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Does inattentiveness matter for DSGE modeling? An empirical investigation ☆

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ABSTRACT

The purpose of this paper is to investigate the empirical performance of the standard New Keynesian dynamic stochastic general equilibrium (DSGE) model in its usual form with full-information rational expectations and compare it with versions assuming inattentiveness—namely sticky information and imperfect information data revision. Using a Bayesian estimation approach on US quarterly data (both real-time and survey) from 1969 to 2015, we find that the model with sticky information fits best and is the only one that can generate the delayed responses observed in the data. The imperfect information data revision model is improved fits better when survey data is used in place of real-time data, suggesting that it contains extra information.

1. Introduction

Macroeconomic forecasts are widely depicted as inattentive, by which we mean failing to be continuously updated with full current information under rational expectations as assumed in the standard New Keynesian model. Empirical investigations (Coibion and Gorodnichenko, 2015; Andrade and Le Bihan, 2013) have clearly established that professional forecasters are no less susceptible to this failure. While, on the other hand, the New Keynesian framework, characterized by full-information rationality assumption and sticky prices, has failed to explain some facts observed in actual data. For instance, (Fuhrer and Moore, 1995) argue that monetary policy shock has a delayed or gradual impact on inflation, which cannot be explained by the original New Keynesian-type model. Furthermore, the observed delayed response to monetary shock on inflation cannot be produced without any information friction (i.e some inattentiveness feature) or price indexation (Mankiw and Reis, 2010). However, an unresolved question is which form of inattentiveness is more prevalent and therefore, better explains macroeconomic dynamics.

The main purpose of the current paper is to verify which inattentiveness features matter in explaining economic dynamics, specifically in the US. First, we consider whether the inclusion of inattentive features in the original New Keynesian DSGE model can better replicate some important stylized facts.[1] The key question is whether such an inclusion can help yield better overall performance. Second, we contribute to the ongoing debate on whether the different types of inattentive features have distinctive explanations for the dynamics of observed actual data. Our analysis considers three competing models: the model with full-information rationality, the model with sticky information expectation, and the model with imperfect information data revision expectation. Each model will be evaluated through the Bayesian estimation method.

Recent models have focused on deviations from full information and rational expectations (FIRE) due to informational rigidities (Mankiw and Reis, 2002; Woodford, 2001; Sims, 2003). The different forms of

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[1] The persistence property of output and inflation, and the delay effect of monetary policy shock on inflation. Such stylized facts are taken as serviceable norms that assist in evaluating certain models. The observed hump-shaped response of inflation to monetary policy shock has been emphasized in recent years. This is because the hump-shaped response is not only robust but also difficult to generate in a simple model. Most notably, the New Keynesian Phillips curve, which is based on the assumption that firms face expense to adjust price, is unable to reproduce such a response without any information rigidities (Mankiw and Reis, 2002).

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information rigidities, or agents' inattentiveness, form the basis of the competing rational expectations models with informational frictions. First, there is the sticky information (SI) model of Mankiw and Reis (2002). Here, agents update their information set sporadically. They do not continuously update their expectations but choose an optimal time at which to be inattentive, that is, they receive no news about the economy until it is time to plan again. The slow diffusion of information is due to the costs of acquiring information and conducting re-optimization (Reis, 2006a,b). Such sticky information expectations have been used to explain inflation dynamics (Mankiw and Reis, 2002), aggregate outcomes in general (Mankiw and Reis, 2006), and the implications for monetary policies (Ball et al., 2005).

In the second type of informational friction (IF) model (Sims, 2003; Aruoba, 2008; Woodford, 2011; Casares and Vázquez, 2016) it is argued that agents update their information set continuously but can never fully observe the true state due to signal extraction problems. We take data revision as a solution of the signal extraction problem, which indicates that imperfect information has an impact on agents, mainly through the data revision process aimed at reducing noise and incorporating all the relevant information, in terms of forming their expectations on the state of the economy. The details and definition of the data revision process follow from Casares and Vázquez (2016) and Vázquez et al. (2010, 2012) (details can be found in the Appendix).

In the present paper, we use a full New Keynesian DSGE model, rather than one based on a single equation (Coibion and Gorodnichenko, 2015). The current analysis compares a DSGE model of this type under FIRE with two different inattentive conditions, namely the sticky information assumption and the imperfect information data revision assumption. We assess which of these expectation models best explains the US economy for a period of five decades (sample period US quarterly data from 1969 to 2015). Our findings reveal that the three US main economic quarterly real-time data strongly favor the model under the assumption of sticky information. Through the Bayesian estimation approach, we find that the specification with the sticky information outperforms other versions according to marginal likelihood and the formal criterion Bayes factor. Furthermore, the estimated parameters have reasonable values that agree with those that have been typically analyzed in the literature. The model with imperfect information data revision ranks as the second best performing model. The baseline under the FIRE type model performs worse than either of the inattentive assumption models. We interpret these findings through the Bayesian estimation approach, which suggests that incorporating inattentive feature is needed so that the New Keynesian rational expectation model can be a better monetary business cycle model. Moreover, different levels of inattentiveness have an impact on the three aspects that are used to explain the economic dynamics, namely, estimated posterior distribution, estimated impulse response function (IRF), and significant different values of log marginal likelihood.

A few recent studies have tried to compare the full-information rationality DSGE model with the alternative sticky information DSGE model. Paustian and Pytlarczyk (2006), for instance, evaluated the DSGE model for the Euro area based on Smets and Wouters (2003)'s Bayesian estimation approach and find that the Calvo FIRE model overwhelmingly dominates the model with sticky information. Trabandt (2007), meanwhile, used the full-specified DSGE model under the sticky information assumption and compares it to the Calvo FIRE model. Allowing for the dynamic inflation indexation (Christiano et al., 2005), they find that both models fare equally well. Meanwhile, other studies aimed to compare the FIRE model with the Imperfect Information data revision model (Paloviita, 2007, 2008; Vázquez et al., 2010; Casares and Vázquez, 2016) They argue that the use of real-time data variables improves the empirical performance of the classical New Keynesian model. In the present paper, by comparing the full range of models with inattentive expectations against the FIRE model we fill an important gap in the existing literature. This topic matters for policymaking, for instance, if we found that suppliers have an inaccurate estimate of current aggregate conditions not because of the unavailability of good data in the public region, but because of the cost of using updated available public information is too high then they choose to use outdated information to perceive the future, it is quite possible for the monetary authority to affect real activity in ways that are correlated with that outdated public information they use. This should greatly increase the reasonable range of conducted policy. In contrast to the most recent related work (Ilabaca et al., 2020),[2] we consider a DSGE model to study how people form their expectation, more specifically we check the different specification of inattention to see which one is suited to mimic the way people expect the future.

The remainder of the paper is organized as follows: Section 2 briefly outlines the New Keynesian DSGE model with the competing expectations under consideration. Section 3 presents and assesses the empirical analysis following a Bayesian approach. Finally, Section 4 presents the main conclusions of this work.

2. New Keynesian DSGE model with competing expectations

We consider three models based on the reduced-form New Keynesian-type DSGE model for a small-scale closed economy.[3] The economy consists of three types of agents: households, firms, and monetary authorities. The baseline model that has been largely applied in previous studies (Milani and Rajbhandari, 2012) is the standard Calvo model without any inattentive features. Meanwhile, the competing inattentive models are characterized by sticky information following Mankiw and Reis (2007) and that based on the imperfect information data revision constructed by Casares and Vázquez (2016). A key difference between the two inattentive expectation model settings is that we use the small-scale instead of the medium-sized DSGE model. We focused on a simple version of the NK model, rather than a medium-scale NK model (Smets and Wouters, 2007; Casares and Vázquez, 2016),[4] for two main reasons. First, our goal is to examine how people form their expectations without incorporating too many constraints

[2] The setting of the Behavioral NK model (i.e., Ilabaca et al., 2020) is different from our SI-NK model. Precisely, the aggregate-level inattentive parameter M, M^f cannot be adjusted by the j. In other words, it cannot provide us with more specified results regarding whether people will incorporate how many periods' lagged information into their consumption/production decision to form their expectation. This j matters because once we find which j-periods' information is closely relevant to people's expectations, it is quite possible for the monetary authority to affect real activity in ways correlated with that j-period information they use. This should significantly increase the reasonable range of conducted policy. Apart from that, the paper proposed by Ilabaca et al. (2020) is not intended to compare the different information rigidity as we did.

[3] We chose the benchmark model as a simple New Keynesian model to include widely-used NK features, as illustrated by the literature; our focus is to see the added value for this simple model created by information frictions. To redo the analysis for the different and more complex SW model would involve a complete new body of work and is beyond the scope of this paper. In addition, the drawbacks of the SW model as benchmark have been clarified in Le et al. (2011), specifically they have found the SW model as estimated was strongly rejected by indirect inference., so is not really suitable as a benchmark. Moreover, when we survey the literature, the SW model with information rigidity exist and support our idea. Incorporate information rigidity is essential to explain the cyclical fluctuation (Casares and Vázquez, 2016). Their results suggest that the DSGE model that ignores IF data revision may overestimate the role of other sources of cyclical fluctuations and result in bias estimation.

[4] The recent work proposed by Paustian and Pytlarczyk (2006) compares SW medium-scale DSGE model with sticky information assumption to the one without any information friction, and they find that models without information friction (i.e., Calvo model), overwhelmingly dominate the model with sticky information in terms of post-ratio ratios. The root cause of poor fit seems to be that the sticky information model cannot match both self-correlation and inflation and real wage volatility. Their analysis reverses Mankiw and Reis's

and too much structure in the characterization of the private sector of the economy. Second, by considering a basic NK model, we can deal with a small set of observable variables and treat all parameters that characterize private agents' decisions as fixed in order to focus on the characterization of monetary policy, sticky information process, and data revision process parameters.

2.1. Baseline model: Reduced-form new Keynesian model without inattentive feature

Here, we present a more traditional version of the micro-foundation under the assumption of full-information rationality.[5] The details of the derivation have been presented in the Supporting Annex at the end of this paper. The baseline model is as follows:

IS Equation:

$$x_t = E_t x_{t+1} - \sigma(\tilde{r}_t - E_t \pi_{t+1}) + g_t \tag{1}$$

PC Equation:

$$\pi_t = \beta E_t \pi_{t+1} + \gamma((1-\alpha)(1-\alpha\beta)/\alpha) x_t + u_t \tag{2}$$

Interest rate smoothed Taylor Rule:

$$\tilde{r}_t = \rho_r \tilde{r}_{t-1} + (1-\rho_r)[\chi_\pi \pi_t + \chi_x x_t] + \upsilon_t \tag{3}$$

The aggregate economy under the reduced-form New Keynesian-type model with full-information rationality, which can be characterized by the dynamics of the three main economic variables (i.e., output gap, inflation, and interest rate). In the equations, x_t represents output gap, which is the difference between actual and potential outputs (i.e., this is the output under flexible price economy). The coefficient σ represents the elasticity of the intertemporal substitution. The new Keynesian Phillips curve (PC) derived under the full-information rationality assumption, is equivalent to the current inflation π_t which is driven by the expectation of future inflation $E_t \pi_{t+1}$, current output gap x_t and the supply shock u_t. The coefficient β represents the time discount factor, and γ is the combined parameter.[6] The interest rate equation follows the simple "interest-rate smoothed" (Taylor, 1993). Monetary policymakers set the interest rate based on the simple Taylor rule. The interest rate $\tilde{r}_t$ is driven by the π_t current inflation and the current output gap x_t.

(2002) view that models with sticky information are better than traditional models without any information friction. Through surveying the literature, the results are mixed, for comparing different models, and so far there is no unified model to simulate people's expectation behavior, and our work is designed to contribute to finding which inattentive feature is critical to improve the expectation model's performance.

[5] The FIRE type model applied in this paper is chosen without indexation to past inflation and habit formation in consumers' preference, because the premise of indexation has been shown to be inconsistent with the microeconomic evidence on price set (Nakamura and Steinsson, 2008). The evidence regarding agents' habit formation is less obvious, but it seems difficult to find supportive evidence through household consumption data (Dynan, 2000).

[6] Where $\gamma = \chi + \sigma^{-1}$ the composite parameter $\gamma = 0.15$ has been taken as fixed and less than 1, thus implying strategic complementary, to keep it as fixed and less than 1 in line with the suggestion from the literature (Woodford, 2001; Ball et al., 2005). Besides, Woodford (2001) surveys and discusses the existing literature at length and concludes that firms' pricing decisions should be strategic complements rather than strategic substitutes to allow for potential inflation inertia. This assumption has been tested in some recent works, such as Coibion et al. (2006). These authors posited that when $\gamma > 1$, this produces inconsistent results with the actual data.

2.2. Competing models: Reduced-form New Keynesian model with inattentive features

The two different inattentive features can be taken as two distinct information arrivals. One of the principal purposes of this paper is to verify whether different inattentive features matter in explaining economic dynamics. Furthermore, under the premise of confirming the determinacy of inattentive features, we aim to explore which feature can better explain the US economy situation from 1969 to 2015.[7]

Sticky information model (SI):

In this economy, three main players are making decisions: consumers, companies and monetary authorities. We assume that at each time, a small group of consumers and a small group of companies are randomly selected from their respective populations to obtain new information and calculate their best actions. The assumption of sticky information can be demonstrated by the cost of acquiring, absorbing and processing information (Mankiw and Reis, 2002; Reis, 2006a,b). Detailed derivation for SI model follows (Mankiw and Reis, 2002). Monetary authorities are always attentive and it is costless for them to obtain all the necessary information to make decisions.

The sticky information form of inattentiveness assumes that, on the one hand, only a small percentage of economic agents would be willing to use current arrived information to adjust their plans. On the other hand, the rest of the people will still use the old information and the old plan. The PC and IS equations with sticky information are presented as follows:

IS equation:

$$x_t = \delta \sum_{j=0}^{\infty} (1-\delta)^j E_{t-j} x_{t+1} - \sigma(\tilde{r}_t - \pi_{t+1}) + g_t \tag{4}$$

PC equation:

$$\pi_t = \beta\lambda \sum_{j=0}^{\infty} (1-\lambda)^j E_{t-j} \pi_{t+1} + \gamma\left(\frac{(1-\alpha)(1-\alpha\beta)}{\alpha}\right) x_t + u_t \tag{5}$$

According to the SI model, the two parameters δ and λ are the share of updating households and the share of updating firms, respectively, in any given period (e.g., if there is no information stickiness of firms, then $\lambda = 1$). In order to compare this with the baseline model, we assume that the households and firms set update their information sets at the rates of δ and λ, respectively (Mankiw and Reis, 2002, 2007; Reis, 2006a,b, 2009). Under the assumption of sticky information, the PC not only depends on the current expectation but also on past expectations about the future (Mankiw and Reis, 2002).[8]

It is more challenging to solve the model with sticky information, as it involves infinity lagged expectation, which then leads to the question of how we can approximate the model with sticky information in the DSGE equilibrium framework. First, from the SI model setting, we can see that the proportion of lagged expectations diminish geometrically. In other words, the impact on economic agents' expectations derived from the current state is far greater than that of previous periods. Consequently, the expectations that are formed very far from the present situation might not influence the current inflation or output gap due to the minimal weight (i.e., may approximate to zero) attached to them.

[7] In order to construct the revised data in the IF data revision model, the sample period actually covers 1969Q1 to 2016Q4.

[8] Unlike the sticky information PC model of Mankiw and Reis (2002), the current inflation in our New Keynesian three-equation model is determined by both the current expectation and the past expectation of the future inflation rate. In contrast, the current inflation in Mankiw and Reis' model is inferred from the flexible price assumption.

Thus, we set $j = 4$[9] (which means the incorporation of lag information is up to 4 periods) as the benchmark. To present the inattention total for four periods, we obtain the following:

$$E_t^{SI} x_{t+1} = \delta \sum_{j=0}^{4} (1-\delta)^j E_{t-j} x_{t+1} \tag{6}$$

$$E_t^{SI} \pi_{t+1} = \lambda \sum_{j=0}^{4} (1-\lambda)^j E_{t-j} \pi_{t+1} \tag{7}$$

Then, the PC and IS equations are transformed as follows,

IS equation:

$$x_t = \delta \sum_{j=0}^{4} (1-\delta)^j E_{t-j} x_{t+1} - \sigma(\tilde{r}_t - E_t \pi_{t+1}) + g_t \tag{8}$$

PC equation:

$$\pi_t = \beta\lambda \sum_{j=0}^{4} (1-\lambda)^j E_{t-j} \pi_{t+1} + \gamma(\frac{(1-\alpha)(1-\alpha\beta)}{\alpha}) x_t + u_t \tag{9}$$

Imperfect information data revision model (IF):

The IF model with data revision includes both real-time data and revised data. Thus, agents are either using real-time analysis or accounting for data revision. The PC and IS with imperfect information data revision are presented as follows:

IS equation:

$$x_t = (1+b_x) E_t(x_{t+1}^r) - \sigma(\tilde{r}_t - (1+b_\pi) E_t(\pi_{t+1}^r)) + g_t \tag{10}$$

PC equation:

$$\pi_t = (1+b_\pi)\beta E_t(\pi_{t+1}^r) + \gamma(\frac{(1-\alpha)(1-\alpha\beta)}{\alpha}) + u_t \tag{11}$$

0Where $\pi_t^r = (1/(1+b_\pi))(\pi_t - e_t^\pi)$ and $x_t^r = (1/(1+b_x))(x_t^r - e_t^x)$. Data revision is critical in both theoretical and empirical investigations. Although many economic researchers have made inappropriate assumptions about the data available to economic agents at each point in time, the applied assumption of data is that they are available immediately, yet the reality is that such data are announced with a few lags. Furthermore, the data revision could either be non-existent or small. Nevertheless, data revision still has a significant impact on empirical results. This is especially the case for those variables that are defined conceptually, such as output gap. The data revision version in the current work closely follows that of Casares and Vázquez (2016).

Two further points needs to be clarified. First, under imperfect information data revision hypothesis, information on the real state of the economy matters, including firms' price-setting decision depending on the expectation of marginal revenue and the future nominal marginal costs. Thus, depending on the future aggregate price level, the information friction or inattentive feature underlined across this paper must be taken seriously, and such inattentive assumption needs to be reasonable. Here, the nominal interest rates made through professional monetary authority are fully observable without any noise disturbance, and the observations of the output gap and inflation are influenced by noises. In other words, both variables involve data revision processes.

Collard and Dellas (2010) argue that the data revision process reveals only a few aggregate variables that can be observed accurately. Hence, firms and households make their price-setting and consumption decisions, respectively, without fully observing the aggregate economy. Following the above three-equation model, where x_t^r and π_t^r are taken as the observed variable realized at time t, we consider these as the real-time data. In addition, x_t and π_t, the final revised variables, are respectively stated as follows:

$$x_t \equiv x_t^r + v_t^x \tag{12}$$

$$\pi_t \equiv \pi_t^r + v_t^\pi \tag{13}$$

In addition, we follow the argument of Aruoba (2008) that the revisions of many US aggregate time series data (e.g., inflation and output) are not rational forecast errors and are supposed to be connected to their initial realized variables x_t^r and π_t^r. Following Aruoba (2008), we presume that the final revision process of US output gap and inflation are defined as follows:

$$v_t^x = b_x x_t^r + e_t^x \tag{14}$$

$$v_t^\pi = b_\pi \pi_t^r + e_t^\pi \tag{15}$$

The data revision processes mentioned above intend to provide a simple framework to assess whether departures from the hypothesis of the well-behaved revision processes (i.e., white noise draw) may have an impact on the estimates of behavioral and policy parameters. More precisely, these processes allow for the following:

(1) the existence of nonzero correlations between output gap and inflation revisions and their initial announcements and

(2) the presence of persistence revision process. It is critical to provide an example of how the data revisions kick in. Specifically, the revision process shocks e_t^x and e_t^π are assumed to follow the AR (1) processes. From Eq. (12), (13), (14), and (15) defined above, we obtain

$$x_t \equiv x_t^r + v_t^x = (1+b_x)x_t^r + e_t^x \tag{16}$$

$$\pi_t \equiv \pi_t^r + v_t^\pi = (1+b_\pi)\pi_t^r + e_t^\pi \tag{17}$$

Furthermore, the final revision process of output gap and inflation also imply the identities' respective equations:

$$v_t^x = E_{t+1} v_t^x + e_t^x = b_x x_t^r + e_t^x \tag{18}$$

$$v_t^\pi = E_{t+1} v_t^\pi + e_t^\pi = b_\pi \pi_t^r + e_t^\pi \tag{19}$$

$$E_{t+1} v_t^x = b_x e_t^r \tag{20}$$

$$E_{t+1} v_t^\pi = b_\pi \pi_t^r \tag{21}$$

Finally, we assume that the revisions process is linear (Casares and Vázquez, 2016), and our estimated model is a linearized-reduced form version of a closed small-scale New Keynesian model.

Each model (with and without inattentive features) disturbance is assumed to follow an AR (1) process. Thus, the omitted variables are captured by the disturbances in each structural equation. All the variables (i.e., output gap, interest rate, and inflation) have a quarterly frequency and are detrended follow by Smets and Wouters (2007). These three models have different information friction constraints; thus, they have different IS and PC with varying impacts on monetary policy. By comparing their respective abilities to fit the data (i.e., log marginal likelihood and Bayes' factor), we can determine which inattentive feature from the previous literature best explains the US economy.

In the present analysis, the Bayesian estimation approach is used to evaluate each model's performance by using US quarterly data. An important advantage of the Bayesian estimation approach is that it provides a solution to find the relatively "best" model, assuming that the priors are correct. At this point, it could be useful to assume that the priors only apply to the structural parameters of the New Keynesian model, which may be slightly controversial. Hence, apart from the information model, each model share roughly the same structure. Furthermore, the relative likelihood shall depend only on how relatively close to the data each information model is compared to others. In this case, the Bayes factor is close to the frequentist likelihood test. Thus, the models for forecasting and policy analysis can be verified by the benchmark of the performance of prediction.[10] Meanwhile, another

[9] The result in Trabandt (2007) indicates that by setting maximum $j = 19$, the convergence of the recursive equilibrium law of motion can be achieved for the sticky information PC model. However, in our selection of sticky information model, we use fewer period j, which is sufficient to reach convergence.

[10] However, not using a predictive test would probably be a poor test (Minford et al., 2015).

criterion to verify the relatively "best" model is the Bayes factor. Different prior distributions and types of observations are used for the robustness check.

3. Estimation through the Bayesian approach

The three aims of the empirical analysis are as follows: (1) to explore which expectation model can reproduce the dynamics behavior of the US real-time data best (survey data are also used as the alternative observations in the robustness check), (2) to verify whether incorporating inattentive features can improve the model's performance, and (3) to discuss how different inattentive ingredients influence the dynamics of the economy using the estimated IRFs.

Using the Bayesian estimation approach, we can evaluate different models by comparing their respective marginal likelihood. The analysis considers the structural shocks derived by three key quarterly macro data in the US economy, namely, output gap (using the real GDP, in which the output gap is the difference of log of real GDP and log of potential GDP), inflation (log of implicit price deflator), and nominal interest rate (effective federal funds rate). We evaluate each competing model in three stages. The first stage involves integrating the prior information of the parameters and the likelihood of the data to obtain the log of posterior function. This can be achieved by computing the maximum of which the mode of the posterior distribution can be reached. Second, we implement the Metropolis–Hastings (MH) algorithm which enables us to obtain a full picture of the posterior distribution and allows for the evaluation of the model's marginal likelihood. The third stage includes the comparison and analysis of the performances of the three models, namely, FIRE model, SI model, and IF data revision model.

3.1. Data and priors

In order to explain the state of the US economy, most of the parameters' prior distribution are chosen from the previous literature within a reasonable range. For instance, the price stickiness, which is represented as α with a value of 0.6 has been used in many empirical studies (Blinder et al., 1998; Nakamura and Steinsson, 2008; Milani and Rajbhandari, 2012). Additionally, the values of sticky information parameters λ and δ (both at 0.5) are borrowed from Mankiw and Reis (2007).[11] Moreover, the values of the parameters b_t and b_π regarding imperfect-information data-revision are set with a mean value of 0 under the circumstance of allowing large standard deviation from Casares and Vázquez (2016). Meanwhile, some of the parameter priors are very strict and are fixed before the exercise. Taking the time discount factor β and the strategic complementary parameter γ as examples, they are fixed as 0.99 and 0.15, respectively. We have little knowledge regarding the process that describes the forcing variables; thus, we impose a beta distribution that is centered at 0.5 for the AR coefficients in order to guarantee the stationary shock process. An inverse gamma distribution is used to restrict the volatility of shock to guarantee its positive value with the mean values of 0.33 for the demand shock, 0.33 for cost-push shock, and 0.25 for policy shock (Milani, 2012). To capture the uncertainties, the same strategy is applied to the standard deviation of the revision shocks in the IF data revision model with the mean value 0.25 and relative higher volatility 4. Based on previous studies, we assign a mean value of 1 to the intertemporal elasticity of substitution (i.e., σ) as the implication of log utility in consumption (Galí, 2002; Galı et al., 2003; Meyer-Gohde, 2010), while we set a wide standard deviation σ value of 0.5 in order to restrict the fluctuation in a reasonable range.

Regarding the priors for the Taylor rule, we use the most common preceding selection (Smets and Wouters, 2003, 2007; Meyer-Gohde, 2010) by assigning values of 1.5 and 0.25 as the mean value of the reaction to inflation and the standard deviation, respectively; we also follow the normal distribution. The same distribution is applied to restrict the reaction to output gap but with a different mean value of 0.12 and standard deviation of 0.05. The lagged interest rate coefficient is also restricted by the same distribution, but we assign 0.75 as its mean value and 0.1 as its standard error; we also describe the persistent property of the policy rule. The specifications of priors (i.e., distribution types, mean, and standard deviation) and the estimated mean values of posterior of the rival models' parameters are outlined in the Appendix along with the shock processes.

The posterior distribution following the Bayesian approach can be established by combining the prior distribution and the likelihood function using the Kalman filter. After implementing the Kalman recursion as well as evaluation and maximization to obtain the log likelihood function and log prior density, the posterior is estimated through Chris Sim's csminwel.[12] Thereafter, the posterior distribution can be achieved by running 20,0000 draws using the MH algorithm with optimal acceptance rate (i.e., between 20% and 40%). From the 20,0000 draws, the initial 20% are discarded and the rest are kept in order to eliminate any dependence of chain from its steady state.

Table 1 presents the estimated posterior distribution of the parameters for each group of reduced-form New Keynesian DSGE model with and without inattentiveness. Incorporating inattentive feature into modeling expectation has a significant effect on the estimation results of the parameters. For instance, although the estimated intertemporal elasticity of substitution σ is less than the prior's value in all three competing models, it still varies significantly. Specifically, the estimated σ of the model without inattentive feature is 0.0422. Meanwhile, the values of the estimated σ of the model with sticky information expectation is around twelve times higher than that without an inattentive feature. A relatively higher intertemporal substitution σ implies that the large changes in consumption are not very costly to consumers through the Euler equation. Conversely, if σ is low, the motivation of the consumption smoothness will be very high as consumers will be more reluctant to save relative to the former case.

Regarding the IF data revision model, the economic agents engage in signal extraction (data revision) to understand the real state of the economy. Thus, the value of σ is estimated to be 0.4578, which is ten times larger than the one estimated in the baseline model. Additionally, the estimated AR coefficients of the IF data revision model, especially the AR coefficients of demand shock and cost-push shock, shift to a relatively lower value compared with that of the baseline model. In terms of the estimated parameters (i.e., the reaction toward inflation and the reaction toward the output gap) in monetary policy function, the values are estimated to be slightly different under the three models of the estimating results

Most of the results presented in Table 1 are remarkably consistent with the findings of previous studies. We find that the reaction toward the inflation χ_π is not far from the presumed prior 1.5 under the three models. The reaction toward the output gap is also not volatile under different expectation assumptions (i.e., χ_x varies between 0.1827 and 0.2196). Moreover, the estimated result of ρ shows a reasonably high degree of interest-rate smoothness (i.e., ρ varies between 0.8339 and 0.8837) under different expectation assumptions. However, higher overall policy coefficients and some structural parameters show a major shift (i.e., σ varies between 0.04 and 0.5). The estimates of the AR coefficients of the shock processes reflect the existence of substantial degree of persistence in the data. The highly persistent performances are captured by the high degree autocorrelation in demand shock ρ_g,

[11] The values $\lambda = 0.5$ and $\delta = 0.5$ are both centered at 0.5, implying average information update every two quarters.

[12] Chris Sim's csminwel is a minimization routine, which is carried out to minimize the negative likelihood.

Table 1
Summary of the estimation results of different expectation formations.

Prior distribution				Posterior distributions								
				FIRE			SI			IF		
Parameters	Distr.	Mean	S.D.	Mean	90% HPDIs		Mean	90% HPDIs		Mean	90% HPDIs	
σ	G	1	0.5	0.0422	0.0108	0.0729	0.5449	0.0443	1.0287	0.4578	0.1149	0.7885
α	B	0.6	0.05	0.7141	0.6658	0.7645	0.4982	0.4183	0.5872	0.5996	0.5167	0.6838
ρ	B	0.75	0.1	0.8339	0.7900	8734	0.8451	0.8044	0.8859	0.8787	0.8386	0.9199
χ_π	N	1.5	0.25	1.4092	1.1251	1.6865	1.4473	0.2577	1.6346	1.0240	0.6547	1.3925
χ_x	N	0.12	0.05	0.2196	0.1453	0.2914	0.2405	0.1593	0.3310	0.1827	0.1167	0.2477
ρ_g	B	0.5	0.15	0.8011	0.7565	0.8470	0.8419	0.7971	0.8883	0.4977	0.2488	0.7482
ρ_u	B	0.5	0.15	0.7758	0.7338	0.8152	0.8663	0.8162	0.9175	0.3052	0.1254	0.4602
ρ_r	B	0.5	0.15	0.2671	0.1651	0.3734	0.2554	0.1444	0.3589	0.2387	0.1261	0.3436
e_g	IG	0.33	1	0.1594	0.1214	0.1988	0.1233	0.0886	0.1587	0.1923	0.0845	0.3015
e_u	IG	0.33	1	0.0701	0.0568	0.0834	0.3416	0.2140	0.4524	0.4098	0.2636	0.5605
e_r	IG	0.25	1	0.2210	0.2015	0.2384	0.2201	0.2000	0.2396	0.2228	0.2020	0.2437
b_x	N	0	2	–	–	–	–	–	–	2.6077	0.7449	4.3448
b_π	N	0	2	–	–	–	–	–	–	1.6401	0.9393	2.3516
ρ_x	B	0.5	0.2	–	–	–	–	–	–	0.8091	0.7558	0.8617
ρ_π	B	0.5	0.2	–	–	–	–	–	–	0.9232	0.8790	0.9685
e_x	IG	0.25	4	–	–	–	–	–	–	2.3924	0.9873	3.6792
e_π	IG	0.25	4	–	–	–	–	–	–	0.2474	0.1427	0.3485
λ	B	0.5	0.2	–	–	–	0.2520	0.1929	0.3142	–	–	–
δ	B	0.5	0.2	–	–	–	0.0127	0.0000	0.0320	–	–	–

Note: (1) Sample period: 1969Q1–2015Q4 US macro data; (2) FIRE: Full-Information Rational Expectation Model; SI: Sticky Information Expectation Model; IF: Imperfect Information Data Revision Model.

which is estimated above 0.8 in both baseline model and SI model, however regarding the IF data revision model, the estimated ρ_g is relatively low (around 0.5) . The autocorrelation in the cost-push shock ρ_u is estimated to be around 0.8 in both baseline model and SI model,however, regarding the IF model, the estimated ρ_u is quite low (ρ_u is estimated to be 0.3052) . Compared to ρ_g and ρ_u, the coefficients of the monetary policy shock ρ_r in all three models are estimated to be relatively small (around 0.2).

The estimation results illustrated above concerning the estimated posterior mean are not meant to show that one specified model is superior to the other models. Rather, by comparing the variation between estimated posterior results under the two different specifications (i.e., with and without inattentive feature), we can check the sensitivity of the results. Furthermore, we are able to check for sensitivity through the evaluation of the posterior results under the models with two different inattentive expectation assumptions. The necessity of checking the sensitivity of variation of the models with different inattentive expectation assumptions is derived from the case, which has been largely ignored by previous studies.

3.2. Model comparison

Table 2 reports the marginal likelihood of each model with different expectation assumptions. The marginal likelihoods are computed using Geweke's Harmonic mean approximation. Comparing the values of marginal likelihood is a standard Bayesian approach to determine which model fits the data best. The model under the conventional assumption without any inattentive feature produces the lowest value of model fit. Here, the models' performances are improved by maintaining rationality while also extending them to include inattentive ingredients. Particularly, the model with sticky information expectation achieves the best model fit among the three competing models.[13]

On the one hand, implementing the sticky-information model requires a predicting horizon (i.e., truncation point j), but there is no clear approach to select the value of j. If the short forecasting horizon (i.e., small value of j) is supposed to be two or three quarters, which are comparably short periods, it would lead to the misperception of the distribution of agents regarding the updating of their information relative to the distribution given by theoretical model. On the other hand, a long forecasting horizon will include too much forecast errors, which tend to form bias to reduce the estimated share of updating agents, i.e., λ and δ (Khan and Zhu, 2002). Balancing the reduction of forecast error and the frequency of updating information theoretically, we set $j = 4$, as in practice, the longest information lag is truncated as four quarters (Kiley, 2007).[14]

Table 2
Model fit comparison.

Model	Log marginal likelihood	Bayes factor relative to FIRE
FIRE model	−267.05	1
SI model	−241.75	$e^{25.3}$
IF model	−246.21	$e^{20.84}$

Note: (1) Sample period: 1969Q1–2015Q4 US macro data; (2) FIRE: Full-Information Rational Expectation Model; SI: Sticky Information Expectation Model; IF: Imperfect Information Data Revision Model.

Following (Jeffreys, 1961), we are able to evaluate the relative superiority of the models. The details of the guidelines are presented in Table 3. Based on the information presented, the Bayes factor values in Table 2 indicate "decisive" evidence for both models with inattentive expectation assumptions against the baseline model with full-information rational expectation assumption. In addition, using the IF data revision model as the null hypothesis, the model with sticky information shows the "strong" evidence as a preferable choice (Bayes factor $e^{4.46} \approx 86.49$).

Nevertheless, an obvious limitation of this approach is that the evaluation of model fit can only lead to a relative conclusion. Thus, the best estimated model may still be inaccurate in capturing the crucial dynamics of our selected sample data.

The focus in this section is to verify the most viable inattentive feature that affects the macroeconomic model. In particular, we focus on the delayed impact of a monetary policy shock on key macro

13 We also compare the simulated moments from each model as an additional test to examine the performance of the three models, and the test result suggests that the model with sticky information performs the best among the three rivals (i.e. FIRE, SI and FIRE).

14 Paustian and Pytlarczyk (2006) examined the sticky information with different truncation points j = 12 and 24 and found that in the SI model, the model fit is not sensitive to the increase in the maximum lag for outdated information.

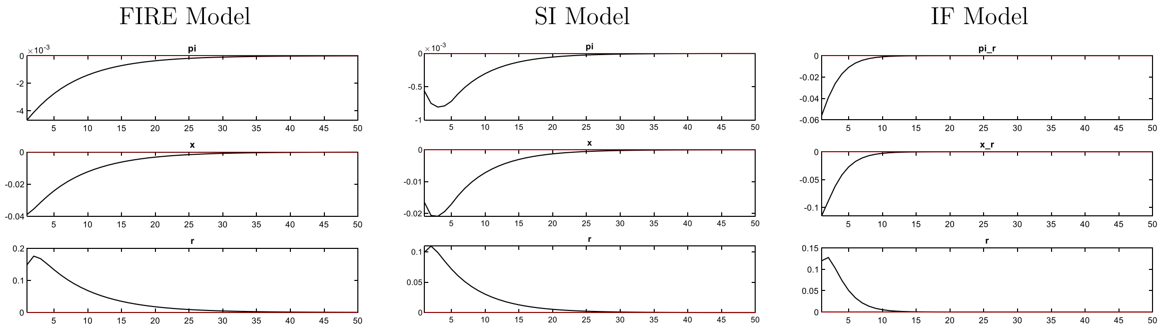

Fig. 1. Estimated impulse response function of one unit of positive policy shock to the main variables.
Notes: x indicates output gap, pi indicates inflation and r indicates interest rate.

Table 3
Jeffrey's guidelines for interpreting the Bayes factor.

Bayes factor	Interpretation
1 to 3.2	Not worth more than a bare mention evidence
3.2 to 10	Substantial evidence
10 to 100	Strong evidence
100	Decisive evidence

Note: The use of the Bayes factor to compare models was first suggested by Jeffreys (1961), who later recommended the rule of thumb for interpreting the Bayes factor.

Table 4
Model fit comparison.

Model	log marginal likelihood (Benchmark priors)	Log marginal likelihood (Using diffuse prior)
FIRE model (baseline)	−267.05	−261.31
SI model	−241.75	−244.39
IF model	−246.21	−245.66

Note: (1) Sample period: 1969Q1–2015Q4 US macro data; (2) FIRE: Full-Information Rational Expectation Model; SI: Sticky Information Expectation Model; IF: Imperfect Information Data Revision Model.

variables (i.e., the delay effects of inflation and output gap). The estimated IRF results will provide a graphic depiction of the impact of positive monetary policy on the key major macro variables, which can help distinguish between the two different inattentive models and the baseline model.

As Fig. 1 indicates, the model with sticky information can generate a persistence and a delay response of inflation and output gap, which is mostly in line with the suggestions made in previous studies (Mankiw and Reis, 2002). Conversely, neither the model without any inattentive features nor that with imperfect information can accomplish the goal. The IF data revision model generates results that are contrary to previous studies (Collard et al., 2009). In addition, the estimated IRFs generated under this model are comparable with those generated from the baseline model. In general, the positive monetary policy shock results in an increase in the nominal interest rate for the three competing models.

The IRFs for the baseline model indicate that, due to the increasing interest rates, a negative effect on the demand of households' consumption leads to holding off consumption. The two alternative competing models are quantitatively similar to the baseline model in terms of the IRFs of the positive monetary policy shock to the main variables. Specifically, in the model with sticky information, the positive impact of monetary policy can produce a persistence and gradual response of inflation and output gap.

Next, we turn to the effects of the positive demand shock on the three main variables under three competing models through the estimated IRF. The estimated IRF is outlined in Fig. 2. The positive demand shock has a relatively long effect on interest rate, as this variable converges after around 25 periods in both SI model and FIRE model, while relatively short effect in IF model (around 10 periods). Meanwhile, the demand shock has a relatively significant impact upon the output gap. The two long-run effect converges after 30 periods with respect to the FIRE and SI models. It only takes around 12 periods to converge under IF model.

In general, the demand shock impacts inflation positively and converges quickly compared with the effect on nominal interest rate under the three competing models. In the IF data revision model, agents' uncertainty around data revision at the initial stage leads to minor impacts on inflation and output gap. The turning point appears at the fifth period, during which agents have clearer expectations following the reduction in uncertainty. Thus, inflation and output gap under imperfect information rapid convergence than those under full information or sticky information environments.

The positive cost-push shock has a positive impact on inflation and interest rate for all three competing models, as shown in Fig. 3. The positive cost-push shock, however, leads to slightly different outcomes for the different models. Specifically, there is a larger effect for the baseline model, whereas in the case of the SI and IF models, there are relatively small effects on the output gap. This distinction may be due to the fact that the agents' inattentiveness has lessened the effect of the cost-push shock, as presented in Fig. 3. The economic agents under imperfect information assumption environment cannot observe the real state of the economy. Thus, people reduce noise through the data revision process and only take actions in reaction to their expected revised data based on the effect of the cost-push shock on inflation in the short run. In comparison, the SI model generates more persistent effects on output gap. Furthermore, in the aggregate level, the variables under the economic agents involving data revision and sticky information issues converge less quickly than that under the baseline model.

3.3. Robustness check

3.3.1. Different prior

In Table 4 below, we set $\alpha = 0.7$ after, and this is also one of the common options applied in number studies (Eichenbaum and Fisher, 2004; Woodford, 2001). It may be worth repeating the analysis with relatively flatter prior, namely, uninformative prior (i.e., the prior is assumed to follow uniform distribution instead of beta distribution and is used in starting comparison). The parameter depends on uniform distribution, which is assumed to be within a fixed range of values (i.e., between 0 and 1). The estimated results in Table 4 show that the ranking of three competing models is the same as that reported previously, although different degree of tightness of priors lead to varying performances for all models. The robustness check helps us to eliminate the concerns that our estimation results may seriously be driven by the presumed distribution of the priors and give no chance to let the data speak.

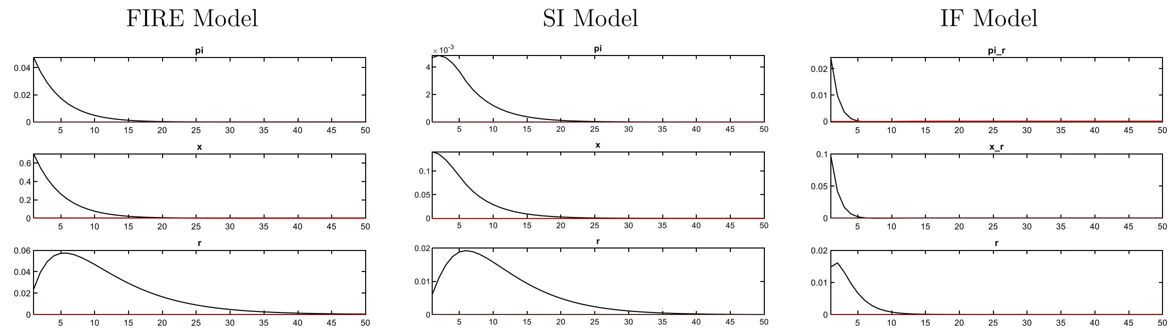

Fig. 2. Estimated impulse response function of one unit of positive demand shock to the main variables.
Notes: x indicates output gap, pi indicates inflation and r indicates interest rate.

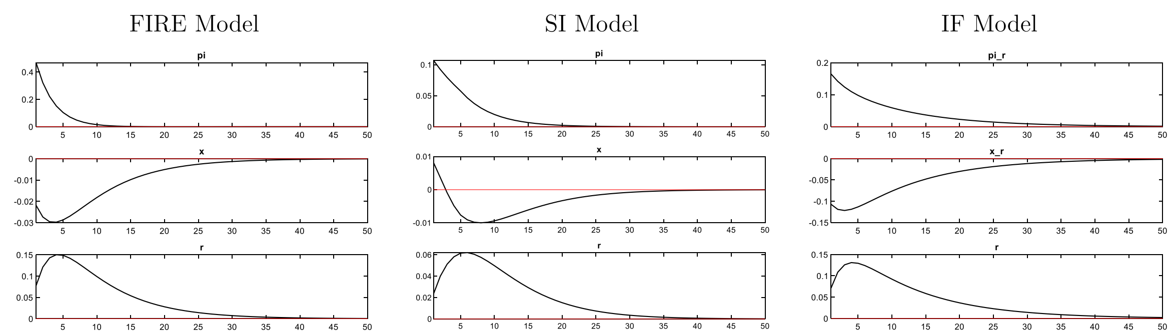

Fig. 3. Estimated impulse response function of one unit of positive cost-push shock to the main variables.
Notes: x indicates output gap, pi indicates inflation and r indicates interest rate.

Table 5
Model fit comparison.

Model	Log marginal likelihood (Benchmark Priors)	Log marginal likelihood (Using Uninformative Prior λ and δ)
FIRE model (baseline)	−267.05	−267.05
SI model	−241.75	−245.59
IF model	−246.21	−246.21

Note: (1) Sample period: 1969Q1–2015Q4 US macro data; (2) FIRE: Full-Information Rational Expectation Model; SI: Sticky Information Expectation Model; IF: Imperfect Information Data Revision Model.

Table 6
Model fit comparison.

Model	Log marginal likelihood (benchmark TR)	Log marginal likelihood (more complex TR)
FIRE model	−267.05	−260.47
SI model	−241.75	−240.95
IF model	−246.21	−254.41

Note: (1) Sample period: 1969Q1–2015Q4 US macro data; (2) FIRE: Full-Information Rational Expectation Model; SI: Sticky Information Expectation Model; IF: Imperfect Information Data Revision Model.

The models with inattentive feature continue to be superior to the baseline model in terms of model fit. Although and the gap between the SI model and IF data revision model is narrowed, SI model still superior to the other two rivals.

Because λ and δ are the key parameters that govern behavior of SI model, once again, we use uninformative prior density instead of beta prior density for λ and δ. The estimated results in Table 5 indicates that the ranking of three rivals still hold.

3.3.2. Different specification of Taylor rule

Different monetary policy specifications may influence the estimation results. Thus, we re-estimate each model with an alternative specifications of the Taylor rule (Smets and Wouters, 2003, 2007). The "more complex Taylor rule", which includes the change of output gap and the change of inflation in monetary authority reaction function, whose parameters are represented as $\chi_{\triangle\pi}$ and $\chi_{\triangle x}$, respectively. We set the mean values and standard deviations equal to 0.12 and 0.05, respectively, for both parameters $\chi_{\triangle\pi}$ and $\chi_{\triangle x}$ (Smets and Wouters, 2003, 2007) and enable the priors to follow the normal distribution. The alternative specification is presented respectively as follows:

$$\tilde{r}_t = \rho_r \tilde{r}_{t-1} + (1-\rho_r)[\chi_\pi \pi_t + \chi_x x_t] + \chi_{\triangle\pi}(\pi_t - \pi_{t-1}) + v_t \tag{22}$$

The estimation results are presented in Table 6. We can see that with the introduction of the "more complex Taylor rule" the model with inattentive features outperforms the baseline model, and the ranking among the three models is identical to the previous results.[15]

3.3.3. Survey of professional forecaster data

Next, for further robustness, we use the Survey of Professional Forecaster (SPF) data. Now, we are able to reflect directly the views of professional forecasters or experts (Fuhrer, 2017). As Ormeño and Molnár (2015) assert, the survey data of inflation forecasts enable the modeling of agent expectations and provide useful information that cannot be obtained from macro data.

We examine each model by using a different type of sample data (i.e., survey data). The estimation results obtained by using survey data are summarized in Table 7. The estimation results obtained through the IF data revision model indicate that this performs best among the three competing models. The gap of log marginal likelihoods of the model with imperfect information data revision and that with full-information

[15] Of course, there are various monetary policy rule suggested in the previous studies, here we just choose the popular one from (Smets and Wouters, 2007) to do robustness check, the further research may necessary to consider more different monetary policy rules detailed and carefully.

Table 7
Model fit comparison.

Model	(1)	(2)	(1) − (2)
FIRE model (baseline)	−36.08	−267.05	230.97
SI model	−23.12	−241.75	218.63
IF model	−16.44	−246.21	229.77

Note: (1) The first column indicates the log marginal likelihood for each model by using SPF data;(2) The second column shows the log marginal likelihood for each model by using real-time data;(3) The third column shows that the gap of log marginal likelihoods of each model by using different types of data.

Table 8
Summary of the estimation results of different expectation formations (with survey data).

Prior distribution				Posterior distribution (mean)		
Parameters	Distr.	Mean	S.D.	FIRE	SI	IF
σ	G	1	0.5	0.0159	0.1344	0.0371
α	B	0.6	0.05	0.6519	0.6277	0.6543
ρ	B	0.75	0.1	0.8857	0.9164	0.9219
χ_π	N	1.5	0.25	1.4669	1.4146	1.3836
χ_x	N	0.12	0.05	0.1236	0.1214	0.1243
ρ_g	B	0.5	0.15	0.5681	0.5983	0.4922
ρ_u	B	0.5	0.15	0.6928	0.7033	0.4483
ρ_r	B	0.5	0.15	0.3473	0.3234	0.311
e_g	IG	0.33	1	0.1158	0.2487	0.2446
e_u	IG	0.33	1	0.0759	0.2106	0.1552
e_r	IG	0.25	1	0.2384	0.2367	0.2414
b_x	N	0	2	–	–	1.9627
b_π	N	0	2	–	–	1.5134
ρ_x	B	0.5	0.2	–	–	0.5612
ρ_π	B	0.5	0.2	–	–	0.7457
e_x	IG	0.25	4	–	–	0.2190
e_π	IG	0.25	4	–	–	0.1132
λ	B	0.5	0.2	–	0.4474	–
δ	B	0.5	0.2	–	0.0916	–
Log marginal likelihood				−36.08	−23.11	−16.44
Bayes Factor relative to the FIRE				1	$e^{12.97}$	$e^{19.64}$

Note: The posterior estimated value of σ is quite different from the prior mean, which may be due to fact that the selected prior is suitable for the final revised data but not suitable for real-time data or SPF data.

rationality is 20.84, which can be interpreted as Bayes factor $e^{20.84}$ (taking the baseline model as the null hypothesis). Similarly, the gap of log marginal likelihoods of the model with IF data revision model and that with sticky information ($j = 4$) is 4.46, which can be interpreted as Bayes factor $e^{4.46}$ (taking the SI model as the null hypothesis).

Furthermore, when the survey data are introduced as observables, the performance of each model improves significantly. The number of log marginal likelihood increased greatly in the three competing models, indicating that there is extra information in the survey data to improve the performance of each model. However, regardless of the type of resource we are using to peruse the estimation result, the model with inattentive expectation is always superior to the baseline model in terms of model fit. However, under the same premise, the ranking of SI model and imperfect information is switched, which may be due to the fact that the extra information contained in survey data is in favor of the model with imperfect information data revision.

Next, we compare the estimation results with survey data, which are presented in Table 8 with the results using real-time data (outlined in Table 1). As can be seen, most of the estimated values of the common parameters are not significantly different. Some differences, however, are still found: the AR coefficients of cost-push shocks are lower than the findings reported in Table 1, the estimated share of updating consumers is much lower than that estimated by using real-time data, and the estimated share of updating firms is relatively larger than that estimated by using real-time data.

A more recent research using survey data investigated whether a DSGE model with perfect or imperfect information can reproduce a series of expected inflation that match the survey inflation data.

Table 9
Excluding the period after 2008 financial crisis.

Prior distribution				Posterior distributions (mean)		
Parameters	Distr.	Mean	S.D	FIRE	SI	IF
σ	G	1	0.5	0.0419	0.1254	0.5118
α	B	0.6	0.05	0.7334	0.6498	0.6006
ρ	B	0.75	0.1	0.8358	0.8548	0.8762
χ_π	N	1.5	0.25	1.4602	1.4710	1.2113
χ_x	N	0.12	0.05	0.205	0.2238	0.1804
ρ_g	B	0.5	0.15	0.7933	0.8183	0.5019
ρ_u	B	0.5	0.15	0.7087	0.7679	0.4113
ρ_r	B	0.5	0.15	0.3174	0.3026	0.3003
e_g	IG	0.33	1	0.1736	0.5381	0.2147
e_u	IG	0.33	1	0.0651	0.1770	0.2404
e_r	IG	0.25	1	0.2506	0.2489	0.2567
b_x	N	0	2	–	–	2.8235
b_π	N	0	2	–	–	2.1411
ρ_x	B	0.5	0.2	–	–	0.8729
ρ_π	B	0.5	0.2	–	–	0.8383
e_x	IG	0.25	4	–	–	2.6639
e_π	IG	0.25	4	–	–	0.3132
λ	U	0.5	0.2	–	0.1017	–
δ	U	0.5	0.2	–	0.2959	–
Log marginal likelihood				−199.85	−173.68	−176.62
Bayes Factor relative to the FIRE				1	$e^{26.17}$	$e^{23.23}$

Note: : (1) The posterior distribution is obtained using the Metropolis–Hastings algorithm. 200000 draws with acceptance rate between 20% and 40%, and we discard the initial 20% of MH draw and keep 160000 draws. (2) For the prior densities, we used Beta (B), Gamma (G), Normal (N), inverse Gamma (IG) distributions, and uninformative (U) distributions.

For instance, Aruoba and Schorfheide (2011) applied inflation survey forecasts as additional information when assessing the time-varying Fed's Inflation Target. Fuhrer (2017) examined the endogenizing survey expectation in a standard DSGE model and asserted that the most persistent in aggregate data is due to the slow-moving expectations but not habits, indexation, or autocorrelated structural shocks.

Our findings indicate that SI expectation has a clear ability to generate more persistence and reproduce delay responses, whereas the model with imperfect information data revision expectation cannot achieve these. Nevertheless, failure to reproduce the delay response is not the only reason for model invalidation. In fact, the result may be due to two key factors missing in our estimated inattentive expectation models. The origins are wage rigidities and the inclusion of capital variable utilization (Christiano et al., 2005).

3.3.4. Excluding zero lower bound (ZLB) period

The alternative sample excluded the ZLB period is used to test whether the ranking of three competing models are robust. Following previous research, the sample period ended in 2008 to avoid the ZLB period that begin in January 2009, when the Fed's traditional monetary policy instrument, the federal funds rate, was virtually zero. However, we found that excluding ZLB period does not change the main results of our model, SI model is superior to the other two competitors (as shown in Table 9).

3.3.5. Out-of-sample forecasting

The results presented in Table 10 compare the models' forecasting ability, where the root mean square forecasting error (RMSFE) is calculated to examine how the predicted values from each model fit the actual data. A small value of RMSFE indicates fewer differences between the predicted values and the observed values, thus a better model fit (and vice versa).

Table 10 shows that the FIRE model consistently performs worse than the models with bounded rationality (i.e., SI and IF models) in forecasting the output gap in both the shorter (4 quarters) and the longer horizon (8 quarters). Furthermore, the IF model best predicts the output gap among the three competing models in the longer horizon.

Table 10
The forecasting output gap, inflation, and interest rate (RMSFE).

Model	Horizon	Variable	RMSFE
FIRE	4 quarters	x	0.663
	4 quarters	π	0.206
	8 quarters	x	0.911
	8 quarters	π	0.280
SI	4 quarters	x	0.539
	4 quarters	π	0.160
	8 quarters	x	0.838
	8 quarters	π	0.249
IF	4 quarters	x	0.537
	4 quarters	π	0.150
	8 quarters	x	0.775
	8 quarters	π	0.303

Note: This table reports the root mean square forecasting error (RMSFE) of each typical model (i.e., FIRE, SI, and IF). x represents the output gap, and π stands for inflation.

For forecasting inflation, the IF model has a lower RMSFE than the SI model within the shorter horizon (4 quarters). However, the SI model outperforms the IF modeling for the longer horizon (8 quarters). In general, both SI and IF outperform FIRE in forecasting inflation.

4. Conclusion

In this paper, we evaluated the consequences of including inattentive expectations in a small-scale reduced-form New Keynesian DSGE model. We find that the model is sensitive to the inattentive features using a Bayesian estimation approach. The sensitive analysis focuses on comparing different inattentive feature, thereby filling a gap in the existing literature. The empirical evidence indicates that incorporating inattentive expectations significantly improves the model ability to fit macroeconomic time series.

In this paper, we estimate and test New Keynesian reduced-form-type models with respect to two different expectation assumptions (i.e., with and without inattentiveness) using US macro-economic data (survey of professional forecaster data adopted in the robust check section). In choosing inattentive models for comparison, many options are left, but they can be developed in future works in several ways. First, we only considered inattentive expectation in a small-closed economy. Future works could be conducted through empirically evaluating small-open economies by incorporating exchange rate, imports, and exports, thus developing more complicated models for comparison. Second, we can investigate mix-inattentive model (Dräger, 2016) and compare this with the single-inattentive model. This process could also be applied in both close and open economies. Third, the robust check in this paper regarding the different specifications of monetary policy shows that, although the rank among three competing models do not switch, each model's performance changes significantly with respect to different monetary policy specifications. Thus, further research can take the inattentive expectation as the base structure model but with different monetary policies to examine whether the monetary authority does a good job over recent decades. This can also be carried out through the Bayesian approach.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Table A.1
Priors mean of parameters.

Common structural parameter		
σ	Elasticity of intertemporal substitution	1
α	Sticky price degree	0.6
γ	Strategic complementary	0.15
Common Taylor rule in three models		
ρ	Degree of partially adjustment in Taylor rule	0.75
χ_π	Coefficient of inflation on Taylor rule	1.5
χ_x	Coefficient of output gap in Taylor rule	0.12
Common forcing variables in three models		
ρ_g	AR coefficient of demand shock	0.5
ρ_u	AR coefficient of cost-push shock	0.5
ρ_r	AR coefficient of policy shock	0.5
ρ_g	Standard deviation of demand shock	0.33
ρ_u	Standard deviation of cost-push shock	0.33
ρ_r	Standard deviation of policy shock	0.33

Note: The priors of parameter are mostly chosen from previous literature (Milani and Rajbhandari, 2012; Smets and Wouters, 2003, 2007).

Table A.2
Priors mean of parameters.

Imperfect information model		
b_x	Output coefficient in output revision process	0
b_π	Inflation coefficient in inflation revision process	0
ρ_x	AR term of shock in final revision process of x	0.5
ρ_π	AR term of shock in final revision process of π	0.5
e_x	SD of measurement error of x	0.25
e_π	SD of measurement error of π	0.25
Sticky information model		
λ	Share of updating firms	0.5
δ	Share of updating consumer	0.5

Note: The priors of parameter for SI model are chosen from Mankiw and Reis (2007) , and those for IF model are borrowed from Casares and Vázquez (2016).

Table B.1
Parameter estimate of full-information rationality.

Prior distribution				Posterior distributions			
Parameter	Distr.	Mean	S.D.	Mode	Mean	90% HPDIs (Bayesian confidence bands)	
σ	G	1	0.5	0.0330	0.0422	0.0108	0.0729
α	B	0.6	0.05	0.7173	0.7141	0.6658	0.7645
ρ	B	0.75	0.1	0.8404	0.8339	0.7900	0.8734
χ_π	N	1.5	0.25	1.4051	1.4092	1.1251	1.6865
χ_x	N	0.12	0.05	0.2165	0.2196	0.1453	0.2914
ρ_g	B	0.5	0.15	0.8091	0.8011	0.7565	0.8470
ρ_u	B	0.5	0.15	0.7822	0.7758	0.7338	0.8152
ρ_r	B	0.5	0.15	0.2547	0.2671	0.1651	0.3734
e_g	IG	0.33	1	0.1493	0.1594	0.1214	0.1988
e_u	IG	0.33	1	0.0673	0.0701	0.0568	0.0834
e_r	IG	0.25	1	0.2183	0.2210	0.2015	0.2384
Log Marginal Likelihood				−267.05			

Note: (1) The posterior distribution is obtained using the Metropolis–Hastings algorithm. 200000 draws with acceptance rate between 20% and 40%, and we discard the initial 20% of MH draw and keep 160000 draws. (2) For the prior densities, we used Beta (B), Gamma (G), Normal (N), and inverse Gamma (IG) distributions.

Appendix A. Prior interpretation

See Tables A.1 and A.2.

Appendix B. Estimates without survey data

See Tables B.1–B.3
See Figs. B.1–B.12.

Appendix C. Data description

All data are of a quarterly frequency and are seasonally adjusted. All the series are demeaned before estimation.

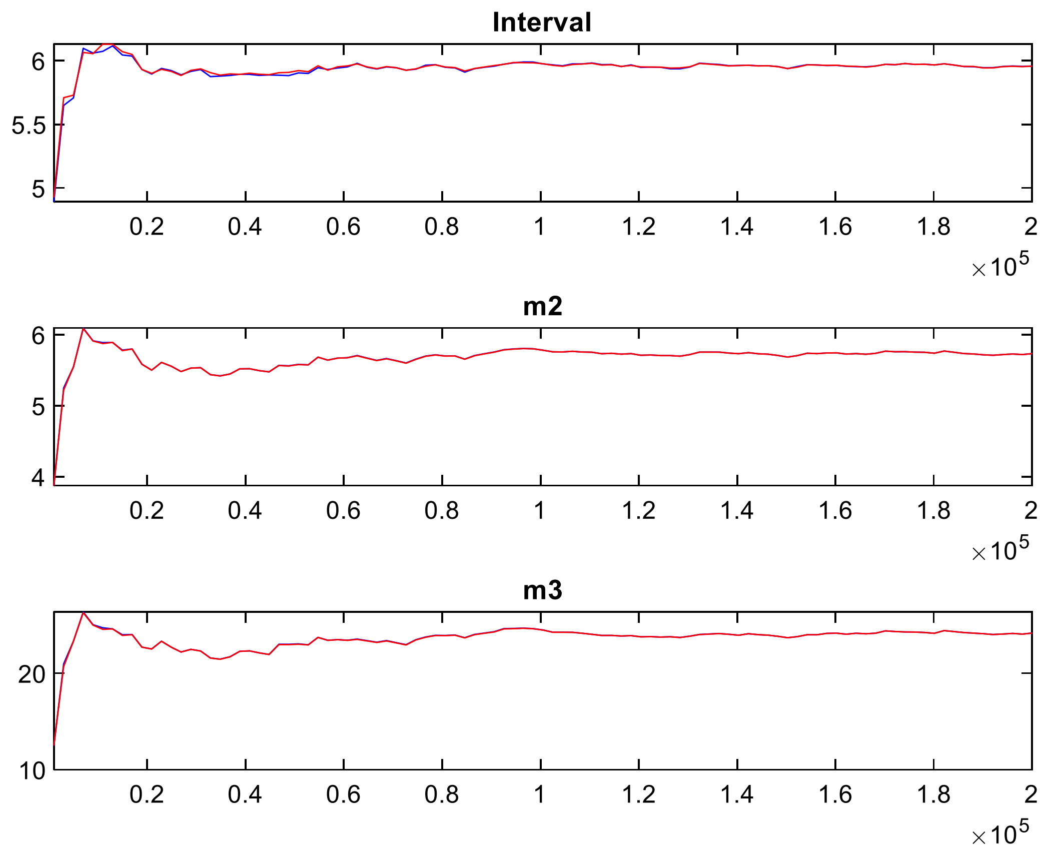

Fig. B.1. Full-information rational expectation multivariate MH convergence diagnosis.

Table B.2
Parameters estimate of sticky information.

Prior distribution				Posterior distributions			
Parameter	Distr.	Mean	S.D.	Mode	Mean	90% HPDIs (Bayesian confidence bands)	
σ	G	1	0.5	0.6248	0.5449	0.0443	1.0287
α	B	0.6	0.05	0.5000	0.4982	0.4183	0.5872
ρ	B	0.75	0.1	0.8512	0.8451	0.8044	0.8859
χ_π	N	1.5	0.25	1.4490	1.4473	1.2577	1.6346
χ_x	N	0.12	0.05	0.2376	0.2405	0.1593	0.3310
ρ_g	B	0.5	0.15	0.8501	0.8419	0.7971	0.8883
ρ_u	B	0.5	0.15	0.8558	0.8663	0.8162	0.9175
ρ_r	B	0.5	0.15	0.2478	0.2554	0.1444	0.3589
e_g	IG	0.33	1	0.1129	0.1233	0.0886	0.1587
e_u	IG	0.33	1	0.3019	0.3416	0.2140	0.4524
e_r	IG	0.25	1	0.2171	0.2201	0.2000	0.2396
λ	B	0.5	0.25	0.2663	0.2520	0.1929	0.3142
δ	B	0.5	0.25	0.0027	0.0127	0.0000	0.0320
Log Marginal Likelihood				−241.75			

Note: (1) The posterior distribution is obtained using the Metropolis–Hastings algorithm. 200000 draws with acceptance rate between 20% and 40%, and we discard the initial 20% of MH draw and keep 160000 draws. (2) For the prior densities, we used Beta (B), Gamma (G), Normal (N), and inverse Gamma (IG) distributions.

Table B.3
Parameter estimate of imperfect information data revision.

Prior distribution				Posterior distributions			
Parameter	Distr.	Mean	S.D.	Mode	Mean	90% HPDIs (Bayesian confidence bands)	
σ	G	1	0.5	0.2169	0.4578	0.1149	0.7885
α	B	0.6	0.05	0.6022	0.5996	0.5167	0.6838
ρ	B	0.75	0.1	0.8749	0.8787	0.8386	0.9199
χ_π	N	1.5	0.25	1.0122	1.0240	0.6547	1.3925
χ_x	N	0.12	0.05	0.1995	0.1827	0.1167	0.2477
b_x	N	0	2	0.9625	2.6077	0.7449	4.2448
b_π	N	0	2	1.4471	1.6401	0.9393	2.3516
ρ_x	B	0.5	0.2	0.7968	0.8091	0.7558	0.8617
ρ_π	B	0.5	0.2	0.9304	0.9232	0.8790	0.9685
ρ_g	B	0.5	0.15	0.4905	0.4977	0.2488	0.7482
ρ_u	B	0.5	0.15	0.2602	0.3052	0.1254	0.4602
ρ_r	B	0.5	0.15	0.2198	0.2387	0.1261	0.3436
e_g	IG	0.33	1	0.1371	0.1923	0.0845	0.3015
e_u	IG	0.33	1	0.3924	0.4098	0.2636	0.5605
e_r	IG	0.25	1	0.2181	0.2228	0.2020	0.2437
e_x	IG	0.25	4	1.1750	2.3924	0.9873	3.6792
e_π	IG	0.25	4	0.2152	0.2474	0.1427	0.3485
Log Marginal Likelihood				−246.21			

Note: (1) The posterior distribution is obtained using the Metropolis–Hastings algorithm. 200000 draws with acceptance rate between 20% and 40%, and we discard the initial 20% of MH draw and keep 160000 draws. (2) For the prior densities, we used Beta (B), Gamma (G), Normal (N), and inverse Gamma (IG) distributions.

United States Data Source:

Effective Federal Funds Rate is indicated by FEDFUNDS, the federal funds rate is divided by four to express it in quarterly rates. The observable data are matched to the variable r_t, where $r_t = \frac{FEDFUNDS_t}{4}$.

The real-time data from the real-time data set for macroeconomists hosted by the Federal Reserve Bank of Philadelphia.[16] The real-time Real GDP is indicated by ROUTPUT which is initially released in 2016Q1 (i.e., which only contains real-time Real GDP up to time 2015Q4); the quarterly real-time GDP is the deviation of the natural logarithm of total real-time GDP. For the IF model to construct the revised observables corresponding to the output gap up to 2015Q4, the real-time data released after one period (2016Q1) and the real-time data of GDP released after three periods are also applied (2016Q3).

[16] https://www.philadelphiafed.org/research-and-data/real-time-center/real-time-data/data-files

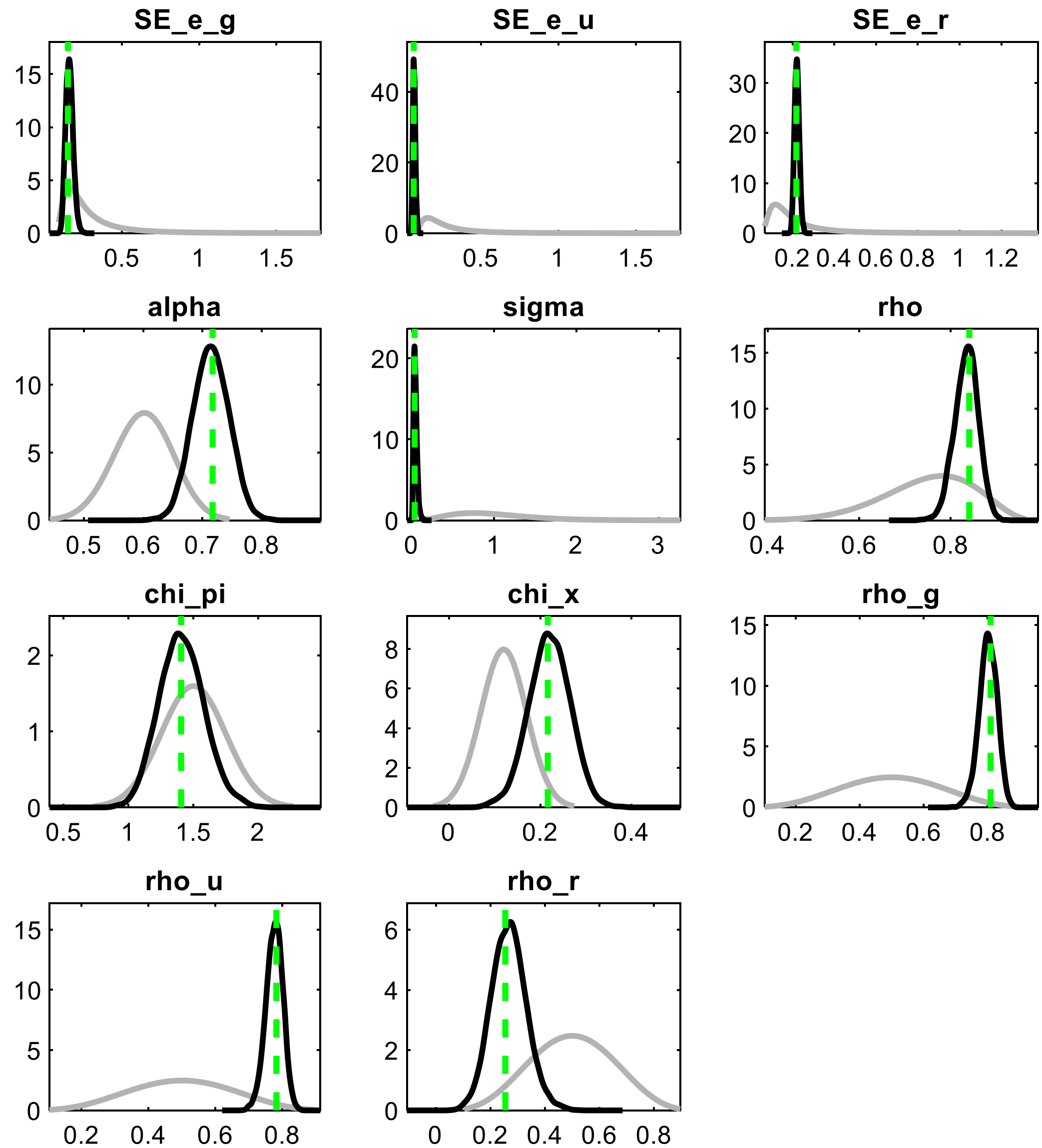

Fig. B.2. Estimated parameters distribution of full-information rationality.
Notes: Black line indicates posterior distribution mean while green line indicates posterior mean. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Real-time Implicit Price Deflator is indicated by P. The series is demeaned for the index level which is initially released in 2016Q1 (i.e., which only contains real-time Implicit Price Deflator up to 2015Q4), which is seasonally adjusted and is also from the real-time data set from Federal Reserve Bank of Philadelphia. The real-time inflation $\pi_t^r = (lnP_t - lnP_{t-1}) * 100$. Similarly, to construct the revised observables corresponding to inflation up to 2015Q4, the real-time data of the Implicit Price Deflator released after one period and the data released after three periods are also used.

The survey data used in the robust check section is the median of the Survey of Professional Forecaster one-quarter ahead forecasts of the GDP deflator and real GDP. In the IF data revision model, both one-quarter ahead and four-quarter ahead forecasts are used to construct the final revised observables.

Appendix D. Model derivation

IS curve in the sticky information model

Now, we assume that economic agents and households under the sticky information economy use the outdated information from all past periods up to t to form their forecast. In the aggregate level, not all of them use the updated information to form their forecasts, $E_t^{SI} = \delta \sum_{j=0}^{\infty} (1-\delta)^j E_{t-j}$. Thus, we have the following IS equation[17] :

$$x_t = \delta \sum_{j=0}^{\infty} (1-\delta)^j E_{t-j} x_{t+1} - \sigma(\tilde{r}_t - \pi_{t+1}) + g_t \tag{D.1}$$

[17] Initially, this is $x_t = E_t^{SI} x_{t+1} - \sigma(\tilde{r}_t - E_t^{SI} \pi_{t+1}) + g_t$.

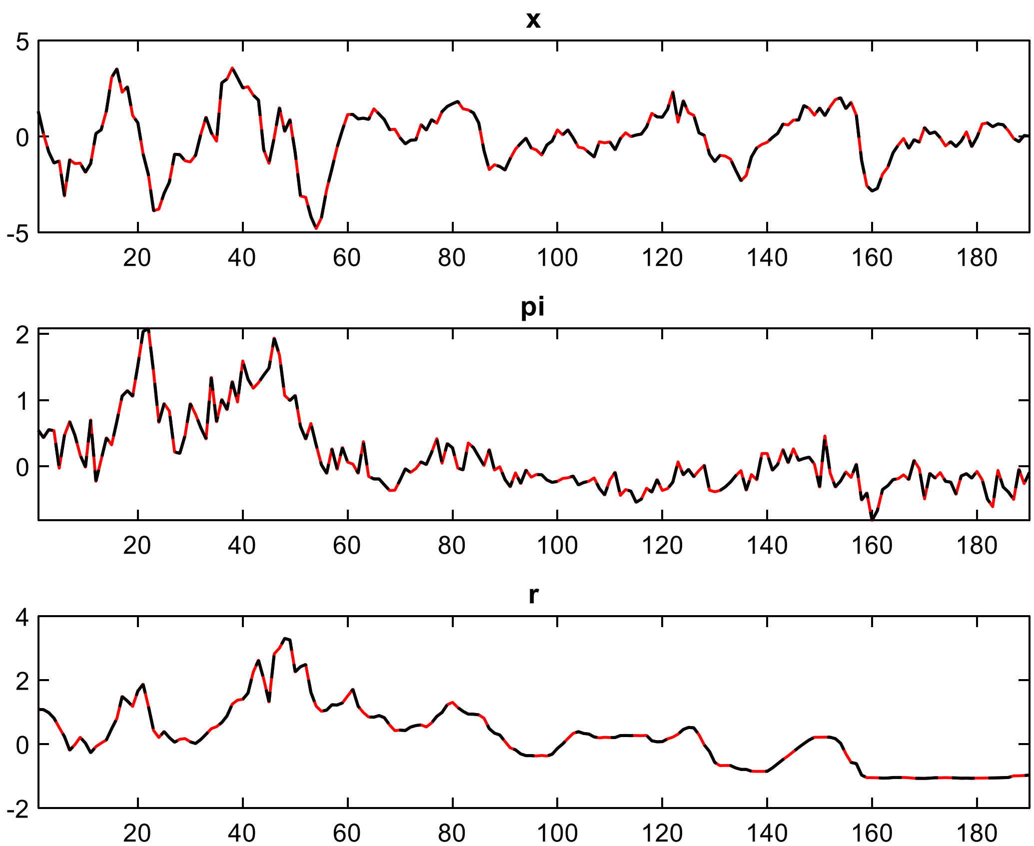

Fig. B.3. Full-information rational expectation smoothed variables.
Notes: Dotted black line depicts the actually observed data, while the red line depicts the estimate of the smoothed variables ('best guess for the observed variables given observations') derived from Kalman smoother at the posterior mode or posterior mean. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

where δ denotes the share of updating households.

Phillips curve in the sticky information model

Similarly, for firms that are also subject to sticky information, and because they do not all use the updated information to form their forecast at the aggregate level, firms must use the outdated information up to time t to form their forecast $E_t^{SI} = \lambda \sum_{j=0}^{\infty}(1-\lambda)^j E_{t-j}$. Then, we have the following PC equation[18]:

$$\pi_t = \beta\lambda \sum_{j=0}^{\infty}(1-\lambda)^j E_{t-j}\pi_{t+1} + \gamma(\frac{(1-\alpha)(1-\alpha\beta)}{\alpha})x_t + u_t \tag{D.2}$$

where λ denotes the share of the updating firms.

From above, we can see that the current inflation depends on the current output gap and on current and past expectations of the future inflation rate.

Imperfect information data revision

The derivation of the imperfect information data revision model follows the deriving procedure and assumption explanation provided by Aruoba (2008), Vázquez et al. (2010, 2012) and Casares and Vázquez (2016). First, we consider the following identities regarding revised data related to the cyclical of output gap and inflation, which can also refer to the combination of the initial announcement and the final revisions. This can be interpreted in the sense of noise: x_t^r and π_t^r are taken as the observed variables realized at time t (they are the real-time data). In addition, x_t and π_t are the final revised variables, which are defined respectively as follows:

$$x_t \equiv x_t^r + v_t^x \tag{D.3}$$

$$\pi_t \equiv \pi_t^r + v_t^\pi \tag{D.4}$$

We also follow the argument of Aruoba (2008) that, for many US aggregate time-series (e.g., inflation and output), their revisions are not rational forecast errors and are supposed to be connected to their initial realized variables, x_t^r and π_t^r. Thus, following his argument, we presume that the final revision process of the US output gap and inflation are defined as follows:

$$v_t^x = b_x x_t^r + e_t^x \tag{D.5}$$

$$v_t^\pi = b_\pi \pi_t^r + e_t^\pi \tag{D.6}$$

These revision processes allow for the existence of non-zero correlation between final true variables (i.e., output gap and inflation) and their initial realized variables along with the existence of persistence revision processes. In particular, the shocks of the revision processes, e_t^x and e_t^π, are both AR (1) processes. The two data revision processes

[18] Initially, this is $\pi_t = \beta E_t^{SI}\pi_{t+1} + \gamma(\frac{(1-\alpha)(1-\alpha\beta)}{\alpha})x_t + u_t$.

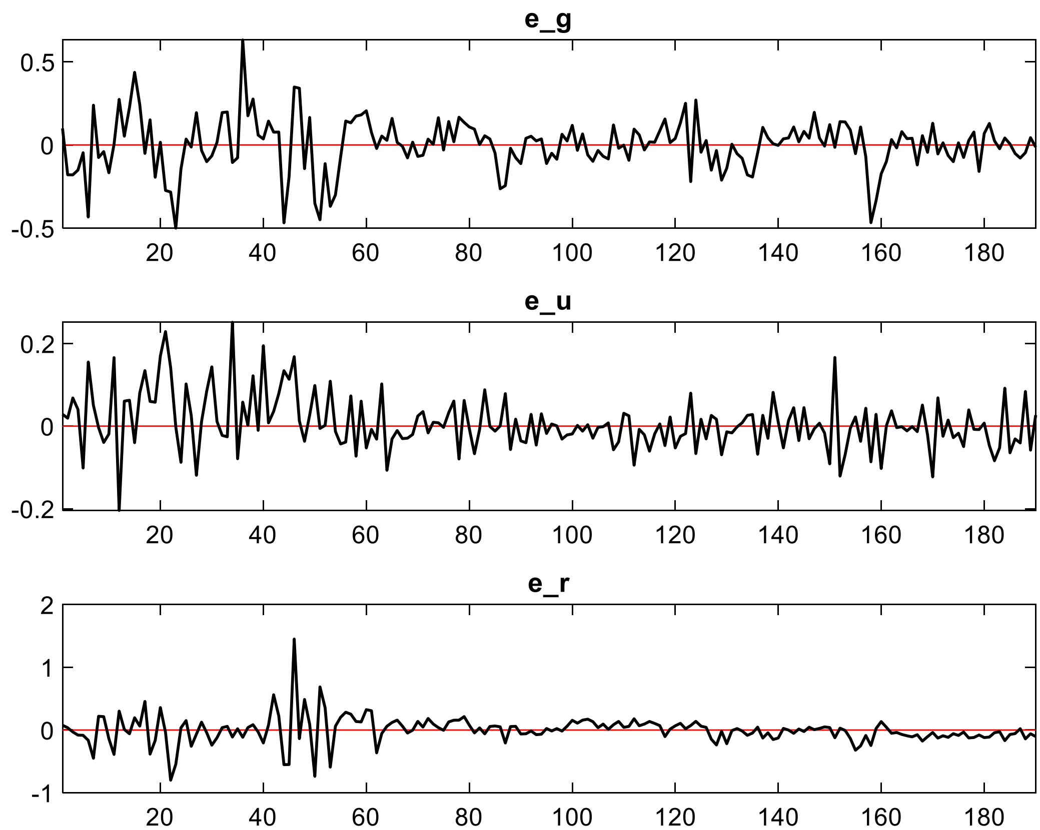

Fig. B.4. Full-information rational expectation smoothed shocks.

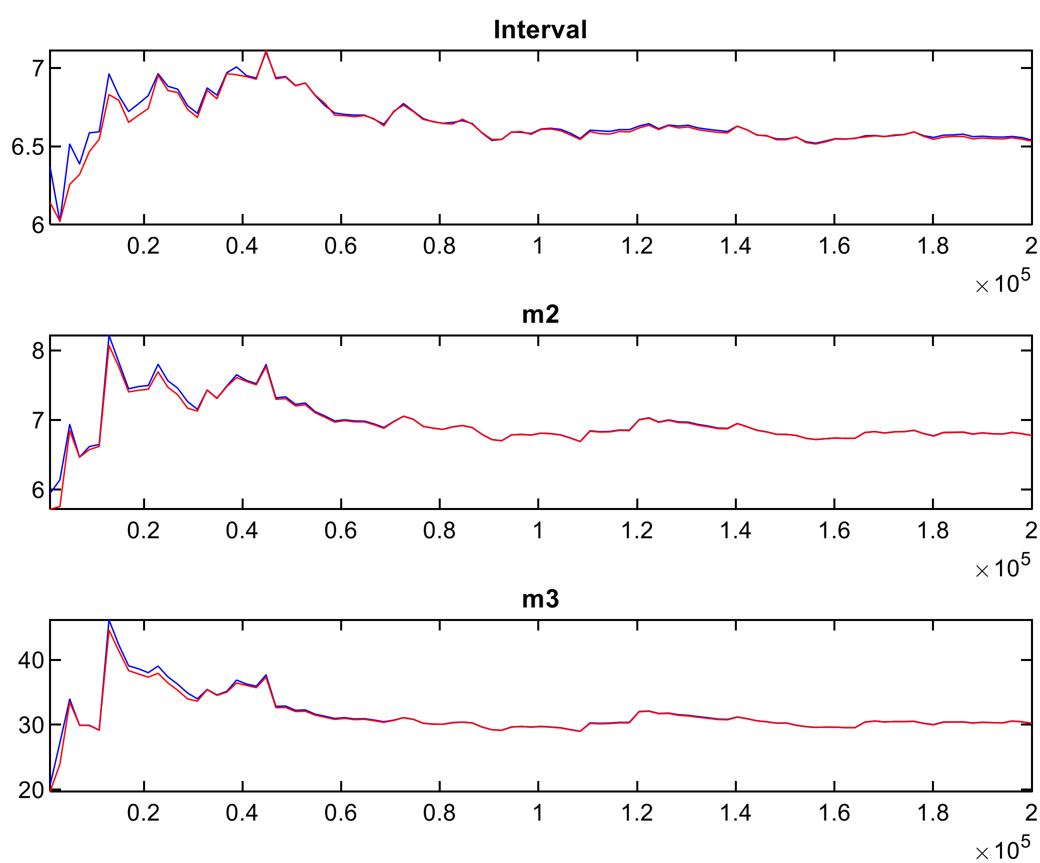

Fig. B.5. Sticky information multivariate MH convergence diagnosis.

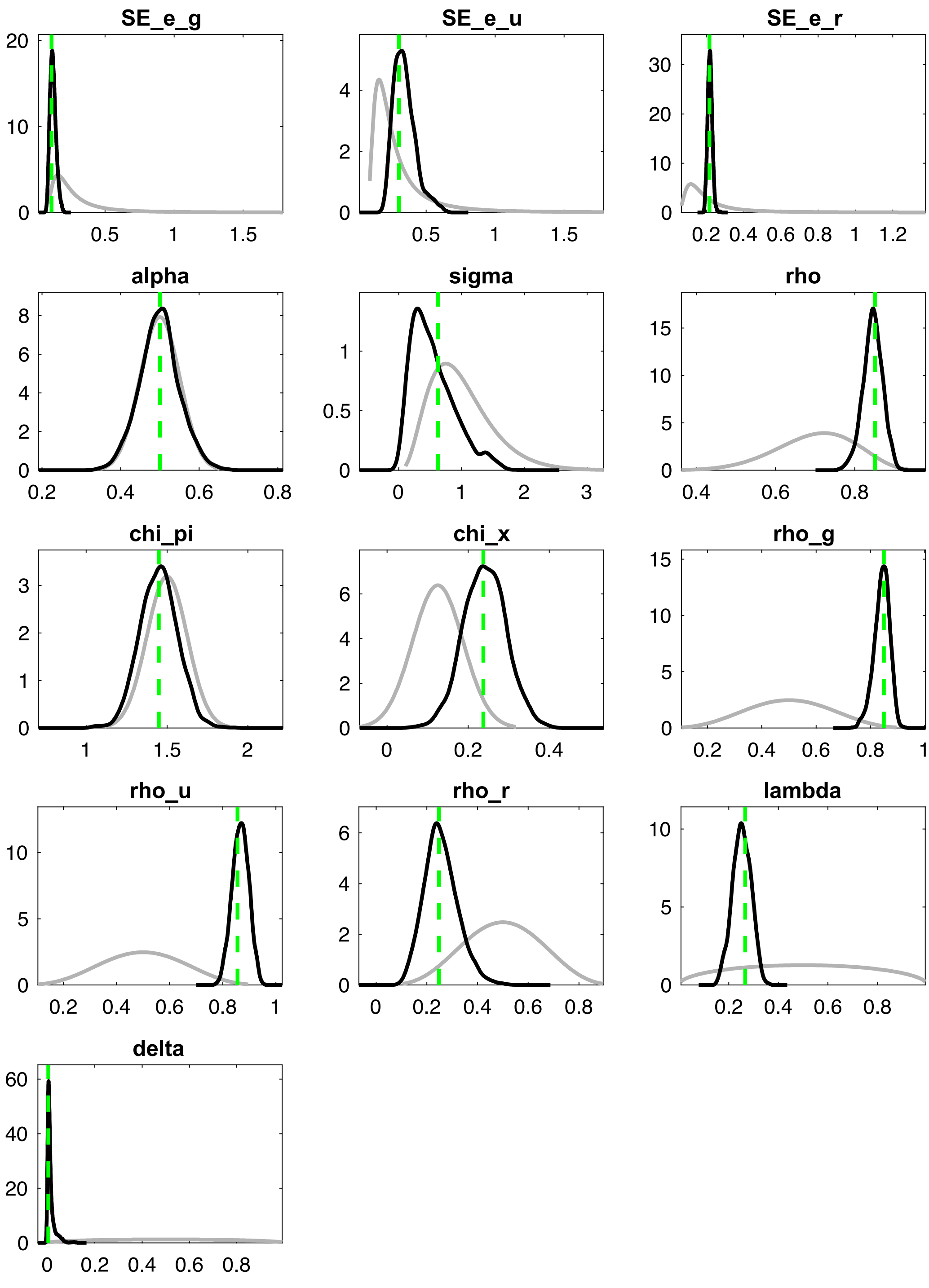

Fig. B.6. Estimated parameters distribution of sticky information.
Notes: Black line indicates posterior distribution mean while green line indicates posterior mean. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

aim to offer a simple framework to approximate the "true" revision processes and examine whether the deviation in the way we use the assumption of well-behaved revision processes (i.e., white noise) influences the estimation of policy and behavioral parameters. Therefore, from the defined equation above, we can obtain the following:

$$x_t \equiv x_t^r + v_t^x = (1 + b_x)x_t^r + e_t^x \tag{D.7}$$

$$\pi_t \equiv \pi_t^r + v_t^\pi = (1 + b_\pi)\pi_t^r + e_t^\pi \tag{D.8}$$

Furthermore, notice that the final revision process of output gap and inflation also implies the identities' respective equations as follows:

$$v_t^x = E_{t+1}v_t^x + e_t^x = b_x x_t^r + e_t^x \tag{D.9}$$

$$v_t^\pi = E_{t+1}v_t^\pi + e_t^\pi = b_\pi \pi_t^r + e_t^\pi \tag{D.10}$$

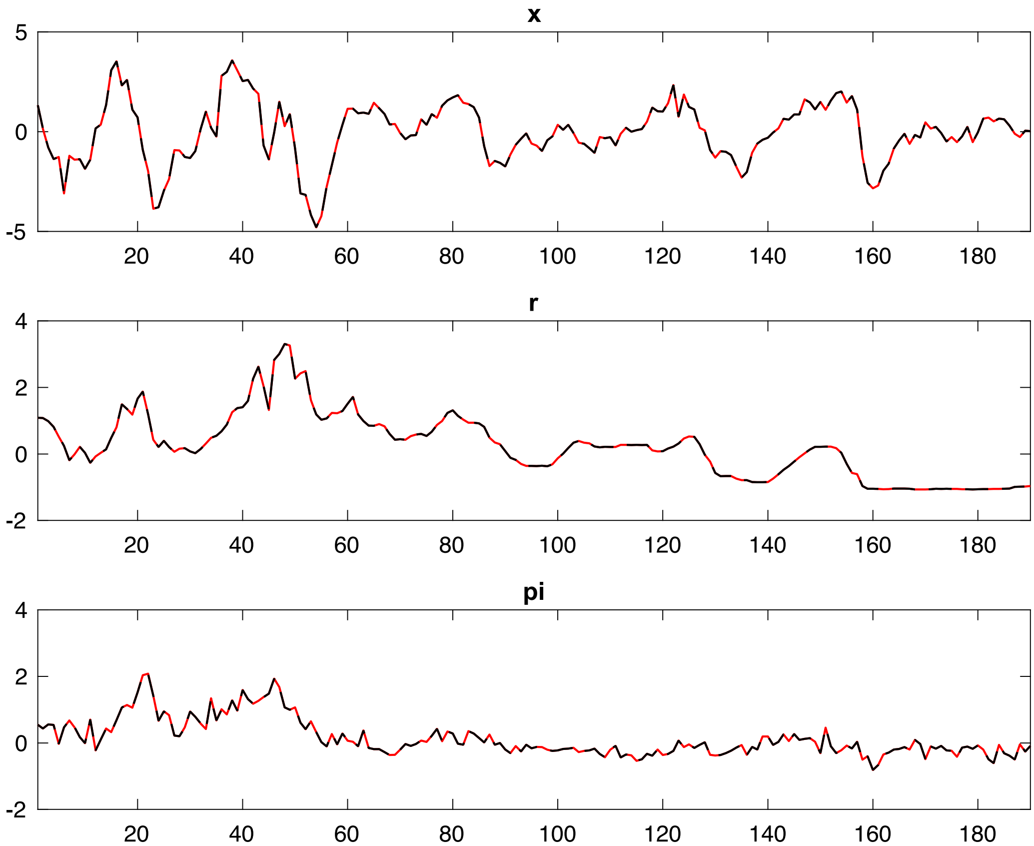

Fig. B.7. Sticky information smoothed variables.

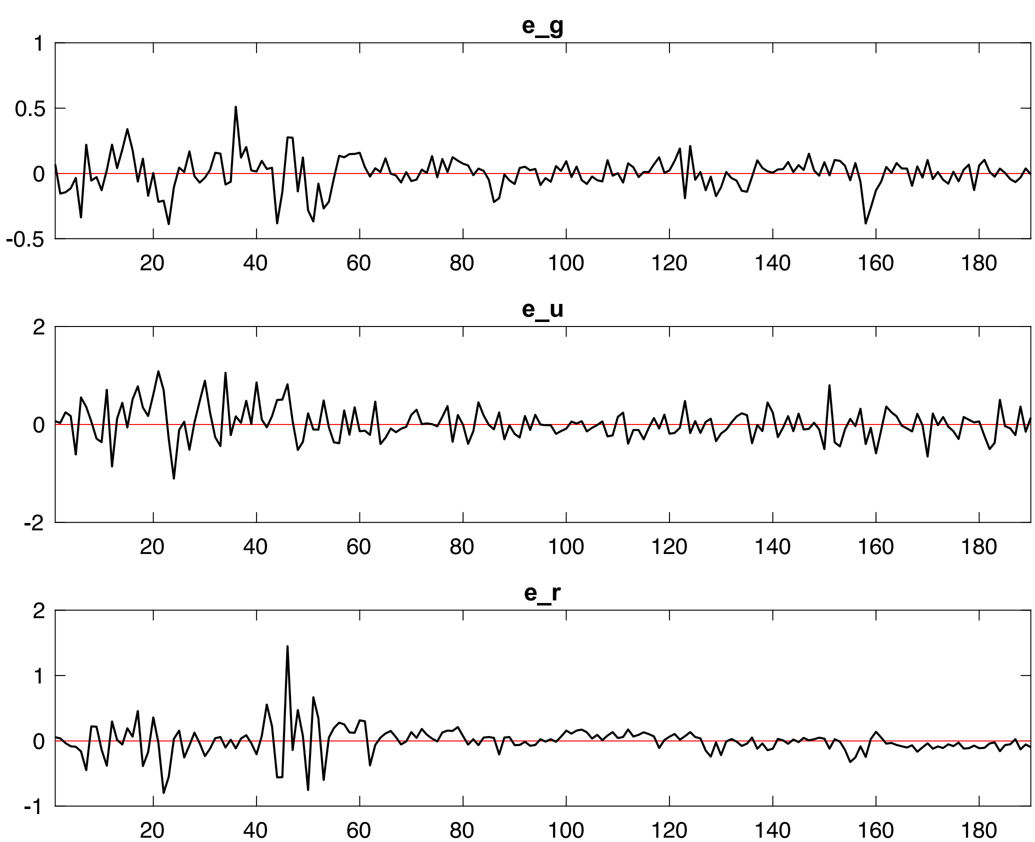

Fig. B.8. Sticky information smoothed shocks.

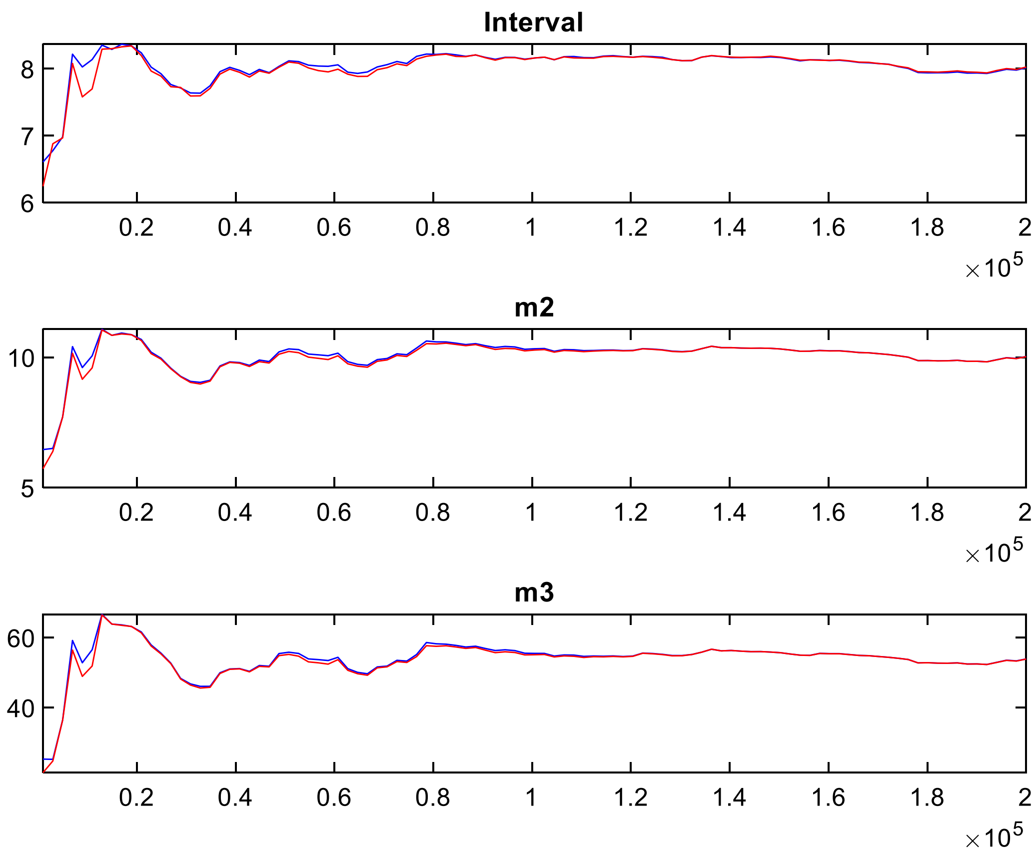

Fig. B.9. Imperfect information multivariate MH convergence diagnosis.

$$E_{t+1}\upsilon_t^x = b_x x_t^r \tag{D.11}$$

$$E_{t+1}\upsilon_t^\pi = b_\pi \pi_t^r \tag{D.12}$$

IS curve in the imperfect information model

We use the imperfect information data revision assumption to distinguish the baseline FIRE model. We can obtain the IS equation below[19]:

$$x_t = E_t(x_{t+1}^r + E_{t+2}\upsilon_{t+1}^x) - \sigma[\tilde{r}_t - E_t(\pi_{t+1}^r + E_{t+2}\upsilon_{t+1}^\pi)] + g_t \tag{D.13}$$

where households involve data revision issues, because these imperfect-information-type of people react to the expected revised values of inflation and output gap.

We also use the identity equations $E_{t+2}\upsilon_{t+1}^x = b_x x_{t+1}^r$ and $E_{t+2}\upsilon_{t+1}^\pi = b_\pi \pi_{t+1}^r$ to substitute out $E_{t+2}\upsilon_{t+1}^x$ and $E_{t+2}\upsilon_{t+1}^\pi$ respectively, to obtain the imperfect information IS equation below[20]:

$$x_t = (1 + b_x)E_t(x_{t+1}^r) - \sigma[\tilde{r}_t - (1 + b_\pi)E_t(\pi_{t+1}^r)] + g_t \tag{D.14}$$

Phillips curve in the imperfect information model

For firms with data revision issues (noise disturbance) we can obtain the imperfect information PC using the following equation:

$$\pi_t = \beta E_t(\pi_{t+1}^r + E_{t+2}\upsilon_{t+1}^\pi) + \gamma(\frac{(1-\alpha)(1-\alpha\beta)}{\alpha})x_t + u_t \tag{D.15}$$

Similarly, we use the identity equation to substitute out $E_t\upsilon_{t+1}^\pi$ from the above equation to obtain[21]

$$\pi_t = \beta E_t^{IF}\pi_{t+1} + \gamma(\frac{(1-\alpha)(1-\alpha\beta)}{\alpha})x_t + u_t \tag{D.16}$$

Meanwhile, the monetary policy assumed to be perfect is observed to have no data revision issue

$$\tilde{r}_t = \rho_r\tilde{r}_{t-1} + (1-\rho)[\chi_\pi x_t + \chi_x \pi_t] + \upsilon_t \tag{D.17}$$

where the final revisions υ_t^x and υ_t^π their data can be constructed as demeaned observables between the first released $x_{t,t+1}^r$ and the latest released $x_{t,t+s}^r$ as follows:

$$\upsilon_t^x = (x_{t,t+1}^r - x_{t,t+s}^r) - M^{\upsilon x} \tag{D.18}$$

$$\upsilon_t^\pi = (\pi_{t,t+1}^r - \pi_{t,t+s}^r) - M^{\pi x} \tag{D.19}$$

Thus, for the analysis, we choose $s = 3$ to construct the observations of the final revisions υ_t^x and υ_t^π :

$$\upsilon_t^x = (x_{t,t+1}^r - x_{t,t+3}^r) - M^{\upsilon x_3} \tag{D.20}$$

$$\upsilon_t^\pi = (\pi_{t,t+1}^r - \pi_{t,t+3}^r) - M^{\pi x_3} \tag{D.21}$$

Therefore, we can also construct the observations of the revised data x_t and π_t.

Note that, as argued by Croushore (2011), if we look at the US data, we can see that s is neither constant with the passage of time nor across variables. One may need to check whether the alternative of s will significant influence the performance of the imperfect information data revision. Here we choose $s = 3$, $x_{t,t+1}^r$ as the data released in 2016Q1, and $x_{t,t+3}^r$ as the data released in 2016Q3 to construct the revision process corresponding to the sample period from 1969Q1 up 2015Q4. For the simplicity of the analysis procedure, we consider the number of periods after which no more revisions can be done (except benchmark revisions, which is represented by s) and whether it is constant.

19 Initially, this is $x_t = E_t^{IF}x_{t+1} - \sigma(\tilde{r}_t - E_t^{IF}\pi_{t+1}) + g_t$.

20 Initially, this is $x_t = E_t(x_{t+1}^r + b_x x_{t+1}^r) - \sigma[\tilde{r}_t - E_t(\pi_{t+1}^r + b_\pi\pi_{t+1}^r)] + g_t$.

21 Initially, this is $\pi_t = (1 + b_\pi)\beta E_t(\pi_{t+1}^r) + \gamma(\frac{(1-\alpha)(1-\alpha\beta)}{\alpha})x_t + u_t$.

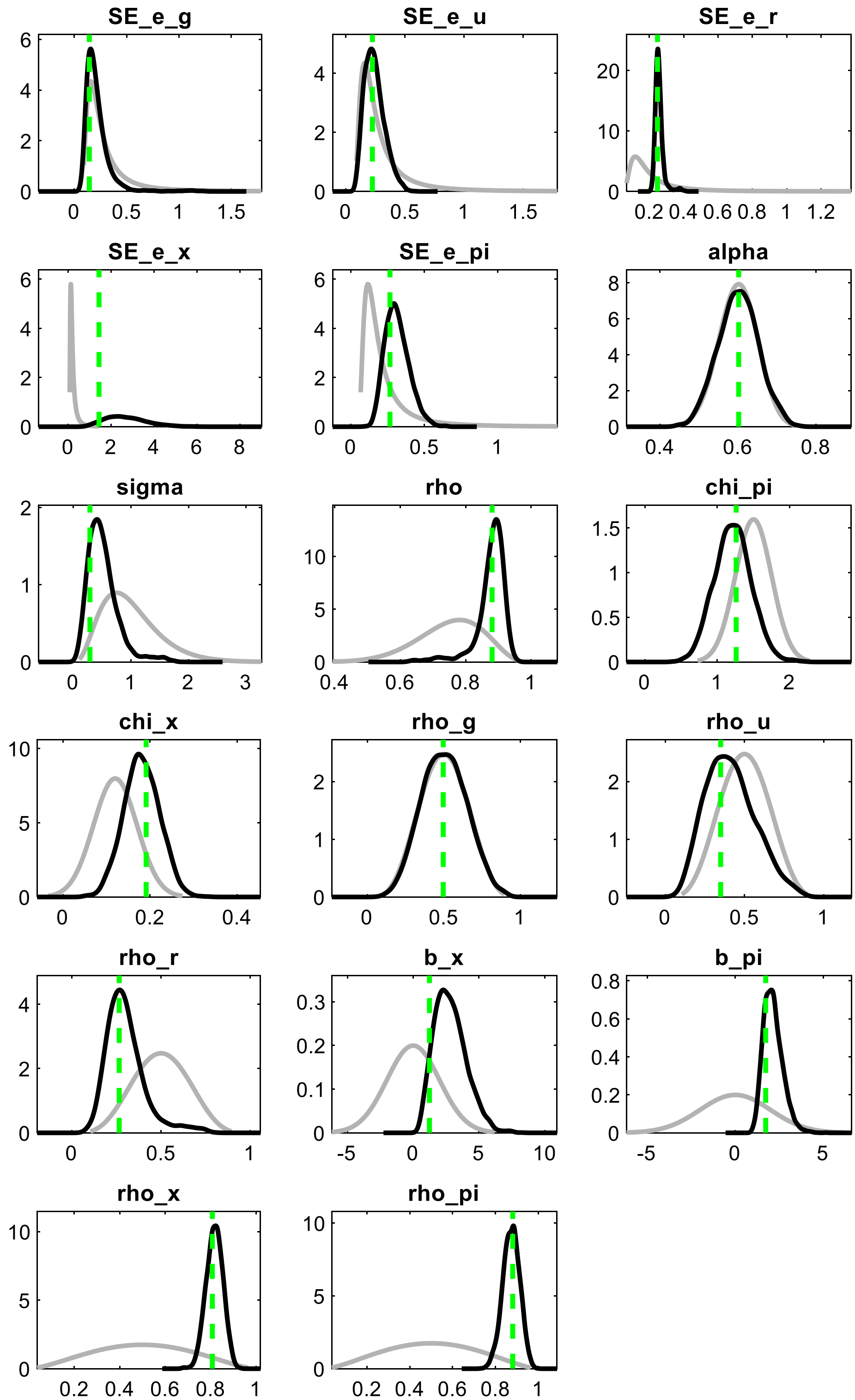

Fig. B.10. Estimated parameters distribution of imperfect information model.
Notes: Black line indicates posterior distribution mean while green line indicates posterior mean. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

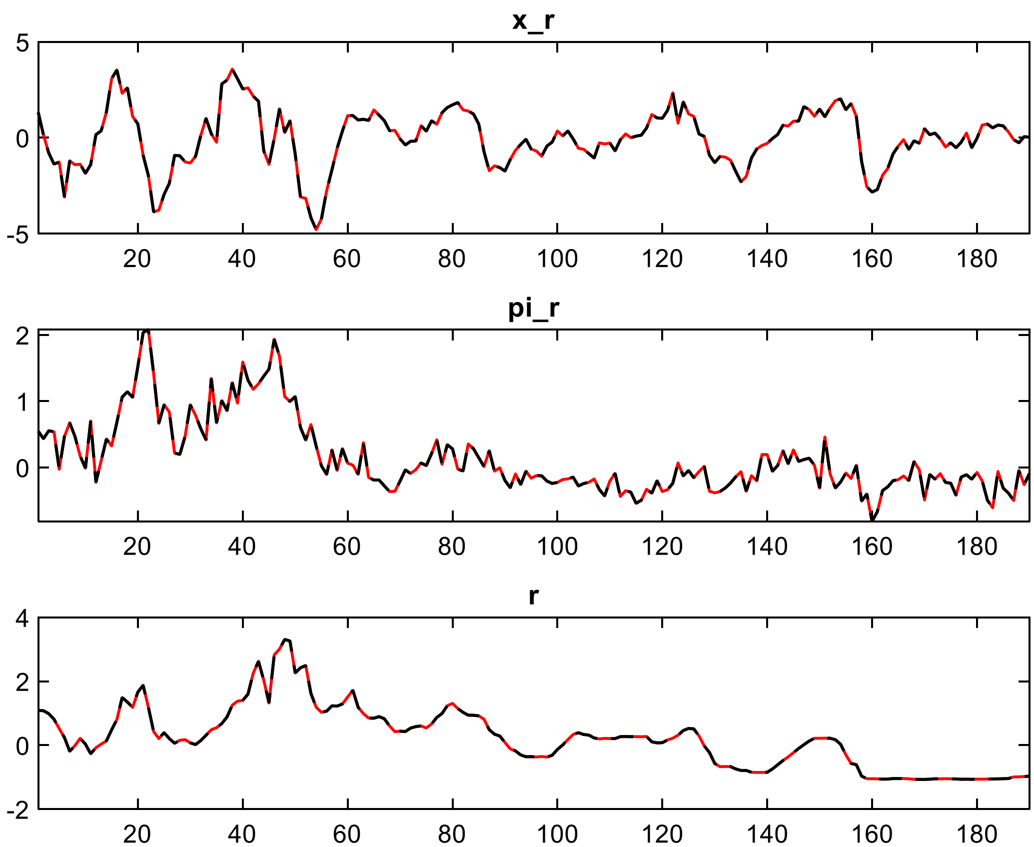

Fig. B.11. Imperfect information data revision smoothed variables. **Notes:** In IF model x_t^r and π_t^r are taken as the observed variables realized at time t.

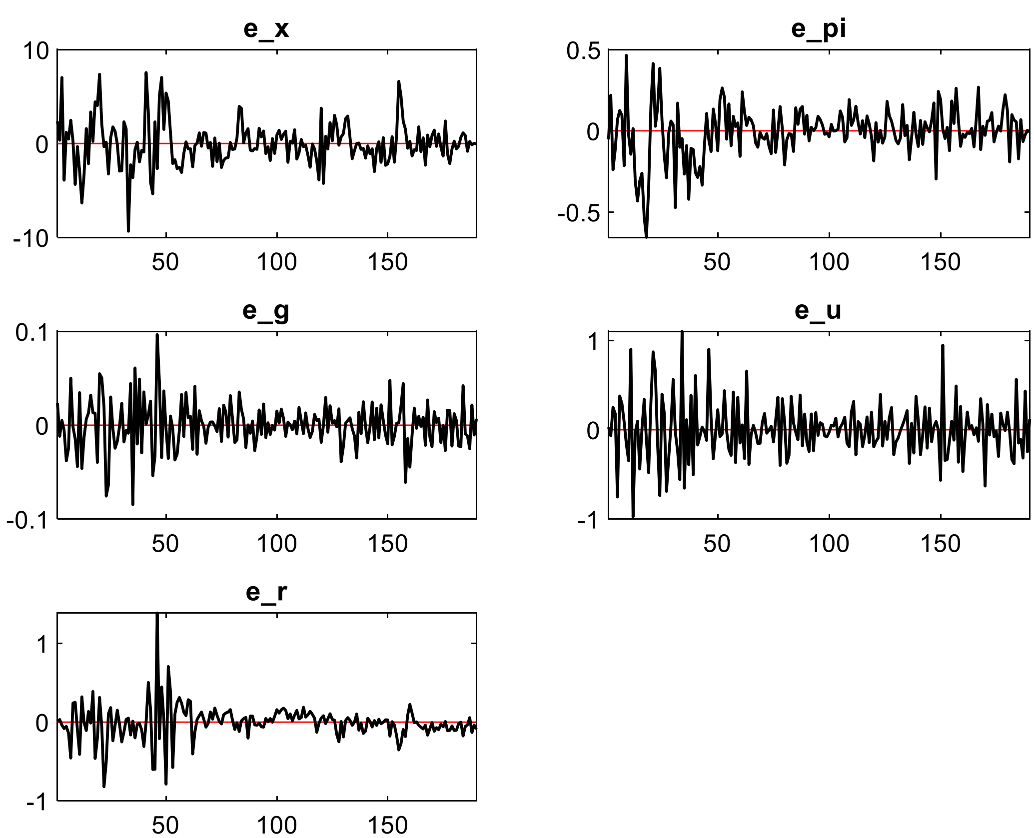

Fig. B.12. Imperfect information data revision smoothed shocks.

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