

Table 36: CG regressions with SPF: adding controls

	$X_t = [\pi_t]$			$X_t = [\pi_t\ gas_t]$			$X_t = [\pi_t\ gscpi_t]$		
	Nowcast	1-quarter	1-year	Nowcast	1-quarter	1-year	Nowcast	1-quarter	1-year
c	-0,18	-0,97	0,86	-0,72	0,23	1,39	-0,18	-0,92	0,94
p-val	0,60	0,00	0,44	0,02	0,55	0,30	0,60	0,00	0,18
β_{GT}	0,046	0,055	-0,029	0,035	0,070	-0,021	0,046	0,041	-0,078
p-val	0,039	0,031	0,795	0,051	0,001	0,852	0,134	0,084	0,286
β_{WSJ}	-0,024	0,005	-0,029	-0,020	-0,005	-0,034	-0,024	0,003	-0,034
p-val	0,083	0,559	0,379	0,087	0,587	0,316	0,076	0,710	0,146
λ_π	0,34	0,44	-0,19	0,61	-0,15	-0,44	0,34	0,44	-0,14
p-val	0,00	0,00	0,42	0,00	0,37	0,26	0,00	0,00	0,42
λ_{GAS}				-0,02	0,05	0,02			
p-val				0,14	0,00	0,27			
λ_{GSCPI}							0,00	0,20	1,13
p-val							0,99	0,23	0,00
$\bar{R}^2$	0,27	0,49	0,05	0,30	0,61	0,05	0,26	0,49	0,27

Note: This table presents results from the CG regression in (7) augmented with the current quarter inflation (constructed as the average of the first two months) and either the average gas price (average of three months, left panel) or the global supply chain pressure index (average of two months, right panel). The dependant variable, $\pi_{t+h} - \pi_{t+h,t}$, is the forecast error when the year-over-year CPI inflation is predicted by the SPF mean nowcast ($h = 0$), 1-quarter ahead forecast ($h = 1$) or the 1-year ahead forecast ($h = 4$). Inference is performed using Newey-West standard errors. $\bar{R}^2$ is the adjusted R^2.

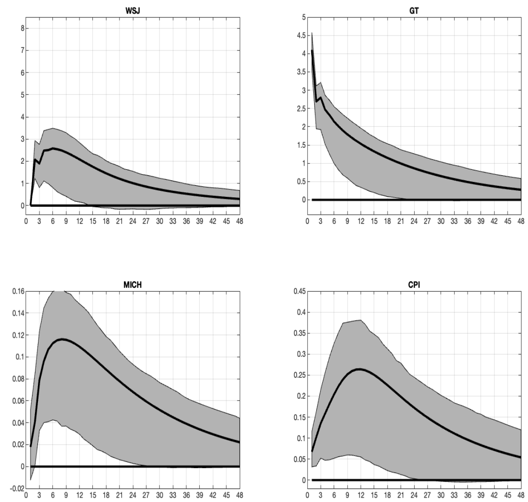
Table 37: CG regressions with monthly surveys: adding controls

	Michigan			Atlanta Fed*			New York Fed		
c	-0,90	-0,77	-0,85	-2,14	-2,06	0,50	-4,11	-3,99	-4,90
p-val	0,51	0,58	0,54	0,11	0,04	0,60	0,01	0,00	0,01
β_{GT}	0,040	0,041	0,044	0,080	0,080	0,008	0,103	0,102	0,076
p-val	0,276	0,263	0,204	0,078	0,073	0,807	0,035	0,027	0,052
β_{WSJ}	-0,037	-0,038	-0,040	-0,017	-0,017	-0,009	-0,005	-0,006	0,018
p-val	0,101	0,096	0,093	0,473	0,498	0,571	0,847	0,837	0,375
λ_π	-0,37	-0,45	-0,33	-0,22	-0,26	-0,33	-0,29	-0,33	-0,13
p-val	0,09	0,13	0,09	0,36	0,55	0,05	0,34	0,56	0,68
λ_{GAS}		0,01			0,00			0,00	
p-val		0,57			0,93			0,92	
λ_{FOOD}			-0,09			1,44			0,63
p-val			0,62			0,00			0,13
$\bar{R}^2$	0,12	0,12	0,12	0,13	0,12	0,50	0,13	0,12	0,23

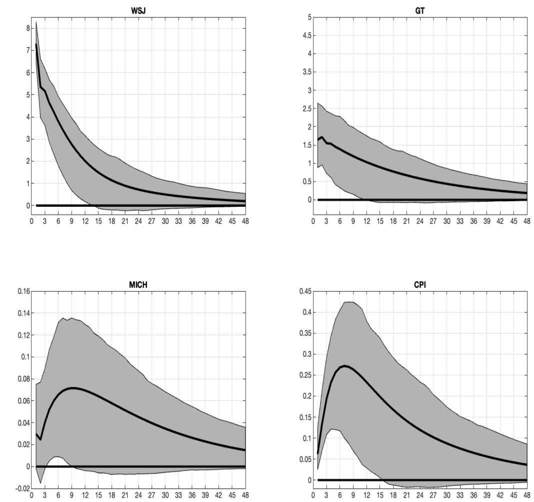
Note: This table presents results from the CG regression in (36) augmented with the previous month CPI inflation and either the current month gas price (or the previous month global supply chain pressure index in the case of Atlanta Fed business survey) and the previous month Food CPI inflation. The dependant variable is either Michigan 1-year ahead consumer *inflation expectation, Atlanta Fed 1-year ahead* business *inflation expectation or New York Fed 1-year ahead* consumer *inflation expectation implied forecast errors. Data are in monthly frequency. In the case of Atlanta Fed, full sample starts in 2011M10 while the New York Fed data are available from 2013M08. Inference is performed using 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.*

A.5 Additional VAR analysis

Figure 10: SVAR IRF robustness analysis: WSJ is predetermined to GT



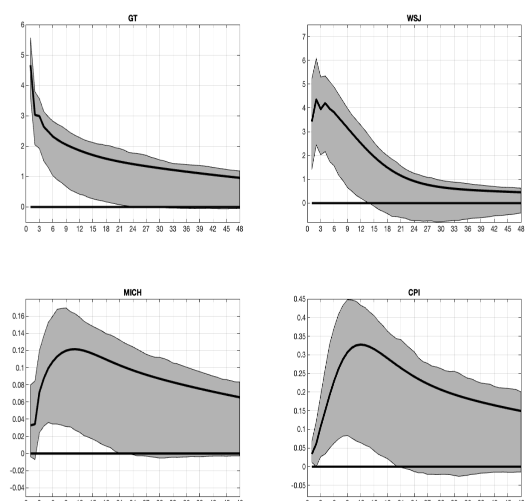
(a) Shock to GT



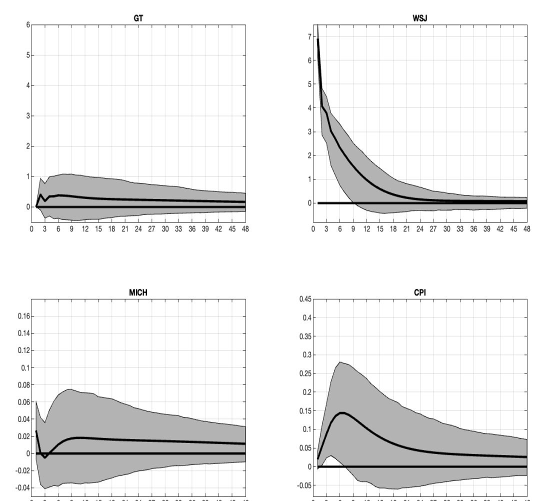
(b) Shock to WSJ

Note: The left panel plots the IRFs after a one-standard deviation positive shock to GT, and the right panel those after a one-standard deviation positive shock to WSJ. We used 5000 bootstrap replications to construct the 90% confidence intervals.

Figure 11: SVAR IRF robustness analysis: GAS instead of OIL



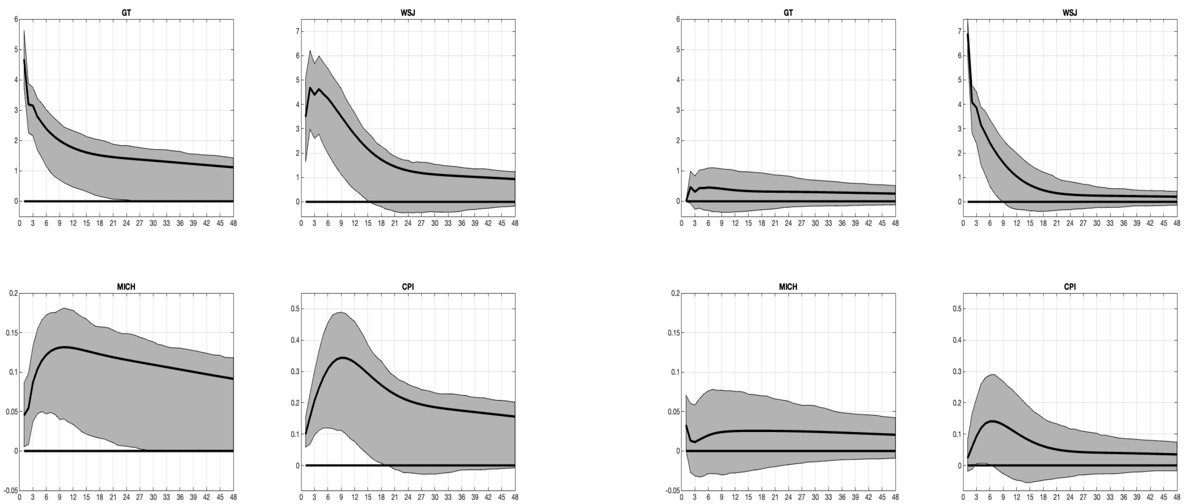
(a) Shock to GT



(b) Shock to WSJ

Note: The left panel plots the IRFs after a one-standard deviation positive shock to GT, and the right panel those after a one-standard deviation positive shock to WSJ. We used 5000 bootstrap replications to construct the 90% confidence intervals.

Figure 12: SVAR IRF robustness analysis: CPI-FOOD instead of OIL

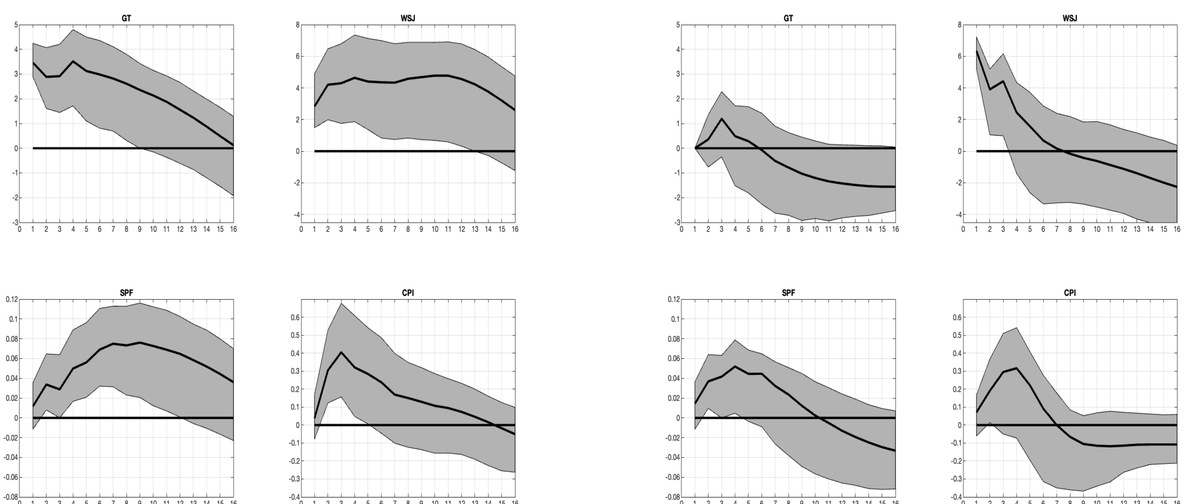


(a) Shock to GT

(b) Shock to WSJ

Note: The left panel plots the IRFs after a one-standard deviation positive shock to GT, and the right panel those after a one-standard deviation positive shock to WSJ. We used 5000 bootstrap replications to construct the 90% confidence intervals.

Figure 13: SVAR IRF robustness analysis: SPF



(a) Shock to GT

(b) Shock to WSJ

Note: The left panel plots the IRFs after a one-standard deviation positive shock to GT, and the right panel after a one-standard deviation positive shock to WSJ. We used 5000 bootstrap replications to construct the 90% confidence intervals.

A.6 Additional forecasting analysis

Table 38: Pseudo-out-of-sample prediction of CPI inflation

Models	$Z_t = \text{GT}$ Full	>2020	<q10	>q90	$Z_t = \text{WSJ}$ Full	>2020	<q10	>q90	$Z_t = \text{GT / WSJ}$ Full	>2020	<q10	>q90
AR (MSE)	0,428	0,492	0,536	0,608	0,428	0,492	0,536	0,608	0,428	0,492	0,536	0,608
Augmented ARs												
AR-Z	**1.008**	**0.792*****	1.232**	0.66***	**0.98**	**0.87*****	0.967	0.881***	**1.016**	**0.788*****	1.181*	0.668***
AR, HWI	1.025	1.069	1.183*	0.931**	1.025	1.069	1.183*	0.931**	1.025	1.069	1.183*	0.931**
AR-Z, HWI	1.031	0.884	1.329***	0.652***	1.012	0.963	1.152	**0.826*****	1.04	0.885	1.283**	0.663***
AR, CLAIMS	1.113	1.38	0.879	0.945	1.113	1.38	0.879	0.945	1.113	1.38	0.879	0.945
AR-Z, CLAIMS	1.102	1.236	0.931	**0.651*****	1.097	1.239	0.823	0.851**	1.106	1.192	0.869	**0.662*****
NKPC-												
CLVF, HWI	1.035	1.141**	1.037	0.991	1.035	1.141**	1.037	0.991	1.035	1.141**	1.037	0.991
CLVF-Z, HWI	1.028	0.91	1.103	0.671***	1.017	1.021	0.989	0.871**	1.036	0.91	1.046	0.676***
CLVF, CLAIMS	1.103	1.328	0.94	0.987	1.103	1.328	0.94	0.987	1.103	1.328	0.94	0.987
CLVF-Z, CLAIMS	1.081	1.138	1.042	0.661***	1.085	1.175	0.878	0.88*	1.084	1.095	0.974	0.669***
MICH, HWI	1.052*	1.05	1.186**	0.967	1.052*	1.05	1.186**	0.967	1.052*	1.05	1.186**	0.967
MICH-Z, HWI	1.055	0.893	1.349***	0.762***	1.041	0.964	1.159	0.873	1.064	0.899	1.309**	0.769***
MICH, CLAIMS	1.15	1.419	**0.867**	0.989	1.15	1.419	0.867	0.989	1.15	1.419	**0.867**	0.989
MICH-Z, CLAIMS	1.131	1.247	0.938	0.742***	1.129	1.266	**0.812**	0.909	1.13	1.192	0.871	0.756***
Data-rich NKPC-												
ARDI	1.159*	1.07	1.092	0.97	1.159*	1.07	1.092	0.97	1.159*	1.07	1.092	0.97
ARDI-Z	1.108*	0.988	1.252	0.775	1.183*	0.921	1	0.86**	1.14**	0.95	1.161	0.795
ARDI-CLVF, HWI	1.201**	1.146	1.162	1.026	1.201**	1.146	1.162	1.026	1.201**	1.146	1.162	1.026
ARDI-CLVF-Z, HWI	1.126**	0.974	1.349	0.706**	1.163*	1.002	1.039	0.919	1.126**	0.941	1.255	0.709**
ARDI-CLVF, CLAIMS	1.442*	2.013	1.062	1.049	1.442*	2.013	1.062	1.049	1.442*	2.013	1.062	1.049
ARDI-CLVF-Z, CLAIMS	1.314	1.746	1.323**	0.692**	1.415	1.928	0.94	0.961	1.324	1.753	1.225**	0.692**
ARDI-MICH, HWI	1.198*	1.087	1.155	0.956	1.198*	1.087	1.155	0.956	1.198*	1.087	1.155	0.956
ARDI-MICH-Z, HWI	1.153**	0.995	1.338	0.691***	1.179*	0.985	1.09	0.846**	1.155**	0.968	1.257	0.692***
ARDI-MICH, CLAIIMS	1.373*	1.721	1.061	1.009	1.373*	1.721	1.061	1.009	1.373*	1.721	1.061	1.009
ARDI-MICH-Z, CLAIMS	1.258**	1.412	1.269**	0.68***	1.343*	1.602	0.97	0.912	1.259**	1.401	1.165**	0.686***
ARDI-CLVF	1.204	1.093	1.028	1.039	1.204	1.093	1.028	1.039	1.204	1.093	1.028	1.039
ARDI-CLVF-Z	1.106**	0.889	1.271	0.699**	1.16	0.922	0.914	0.915	1.106**	0.851	1.169	0.7**
ARDI-MICH	1.195*	1.018	1.027	0.98	1.195*	1.018	1.027	0.98	1.195*	1.018	1.027	0.98
ARDI-MICH-Z	1.131**	0.889	1.252	0.689***	1.171	0.886	0.972	0.853**	1.132**	0.855	1.163	0.688***
↓MSE with Z: %	79	100	0	100	93	100	100	100	71	100	7	100
↓MSE with Z: #	11	14	0	14	13	14	14	14	10	14	1	14

Note: This table shows out-of-sample predictive performance of various models augmented by GT and WSJ. The group of Augmented ARs is given by equation (16) where π_t is the year-over-year CPI inflation. The second group consists of NKPC-type models as in equation (17). The final group is made of "hybrid" NKPC models defined in (18). The full *out-of-sample period is 2007M06 - 2022M03, >2020 represent the subsample since 2020, while <q10 and >q90 are defined as before. 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 39: Pseudo-out-of-sample prediction of CPI inflation 3 months ahead

Models	Z_t = GT				Z_t = WSJ				Z_t = GT / WSJ			
	Full	>2020	<q10	>q90	Full	>2020	<q10	>q90	Full	>2020	<q10	>q90
AR (MSE)	1,258	1,629	1,949	2,048	1,258	1,629	1,949	2,048	1,258	1,629	1,949	2,048
Augmented ARs												
AR-Z	**0.997**	**0.826**	1.089	0.74***	**0.99**	0.856	1.033	0.927	1.008	**0.796**	1.127	0.747**
AR, HWI	1.002	0.987	1.022**	0.978	1.002	0.987	1.022**	0.978	1.002	0.987	1.022**	0.978
AR-Z, HWI	0.989	0.828	1.085**	0.727***	0.996	0.854	1.06*	0.919	**0.999**	0.798	1.12*	0.738**
AR, CLAIMS	2.285	4.168	1.924	0.987***	2.285	4.168	1.924	0.987***	2.285	4.168	1.924	0.987***
AR-Z, CLAIMS	2.233	4.13	1.798	0.764**	2.225	3.988	1.932	0.898	2.173	3.975	1.766	0.76**
NKPC-												
CLVF, HWI	1.078	1.092**	1.263	1.045	1.078	1.092**	1.263	1.045	1.078	1.092**	1.263	1.045
CLVF-Z, HWI	1.023	0.901	1.244	0.771**	1.069	0.95	1.313	0.96	1.029	0.869	1.271	0.775*
CLVF, CLAIMS	2.135	3.807	1.897	1.04	2.135	3.807	1.897	1.04	2.135	3.807	1.897	1.04
CLVF-Z, CLAIMS	2.06	3.751	1.684	0.789**	2.066	3.602	1.904	0.934	1.997	3.584	1.659	0.781*
MICH, HWI	1.024	0.956	1.008	0.931*	1.024	0.956	**1.008**	0.931*	1.024	0.956	**1.008**	0.931*
MICH-Z, HWI	1.007	0.836	1.068*	**0.717*****	1.028	**0.844**	1.075**	0.891	1.02	0.805	1.124	**0.72****
NKPC-MICH, CLAIMS	2.461	4.527	2.155	0.874***	2.461	4.527	2.155	**0.874*****	2.461	4.527	2.155	0.874***
NKPC-MICH-Z, CLAIMS	2.441	4.56	1.941	0.759**	2.41	4.393	2.009	0.876	2.373	4.389	1.905	0.754**
Data-rich NKPC-												
ARDI	1.232	1.54	1.295	1.079	1.232	1.54	1.295	1.079	1.232	1.54	1.295	1.079
ARDI-Z	1.122	1.458	1.002	0.826	1.194	1.395	1.344	0.992	1.108	1.375	1.047	0.843
ARDI-CLVF, HWI	1.309	1.555	1.505	1.111	1.309	1.555	1.505	1.111	1.309	1.555	1.505	1.111
ARDI-CLVF-Z, HWI	1.162	1.475	1.088	0.856	1.267	1.412	1.556	1.027	1.152	1.39	1.148***	0.871
ARDI-CLVF, CLAIMS	1.793	2.897	1.704	1.095	1.793	2.897	1.704	1.095	1.793	2.897	1.704	1.095
ARDI-CLVF-Z, CLAIMS	1.642	2.732	1.298	0.871	1.757	2.77	1.758	0.998	1.639	2.701	1.366	0.868
ARDI-MICH, HWI	1.212	1.482	1.154	1.025	1.212	1.482	1.154	1.025	1.212	1.482	1.154	1.025
ARDI-MICH-Z, HWI	1.129	1.434	0.987	0.804*	1.182	1.373	1.204	0.971	1.121	1.358	1.044	0.808
ARDI-MICH, CLAIMS	1.582	2.487	1.38	1.014	1.582	2.487	1.38	1.014	1.582	2.487	1.38	1.014
ARDI-MICH-Z, CLAIMS	1.518	2.439	1.252	0.831	1.547	2.337	1.444	0.94	1.508	2.376	1.307	0.818
ARDI-CLVF	1.302	1.582	1.492	1.107	1.302	1.582	1.492	1.107	1.302	1.582	1.492	1.107
ARDI-CLVF-Z	1.151	1.49	1.027	0.842	1.257	1.432	1.536	1.007	1.14	1.407	1.089	0.854
ARDI-MICH	1.208	1.509	1.117	1.034	1.208	1.509	1.117	1.034	1.208	1.509	1.117	1.034
ARDI-MICH-Z	1.122	1.449	**0.95**	0.81*	1.177	1.397	1.172	0.967	1.115	1.375	1.011	0.81
↓MSE with Z: %	100	93	79	100	93	100	7	93	93	100	71	100
↓MSE with Z: #	14	13	11	14	13	14	1	13	13	14	10	14

Note: This table shows out-of-sample 3-month ahead predictive performance of various models augmented by GT and WSJ. The group of Augmented ARs is given by equation (16) where π_{t+3} is the year-over-year CPI inflation. The second group consists of NKPC-type models as in equation (17). The final group is made of "hybrid" NKPC models defined in (18). The full *out-of-sample period is 2007M06 - 2022M03, >2020 represent the subsample since 2020, while <q10 and >q90 are defined as before. 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 40: Pseudo-out-of-sample prediction of PCE inflation

	Z_t = GT				Z_t = WSJ				Z_t = GT / WSJ			
Models	Full	>2020	<q10	>q90	Full	>2020	<q10	>q90	Full	>2020	<q10	>q90
AR (MSE)	0,303	0,367	0,394	0,377	0,303	0,367	0,394	0,377	0,303	0,367	0,394	0,377
Augmented ARs												
AR-Z	**1.026**	**0.881****	1.133**	0.746**	**0.988**	**0.916****	1.009	0.884**	**1.032**	**0.879***	1.124	**0.75****
AR, HWI	1.034*	1.098	1.182*	0.962*	1.034*	1.098	1.182*	0.962*	1.034*	1.098	1.182*	0.962*
AR-Z, HWI	1.053	0.99	1.253**	0.745**	1.026	1.023	1.182	**0.857****	1.059	0.988	1.242**	**0.75****
AR, CLAIMS	1.145	1.496	0.902	0.989	1.145	1.496	0.902	0.989	1.145	1.496	0.902	0.989
AR-Z, CLAIMS	1.151	1.431	0.924	**0.741****	1.133	1.41	0.856	0.915	1.149	1.395	0.874	0.752**
NKPC-												
CLVF, HWI	1.049	1.152*	1.123	1.009	1.049	1.152*	1.123	1.009	1.049	1.152*	1.123	1.009
CLVF-Z, HWI	1.06	1.02	1.136	0.763**	1.035	1.069	1.09	0.896*	1.063	1.018	1.097	0.764**
CLVF, CLAIMS	1.153	1.51	0.988	1.014	1.153	1.51	0.988	1.014	1.153	1.51	0.988	1.014
CLVF-Z, CLAIMS	1.155	1.432	1.04	0.752**	1.139	1.419	0.933	0.934	1.152	1.395	0.982	0.761**
MICH, HWI	1.06**	1.106	1.19*	1.018	1.06**	1.106	1.19*	1.018	1.06**	1.106	1.19*	1.018
MICH-Z, HWI	1.073**	1.01	1.273***	0.839*	1.052	1.042	1.189	0.92	1.08**	1.011	1.268**	0.838
MICH, CLAIMS	1.168	1.494	**0.899**	1.057	1.168	1.494	0.899	1.057	1.168	1.494	0.899	1.057
MICH-Z, CLAIMS	1.162	1.393	0.93	0.831*	1.148	1.376	**0.845**	0.992	1.156	1.339	**0.871**	0.843
Data-rich NKPC-												
ARDI	1.179	1.326	1.435	1.013	1.179	1.326	1.435	1.013	1.179	1.326	1.435	1.013
ARDI-Z	1.161	1.282	1.488	0.871	1.197*	1.222	1.337	0.925	1.178*	1.233	1.391	0.888
ARDI-CLVF, HWI	1.221*	1.398	1.553	1.031	1.221*	1.398	1.553	1.031	1.221*	1.398	1.553	1.031
ARDI-CLVF-Z, HWI	1.191	1.336	1.644	0.801	1.19*	1.302	1.455	0.936	1.184*	1.296	1.557	0.805
ARDI-CLVF, CLAIMS	1.367*	1.82	1.286	1.07	1.367*	1.82	1.286	1.07	1.367*	1.82	1.286	1.07
ARDI-CLVF-Z, CLAIMS	1.308*	1.709	1.455*	0.789*	1.353*	1.773	1.182	0.995	1.318*	1.717	1.352*	0.789*
ARDI-MICH, HWI	1.224*	1.369	1.531	0.998	1.224*	1.369	1.531	0.998	1.224*	1.369	1.531	0.998
ARDI-MICH-Z, HWI	1.207*	1.338	1.605	0.774**	1.207*	1.296	1.462	0.89	1.202*	1.304	1.522	0.772**
ARDI-MICH, CLAIMS	1.288**	1.495	1.24	1.079	1.288**	1.495	1.24	1.079	1.288**	1.495	1.24	1.079
ARDI-MICH-Z, CLAIMS	1.228***	1.342	1.337*	0.77**	1.264**	1.394	1.138	0.984	1.227***	1.321	1.221	0.772**
ARDI-CLVF	1.216*	1.347	1.438	1.06	1.216*	1.347	1.438	1.06	1.216*	1.347	1.438	1.06
ARDI-CLVF-Z	1.17	1.265	1.554	0.798*	1.178	1.233	1.333	0.946	1.162	1.221	1.454	0.801
ARDI-MICH	1.213*	1.307	1.419	1.035	1.213*	1.307	1.419	1.035	1.213*	1.307	1.419	1.035
ARDI-MICH-Z	1.183*	1.254	1.504	0.775**	1.189	1.212	1.343	0.908	1.177*	1.212	1.408	0.771**
↓MSE with Z: %	57	100	0	100	93	100	86	100	64	100	57	100
↓MSE with Z: #	8	14	0	14	13	14	12	14	9	14	8	14

Note: This table shows out-of-sample predictive performance of various models augmented by GT and WSJ as in the Table 12, except that the target variable is the year-over-year PCE inflation.

Table 41: Pseudo-out-of-sample prediction of PCE inflation: 3 months ahead

Models	Z_t = GT				Z_t = WSJ				Z_t = GT / WSJ			
	Full	>2020	<q10	>q90	Full	>2020	<q10	>q90	Full	>2020	<q10	>q90
AR (MSE)	0,948	1,39	1,38	1,373	0,948	1,39	1,38	1,373	0,948	1,39	1,38	1,373
Augmented ARs												
AR-Z	1.035	**0.899**	1.094	0.809**	1.013	**0.887**	**1.02**	0.935	1.05	**0.874**	1.122	0.803**
AR, HWI	**1.005**	1.026	1.028***	0.994	**1.005**	1.026	1.028***	0.994	**1.005**	1.026	1.028***	0.994
AR-Z, HWI	1.031	0.934	1.108	0.807**	1.018	0.918	1.055**	0.936	1.043	0.906	1.134	0.803*
AR, CLAIMS	2.424	4.851	2.13	0.996	2.424	4.851	2.13	0.996	2.424	4.851	2.13	0.996
AR-Z, CLAIMS	2.386	4.824	2.028	0.83**	2.392	4.742	2.139	0.921	2.342	4.706	2	0.817*
NKPC-												
CLVF, HWI	1.082	1.127**	1.186	1.058*	1.082	1.127**	1.186	1.058*	1.082	1.127**	1.186	1.058*
CLVF-Z, HWI	1.074	1.014	1.208	0.856	1.088	1.014	1.226	0.98	1.079	0.986	1.237	0.847
CLVF, CLAIMS	2.411	4.788	2.158	1.049	2.411	4.788	2.158	1.049	2.411	4.788	2.158	1.049
CLVF-Z, CLAIMS	2.362	4.757	2.025	0.863	2.374	4.667	2.171	0.96	2.314	4.631	2	0.848
MICH, HWI	1.03*	1.014	1.061*	0.961*	1.03*	1.014	1.061*	0.961*	1.03*	1.014	1.061*	0.961*
MICH-Z, HWI	1.043	0.943	1.12	**0.802****	1.044	0.917	1.11*	0.917	1.058	0.913	1.165	**0.791****
MICH, CLAIMS	2.582	5.192	2.411	0.916***	2.582	5.192	2.411	0.916***	2.582	5.192	2.411	0.916***
MICH-Z, CLAIMS	2.577	5.24	2.162	0.826**	2.537	5.069	2.212	**0.908**	2.517	5.087	2.124	0.813*
Data-rich NKPC-												
ARDI	1.225	1.756	1.308	1.092	1.225	1.756	1.308	1.092	1.225	1.756	1.308	1.092
ARDI-Z	1.135	1.699	0.996	0.881*	1.201	1.654	1.358	1.014	1.121	1.627	1.047	0.881
ARDI-CLVF, HWI	1.305	1.817	1.447	1.124	1.305	1.817	1.447	1.124	1.305	1.817	1.447	1.124
ARDI-CLVF-Z, HWI	1.189	1.77	1.092	0.921	1.276	1.718	1.505	1.053	1.177	1.695	1.151	0.924
ARDI-CLVF, CLAIMS	1.99	3.709	1.848	1.106	1.99	3.709	1.848	1.106	1.99	3.709	1.848	1.106
ARDI-CLVF-Z, CLAIMS	1.905	3.663	1.557	0.924	1.979	3.661	1.904	1.023	1.917	3.678	1.625	0.913
ARDI-MICH, HWI	1.229	1.752	1.174**	1.049	1.229	1.752	1.174**	1.049	1.229	1.752	1.174**	1.049
ARDI-MICH-Z, HWI	1.157	1.715	0.937	0.866*	1.205	1.667	1.23**	0.999	1.142	1.643	0.974	0.858
ARDI-MICH, CLAIMS	1.707	3.08	1.498	1.036	1.707	3.08	1.498	1.036	1.707	3.08	1.498	1.036
ARDI-MICH-Z, CLAIMS	1.697	3.161	1.355	0.876*	1.68	2.967	1.557*	0.97	1.688	3.12	1.401	0.858
ARDI-CLVF	1.303	1.837	1.448	1.112	1.303	1.837	1.448	1.112	1.303	1.837	1.448	1.112
ARDI-CLVF-Z	1.181	1.781	1.048	0.899	1.272	1.736	1.5	1.024	1.17	1.71	1.11***	0.896
ARDI-MICH	1.229	1.776	1.153**	1.047	1.229	1.776	1.153**	1.047	1.229	1.776	1.153**	1.047
ARDI-MICH-Z	1.152	1.729	**0.899**	0.86*	1.205	1.691	1.213**	0.983	1.139	1.661	**0.938**	0.845*
↓MSE with Z: %	79	86	71	100	71	100	7	100	79	93	71	100
↓MSE with Z: #	11	12	10	14	10	14	1	14	11	13	10	14

Note: This table shows out-of-sample predictive performance of various models augmented by GT and WSJ as in the Table 39, except that the target variable is the year-over-year PCE inflation.

Table 42: Pseudo-out-of-sample prediction of Core CPI inflation

	Z_t = GT				Z_t = WSJ				Z_t = GT / WSJ			
Models	Full	>2020	<q10	>q90	Full	>2020	<q10	>q90	Full	>2020	<q10	>q90
AR (MSE)	0,167	0,355	0,118	0,384	0,167	0,355	0,118	0,384	0,167	0,355	0,118	0,384
Augmented ARs												
AR-Z	0.958*	0.928**	0.985	0.916**	0.966	0.945**	1.057	0.936*	0.954	0.918**	1.078	0.906*
AR, HWI	1.003	1.003	1.366	0.979	1.003	1.003	1.366	0.979	1.003	1.003	1.366	0.979
AR-Z, HWI	0.966	0.934	1.348	**0.896****	0.976	0.957	1.396	0.923*	0.965	0.928	1.407	**0.891***
AR, CLAIMS	0.977	0.958	1.148	1.006	0.977	0.958	1.148	1.006	0.977	0.958	1.148	1.006
AR-Z, CLAIMS	**0.931**	**0.874***	1.132	0.912**	0.956	0.914	1.141	0.949	**0.938**	**0.873***	1.135	0.91*
NKPC-												
CLVF, HWI	1.01	1.008	1.39	0.985	1.01	1.008	1.39	0.985	1.01	1.008	1.39	0.985
CLVF-Z, HWI	0.974	0.938	1.369	0.902**	0.983	0.96	1.409	0.927*	0.972	0.932	1.418	0.896*
CLVF, CLAIMS	0.985	0.964	1.137	1.005	0.985	0.964	1.137	1.005	0.985	0.964	1.137	1.005
CLVF-Z, CLAIMS	0.941	0.881*	1.136	0.915*	0.963	0.918	1.157	0.949	0.948	0.88*	1.142	0.914
MICH, HWI	0.995	0.987	1.396	0.967	0.995	0.987	1.396	0.967	0.995	0.987	1.396	0.967
MICH-Z, HWI	0.97	0.934	1.383	0.903*	0.976	0.955	1.443	0.926*	0.968	0.929	1.444	0.896*
MICH, CLAIMS	0.973	0.946	1.135	0.992	0.973	0.946	1.135	0.992	0.973	0.946	1.135	0.992
MICH-Z, CLAIMS	0.936	0.875*	1.133	0.914*	**0.955**	**0.911**	1.145	0.95	0.94	0.874*	1.143	0.914*
Data-rich NKPC-												
ARDI	1.077	1.103	1.98	1.009	1.077	1.103	1.98	1.009	1.077	1.103	1.98	1.009
ARDI-Z	1.064	1.057	2.08	0.942	1.053	1.054	1.955	0.954*	1.068	1.048	2.058	0.944
ARDI-CLVF, HWI	1.045	1.047	1.746	0.973	1.045	1.047	1.746	0.973	1.045	1.047	1.746	0.973
ARDI-CLVF-Z, HWI	1.022	0.997	1.843	0.902**	1.026	1.007	1.775	0.924**	1.024	0.99	1.87	0.898**
ARDI-CLVF, CLAIMS	1.164	1.218	0.98	1.007	1.164	1.218	0.98	1.007	1.164	1.218	0.98	1.007
ARDI-CLVF-Z, CLAIMS	1.148	1.182	0.992	0.918**	1.137	1.165	0.978	0.955*	1.142	1.159	0.992	0.92*
ARDI-MICH, HWI	1.016	1.003	1.64	0.948	1.016	1.003	1.64	0.948	1.016	1.003	1.64	0.948
ARDI-MICH-Z, HWI	1.008	0.973	1.721	0.901**	1.003	0.982	1.687	**0.919****	1.005	0.969	1.76	0.897**
ARDI-MICH, CLAIMS	1.141	1.185	**0.949**	0.993	1.141	1.185	0.949	0.993	1.141	1.185	**0.949**	0.993
ARDI-MICH-Z, CLAIMS	1.13	1.154	0.96	0.922**	1.118	1.15	**0.941**	0.96*	1.119	1.138	0.956	0.923**
ARDI-CLVF	1.081	1.103	1.958	1.014	1.081	1.103	1.958	1.014	1.081	1.103	1.958	1.014
ARDI-CLVF-Z	1.047	1.043	2.054	0.927**	1.049	1.051	1.978	0.952*	1.042	1.031	2.071	0.92*
ARDI-MICH	1.056	1.065	1.884	0.988	1.056	1.065	1.884	0.988	1.056	1.065	1.884	0.988
ARDI-MICH-Z	1.038	1.026	1.968	0.926**	1.033	1.033	1.918	0.947**	1.03	1.018	1.995	0.919**
↓MSE with Z: %	100	100	50	100	100	100	29	100	100	100	7	100
↓MSE with Z: #	14	14	7	14	14	14	4	14	14	14	1	14

Note: This table shows out-of-sample predictive performance of various models augmented by GT and WSJ. The group of Augmented ARs is given by equation (16) where π_t is the year-over-year Core CPI inflation. The second group consists of NKPC-type models as in equation (17). The final group is made of "hybrid" NKPC models defined in (18). The full *out-of-sample period is 2007M06 - 2022M03, >2020 represent the subsample since 2020, while <q10 and >q90 are defined as before. 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 43: Pseudo-out-of-sample prediction of Core CPI inflation 3 months ahead

Models	Z_t = GT				Z_t = WSJ				Z_t = GT / WSJ			
	Full	>2020	<q10	>q90	Full	>2020	<q10	>q90	Full	>2020	<q10	>q90
AR (MSE)	0,496	1,14	0,518	1,333	0,496	1,14	0,518	1,333	0,496	1,14	0,518	1,333
Augmented ARs												
AR-Z	0.873	0.824	**0.972**	0.806	0.936	0.915	1.058	0.908	0.872	0.814	1.053	0.799
AR, HWI	0.981	0.975	1.001	0.974	0.981	0.975	1.001	0.974	0.981	0.975	1.001	0.974
AR-Z, HWI	**0.856**	**0.8**	0.976	**0.782**	**0.925**	0.897	1.07	0.891	**0.858**	**0.793**	1.054	**0.778**
AR, CLAIMS	1.02	1	1.013	1.001	1.02	1	1.013	1.001	1.02	1	1.013	1.001
AR-Z, CLAIMS	0.893	0.809	1.011	0.797	0.963	0.919	1.072	0.916	0.898	0.806	1.069	0.793
NKPC-												
CLVF, HWI	0.996	0.983	0.997	0.983	0.996	0.983	0.997	0.983	0.996	0.983	0.997	0.983
CLVF-Z, HWI	0.873	0.805	0.974	0.789	0.934	0.901	1.065	0.894	0.873	0.797	1.05	0.783
CLVF, CLAIMS	1.029	1.005	1.095	1.003	1.029	1.005	1.095	1.003	1.029	1.005	1.095	1.003
CLVF-Z, CLAIMS	0.9	0.816	1.141	0.798	0.971	0.927	1.219	0.913	0.906	0.815	1.216	0.793
MICH, HWI	0.964	0.95	0.986	0.95	0.964	0.95	**0.986**	0.95	0.964	0.95	**0.986**	0.95
MICH-Z, HWI	0.861	0.803	**0.972**	0.787	0.927	**0.892**	1.096	**0.887**	0.864	0.797	1.078	0.781
MICH, CLAIMS	1.004	0.966	1.035	0.964	1.004	0.966	1.035	0.964	1.004	0.966	1.035	0.964
MICH-Z, CLAIMS	0.897	0.813	1.02	0.801	0.959	0.915	1.095	0.913	0.892	0.809	1.1	0.795
Data-rich NKPC-												
ARDI	1.051	1.046	1.118	1.043	1.051	1.046	1.118	1.043	1.051	1.046	1.118	1.043
ARDI-Z	0.927	0.85	1.089	0.834*	0.996	0.969	1.161	0.961	0.925	0.844	1.134	0.829
ARDI-CLVF, HWI	1.036	1.017	1.177	1.005	1.036	1.017	1.177	1.005	1.036	1.017	1.177	1.005
ARDI-CLVF-Z, HWI	0.921	0.843	1.148	0.823*	0.987	0.949	1.225**	0.937	0.921	0.838	1.195*	0.822
ARDI-CLVF, CLAIMS	2.047	2.217	5.316	1.04	2.047	2.217	5.316	1.04	2.047	2.217	5.316	1.04
ARDI-CLVF-Z, CLAIMS	2.021	2.173	5.462	0.83*	1.999	2.156	5.264	0.963	2.009	2.152	5.418	0.83
ARDI-MICH, HWI	1	0.975	1.119	0.965	1	0.975	1.119	0.965	1	0.975	1.119	0.965
ARDI-MICH-Z, HWI	0.922	0.841	1.106	0.822*	0.974	0.94	1.199*	0.927*	0.917	0.84	1.181	0.821*
ARDI-MICH, CLAIMS	1.977	2.139	5.108	1.016	1.977	2.139	5.108	1.016	1.977	2.139	5.108	1.016
ARDI-MICH-Z, CLAIMS	1.966	2.108	5.251	0.838*	1.95	2.1	5.086	0.967	1.956	2.094	5.237	0.837*
ARDI-CLVF	1.061	1.046	1.149	1.043	1.061	1.046	1.149	1.043	1.061	1.046	1.149	1.043
ARDI-CLVF-Z	0.927	0.853	1.123	0.838	0.999	0.964	1.202*	0.958	0.925	0.844	1.171	0.832
ARDI-MICH	1.028	1.01	1.102	1.008	1.028	1.01	1.102	1.008	1.028	1.01	1.102	1.008
ARDI-MICH-Z	0.931	0.854	1.088	0.84*	0.991	0.962	1.184	0.954	0.923	0.85	1.164	0.835*
↓MSE with Z: %	100	100	79	100	100	100	14	100	100	100	0	100
↓MSE with Z: #	14	14	11	14	14	14	2	14	14	14	0	14

Note: This table shows out-of-sample 3-month ahead predictive performance of various models augmented by GT and WSJ. The group of Augmented ARs is given by equation (16) where π_{t+3} is the year-over-year Core CPI inflation. The second group consists of NKPC-type models as in equation (17). The final group is made of "hybrid" NKPC models defined in (18). The full *out-of-sample period is 2007M06 - 2022M03, >2020 represent the subsample since 2020, while <q10 and >q90 are defined as before. 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.*