Inattention and the Impact of Monetary Policy*

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Abstract

We develop and estimate a novel measure of inattention as the common component in agents' inattentiveness to many economic variables. Applying this measure to U.S. Survey of Professional Forecasters enables us to establish the following empirical evidence. Professional forecasters update their information sets every four months on average, but do so more frequently in response to high market volatility and policy uncertainty. Monetary policy shocks have larger real effects when the degree of inattention is higher. We advance a general equilibrium model with state-dependent information rigidity to explain our empirical findings.

JEL classification: E32; E52

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1 Introduction

The current resurgence of interest in the expectation formation process builds upon a long tradition of research on imperfect information. Mankiw and Reis (2010) and Gabaix (2019) provide two excellent surveys. These frictions are important for explaining why economic agents may be inattentive to news and have divergent views. From this literature, we draw one prominent model of information frictions: the sticky information model of Mankiw and Reis (2002). The sticky information model explains inattention as a rational response to limited resources and the cost of updating information. 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 first propose a micro-data based measure of aggregate inattention of professional forecasters. A forecaster is considered as being inattentive if she does not revise her forecasts for *all* target variables. Aggregate inattention is defined as the proportion of inattentive forecasters in each period. Applying this definition to U.S. Survey of Professional Forecasters (SPF), we find that these professionals update their information sets every four months on average. Inattention is highly pro-cyclical, as inattention significantly declines 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 firms. This model mostly resembles a standard New Keynesian framework, but with sticky information. In each period, only a fraction of firms update their information sets and make rational plans based on the current information set, while the remaining firms set their prices based on outdated information. Therefore, the aggregate price level is the weighted average of prices across firms using different information vintages. The key innovation of our model is to allow for inattention to be endogenous and state-dependent in two alternative ways. First, firms pay close attention when output is low or when inflation is high, as suggested by the empirical evidence. In this respect, the degree of inattention in the model is determined through an ad-hoc rule that is based on the empirical findings. Second, we let firms optimally choose when to update their information sets. In this case, firms face a cost of adjusting their information sets, and they choose to adjust if and only if the benefit from updating exceeds that from not updating.

We calibrate the model to the U.S. data to study the impact of information frictions on the responses of macroeconomic variables to a monetary policy shock. By comparing the differences in the impulse response functions under various levels of inattention, our simulation results show that when information rigidity is higher, a monetary policy shock has a larger effect on output. This conclusion holds for all three scenarios that we consider in our study: constant inattention, an ad-hoc rule for inattention and when the degree of inattention is a result of firm optimization.

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. For examples, Mankiw et al. (2003) find about ten months of information frictions from the Livingston survey, Coibion and Gorodnichenko (2015) identify an information lag of six to seven months using U.S. SPF data. Another approach explores the expectation formation process based on individual-level survey data. For example, Andrade and Le Bihan (2013) find four months of inattentiveness using European Central Bank SPF data. Dräger and Lamla (2017) document more than six 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. The variations in empirical findings reflect the challenges and differing methodologies for measuring information frictions.

Similar to Andrade and Le Bihan (2013), Dräger and Lamla (2017) and Giacomini et al. (2020), we use micro-level data on forecast revisions to non-parametrically measure inattention. We differ from their measures by defining information frictions in a multivariate context, rather than inattentiveness to a particular variable, e.g., inflation. This is important, because the univariate measurement would substantially overestimate the degree of information stickiness. Furthermore, we find that information processing is state dependent, as professional forecasters pay close attention during highly volatile episodes. This evidence supports the recent theory in Reis (2006b) and Baker et al. (2020).[1]

[1] Reis (2006b) proposes a sticky information model in which more volatile shocks lead to more frequent updating since inattention is more costly in a world that is rapidly changing. Baker et al. (2020) develop a learning model in which large shocks like natural disasters induce an immediate increase in updating of information for inattentive agents (extensive margin). To compensate for the higher uncertainty following shocks, some attentive agents will increase their acquisition of private information (intensive margin).

Our paper is closely related to the literature on sticky information and business cycle fluctuations. 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.

In our model, firm's attention is allowed to be time varying rather than constant. This new feature is consistent with the recent empirical evidence for state dependence in the information updating process (e.g. Coibion et al. 2018 and Baker et al. 2020). According to Coibion et al. (2018), over 75% of firms report that they are more likely to seek new information when they receive bad news about the economy. Matching forecasts from a panel of 54 countries to a detailed set of natural disasters, Baker et al. (2020) document that information rigidity declines significantly following large, unexpected natural disaster shocks.[2]

Our paper contributes to the vast literature on the transmission of monetary policy shocks, summarized at one stage by Christiano et al. (1999). 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. What is not readily recognized in the literature is that the impact on output is significantly larger with state-dependent inattention than constant inattention. Since inattention falls during recessions and periods of high uncertainty, our results provide a new explanation for why monetary shocks have less impact on output and prices during these episodes (Caggiano et al., 2014; Tenreyro and Thwaites, 2016; Aastveit et al., 2017). Finally, our findings are particularly relevant to the recent studies that highlight the central bank information shocks (Nakamura and Steinsson, 2018; Jarocinski and Karadi, 2020), because the impact of information shocks on the economy depends on whether households and firms pay attention to the central bank's assessment of the economic outlook.

The paper proceeds as follows. Section 2 proposes the measure of aggregate inattention, empir-

[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.

ically estimates it using the U.S. 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 demonstrates how inattention alters the effect of monetary policy on economic dynamics. Section 4 concludes.

2 Measuring Inattention

This section starts with developing a new measure of inattention in a multivariate context. Applying this measure to survey of professional forecasters, 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

Our measure of inattention builds on Andrade and Le Bihan (2013), in which inattention is measured non-parametrically by calculating the proportion of forecasters who do not make any revision within a given period. By using individual-level data and considering the binary choice between revising and not revising a forecast, their measure focuses on the cost of updating and the expected loss of not updating information for professional forecasters, a feature of the sticky information model. Complementing the measure's simplicity is its insensitivity to outliers and no need for actual values that are subject to multiple revisions. However, the limitation of this simple approach is its focus on the frequency component of forecast revisions in predicting one variable only, ignoring the multivariate nature of expectations formation. Information rigidity in predicting a single variable does not represent the overall inattentiveness of forecasters. 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 vary across variables. Information friction should be measured at the level of individual agent rather than individual variable. This is important because imperfect information theories of the business cycle typically require the existence of inattention for economic agents, such as consumers and firms, not inattention to a single variable.

To address this limitation, we propose a new measure of forecaster inattention in a multivariate context. Ideally, a measure of attentiveness should directly measure information update. However, agents' information sets are not directly observable. Forecast revisions offer an observable proxy for information update.[3] As agents update their information sets, they will revise their forecasts for at least one variable. Accordingly, no forecast revision for *all* variables is interpreted as no information update for professional forecasters. Formally, 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:

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

Forecaster i is considered as being inattentive if she does not revise forecasts for *all* target variables (i.e., $I_{ith} = 1$). On the contrary, revising the forecast for one or more target variables indicates that forecaster i has updated her information set. This definition is appropriate when m is finite, namely, with a fixed number of variables being forecasted.

In line with the sticky information model, the probability of not updating information is assumed to be homogeneous across agents. Under this assumption, inattention is defined as the proportion of forecasters who do not revise their forecasts:

$$IA_{th} = \frac{1}{N_t} \sum_{i=1}^{N_t} I_{ith}. \tag{2}$$

The novel feature of this definition is that aggregate inattention is not equal to inattention to a single variable as in Andrade and Le Bihan (2013), and Dräger and Lamla (2017). As far as the underlying information processes of these economic variables have commonalities, professionals should have common time variation in information rigidities. Coibion et al. (2018) provide the direct evidence that, conditional on tracking multiple variables, over 90 percent of firms try to synchronize their acquisition of information across the variables they track. Our inattention measurement complements the recent studies that emphasize the multivariate nature of expectation formation, such as Banternghansa and McCracken (2009), Dovern (2015) and Andrade et al. (2016).[4] This

[3]This proxy rules out revisions due to strategic reasons. Professionals might shade their forecasts towards the consensus to avoid unfavorable publicity when wrong, or deviate in order to stand out, e.g., Giacomini et al. (2020). This is less of a concern, since the forecasters in our survey are anonymous.

[4]Banternghansa and McCracken (2009) analyze the level of multivariate disagreement among individual members of the Federal Open Market Committee. Dovern (2015) documents multivariate forecast disagreement among professional forecasters of the Euro area economy and modifies models of heterogeneous expectation formation by introducing learning mechanisms and heterogeneous signal-to-noise ratios. To match the entire term structure of disagreement, Andrade et al. (2016) enrich the benchmark expectations formation model by (i) disentangling low-

distinction is important since the univariate measurement would substantially overestimate the degree of agents' information stickiness, as shown in the next subsection.

2.2 Professionals Update their Information Every Four Months on Average

Our dataset comes from the U.S. Survey of Professional Forecasters, published by the Federal Reserve Bank of Philadelphia. Survey data on professionals fit the study of information rigidity due to a variety of strength. 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 those of other economic agents via news media. Due to these characteristics, inattention is expected to be the lowest for professional forecasters. Consequently, the findings in this paper represent conservative estimates of inattention for firms.

The SPF survey is anonymous, and each survey participant is assigned with 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 afterwards 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 horizon ranging from 1- to 4-quarter ahead. We focus on three closely-monitored macro variables – real GDP growth, CPI inflation, and unemployment rate. Only those who give their forecasts for all three variables, covering more than 96% respondents in the survey, are included in our analysis.

Table 1 provides summary statistics. At 3- and 4-quarter ahead, about 18% of professionals do not revise their forecasts for any of three macro variables within a quarter, implying their inattentiveness of about 3.7 months on average.[5] By contrast, the probability of not revising forecasts of a single variable is much higher. Taking inflation as an example, as is commonly done in the literature, one would conclude that professional forecasters update their information sets about

frequency shifts in the fundamentals of the economy from short-term fluctuations, and (ii) taking into account the dynamic interactions between variables when making forecasts.

[5] Frequency of updating is calculated as $3.7 = 3/(1-0.18)$. Note that, in the quarterly SPF survey, respondents cannot revise more frequently than every 3 months. The survey frequency forms a lower bound for the degree of inattention; see also Binder (2017).

7-8 months on average.[6] These results support measuring inattention in a multivariate context, because the univariate measurement would substantially overestimate the degree of information stickiness.[7] At 1- and 2-quarter ahead, more than 90% 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. Since the estimated degrees of inattention are highly correlated across four different horizons, for brevity, we focus on aggregate inattention at 4-quarter ahead 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. The movement in aggregate inattention is not driven by inattention to any single variable. In particular, the correlations between overall inattention and variable-specific inattention range from 0.67 to 0.85. Turning to conditional probability, the probability of revising unemployment forecast given the revision of GDP forecast is 0.64. Similar results hold for the probability of revising unemployment forecast given the revision of inflation forecast. These results suggest that a substantial proportion of participants form expectations consistent with the Okun law and the Phillips curve; see Dräger et al. (2016).

2.3 Inattention is Pro-cyclical

Inattention varies over time, as illustrated in Figure 1. Panel A plots the inattention to macroeconomic condition and panel B shows the inattention to a single variable, namely, GDP growth, inflation or unemployment.[8] Three points are worth noting. First, inattention shows substantial variations at multiple frequencies. Inattention 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 2007-09 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

[6] Using randomized controlled trials, Meyer et al. (2020) find that only a small minority of firms view overall inflation as having a significant influence on their business and pricing decisions, suggesting that firms operating in the current low and stable inflation environment rationally do not pay much attention to overall inflation.

[7] 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.

[8] In various robustness checks, we calculate aggregate inattention using different sets of macro variables, such as (i) inflation and unemployment rate and (ii) GDP growth, inflation and interest rate, and find very similar results as our baseline inattention measure. Furthermore, we divide professional forecasters into financial versus non-financial sectors and find very similar levels of inattention across sectors. To save space, these results are not reported but available upon request.

uncertainty have been low since the 2007-09 recession (Figure 2), and so professionals pay less attention. Furthermore, the significant independent variation in our measure suggests that we capture a novel dimension of macroeconomic salience that is not subsumed in existing volatility and uncertainty measures. A similar trend is also observed for less sophisticated agents. In Figure 3, we plot an alternative measure of inattention based on the search frequency in Google, finding the co-movement between the professionals and the general public in their attention paid to key macro variables.[9]

Next, we examine what drives the fluctuations in inattention over time. According to sticky information model, more volatile shocks lead to more frequent updating since inattention is more costly in a world that is rapidly changing. We observe the sharp decline of inattention during recessions. There are many other factors that account for the degree of inattention. For example, professionals pay more attention when inflation or unemployment rate is higher. Differences in inattention could also be driven by market conditions. To assess the relative importance of these potential determinants, we regress aggregate inattention on two groups of variables. The first group includes macroeconomic fundamentals, such as output growth, inflation, and unemployment rate.

The second group of explanatory variables focuses on market volatility and uncertainty. Specifically, we include the volatility of the S&P 500 index, calculated as 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. 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.

Since the dependent variable is a fractional variable, we use the quasi-maximum likelihood

[9] We use Google Trends to construct a topic search of keywords including Gross Domestic Product, Consumer Price Index, and Unemployment that match the target variables predicted by professionals. We scale the resulting monthly series between 0 and 100, and calculate the quarterly attention measure as the weighted average of monthly series, where the weight depends on the horizons to the target period as suggested by Dovern et al. (2012). Finally, we take the negative value of the quarterly attention series to obtain the inattention measure for the general public.

method in Papke and Wooldridge (1996) to estimate the nonlinear model:

$$E(IA_t|\mathbf{X}_{t-1}) = G(\beta\mathbf{X}_{t-1}) \tag{3}$$

where $G(\cdot)$ is the logistic function. In equation (3), IA_t denotes inattention at time t and is bounded between 0 and 1, $\mathbf{X}_{t-1}$ is a vector of lagged potential macroeconomic and financial market determinants as discussed above. The correlations among these explanatory variables are modest, ranging from -0.62 to 0.56.

Table 3 presents the estimated marginal effects evaluated at the mean level of explanatory variables. Columns (1)-(3) study quarterly variations in the inattention series. High output growth is positively associated with inattention, but high unemployment is negatively related to inattention, confirming the idea that "bad" news decreases inattention. Jumps in policy uncertainty and macro uncertainty 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. As expected, higher market returns lead to higher inattentiveness of professionals. The impact of inflation and market volatility on inattention takes the correct sign, though not statistically significant.[10]

Columns (4)-(6) report the results with four-quarter moving average of inattention as the dependent variable. High macro uncertainty brings down inattention, but high market returns do the opposite. The contribution of inflation now becomes significant, and higher inflation makes professionals pay more attention, in line with the sticky information theory. In short, fluctuations in inattention are driven by economic fundamentals, market returns, policy and macro uncertainty. These results suggest that information processing is state dependent, as in Reis (2006b) and Baker et al. (2020). The next subsection explores the role of inattention in the transmission of monetary policy.

[10] Baker et al. (2020) distinguish the two effects of uncertainty following large unexpected shocks. On one hand, uncertainty raises forecasters' attention and results in more forecast revision. On the other hand, due to high uncertainty, forecasters choose to wait and see, and so they are less likely to revise their forecasts.

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). In the first approach, we include inattention and its interaction with macroeconomic variables directly into the model specification.[11] In the second approach, we separate inattention into high versus low regimes using the Markov-switching model and then estimate the policy effect under different regimes.[12]

The baseline local projection model is as follows:

$$y_{t+h} - y_{t-1} = \beta_h MPS_t + \phi_h(L) z_{t-1} + \alpha_h + \varepsilon_{t+h} \qquad \text{for} \qquad h = 0, 1, 2, \ldots \tag{4}$$

where $y_{t+h} - y_{t-1}$ measures the growth rate of the target variable between $t-1$ and $t+h$, including real GDP growth and CPI inflation. MPS_t is the monetary policy shock. Identification of an exogenous policy shock is critical to estimate the impact of monetary policy. Notable examples include using innovations to the Federal Funds rate in vector autoregressions (Christiano et al., 1999), a narrative approach (Romer and Romer, 2004) and using changes in interest rate future prices around FOMC announcement (Nakamura and Steinsson, 2018). Our monetary policy shock series comes from Bu et al. (2020), denoted as BRW hereafter. Compared to the existing measures, the BRW shock series has a very mild data requirement to construct, covers a long sample period from 1975Q1 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, GDP growth, 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 and Zakrajšek, 2012). We estimate equation (4) 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 growth increases and reaches the peak in about a

[11] Aastveit et al. (2017) apply this method to estimate the impact of monetary policy under different levels of uncertainty.

[12] Auerbach and Gorodnichenko (2012) and Ramey and Zubairy (2018) use similar techniques to estimate the state-dependent impact of fiscal policy.

year. The response of inflation is significantly positive and persistent.

Having established the baseline result, we now add inattention, denoted by I_t, interacted with the monetary policy shock to an otherwise standard local projections model:

$$\begin{aligned} y_{t+h} - y_{t-1} =& \beta_{a,h} MPS_t + \phi_{a,h}(L) z_{t-1} \\ &+ \beta_{b,h} MPS_t * I_t + \phi_{b,h}(L) z_{t-1} * I_{t-1} \\ &+ \gamma_h * I_t + \alpha_h + \varepsilon_{t+h} \quad \text{for} \quad h = 0, 1, 2, ... \end{aligned} \tag{5}$$

The coefficient $\beta_{b,h}$ measures the extent to which inattention alters the impact of monetary policy. After estimating equation (5), we construct impulse response functions under different levels of inattention. Time periods of high inattention are identified by situations in which inattention is above the 90th percentile and low inattention as those below the 10th percentile. As shown in Figure 5, at the high inattention scenario, an expansionary monetary policy shock brings up real GDP. Such an effect reaches its maximum in 3 quarters and dies out in about 8 quarters. In contrast, monetary policy does not have a significant impact on real GDP at the low inattention scenario, with confidence intervals computed following the standard delta method. Similar results hold for inflation, as monetary policy shocks have larger and more persistent effects when inattention is higher. To further illustrate the difference across two scenarios, the right panels of Figure 5 plot the coefficient on the interaction term of inattention and monetary policy shock. The responses of real GDP to monetary policy shocks differ substantially between high and low inattention scenarios at most horizons, but the responses of inflation are (statistically) similar across two scenarios.[13]

Alternatively, we 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

[13] In a previous version of this paper, we consider VAR models that yield output and inflation responses to Cholesky-identified monetary policy innovations, with Federal Funds rate or one-year constant-maturity treasury yield ordered last. Specifically, we estimate VAR models using data on inattention, CPI inflation, real GDP growth, a common factor that summarizes macroeconomic activities and monetary policy rate. We obtain this common factor as the first principal component from a balanced panel of 132 monthly economic series provided by Jurado et al. (2015) and updated by the authors. Our sample for the baseline VAR model runs from 1970:Q1 to 2019:Q3 for quarterly data. We use two lags in all VAR specifications based on the Akaike information criteria. Our analysis based on VAR models yields the same result that inattention amplifies the impact of monetary policy.

across two scenarios. Specifically,

$$
\begin{aligned}
y_{t+h} - y_{t-1} = & G_t[\beta_{a,h} MPS_t + \phi_{a,h}(L) z_{t-1}] \\
& + (1 - G_t)[\beta_{b,h} MPS_t + \phi_{b,h}(L) z_{t-1}] \\
& + \gamma_h * G_t + \alpha_h + \varepsilon_{t+h} \quad \text{for} \quad h = 0, 1, 2, ...,
\end{aligned} \tag{6}
$$

where G_t is the smooth transition function between states. With this specification, we allow the coefficients to vary with the levels of inattention. The coefficients $\beta_{a,h}$ and $\beta_{b,h}$ measure the impact of monetary policy shocks at the high and low inattention scenarios, respectively. The results, reported in Figure 6, display the same pattern in which inattention, like nominal rigidities, amplifies the response of real GDP to a given set of monetary policy shocks.[14]

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 firm 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 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. These firms also update their information sets in a staggered fashion. Final-good firms operate in a perfectly competitive environment; they transform intermediate goods into final goods using a constant return to scale technology. The key innovation in our model is to allow inattention paid by firms to be endogenous.

3.1 Households

In each period t, the representative household derives utility from consumption (c_t), supplies labor (n_t) and holds bonds (b_t). The problem of the representative household is given by:

[14] Our results still hold if we use a different function for the smooth transition path between high- and low-inattention states as $G(w_t) = exp(-\gamma w_t)/[1 + exp(-\gamma w_t)]$, where $\gamma = 1.5$ and w_t is the measure of inattention normalized to have zero mean and unit variance; see also Auerbach and Gorodnichenko (2012) and Ramey and Zubairy (2018).

$$\max_{\{b_t, c_t, n_t\}_{t=0}^{\infty}} \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t u(c_t, n_t) \tag{7}$$

with $\beta < 1$ being the household's subjective discount factor, $u(c_t, n_t)$ is the period utility function and $\mathbb{E}_t$ is the expectations operator. Maximization is subject to the sequence of budget constraints (in real terms):

$$c_t + b_t = w_t n_t + \frac{R_{t-1} b_{t-1}}{\pi_t} \tag{8}$$

where w_t is the real wage, R_t is the gross nominal interest rate on bonds and π_t is the gross inflation rate.

The optimal choices of consumption, labor and bond holdings yield the following optimization conditions:

$$-\frac{u_{n,t}}{u_{c,t}} = w_t \tag{9}$$

$$u_{c,t} = \beta R_t \, \mathbb{E}_t \left(\frac{u_{c,t+1}}{\pi_{t+1}} \right) \tag{10}$$

where $u_{c,t}$ is the marginal utility of consumption in period t, and $u_{n,t}$ is the marginal disutility of supplying labor in period t. Equation (9) is the standard labor supply condition stating that, at the optimum, the marginal rate of substitution between labor and consumption equals the real wage. Equation (10) is the standard consumption Euler equation.

3.2 The Production Sector

As is standard in the literature, two types of firms operate in this sector: monopolistically-competitive intermediate-good firms who produce differentiated products and perfectly-competitive firms who transform intermediate goods into final goods using a constant return to scale technology.

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:

$$y_t = \left(\int_0^1 y_{j,t}^{\frac{\varepsilon-1}{\varepsilon}} \, dj \right)^{\frac{\varepsilon}{\varepsilon-1}} \tag{11}$$

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:

$$y_{j,t} = \left(\frac{P_{j,t}}{P_t}\right)^{-\varepsilon} y_t \tag{12}$$

where $P_t = \left(\int_0^1 P_{j,t}^{1-\varepsilon}\, dj\right)^{\frac{1}{1-\varepsilon}}$ is the Dixit-Stiglitz aggregate price level.

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. A firm that last updated its information set j periods ago sets its price $P_{j,t}$ and chooses labor $n_{j,t}$ to:

$$\max_{\{n_{j,t},P_{j,t}\}_{t=0}^{\infty}} \mathbb{E}_{t-j}\left[\frac{P_{j,t}}{P_t} y_{j,t} - w_t n_{j,t}\right] \tag{13}$$

subject to the demand curve for the firm's product (12) and the production technology:

$$y_{j,t} = z_t n_{j,t}^{1-\alpha} \tag{14}$$

with z_t being total factor productivity (which is common to all firms).

Profit maximization gives the following demand condition for labor:

$$mc_{j,t} = \frac{w_t}{(1-\alpha) z_t n_{j,t}{}^{-\alpha}} \tag{15}$$

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 $mc_{j,t} = \frac{w_t}{z_t}$, as is standard in the New Keynesian model with linear-in-labor technology. In addition, since the real wage is the same for all firms, the marginal cost is the same for all firms that updated their information sets j periods ago.

3.3 Constant Sticky Information

Each period t, a fraction λ of firms update their information sets. Therefore, in what follows, this parameter measures the degree of attention and $(1-\lambda)$ measures the degree of inattention. A firm that last updated its information set j periods ago, will choose the following price:

$$P_{j,t} = \frac{\varepsilon}{\varepsilon - 1} \frac{\mathbb{E}_{t-j}\left(w_t y_{j,t}^{\frac{1}{\alpha}} z_t^{-\frac{1}{\alpha}}\right)}{\mathbb{E}_{t-j}\left(\alpha y_{j,t}/P_t\right)} \tag{16}$$

and then the aggregate price level reads:

$$P_t = \lambda \sum_{j=0}^{\infty} (1-\lambda)^j P_{j,t}. \tag{17}$$

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

3.4 Time-Varying Sticky Information

We now assume that the probability that a firm updates its information set is not constant. In particular, in period t, a fraction λ_t of firms have the current information, a fraction $\lambda_{t-1}(1-\lambda_t)$ have a one-period old information, a fraction $\lambda_{t-2}(1-\lambda_{t-1})(1-\lambda_t)$ have a two-period old information, etc. Under this scenario, the aggregate price level can be re-written as:

$$P_t = \lambda_t P_{0,t} + \sum_{j=1}^{\infty} \lambda_{t-j} P_{j,t} \Big(\prod_{i=0}^{j-1} (1-\lambda_{t-i}) \Big) \tag{18}$$

which restores condition (17) when λ_t is constant. The first term on the right-hand side corresponds to the firms that updated their information zero period ago (namely, firms with the current information), and the second term corresponds to the firms that have at least one-period old information. The behavior of λ_t is specified in what follows.

3.5 State-Dependent Sticky Information

In this subsection, we derive the probability that a firm updates its information by solving an optimization problem. As such, we do not impose any specific rules to govern the behavior of information rigidity. Specifically, we assume that firms face menu costs of adjusting their information sets, which are distributed *i.i.d.* across firms and over time.[15]

Let $f(\kappa_t)$ and $F(\kappa_t)$ denote the probability density function and cumulative distribution function of the menu cost, respectively. κ_t is measured in units of labor time so that the total cost of updating information by a firm is $\kappa_t w_t$, with w_t being the real wage. Let also $v_{0,t}$ 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 let $v_{j,t}$ denote the value of a firm that updated its information j periods ago (a vintage-j firm), with $j = 1, ..., J-1$, and J being the number of vintages. A vintage-j firm will update its information set only if the value of updating, $v_{0,t} - \kappa_t w_t$, is greater than the value of not updating, $v_{j,t}$. Therefore, only firms with a draw of $\kappa_t < \frac{v_{0,t}-v_{j,t}}{w_t}$ will update. As such, the probability that a vintage-j firm updates its information set in period t is given by:

$$\theta_{j,t} = F\Big(\frac{v_{0,t} - v_{j,t}}{w_t}\Big) \tag{19}$$

with $j = 1, ..., J-1$. We further assume that after J periods, all firms update their information sets, and hence $\theta_{J,t} = 1$. Let $\kappa_t^* = \frac{v_{0,t}-v_{j,t}}{w_t}$ denote the cut-off value of κ_t for which a firm is indifferent between updating its information and not updating.

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

$$\lambda_t = \sum_{j=1}^{J} \psi_{j,t}\theta_{j,t} \tag{20}$$

and the total fraction of firms that last updated their information j periods ago is:

$$\lambda_{t-j} = \psi_{j,t}(1 - \theta_{j,t}), \qquad \forall j = 1, ..., J. \tag{21}$$

[15] Dotsey et al. (1999), Bakhshi et al. (2007) and Nakov and Thomas (2014) use similar setups for state-dependent price rigidity.

Therefore, the total fraction of firms that did not update their information set in period t is given by $1 - \lambda_t$, which also measures the degree of inattention in this model.

The value of firm j in case of not updating its information set is given by:

$$v_{j,t} = \max \mathbb{E}_{t-j} \left\{ \left[\frac{P_{j,t}}{P_t} y_{j,t} - w_t n_{j,t} \right] + \beta Q_{t,t+1} \left[(1 - \theta_{j+1,t+1}) v_{j+1,t+1} + \theta_{j+1,t+1} v_{0,t+1} - \Gamma_{j+1,t+1} \right] \right\} \quad (22)$$

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

Similarly, the value of a firm when updating information in period t is:

$$v_{0,t} = \frac{P_{0,t}}{P_t} y_{0,t} - w_t n_{0,t} + \beta \mathbb{E}_t \{ Q_{t,t+1} \left[(1 - \theta_{1,t+1}) v_{1,t+1} + \theta_{1,t+1} v_{0,t+1} - \Gamma_{1,t+1} \right] \} \quad (23)$$

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

3.6 Market Clearing

In equilibrium, the resource constraint of the economy reads:

$$z_t n_t^{1-\alpha} = c_t \quad (24)$$

and bonds are in zero net supply ($b_t = 0$).

3.7 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:

$$\ln\left(\frac{R_t}{\overline{R}}\right) = \rho_R \ln\left(\frac{R_{t-1}}{\overline{R}}\right) + (1 - \rho_R)\left(\rho_\pi \ln\left(\frac{\pi_t}{\overline{\pi}}\right) + \rho_y \ln\left(\frac{y_t}{\overline{y}}\right)\right) + \varepsilon_{R,t} \quad (25)$$

with $\overline{y}$ being the steady-state value of output, $\overline{\pi}$ being the steady-state value of the inflation rate, $\rho_\pi > 1$, $\rho_y > 0$ and $\rho_R > 0$ being the coefficients of inflation, output and interest rate smoothing, respectively, $\varepsilon_{R,t}$ is a shock to the nominal interest rate.

3.8 Calibration

A summary of the parameter values is presented in Table 4. The time unit is a quarter and the discount factor β is set such that the steady-state annual interest rate is roughly 4%. Households' preferences are governed by the following period utility function:

$$u(c_t, n_t) = \frac{c_t^{1-\sigma}}{1-\sigma} - \chi \frac{n_t^{1+\nu}}{1+\nu} \tag{26}$$

where 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 set to 1.5, which is in the middle of the standard values assumed in the literature.

The value of λ is consistent with our findings about the average degree 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. Also, since we study impulse responses to monetary policy shocks, we leave total factor productivity at its steady-state level. Therefore $z_t = \overline{z}$, and we normalize the steady-state of TFP to 1.

3.9 Numerical Results

The main numerical results are presented in this section. We start by showing the impact of a monetary policy shock on output and inflation rate when the degree of inattention is constant. We then turn to the cases when inattention is time varying and state dependent.

Constant Inattention

This subsection presents the responses of output and inflation for two different values of the i-nattention parameter. As Figure 7 indicates, when inattention (denoted by $1 - \lambda$) is higher, an expansionary monetary policy has a significantly bigger stimulative effect on output, in line with the empirical evidence. On the other hand, the response of inflation is smaller when inattention is higher. A possible explanation for this result is that 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). Thus, more information rigidity introduces some rigidity in price changes even though prices are not inherently rigid.[16] As is well known, monetary policy tends to be neutral when prices are fully flexible. In our model, prices are fully flexible, but rigid information, through the mechanism that is outlined above, renders monetary policy non-neutral. Therefore, while price rigidity and information rigidity are distinct from each other, there is some similarity in their implications for monetary policy.

Time-varying Inattention

This subsection studies the case when inattention is time varying. In particular, inattention becomes higher when output is relatively low or inflation is relatively high. In addition, we allow for persistence in inattention, which is consistent with our empirical findings.

Specifically, we assume that λ_t is governed by the following condition:

$$\ln\left(\frac{\lambda_t}{\overline{\lambda}}\right) = \rho_\lambda \ln\left(\frac{\lambda_{t-1}}{\overline{\lambda}}\right) - (1-\rho_\lambda)\theta_y \ln\left(\frac{y_t}{\overline{y}}\right) + (1-\rho_\lambda)\theta_\pi \ln\left(\frac{\pi_t}{\overline{\pi}}\right) \tag{27}$$

with $\overline{\lambda}$ and ρ_λ being, respectively, the steady-state value and the persistence parameter of λ_t, θ_y is the response of λ_t to deviations of output from its steady state, and θ_π is the response of λ_t to deviations of the inflation rate from its steady state. This equation assumes that inattention (denoted by $1-\lambda_t$) rises when output is relatively high and falls when inflation is relatively high.

Figure 8a presents the results. For illustration, we consider two values of the parameters θ_y and θ_π. Consider first the case with $\theta_y = \theta_\pi = 1$: when inattention rises, the response of output is

[16] 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 to the scenario with perfect information. Drenik and Perez (2019) use the manipulation of inflation statistics that occurred in 2007 in Argentina to understand the effects of information frictions on price level dispersion and monetary policy. They find that monetary policy is more effective when there is less precise information, since 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.

slightly bigger than when inattention is constant. By contrast, when inattention is very responsive to output and inflation ($\theta_y = \theta_\pi = 5$), the initial rise in output is considerably bigger than under the scenario of a constant inattention parameter. This large increase in output occurs even though inattention rises only slightly (from 0.25 to roughly 0.255), suggesting that even small changes in inattention may have a profound impact on the response of output to monetary policy shocks.

This result can be better seen in Figure 8b, where we assume that the steady-state level of inattention is 0.75. In this case, with a time-varying inattention, the rise in output is significantly larger than with a constant inattention parameter, particularly when inattention is very responsive to output and inflation ($\theta_y = \theta_\pi = 5$). For this reason, if inattention is treated as a fixed parameter, the effectiveness of monetary policy in raising output will be considerably underestimated.[17]

State-Dependent Inattention

In order to solve the model, we assume $J = 4$, implying that all firms update their information sets after 4-periods (quarters).[18] In addition, we let the cumulative distribution function for the cost of updating the information set be given by:

$$F(\kappa_t) = \frac{\zeta + \kappa_t}{\eta + \kappa_t} \tag{28}$$

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

Using condition (19), condition (28) can be rewritten as:

$$F(\kappa_t) = \frac{\zeta + (v_{0,t} - v_{j,t})/w_t}{\eta + (v_{0,t} - v_{j,t})/w_t} \tag{29}$$

implying that the probability for the firm to update its information set is increasing in the gain from adjustment $(v_{0,t} - v_{j,t})$. In what follows, we set the values of ζ and η in order to obtain $\overline{\lambda} = 0.75$, as in our benchmark analysis.

Figure 9 presents the impulse responses to the expansionary monetary policy. As a result of the decline in the nominal interest rate, output and inflation rise as expected. In addition, the real

[17] We also note that if the response of λ_t to output is bigger than the response to the inflation rate (i.e. $\theta_y > \theta_\pi$), then inattention will rise more than indicated in Figure 8a and Figure 8b. As a result, the model with a time-varying inattention will generate even a bigger stimulative effect of monetary policy than indicated in these two figures.

[18] Our results hold also for $J = 8$ and other values of this parameter.

wage rises, which leads to a decline in the cut-off value of $\kappa_{j,t}$, leading to a decline in the fraction of vintage-j firms that choose to update their information sets (i.e. a decline in θ_j). Therefore, information rigidity rises following the expansionary monetary policy, which is consistent with our analysis above. Comparing the response of output across two scenarios reveals that the increase of output following the expansionary monetary policy with state-dependent inattention is much larger than with constant inattention. Therefore, assuming a constant inattention parameter as done in most studies leads to under-estimation of the effectiveness of monetary policy in raising output.

The left panel of Figure 10 shows that, on average (and in the non-stochastic steady state of the model), the probability that a firm of vintage j updates its information set is increasing in j. Intuitively, a firm with an older information set is more likely to update its information set in the current period than a firm with a newer information set (and for $j = J = 4$, this probability is assumed to be exactly 1).

Figure 10 also shows the distribution of firms according to the time that they last updated their information (i.e. the values of $\psi_{j,t}$). As expected, the share of firms with j-period old information sets declines as j rises. For example, 75% of the firms have updated their information sets one period ago, roughly 20% of the firms have a two-period old information, etc. No firm has a J-period old information as all firms in that vintage are assumed to update information in the current period. As such, while firms of a higher vintage (larger j) are more likely to update their information sets in period t than firms in a lower vintage, there are fewer firms in the higher vintage.

The right panel of Figure 10 shows the cut-off values of $\kappa_{j,t}$, for which a firm j is indifferent between updating and not updating its information set. The smaller j is, the smaller this cut-off. As a result, firms that updated j periods ago are less likely to update in the current period than firms that updated $j + i$ periods ago for all $i = 1, ..., J - j$. Put differently, firms that updated in period $t - 1$ are less likely to update information in period t than firms that updated information in period $t - 2$ or earlier.

We close this section with two comments. First, our model assumes firm-side inattention only. It is possible that adding household inattention would dampen the response of consumption (hence output) to a monetary policy shock. This would reflect a slower adjustment of consumption when households are inattentive; see Reis (2006a) for a discussion. In our model, adding household inattention may weaken the response of output under *all* scenarios (constant inattention, time-varying inattention and state-dependent inattention), but it would not change the main conclusion of the paper.

Second, in a model with firm-side inattention only (i.e. no sticky prices or wages), Mackowiak and Wiederholt (2015) show that output rises, but in a monotonic way, as in our DSGE-based analysis. However, when household inattention is introduced in their model, the response of output becomes hump shaped. As noted above, we abstract from household inattention in all cases, and the lack of household inattention may not be material for our main result that monetary policy shocks have larger real effects when the degree of inattention is higher and state-dependent.

4 Conclusion

We propose a micro-data based measure of inattention that captures the common component in professional forecasters' inattentiveness to many economic variables. Applying this measure to the U.S. SPF survey, we find that professional forecasters update their information sets every four 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.

To explain these empirical findings, we develop a DSGE model with inattentive firms. The model mostly resembles a standard New Keynesian framework, but with sticky information replacing sticky prices. The key innovation in our model is to allow attention paid by firms to be endogenous. Simulation results indicate that, when inattention is higher, an expansionary monetary policy has a much bigger stimulative effect on output, in line with the empirical evidence. Such an increase in output with state-dependent inattention is significantly larger than with constant inattention. Thus, treating inattention as a structural parameter, as assumed in most studies, would lead to significant under-estimation of the effectiveness of monetary policy in raising output.

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Table 1: Summary Statistics of Inattention Estimates

	Overall		RGDP		Inflation		Unemp	
Horizon	Mean	Std	Mean	Std	Mean	Std	Mean	Std
4Q ahead	0.19	0.15	0.49	0.21	0.62	0.19	0.43	0.16
3Q ahead	0.17	0.15	0.46	0.22	0.62	0.20	0.41	0.15
2Q ahead	0.08	0.09	0.42	0.22	0.58	0.20	0.24	0.16
1Q ahead	0.06	0.07	0.29	0.18	0.46	0.19	0.27	0.16

Notes: Inattention is defined in equation (2), measured as the proportion of forecasters who do not revise their forecasts for all target variables. Survey data come from U.S. Survey of Professional Forecasters from the first quarter of 1970 to the second quarter of 2020.

Table 2: Correlation between Overall and Variable-specific Inattention

A. Unconditional Correlation				
	RGDP	Inflation	Unemp	Overall
RGDP	1.00			
Inflation	0.76	1.00		
Unemp	0.67	0.58	1.00	
Overall	0.85	0.77	0.77	1.00
B. Conditional Probability of Revising				
Given the revision of	RGDP	Inflation	Unemp	
Probability of revising				
RGDP	1.00	0.64	0.57	
Inflation	0.47	1.00	0.41	
Unemp	0.64	0.63	1.00	

Notes: Panel A shows unconditional correlations, and Panel B gives the conditional probability of revising a forecast.

Table 3: Sources of Inattention

	Higher Frequency			Lower Frequency		
	(1)	(2)	(3)	(4)	(5)	(6)
GDP Growth	0.801***		0.399**	0.615***		-0.502**
	(0.190)		(0.172)	(0.212)		(0.210)
Inflation	-0.338		-0.161	-1.172***		-0.998***
	(0.302)		(0.313)	(0.219)		(0.230)
Unemployment	-0.119***		-0.077***	-0.042**		-0.033*
	(0.025)		(0.025)	(0.017)		(0.017)
Volatility		-0.342	-0.248		0.442	-0.297
		(0.525)	(0.464)		(0.346)	(0.402)
Return		0.553*	0.577**		1.244***	1.287***
		(0.293)	(0.292)		(0.352)	(0.341)
Policy Unc.		-1.619***	-1.032**		-0.862*	-0.572
		(0.489)	(0.471)		(0.465)	(0.550)
Macro Unc.		-5.144***	-3.829***		-3.875***	-3.116***
		(0.950)	(1.050)		(0.677)	(0.768)
Obs	202	202	202	199	199	199

Notes: For columns (1) - (3), the dependent variable is the quarterly inattention series. For columns (4) - (6), the dependent variable is the 4-quarter moving average of inattention. Policy uncertainty is from Baker et al. (2016), and macro uncertainty is from Jurado et al. (2015). All regressions control for the time trend. *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

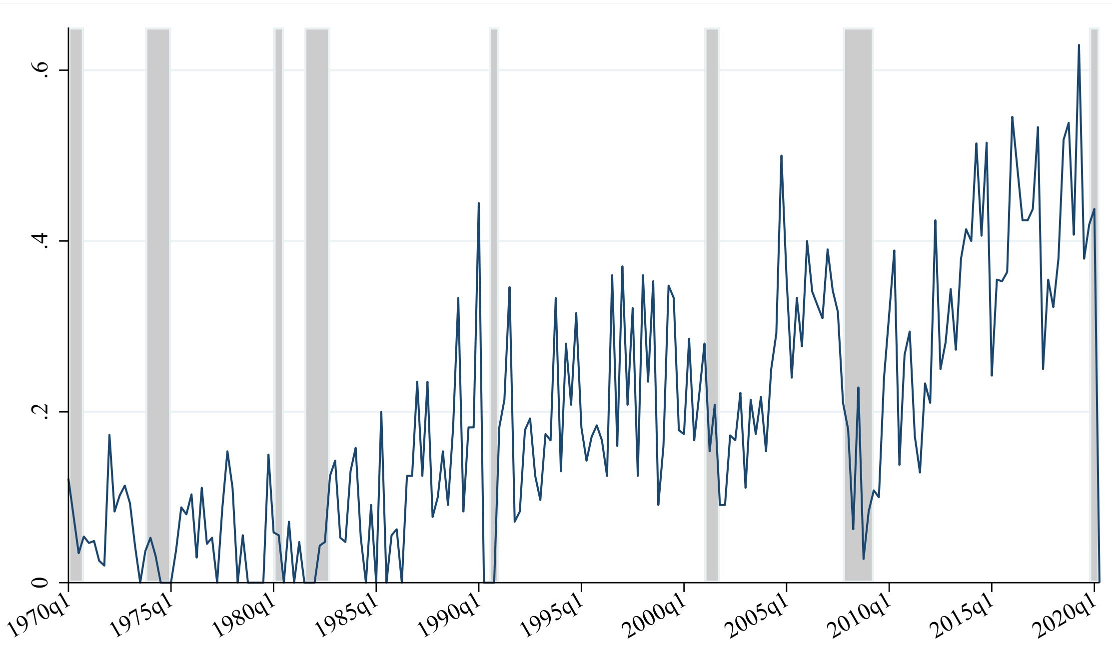
Table 4: Values of the Parameters

Parameter	Description	Value
β	Households' discount factor	0.99
σ	Consumption curvature parameter	1.50
ν	Inverse of labor supply elasticity	0.5
$1-\alpha$	Labor share of output	0.66
ε	Elasticity of subs. between goods	6.00
λ	Information flexibility parameter	0.75
ϕ_π	Coefficient on inflation in the interest-rate rule	1.50
ϕ_y	Coefficient on output in the interest-rate rule	0.125
ρ_R	Interest-rate smoothing parameter	0.90

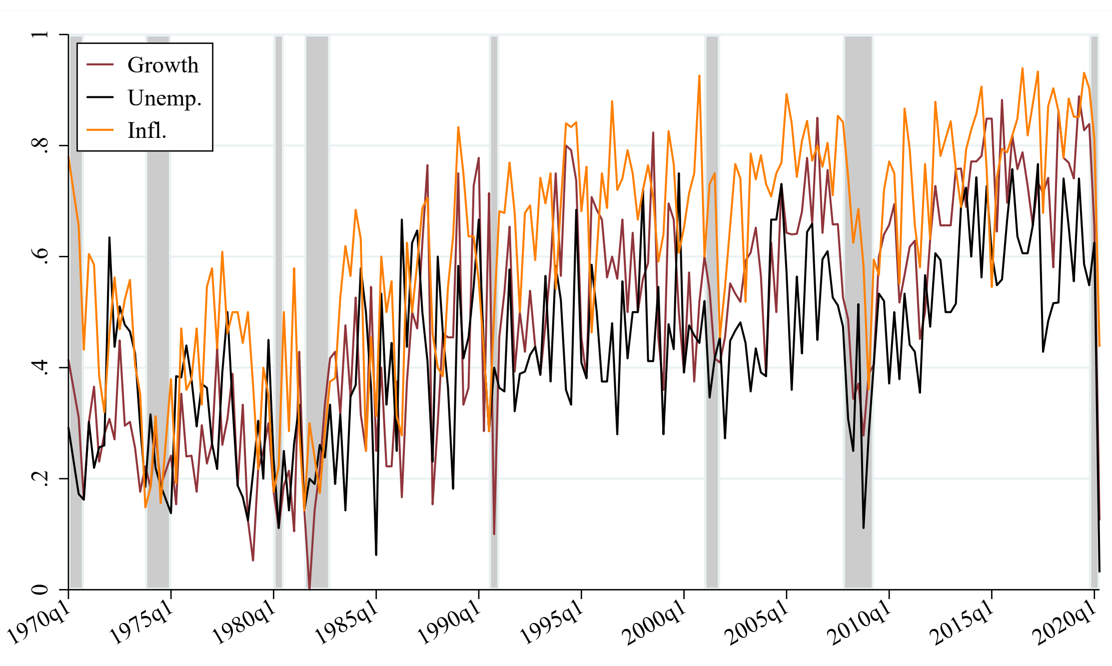
Notes: $\phi_\pi = (1-\rho_R)\rho_\pi$ and $\phi_y = (1-\rho_R)\rho_y$.

Figure 1: Time Series of Inattention

(a) Inattention to Macroeconomic Condition



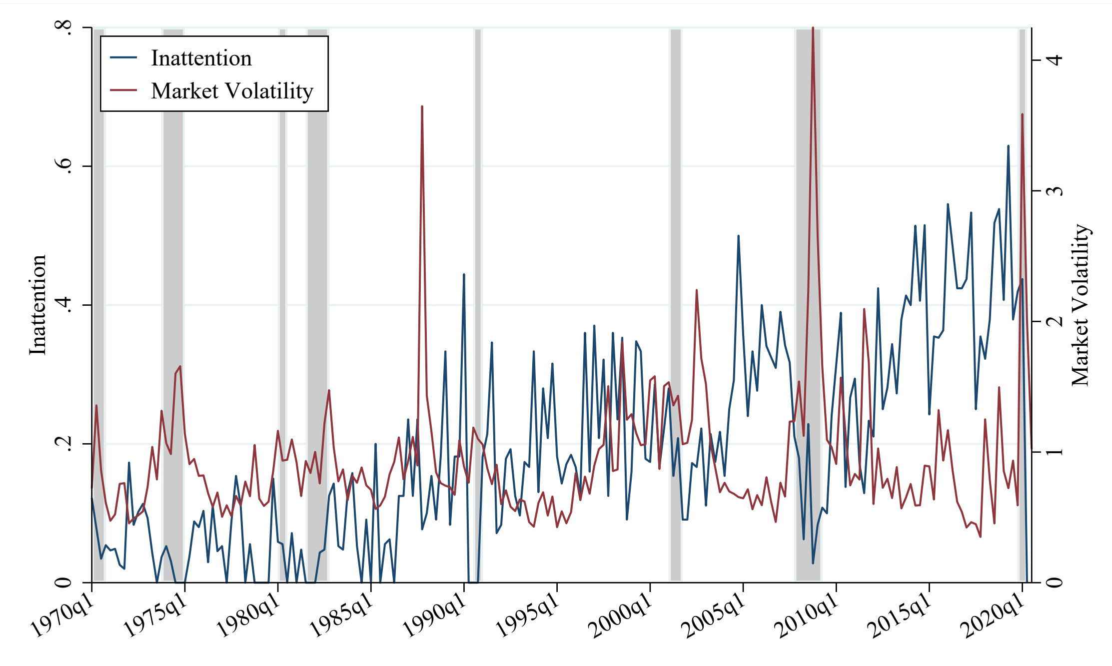
(b) Inattention to Single Variables



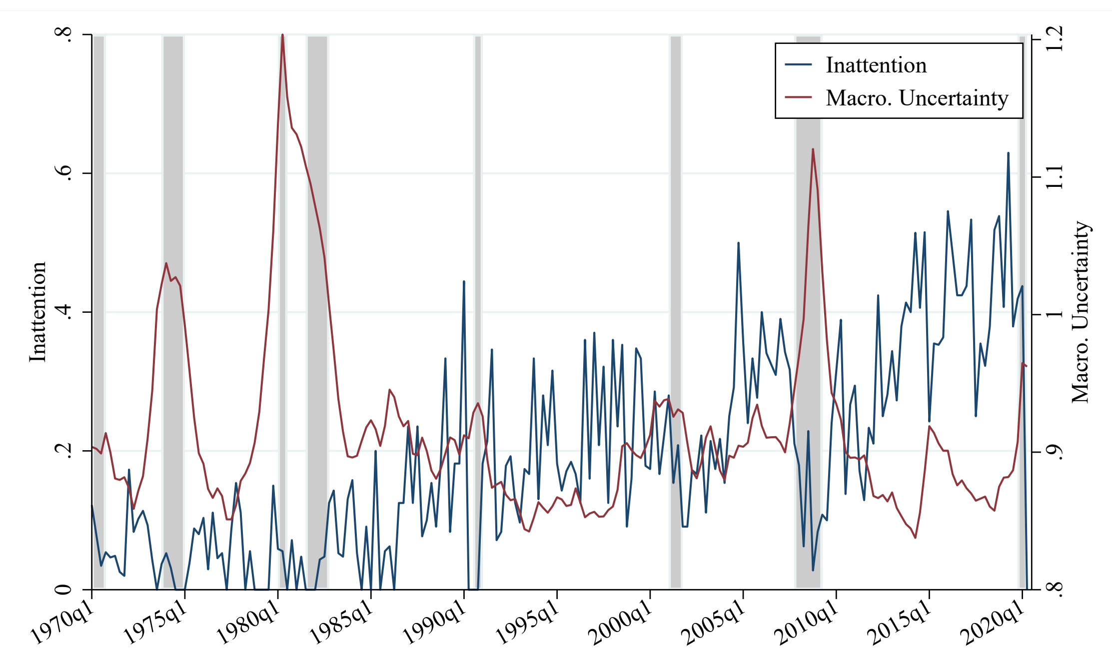
Notes: This figure plots quarterly inattention from the first quarter of 1970 to the second quarter of 2020. Panel A is the inattention to macroeconomic condition as defined in equation (2), and panel B is the inattention to single macro variables – real GDP growth, CPI inflation or unemployment rate. Inattention measures for 1970Q2 and 1974Q4 are not available due to the missing data from SPF, and the values for these two periods are linearly interpolated.

Figure 2: Inattention, Market Volatility and Macro Uncertainty

(a) Inattention and Market Volatility

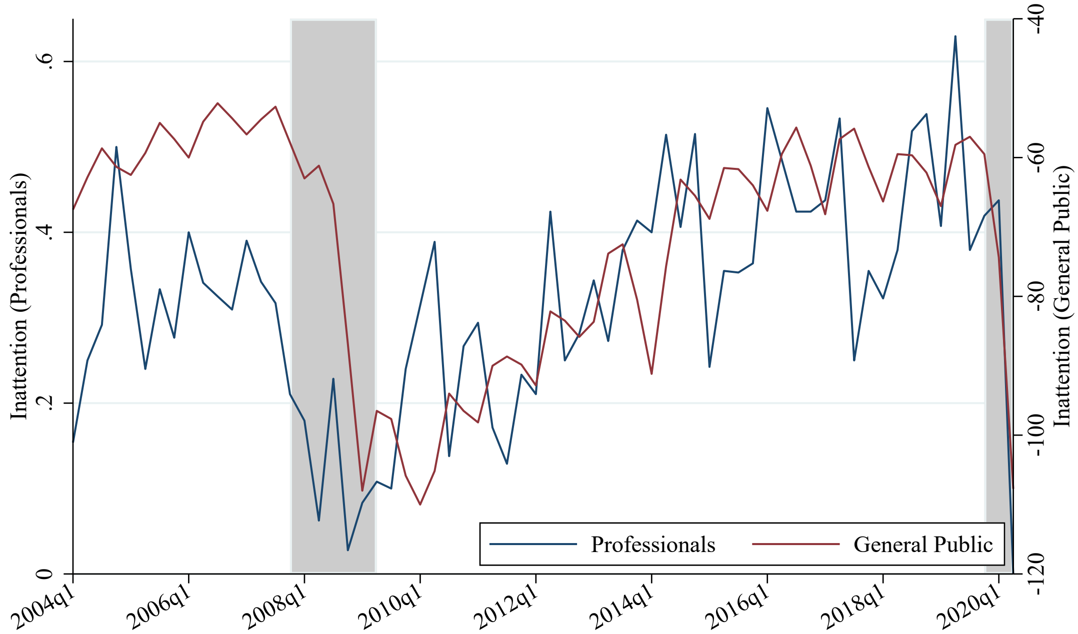


(b) Inattention and Macroeconomic Uncertainty



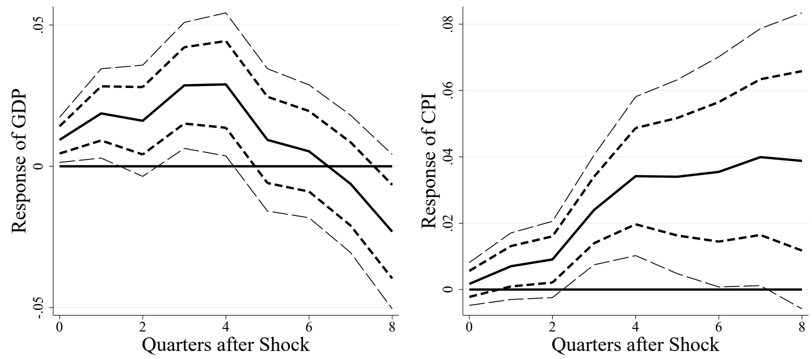
Notes: The upper panel plots inattention against stock market volatility, and the lower panel plots inattention against macro uncertainty, proposed by Jurado et al. (2015). The shaded areas represent NBER designated recessions.

Figure 3: Inattention: Professionals vs. General Public



Notes: The alternative measure of inattention is based on the popularity of search queries in Google. To construct this measure, we first calculate Google Trends frequency of topic search on Gross Domestic Product, Consumer Price Index, and Unemployment, and then take the negative value of the frequency to obtain the inattention measure of the general public. The shaded area represents NBER designated recessions.

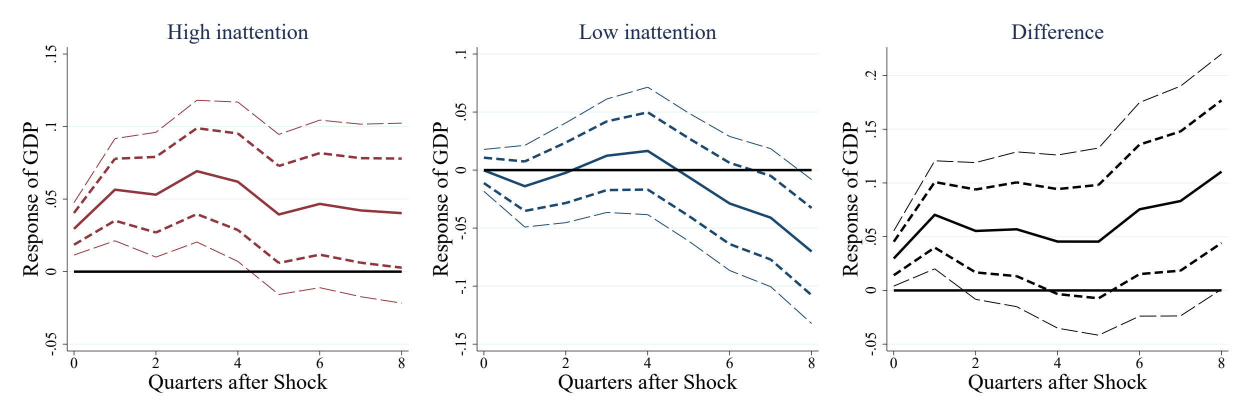
Figure 4: Impact of Monetary Policy: Baseline Results



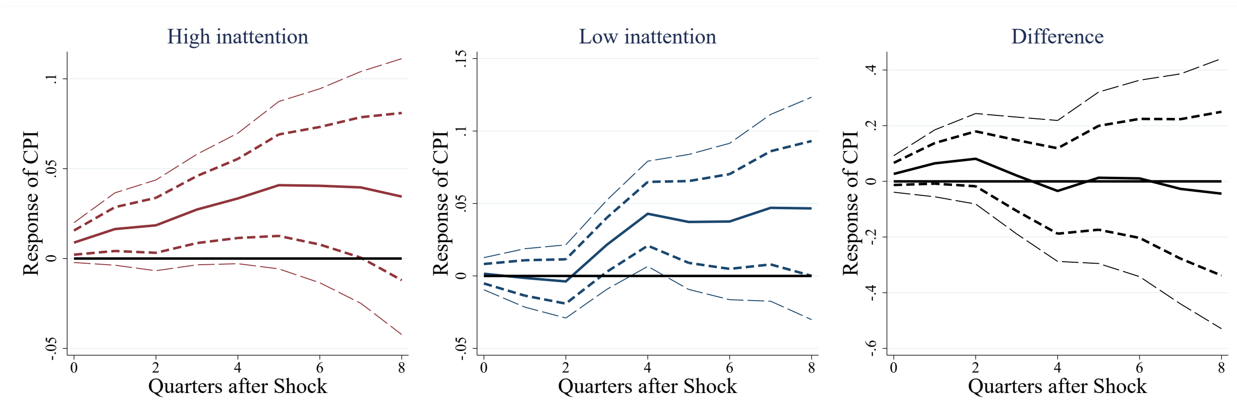
Notes: This figure shows the impulse response of macroeconomic variables to an expansionary monetary policy shock, measured as 100 basis points decrease in the BRW monetary policy shock series. The impulse responses are estimated based on the sample period 1975Q1-2019Q3. The dashed and dotted lines indicate the 90% and 68% confidence intervals produced by the Newey-West method.

Figure 5: Inattention and the Impact of Monetary Policy: Local Projections with Interacted Variables

(a) GDP Growth



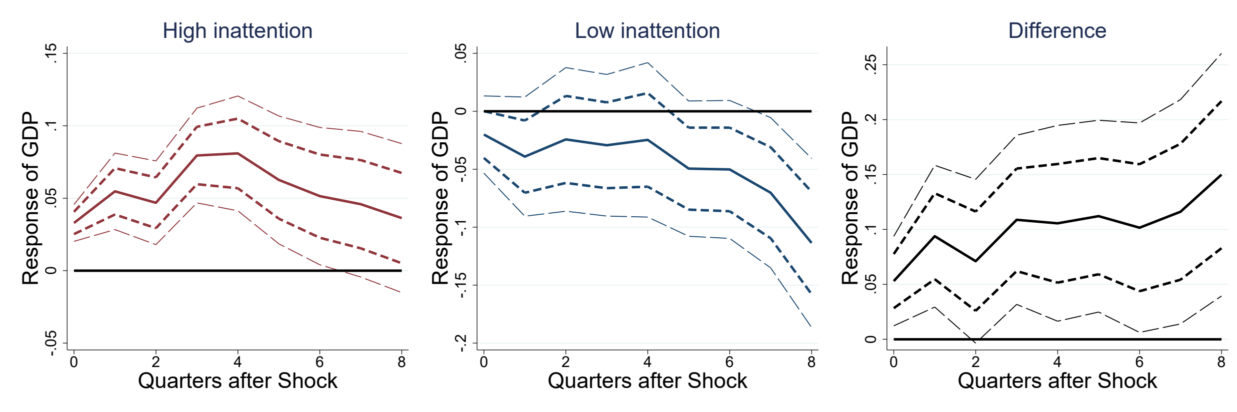
(b) CPI Inflation



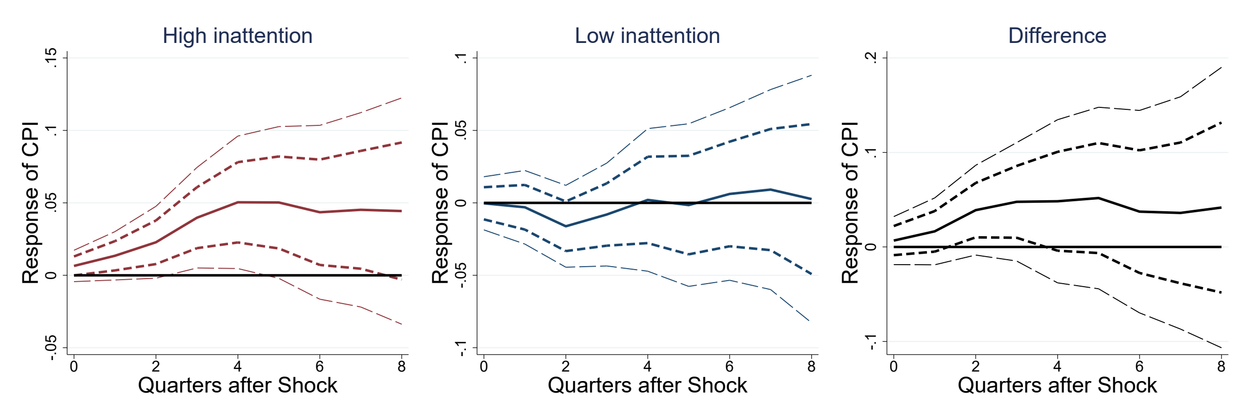
Notes: This figure shows the impulse response of macroeconomic variables to an expansionary monetary policy shock, measured as 100 basis points decrease in the BRW monetary policy shock series. The impulse responses are estimated based on the sample period 1975Q1-2019Q3. We identify high inattention with sub-samples with the 10% highest values, and low inattention with the 10% lowest values. The dashed and dotted lines indicate the 90% and 68% confidence intervals produced by the Newey-West method.

Figure 6: Inattention and the Impact of Monetary Policy: Smooth Transition Local Projections

(a) GDP Growth

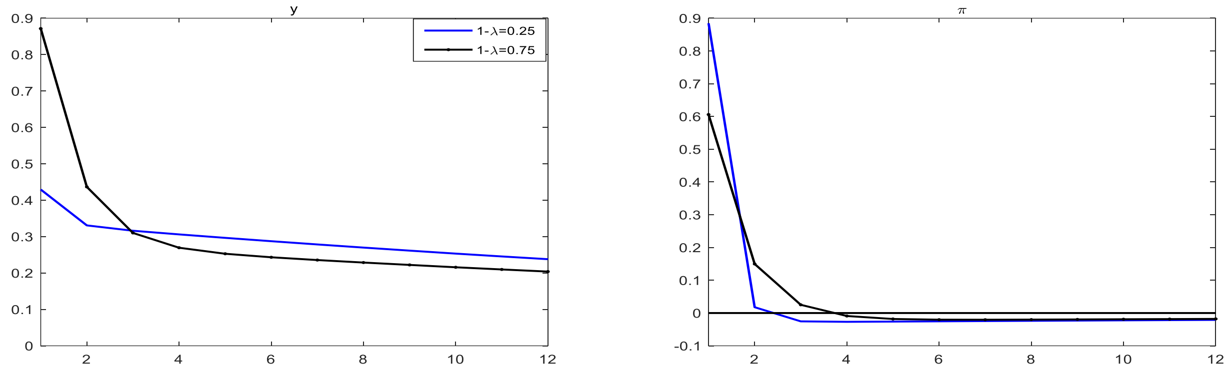


(b) CPI Inflation



Notes: This figure shows the impulse response of macroeconomic variables 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 1975Q1-2019Q3. The smooth transition path between high- and low-inattention states is estimated using the Markov switching model. The dashed and dotted lines indicate the 90% and 68% confidence intervals produced by the Newey-West method.

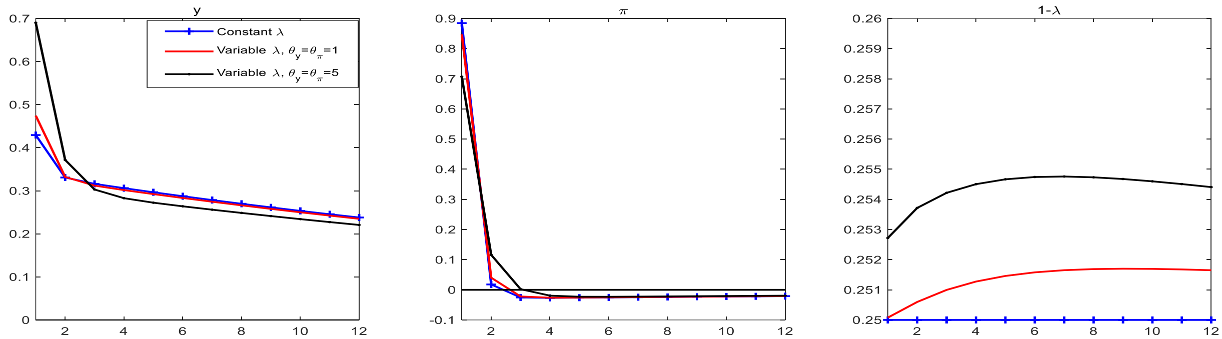
Figure 7: Responses to Expansionary Monetary Policy: Constant Inattention



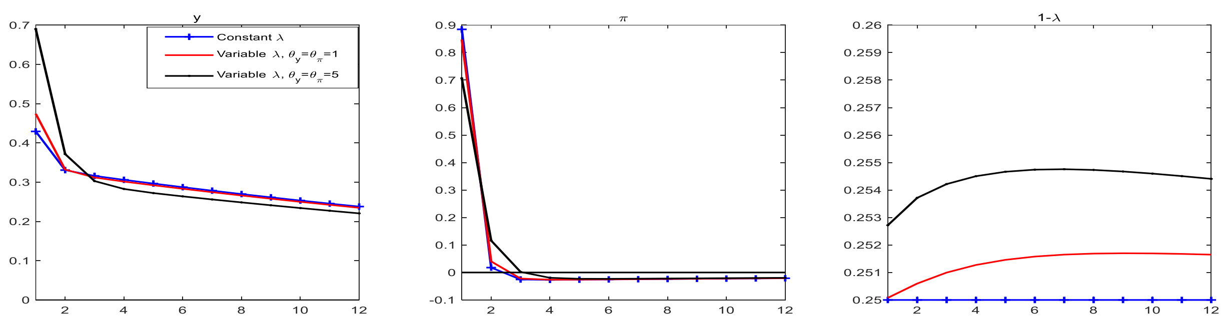
Notes: Responses to an expansionary monetary policy (R_t) shock for two different values of the inattention parameter $(1-\lambda)$. Output and inflation are expressed as percentage deviations from the deterministic steady state.

Figure 8: Responses to Expansionary Monetary Policy: Time-varying Inattention

(a) With A Low Value of Inattention at the Steady-State

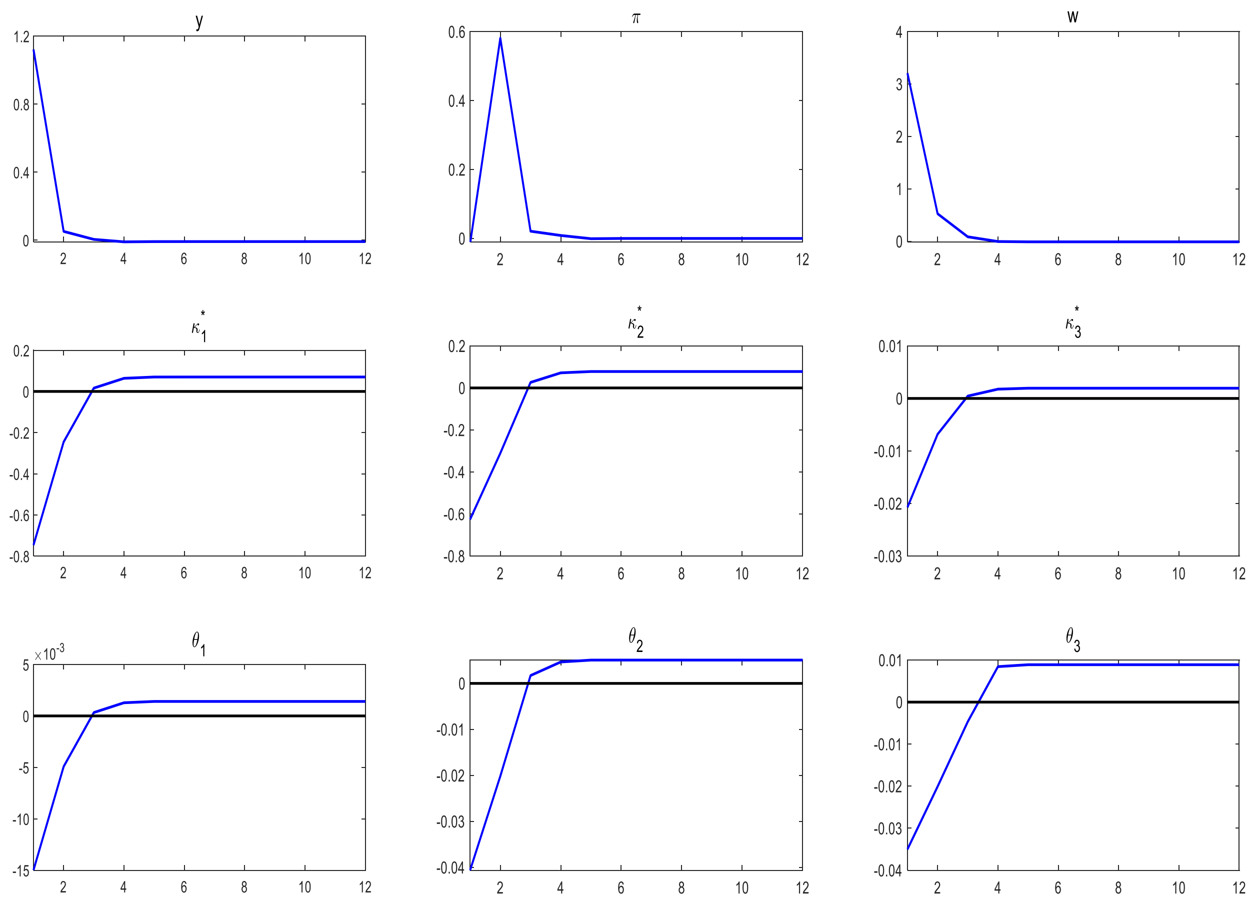


(b) With A High Value of Inattention at the Steady-State



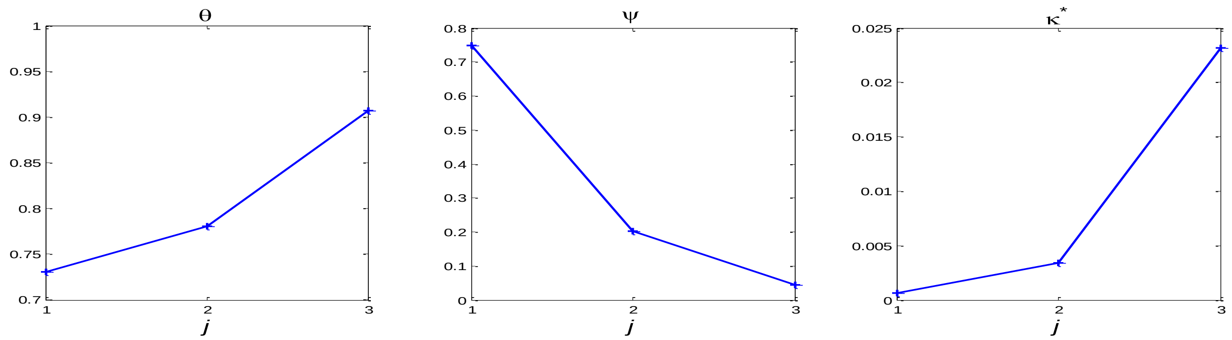
Notes: Responses to an expansionary monetary policy (R_t) shock. Output and the inflation rate are expressed as percentage deviations from the deterministic steady state. For the inattention parameter $(1-\lambda)$, the actual value is shown. In Figure 8a, $1-\overline{\lambda} = 0.25$ and $\rho_\lambda = 0.73$. In Figure 8b, $1-\overline{\lambda} = 0.75$ and $\rho_\lambda = 0.73$.

Figure 9: Responses to Expansionary Monetary Policy: State-Dependent Inattention



Notes: Responses to an expansionary monetary policy (R_t) shock in the model with state-dependent information rigidity. All variables are expressed as percentage deviations from the deterministic steady state.

Figure 10: Updating Probabilities and the Cut-Off Values for Updating



Notes: θ_j is the probability that a firm that updated its information set j period ago (a "vintage-j" firm) will update its information set in period t, ψ_j is the share of each vintage in the total number of firms, and κ_j^* is the cut-off value for updating the information set for each vintage.