Received: 2 November 2020 | Revised: 26 November 2022 | Accepted: 1 January 2023

DOI: 10.1002/jae.2960

WILEY Journal of APPLIED ECONOMETRICS

RESEARCH ARTICLE

Inattention and the impact of monetary policy

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Summary

We measure aggregate inattention as the common component in agents' inattentiveness to many economic variables. Applying this measure to the US Survey of Professional Forecasters enables us to establish the following empirical evidence. Professional forecasters update their information sets every 5 months on average but do so more frequently in response to high inflation and unemployment, as well as rising market volatility and policy uncertainty. Monetary policy shocks have larger real effects when the degree of inattention is higher. To explain our empirical findings, we propose a general equilibrium model with state-dependent information rigidity in both the production and household sectors.

KEYWORDS

inattentive firms, inattentive households, monetary policy, state dependence, sticky information

1 | INTRODUCTION

The current resurgence of interest in the expectation formation process builds upon a long tradition of research on imperfect information; see Mankiw and Reis (2010) and Gabaix (2019) for surveys. These frictions are important for explaining why economic agents may be inattentive to news and have divergent views. Despite a growing body of work on quantifying information frictions, it remains a great challenge in directly estimating the degree of inattention and exploring its impact on macroeconomic dynamics.

To address this challenge, we extend the Andrade and Le Bihan (2013) measure of inattention based on a single variable to multiple variables. A forecaster's inattention to an economic variable is the probability that the forecaster does not update the information on the variable in a given period. Aggregate inattention is defined as the common component in professional forecasters' inattentiveness to many economic variables. Applying this definition to the US Survey of Professional Forecasters (SPF) during 1970Q1–2021Q1, we find that these professionals update their information sets every 5 months on average. Inattention is highly pro-cyclical, as inattention declines (that is, attention rises) significantly during periods of recession, high inflation, and high market volatility. We then explore how state-dependent inattention alters the impact of monetary policy, finding that monetary policy shocks have much larger real effects when economic agents pay less attention.

To match these stylized facts, we develop a dynamic stochastic general equilibrium (DSGE) model with inattentive households and firms. This model mostly resembles a standard New Keynesian framework but with sticky information replacing sticky prices. Each period, only a fraction of households and firms update their information sets and make rational plans based on current information, whereas the remaining households and firms make their decisions based on outdated information. The key innovation of our model is to allow for inattention to be endogenous. Dotsey et al. (1999) build a framework for state-dependent price setting, and we modify their setup to an environment with state-dependent information processing.[1] Facing the fixed cost of collecting and processing information, households and firms in our model choose to update their information sets if and only if the benefit from updating exceeds that from not updating.

To our knowledge, this is the first paper applying Dotsey et al. (1999) for information frictions. This modeling strategy is simple, parsimonious, fast to compute and there is a data counterpart. We calibrate the model to the US economy. Our simulation results show that when information rigidity is higher, a monetary policy shock has a much larger impact on output. Furthermore, inattention in both production and household sectors matters. High levels of inattention among firms amplify the real impact of monetary policy. Inattentive households lead to delayed and weaker responses of output to monetary policy shocks. By incorporating both firm and household inattention, our model can match the data well, whereas a model with sticky prices and inattentive households fails to do so.[2]

Our paper builds on the literature that estimates information rigidity through survey data. One approach uses aggregate forecasts together with a set of auxiliary assumptions about the economy to estimate a structural parameter of information frictions (Coibion & Gorodnichenko, 2015; Mankiw et al., 2003).[3] Another approach explores the expectation formation process based on individual-level survey data (Andrade & Le Bihan, 2013; Dräger & Lamla, 2017; Giacomini et al., 2020).[4] Following the latter approach, we use micro data on forecast revisions to estimate inattention. We differ from these studies by defining information frictions in a multivariate context, rather than inattentiveness to a particular variable such as inflation. This is important because the univariate measurement would substantially over- or under-estimate the degree of information stickiness.

Taking advantage of the long sample period of the aggregate inattention measure during 1970Q1–2021Q1, we are able to analyze its potential determinants. We find that economic agents pay close attention during recessions, high inflation and unemployment, as well as rising market volatility and policy uncertainty episodes. This allows us to generalize the results that attention rises after large shocks such as the Great Recession (Andrade & Le Bihan, 2013), 9/11 (Coibion & Gorodnichenko, 2015), or natural disaster shocks (Baker et al., 2020), as well as to better understand the factors driving the variations of inattention over time.

Finally, our paper contributes to the vast literature on the transmission of monetary policy shocks. We show both empirically and theoretically that inattention, like nominal rigidities, amplifies the response of the economy to a given set of monetary policy shocks (Ball et al., 2005; Christiano et al., 2021; Mankiw & Reis, 2002; Reis, 2009).[5] What is not readily recognized in the literature is that the impact on output is larger with state-dependent inattention than with constant inattention. When economic agents pay less attention, monetary policy has larger real impacts. Because attention rises during recessions and periods of high uncertainty, our results provide a new explanation for why monetary shocks have less impact on output during these episodes (Aastveit et al., 2017; Afrouzi & Yang, 2021; Caggiano et al., 2014; Tenreyro & Thwaites, 2016).

The paper proceeds as follows. Section 2 proposes the measure of aggregate inattention, empirically estimates it using the US SPF dataset, explores the potential determinants of its variation, and studies how inattention affects the transmission of monetary policy. Section 3 outlines a general equilibrium model with inattentive firms and households with both constant and state-dependent inattention. Section 4 demonstrates, through calibration and simulation, how inattention

[1]Dotsey et al. (1999) is an important paper showing how to solve a menu cost model in a tractable general equilibrium. This model was used in other fields to obtain seminal results. For example, Thomas (2002) applies this modeling strategy to capital and shows for the first time the neutrality of microadjustment friction for aggregate capital dynamics.

[2]Rational inattention, proposed by Sims (2003), is an alternative framework to have endogenous information processing. Mackowiak and Wiederholt (2015) develop a DSGE model with rational inattention. Zhang (2017) considers a rational inattention model with volatility uncertainty and endogenous information formation, finding that firms optimally process more information when uncertainty rises. Afrouzi and Yang (2021) link monetary non-neutrality and the slope of the Phillips curve to inattention.

[3]Mankiw et al. (2003) find about 10 months of information frictions from the Livingston survey. Coibion and Gorodnichenko (2015) identify an information lag of 6 to 7 months using US SPF data.

[4]Andrade and Le Bihan (2013) find 4 months of inattentiveness using European Central Bank SPF data. Dräger and Lamla (2017) document more than 6 months of consumer inattentiveness using the Michigan Survey of Consumers. Giacomini et al. (2020) find that, on average, 40% to 50% of market participants update at least once a month. See also Fuhrer (2018), Bordalo et al. (2020) and Broer and Kohlhas (2022) that use individual data from the US SPF to study the role of cognitive limits in the expectation formation process.

[5]In response to the weakness of the New Keynesian model with sticky prices, Mankiw and Reis (2002) assume that a certain fraction of firms do not update their information sets periodically. They show that the New Keynesian model with sticky information generates results that are consistent with the empirical evidence on the effects of monetary policy on the economy. Ball et al. (2005) consider information stickiness in the price setting and study its implication for optimal monetary policy. Reis (2009) considers a more general information stickiness across firms, consumers, and workers, and studies the impact of sticky information on the response to monetary policy shocks and on the optimal targeting rules. Christiano et al. (2021) show that information rigidity is crucial for generating the delayed response of households' expenditures on durable and nondurable goods to monetary policy shocks.

alters the effect of monetary policy on economic dynamics, and provides a comparison between the model predictions and the empirical findings. Section 5 concludes. Additional empirical estimation results and theoretical analyses are relegated in the supporting information.

2 | MEASURING INATTENTION

This section starts with developing a new measure of inattention in a multivariate context. Applying this measure to surveys of professional forecasters and households, we explore the properties of aggregate inattention and study its role in amplifying the impact of monetary policy.

2.1 | A multivariate measure of inattention

We extend the Andrade and Le Bihan (2013)'s approach by going beyond whether or not agents revise a single variable to measure inattention based on forecast revisions of multiple variables. Specifically, let F^m_{ith} be the forecast made by individual i at time t, for the target variable m at h period ahead. Then an indicator function I_{ith} for forecast revision is defined as

$$I^m_{ith} = \begin{cases} 1 \text{ if } F^m_{ith} = F^m_{it-1,h+1}; \\ 0 \text{ otherwise.} \end{cases} \tag{1}$$

Using this indicator, we define forecasters' inattention to a single variable m as

$$IA^m_{th} = \frac{1}{N}\sum_{i=1}^{N} I^m_{ith}. \tag{2}$$

Then forecasters' aggregate inattention, IA_{th}, can be expressed as the averaged inattention across variables:

$$IA_{th} = \frac{1}{M}\sum_{m=1}^{M} IA^m_{th}. \tag{3}$$

The novel feature of this definition is that aggregate inattention is not equal to inattention to a single variable. Instead, it is a measure of the common variation in inattention to many series. This common variation is critical for the study of business cycles because imperfect information theories typically require the existence of inattention for economic agents, not their inattention to any single variable. As far as the underlying information processes of these economic variables have commonalities, professionals should have common time variations in information rigidities. Our inattention measurement complements the recent studies that emphasize the multivariate nature of expectation formation, such as Dovern (2015) and Andrade et al. (2016). This distinction is important because some univariate measurements would substantially over or underestimate the degree of agents' information stickiness.

Ideally, a measure of attentiveness should directly measure information updates. However, agents' information sets are not directly observable. Forecast revisions offer an observable proxy for information updates. In line with the literature, we interpret no forecast revision as no update to the information set. As such, our measure of inattention is subject to some important caveats.[6]

[6]First of all, it is possible that a forecaster updates information set and nevertheless keeps prediction constant due to misreporting/rounding errors. This is an inherent limitation of using forecast revisions as a proxy for information updates. However, as discussed in Andrade and Le Bihan (2013), the new information is highly unlikely to lead to the same forecast. Another complication arises when professional forecasters are motivated to make small revisions due to strategic reasons, such as the “peer pressure” (Ehrbeck & Waldmann, 1996) and reputation (Giacomini et al., 2022). This is less of a concern, because the forecasters in our surveys are anonymous. A third concern arises when using the unbalanced panel in the survey to measure inattention. To explore the possibility that more attentive forecasters are added to the survey during recessions, we regress the number of forecasters, the forecasters who enter the survey, or the forecasters who exit from the survey on recession dummies. None of the coefficients on recession are significant. Thus, we can safely rule out the possibility of forecaster selection bias, and the compositional changes in the SPF do not have any meaningful impact on our inattention measure. Finally, it is possible that a forecaster revises forecasts for some variables but not for all. The intuition is straightforward. Some variables are easier to predict, or they matter more to economic agents than others. As such, the expected loss of not revising forecasts, and hence, forecasters' inattention varies across variables. Our measure of aggregate inattention captures the common component but ignores the idiosyncratic component in attention across many variables. We leave it to future research to address this limitation.

TABLE 1 Summary statistics of inattention estimates.

Horizon	AGGR	RGDP	PGDP	U	CPROF	IP	HOU
4Q ahead	0.36	0.49	0.62	0.20	0.19	0.45	0.21
	(0.12)	(0.21)	(0.20)	(0.13)	(0.12)	(0.17)	(0.10)
3Q ahead	0.34	0.46	0.62	0.20	0.18	0.43	0.19
	(0.11)	(0.22)	(0.20)	(0.13)	(0.11)	(0.16)	(0.10)
2Q ahead	0.30	0.41	0.58	0.19	0.17	0.38	0.14
	(0.10)	(0.22)	(0.20)	(0.10)	(0.12)	(0.16)	(0.09)
1Q ahead	0.23	0.28	0.46	0.19	0.13	0.26	0.04
	(0.08)	(0.18)	(0.19)	(0.13)	(0.10)	(0.14)	(0.05)

Note: Aggregate inattention (AGGR) is constructed based on Equation (3), which is the average of inattention to each of six macroeconomic variables: real GDP growth (RGDP), GDP deflator inflation (PGDP), unemployment rate (U), corporate profits after tax (CPROF), industrial production (IP) and housing starts (HOU). Inattention to each individual variable is defined in Equation (2) as the proportion of forecasters who do not revise their forecasts of such a target variable. Standard deviations of aggregate inattention are reported in parentheses. Survey data come from the US SPF from the first quarter of 1970 to the first quarter of 2021.

2.2 | Professionals update their information every 5 months on average

Our main dataset comes from the US Survey of Professional Forecasters (SPF), provided by the Federal Reserve Bank of Philadelphia. Survey data on professionals fit the study of information rigidity due to a variety of strengths. Professional forecasters have access to a wide range of macroeconomic news and data, and they have a comparative advantage in allocating resources to process the news, relative to other economic agents. Furthermore, Carroll (2003) describes how the expectations of professionals affect households via news media. Due to these characteristics, inattention of professional forecasters is expected to be the lowest, and consequently, represents conservative estimates of inattention for firms.[7]

The SPF survey is anonymous, and each survey participant is assigned a unique identification number. According to Engelberg et al. (2011), the Federal Reserve Bank of Philadelphia must decide, based on judgment, whether a particular identification number should follow a forecaster when she changes employer. The number of respondents is about 26 before 1991 and 36 afterward on average. Respondents are typically banks, securities firms, econometric modelers, industrial corporations, and independent forecasters. The survey panelists make fixed-horizon forecasts in the middle month of each quarter, with forecast horizons ranging from 1- to 4-quarter ahead. Our sample covers six variables, namely, real GDP growth, inflation (based on GDP deflator), unemployment rate, corporate profits after tax, industrial production and housing starts from the first quarter of 1970 to the first quarter of 2021. We use the forecast revisions from all respondents in our main analysis.

Table 1 provides summary statistics. At the 4-and 3-quarter ahead, about 36% of professionals do not revise their forecasts within a quarter, implying their overall inattentiveness of about 4–5 months on average.[8] Inattention varies across variables, ranging from 19% in forecasting after-tax corporate profits to 62% in forecasting GDP deflator inflation. Taking inflation as an example, one would conclude that professional forecasters update their information sets about 7–8 months on average. On the other hand, focusing on corporate profits alone would yield an inattention of only 3–4 months. These results support measuring inattention in a multivariate context because the univariate measurement would substantially overestimate or underestimate the degree of information stickiness.[9]

At 1- and 2-quarter ahead, more than 70% revise their forecasts at least once within a quarter, possibly due to the arrival of relevant information regarding the target variables in these short horizons. Despite these differences, professionals on average update their forecasts in about 3.9–4.3 months at 1- and 2-quarter ahead, compared with 4.5–4.7 months at 3- and

[7]Interestingly, Meyer and Sheng (2021) present the new evidence from the Atlanta Fed's business survey that firms' inflation expectations are similar to those of professional forecasters.

[8]Frequency of updating is calculated as $4.7 = 3/(1 - 0.36)$. Note that, in the quarterly SPF survey, respondents cannot revise more frequently than every 1 quarter. The survey frequency forms a lower bound for the degree of inattention; see also Binder (2017).

[9]Inattention at the forecaster level is significantly positively related to the corresponding forecast error, where the multivariate forecast errors are measured as the Mahalanobis distance between the vector of forecasts and the vector of actual values.

TABLE 2 Correlation between aggregate and variable-specific inattention.

	RGDP	PGDP	U	CPROF	IP	HOU	AGGR
Panel A. Unconditional correlation							
RGDP	1						
PGDP	0.73	1					
U	0.43	0.41	1				
CPROF	0.53	0.52	0.33	1			
IP	0.57	0.51	0.39	0.47	1		
HOUSING	0.39	0.36	0.26	0.28	0.33	1	
AGGR	0.88	0.85	0.62	0.69	0.76	0.54	1
Panel B. Conditional correlations							
			Probability of updating				
Given revising							
RGDP	1	0.49	0.91	0.85	0.62	0.82	
PGDP	0.60	1	0.91	0.85	0.63	0.83	
U	0.50	0.37	1	0.83	0.56	0.81	
CPROF	0.57	0.41	0.83	1	0.59	0.83	
IP	0.60	0.42	0.83	0.87	1	0.83	
HOUSING	0.52	0.38	0.81	0.84	0.57	1	

Note: This table shows unconditional and conditional correlations between aggregate (AGGR) and variable-specific inattention. Aggregate inattention is constructed based on Equation (3), which is the average of inattention to each of six macroeconomic variables: real GDP growth (RGDP), GDP deflator inflation (PGDP), unemployment rate (U), corporate profits after tax (CPROF), industrial production (IP) and housing starts (HOU). Inattention to each variable is defined in Equation (2) as the proportion of forecasters who do not revise their forecasts of such a target variable. Conditional correlations are calculated using Equation (1). Survey data come from the US SPF from the first quarter of 1970 to the first quarter of 2021.

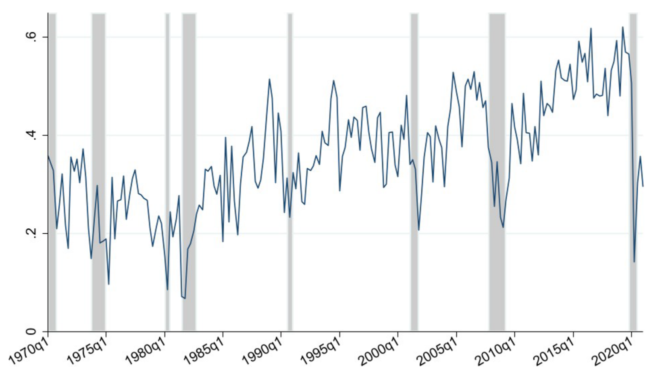

FIGURE 1 Aggregate inattention. *Note*: This figure plots quarterly aggregate inattention from the first quarter of 1970 to the first quarter of 2021. It is constructed based on Equation (3), which is the average of inattention to the six individual variables: real GDP growth, GDP deflator inflation, unemployment rate, corporate profits after tax, industrial production and housing starts. Inattention to each individual variable is defined in Equation (2) as the proportion of forecasters who do not revise their forecasts of such a target variable. The baseline inattention measure is based on 4-quarter ahead forecasts from the US SPF. The shaded areas represent NBER designated recessions.

4-quarter ahead. And, the estimated degrees of inattention are highly correlated across the four different horizons.[10] For these reasons, we focus on aggregate inattention at 4-quarter ahead in our analysis below.

The degrees of inattention across variables are imperfectly correlated, as shown in Table 2, and the correlation between inflation and real GDP is the highest (panel A). The movement in aggregate inattention is not driven by inattention to any single variable; see Figure A.2 in the supporting information. In particular, the correlations between aggregate inattention and variable-specific inattention range from 0.54 for housing start to 0.88 for real GDP. Turning to conditional correlation (panel B), the probability of revising unemployment forecasts given the revision of GDP forecasts is 0.91. Similar results hold for the probability of revising unemployment forecasts given the revision of inflation forecasts. These results suggest that a substantial proportion of participants form expectations consistent with the Okun law and the Phillips curve; see also Dräger et al. (2016).

[10]Inattention at 4-quarter ahead is highly correlated with inattention at 3-quarter ahead (0.93), with inattention at 2-quarter ahead (0.89) and with inattention at 1-quarter ahead (0.81); see Table A.1 and Figure A.1. in the supporting information.

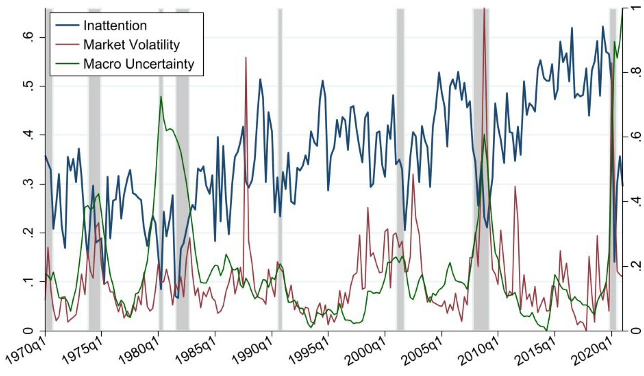

FIGURE 2 Inattention, market volatility, and macro uncertainty. *Note*: The figure plots inattention against stock market volatility, measured as the standard deviation of market return in the S&P 500 index within each quarter, and macro uncertainty proposed by Jurado et al. (2015). The shaded areas represent NBER designated recessions.

2.3 | Inattention is pro-cyclical

Inattention varies over time, as illustrated in Figure 1. Three points are worth noting. First, inattention shows substantial variations at multiple frequencies. Inattention not only changes a lot at quarterly intervals but also shows variations that last over several years. Second, inattention is pro-cyclical. Professionals pay close attention during recessions, especially during the 2007–2009 and the COVID-induced recessions. Third, the degree of inattention steadily increases after the Great Recession and remains elevated till 2019. To better understand this upward trend, note that both market volatility and macro uncertainty have been low since 2009 (Figure 2), and so professionals pay less attention. A similar trend is also observed from surveys of consumers, despite the fact that consumers are much more inattentive to macro conditions relative to professional forecasters; see Figure 3. According to the University of Michigan Surveys of Consumers, households update their information sets every 8 months on average. To sum up, our inattention measure is highly correlated with various uncertainty measures and co-moves with the business cycle. But inattention also exhibits independent variations due to information frictions and captures a novel dimension of macroeconomic salience—labeled as inattention shocks and explored further in the next section.[11]

Next, we examine what drives the fluctuations in inattention over time. According to the sticky information model, more volatile shocks lead to more frequent updating because inattention is more costly in a world that is rapidly changing. We observe a sharp decline of inattention during recessions. Other factors might also explain the dynamics of inattention. To assess the relative importance of potential determinants, we regress aggregate inattention on two groups of variables. The first group includes macroeconomic fundamentals and policy, such as output growth, inflation, unemployment rate, and monetary policy shock. The second group focuses on market volatility and uncertainty. Specifically, we include the volatility of the S&P 500 index, calculated as the standard deviation of daily returns for the period, to identify economic news reflected in market price changes. In periods of high market volatility, sticky information theory would imply that professional forecasters, especially those associated with financial institutions, are more attentive to new information. Similar to the expected negative association between financial market volatility and inattentiveness, higher policy and macro uncertainty may also motivate professionals to pay more attention to news. Accordingly, the next two variables in this block are the policy uncertainty by Baker et al. (2016) and macro uncertainty by Jurado et al. (2015). Finally, we include market returns, calculated as the log value of the end-of-period price over the end-of-previous-period price, as one would expect high inattentiveness in periods of high returns due to complacency.

Because the dependent variable is a fractional variable, we use the quasi-maximum likelihood method in Papke and Wooldridge (1996) to estimate the nonlinear model:

$$E(IA_t|\mathbf{X}_{t-1}) = G(\boldsymbol{\beta}\mathbf{X}_{t-1}) \tag{4}$$

[11]This result holds in a variety of robustness checks by (i) weighting the variable-specific inattention by the 10-year rolling window standard deviation of each target variable, (ii) including nine additional variables available in the SPF since 1981, (iii) measuring inattention as the proportion of forecasters who do not revise their forecasts of any target variables in real GDP growth, inflation or unemployment rate, (iv) restricting the analysis to regular forecasters who participated in the survey for at least 5 or 10 years, and (v) measuring inattention across financial versus non-financial sectors. See Figures A.3–A.7 in the supporting information.

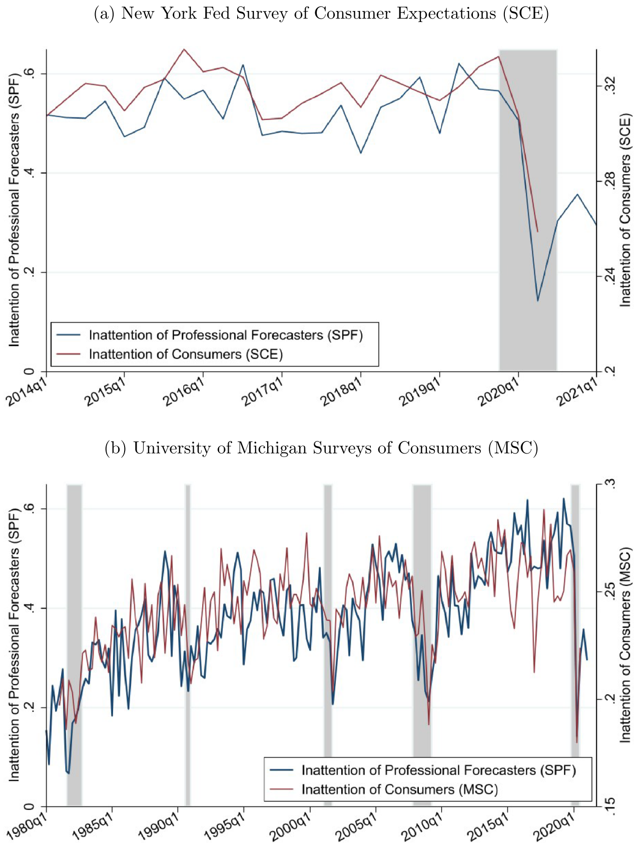

FIGURE 3 Inattention of professional forecasters and consumers. *Note*: The upper panel plots the inattention of consumers from 2014Q1 to 2021Q1, measured using the New York Fed's Survey of Consumer Expectations (SCE). Each month since 2013, the SCE reports 1-year ahead forecasts for 7 major variables (growth rate in price level, home price, earnings, household income, household spending, personal taxes and government debt) of 1300 consumers on average. Each consumer is associated with a unique ID number, based on which the forecast revisions can be calculated. SCE reports fixed-horizon forecasts; hence, each forecast revision overlaps 11 out of 12 months. Quarterly inattention is calculated as the averaged monthly inattention. The lower panel plots the inattention of consumers from 1980Q1 to 2021Q1, measured using the Michigan Survey of Consumers (MSC). Every month since January 1981, MSC reports 1-year ahead forecasts for 5 major variables (growth rate in price level and family income, if business conditions will be better or worse, if unemployment and interest rates will go up or down) of 500 consumers on average. Each consumer is associated with a unique ID number, based on which the forecast revisions can be calculated. The MSC reports fixed-horizon forecasts, and the rotating panel is taken semiannually. Hence, each forecast revision overlaps only 6 out of 12 months.

where $G(\cdot)$ is the logistic function. In Equation (4), IA_t denotes inattention at time t and is bounded between 0 and 1, $\mathbf{X}_{t-1}$ is a vector of lagged macroeconomic and financial market variables as discussed above. The correlations among these explanatory variables are modest, ranging from −0.49 to 0.46 at the quarterly frequency.

Table 3 presents the estimated marginal effects evaluated at the mean level of explanatory variables. Columns (1)-(3) study quarterly variations in the aggregate inattention series. High output growth is positively associated with inattention, but high inflation and unemployment are negatively related to inattention, confirming the idea that “bad” news decreases inattention. Jumps in policy uncertainty, macro uncertainty and market volatility significantly decrease inattention, consistent with the argument from sticky information theory that agents update their information more frequently in response to high volatility and uncertainty. The impact of market returns on inattention takes the expected positive sign, though not statistically significant. Inattention declines significantly during recessions, again pointing to the pro-cyclical nature of information rigidity.[12]

Columns (4)–(6) report the results with the four-quarter moving average of aggregate inattention as the dependent variable. Inattention tends to be low following expansionary monetary policy shocks, during recessions, and in episodes of high inflation, rising market volatility, policy and macro uncertainty. This allows us to generalize the results that inattention declines after large shocks such as the Great Recession (Andrade & Le Bihan, 2013), 9/11 (Coibion & Gorodnichenko, 2015), or natural disaster shocks (Baker et al., 2020), as well as to better understand the factors driving the variations of inattention over time. The next subsection explores the role of the dynamics of inattention in the transmission of monetary policy.

[12]In Tables A.2 and A.3 of the supporting information, we analyze the factors driving inattention to each of six variables, one at a time, including real GDP growth, inflation, unemployment rate, corporate profits after tax, industrial production and housing starts. We find that unemployment is a driver of the inattention not only to unemployment but also to inflation and housing starts. Similarly, inflation is also a driver of the inattention to real GDP growth, unemployment and industrial production. These results confirm the multivariate nature of expectation formation and support measuring inattention at the aggregate level.

TABLE 3 Sources of inattention.

	High frequency			Low frequency		
	(1)	(2)	(3)	(4)	(5)	(6)
Growth	0.231**		0.039	−0.073		−0.333***
	(0.097)		(0.093)	(0.087)		(0.097)
Inflation	−0.336***		−0.250**	−0.804***		−0.745***
	(0.130)		(0.105)	(0.092)		(0.105)
Unemployment	−0.063***		−0.040***	−0.015*		0.007
	(0.013)		(0.014)	(0.008)		(0.010)
MP Shock	−0.223		−0.016	−1.037***		−0.728***
	(0.145)		(0.167)	(0.226)		(0.212)
Volatility		−0.622***	−0.606***		0.147	−0.435*
		(0.209)	(0.220)		(0.249)	(0.264)
Return		0.013	−0.063		0.082	−0.112
		(0.150)	(0.152)		(0.207)	(0.166)
Policy U		−0.408*	−0.430		−0.581*	−0.588*
		(0.237)	(0.307)		(0.307)	(0.311)
Macro U		−2.114***	−1.690***		−2.204***	−1.092***
		(0.374)	(0.511)		(0.397)	(0.393)
Recession	−0.489***	−0.228***	−0.277***	−0.427***	−0.267***	−0.325***
	(0.086)	(0.074)	(0.082)	(0.058)	(0.083)	(0.067)
Pseudo R^2	0.69	0.73	0.75	0.65	0.70	0.69
Obs	200	205	200	200	202	200

Note: For columns (1)–(3), the dependent variable is the quarterly aggregate inattention series from the first quarter of 1970 to the first quarter of 2021. It is constructed based on Equation (3), which is the average of inattention to six individual variables. For columns (4) - (6), the dependent variable is the 4-quarter moving average of aggregate inattention. The monetary policy shock is from Bu et al. (2021), measured as 100 basis points decrease in their shock series. Stock market volatility is measured as the standard deviation of daily market return in the S&P 500 index within each quarter. Market returns are calculated as the log value of the end-of-period price over the end-of-previous-period price. Policy uncertainty is from Baker et al. (2016), and macro uncertainty is from Jurado et al. (2015). Recession, as designated by the NBER, is a dummy variable. All regressions control for the time trend. *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

2.4 | Inattention amplifies the impact of monetary policy

We empirically investigate how inattention alters the impact of monetary policy. To this end, we adopt the local projections method by Jordà (2005), specified as follows:

$$y_{t+h,t} = \beta_h MPS_t + \phi_h(L)z_{t-1} + \alpha_h + \varepsilon_{t+h} \quad \text{for} \quad h = 0, 1, 2, \ldots \tag{5}$$

where $y_{t+h,t}$ measures the cumulative cyclical component, through the Hamilton (2018)'s filter, of real GDP and CPI inflation. Our monetary policy shock series, MPS_t, comes from Bu et al. (2021), denoted as BRW hereafter. The BRW measure can be thought of as an average effect of Federal funds rate changes, forward guidance, and asset purchases following the FOMC meeting. Compared with the existing measures, the BRW shock series has a very mild data requirement to construct, covers a long sample period from 1972Q1 to 2019Q3, and is free of the Fed information effect. z_{t-1} is a vector of control variables, including lags of monetary policy shocks, cyclical components of real GDP and CPI inflation, commodity prices inflation, and change in excess bond premium. We include commodity prices to control for price puzzle (Christiano et al., 1996) and the excess bond premium in light of its ability to explain business cycles (Gilchrist & Zakrajšek, 2012). We estimate Equation (5) using the OLS method with Newey–West standard errors. The Akaike information criterion indicates two lags for the control variables. Figure 4 plots the impact of monetary policy shock (i.e., β_h) at each horizon h, together with 68% and 90% confidence intervals. Following an expansionary monetary policy shock, measured as 100 basis points decrease in the BRW shock series, output increases and reaches the peak in about a year. The response of inflation is significantly positive and persistent.

We now add inattention interacted with the monetary policy shock to an otherwise standard local projections model. As shown earlier, inattention tends to be low during episodes of high uncertainty and recessions. Furthermore, the transmission of monetary policy shocks is state dependent (Tenreyro & Thwaites, 2016), as well as affected by the level of

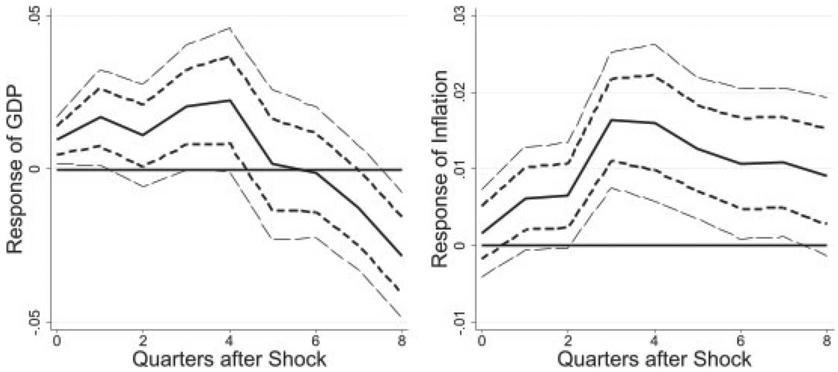

FIGURE 4 Impact of monetary policy. *Note*: This figure shows the impulse response of real GDP and inflation to an expansionary monetary policy shock, measured as 100 basis points decrease in the BRW monetary policy shock series. The impulse responses are estimated based on the sample period 1972Q1–2019Q3. The dashed and dotted lines indicate the 90% and 68% confidence intervals produced by the Newey–West method.

uncertainty (Aastveit et al., 2017; Pellegrino, 2021). To ensure that it is inattention, but not uncertainty, that alters the effect of monetary policy, we first regress inattention on a recession dummy and uncertainty measures, including both Baker et al. (2016)'s policy uncertainty and Jurado et al. (2015)'s macro uncertainty. We obtain the residual from this regression, denoted by I_t, and include it in the local projections model:

$$y_{t+h,t} = \beta_{a,h}MPS_t + \phi_{a,h}(L)z_{t-1} + \beta_{b,h}MPS_t * I_t + \phi_{b,h}(L)z_{t-1} * I_{t-1} + \gamma_h * I_t + \alpha_h + \varepsilon_{t+h}. \tag{6}$$

The coefficient $\beta_{b,h}$ measures the extent to which inattention alters the impact of monetary policy. After estimating Equation (6), we construct impulse response functions under different levels of inattention. Periods of high inattention are identified as the episodes in which inattention is above the 90th percentile and low inattention as those below the 10th percentile.

With high inattention, an expansionary monetary policy shock brings up real GDP, reaches its maximum impact in two quarters and its effect dies out in about five quarters (Figure 5). In contrast, monetary policy does not have a sizable real impact with low inattention. As further illustrated in the right panel of Figure 5, the differential responses of real GDP between high and low inattention scenarios are statistically significant and economically meaningful. The opposite results hold for inflation: monetary policy shocks have a larger and more persistent effect when inattention is lower. We perform a battery of robustness checks and find that our baseline results in Figure 5 still hold; see Appendix B in the supporting information.[13]

3 | QUANTITATIVE MODEL

In this section, we outline a quantitative model with sticky information to show that the effects of monetary policy on output depend on the level and cyclicality of inattention. The model mostly resembles a standard New Keynesian framework but with sticky information replacing sticky prices. The economy is populated by a continuum of infinitely-lived

[13]First, we follow Auerbach and Gorodnichenko (2012) and Ramey and Zubairy (2018) and estimate the smooth transition path between high and low inattention states as $G_t = exp(-\gamma I_t)/[1 + exp(-\gamma I_t)]$, where $\gamma = 1.5$ and I_t is the measure of inattention normalized to have zero mean and unit variance. With this specification, we allow the coefficients to vary with the levels of inattention. The results, reported in Figure B.1 in the supporting information, display the same pattern as our baseline. Second, related to the first exercise, we re-estimate the probability of high and low inattention using the Markov switching model and use the fitted smooth transition path to explore the effect of monetary policy shocks across two scenarios. Our main result on the differential real impacts of monetary policy between high versus low inattention still holds (Figure B.2 in the supporting information). Third, we define dummy variables for high, medium and low inattention scenarios, where the threshold values for high and low inattention are defined as above the 90th percentile and below the 10th percentile, respectively. Including these dummy variables and their interactions into the local projection specification yields the same results as our baseline (Figure B.3 in the supporting information). Fourth, as an alternative to the standard delta method, we follow Mertens and Ravn (2013) and Cloyne et al. (2020) to compute the confidence intervals using the bootstrap method. The confidence intervals now become slightly wider. Yet, the statistical significance still remains (Figure B.4 in the supporting information). Fifth, we augment Equation (6) by adding an additional interaction term of inattention and large monetary policy shocks, measured as those above the 90th percentile or below the 10th percentile of the BRW shock series. Inattention, like nominal rigidities, plays an even larger role in amplifying the real impact of large monetary policy shocks (Figure B.5 in the supporting information). Sixth, we experiment with the Romer and Romer (2004)'s monetary policy shocks during 1972Q1–2007Q4. The results, presented in Figure B.6 in the supporting information, are consistent with our baseline results for real GDP. For inflation, however, there is no significant difference between high and low inattention scenarios. Finally, we construct monthly inattention series from January 1990 to August 2020 using the Consensus Forecasts data and redo the estimation by replacing quarterly real GDP with monthly industrial production. As shown in Figure B.7 in the supporting information, high inattention still amplifies the real impact of monetary policy, though the differences across high and low inattention scenarios become less significant.

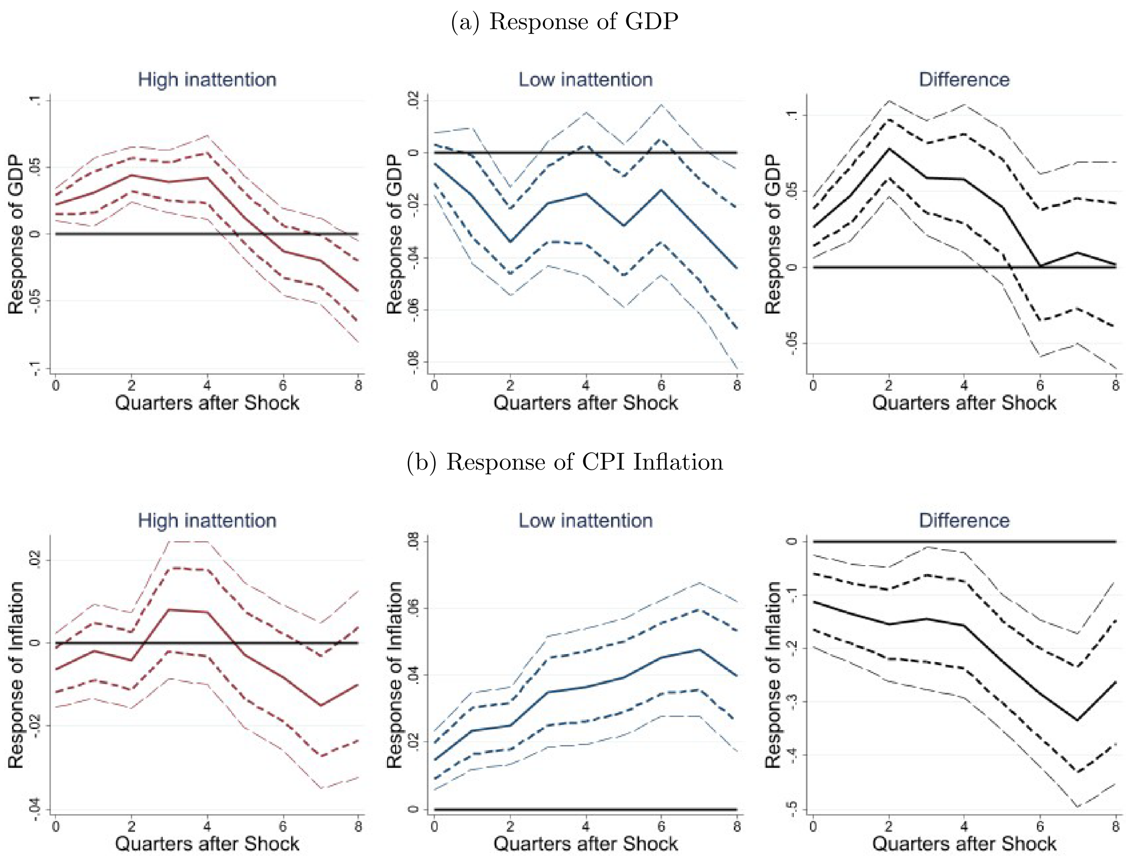

FIGURE 5 Inattention and the impact of monetary policy: Baseline result. *Note*: This figure shows the impulse response of real GDP and inflation to an expansionary monetary policy shock, measured as 100 basis points decrease in the BRW shock series. The impulse responses are estimated based on the sample period during 1972Q1–2019Q3. We identify high inattention as the top 10% of the inattention series, and low inattention as the bottom 10%. The dashed and dotted lines indicate the 90% and 68% confidence intervals constructed by the Newey–West method.

households, intermediate-good firms and final-good firms. Intermediate-good firms are monopolistically-competitive that produce differentiated products and sell them to final-good firms. Final-good firms operate in a perfectly competitive environment; they transform intermediate goods into final goods using a constant return to scale technology. Households and intermediate-good firms update their information sets in a staggered fashion.

In the first subsection, we assume that inattention is constant over the business cycle. We relax this assumption in the second subsection by allowing for endogenous information processing for both firms and households. This modeling strategy is motivated by our empirical evidence and builds on the frameworks of state-dependent price setting in Dotsey et al. (1999), Bakhshi et al. (2007) and Nakov and Thomas (2014).

3.1 | Constant sticky information

In this subsection, we consider the case with constant inattention both in the households and production sectors.

3.1.1 | Households

In each period t, household i derives utility from consumption ($c_{i,t}$), supplies labor ($n_{i,t}$) and holds bonds ($b_{i,t}$). Furthermore, only a fraction λ^h of households update their information sets each period. Therefore, in what follows, $(1-\lambda^h)$ measures the degree of household inattention. The problem of household i is then given by

$$\max_{\{b_{i,t},c_{i,t},n_{i,t}\}_{t=0}^{\infty}} \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left(\frac{c_{i,t}^{1-\sigma}}{1-\sigma} - \chi \frac{n_{i,t}^{1+\nu}}{1+\nu} \right) \tag{7}$$

with $\beta \in (0,1)$ being the subjective discount factor of the household, σ is the consumption curvature parameter, ν is the inverse of the labor supply elasticity, χ is the disutility-of-labor parameter and $\mathbb{E}_t$ is the expectations operator. Maximization is subject to the sequence of budget constraints (in real terms):

$$c_{i,t} + b_{i,t} = w_{i,t} n_{i,t} + \frac{R_{t-1} b_{i,t-1}}{\pi_t} \tag{8}$$

where $w_{i,t}$ is the real wage, R_t is the gross nominal interest rate on bonds and π_t is the gross inflation rate. Optimization over consumption, labor and bond holdings by a household with the most up-to-date information gives

$$c_{0,t}^{-\sigma} = \beta R_t \mathbb{E}_t \left(\frac{c_{0,t+1}^{-\sigma}}{\pi_{t+1}} \right) \tag{9}$$

$$\chi n_{0,t}^{\nu} c_{0,t}^{\sigma} = w_{0,t} \tag{10}$$

with equations (9)-(10) being the standard consumption Euler condition and the labor supply condition, respectively.

For the inattentive household who last updated information i period ago, the labor supply and Euler conditions read

$$c_{i,t}^{-\sigma} = \mathbb{E}_{t-i} \left(c_{0,t}^{-\sigma} \right) \tag{11}$$

$$\frac{n_{i,t}^{\nu}}{w_{i,t}} = \mathbb{E}_{t-i} \left(\frac{n_{0,t}^{\nu}}{w_{0,t}} \right) \tag{12}$$

As such, the inattentive household sets the marginal utility of consumption at time t to be equal to her expectation of the marginal utility of consumption of the attentive household. Similarly, for the inattentive household, the marginal disutility of supplying an additional unit of labor relative to the marginal benefit of an additional unit of labor equals the expected ratio of the attentive household.

3.1.2 | Final-good firms

Firms in this sector purchase a continuum of intermediate goods from intermediate-good producers, indexed by $j \in (0,1)$, and assemble them into final goods using the following technology:

$$y_t = \left(\int_0^1 y_{j,t}^{\frac{\varepsilon-1}{\varepsilon}} \, dj \right)^{\frac{\varepsilon}{\varepsilon-1}} \tag{13}$$

with $y_{j,t}$ being the quantity of intermediate-good j that is purchased by a final-good firm and $\varepsilon > 1$ is the elasticity of substitution between two differentiated types of intermediate goods. Profit maximization gives the following downward-sloping demand function for the product variety j:

$$y_{j,t} = \left(\frac{P_{j,t}}{P_t} \right)^{-\varepsilon} y_t \tag{14}$$

where P_t is the aggregate price level.

3.1.3 | Intermediate-good firms

Firms in this sector hire labor as the only production input. They operate in an environment of fully flexible prices but may not update their information sets every period. Each period t, a fraction λ^f of firms update their information sets. Therefore, in what follows, $(1 - \lambda^f)$ measures the degree of firms' inattention.

A firm that last updated its information set j periods ago sets its price $P_{j,t}$ and hires labor $n_{j,t}$ from households to

$$\max_{\{n_{j,t},P_{j,t}\}_{t=0}^{\infty}} \mathbb{E}_{t-j}\left[\frac{P_{j,t}}{P_t}y_{j,t} - w_{j,t}n_{j,t}\right] \tag{15}$$

subject to the demand curve for the firm's product (14) and the production technology

$$y_{j,t} = z_t n_{j,t}^{1-\alpha} \tag{16}$$

with z_t being total factor productivity (which is common to all firms). Profit maximization gives the following demand condition for labor:

$$mc_{j,t} = \frac{w_{j,t}}{(1-\alpha)z_t n_{j,t}{}^{-\alpha}} \tag{17}$$

where $mc_{j,t}$ is the real marginal cost of firm j. As expected, the firm hires labor so that the marginal product of labor is a markup over the real wage. With a linear production function ($\alpha = 0$), this condition becomes $mc_{j,t} = \frac{w_{j,t}}{z_t}$, as is standard in the New Keynesian model with linear-in-labor technology.

A firm that last updated its information set j periods ago will choose the following price:

$$P_{j,t} = \frac{\epsilon}{\epsilon - 1}\frac{\mathbb{E}_{t-j}\left(w_{j,t}y_{j,t}^{\frac{1}{\alpha}}z_t^{-\frac{1}{\alpha}}\right)}{\mathbb{E}_{t-j}\left(\alpha y_{j,t}/P_t\right)} \tag{18}$$

and then the aggregate price level is given by

$$P_t = \lambda^f \sum_{j=0}^{\infty}(1-\lambda^f)^j P_{j,t}. \tag{19}$$

The inflation rate, defined as $\pi_t = P_t/P_{t-1}$ in our model, replaces the inflation that is governed by the forward-looking sticky-price New Keynesian Phillips curve.

3.2 | State-dependent sticky information

In this subsection, we derive the probability that firms and households update their information sets by solving optimization problems. We assume that firms and households face fixed costs of collecting and processing information, which are distributed *i.i.d.* across firms and over time.

Let $f(\kappa_t^f)$ and $F(\kappa_t^f)$ denote the probability density function and cumulative distribution function of the firm's fixed cost, respectively. κ_t^f is measured in units of labor time so that the total cost of updating information by a firm is $\kappa_t^f w_{j,t}$. Let $V_{0,t}^f$ be the value of a firm with the most up-to-date information set (i.e., the firm has updated its information in period t), and $V_{j,t}^f$ be the value of a firm that updated its information j periods ago (a vintage-j firm), with $j = 1, \ldots, J-1$, and J being the number of vintages. A vintage-j firm updates its information set if the value of updating, $V_{0,t}^f - \kappa_t^f w_{j,t}$, is greater than the value of not updating, $V_{j,t}^f$. Therefore, firms with a draw of $\kappa_t^f < \frac{V_{0,t}^f - V_{j,t}^f}{w_{j,t}}$ will update. As such, the probability that a vintage-j firm updates its information set in period t is given by

$$\theta_{j,t}^f = F\left(\frac{V_{0,t}^f - V_{j,t}^f}{w_{j,t}}\right) \tag{20}$$

with $j = 1, \ldots, J-1$. We further assume that after J periods, all firms update their information sets; therefore, $\theta_{J,t}^f = 1$. In addition, $\kappa_t^{f*} = \frac{V_{0,t}^f - V_{j,t}^f}{w_{j,t}}$ denotes the cut-off value of κ_t^f for which a firm is indifferent between updating its information set and not updating.

Each period, there is a fraction $\psi^f_{j,t}$ of vintage-j firms, so that $\sum_{j=1}^{J} \psi^f_{j,t} = 1$. The total fraction of firms with the up-to-date information set is thus given by

$$\lambda^f_t = \sum_{j=1}^{J} \psi^f_{j,t}\theta^f_{j,t}. \tag{21}$$

Then, the total fraction of firms that did not update their information set in period t is given by $1-\lambda^f_t$, which also measures the degree of firms' inattention in this model. In this model, λ^f_t provides a micro-foundation for the frequency of information updating, and its role is similar to the frequency of price changes in the New Keynesian model with Calvo pricing.

The value of firm j that does not update its information set:

$$V^f_{j,t} = \max \mathbb{E}_{t-j}\left\{\left[\frac{P_{j,t}}{P_t}y_{j,t} - w_{j,t}n_{j,t}\right] + \beta Q_{t,t+1}\left[(1-\theta^f_{j+1,t+1})V^f_{j+1,t+1} + \theta^f_{j+1,t+1}V^f_{0,t+1} - \Gamma^f_{j+1,t+1}\right]\right\} \tag{22}$$

with $j = 1, \ldots, J-1$, and $Q_{t,t+1}$ being the stochastic discount factor between periods t and $t+1$. Intuitively, with a probability $(1-\theta^f_{j+1,t+1})$, the firm does not update its information set in period $t+1$ and thus has the value of not updating. With a probability $\theta^f_{j+1,t+1}$, the firm updates the information set in period $t+1$ and gets the value of updating net of the cost of doing so ($\Gamma^f_{j+1,t+1}$).

Similarly, the value of a firm that updates information in period t is

$$V^f_{0,t} = \frac{P_{0,t}}{P_t}y_{0,t} - w_{0,t}n_{0,t} + \beta\mathbb{E}_t\left\{Q_{t,t+1}\left[(1-\theta^f_{1,t+1})V^f_{1,t+1} + \theta^f_{1,t+1}V^f_{0,t+1} - \Gamma^f_{1,t+1}\right]\right\} \tag{23}$$

with $V^f_{1,t+1}$ being the value of not updating the information set next period and $V^f_{0,t+1}$ being the value of updating.[14]

On the household side, we have a similar problem but with the fixed cost being in units of consumption. Let $g(\kappa^h_t)$ and $G(\kappa^h_t)$ be the probability density function and cumulative distribution function respectively for the fixed cost κ^h_t. Then, the probability that a vintage-i household updates its information set in period t is given by

$$\theta^h_{i,t} = G\left(\frac{V^h_{0,t} - V^h_{i,t}}{c_{i,t}}\right) \tag{24}$$

with $i = 1, \ldots, I-1$, $\theta_{I,t} = 1$ and $\kappa^{h*}_t = \frac{V^h_{0,t}-V^h_{h,t}}{c_{i,t}}$ being the cut-off value of κ^h_t for which a household is indifferent between updating its information and not updating. Also, there is a fraction $\psi^h_{i,t}$ of vintage-i households, $\sum_{i=1}^{I}\psi^h_{i,t} = 1$. The total fraction of households with the up-to-date information is given by

$$\lambda^h_t = \sum_{i=1}^{I} \psi^h_{i,t}\theta^h_{i,t} \tag{25}$$

and, thus, $1-\lambda^h_t$ is the degree of inattention in the household sector.

The value of household i that does not update information in period t:

$$V^h_{i,t} = \max \mathbb{E}_{t-i}\left\{u(c_{i,t}, n_{i,t}) + \beta Q_{t,t+1}\left[(1-\theta^h_{i+1,t+1})V^h_{i+1,t+1} + \theta^h_{i+1,t+1}V^h_{0,t+1} - \Gamma^h_{i+1,t+1}\right]\right\} \tag{26}$$

[14]As the first part in Equation (23) is independent of expectations, it may appear that the firm has the most up-to-date information prior to making a decision whether or not to update information in period t. There is a bit of a tension. However, one might view the firm's problem as follows: the firm first makes the decision about updating information at the beginning of the period (before prices and quantities are realized). Then prices and quantitative are realized and $\frac{P_{0,t}}{P_t}y_{0,t} - w_{0,t}n_{0,t}$ is determined. An alternative assumption is that the decision to update the information set is made at the very last instance of period $t-1$ at which point the firm does not know the values of $P_{0,t}, y_{0,t}, w_{0,t}$ or $n_{0,t}$.

with $h = 1, \ldots, I-1$. With a probability $(1-\theta^h_{j+1,t+1})$, the household does not update its information set in period $t+1$ and has the value of not updating. With a probability $\theta^h_{j+1,t+1}$, the household updates the information set in period $t+1$ and gets the value of updating net of the cost of doing so $(\Gamma^h_{j+1,t+1})$.

The value of a household that updates information

$$V^h_{0,t} = u(c_{0,t}, n_{0,t}) + \beta \mathbb{E}_t \left\{ Q_{t,t+1} \left[(1-\theta^h_{1,t+1}) V^h_{1,t+1} + \theta^h_{1,t+1} V^h_{0,t+1} - \Gamma^h_{1,t+1} \right] \right\} \tag{27}$$

with $V^h_{1,t+1}$ being the value of not updating the information set next period and $V^h_{0,t+1}$ being the value of updating.

3.3 | Market clearing

In equilibrium, the resource constraint of the economy reads

$$z_t n_t^{1-\alpha} = c_t \tag{28}$$

with c_t being aggregate consumption

$$c_t = \lambda^h \sum_{i=0}^{I} (1-\lambda^h)^i c_{i,t}. \tag{29}$$

The total factor productivity (TFP) follows the following AR(1) process:

$$\ln\left(\frac{z_t}{\bar{z}}\right) = \rho_z \ln\left(\frac{z_{t-1}}{\bar{z}}\right) + \varepsilon_{z,t} \tag{30}$$

with ρ_z being the AR(1) coefficient and $\varepsilon_{z,t} \sim \mathcal{N}(0, \sigma_z^2)$ is a shock to TFP.

The total amount of labor demand is equal to the sum of the labor demand by all firms

$$n_t = \sum_{j=0}^{J} n_{j,t}. \tag{31}$$

In addition, bonds are in zero net supply.

3.4 | Monetary policy

Monetary policy is governed by a Taylor-type rule with interest rate smoothing whereby the nominal interest rate responds to deviations of inflation and output from their steady-state values as follows:

$$\ln\left(\frac{R_t}{\bar{R}}\right) = \rho_R \ln\left(\frac{R_{t-1}}{\bar{R}}\right) + (1-\rho_R)\left(\rho_\pi \ln\left(\frac{\pi_t}{\bar{\pi}}\right) + \rho_y \ln\left(\frac{y_t}{\bar{y}}\right)\right) + \varepsilon_{R,t} \tag{32}$$

with $\bar{y}$ being the steady-state value of output, $\bar{\pi}$ being the steady-state value of the inflation rate, $\rho_\pi > 1$ (to insure that the Taylor principle is satisfied), $\rho_y > 0$ and $\rho_R > 0$ being the coefficients of inflation, output and interest rate smoothing, respectively, and $\varepsilon_{R,t} \sim \mathcal{N}(0, \sigma_R^2)$ is a shock to the nominal interest rate.

In the preliminary analysis, we consider a two-period model with information rigidity in both the household and firm sectors, and use a log-linearized version of the model to obtain analytical results; see Appendix C in the supporting information for the details. The key finding is that firm and household information rigidity have opposing effects. In particular, information rigidity in the firm sector amplifies the real impact of monetary policy whereas information rigidity in the household sector dampens it. The net effect depends on firms' inattention relative to households' inattention, and we evaluate it numerically in the next section.

TABLE 4 Values of the parameters in the benchmark analysis.

Parameter	Description	Value
β	Households' discount factor	0.99
σ	Consumption curvature parameter	1.50
ν	Inverse of labor supply elasticity	0.5
$1-\lambda^h$	Households' inattention	0.62
$1-\alpha$	Labor share of output	0.66
ϵ	Elasticity of substitution between goods	6.00
$1-\lambda^f$	Firms' inattention	0.36
ϕ_π	Coefficient of inflation in the Taylor rule	1.50
ϕ_y	Coefficient of output in the Taylor rule	0.125
ρ_R	Interest rate smoothing parameter	0.90

Note: $\phi_\pi = (1-\rho_R)\rho_\pi$ and $\phi_y = (1-\rho_R)\rho_y$.

4 | MODEL-BASED NUMERICAL RESULTS

We start with an outline of our parameter values, then turn to results from the model with constant inattention, and conclude with numerical results obtained from the state-dependent inattention model.

4.1 | Parameterization

Table 4 presents a summary of the parameter values. The time unit is a quarter and the discount factor β is set such that the steady-state annual interest rate is roughly 4%. The disutility-of-labor parameter χ is set such that the steady-state value of n is 0.3. The parameter ν is set such that the labor supply elasticity is 2. This value helps in capturing the volatility of total hours in a model with no extensive margin, as is the case in this paper. The consumption curvature parameter σ is in the middle of the standard values assumed in the literature.

The benchmark values of $1-\lambda^f$ and $1-\lambda^h$ are based on our findings about the average degrees of inattention, the value of α implies a labor share of roughly two thirds, ϵ is consistent with a price markup of 20%, and the parameters of the Taylor rule are standard in the literature. In addition, our benchmark results assume a steady-state inflation rate of zero, but we provide a robustness analysis with a positive steady-state inflation rate in Appendix D in the supporting information. Finally, as we study impulse responses to monetary policy shocks, we leave total factor productivity at its steady-state level. Therefore, $z_t = \bar{z}$, and we normalize it to 1. In Appendix E of the supporting information, we consider the cases with a time-varying total factor productivity and firm-level productivity shocks.

4.2 | Numerical results

Following Nakov and Thomas (2014), we solve the full non-linear model using a first-order approximation. To ease comparison with the empirical findings, we present the cumulative effects of monetary policy on our variables of interest using the impulse response functions.

4.2.1 | Constant inattention

The top panel of Figure 6 presents the responses of output and inflation to a monetary policy shock for two different scenarios: the benchmark model with firm and household inattention and the model with full attention in both sectors. Without inattention, output is irresponsive to a monetary policy shock. Intuitively, as prices are fully flexible, and firms are fully attentive, monetary policy is neutral. On the other hand, with inattention, output rises in a hump-shaped fashion in response to a decline in the nominal interest rate. In our model, prices are fully flexible, but rigid information renders monetary policy not neutral.

In the bottom panel of Figure 6, we show results with firm inattention or household inattention only. With firm inattention only, output rises strongly and monotonically. The addition of household inattention dampens the response of output and leads to a hump-shaped behavior. Crucial for our study, adding inattention in both sectors leads to a bigger response of output than in the model with full attention.

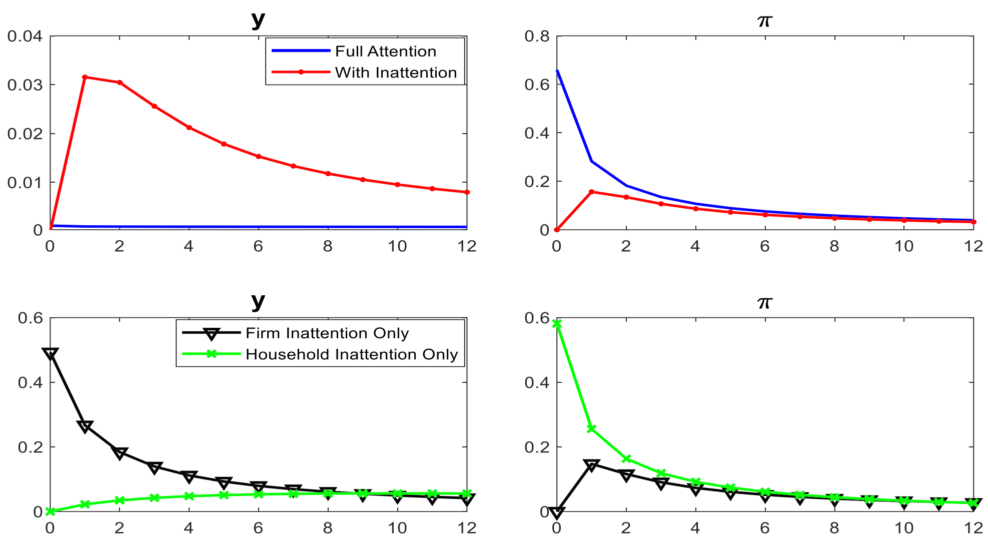

FIGURE 6 Responses to expansionary monetary policy: Constant inattention. *Note*: Responses of output (y) and inflation (π) to an expansionary monetary policy shock. Full Attention: $1-\lambda^f=0, 1-\lambda^h=0$. With Inattention: $1-\lambda^f=0.36, 1-\lambda^h=0.62$. Firm inattention only: $1-\lambda^f=0.36, 1-\lambda^h=0$. Household inattention only: $1-\lambda^f=0, 1-\lambda^h=0.62$.

On the other hand, the response of the inflation rate is smaller when inattention is higher. A possible explanation for this result is the following: If fewer firms pay attention, then fewer firms will update their prices (in particular, fewer firms will raise their prices following an expansionary monetary policy shock). Consequently, more information rigidity introduces some rigidity in prices even though prices are not inherently rigid.[15] Therefore, although price rigidity and information rigidity are distinct from each other, there is some similarity in their implications for monetary policy.

The different effects of household and firm inattention on the behavior of output and inflation can be explained as follows. When firms are fully attentive and households are inattentive, firms respond immediately by raising prices (as prices are fully flexible), whereas consumption does not respond yet. As such, demand and output do not respond on impact. Then, as the information disseminates, consumers start raising their demand, leading to a rise in output (which peaks after roughly four quarters), at the same time when inflation starts reverting to its steady-state level.

On the other hand, when consumers are fully attentive and firms are inattentive, consumers raise their spending on impact, which triggers an immediate increase in output. At the same time, inflation does not respond as firms are inattentive and have not yet made changes to their prices. Over time, as firms update their information, prices start to rise whereas the effects on output gradually decline.

4.2.2 | State-dependent inattention

In order to solve the model, we assume $I = J = 4$, implying that all firms and households update their information sets within four periods (quarters). In addition, we let the cumulative distribution function for the cost of updating the information set by firms be

$$F(\kappa_t^f) = \frac{\zeta^f + \kappa_t^f}{\eta^f + \kappa_t^f} \tag{33}$$

where ζ^f and η^f are positive parameters and $\zeta^f < \eta^f$. This cumulative distribution function is bounded from below by ζ^f/η^f.

Using condition (20), condition (33) can be rewritten as

$$F(\kappa_t^f) = \frac{\zeta^f + (V_{0,t}^f - V_{j,t}^f)/w_t}{\eta^f + (V_{0,t}^f - V_{j,t}^f)/w_t} \tag{34}$$

[15]Anderson et al. (2017) refer to this case as "sticky plans" whereby firms do not always make pricing decisions when their information sets are old. In addition, Mackowiak and Wiederholt (2009) show that in the absence of perfect information, the response of prices to aggregate shocks is weaker and delayed compared with the scenario with perfect information. Drenik and Perez (2020) find that monetary policy is more effective when there is less precise information, because firms assign less weight to it while setting prices. Baley and Blanco (2019) demonstrate that, when aggregate uncertainty is large, firms learn faster (e.g., because firms pay more attention). As a result, monetary policy shocks have smaller real effects. These findings also align with ours.

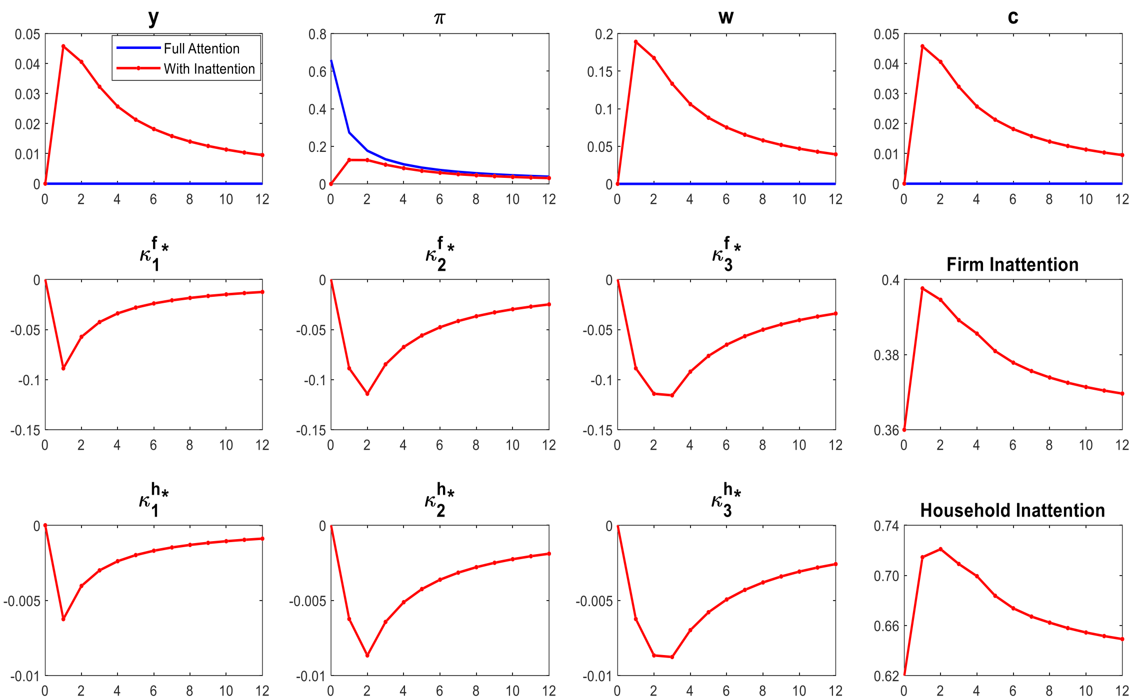

FIGURE 7 Responses to expansionary monetary policy: State-dependent inattention. *Note*: Responses of output (y), inflation (π), real wage (w) and consumption (c) to an expansionary monetary policy shock in the model with state-dependent information rigidity. Household and firm inattention are expressed in levels. κ_j^{f*} is the cutoff cost for a firm of vintage j to update its information set. κ_i^{h*} is the cutoff cost for a household of vintage i to update its information set. Steady-state inattention: $1-\overline{\lambda}^f = 0.36, 1-\overline{\lambda}^h = 0.62$.

implying that the probability for the firm to update its information set is increasing in the gain from adjustment $(V_{0,t}^f - V_{j,t}^f)$. Note that the real wage here is not firm specific.

For symmetry, we assume a similar distribution function for households. Therefore,

$$F(\kappa_t^h) = \frac{\zeta^h + (V_{0,t}^h - V_{i,t}^h)/c_{i,t}}{\eta^h + (V_{0,t}^h - V_{i,t}^h)/c_{i,t}} \tag{35}$$

with the values of ζ^f, η^f, ζ^h and η^h being set so that, at the steady state, $1-\overline{\lambda}^f = 0.36$ and $1-\overline{\lambda}^h = 0.62$, as in our analysis with constant inattention.

The findings, presented in Figure 7, confirm our conclusions from the model with constant inattention. Following the expansionary monetary policy, output and inflation rise. The real wage rises, which reduces the likelihood for firm j to update information (i.e., $\kappa^{f\star}$ falls), leading to a decline in the fraction of vintage-j firms that choose to update their information sets. Indeed, firm inattention rises from its steady-state value of 0.36 to roughly 0.40. In the household sector, the rise in consumption reduces the probability for household i to update information; as a result, household inattention rises (from its steady-state value of 0.62 to roughly 0.72).

4.3 | High versus low inattention

So far, we have used the benchmark values of household and firm inattention, with the former being significantly larger than the latter. In this experiment, we let inattention in both sectors be the same and then consider two different values. Specifically, we use $1-\overline{\lambda}^f = 1-\overline{\lambda}^h = 0.16$ for low inattention and $1-\overline{\lambda}^f = 1-\overline{\lambda}^h = 0.55$ for high inattention, which correspond to the averages of inattention for each scenario in the data.

Our results with state-dependent inattention are very similar to those with constant inattention (Figure 8). With higher inattention, monetary policy has larger stimulative effects on output whereas the impact on inflation is weaker. Yet comparing the responses of output between the two models reveals an important difference: with state-dependent inattention,

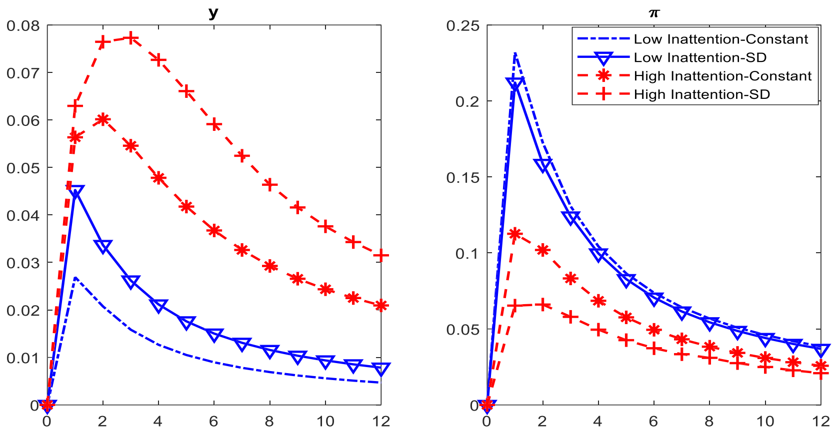

FIGURE 8 Responses to expansionary monetary policy: Constant versus state-dependent inattention. *Note*: Responses of output (y) and inflation (π) to an expansionary monetary policy shock in the model with constant versus state-dependent (SD) information rigidity for two different steady-state values of the inattention parameters. Low inattention: $1-\overline{\lambda}^f = 1-\overline{\lambda}^h = 0.16$. High inattention: $1-\overline{\lambda}^f = 1-\overline{\lambda}^h = 0.55$. When inattention is constant, it is set to equal these steady-state values every period.

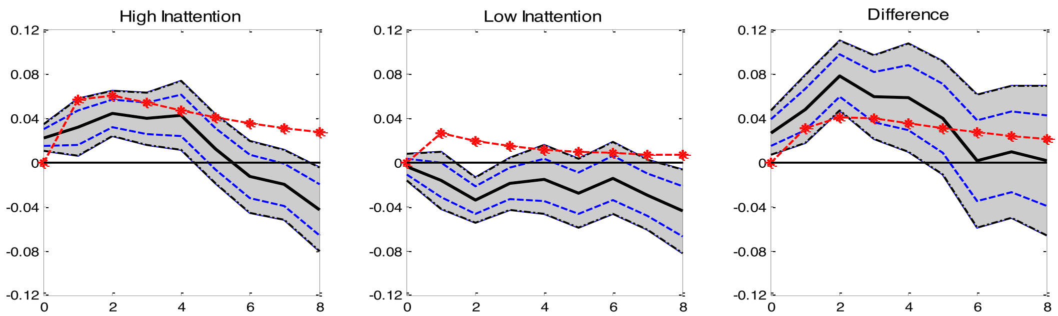

FIGURE 9 Responses of output to expansionary monetary policy: Model versus data. *Note*: Responses of output to an expansionary monetary policy shock in the model with state-dependent information rigidity for two different steady-state values of the inattention parameters. Low steady-state Inattention: $1-\overline{\lambda}^f = 1-\overline{\lambda}^h = 0.16$. High steady-state Inattention: $1-\overline{\lambda}^f = 1-\overline{\lambda}^h = 0.55$. Red line with stars: the estimate from the model. Solid black line: the point estimate from the data. Shaded area: 68% and 90% confidence intervals.

output rises by more following a fall in the nominal interest rate than with constant inattention. To our knowledge, this is new in the literature.

4.4 | Taking the model to the data: Impact of monetary policy

We explore the ability of the model with state-dependent inattention to match the observed responses of output under low and high inattention. The responses of output under high inattention mostly lie inside the confidence intervals of the empirical counterpart (Figure 9). The difference in the responses between high and low inattention is also within the confidence intervals. For low inattention, the model predictions are mostly close to the upper bounds of the confidence intervals.

In Appendix F in the supporting information, we show that if the steady-state inattention is reduced to 0.07 (which is the lowest value documented in the empirical part and corresponds to updating information about 3 months on average), then the model better accounts for the response of output. Therefore, to fit the data under the low inattention scenario, a very low inattention level suffices, and no further modifications to the model are necessary.

4.5 | Inattention measurement: Model versus data

The goal of this section is to illustrate that our empirical measure of inattention is consistent with the model-implied counterpart. To do so, we estimate the model using Bayesian techniques and obtain parameter values. We then use these parameters to simulate the model and construct the inattention measure. We consider two cases. In the first case, our model has one observable—the nominal interest rate, and we estimate the standard deviation of the shock to monetary policy. In the second case, we expand the model with four more observed variables—the growth rates of GDP, real wage,

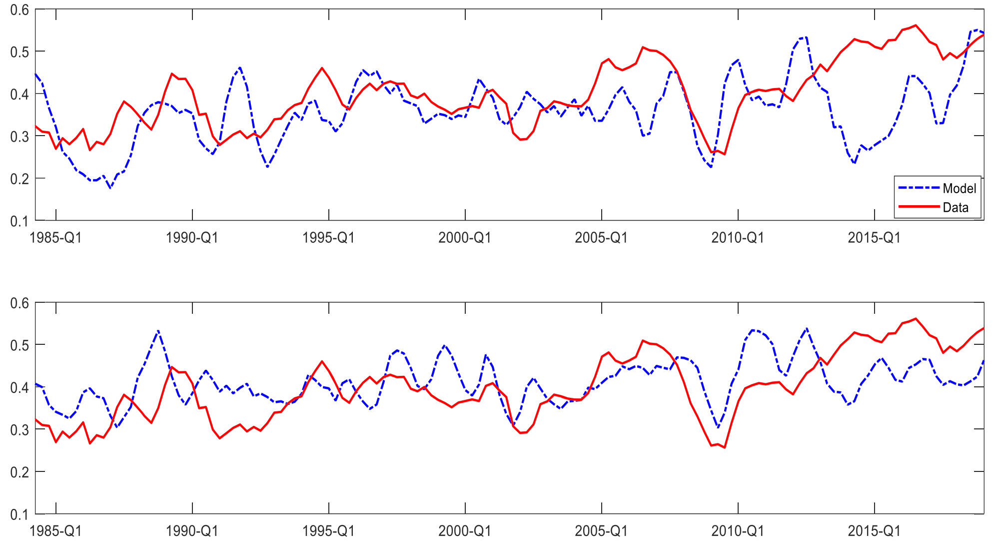

FIGURE 10 Empirical and model-based measures of inattention. *Note*: Red solid line: empirical estimates of inattention from the data. Blue dotted line: estimates of inattention from the model. Four-quarter moving averages are plotted. Top panel: the model with one observed variable. Bottom panel: the model with multiple observed variables.

hours and consumption, enlarge the shock structure by allowing for the possibility of measurement errors (that affect the observed variables only), and estimate the standard deviations of all five shocks and other parameters.

Because our model includes both firm and household inattention, aggregate inattention is estimated as the weighted average of the two. Here, we present the results with equal weights starting from 1984Q1 (the beginning of the Great Moderation). Figure 10 plots four-quarter moving averages of the inattention series. The empirical estimate of inattention is moderately related to the model-based inattention, with correlations of 0.34 for the first case and 0.38 for the second. Moreover, the degrees of inattention on average are pretty similar across both the data and the model: 0.40 (data) versus 0.36 for the first case and 0.41 for the second.[16]

5 | CONCLUSION

We propose a microdata based measure of inattention that captures the common component in the inattentiveness of professional forecasters to multiple economic variables. Applying this measure to the US SPF survey, we find that professional forecasters update their information sets every 5 months on average. Inattention is pro-cyclical, as professionals pay close attention during episodes of recessions, high policy uncertainty and macro uncertainty. This finding provides supportive evidence for sticky information theory in which more volatile shocks lead to more frequent updating. Using the local projections method, we show that inattention, like nominal rigidities, amplifies the response of the economy to a given set of monetary policy shocks, and the amplification effect becomes much stronger when the degree of inattention is higher.

We then develop a DSGE model with inattentive firms and households. The key innovation in our model is to allow for endogenous information processing by firms and households. Simulation results indicate that, when inattention is higher, an expansionary monetary policy has a bigger stimulative effect on output, in line with the empirical evidence. A model with sticky prices but not sticky information, in the production sector yields the opposite results. Furthermore, the increase in output is larger with state-dependent inattention than constant inattention. Therefore, treating inattention as a structural parameter, as assumed in most studies, might lead to underestimation of the real impact of monetary policy.

ACKNOWLEDGMENTS

This paper was presented at AEA, IAAE, FFC, ISF, National Bank of Poland, George Washington University, and American University. We thank John Rogers for sharing their monetary policy shock measure, and Philippe Andrade, Matt

[16]In line with the practice of Del Negro and Schorfheide (2009), we exclude the high inflation era of the 1970s and early 1980s. The Hodrick–Prescott filtered long-term trend of the empirical inattention measure tends to move in step with that of the model-implied inattention, with a correlation of 0.75 for the first case and 0.78 for the second. The results with the full sample starting from 1972Q1 and with different weights of firm and household inattention are presented in Appendix G in the supporting information.

Klepacz, Jonathan Wallen, and conference participants for helpful comments. We are indebted to the editor, Marco Del Negro, and five anonymous referees for very useful comments that have significantly improved the paper.

OPEN RESEARCH BADGES

This article has been awarded Open Data Badge for making publicly available the digitally-shareable data necessary to reproduce the reported results. Data is available at http://doi.org/10.15456/jae.2023018.1556704705.

DATA AVAILABILITY STATEMENT

The data used in this paper are publicly available. For the data access and management, see the replication package for details.

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How to cite this article: An, Z., Abo-Zaid, S., & Sheng, X. S. (2023). Inattention and the impact of monetary policy. *Journal of Applied Econometrics*, *38*(4), 623–643. https://doi.org/10.1002/jae.2960