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Essays on Macroeconomics: A Tale of Expectations

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Essays on Macroeconomics: A Tale of Expectations

DISSERTATION

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for the degree of

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in Economics

by

Lacliy Carolina Acuña Armenta

Dissertation Committee:
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2022

DEDICATION

To Luis and my parents

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ABSTRACT OF THE DISSERTATION

Essays on Macroeconomics: A Tale of Expectations

By

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Doctor of Philosophy in Economics

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Professor Fabio Milani, Chair

This dissertation uses Bayesian methods to understand how expectations are formed and their role in macroeconomic fluctuations. All three essays study expectations formation through different perspectives and econometric tools.

The first chapter analyzes the impact of central bank transparency on the evolution of agents' expectations for the Mexican case via a New Keynesian model with adaptive learning and survey forecasts. Among multiple scenarios, the data prefer the observed transparency degree followed by the Mexican central bank, where the central bank credibly communicates the inflation target and discloses relevant information about its policy rule. The results show that agents exhibit a faster learning speed than the U.S. and a declining perceived inflation persistence. Plus, the model-implied learning mechanism can match the empirical inflation expectations from the Survey on Expectations of Private Sector Specialists. Moreover, there is evidence suggesting that higher degrees of transparency increase the effectiveness of monetary policy in stabilizing the economy.

Chapter 2 assesses the role of economic conditions in inflation expectation formation using a Bayesian latent class ordinal model and qualitative survey data from the Michigan Survey of Consumers. The results show evidence that inflation expectations have been formed distinctly depending on the economic conditions faced by individuals. Furthermore, the

effect of demographic indicators, such as age, gender, education, and income, on inflation expectations varies with the level of distress of the economy.

Lastly, the final chapter develops and estimates a model with informational frictions. Agents are inattentive and form subjective expectations using an economic model. The proposed expectation formation mechanism is estimated using Bayesian methods and tested against rational expectations. The paper yields three novel results. First, the model embedding inattention à la Mankiw and Reis (2002) and subjective expectations under adaptive learning provides the best fit of the data. Secondly, the degree of inattention is susceptible to how the expectation formation process is modeled. In particular, the level of inattention is considerably reduced when I depart from the rational expectation assumption. Finally, this result remains unchanged when tested using real-time macroeconomic series and expectations data from the U.S. Survey of Professional Forecasters.

Chapter 1

Central Bank Transparency under Adaptive Learning

1.1 Introduction

"Clarity about the aims of future policy and about how the central bank likely would react under various economic circumstances reduces uncertainty and —by helping households and firms anticipate central bank actions— amplifies the effect of monetary policy."

Bernanke (2010)

Central bank transparency has been an important feature of monetary policy for the past decades. This is true for monetary policy authorities following an inflation targeting regime but also for those operating outside this framework. Institutional transparency promotes a greater openness which extends to publications of analysis and forecasts of the economic environment, the central bank's policy agenda, minutes from the Board meetings, and, in some cases, explicit communication of the objective for inflation.

All these actions decrease the information gap between the monetary policymakers and the public. This allegedly helps the public to better understand the policy rule and leads to better anchor inflation expectations, and consequently, has a stabilizing effect on macroeconomic activity.

However, can these effects of central bank transparency be seen on agents' expectations formation and evolution? In order to answer this question, I will follow an adaptive learning approach that accommodates the two key assumptions. First, it allows for not perfectly anchored expectations. Plus, it posits that agents lack knowledge of the true model of the economy and the monetary policy conducted by the central bank.

Some examples of literature linking central bank transparency and adaptive learning include Berardi and Duffy (2007), Eusepi (2005), Orphanides and Williams (2007), and Eusepi and Preston (2010). The first two papers examine the effects of central bank transparency on the performance of optimal inflation targeting rules. Berardi and Duffy (2007) construct a model where central bank transparency allows the private agents to correctly specify their Perceived Law of Motion for inflation and output gap; thus, they can converge to the rational expectations equilibrium. The authors find that the policy loss from central bank transparency is lower than its alternative (i.e., intransparency). Eusepi (2005) posits transparency as the economic agents' knowledge of the monetary policy rule. Thus, the central bank transparency reduces agents' uncertainty, as the central bank communicates the policy rule. He finds that a transparent central bank plays an important role in stabilizing the public's learning process and expectations of the public.

While Orphanides and Williams (2007) model transparency by assuming that agents incorporate the information of the announcement of the inflation target into their learning algorithm. So, in this manner, they need to estimate a smaller number of parameters compared to the case where they did not receive this information. They point out that central bank transparency, including explicit communication of the inflation target, can influence inflation expectations by facilitating the learning of the central bank policy and, consequently, improving macroeconomic performance.

Finally, Eusepi and Preston (2010) explore the effects of different central bank communication strategies on expectations stabilization and the learning mechanism of the agents. That is to say; they evaluate the value of monetary policy information. Even when the paper uses different terminology, central bank communication can be closely related to the term of *transparency*. They find that a more transparent monetary policy authority can prevent expectation-driven fluctuation as agents are capable of constructing more accurate forecasts.

Similar to all the previously mentioned work, this paper models central bank transparency as the available information about the monetary policy that economic agents have at their disposal. Nevertheless, it contrasts with them as it does not focus on the stability of the rational equilibrium but on the empirical role of central bank transparency on the learning process used by economic agents while they form expectations.

Along these lines, this paper aims to contribute to the literature by estimating, via Bayesian methods, a baseline New Keynesian model with adaptive learning to empirically study the effects of central bank transparency on the agents' learning process and expectations. I propose four scenarios that consider different degrees of transparency; within each case, the central bank releases various information related to the conduction of the monetary policy. Additionally, I incorporate time series information about expectations on inflation and nominal interest rate taken from the Survey on Expectations of Private Sector Specialists conducted by the Mexican central bank to identify the best-fitting evolution of agents' beliefs, as well as the learning speed.

The empirical analysis focuses on the Mexican experience as numerous measures of central bank transparency had been implemented during the last decades, in addition to the adoption of the inflation targeting framework in 2001. Plus, after experiencing chronic high inflation during the 70s and 80s and a disinflation process in the 90s, interrupted by the Tequila crisis, the central bank has successfully reduced and stabilized inflation and inflation expectations (Ramos-Francia and Torres (2005)). In the past two decades, the economy has shown a period of moderate but persistent inflation. Table 1.1 summarizes the communication strategy of the Mexican central bank.

Implementation date	**Transparency measures description**
2000	Release of a Quarterly Report on Inflation.
2001	Inflation targeting framework adoption.
2003	Announcement of a band for the inflation target (3% ± 1%)
	Press releases on the Meeting of Banco de México's Governing Board regarding monetary policy decisions, plus disclosure of the dates of the meeting in advance.
2010	Release of a Quarterly Report on Inflation in English.
	Fan charts are incorporated into the Quarterly Report on Inflation.
2011	Publication of minutes on the Meeting of Banco de México's Governing Board.
2012	Online broadcasting of the Quarterly Report.
2017	Disclosure of the (anonymous) votes of Banco de México's Governing Board on monetary policy decisions.
2018	Disclosure of the voter identities of Banco de México's Governing Board on monetary policy decisions.
	Release of the transcript from the Meeting of Banco de México's Governing Board regarding monetary policy decisions, after 3 years of the reunion.
	Publication of Governing Board's speeches and presentations, after 2 days of their exposition.
2019	Figures on the Quarterly Report are accompanied with a link to the source of the data used on them.

Table 1.1: Banco de México transparency timeline.

Moreover, previous literature on the Mexican case has not explored the adaptive learning approach yet to analyze the effect of central bank transparency on the learning process of agents and their expectations.[1]

The results show that the partially transparent regime best fits the data among all four specifications. Other findings indicate that private agents exhibit a fast learning speed; they react strongly to forecast errors. Also, results indicate that agents' perception of inflation

[1] There are some recent papers, Ramos-Francia et al. (2018) and López-Martín et al. (2018), that consider the assumption that agents updated their beliefs using a constant-gain algorithm (as in Sargent et al. (2009)) to study, in contrast, the interaction between inflation, inflation expectations, and fiscal deficits in Mexico.

persistence has decreased over time.

Accordingly to the estimation, central bank transparency has a relatively small impact on inflation and output gap responses to structural shocks. Nonetheless, the results suggest that higher degrees of transparency increase the effectiveness of the monetary policy in stabilizing the economy and monetary policy expectations of the public.

Finally, the model-implied one-period-ahead inflation expectations are able to closely match the empirical expectations from the surveys of professional forecasters. Then this gives some evidence that the learning process estimated by the model resembles the one followed by the agents in the Mexican economy.

Monetary policy implications for this paper come from two routes. First, expectations are the channel through which monetary policy impacts the economy. Second, as Bernanke (2007) points out, *"a fuller understanding of the public's learning rules would improve the central bank's capacity to assess its own credibility, to evaluate the implications of its policy decisions and communication strategy, and perhaps to forecast inflation"*. Also, he emphasizes that inflation expectations can heavily influence actual inflation thus, their understanding is crucial for policymakers.

The paper is organized as follows. Section 1.2 describes the model and how expectations are formed. Later, estimation and the results are discussed in Sections 1.3 and 1.4, respectively. Finally, the paper is concluded in Section 1.5.

1.2 The Model

A basic New Keynesian model,[2] as presented in Woodford (2003), is followed to describe the economy dynamics.[3,4]

$$\pi_t = \hat{E}_{t-1}(\kappa x_t + \beta \pi_{t+1} + u_t) \tag{1.1}$$

$$x_t = \hat{E}_{t-1}(x_{t+1} - \sigma(i_t - \pi_{t+1} - r_t^n)) \tag{1.2}$$

$$i_t = \rho i_{t-1} + (1-\rho)(\chi_\pi \pi_{t-1} + \chi_x x_{t-1}) + \varepsilon_t^{mp} \tag{1.3}$$

where π_t, x_t and i_t are inflation, output gap and interest rate, respectively.

The New Keynesian Phillips Curve is described by Equation (1.1). It is derived from the firm's problem solution under a competitive monopoly and Calvo price setting environment. It shows the inflation dynamics given the expected path for output gap in $t+1$, the future inflation, and the cost-push shock, u_t. κ is a decreasing function of the degree of price stickiness, and β is the discount factor.[5]

Next, Equation (1.2) represents the Euler equation that arises from the households' optimal choice of consumption. In this equation can be seen that the output gap depends on its future expected levels and deviations of the real interest rate from the natural rate of interest, r_t^n. But most importantly, the output gap depends on expectations about the nominal interest rate. Now, aggregate demand is affected by the expectations of the central bank decisions. As previously mentioned, this will allow to identify the role of central bank transparency in

[2]As a closed-economy model, it does not consider the foreign sector and the exchange rate which are relevant characteristics for an economy as the Mexican. In spite of this limitations, I selected this model for simplicity, and since the main objective study the role of central bank transparency on the formation of expectations; and not the analysis of the external sector.

[3]All variables are expressed as log-deviations from their steady-state values.

[4]This model does not explicitly consider an inflation target, then, it is assumed that the target pursued by the central bank corresponds to the steady-state value of inflation.

[5]The discount factor is calibrated to 0.9946, which is the value consistent with the average of the real interest observed during the sample period.

the economy.

A Taylor-type interest rate rule is presented in Equation (1.3). It describes how the central bank conducts the monetary policy. That is to say, how the nominal interest rate evolves over time in reaction to changes in the levels of output gap and inflation. Responses of the monetary authority are captured by χ_π and χ_x, while ρ reflects any history dependence in the monetary policy.

Finally, the structural shocks of the system are denoted as ε_t^{mp}, u_t, and r_t^n:

$$\varepsilon_t^{mp} \overset{iid}{\sim} N(0, \sigma_{mp}^2) \tag{1.4}$$

$$u_t = \rho_u u_{t-1} + \varepsilon_t^u \tag{1.5}$$

$$r_t^n = \rho_r r_{t-1}^n + \varepsilon_t^r \tag{1.6}$$

where the cost-push shock and the natural rate of interest follow an AR(1) process. Meanwhile, the monetary policy shock, ε_t^{mp}, is assumed to be independently and identically distributed with homoskedastic variance. The same assumptions hold for $\varepsilon_t^u \overset{iid}{\sim} N(0, \sigma_u^2)$ and $\varepsilon_t^r \overset{iid}{\sim} N(0, \sigma_r^2)$.

So far, the model follows the benchmark New Keynesian model. However, it deviates from the rational expectations assumption. Following the literature on adaptive learning, I assume that economic agents behave as econometricians and forecast their expectations using an economic model and past data. Let $\hat{E}_t(.)$ denotes subjective expectations.

Additionally, I suppose that agents dispose of information up to period $t-1$,[6] thus, prices and consumption decisions are predetermined. This assumption allows me to introduce two elements to the analysis: i) the role of central bank transparency via expectations about

[6]This is referred to as the "standard timing" assumption in Evans and Honkapohja (2001). It has the advantage of avoiding simultaneity issues between regressors and parameters in the model used by the agents to form their expectations.

Central banks communicates:	**Full transparency**	**Partial transparency**	**Only target known**	**Opacity**
Monetary policy coefficients	✓	-	-	-
Relevant variables for monetary policy	✓	✓	-	-
Inflation target	✓	✓	✓	-

Table 1.2: Central bank transparency regimes.

nominal interest rate, and ii) survey data on expectations which are usually estimated one period in advance.

1.2.1 Central Bank Transparency and Expectation Formation

Moreover, I assume that the central bank transparency degree impacts the model used by agents to compute their expectations on future conditions of the economy and the monetary policy. I posit four scenarios assuming different degrees of central bank transparency. Table 1.2 summarizes the assumptions of the different degrees of transparency proposed.

Assuming that agents observe the structural shocks and use all available information communicated by the central bank, they compute the following model:

$$Z_t = a_t + b_t Z_{t-1} + c_t u_{t-1} + d_t r^n_{t-1} + e_t \tag{1.7}$$

where $Z_t = \{\pi_t, x_t, i_t\}'$ is a vector containing the endogenous variables of the model; a_t, b_t, c_t and d_t are a matrix and vectors of appropriate dimensions containing the beliefs.

Equation (1.7) is known as the Perceived Law of Motion (PLM) and it describes the model used by the agents to form their expectations about relevant variables. Note that agents are allowed to learn about the economy (π_t and x_t) and the monetary policy rule (i_t). The model for the nominal interest rate will assess the public's perception of the monetary policy under each of the four specifications proposed considering different degrees of central bank transparency.

It is important to remark that central bank releases will impact the PLM of monetary policy of the agents, since they will be exposed to different sets of information. For example, under *fully transparency* and *partial transparency*, the central bank credible communicates the target for inflation and the relevant variables for monetary policy. Thus, agents will not include an intercept in their PLM nor will consider the past information of the structural shocks for their model to forecast the nominal interest rate. See more details in Appendix A.

In this sense, central bank transparency facilitates the learning process because it reduces the number of parameters to be estimated by the agents in order to form their expectations. In contrast, in the *opaque* regime, agents do not receive any information from the central bank regarding its objectives nor the data it takes into account while making monetary policy decisions. So, the agents' PLM for nominal interest rate will consider an intercept and the lagged information about the structural shocks.

Agents update their estimates of the PLM coefficients each time new information is available using a Constant-Gain learning algorithm:

$$\Phi_t = \Phi_{t-1} + gR_t^{-1}X_t(Z_t - X'_{t-1}\Phi_{t-1}) \tag{1.8}$$

$$R_t = R_{t-1} + g(X_tX'_t - R_{t-1}) \tag{1.9}$$

where g is the constant gain parameter, X_t is the set of regressors used in the PLM, and $\Phi_t = (vec(a'_t, b_t)')'$. Recall that the model used by agents for the nominal interest rate will differ as a result of central bank transparency degree. Then, X_t, R_t and Φ_t will be adjusted to the assumed information set available to the public.

Equations (1.8) and (1.9) give the updating rules for the beliefs, Φ_t, and the matrix of second moments of the regressors employed in the PLM, R_t.

Therefore, agents form their expectations for t and $t+1$ using the PLM, the most recent coefficient estimates, and all available information regarding monetary policy published by the central bank:[7]

$$\hat{E}_{t-1}\begin{pmatrix}\pi_t\\ x_t\\ i_t\end{pmatrix}=\begin{pmatrix}a_{1,t}\\ a_{2,t}\\ a_{3,t}\end{pmatrix}+\begin{pmatrix}b_{11,t} & b_{12,t} & b_{13,t}\\ b_{21,t} & b_{22,t} & b_{23,t}\\ b_{31,t} & b_{32,t} & b_{33,t}\end{pmatrix}\begin{pmatrix}\pi_{t-1}\\ x_{t-1}\\ i_{t-1}\end{pmatrix}+\begin{pmatrix}c_{1,t}\\ c_{2,t}\\ c_{3,t}\end{pmatrix}u_{t-1}+\begin{pmatrix}d_{1,t}\\ d_{2,t}\\ d_{3,t}\end{pmatrix}r^n_{t-1}+\begin{pmatrix}0\\ 0\\ e^i_{t-1}\end{pmatrix} \tag{1.10}$$

$$\hat{E}_{t-1}\begin{pmatrix}\pi_{t+1}\\ x_{t+1}\\ i_{t+1}\end{pmatrix}=\begin{pmatrix}a_{1,t}\\ a_{2,t}\\ a_{3,t}\end{pmatrix}+\begin{pmatrix}b_{11,t} & b_{12,t} & b_{13,t}\\ b_{21,t} & b_{22,t} & b_{23,t}\\ b_{31,t} & b_{32,t} & b_{33,t}\end{pmatrix}\hat{E}_{t-1}\begin{pmatrix}\pi_t\\ x_t\\ i_t\end{pmatrix}+x\begin{pmatrix}c_{1,t}\\ c_{2,t}\\ c_{3,t}\end{pmatrix}E_{t-1}u_t+\begin{pmatrix}d_{1,t}\\ d_{2,t}\\ d_{3,t}\end{pmatrix}E_{t-1}r^n_t+\begin{pmatrix}e^\pi_{t-1}\\ 0\\ 0\end{pmatrix} \tag{1.11}$$

where e^π_t and e^i_t are expectation shocks related to inflation and the nominal interest rate, as in Milani (2011). They are assumed to be independent and follow an AR(1) process:

$$e^\pi_t=\rho_{e^\pi}e^\pi_{t-1}+\varepsilon^{e^\pi}_t \tag{1.12}$$

$$e^i_t=\rho_{e^i}e^i_{t-1}+\varepsilon^{e^i}_t \tag{1.13}$$

where $\varepsilon^{e^j}_t \overset{iid}{\sim} N(0,\sigma^2_{e^j})$ for $j=\{\pi,i\}$. Recall that vectors a_t, c_t and d_t and matrix b_t change accordingly to the degree of central bank transparency.

These expectation shocks reflect exogenous variations on expectations unrelated to fundamentals. So, they can capture sentiments or psychological factors that affect expectations formation.[8] In order to extract a better signal of these expectation shocks and the learning process, I will be using data on expectations during the estimation of the model.

Therefore, the model can be summarized by the economy dynamics, described in Equations (1.1)-(1.6); the agents' PLM, captured by Equation (1.7); the updating rules, expressed in Equations (1.8) and (1.9); and the forecasting rule shown in Equations (1.10) and (1.11).

[7] While forming expectations about the structural shocks, agents are assumed to know their autocorrelation coefficients, but they do compute expectations about these shocks.

[8] In this case, I did not consider expectation shocks for output gap expectations as this paper focuses mainly in inflation and monetary policy.

1.3 Bayesian Estimation

The structural parameters are estimated via Bayesian techniques, following Herbst and Schorfheide (2016). First, a prior distribution is assigned to the parameters: $p(\theta)$, based on past literature. Then, the likelihood is obtained using the Kalman filter: $L(Y_{t=1:T}|\theta)$. A random-walk Metropolis-Hastings algorithm is implemented to estimate the posterior distribution of the parameters. I run 500,000 iterations, discarding 25% of the draws as the burn-in period. The posterior means are used as estimates for the parameters of the model.

1.3.1 State-Space Form

The model with adaptive learning expressed by Equations (1.1)-(1.6) and with agents' expectations formed as in (1.10) and (1.11) can be expressed in state-space form:

$$S_t = F_t S_{t-1} + G\varepsilon_t + \tilde{C}_t \tag{1.14}$$

$$Y_t = BS_t + m_t \tag{1.15}$$

where ε_t=(ε_t^{mp},ε_t^u,ε_t^r) are the structural disturbances; S_t is a state vector which includes endogenous variables, $S_t = (\pi_t, x_t, i_t, u_t, r_t^n, E_{t-1}\pi_{t+1}, E_{t-1}x_{t+1}, E_{t-1}i_{t+1}, E_{t-1}u_{t+1}, E_{t-1}r_{t+1}^n, ...,$ $E_{t-1}\pi_t, E_{t-1}x_t, E_{t-1}i_t, E_{t-1}u_t, E_{t-1}r_t^n, e_t^\pi, e_t^i)$; Y_t is the vector of observable variables, Y_t=(π_t,x_t, i_t,$E_{t-1}\pi_{t+1}$,$E_{t-1}i_t$); B is a matrix compose of zeros and ones whence the variable is observable; m_t are the measurement errors;[9] and F_t, G and $\tilde{C}_t$ are matrices composed by the structural parameters, θ:

$$\theta = (\sigma, \kappa, \rho, \chi_\pi, \chi_x, \rho_u, \rho_r, \sigma_{mp}, \sigma_u, \sigma_r, g, \rho_{e^\pi}, \rho_{e^i}, \sigma_{e^\pi}, \sigma_{e^i}) \tag{1.16}$$

[9]Measurement errors are only assumed for the time-series for $E_{t-1}\pi_{t+1}$ and $E_{t-1}i_t$ since the first one is taken from a survey and the latter is computed. They are assumed to be 30% of the variance of the observable series.

While F_t and $\tilde{C}_t$ also depend on the PLM reduced-form parameters, Φ_t.[10]

Equations (1.14) and (1.15) are the state-transition and measurement equations, respectively.

1.3.2 Data

The data used for the estimation has a quarterly frequency, and it comprises the period between 2001-I and 2018-IV. This choice relies on information availability and the paper's objective; to study the evolution of expectations during a period when the Banco de México followed transparency measures.

Inflation was constructed using the Mexican CPI (in Spanish Índice Nacional de Precios al Consumidor, INPC).[11] Output gap is estimated as the log difference of the detrended and seasonally adjusted Mexican GDP (in Spanish Producto Interno Bruto, PIB). Finally, the interest rate measure is taken from the 91 days yield Certificates of the Treasury of the Federation rate (in Spanish Certificados de la Tesoreria de la Federación, CETES), which are government securities equivalent to the 3-month T-bill.

Additionally, I incorporate time series information about inflation and nominal interest rate expectations. The one-period-ahead inflation expectations are taken from the Survey on Expectations of Private Sector Specialists conducted by the Mexican central bank. I use the mean across all available answers. Meanwhile, the expected nominal interest rate is computed using the expectation theory of the term structure, as information is not available. For this estimation, data on 91 and 182 days yield Certificates of the Treasury of the Federation rate is used.

[10] The initial values for agent beliefs are set as 0.7 for the persistence for all variables, while the perceived reaction coefficients of the monetary policy to inflation and output gap are chosen close to the Taylor (1993) values, 1 and 0.5, respectively.

[11] As the Mexican central bank does not react to the GDP deflator in practice, CPI is considered as the measure of inflation despite the model being a closed-economy one.

All variables are expressed as deviations from the sample averages and expressed as quarterly rates.

The series for INPC and PIB were obtained from INEGI (Instituto Nacional de Estadística y Geográfica) and CETES information was acquired from Banco de México.

1.3.3 Priors

The prior distributions used in the Bayesian estimation of the baseline New Keynesian model with adaptive learning for the Mexican case can be seen in Table 1.3.

Parameter	**Description**	**Distribution**	**Mean**	**SDs**
σ	IES	Gamma	1	0.75
κ	Slope of PC	Gamma	0.5	0.2
ρ	Interest rate smoothing	Beta	0.8	0.1
χ_π	Inflation response coefficient	Gamma	1.5	0.25
χ_x	Output gap response coefficient	Gamma	0.5	0.25
ρ_u	AR coefficient - Cost-push shock	Beta	0.8	0.1
ρ_r	AR coefficient - Demand shock	Beta	0.8	0.1
σ_{mp}	SD - MP shock	Inverse Gamma	1	0.5
σ_u	SD - Cost-push shock	Inverse Gamma	1	0.5
σ_r	SD - Demand shock	Inverse Gamma	1	0.5
g	Constant gain	Uniform	0.5	$\sqrt{\frac{1}{12}}$
ρ_{e^π}	AR coefficient - Expectational shock for π	Beta	0.8	0.1
ρ_{e^i}	AR coefficient - Expectational shock for i	Beta	0.8	0.1
σ_{e^π}	SD - Expectational shock for π	Inverse Gamma	1	0.5
σ_{e^i}	SD - Expectational shock for i	Inverse Gamma	1	0.5

Table 1.3: Prior distributions.

The choice of the priors is based on previous literature related to New Keynesian model estimation, learning, and the Mexican case. Following Milani (2011), a gamma prior was assigned to the inter-temporal elasticity of substitution, σ, with mean of 1 and a sizable standard deviation, as there is a large uncertainty on its value in the literature. For the autoregressive coefficients of the structural and expectational shocks, and the interest rate smoothing a Beta distribution center at 0.8 was used, as in Best (2013). The same paper was followed to choose the prior for the slope of the Phillips curve, κ. As most of the literature, the priors for the feedback of inflation and output gap in the Taylor-type rule were centered on the values estimated by Taylor (1993). At the same time, inverse gamma priors are chosen for the standard deviations of the structural and expectational disturbances. Lastly, a uniform distribution bounded in the $[0,1]$ interval is assigned as a prior for the constant-gain parameter, g. In this manner, there are no pre-judgments attached to the learning process.

1.4 Results

In this section, I present the estimation results. Firstly, I estimate the model under the four scenarios considering contrasting degrees of central bank transparency to asses which is able to better explain the data for the Mexican case. Arguably the *partially transparent* regime is the most realistic case for the modern Mexican experience. However, I let the data speak and estimate all scenarios.

Next, I present the results for the scenario with the best performance: partial transparency.

1.4.1 Transparency Degrees: An Empirical Comparison

First, I compare the marginal likelihoods and posterior odds for the specifications under different degrees of transparency. Table 1.4 shows the results. It can be seen that the model under a partially transparent regime fits the data better than all other regimes. In particular, the difference is significant when contrasting it versus the opaque scenario (posterior odds 8 x 10^4). These results may suggest that the empirical evidence supports the existence of a high degree of transparency in Mexico, where the central bank not only credibly communicates the inflation target but also discloses the relevant information so the public can better understand how the monetary policy is conducted.

	Full transparency	**Partial transparency**	**Only target known**	**Opacity**
Log marginal likelihood	-274.47	-272.00	-275.80	-283.29
Posterior odds	12	1	45	8 x 10^4

Table 1.4: Model comparison under different degrees of central bank transparency.

Additionally, I would like to investigate further the impact of central bank transparency on inflation, output, and expectations. In order to do so, I compute impulse response functions of these variables to various shocks under the different degrees of central bank transparency, see Figure 1.1 and 1.2.

Let us recall that inflation and output gap indirectly depend on how agents are forming their expectations on monetary policy via the aggregate demand channel, consequently on central bank transparency. In these lines, I examine the response of output and inflation to the structural shocks. For the cases of the cost-push and demand shocks, their magnitude within different degrees of transparency is quite similar. In contrast, the impact of the monetary policy shock show is increasing with the degree of transparency. Thus, the effectiveness of monetary policy is closely related to central bank transparency.

On the other hand, inflation expectations seem to be slightly more reactive, or less anchored in Bernanke's terms, when the central bank decides not to disclose relevant information about monetary policy conduction, such as the inflation target and the variables included in the rule used by the monetary authority. Whereas monetary policy expectations react highly when the public is exposed to the highest degree of transparency, especially to monetary policy shocks. Overall, higher degrees of transparency seems to deliver a better management of the public's inflation expectations.

In contrast, interest rate expectations are formed similarly under most scenarios except

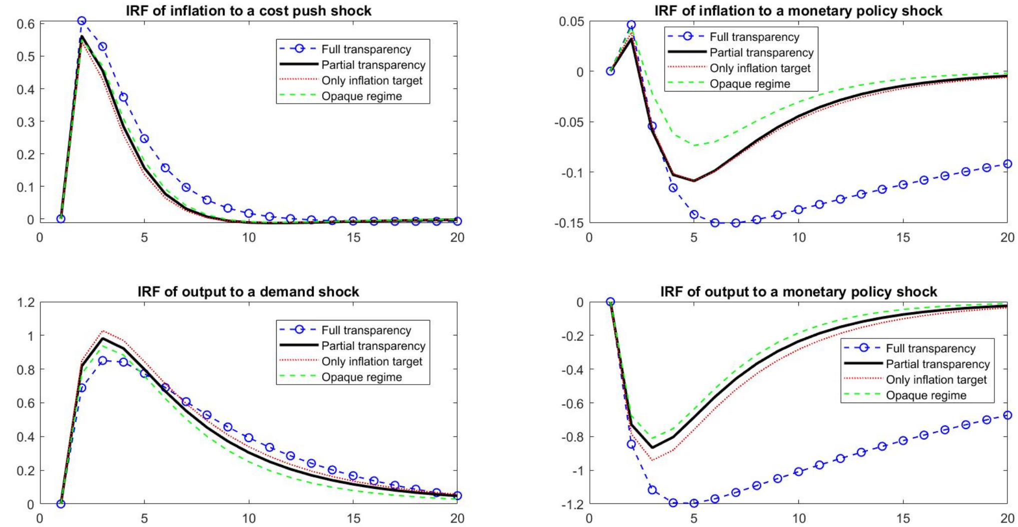


Figure 1.1: Impulse response function of inflation and output gap under different degrees of central bank transparency.

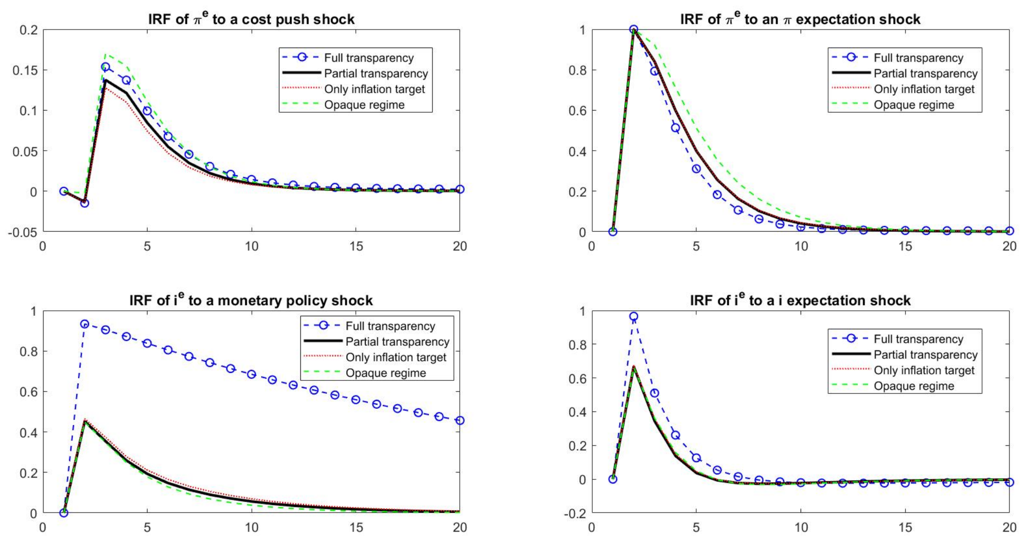


Figure 1.2: Impulse response function of expectations under different degrees of central bank transparency.

for full transparency, where agents heavily adjust their expectations about the future of monetary policy. In this case, the publication of all monetary policy information (i.e., the monetary policy rule coefficients) seems to increase the reaction of the public's interest rate expectations.

1.4.2 The Partially Transparent Regime: Empirical Findings

In this subsection, I present the estimation results for the scenario that better fitted the data: partial transparency. That is to say, when the target for inflation and the relevant variables for monetary policy decisions are credibly and clearly communicated by the central bank, but agents still have to estimate beliefs about the monetary policy rule coefficients. First, I discuss the estimates of the structural parameters. Next, the evolution of the agent's beliefs is described. Later on, the inflation expectations implied by the model are compared to the actual inflation dynamics and the expectations from the Survey on Expectations of Private Sector Specialists.

Structural Parameters

Parameter	**Posterior mean**	**5% percentile**	**95% percentile**
σ	0.803	0.596	1.095
κ	0.233	0.120	0.364
ρ	0.883	0.774	0.953
$\chi\pi$	1.420	1.065	1.822
χx	0.259	0.102	0.514
ρ_u	0.580	0.434	0.727
ρ_{r^n}	0.892	0.811	0.949
σ_{mp}	0.345	0.297	0.400
σ_u	0.963	0.754	1.231
σ_{r^n}	1.114	0.813	1.510
g	0.035	0.025	0.047
$\rho_{e_p i}$	0.592	0.438	0.739
ρ_{e_i}	0.854	0.668	0.954
$\sigma_{e^{pi}}$	0.351	0.297	0.412
σ_{e^i}	0.362	0.298	0.434

Table 1.5: Posterior estimates.

Table 1.5 shows the parameter estimates under the partially transparent regime for the Mexican case. According to the results, the monetary policy rule presents a feedback coefficient to inflation and output gap equal to 1.42 and 0.26, respectively, and a sizable history dependence. This suggests that the Mexican monetary policy rule exhibits a strong reaction to inflation and complies with the Taylor Principle. Also, Eusepi (2005) suggests that nominal interest smoothing makes the monetary policy more predictable, which can help the learning process of the economic agents. The posterior mean for the New Keynesian Phillips Curve slope is 0.23, which is lower than the one estimated by Best (2013) for the period 1995-2005, 0.44. This may be evidence supporting a smaller reaction of inflation to movements in the output gap in the past decade; namely, the economy is presenting a higher degree of price stickiness. Meanwhile, the intertemporal elasticity of substitution estimate is 0.8, similar to previous findings in the literature. Recall that σ will capture the demand channel of the monetary policy. Then, in this case, the effect of expected monetary policy decisions seems to have a near one-to-one impact on the aggregate demand.

As the focus of this paper is the learning process, a key parameter is the constant-gain coefficient, as it reflects the learning speed; higher values of g would imply faster learning. The posterior estimates suggest a relatively high learning speed but still within the range proposed by Orphanides and Williams (2005). A constant-gain of 0.035 is equivalent to saying that agents use 28.6 quarters of past information to compute their expectations, reflecting efficiency in how agents update the information used in their forecast. This result contrasts with the findings in the U.S. learning literature, implying that expectations for Mexican agents seem less sluggish.

Beliefs Evolution

In this subsection, I will address the evolution of agents' beliefs about inflation and monetary policy under the partially transparent regime. First, the evolution of agents' beliefs about inflation is reported in Figure 1.3. The solid line shows the evolution of the autoregressive coefficient of the inflation PLM, and it represents the perceived persistence of inflation. Agents' started the period with a high level of perceived persistence that decreased for most of the sample. A pronounced fall was observed in the first quarter of 2010. A transitory increment can explain this perceived drop in inflation caused by a spike in the prices of certain vegetables due to adverse conditions of the weather.[12]

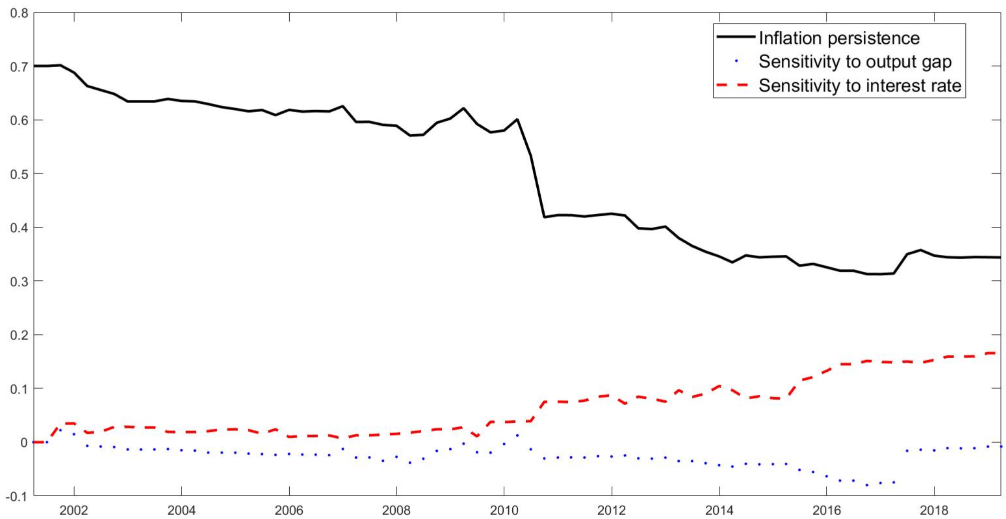


Figure 1.3: Evolution of agents' beliefs about inflation.

Additionally, Figure 1.3 shows the perceived sensibility of inflation to output gap and interest rate (dotted and dash lines, respectively). Beliefs show that inflation expectations are constructed under the belief that inflation is almost insensitive to changes in these variables, as the evolution of these coefficients remains close to zero. At the end of the sample, a slightly positive effect of the interest rate on inflation can be observed. Agents' learning seems to capture an episode of rising inflation, due to gasoline prices liberalization and external shocks as the uncertainty about U.S.-Mexico bilateral relationship associated to the new United States government, combined with a contractionary monetary policy that showed sluggish effects on inflation.

On the other hand, Figure 1.4 shows the evolution of agents' perceived coefficients of the monetary policy rule. The results suggest that despite the strong communication of the central bank, the public cannot learn the exact "structural" rule. Nonetheless, their perceptions

[12] Inflation Report, January-March 2010, Banco de México.

of the monetary policy are close to the estimates, especially for the persistence. This result is particularly relevant as the central bank is implementing a strong interest rate smoothing. Moreover, at the end of the sample, agents wrongly believe that the feedback of output gap is higher than the one of inflation.

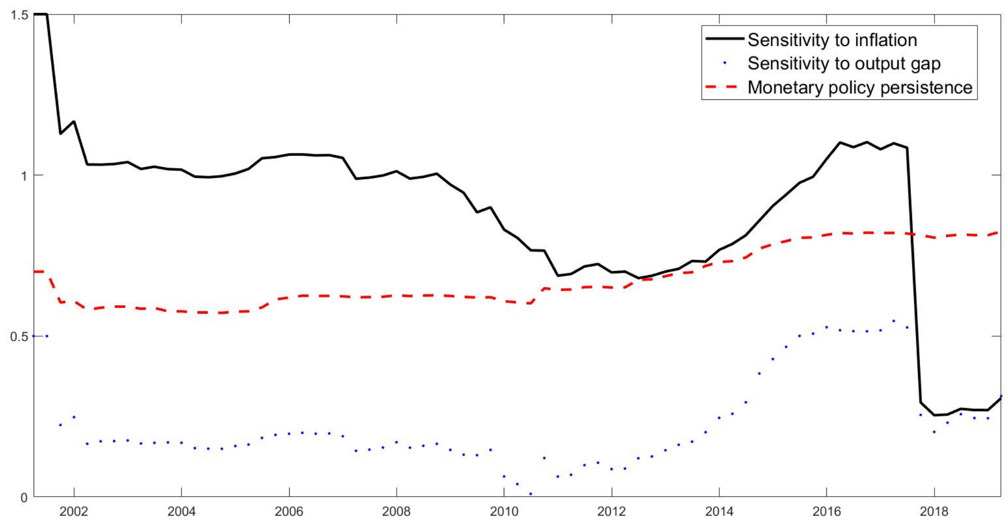


Figure 1.4: Evolution of agents' beliefs about the monetary policy rule.

Inflation Expectations: Observed vs Estimated

Next, I would like to analyze if the constant-gain learning algorithm generates plausible inflation expectations. In order to do this, I use inflation expectations data collected by the Mexican central bank.[13] Figure 1.5 contrasts the one-quarter ahead estimated expectations (dashed blue line) versus the inflation expected by professional forecasters (red line) from 2001 to 2018.[14] Overall, the results show that the match between model-implied and empirical inflation expectations is close. Particularly, the model captures the decline of expectations at the beginning of the sample and the continuous movement around a 4%

[13]For reasons of comparability, the inflation expectations for the next quarter are taken from the survey. The professional forecasters formed their expectations in quarter t with information until quarter t-1. The mean across all the responses to the survey within each quarter is considered.

[14]The plot shows annualized rates.

mean. This coincidence between model forecasts and survey data gives some evidence that the learning process estimated for inflation resembles the one followed by the agents in the Mexican economy.

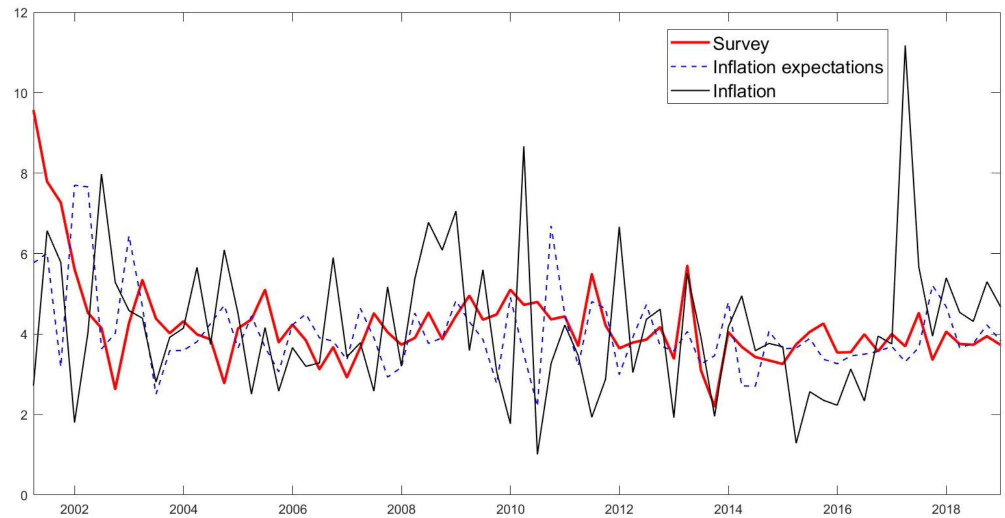


Figure 1.5: Empirical and model implied inflation expectations: One-quarter ahead.

Nevertheless, the inflation expectations implied by the model are "flatter" than the observed inflation dynamics (black line), although both series move, more or less, across the same mean. The implications of the latter are twofold. First, the learning process fails to generate enough persistence, so the inflation expectations implied by the model resemble the actual dynamics of inflation in the last two decades for the Mexican case. Second, the reduced perceived coefficients of inflation for persistence can suggest that the central bank has managed to well-anchored the agents' expectations, in the sense that they do not respond to movements in the actual inflation.

1.5 Conclusions and Future Research

This paper assesses the role of central bank transparency on the evolution of expectations and the economy for the Mexican case under an adaptive learning approach. The results show that the partially transparent regime, where the central bank communicates the inflation target and all relevant variables for the conduction of the monetary policy, exhibits the best fit to the data among all four specifications. This suggests that the Mexican central bank has been able to clearly and credibly communicate with the public, as economic agents consider all available information in the model used to form their expectations.

Other findings indicate there is evidence that private agents exhibit a fast learning speed, meaning that they react strongly to forecast errors. In contrast to the U.S. experience, Mexican agents seem to present a less sluggish process of forming their expectations.

Also, results indicate that agents' perception of inflation persistence has decreased over time, particularly since the 2010s. Plus, they formed their inflation forecasts under the belief that this variable is almost unaffected by movements in the output gap. Together with the lower reaction of inflation expectations to structural and expectation shocks, in comparison to other central bank regimes, this may suggest that the partially transparent regime followed by the central bank has helped to better anchor inflation expectations. On the other hand, agents are not able to learn the "structural" monetary rule, with the exception being the perceived persistence of monetary policy, which is close to the estimate, despite the transparency measures of the central bank.

Accordingly to the estimation, central bank transparency has a relatively small impact on inflation and output gap responses to structural shocks. Nonetheless, the results suggest that higher degrees of transparency increase the effectiveness of the monetary policy in stabilizing the economy and monetary policy expectations of the public.

Additionally, the model-implied one-period-ahead inflation expectations is able to closely match the empirical expectations from the surveys of professional forecasters. Then, this gives some evidence that the learning process estimated by the model resembles the one followed by the agents in the Mexican economy.

In sum, the transparency adopted by the Mexican Central bank played a role in the evolution of agents' beliefs and expectations formation. As suggested by Orphanides and Williams (2007), it seems to promote a better guidance for the formation of inflation expectation since inflation responds less to shocks in contrast to the alternative central bank transparency scenarios. Nonetheless, it did not necessarily ease a perfect understanding of monetary policy.

Overall, this paper gets us closer to understanding how expectations are formed and how they are impacted by central bank transparency, both key issues for monetary policy.

In the future, additional elements could be incorporated into this paper to enrich the analysis. Some of these are discussed next.

Mexico as an small open economy. As mentioned at the beginning, the model does not consider two key elements that greatly impact the dynamics and expectations of inflation for the Mexican case: exchange rate and external sector. Considering an open economy model would allow to better explain both of these variables.

Inflation target: empirical vs observed. Currently, I am assuming that the target for inflation is equal to its steady-state value (or sample mean) for simplicity and because the sample mean is close to the upper band of the inflation target. Nevertheless, one issue I encountered during the estimation of the model was that the central bank's inflation target does not coincide with the sample mean for inflation. Therefore, some changes will be implemented to the model in order to address this discrepancy.

Unique learning speed. Previous literature suggests the learning speed can differ across variables.[15] Then, allowing the constant-gain parameter for inflation, output gap, and nominal interest rate to be different from each other may lead to uncovering new lessons.

Supply channel for monetary policy. Finally, the model considered so far only exhibits a demand channel for monetary policy. Nevertheless, incorporating a supply channel would greatly enrich the analysis. Considering a model with a cost-channel of monetary policy, such as the one presented in Eusepi (2005), would make this possible.

[15] Branch and Evans (2006).

Chapter 2

Do Economic Conditions Matter for Inflation Expectations? Survey Evidence

2.1 Introduction

Expectations are a crucial determinant for individuals' decision-making and, consequently, macroeconomic dynamics. However, how they are formed is still an open question. Survey data on expectations have shown that, as individuals' decisions, expectations differ across economic agents. Consumers, professional forecasters, and central bank researchers tend to have contrasting beliefs about the current and future fundamentals. Moreover, heterogeneity seems to exist even within the same type of agents.

Many papers have documented expectations heterogeneity. Some attribute it to demographics; for example, Malmendier and Nagel (2016) propose that age plays an important role through personal experiences; Burke and Manz (2014) attribute this heterogeneity to literacy, and Duca et al. (2018) find gender, age, education, income, and employment status relevant elements to divergent expectations. Another stream of literature attributes inflation expectations heterogeneity to information frictions faced by economic agents and remarks that it can co-move with macroeconomic variables and even be state-dependent (e.g., Mankiw et al. (2003)).

Building on this literature, I assess the role of economic conditions in inflation expectations heterogeneity in this paper. I posit the following research question: do economic conditions lead to individual-level heterogeneity in inflation expectations?

To answer this question, I exploit data on inflation expectations recorded as ordinal outcomes from the Michigan Survey of Consumers. On the contrary to most literature on inflation expectations, I use qualitative data on inflation expectations rather than point forecasts for two reasons.[1] First, individuals are not expert forecasters; then, qualitative responses are more likely to measure their beliefs accurately. Also, survey questions that accept categorical answers tend to reduce misunderstanding, uncertainty, and burden for the respondent, helping to ensure the quality of the responses. Whereas for the economic conditions variables, I use data from the Bureau of Labor Statistics for observable variables associated with regional economic conditions, such as unemployment and inflation rates.

Following Sharma (2020), I propose a Bayesian latent class ordinal model to empirically assess expectation heterogeneity by assigning individuals into classes in a probabilistic manner. This econometric strategy has multiple advantages. First, it accommodates the ordinal nature of survey inflation expectations while identifying heterogeneity due to economic con-

[1] It is important to remark that many papers analyze qualitative data of expectations. See, for example, Horvath, Nerlove and Wilson (1992). These authors utilize qualitative expectational survey data and a parametric model to test the rationality of expectations of price increases in U.K. Other work, such as Smith and McAleer (1995), Entorf (1993), and Lee (1994), also use qualitative expectations data to compute forecasts about the macroeconomic variables. Nonetheless, this literature follows a different empirical approach; focusing on the "*quantification of qualitative expectations*" that frequently consists of conversion techniques of qualitative survey data into aggregate measures of expectations, such as the probability approach of Carlson and Parkin (1975) and the regression approach of Pesaran (1984) and Pesaran (1987).

ditions. Second, it addresses the uncertainty of class assignment by avoiding deterministic classification. This feature is utterly useful as the economic environment faced by individuals while forming their expectations on inflation is not observed since survey data only gives the outcome for the inflation expectations but not the underlying conditions where they were formed.

The results from a simulation study show that the MCMC algorithm designed to fit the latent class ordinal model is able to recover all true parameters from the data generating process accurately, and the constructed credibility intervals contain all of them. On applying this methodology to study survey data, I discover several insightful findings. First, the regional economic conditions, measured with the unemployment and inflation rate, are important determinants in assigning individual expectation formation into two states of nature associated with low and high regional economic distress. Second, individuals expect, on average, positive inflation no matter the economy's performance. This shows that they do not understand the negative theoretical relation between inflation and unemployment stated by the Phillips curve.

Third, the role of demographic characteristics in inflation expectations varies with the conditions of the economy. Individuals with similar characteristics will form different inflation expectations if exposed to different economic environments. In particular, the demographic characteristics are statistically relevant for expectations of (positive) inflation and when economic conditions are challenging. In a distressed regional economy, the probability of expecting inflation is affected positively by being older and female. In contrast, holding a college degree and higher real income decreases it.

Finally, I find that the level of disagreement about inflation expectations is also dependent on economic conditions. Consumers tend to disagree more about inflation in distressed economic conditions.

Summarizing this heterogeneity in expectations can be relevant for understanding macroeconomics dynamics and policy design and implementation. For instance, Fed's Vice Chair Clarida (2019) recently stated that an essential input into "any monetary policy assessment is the state of inflation expectations". Plus, former Fed Chair Bernanke (2007) points out that inflation expectations can heavily influence actual inflation. Thus, their understanding is crucial for policymakers.

The present paper is organized as follows. Section 2.2 describes the data from the Michigan Survey of Consumers and the regional economic variables. The model is presented in Section 2.3, including the MCMC algorithm and a simulation study. The empirical approach can be found in Section 2.4. Future research is discussed in Section 2.5. Conclusions are provided in Section 2.6.

2.2 Data

In this paper, inflation expectations are characterized by the 12-month price expectations in the University of Michigan Surveys of Consumers (MSC) conducted by the Survey Research Center (SRC). This survey is applied monthly to a minimum of 500 households and comprises approximately 50 questions related to consumer attitudes and expectations about personal finances, business conditions, and buying conditions. Plus, it includes the demographics of the interviewees. The SRC designed the samples for the survey in order to be representative of American households in the conterminous United States.

As mentioned before, this paper uses ordinal data as inflation expectations because it has the advantage of coming from questions not demanding a point forecast from individuals that are not professional forecasters. As Bullard (2016) mentions, (continuous) inflation expectations from the University of Michigan's survey of consumers tends to overstate inflation. Then, using ordinal inflation expectations instead can minimize this issue.

In specific, inflation expectations are taken from responses to question A.12 in the Michigan survey questionnaire:

A12. *During the next 12 months, do you think that prices in general will go up, down, or stay where they are now?*

Table 2.1 shows the ordered responses to this question:.

Response	Prices will:
1	Go up
2	Go up (at same rate)
3	Same
5	Go down

Table 2.1: Survey responses on price expectations.

Note that even when the survey asks for changes *in the level of prices*, inflation expectations can be extracted from the same question taking advantage of the additional probe question introduced in 1982, known as the"same probe".[2] Its introduction acts as a further investigation of individuals' opinions and avoids the confusion from interviewees between changes in the level of prices and changes in the rate of inflation. Thus, category 1 and 2 reflects positive inflation expectations, whereas the "same" category implies zero inflation, and deflationary expectations are captured by category 5.

This paper uses a sample of 70,000 individuals from the MSC, spanning the period between 1987:01-2020:09, from whom answers for question A.12 and demographic variables are available. This survey data are combined with monthly-regional economic information from the

[2]This question appears as follows in the questionnaire: "Do you mean that prices will go up at the same rate as now, or that prices in general will not go up during the next 12 months?"

Bureau of Labor Statistics about unemployment rate (u) and inflation (π).[3] These variables are used as controls for the economic conditions that are assumed to impact the formation of inflation expectations.[4]

Table 2.2 shows the sample's descriptive statistics for the demographic characteristics of the surveyed individuals, as well as the regional economic variables.[5] For the estimation of the

Variable	**Mean**	**S.D.**	**Min.**	**Max.**
Age	48.748	17.025	18	97
Gender	0.509	0.500	0	1
College	0.450	0.498	0	1
Real income	34,975	31,745	0.6835	447,230
Unemployment rate	5.861	1.769	3.300	15.700
Inflation rate	0.212	0.355	-2.200	1.500

Table 2.2: Descriptive statistics of covariates.

model, I relabel the categories from the survey price expectations into ordered groups that better reflects inflation expectations. First, categories 1 and 2 are combined to form the last third ordinal group reflecting inflationary expectations, and categories "same" and "down" are labeled as zero inflation expectations and deflationary expectations, respectively. The composition of expectations about inflation can be seen in Table 2.3. This implies that the 82.23%, 14.39% and 3.39% of the observations are within newly relabeled category 3, 2, and 1, respectively.[6]

[3]The regions are defined as in the U.S. Census: South, West, Midwest, and Northeast.

[4]The selection of the sample is driven by the availability of information about the variables of interest and the computational costs of the estimation. This sample was randomly taken from a pool of 192,233 individuals from whom answers are registered for the relevant variables for this study.

[5]The reported income in the survey is adjusted by inflation using the corresponding regional CPI (base 1982-1984). Real income is expressed in constant dollars.

[6]The descriptive statistics for the complete sample consisting in the 192,233 observations with available information for the relevant variables can be seen in Appendix B. The sample of 70,000 observations presents similar values for all presented statistics, as well as alike distribution of inflation expectations across the three response categories.

Response	Observations
1: Deflation	2,370
2: No inflation	10,071
3: Inflation	57,559

Table 2.3: Distribution of survey responses on inflation expectations.

2.3 The Model

In macroeconomics literature, heterogeneity in expectations has been commonly studied using continuous data. Nonetheless, this paper analyzes inflation expectations reported as ordinal outcomes from the MSC for two main reasons. First, consumers' ability to project accurate forecasts may be limited, as they are not professional forecasters. They likely find it easier to forecast their expectations into categories. Second, it is well documented in the literature that consumers' expectations seem to be upwardly biased; see, for example, Ehrman et al. (2015).

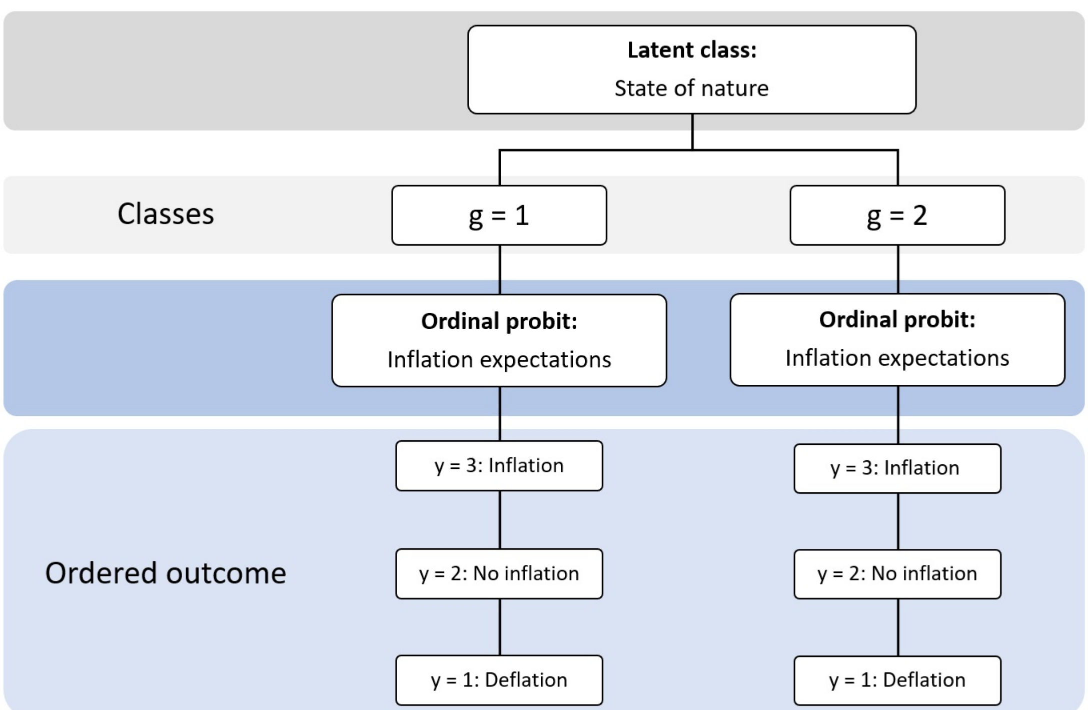


Figure 2.1: Model structure.

To identify heterogeneity in ordered expectations, I use a latent class ordinal model which is described in this section. Inflation expectation formation is viewed as a hierarchical process described by Figure 2.1. Individuals form expectations depending on the state of nature they are facing, viz., the latent class g_i into which they are classified. Firstly, to estimate the class membership model, it is assumed that the researcher does not directly observe this latent class, and it is described as a discrete variable, which can take the values of 1 or 2. Then, a binary choice problem is used to model the latent class. A latent variable, l_i, is introduced to identify the class membership of each individual, g_i:

$$l_i = W_i'\alpha + \nu_i, \qquad \nu_i \sim \mathcal{N}(0,1) \tag{2.1}$$

where W are a set of covariates that help to identify both states of nature, and depend on the related literature surrounding the hypothesis I am testing, α is a vector of coefficient associated to W, and ν_i is assumed to be distributed $\mathcal{N}(0,1)$.

Note that the relationship between both latent variables, continuous, l_i, and discrete, g_i, is given by:

$$g_i = \begin{cases} 2, & \text{if } l_i > 0 \\ 1, & \text{otherwise} \end{cases} \tag{2.2}$$

Taking into account that $\nu_i \sim \mathcal{N}(0,1)$ and the class g is binary, the class membership model can be described using a probit model as follows:

$$\pi_{ig} = \Phi\left(W_i'\alpha\right)^{g_i'} \left[\, 1 - \Phi\left(W_i'\alpha\right)\right]^{\,1-g_i'}, \qquad g = \{1,2\} \quad and \quad g' = g-1. \tag{2.3}$$

Next, conditional on the state of nature, agents form expectations, y, as an ordinal outcome with the following threshold-crossing representation:[7]

$$y_i = \begin{cases} 3: \text{Inflation}, & \text{if } -\infty < z_{i,g_i} \leq \gamma_{1,g_i} \\ 2: \text{No inflation}, & \text{if } \gamma_{1,g_i} < z_{i,g_i} \leq \gamma_{2,g_i} \\ 1: \text{Deflation}, & \text{if } \gamma_{2,g_i} < z_{i,g_i} \leq \infty \end{cases} \tag{2.4}$$

where z_{i,g_i} is a continuous latent random variable associated to the observed ordered outcome y accordingly to (2.4), and γ_{1,g_i} and γ_{2,g_i} are the cut-points parameters that determine the discretization of the data into ordered categories.

I assume that the continuous latent variable, z_{i,g_i}, depends on a vector of covariates X:

$$z_{i,g_i} = X_i'\beta + \epsilon_{i,g_i}, \qquad \epsilon_{i,g_i} \sim \mathcal{N}(0, \sigma_g^2) \tag{2.5}$$

where X includes variables that previous literature has shown that impact inflation expectations, such as demographic characteristics of individuals.

An ordinal probit model is used to model the probability of inflation expectations from individual i, y_i, taking a particular value j conditional on class g given that ϵ_{i,g_i} is assumed to be distributed $\mathcal{N}(0, \sigma_g^2)$:

$$P_{ij|g} = \Phi\left(\frac{\gamma_{j,g_i} - x_i'\beta_g}{\sigma_g}\right) - \Phi\left(\frac{\gamma_{j-1,g_i} - x_i'\beta_g}{\sigma_g}\right), \qquad g = 1, 2. \tag{2.6}$$

Following Jeliazkov and Rahman (2012), I impose $\gamma_{1,g_i} = 0$ and $\gamma_{2,g_i} = 1$, as identification restrictions. In this manner, there is no need to estimate any cut-points and the variance of ϵ_{i,g_i}, σ_g^2, is a free parameter to be estimated which is commonly used as a measure of disagreement in the literature that studies inflation expectations.

[7] This representation considers the relabeling of the original survey data to transform price expectations into inflation expectations which is the variable of interest of this paper.

Likelihood

Then, the likelihood function of the latent class ordinal probit is given by:

$$\mathcal{L} = \prod_{i=1}^{n} P_{ij} \tag{2.7}$$

with:

$$P_{ij} = \sum_{g=1}^{2} \pi_{ig} P_{ij|g}, \tag{2.8}$$

where π_{ig} is the probability of an individual i drawn at random from the full sample belonging to class g and P_{ij} is the probability of the inflation expectations of individual i, y_i, taking the value of j overall, that is, independently to class g.

Note that the likelihood function is a weighted mixture of the ordinal probit contribution by the class membership.

Posterior and prior distributions

The complete, or augmented, posterior distribution for the parameters of the model and both latent variables is given by:

$$\pi(\theta, l, z|y) \propto \prod_{i=1}^{n} \sum_{g=1}^{2} [\ \mathbf{1}(g_i = g)\pi_{ig} f(y_i|z_{i,g_i}) f(z_{i,g_i}|\beta_g, \sigma_g^2)]\ \pi(\alpha)\pi(\beta_1, \sigma_1^2)\pi(\beta_2, \sigma_2^2) \tag{2.9}$$

where $\theta = \{\alpha, \beta_1, \sigma_1^2, \beta_2, \sigma_2^2\}$, $f(y_i|z_{i,g_i}) = \mathbf{1}(\gamma_{y_i-1,g} < z_{i,g} \leq \gamma_{y_i,g})$ and $f(z_{i,g_i}|\beta_g, \sigma_g^2) = f_{\mathcal{N}}(z|x_i'\beta_g, \sigma^{2_g})$ for g = 1, 2.

The prior specification for the model's parameters is as follows. The coefficients β_g are assigned a multivariate normal prior distribution, while an inverse gamma prior is chosen for σ_g^2. Since the prior distributions for β_g and σ_g^2 are independent, the joint density $\pi(\beta_g, \sigma_g^2)$

can be written as:

$$\pi(\beta_g, \sigma_g^2) = f_{\mathcal{N}}(\beta_g|\beta_{0,g}, B_{0,g}) f_{\mathcal{IG}}\left(\sigma_g^2|\frac{\nu}{2}, \frac{d}{2}\right), \qquad for \quad g = 1, 2. \tag{2.10}$$

Similarly, the prior assumed for α is a multivariate normal given by $f_{\mathcal{N}}\ (\alpha|\alpha_0, A_0)$.

2.3.1 MCMC Algorithm

Given the use of data augmentation and the existence of conjugacy due to the selection of the prior distribution, a Gibbs sampler can be implemented to estimate the proposed model. The algorithm followed is described next.[8]

1. Sample β_g from $\beta_g|z, G, \sigma_g^2$ for g = 1,2.

   Where G and z refers to the complete vectors of the continuous latent variables related to the class membership indicators g_i and latent variables z_{i,g_i}, respectively.

2. Sample σ_g^2 from $\sigma_g^2|\beta_g, z, G$ for g = 1,2.

3. In the same block,

   a. Sample α from $\alpha|\beta, \sigma^2, y$ where $\beta = \{\beta_1, \beta_2\}$, $\sigma^2 = \{\sigma_1^2, \sigma_2^2\}$.

   b. Sample l_i from $l_i|\alpha, g$ for i = 1,2,...,n.

4. Sample g_i' from $g_i'|\alpha, \beta, \sigma^2, y$ for i = 1,2,...,n.

5. Sample z_{i,g_i} from $z_{i,g_i}|\beta, \sigma^2, y, G$ for i = 1,2,...,n.

[8]See details in Appendix C.

2.3.2 Covariate Effects

The interpretation of the parameter estimates in discrete outcomes analysis can be a complicated task because of the nonlinearity of the models. To circumvent this in an intuitive manner, the relationship between the ordinal dependent variable and the covariates can be illustrated by covariate effects. Due to the research objective, I focus on obtaining the covariate effects for the estimates in the ordinal probit layer of the hierarchical model, i.e., covariate effects of the β. Since there is a set of parameters β for each class, these covariate effects reflect the heterogeneity of inflation expectations across the two classes.

Following Jeliazkov and Vossmeyer (2018), the covariate effects are computed using the draws for the parameters from the MCMC simulation. For continuous variable x_k conditional on class g, the marginal effect, $\delta^j_{k,g}$, is estimated as follow:

$$\delta^j_{k,g} = \frac{1}{nM} \sum_{i=1}^{n} \sum_{m=1}^{M} \frac{\partial P(y_i = j | x_k, X_{-k}, \theta^m_g)}{\partial x_k}, \qquad g = 1, 2. \tag{2.11}$$

where $\theta^m_g = \{\alpha, \beta_g, \sigma^2_g\}$, n is the number of observations, and M is the total number of draws from the MCMC simulation.

Considering equation 2.6 to account for the probability in the parenthesis, it follows that:

$$\delta^j_{k,g} = \frac{1}{nM} \sum_{i=1}^{n} \sum_{m=1}^{M} \left[\phi\left(\frac{\gamma_{j-1,g_i} - x_i'\beta^m_g}{\sigma^m_g} \right) - \phi\left(\frac{\gamma_{j,g_i} - x_i'\beta^m_g}{\sigma^m_g} \right) \right] \left(\frac{\beta^m_g}{\sigma^m_g} \right), \qquad g = 1, 2. \tag{2.12}$$

Whereas, for a discrete change from the covariate x_κ to x^*_κ, the partial effect can be calculated with $d^j_{\kappa,g}$:

$$d^j_{k,g} = \frac{1}{nM} \sum_{i=1}^{n} \sum_{m=1}^{M} \left[P(y_i = j | x_\kappa, X_{-\kappa}, \theta^m_g) - P(y_i = j | x^*_\kappa, X_{-\kappa}, \theta^m_g) \right] \tag{2.13}$$

where the probabilities inside the brackets can be obtained following equation 2.6.

Note that these quantities have the advantage of considering the variability of both the covariates and the model's parameters.

2.3.3 Estimation with Simulated Data

In this subsection, a simulation study is done to test the performance of the MCMC algorithm described previously. To assess the algorithm under different sample conditions, I construct two scenarios by simulating data inspired by the Michigan Survey of Consumers. First, data are generated assuming that the distribution of the dependent ordinal variable is relatively uniform across all three categories. In the second case, the data are simulated more closely to the actual distribution of inflation expectations in the survey, where most responses are concentrated in one particular category of the ordinal outcome.

In both cases, the simulation assumes n = 20,000, the outcome, y_i, presents three categories, and the covariates matrices for X and W have dimensions (n x 4) and (n x 2), respectively. All covariates are generated from a $\mathcal{N}(0, 1)$ distribution. Accounting for prior uncertainty, the prior distributions selected in this simulation are as follows. The parameters for the covariates in the ordinal probit model, β_g, and those in the class membership model, α, are given uninformative multivariate standard normal priors, $\mathcal{N}(0, I)$. In contrast, the prior distributions for the variances in the ordered probit are an inverse gamma with mean 1, $\mathcal{IG}(2, 1)$. The Gibbs sampler has been implemented on 15,000 iterations, using 25% of the draws as burn-in.

2.3.4 Scenario 1: Evenly Populated Categories

In this first approach, the simulated data for the outcome, y_i, is equitably distributed across all three categories with 31.46%, 29.58%, and 38.96% of the observations pertaining to categories 3, 2, and 1, respectively. The results are shown in Table 2.4. The algorithm can accurately recover all of the true values for the parameters in the simulated study. Plus, the 90% credible intervals contain the true values for all the parameters in both classes.

Note that the credibility intervals for the parameters in class 2 are wider relative to those in class 1. This can be attributed to the fact that class 2 is considerably less populated than class 1. Then, the limited number of observations generates a less precise identification of true parameters.

In addition, I revise how well can the algorithm classify the observations into their true class given that in this study the class is observable. Accordingly to the result, 80.39% of the observations in the sample are correctly assigned, thus, the effectiveness of the algorithm can be described as fair.

2.3.5 Scenario 2: Thinly Populated Categories

Next, new simulated data are constructed to closely resemble the distribution of the MSC, where the majority of responses are concentrated on outcome 3, while category 1 has low counts. Now, the outcome, y_i, has 69.09%, 23.04%, and 7.87% of the observations in categories 3, 2, and 1, respectively.

Table 2.5 shows the results for this exercise. These are similar to the previous exercise. The algorithm is able to recover estimates close to the true values for the parameters from the data generator process, and the constructed 90% credible intervals contain the true values for all the parameters in both classes. However, the correctly classified proportion of

Parameter	True value	Posterior mean	90% Credible interval	
Latent class 1				
β_{11}	0.8	0.795	0.778	0.813
β_{21}	-0.5	-0.511	-0.532	-0.491
β_{31}	-0.4	-0.395	-0.415	-0.377
β_{41}	0.7	0.686	0.658	0.714
β_{51}	-0.2	-0.210	-0.227	-0.193
σ_1^2	0.5	0.486	0.453	0.521
Latent class 2				
β_{12}	0.2	0.213	0.175	0.250
β_{22}	0.8	0.815	0.761	0.873
β_{32}	0.4	0.466	0.425	0.508
β_{42}	0.9	0.930	0.863	1.004
β_{52}	0.2	0.200	0.166	0.235
σ_2^2	0.5	0.500	0.435	0.574
Class membership				
α_1	-0.5	-0.489	-0.524	-0.454
α_2	0.3	0.310	0.286	0.334
α_3	-0.2	-0.192	-0.216	-0.168

Table 2.4: Scenario 1: Results for the latent class ordinal model with simulated data.

the observations has slightly declined to 75.33%. Nonetheless, the algorithm still shows an acceptable classification performance under the assumption that the classes are observable.

The previous results indicate that the model is appropriate to model inflation expectation heterogeneity using the MSC database.

2.4 Empirical Application

The model described in section 2.3 is estimated using observed data from the Michigan Survey of Consumers to assess sources of heterogeneity in inflation expectations, both latent and observable.

I evaluate the hypothesis that individuals form expectations conditional on the state of nature they are facing. Here, the state of nature is captured by the regional economic variables,

Parameter	True value	Posterior mean	90% Credible interval	
Latent class 1				
β_{11}	-0.2	-0.212	-0.243	-0.180
β_{21}	0.3	0.307	0.289	0.326
β_{31}	0.5	0.512	0.492	0.531
β_{41}	-0.3	-0.292	-0.312	-0.272
β_{51}	0.2	0.196	0.180	0.213
σ_1^2	0.5	0.516	0.484	0.548
Latent class 2				
β_{12}	-1.2	-1.423	-1.706	-1.174
β_{22}	-0.15	-0.173	-0.266	-0.091
β_{32}	0.2	0.244	0.168	0.322
β_{42}	0.4	0.464	0.367	0.575
β_{52}	0.2	0.231	0.151	0.318
σ_2^2	0.5	0.572	0.418	0.783
Class membership				
α_1	-0.5	-0.528	-0.596	-0.463
α_2	0.3	-0.325	0.289	0.361
α_3	-0.2	0.210	-0.242	-0.180

Table 2.5: Scenario 2: Results for the latent class ordinal model with simulated data.

specifically unemployment and monthly inflation rates. Thus, these indicators are mapped into two different classes reflecting low or high distress in the regional economy. Additionally, I assess the role of observable factors, like demographics, in expectations heterogeneity.

The same prior distributions and number of iterations as in the simulation study are used in this estimation.

2.4.1 Latent Heterogeneity in Expectations: Regional Economic Conditions

Under the first layer of the model described in Figure 2.1, consisting of the class membership model, I assume that the latent class is defined as the regional economic conditions faced by the individuals when forming expectations. The researcher does not directly observe these conditions, as I observe the outcome, y, but not the state of nature, g. Therefore, I take advantage of the latent class model's probabilistic classification of observations into classes to address the uncertainty of the true state of nature where the inflation expectations were formed.

Table 2.6 shows the posterior means for the parameters in the class membership model that includes the regional economic indicators as covariates. It can be seen that both the unemployment and inflation rate are significant determinants in assigning individual expectation formation into two states of nature. The unemployment and inflation rate associated coefficients are positive and negative, respectively, indicating that class 2 contains individuals forecasting inflation expectations in a distressed regional economic environment. In contrast, inflation expectations formed by individuals in a prosperous regional economy are classified into class 1.[9]

	Posterior mean	**90% credible interval**
Regional u rate	0.377	[0.331, 0.424]
Regional π rate	-0.225	[-0.260, -0.192]

Table 2.6: Posterior mean for the class membership parameters, α.

An interesting result of the class membership is that the proportion of individuals assigned into class 2, the unfavorable regional economy, is low and equivalent to 10.1% of the whole sample. This is consistent with what one would expect since distressed conditions tend to be the lesser part of the business cycle.[10]

With the interpretation for both states of nature or classes stated, I estimate the average probability of expecting different outcomes for inflation to evaluate the state-contingency

[9]Let us recall that individuals pertaining class 2 are modeled as the "success" event in the probit model underlaying the class membership model. Therefore, the interpretation of the parameters α are directly related to class 2.

[10]See, for instance, the NBER-dated recession indicator, https://www.nber.org/research/business-cycle-dating.

of expectation formation mechanism.[11] Table 2.7 shows the average probability of each expected outcome conditional on the regional economic performance. This table gives many interesting findings on inflation expectations.

	Lowly distressed regional economy (Class 1)	**Highly distressed regional economy (Class 2)**
Deflation	0.010	0.117
No inflation	0.106	0.273
Inflation	0.886	0.614

Table 2.7: Average probability of inflation expectations.

First, note that the highest average probability in both states of nature is for expecting inflation. Plus, expecting deflation is the outcome with the lowest probability in both classes. These results are at odds with macroeconomic theory. From the famous Phillips curve, we know that a negative correlation between unemployment and inflation is expected. However, this is not the first time that these results have been found. There is evidence from previous empirical literature on survey data indicating a positive correlation between inflation expectations and unfavorable economic conditions. For example, Kamdar (2019) finds that consumers who believe unemployment will rise also expect higher inflation, and Coibion et al. (2019) show similar results for firms' expectations.

Next, the results show that in a distressed economy (class 2), it is considerably more probable to expect deflation in comparison to a thriving economy. The average probability of deflation increases from 1% in a favorable economic environment to 11.7% in an unfavorable one. The same occurs for no inflation expectations; they rise from 10.6% in good economies to 27.3% in challenging economic conditions. So, even when consumers expect inflation, on average, no matter the economic conditions, the likelihood of deflation and no inflation shifts up under economic downturns.

[11] The average probability of each expectation outcome, j, for each of the classes, g, is estimated as follows: $\overline{Prob(Y=j|g)} = \frac{1}{nM}\sum_{i=1}^{n}\sum_{m=1}^{M} P_{ij|g}^{(m)}$ with $P_{ij|g}^{(m)}$ defined as in equation 2.6.

Finally, I compute the full posterior density of the average probability of each category of inflation expectations across the two latent classes. In Figure 2.2, it can be seen that they are entirely disjoint densities. This shows evidence that the heterogeneity of inflation expectations across both economic performance states is statistically relevant for all categories. Overall, these results involve important lessons for monetary policy as they give evidence of how inflation expectations are formed distinctly depending on economic conditions. As Woodford (2003) remarks, the management of expectations is an important element of monetary policy, so, understanding the underlaying condition of how they are constructed is crucial.

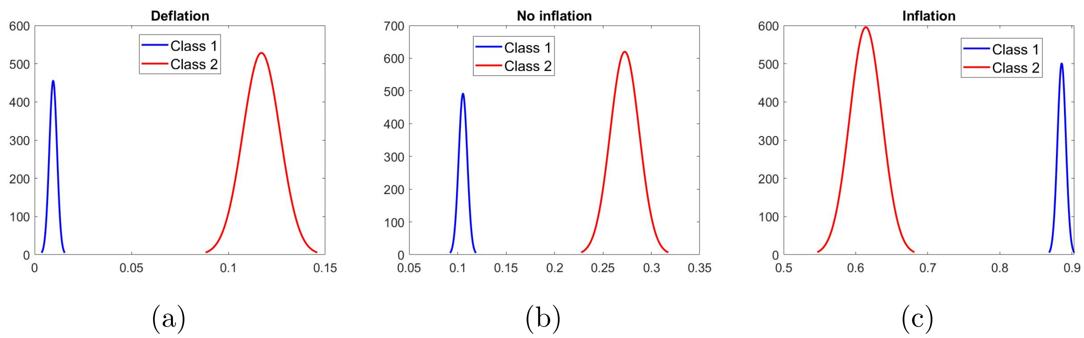


Figure 2.2: Posterior densities of the average probability of inflation expectations.

2.4.2 Observable Heterogeneity in Expectations: Demographic Characteristics

Moving to the next layer of the model, I present the results obtained from the ordinal probit model. The model's parameters show the relationship between inflation expectations and demographic variables in both classes. If inflation expectations were formed differently across economic conditions for the same individuals' characteristics, the parameter estimates magnitude would differ. To avoid the complications associated with the interpretation of parameter estimates in discrete outcomes model, Figure 2.3 shows the covariate effects for classes 1 and 2 in blue and red, respectively. From the figure, it is clear that the magnitudes of these covariate effects contrast for both classes. In particular, it can be seen that demographic characteristics are statistically important for expectations of (positive) inflation.[12]

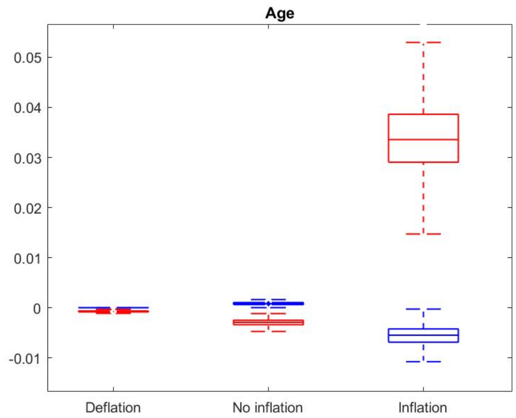
In panel (a) of Figure 2.3 can be observed that age plays a strong role for inflation expectation formation under regional economic distress. As an individual age, the probability of her expecting inflation increases. This result is consistent with Malmendier and Nagel (2016) findings of older individuals expecting higher inflation because they have experienced higher inflation regimes. Here, it is found that these results may be conditional on the state of nature where the expectations are formed since under favorable economic conditions, the covariate effect of age seems almost null.

A similar pattern can be seen for gender in panel (b) of Figure 2.3. Being a woman increases the probability of expecting inflation, but this effect is higher in a distressed economy. Some literature has pointed out the relevance of gender for inflation expectation (e.g., Blanchard's comment in Mankiw et al. (2003) and Duca et al. (2018)). One of the hypotheses of why this occurs is that women's consumption is based on a different basket of goods compared to men.

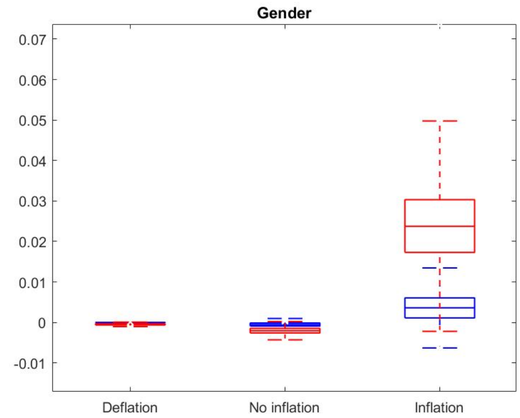
In contrast, a negative impact on inflation expectations is found due to real income level (See panel (d) of Figure 2.3). While different in magnitude, a higher level of real income is related to lower probabilities of expecting inflation in both classes. A possible explanation could be again related to the basket of goods consumed by higher-income individuals; they could concentrate their consumption on goods that are less subject to price fluctuation. Duca et al. (2018) find similar results using a survey on inflation expectations for consumers in the Euro Area.

Finally, the sign of the effect of college attendance is conditional on the class. Previous literature (e.g., Duca et al. (2018)) has found that individuals with low education and

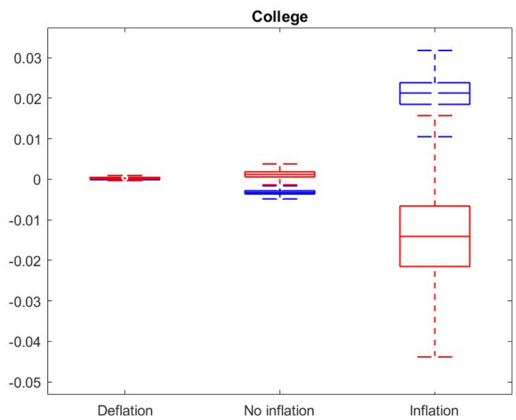
[12]The posterior mean for the ordinal probit parameters can be seen in Appendix D.



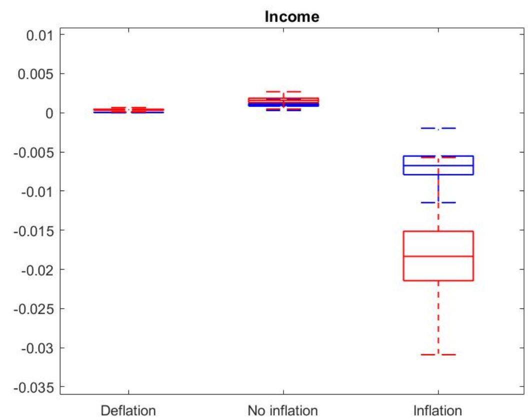
(a)



(b)



(c)



(d)

Figure 2.3: Covariate effects for the ordinal probit model.
Note: Class 1 in blue. Class 2 in red.

without a college degree tend to have higher inflation expectations. Figure 2.3 (c) shows concurring evidence to those findings but only under unfavorable economic conditions. In contrast, holding a college degree in a thriving economy will increase your probability of expecting inflation.

Another interesting conclusion can be extracted from the estimates of the variance parameters for each class, σ_g^2. The posterior means are 0.76 and 1.18 for classes 1 and 2, respectively. Following previous literature (e.g., Mankiw et al. (2003) and Andrade and Le Bihan (2013)), this dispersion measure can be interpreted as the level of disagreement about inflation expectations for both economic conditions states. Then, the results show evidence of heterogeneity in disagreement too. Consumers tend to disagree to a higher degree about inflation in distressed economic conditions. This may be a key finding for monetary policy, as a higher disagreement may complicate the management of inflation expectations when, perhaps, matter the most.

In sum, these results show evidence of heterogeneity in expectations. Individuals with similar observable characteristics, such as age, gender, education, and income, are likely to make different forecasts for expectations of inflation depending on the state of the economy they face.

2.5 Conclusions and Future Research

The analysis of survey inflation expectations can lead to interesting lessons about individuals' mechanisms to form them. To empirically contribute to the literature, this paper assesses the role of economic conditions on heterogeneity in inflation expectations. I propose a Bayesian latent class ordinal model, and I exploit survey data on inflation expectations recorded as ordinal outcomes and regional economic conditions variables.

The results show that individuals do not understand the theory behind the Phillips curve, as they expect, on average, positive inflation no matter the economy's performance. Plus, the role of demographic characteristics in inflation expectations varies with the conditions of the economy. In particular, the demographics are statistically important for expectations of (positive) inflation and within a challenging economic environment. Lastly, I find that disagreement about inflation expectations changes with the economic conditions. It is higher when the economic environment is distressed.

Overall, the analysis in this paper gives evidence of how inflation expectations are formed distinctly depending on the economic conditions. These results involve important lessons for monetary policy as the management of expectations is a vital task of the monetary policy authority. So, understanding the underlying condition of how they are constructed is crucial. Additionally, they suggest a cautionary tale about using consumers' inflation expectations as a policy tool since managing them may not give the results suggested by the macroeconomic theory.

Although not included in this paper, long-run inflation expectations play an important role in monetary policy because they reflect the level of anchoring in expectations and how close expectations are to the central bank's target, both indicators of the monetary policy authority's credibility. In this tenor, a possible extension of the analysis in this paper is to study long-run inflation expectations. This can be easily done by considering inflation expectations for the next five years from the following question from the Michigan Survey of Consumers:

Question A13. *What about the outlook for prices over the next 5 to 10 years? Do you think prices will be higher, about the same, or lower, 5 to 10 years from now?*

The individuals respond to this question in the same ordinal categories as before. Then, the same relabeling approach to reduce the possible outcomes into three categories could be implemented. Plus, the model presented here would be applicable.

Chapter 3

Information Frictions: Learning and Inattention in an Estimated New Keynesian Model

3.1 Introduction

"What information consumes is rather obvious: It consumes the attention of its recipients. Hence a wealth of information creates a poverty of attention, and a need to allocate that attention efficiently among the overabundance of information sources that might consume it."

Herbert Simon (1971)

How are expectations formed? It is still an open question in macroeconomics, and its answer is relevant for monetary policy and understanding the dynamics of the economy. A vast literature has been challenging the existence of full-information rational expectations in recent decades.[1] Thus, many alternatives have been proposed as candidate frameworks, such as the one posited by Mankiw and Reis (2002). The inattention model relies on the assumption that information slowly permeates across inattentive economic agents, viz., information is sticky. Another compelling expectations formation story is adaptive learning (Evans and Honkapohja (2001)), a deviation from the full-information rational expectation hypothesis. In this framework, it is assumed that agents utilize economic models to form expectations as they lack perfect knowledge of the economy's structure.

Multiple papers have studied these frameworks and have found empirical evidence in favor of both (e.g., Mankiw and Reis (2007) and Milani (2007)). Nonetheless, a comparison among them is still missing from the literature. In this context, this paper revisits these research bodies and builds upon them by incrusting subjective expectations into a dual sticky model.[2] Using likelihood-based Bayesian methods, I empirically compare these well-known behavioral stories about how expectations are formed. I aim to answer the following questions: i) which expectational mechanism is preferred by the data; ii) is inattention still relevant when subjective expectations replace rational ones; and iii) are these answers robust to the use of observed expectations and real-time data.

This paper encounters interesting results. First, it shows evidence of the presence of both information and price stickiness for the U.S. case. In contrast to what Mankiw and Reis (2002) seminal paper proposed originally, these rigidities seem to be complementary elements rather than substitutes. Second, a more novel insight is that the degree of inattention depends on the expectation formation mechanism chosen. That is, when departing from the rational expectation assumption, the level of inattention is reduced considerably. Third, it finds that the model embedding inattention and subjective expectations formed with adaptive learn-

[1] See for instance Coibion and Gorodnichencko (2015), Andrade and Le Bihan (2013), and Malmendier and Nagel (2016).

[2] Recall that in Mankiw and Reis (2002) seminal paper, expectations are formed rationally even when agents use old information to make their decisions. In contrast, agents behave as econometricians in the adaptive learning specification and forecast their expectations using an economic model.

ing offers the best data fit compared to its rational expectation version. Fourth, this paper improves existing literature on inattention by exploiting observed data on expectations and real-time macroeconomic series to better identify the degree of inattention along with the learning process while testing the robustness of the previous results. In this case, the main conclusions remain unchanged: there is evidence of the sensitivity of the degree of sticky information on the expectations formation mechanism. In this sense, adaptive learning is able to add persistence without assuming large degrees of inattention. Lastly, the proposed expectation formation mechanism is able to match the observed expectations from the Survey of Professional Forecasts giving evidence in favor of the existence of information frictions in the U.S.

Overall, these empirical findings may suggest that the inclusion of the full-information rational expectations hypothesis in macroeconomic models should be revisited. Moreover, these results not only allow us to understand better how expectations are formed. More importantly, they carry important policy implications. Expectations are an essential determinant for individuals' decision-making and, therefore, they impact macroeconomics outcomes. Thus, understanding how they are formed is crucial not only for understanding macroeconomics dynamics but also for policy design as specific expectations mechanisms will affect the transmission mechanisms of policy measures, the effectiveness of its tools, and moreover, the properties of optimal monetary policy.

Related Literature. The present paper is related to multiple literature branches. First, it contributes with empirical evidence to a vast body of research on the extensive debate about the relative importance of sticky prices versus inattention originated by Mankiw and Reis (2002). In this seminal paper, the authors propose a model of price adjustment based on the assumption that information about macroeconomic conditions permeates slowly through the population; this could arise due to costs of reoptimization, acquisition, and processing of new information. Since its publication, multiple papers have studied this framework. Comparisons with models with nominal and real rigidities have been made (e.g., Coibion (2010), Laforte (2007), and Trabandt (2007)). Alternatively, others have proposed a combination of two types of stickiness: information and prices. This comparative research has been done in nested or non-nested frameworks. Their methods and results are mixed. Within the literature that compare not-nested models, some papers find that models with sticky prices and indexation have better performance than sticky information models (e.g. Coibion (2010), Kiley (2006), Korenok (2008), and Laforte (2007). While others have found that sticky prices and sticky information present similar performance when nominal rigidities are extended with inflation indexation. Evidence of this is enclosed in Trabandt (2007) and Carrillo (2012).

In contrast, this paper finds evidence of the existence of dual stickiness in the U.S. case, as in Dupor et al. (2010) and Knotek (2010). These authors nest both stickiness assumptions into a model and find evidence supporting the existence of dual rigidities for the U.S. case.[3]

However, unlike all previous literature, this paper deviates from the rational expectations hypothesis. In this sense, it shares a common idea with the empirical body of literature that estimates DSGE models without the assumption of rational expectations. In specific, it is closely related to the adaptive learning literature where bounded-rational expectations replace rational ones. More directly, this paper relates to the empirical literature on adaptive learning, which shows that learning can generate persistence endogenously, improve the fit to observed macroeconomic data, and generate business cycle fluctuations.[4]

This paper is also closely linked to the literature relying on survey expectation data to assess inattention and adaptive learning models. For example, Ormeño (2009) and Milani

[3]The theoretical model considered in Carrillo (2012) also allows for dual stickiness. However, his estimation presents identification issues that prohibit the joint estimation of price and information stickiness parameters.

[4]See, for example, Milani (2007, Slobodyan and Wouters (2012), and Milani (2011).

(2011) both exploit observed expectations from the Survey of Professional Forecasters (SPF). Nevertheless, their approach and focus diverge. I follow Milani (2011) closely, including survey data for all expectations present in the model and introducing expectational shocks into the analysis.[5]

Finally, as the present paper instead combines together two behavioral strands, inattention and adaptive learning, it shares common insights with Branch et al. (2006) which adds boundedly rational agents to a sticky information model à la Ball, Mankiw and Reis (2005) with endogenous inattention. However, Branch et al. (2006) focus and empirical strategy is different from the present work.[6] In contrast, this paper estimates a fully-fledged DSGE model using Bayesian techniques to test the sensitivity of the sticky information degree to the expectation formation mechanism, as well as the relative fit of the U.S. data in comparison to a specification under rational expectations.

3.2 The Model

The model describing the aggregate dynamics is presented in this section. It builds on previous literature on DSGE models, such as Smets and Wouters (2007) and Woodford (2003), while sharing common features with Mankiw and Reis (2002) and Evans and Honkapohja (2001). The economy is composed of households, firms, and a monetary policy authority. Households consume from a set of differentiated goods, supply labor, and invest in riskless one-period bonds. The monetary authority conducts its policy following a Taylor-type rule. While firms experience sticky prices à la Calvo, as usually assumed.

[5] Other papers that have used survey data to evaluate sticky information models include Mankiw et al. (2004), Branch (2007), Coibion and Gorodnichenko (2008), and Andrade and Le Bihan (2013). They exhibit divergent results. Mankiw et al. (2004) and Branch (2007) find that the sticky information model is capable of matching some features of the survey expectations. In contradistinction to the previous papers, Coibion and Gorodnichenko (2008) and Andrade and Le Bihan (2013) find mixed evidence in support of the sticky information model while contrasting it to a noisy information framework.

[6] The authors study a theoretical explanation for the decrease in economic volatility during the Great Moderation.

The main novelty in this model is that it nests inattention à la Mankiw and Reis (2002) and adaptive learning. Firstly, I assume that price setters are not able to collect and process the newest information available. Thus, they are inattentive in addition to the existence of nominal rigidities. For households, instead, I assume predetermined expectations; that is, they dispose information up to $t-1$ when solving their optimization problems and forming expectations.[7] Secondly, I deviate from the rational expectations framework and assume that firms and households lack knowledge about the reduced-form parameters of the economy describing the dynamics of the economy. Therefore, they form subjective expectations using an economic model and past data. Finally, economic agents are homogenous; hence they face the same information frictions and shocks.

3.2.1 Households

A continuum of identical households is distributed in the unit interval, indexed by h, that live forever and discount future utility by a factor $\beta \in (0,1)$. They have additively separable preferences and obtain utility each period from consumption and leisure according to:

$$U(C_{t,h}, L_{t,h}) = \frac{C_{t,h}^{1-\frac{1}{\sigma}}}{1-\frac{1}{\sigma}} - \chi \frac{L_{t,h}^{1+\frac{1}{\psi}}}{1-\frac{1}{\psi}} \tag{3.1}$$

where σ is the intertemporal elasticity of substitution, ψ is the Frisch elasticity of labor, and χ reflects consumption-leisure relative preferences. $C_{t,h}$ and $L_{t,h}$ are the consumption and labor supplied by household h at period t, respectively. Households value consumption according to a Dixit-Stiglitz aggregator given by:

$$C_{t,h} = \left(\int_0^1 C_{t,h}(i)^{\frac{\nu}{1-\nu}} \, di \right)^{\frac{\nu-1}{\nu}} \tag{3.2}$$

[7]This assumption rests on empirical reasons; to match the information set available to professional forecasters surveyed in the SPF used in the empirical study.

where ν is elasticity among good varieties i.

At each period t, households face the following budget constraint:

$$P_t C_{t,h} + B_{t,h} = W_{t,h} L_{t,h} + (1 - i_{t-1}) B_{t-1,h} + T_{t,h} + \Pi_{t,h} \tag{3.3}$$

where the expenses of household h at t consist on her nominal consumption plus her nominal bonds holdings, $B_{t,h}$. While, household h wealth is given by the right-hand side of (3.3) where $W_{t,h}$ is the nominal wage earn by household h, i_{t-1} is the nominal net return at date t on a bond purchased at the previous one, $t-1$, $T_{t,h}$, and $\Pi_{t,h}$ are lump-sum nominal transfers received by the household coming from government subsidies and intermediate firms' profits, which are equally owned by all households, respectively. Finally, P_t is the aggregate price index given by:

$$P_t = \left(\int_0^1 P_t(i)^{1-\nu} \, di \right)^{\frac{1}{1-\nu}} \tag{3.4}$$

Remember that households are identical, then, the index h can be dropped, and it can be assumed that there is a representative household. Subject to her budget constraint given by (3.3), she maximizes the following the discounted sum of life-time utility:

$$\max_{C_t, L_t, B_t} \quad \hat{E}_{t-1} \sum_{s=0}^{\infty} \beta^s U(C_t, L_t) \tag{3.5}$$

$$s.t. \quad P_t C_t + B_t = W_t L_t + (1 - i_{t-1}) B_{t-1} + T_t + \Pi_t$$

Information is assumed complete for households. That is to say; they are always attentive. However, due to the use of survey data in the empirical study, it is assumed that expectations are formed with information up to $t-1$, and subjectively, $\hat{E}(.)$.

3.2.2 Firms

Final Goods Sector

The final good firms are assumed to buy intermediate goods f and pack them into a homogenous good, Y_t, which is a composite sold in a perfectly competitive market. Plus, it is assumed that these producers do not experience information frictions, viz., they are fully attentive.

A final good firm maximize its profit:

$$\max_{Y_t, Y_{t,f}} \quad P_t Y_t - \int_0^1 P_{t,f} Y_{t,f} df \tag{3.6}$$

$$s.t. \quad Y_t = \left(\int_0^1 Y_{t,f}^{\frac{\theta_t^p - 1}{\theta_t^p}} df \right)^{\frac{\theta_t^p}{\theta_t^p - 1}} \tag{3.7}$$

subject to its technology with which it combines different varieties of intermediate goods through a Dixit-Stiglitz aggregator with a stochastic elasticity of substitution θ_t^p.[8]

Solving the final goods sector producer program gives the following first-order condition, which describes the demand for an intermediate firm g, $Y_{t,f}$:

$$Y_{t,f} = Y_t \left(\frac{P_{t,f}}{P_t} \right)^{-\theta_t^p} \tag{3.8}$$

where P_t and $P_{t,f}$ are the final and intermediate goods, respectively.

[8]The time-varying elasticity of substitution among firms implies that the optimal pricing problem will be subject to a cost-push shock.

Intermediate Goods Sector

There is a continuum of firms in the unit interval index by f, and are owned by households. These firms produce differentiated goods according to the following technology:

$$Y_{t,f} = A_t N_{t,f}^{\alpha} \tag{3.9}$$

The intermediate good produced by firm g is sold in a monopolistic competitive market. Following Calvo (1983), I assumed that a firm f can re-optimize its price with probability $(1-\alpha_p)$ in each period. If firm f is not able to re-set its prices, it will set the price chosen in the previous period. In addition, and in line with Mankiw and Reis (2002), I assume that at each period, every firm g has a probability of $(1-\lambda_p)$ of obtaining new information to be used in its price-setting process. Otherwise, the firm remains with the previously available information set. Thus, a firm f will dispose an information set updated j periods ago. Therefore, price setters experience dual stickiness about prices and information.[9]

I assume firm f is composed of two departments: sales and human resources. The sales department is in charge of pricing good f and it is assumed to be occasionally inattentive. While human resources decide how much labor to hire, and it is assumed to be always attentive. Then, a sales department in firm f that is allowed to change its price in period t chooses $P_{t,f}$ to maximize the present discounted sum of profit streams according to its available information set, such that the demand for its good is satisfied:

$$\max_{P_{t,f}} \quad \hat{E}_{t-j} \sum_{s=0}^{\infty} (\beta\alpha_p)^s Q_{t,t+s} \left(\frac{P_{t,f}}{P_{t+s}} Y_{t+s,f} - \mu_{t+s}^{f} Y_{t+s,f} \right) \tag{3.10}$$

[9] The probabilities $(1-\alpha_p)$ and (λ_p) are assumed independent of the length of time since firms adjusted their price and information set, and from each other.

$$s.t. \quad Y_{t,f} = Y_t \left(\frac{P_{t,f}}{P_t} \right)^{-\theta_t^p} \tag{3.11}$$

where $\hat{E}_{t-j}$ is the subjective expectation operator corresponding to available information in time $t - j$, μ_{t+s}^f is the real marginal cost, and $\beta^s Q_{t,t+s}$ is the stochastic discount factor.

In addition, firm's f human ressources department hires the optimal amount of labor while minimizing its production costs subject to its desired level of production, described by (3.9):

$$\min_{N_{t,f}} \quad W_t N_{t,f} + \mu_t^f Y_{t,f} \tag{3.12}$$

$$s.t. \quad Y_{t,f} = A_t N_{t,f}^{\alpha}$$

3.2.3 Monetary Policy Authority

The monetary authority is assumed to follow a Taylor-type rule to conduct its policy by adjusting the nominal interest rate in response to deviations of inflation and output gap from their steady-state values.[10]

$$\frac{i_t}{\bar{i}} = \left(\frac{i_{t-1}}{\bar{i}} \right)^{\rho} \left(\frac{\pi_{t-1}}{\bar{\pi}} \right)^{(1-\rho)\chi_\pi} \left(\frac{x_{t-1}}{\bar{x}} \right)^{(1-\rho)\chi_x} e^{\epsilon_t^i} \tag{3.13}$$

where ρ captures the degree of interest rate smoothing, while χ_π and χ_x reflect the level of reaction of the central bank to past inflation and output gap, respectively. Lastly, I assume that the (log) monetary policy shock, ϵ_t^i, follows a first-order autoregressive process with an iid normal error disturbance.

[10]Potential output is defined as the level of output that would prevail under flexible prices, full information and in the absence of shocks.

3.2.4 Equilibrium

A competitive equilibrium of this economy is an allocation of consumption, output and labor supplied for all varieties of goods, such that households and firms behave optimally, the monetary policy authority implements the Taylor rule, and all markets clear.

3.2.5 Log-linearized Model

Let variables with a hat sign denote log-linearized around its steady-state ones.

The dynamic of the economy is, thus, given by:

$$\hat{\pi}_t = \frac{(1-\alpha_p)(1-\lambda_p)}{\alpha_p}\sum_{j=0}^{\infty}\lambda_p^j \hat{p}^*_{t,j-1} \tag{3.14}$$

$$\hat{p}^*_{t,j} = \hat{E}_{t-j}\left((1-\beta\alpha_p)\omega\hat{\mu}^p_t + \beta\alpha_p(\hat{\mu}^p_{t+1} + \hat{\pi}_{t+1}) + \epsilon^p_t\right) \tag{3.15}$$

$$\hat{x}_t = \hat{E}_{t-1}\left(\hat{x}_{t+1} + \sigma(\hat{i}_t + \hat{\pi}_{t+1}) + \epsilon^x_t\right) \tag{3.16}$$

$$\hat{i}_t = \rho\hat{i}_{t-1} + (1-\rho)(\chi_{\hat{\pi}}\pi_{t-1} + \chi_x\hat{x}_{t-1}) + \epsilon^i_t \tag{3.17}$$

with structural shocks given by:

$$\epsilon^p_t = \rho_p\epsilon^p_{t-1} + e^p_t \tag{3.18}$$

$$\epsilon^x_t = \rho_x\epsilon^x_{t-1} + e^x_t \tag{3.19}$$

$$\epsilon^i_t = \rho_i\epsilon^i_{t-1} + e^i_t \tag{3.20}$$

where $e^n_t \overset{iid}{\sim} N(0,\sigma^2_n)$, with $n = \{p, x, i\}$, and ω is a composite parameter governing the strategic complementarity between price setters.

Equation (3.14) gives the dual stickiness Phillips curve (DSPC), where it can be seen that inflation depends on marginal cost, $\hat{\mu}^p_t$, expected future inflation, and a cost-push shock, ϵ^p_t, as usual. But now, it is also a convolution of the degrees of stickiness on prices and information, α_p and λ_p, respectively. In a sense, inflation is a weighted average of all optimal decision rules followed by firms that face sticky prices, inattention, and subjective expectations, described by Equation (3.14). Note that this equation nests both the traditional New Keynesian and Sticky Information curves. When $\lambda_p = 0$, all firms can update their information sets every quarter, then the DSPC becomes the classic New Keynesian Phillips curve. While, the DSPC reduces to Mankiw and Reis (2002) Sticky information Phillips curve when all firms can re-optimize their prices every quarter, i.e., $\alpha_p = 0$.

The log linearized Euler equation that arises from the households' optimal choice of consumption is given by Equation (3.16). The output gap, x_t, depends on expectations about future inflation, nominal interest rates, and future output gap. Also, it is impacted by a demand shock, ϵ_t^p.

The operational Taylor rule followed by the monetary policy to conduct its policy is denoted by Equation (3.17). Finally, Equations (3.18)-(3.20) describe the AR(1) processes followed by the structural shocks.

3.3 Is Inattention still Important when Learning Replaces Rational Expectations?

The Bayesian estimation of the model on U.S. aggregate data in this section aims to answer three questions: i) which expectational mechanism (rational expectations or Euler-equation learning) is preferred by the data; ii) is inattention still relevant when subjective expectations replace rational ones; iii) what are the implications of these results for macroeconomic persistence.

3.3.1 Expectation Formation

The model described in section 3.2 departs from the benchmark New Keynesian framework in two ways. It includes inattention in the supply side and relaxes the rational expectations assumption. Thus, agents are assumed not to know the structural parameters governing the dynamics of the economy, and as a consequence, they form subjective expectations, denoted here as $\hat{E}_t$.

Following adaptive learning literature, I assume that agents behave as econometricians and forecast their expectations using a perceived law of motion (PLM) given by:

$$Z_t = a_t + b_t Z_{t-1} + e_t \tag{3.21}$$

Note that in addition to lacking knowledge about the aggregate relationship among macroeconomic aggregates, I assume that agents cannot observe the realization of the shocks. Thus, they only have at their disposal information about inflation, output gap, and nominal interest rate to incorporate into their model. This assumption is made under the understanding that it would be the most realistic scenario.

The coefficients of the PLM are updated by agents each time new information is available using a Constant-Gain learning algorithm:

$$\Phi_t = \Phi_{t-1} + g R_t^{-1} X_t (Z_t - X_t' \Phi_{t-1}) \tag{3.22}$$

$$R_t = R_{t-1} + g(X_t X_t' - R_{t-1}) \tag{3.23}$$

where: $Z_t = \{\pi_t, x_t, i_t\}'$, a_t and b_t capture agents' beliefs, and $\Phi_t = (a_t', vec(b_t'))'$. g is the constant gain parameter. $X_t = \{1, Z_{t-1}\}$ are the regressors included in the agents' model, while R_t is their second moment matrix. Therefore, agents form their expectations for t and $t+1$ using the PLM, the most recent coefficient estimates, and all available information at their disposal:

$$\hat{E}_{t-j} Z_t = a_{t-j} + b_{t-j} \hat{E}_{t-j} Z_{t-1} \tag{3.24}$$

$$\hat{E}_{t-j} Z_{t+1} = a_{t-j} + b_{t-j} \hat{E}_{t-j} Z_t \tag{3.25}$$

Therefore, the model can be summarized by the economy dynamics, described in Equations (3.14)-(3.20); the agents' PLM, captured by Equation (3.21); the updating rules, expressed in Equations (3.22) and (3.23); and the forecasting rule shown in Equations (3.24) and (3.25).

3.3.2 Empirical Strategy

Data

U.S. data used for the estimation has quarterly frequency and it comprises the period between 1969-Q3 to 2006-Q1. As previously mentioned, this paper considers two different databases in order to achieve its primary objective. Then, both estimations are done with the same sample size for comparability purposes. The sample choice relies on information available on survey data on expectations which is a crucial element of the analysis and to avoid the financial crisis.[11,12]

This section uses revised macroeconomic data (and no survey expectations). The observables consist of a measure of interest rate, I use the effective federal funds rate (expressed on a quarterly basis); inflation is constructed as (100 times) the log difference of the implied deflator of GDP; and output gap, measured as 100 times the log deviation of real GDP from the CBO's estimate of potential GDP. All series are taken from the FRED.

[11]Data on relevant expectation series from the SPF is available from 1968-Q1 onwards. Note, however, that some quarters are lost in their construction since the model requires expectations formed with lagged or old information.

[12]Later on, an estimation is done including the financial crisis period in order to assess to which extent the degree of learning and inattention have changed during this period.

State-Space Form

The dual stickiness model with adaptive learning expressed by Equations (3.14)-(3.20) and with agents' expectations formed as in (3.24) and (3.25) can be expressed in state-space form:

$$S_t = F_t S_{t-1} + G\varepsilon_t + \tilde{C}_t \tag{3.26}$$

$$Y_t = B(\theta)S_t \tag{3.27}$$

where ε_t=(e_t^p,e_t^x,e_t^i)' is a vector containing the iid innovations; S_t is a state vector which includes endogenous variables, expectations and structural shocks; Y_t is the vector of observable variables, Y_t=(π_t,x_t,i_t)'; $B(\theta)$ is a matrix compose of zeros and ones where the variable is observable; and F_t, G, and $\tilde{C}_t$ are matrices composed by the structural parameters, θ:

$$\theta = (\alpha_p, \rho, \chi_\pi, \chi_x, \lambda_p, \rho_x, \rho_p, \rho_i, \sigma_x, \sigma_p, \sigma_i, g) \tag{3.28}$$

While F_t and $\tilde{C}_t$ also depend on the PLM reduced-form parameters, Φ_t. Equations (3.26) and (3.27) are the state-transition and measurement equation, respectively.

Priors

Table 3.1 reports the prior distributions assigned to the estimated parameters.[13] The price and information stickiness, α_p and λ_p are given a diffuse prior, Beta distribution with mean 0.5. In this tenor, there are no pre-judgments attached to neither level of stickiness, and it can be truly assessed their relative relevance when interacting with each other and in the presence of subjective expectations formed under adaptive learning. As the majority of the

[13] In the estimation, some parameters were calibrated. For instance, the discount rate, β, is set to 0.99, implying a steady-state annualized real interest rate of 4%. Plus, following Dupor et al. (2010), a logarithmic utility function is assumed, then, the intertemporal elasticity of substitution, σ, is fixed to 1, and the marginal cost equals output gap.

literature, the priors for the feedback of inflation and output gap in the Taylor-type rule are centered close to Taylor (1993) values. At the same time, the interest rate smoothing is given a Beta distribution.

	Description	**Distribution**	**Mean**	**SDs**
α_p	Price stickiness	Beta	0.5	0.15
λ_p	Information stickiness	Beta	0.5	0.15
ρ	Interest rate smoothing	Beta	0.5	0.15
ϕ_π	Inflation response coefficient	Normal	1.5	0.25
ϕ	Output gap response coefficient	Normal	0.5	0.15
ρ_p	AR coefficient - Supply shock	Beta	0.5	0.15
ρ_x	AR coefficient - Demand shock	Beta	0.5	0.15
ρ_i	AR coefficient - Monetary policy shock	Beta	0.5	0.15
σ_p	SD - Supply shock	Inv. Gamma	0.1	1
σ_x	SD - Demand shock	Inv. Gamma	0.1	1
σ_i	SD - Monetary policy shock	Inv. Gamma	0.1	1
g	Constant gain	Gamma	0.018	0.01

Table 3.1: Prior distributions.

For the autoregressive coefficients of the structural shocks, a Beta distribution centered at 0.5 is used. In comparison, inverse gamma priors are chosen for the standard deviations of these disturbances. Lastly, I chose a Gamma distribution centered on a value found in previous literature and with a sizeable variance. This prior coincides with the adaptive learning literature.[14]

Bayesian Estimation

The structural parameters from the dual stickiness model with adaptive learning are estimated via Bayesian techniques following Herbst and Schorfheide (2016). First, a prior distribution is assigned to the parameters: $p(\theta)$, based on past literature as described previously. Then, the likelihood of the state-space model in (26) and (27) is computed, $L(Y_{t=1:T}|\theta)$

[14]Milani (2007) found a gain parameter equal to 0.018. However, there is a wide range of estimated learning speeds in the literature, ranging from 0.001 to 0.04.

using the Kalman filter. A random-walk Metropolis-Hastings algorithm is implemented to estimate the posterior distribution of the parameters. I run 500,000 iterations and discard 25% of the draws as the burn-in period. The posterior means are used as estimates for the parameters of the model.

The initial beliefs for the learning algorithm are borrowed from Milani (2011), as this paper shares the same starting point for the estimation sample. For instance, the initial values for inflation and output gap persistence are set at 0.7 and 0.8, respectively. While, the perceived history-dependence of the monetary policy is started at a sizeable level, equivalent to 0.75.[15]

3.3.3 Results

In this section, I present the estimation results. First, I estimate the model with dual stickiness and (Euler-equation) adaptive learning to assess the dependence of inattention on the modeling type of expectations. The proposed model is tested against rational expectations.[16]

Posterior Estimates

The posterior estimates are presented in Table 3.2. The 95% credible intervals are also shown in brackets. In both specifications, the estimates for the degree of sticky prices are around 0.5, which implies that, on average, firms update their prices every two quarters. As found by Dupor et al. (2010), the findings suggest that both prices and information rigidities are present in U.S. data.

In addition, the monetary policy rules present close feedback coefficients to inflation and out-

[15]For comparability purposes with other estimations in this paper, the truncation point for the infinite sum in the Phillips curve is set to 4. This truncation is driven by data limitations on survey expectations.

[16]For the inattentive expectations specification, the estimation is done following the method proposed by Meyer-Gohde (2010). This methodology has the advantage of using a convergence criterion for truncation, instead of randomly cutting the number of lagged expectations incorporated into the model.

	Inattention under RE	**Inattention & Adaptive Learning**
α_p	0.564	0.518
	[0.347, 0.752]	[0.302, 0.710]
ρ	0.361	0.727
	[0.239, 0.472]	[0.616, 0.826]
ϕ_π	1.133	1.261
	[0.934, 1.359]	[1.032, 0.1.567]
ϕ_x	0.129	0.103
	[0.060, 0.207]	[0.012, 0.237]
λ_p	0.776	0.173
	[0.618, 0.889]	[0.089, 0.282]
ρ_p	0.576	0.817
	[0.503, 0.666]	[0.744, 0.883]
ρ_x	0.845	0.510
	[0.783, 0.903]	[0.392, 0.624]
ρ_i	0.146	0.121
	[0.063, 0.249]	[0.049, 0.220]
σ_p	3.657	5.580
	[2.011, 6.090]	[3.438, 8.923]
σ_x	0.312	1.720
	[0.206, 0.429]	[1.340, 2.247]
σ_i	0.614	0.537
	[0.551, 0.684]	[0.485, 0.594]
	[0.055, 0.068]	[0.049, 0.059]
g	-	0.003
	-	[0.001, 0.008]
Log. Marginal L.	-439.127	-364.112

Table 3.2: Posterior estimates, baseline model.

NOTE: The log marginal likelihoods are computed using Geweke's Modified Harmonic Mean approximation. The same prior distributions as in Table 3.1 are used for the rational expectation specification estimation.

put gap. However, the specification with subjective expectations exhibits a slightly stronger reaction to inflation and a more persistent interest rate rule, consistent with previous literature findings.

On the other hand, the main differences in the estimates between model specifications are related to the parameters of the structural shocks. The size of the estimates for the autocorrelations and standard deviation differs. Except for the monetary policy shock, all other shocks become more volatile. Plus, the demand and monetary policy shock exhibit lower history dependence under subjective expectations. Nonetheless, this does not occur for the cost-push shock.

Furthermore, the posterior mean for the constant gain parameter is equivalent to 0.003 with a 95% credible interval between 0.001 and 0.008. This estimation is lower than previous estimations, such as Milani (2007), Milani (2011), among others. However, in recent work, Milani and Meggiorini (2021) similarly find a small learning speed in an estimation of a model including Euler-equation learning and myopia.

As the main interest of this section lies in identifying the sensitivity of inattention to how expectations are assumed to be formed, I now contrast the posterior means for λ_p under both scenarios. The proportion of inattentive firms under rational expectations is equal to 0.78, similar to Dupor et al. (2010) results.[17] This level of inattention suggests that, on average, firms update their information set every four quarters. Nevertheless, the relevance of inattention is substantially lessened in the presence of subjective expectations. In the adaptive learning specification, the degree of inattention decreases to 0.17. Implying that, on average, firms update their information more often (in fact, every quarter). Note, however, that the type of inattention proposed by Mankiw and Reis (2002) is still relevant (as the credible interval for λ_p does not include 0). Nonetheless, its importance is reduced under an alternative behavioral mechanism: adaptive learning. In this sense, adaptive learning is able to add persistence without assuming large degrees of inattention.

Lastly, it is important to remark that the data strongly preferred the specification featuring subjective expectations, as seen in Table 3.3. According to the log marginal likelihood, the addition of adaptive learning provides a considerable improvement in data fit.

[17]These authors estimate a dual stickiness model and find an inattention degree parameter equivalent to 0.6 under strategic neutrality. Other authors find different degrees of inattention, such as Mankiw and Reis (2006), that identify an estimate equivalent to 0.3. However, their model only considers information rigidities.

	Inattention under Rational Expectations	Inattention & Adaptive Learning
Log Marginal Likelihood	-439.127	-364.112

Table 3.3: Model comparison, baseline model.

The Role of Learning

Next, I compute impulse response functions of the macroeconomic variables to structural shocks. Figure 3.1 shows them for the inattention under rational expectations and inattention under adaptive learning specifications.[18] While rational expectations can generate a hump-shape response for inflation when a demand shock occurs, this is not the case for the impact of the other disturbances in inflation or output gap. Their effect size is large on impact, but it vanishes quickly. In contrast, learning combined with inattention can generate higher persistence and propagation of shocks. For most shocks, the response for inflation and output gap peaks around the fifth quarter after the hit of the shock and lasts at least three years.[19]

3.4 What Can We Learn from Survey Expectations?

In this section, I repeat the estimation of the dual stickiness model under adaptive learning on U.S. data, but now using survey expectations and real-time data with twofold objectives. First, to assess the robustness of the results under the baseline model from the previous section. Second, to better identify both relevant parameters for this study: inattention

[18]The impulse response functions are derived as an average of the last 5,000 draws from the Metropolis-Hastings algorithm. For the specification under adaptive learning, the figure shows the mean across draws and over the sample.

[19]In the model considering adaptive learning, the response of the output gap to a cost-push shock under the learning specification has the opposite sign as one would expect. This result may be driven by the beliefs; that is, the agents' perception about the relationship between the output gap and inflation (which is positive as it can be seen in Figure 3.2). Recall that agents use a simple model (viz., the PLM) to form beliefs that reflect a *perception* between the macroeconomic aggregates and not the actual structural relationship. This positive relationship between output gap and inflation has been found by other empirical papers, too, see, for example, Kamdar (2019).

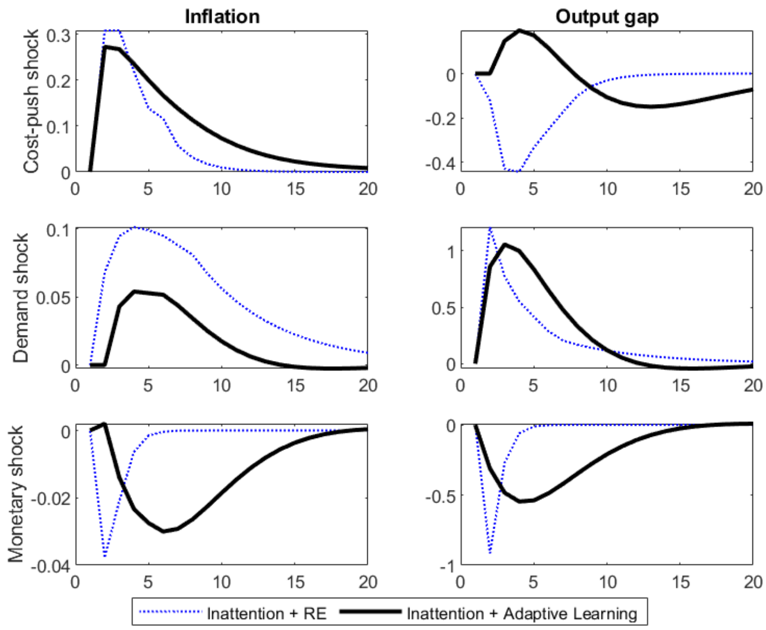


Figure 3.1: Impulse response functions to a one standard deviation positive supply, demand and monetary shock.

degree and constant gain. Note that the changes in data only impact the expectation formation mechanism and some elements in the empirical strategy, but not the model per se. Additionally, some robustness analysis is done.

3.4.1 Expectations Formation

In this section, a further deviation from the baseline model is assumed. Now, $\hat{E}_t$ corresponds to observed survey and market expectations, for which I exploit data from the Survey of Professional Forecasters instead of rational and model-consistent expectations.

As before, I assume that expectations are formed by agents from a near-rational expectations formation mechanism using the same PLM given by (3.21) and the Constant-Gain learning algorithm described by (3.22) and (3.23). However, following Milani (2011), I now assume the existence of expectational shocks. These expectation shocks reflect exogenous variations on expectations unrelated to fundamentals. So, they can capture sentiments or psychological factors that affect expectations formation.[20]

Then, similarly to the estimation done previously, agents form their expectations for t and $t+1$ using the PLM, the most recent coefficient estimates and all available information depending on the degree of inattention they faced. Nonetheless, they experience expectations shocks:

$$\hat{E}_{t-j}\begin{pmatrix}\pi_t\\ x_t\\ i_t\end{pmatrix}=\begin{pmatrix}a_{\pi,t-j}\\ a_{x,t-j}\\ a_{i,t-j}\end{pmatrix}+\begin{pmatrix}b_{\pi\pi,t-j} & b_{\pi x,t-j} & b_{\pi i,t-j}\\ b_{x\pi,t-j} & b_{xx,t-j} & b_{xi,t-j}\\ b_{i\pi,t-j} & b_{ix,t-j} & b_{ii,t-j}\end{pmatrix}\hat{E}_{t-j}\begin{pmatrix}\pi_{t-1}\\ x_{t-1}\\ i_{t-1}\end{pmatrix}+\begin{pmatrix}0\\ e_{t-1}^{x_0,j}\\ e_{t-1}^{i}\end{pmatrix}\tag{3.29}$$

$$\hat{E}_{t-j}\begin{pmatrix}\pi_{t+1}\\ x_{t+1}\\ i_{t+1}\end{pmatrix}=\begin{pmatrix}a_{\pi,t-j}\\ a_{x,t-j}\\ a_{i,t-j}\end{pmatrix}+\begin{pmatrix}b_{\pi\pi,t-j} & b_{\pi x,t-j} & b_{\pi i,t-j}\\ b_{x\pi,t-j} & b_{xx,t-j} & b_{xi,t-j}\\ b_{i\pi,t-j} & b_{ix,t-j} & b_{ii,t-j}\end{pmatrix}\hat{E}_{t-j}\begin{pmatrix}\pi_{t}\\ x_{t}\\ i_{t}\end{pmatrix}+\begin{pmatrix}e_{t-1}^{\pi,j}\\ e_{t-1}^{x_1,j}\\ 0\end{pmatrix}\tag{3.30}$$

where $e_t^{\pi,j}$ and e_t^i are expectation shocks related to inflation and the nominal interest rate, and $e_{t-1}^{x_0,j}$ and $e_{t-1}^{x_1,j}$ refers to expectational shocks related to output gap forecast between $t-1$ and t and among projections for t and $t+1$, respectively. Similarly as in Milani (2011), these shocks are assumed to follow an AR(1) process. Plus, I assumed that disturbances for expectations formed for different variables (e.g. π, x, i) and using dissimilar information sets (i.e. $t-j$ and $t-l$ with $j \neq l$) are independent.

$$e_t^{\pi,j}=\rho_{e^{\pi,j}}e_{t-1}^{\pi,j}+\varepsilon_t^{e^{\pi,j}}\tag{3.31}$$

$$e_t^{i}=\rho_{e^{i}}e_{t-1}^{i}+\varepsilon_t^{e^{i}}\tag{3.32}$$

where $\varepsilon_t^{e^{q,j}}\overset{iid}{\sim}N(0,\sigma^2_{e^{q,j}})$ for $q=\{\pi,i\}$ and $j=\{1,2,3,4\}$.[21]

[20] Note that I only introduce expectational shock in those expectations that enter directly into the model.

[21] The truncation point for the infinite sum in the Phillips curve is fixed at 4 due to data limitations on survey expectations.

In contrast, I allow expectational shocks associated to output gap projections to be correlated, but only within the same level of inattention. That is to say, if the expectations related to both $e_{t-1}^{x_0,j}$ and $e_{t-1}^{x_1,j}$ shocks were formed using similar information sets, then they are dynamically correlated.

$$e_t^{x_0,j} = \rho_{e^{x_0,j}} e_{t-1}^{x_0,j} + \rho_{e^{x01,j}} e_{t-1}^{x_1,j} + \varepsilon_t^{e^{x_0,j}} \tag{3.33}$$

$$e_t^{x_1,j} = \rho_{e^{x_1,j}} e_{t-1}^{x_1,j} + \rho_{e^{x10,j}} e_{t-1}^{x_0,j} + \varepsilon_t^{e^{x_1,j}} \tag{3.34}$$

where $\varepsilon_t^{e^{m,j}} \overset{iid}{\sim} N(0, \sigma^2_{e^{m,j}})$ for $m = \{x_0, x_1\}$ and $j = \{1, 2, 3, 4\}$.

For instance, the dependance of the current output gap forecast shock, $e_t^{x_0,j}$, on the (previous period) shock for the one-quarter ahead output gap projections, $e_t^{x_1,j}$, is captured by $\rho_{e^{x01,j}}$.

3.4.2 Empirical Strategy

The exploitation of survey expectations and real-time data impacts the estimation approach only in three dimensions: data, the definition of the model's state-space form, and prior specification. Meanwhile, the Bayesian method implemented remains as before. For instance, structural parameters are estimated through a random-walk Metropolis-Hastings algorithm with 500,000 iterations and a burn-in period of 25% of the draws. Again, posterior means are used as estimates for the parameters of the model. In addition, initial beliefs for the learning algorithm are unchanged.

Data

The sample size (1969-Q3 to 2006-Q1), as well as the frequency of the U.S. data remains invariant. However, for this estimation of the model, I incorporate time-series information on expectations of inflation, output, and nominal interest rate.

Inflation and output expectation data are taken from the Survey of Professional Forecasters (SPF) conducted by the Federal Reserve Bank of Philadelphia. I use the mean across all available answers to eliminate heterogeneity in the forecasts and focus on homogenous agents as described in the proposed model. In constrast, expectations on nominal interest rate are proxied by market expectation and computed using the expectation theory of the term structure and data on 3-month and 6-month Treasury bill rates. This is done to maximize data length because the SPF has information about nominal interest rate expectations only from 1981-Q3 onwards.[22,23]

Additionally, I use real-time data on macroeconomic series available to the professional forecasters when answering the SPF questionnaires for consistency purposes and to correctly identify the behavioral parameters (i.e., learning speed and degree of inattention). This data are released by the Federal Reserve Bank of Philadelphia.[24] Inflation is constructed using the GDP deflator and real GDP, which is computed as a ratio of Nominal GDP and GDP deflator. While, as a measure of interest rate, I use the three-month Treasury bill (expressed on a quarterly basis).[25]

For additional details on data, see Appendix F.

[22] Expectations from the SPF on nominal interest rate, labeled as "TBILL2", and the computed-projections are quite similar. The correlation among them is 0.988.

[23] However, in the robustness analysis, the estimation was repeated using the SPF data for interest rate expectations and the results remain unchanged.

[24] According to the SPF documentation, the survey questionnaires sent by the Philadelphia Fed include economic information about *"the last known historical quarter at the time we sent the questionnaire to the panelists"* collected from the Bureau of Economic Analysis (BEA), Bureau of Labor Statistics's (BLS), and other government statistic agencies. Thus, in submitting their projections, forecasters' information set includes information up to the previous quarter, i.e., t-1.

[25] As a proxy, for real-time data on three-month T-bill is used the one-period lagged revised series as the Philadelphia Fed does not release information before 1981-Q3.

State-Space Form

For the extension with survey and real-time data, the model is still summarized by Equations (3.14)-(3.20) but now agents' expectations formed by (3.29) and (3.30). This can also be written in state-space form as (3.26) and (3.27).

While e_t, F_t, G, and $\tilde{C}_t$ definitions stay as in Section 3.3, S_t, Y_t, and θ are impacted by this variant of the estimation. Now, S_t includes not only endogenous variables, expectations, and structural shocks, but also contains expectational shocks. While, Y_t^{*}=(π_t,Δy_t,i_t, $E_{t-j}\pi_{t+1}$,$E_{t-j}\Delta y_{t+1}$,$E_{t-j}\Delta y_t$,$E_{t-1}i_t$) for $j = \{1, 2, 3, 4\}$, as due to data limitations on survey expectations, the truncation point must be fixed at 4. Plus, the structural parameters are define as follows:

$$\begin{aligned}\theta^* = (&\theta, \rho_e^{\pi_1}, \rho_e^{\pi_2}, \rho_e^{\pi_3}, \rho_e^{\pi_4}, \rho_e^{x_{0,1}}, \rho_e^{x_{0,2}}, \rho_e^{x_{0,3}}, \rho_e^{x_{0,4}}, \rho_e^{x_{1,1}}, \rho_e^{x_{1,2}}, \rho_e^{x_{1,3}}, \rho_e^{x_{1,4}}, \rho_e^{i}, \\ &\rho_{e_1}^{x_0,x_1}, \rho_{e_2}^{x_0,x_1}, \rho_{e_3}^{x_0,x_1}, \rho_{e_4}^{x_0,x_1}, \rho_{e_1}^{x_1,x_0}, \rho_{e_2}^{x_1,x_0}, \rho_{e_3}^{x_1,x_0}, \rho_{e_4}^{x_1,x_0}, \sigma_e^{\pi_1}, \sigma_e^{\pi_2}, \sigma_e^{\pi_3}, \\ &\sigma_e^{\pi_4}, \sigma_e^{x_{0,1}}, \sigma_e^{x_{0,2}}, \sigma_e^{x_{0,3}}, \sigma_e^{x_{0,4}}, \sigma_e^{x_{1,1}}, \sigma_e^{x_{1,2}}, \sigma_e^{x_{1,3}}, \sigma_e^{x_{1,4}}, \sigma_e^{i})\end{aligned} \tag{3.35}$$

where the additional parameters (not included in the baseline model estimation) are related to expectational shocks.

Finally, I should note that due to available information, the estimation of the model is done to match the growth rate of real GDP and output growth expectations. Plus, output gap is measured as the deviation of the real-time real GDP from the real potential GDP as reported by the U.S. Congressional Budget Office. This implies that I am assuming agents observe the CBO potential GDP and thus, know its growth rate.[26]

[26]Real-time data on potential GDP are not available for the sample used in this estimation. Data only exist from 1991 onwards. Nevertheless, the data on expectations are from professional forecasters; so, it is fairly reasonable to assume that they are sophisticated enough in order to possess this information.

Priors

Prior specification is still given by Table 3.1. Nevertheless, in the estimation using survey expectations and real-time macroeconomic data, additional parameters associated with the expectational shocks are required to be estimated. In this case, their autoregressive coefficients and standard deviations are assigned the same prior distributions as those for the structural shocks. While, coefficients defining the dynamic correlation among $E_{t-j}x_t$ and $E_{t-j}x_{t+1}$ are given a standard normal prior distribution.

3.4.3 Results

Next, I show the results for the estimation using survey expectations and real-time data, aiming to test the results of the previous empirical exercise while improving the identification of both relevant parameters for this study: inattention degree and constant gain.

Posterior Estimates

Table 3.4 compiles the results. Overall, most estimates are similar to those in the baseline model under adaptive learning and consistent with previous literature findings.[27] Nevertheless, the main insight remains as before: the importance of inattention in firms is reduced when subjective expectations formed with adaptive learning are introduced into the model. The inclusion of observed expectations in the estimation confirms that adaptive learning indeed impacts the degree of inattention. Once again, both behavioral elements remain relevant. While the posterior mean for the constant gain is 0.001, slightly lower than the one for the estimation without survey expectations, it presents a tighter credible interval. Similar to the baseline model, this estimation also confirms the existence of dual stickiness,

[27] It is not expected to obtain the exact estimates in both versions of the estimation since they incorporate different data.

as both the information and prices rigidities estimates are statistically important. An ad-

	Posterior mean	95% Credible interval
α_p	0.557	[0.321, 0.758]
ρ	0.832	[0.764, 0.896]
ϕ_π	1.236	[1.024, 1.536]
ϕ_x	0.060	[0.005, 0.144]
λ_p	0.163	[0.081, 0.288]
ρ_p	0.747	[0.665, 0.824]
ρ_x	0.500	[0.394, 0.608]
ρ_i	0.365	[0.236, 0.499]
σ_p	9.281	[5.996, 13.835]
σ_x	1.831	[1.459, 2.323]
σ_i	0.200	[0.182, 0.220]
g	0.002	[0.001, 0.003]

Table 3.4: Posterior estimates, survey expectations and real-time data model.

ditional element in this estimation version lies in the inclusion of expectational shocks, as in Milani (2011). All estimates associated with these shocks are shown in Table G.2. Most of these expectational shocks are quite persistent with posterior means above 0.7, with the exception of the expectational shock for future inflation expectations with information set update at last quarter, $e^{\pi,1}$, and for current output gap expectations formed with more than one-quarter old information, $e^{x_{0,2}}$, $e^{x_{0,3}}$, and $e^{x_{0,4}}$. The correlation for these less persistent expectational shocks is between 0.3 and 0.5. Also, the estimation shows that standard deviations for output gap expectational shocks, for current and future projections, are larger than those for inflation and interest rate expectations. But, on average, more persistent.

Finally, I assume that disturbances for expectation formed for different variables and using distinct information sets are independent. In contrast, I allow expectational shock associated with output gap projections to be correlated but only within the same inattention degree. The results indicate a dependence of the expectational shocks of the nowcast forecast for output gap on the previous period expectational shock of the one-period ahead output gap projection. In contrast, the dependence of the shock for the future output gap expectations on that for current projections is not statistically significant (as most credible intervals for $\rho_{e^{x10,j}}$ include zero).

Evolution of Beliefs

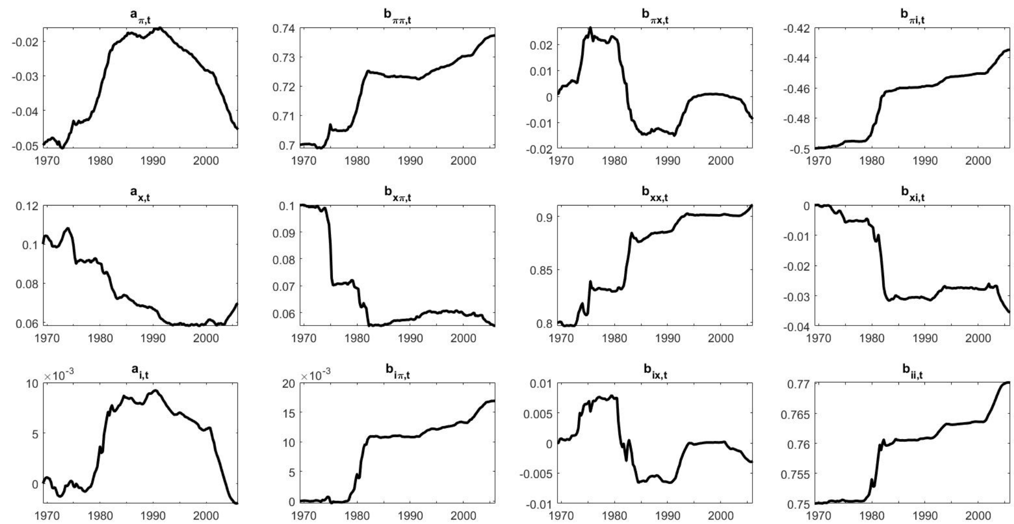


Figure 3.2: Evolution of beliefs, survey expectations and real-time data model.
Note: Coefficients for the perceived law of motion for inflation, output gap, and interest rate are presented in the first, second, and third row, respectively. These beliefs are constructed using the posterior means for the structural parameters.

Figure 3.2 shows the evolution of agents' beliefs which capture the perception of the reduced-form parameters of the economy, assumed unknown for them under the adaptive learning framework. Coefficients for the perceived law of motion for inflation, output gap, and interest rate are presented in the first, second, and third row, respectively. Overall, it can be seen that agents revise their beliefs over the whole sample. Regarding inflation, agents increase steadily (but in a low magnitude) their perception of persistence over the sample. The estimated sensitivity of inflation to interest rate is reduced moderately. While its reaction to output remains close to zero after 1980. Perceptions of deviation from steady-state level for inflation, captured by the intercept, are reduced for the 1970s and 1980s. But, later on, they revert to their initial levels. This seems in accordance with the higher levels of inflation during these decades, in comparison to most recent ones.

Meanwhile, the estimated beliefs using the output gap model reveal a rising perceived persistence throughout the sample, which stabilizes after the 1990s at around 0.9. In comparison, the perceived sensitivity of this variable to inflation declines. Lastly, the perceived intercept for output gap is positive but decreasing toward zero, suggesting that agents started to learn the true level of the potential output after some time.

The perceived law of motion coefficient reflects the market beliefs about monetary policy in the interest rate equation since expectations are constructed using the theory of the term structure and T-bill data. From the start of the 1980s, the markets perceived an increase in monetary policy history dependence, a downward revision of the reaction toward output gap, and a rise in the expected average rate, as indicated by the intercept. In addition, the market beliefs about the Fed's reaction to inflation shifted upwards by the end of the 1970s. All these perceptions are consistent with the monetary policy spanning the estimation sample.

Time-Varying Responses to Shocks

Figure G.1 displays the impulse response functions of macroeconomic variables to structural shocks for the model specification using survey expectations and real-time data.

As it can be seen in the plot, the reaction of macroeconomic aggregates to these shocks depends mainly on the evolution of agents' beliefs. Inflation and output gap have become more responsive to structural shocks by the end of the sample in 2006. This increment is modest in size but steady. The response of inflation to a cost-push shock appears mostly stable through the estimation sample.[28] However, its response to an expectational shock varies in a higher magnitude and has increased during the last decades (as shown in the

[28]Nonetheless, there is slight movement associated with the time-varying beliefs computed with the perceived law of motion for inflation

top-left panel of Figure G.2).

An important feature of these figures is that most of them show a clear hump-shape. Again, this shows evidence that subjective beliefs combined with inattention can generate higher persistence and propagation of shocks, even without the inclusion of the mechanical sources of persistence common in the business cycle fluctuation literature, such as habit formation and indexation to past inflation.

Insights on Survey Expectations

Figure G.3 show the response of future expectations about inflation and output gap, forecasted with different information sets, to the structural shocks. As expected, expectations formed with older information respond with a delay to these shocks. A more interesting result is that the impact of both the demand and cost-push shocks on inflation and output gap expectations depends on the degree of inattention: more attentive agents react greatly to structural shocks.

Furthermore, I would like to analyze if the proposed expectation formation mechanism generates plausible expectations about inflation, output, and nominal interest rate. In order to do this, I contrast observed expectations with the model-implied forecasts constructed using agents' PLM. Figure 3.3 shows this comparison. The results show that the series match is close, except for inflation expectations for the second half of the 1970s, where the information frictions model implied a downward revision. Note, however, that this forecast misspecification of inflation is also present in the observed inflation expectations from the SPF where agents also subestimated the level of inflation. Overall, this gives some evidence that the expectation formation mechanism elicited by the model resembles the one followed by the professional forecasters in the U.S. Therefore, information frictions are presented in expectations formation; revisiting the design of expectation formation in macroeconomic models seems imperative, especially the abandonment of full-information rational expectations hypothesis, which is a workhorse in the literature.

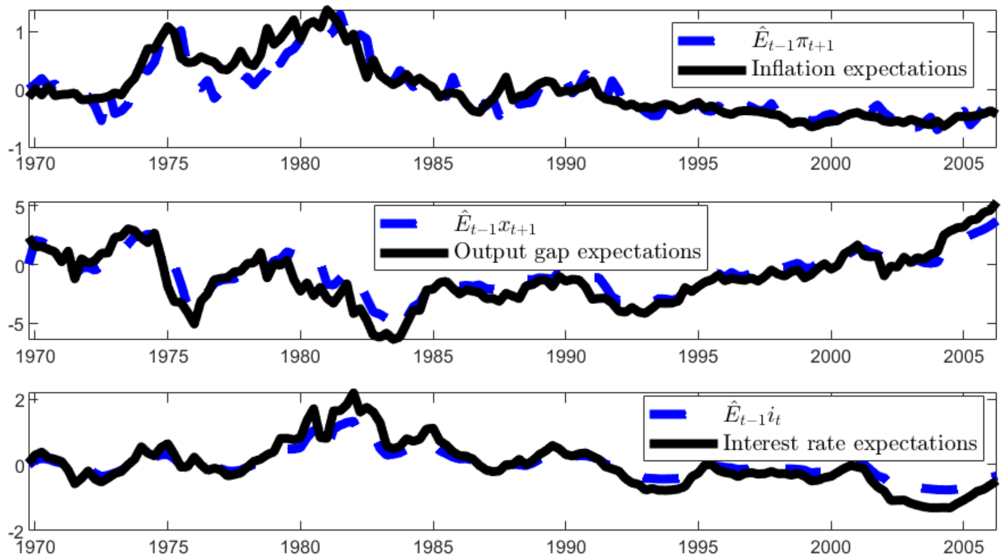


Figure 3.3: Observed and model implied expectations.

3.4.4 Robustness

Extended sample. The estimation, including survey expectations and real-time data, is repeated using a longer sample spanning from 1969:Q3 to 2019:Q4 to examine whether the behavioral features of the model have changed since the occurrence of the Great Recession. Posterior estimates are shown in Table G.1. As it can be observed, both g and λ_p exhibit a decrease in comparison to the shorter sample estimation. However, the main finding of the reduction of inattention remains unchanged when subjective expectations are assumed.

SPF interest rate expectations. Due to data limitations on the length of SPF nominal interest rate expectation data, the model presented previously considered market expectation computed taking advantage of the theory of the term structure. Nevertheless, the estimation is now repeated using available data for observed nominal interest rate expectations, in addition to survey expectations from inflation and output. Table G.1 displays the results. Estimates for the degree of inattention and constant gain are quite similar to those estimated with market expectations rather than with professional forecasters' projections for the interest rate. Once again, the same conclusions still apply.

Behavioral parameters across time. The estimation is repeated with split samples in order to assess the evolution of the degree of inattention and learning speed. The results are displayed in Table 3.5, plus the estimates for the original sample for reference.

During the pre-1980 period, the economy was characterized by high inflation and macroeconomic volatility. In this case, the inattention level estimated is the highest across all samples. This is at odds with previous findings. Higher degrees of inattention could be expected in periods with low volatility. Nonetheless, this result could exhibit an identification problem due to the small sample size; the estimate for λ_p is likely to be driven by the prior distribution. In contrast, the degree of inattention post-1980 increased in comparison to the benchmark sample, as expected. See posterior estimates for all structural parameters in Table G.1.

	1969Q3-2006Q1	**1969Q3-1980Q4**	**1981Q1-2006Q1**	**1969Q3-2019Q4**
λ_p	0.163	0.491	0.202	0.100
g	0.002	0.006	0.003	0.001

Table 3.5: Posterior estimates for λ_p and g, survey expectations and real-time data model.

3.5 Conclusions and Future Research

This paper compares two well-known frameworks that narrate alternative stories about how expectations are formed. On one side, inattention accounts for information frictions caused by costs of absorbing and processing information, inducing agents that do not "keep up" with the newest data about the economy. In contrast, adaptive learning posits a deviation from the rational expectation hypothesis. It proposes that information frictions exist such that agents lack perfect knowledge of the structure of the economy and instead use a model to form beliefs about the structural relationship among macroeconomic aggregates.

For the past decade, the inattention model has been vastly studied, emphasizing its relative importance to nominal rigidities in the form of sticky prices. This paper revisits this strand of literature and builds upon it by embedding subjective expectations into a dual sticky model. In doing so, I can empirically contrast vis-à-vis inattention à la Mankiw and Reis and adaptive learning.

This paper finds interesting results. First, it shows evidence of the presence of both information and price stickiness for the U.S. case. While a more novel insight is that the degree of inattention depends on the expectation formation mechanism chosen. That is, when departing from the rational expectation assumption, the level of inattention is reduced considerably. However, inattention remains relevant. Moreover, the model assuming subjective expectations formed with adaptive learning offers the best fit of the data and matches the survey expectations giving evidence in favor of the existence of information frictions in the U.S. Overall, these empirical results suggest that the inclusion of the full-information rational expectations hypothesis in macroeconomic models should be revisited.

As an additional contribution to the literature, the robustness of this result is tested by incorporating survey expectations and real-time data into the estimation strategy. The sensitivity of the level of inattention is confirmed when using observed expectations and the real-time macroeconomic data set faced by professional forecasters when their projections. Again, in contrast to the rational expectation estimation, agents update their information sets more frequently.

Nevertheless, an important remark to mention is the limitation of survey data, particularly the horizon availability. For the relevant variables to this paper, the SPF releases only a restricted forecasting horizon. Consequently, this causes empirical constraints related to the truncation point, which can affect estimation results, as point out by Meyer-Gohde (2010).

Finally, this paper opens future research possibilities. It would be relevant to investigate the magnitude of inattention across all types of agents, and not only in firms, as proposed by Mankiw and Reis (2007). Plus, the proposed model could be analyzed using other sources of observed expectations to overcome the current data limitations. Lastly, a comparison among these “old behavioral” elements and “newer” ones, such as myopia or cognitive discounting, could disclose new findings.

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Appendix A

Central Bank Transparency Regimes

In this model agents are assumed to form expectation while learning about the economy and the monetary policy conducted by the central bank. In addition, and depending on the central bank transparency, the monetary policy authority communicates various information related to the policy conduction. This will impact the learning process of agents in this economy. In particular, the model for the nominal interest rate will adjust accordingly to the degree of level of transparency followed by the central bank.

The perceived models and the available information sets in each of the four proposed scenarios are explained below.

A.1 Opacity

CB communicates:	**MP rule coefficients**	**Inflation target**	**Variables in MP rule**
Opacity	-	-	-

Under an opaque regime, the PLM becomes:

$$Z_t = a_t + b_t Z_{t-1} + c_t u_{t-1} + d_t r^n_{t-1} + e_t$$

where:

$$a_t = \begin{pmatrix} a_t^\pi \\ a_t^x \\ a_t^i \end{pmatrix}; \quad c_t = \begin{pmatrix} c_t^\pi \\ c_t^x \\ c_t^i \end{pmatrix}; \quad d_t = \begin{pmatrix} d_t^\pi \\ d_t^x \\ d_t^i \end{pmatrix};$$

- $Z_t = \{\pi_t, x_t, i_t\}'$.
- a_t, b_t, c_t and d_t are estimated.

A.2 Only Target Known

CB communicates:	**MP rule coefficients**	**Inflation target**	**Variables in MP rule**
Only target	-	✓	-

When only the inflation target is disclosed by the central bank, agents use the following model to form their expectations:

$$Z_t = b_t Z_{t-1} + c_t u_{t-1} + d_t r^n_{t-1} + e_t$$

where:

$$c_t = \begin{pmatrix} c_t^\pi \\ c_t^x \\ c_t^i \end{pmatrix}; \quad d_t = \begin{pmatrix} d_t^\pi \\ d_t^x \\ d_t^i \end{pmatrix};$$

- $Z_t = \{\pi_t, x_t, i_t\}'$.

- a_t is not estimated.

A.3 Partial Transparency

CB communicates:	MP rule coefficients	Inflation target	Variables in MP rule
Partial transparency	-	✓	✓

Under partial transparency, the model used by the agents to form their expectations is given by:

$$Z_t = b_t Z_{t-1} + c_t u_{t-1} + d_t r^n_{t-1} + e_t$$

where:

$$c_t = \begin{pmatrix} c_t^\pi \\ c_t^x \\ 0 \end{pmatrix}; \quad d_t = \begin{pmatrix} d_t^i \\ d_t^x \\ 0 \end{pmatrix}$$

- $Z_t = \{\pi_t, x_t, i_t\}'$.
- a_t, c_t^i, d_t^i are not estimated.
- b_t^i is estimated by agents.

A.4 Full Transparency

CB communicates:	MP rule coefficients	Inflation target	Variables in MP rule
Full transparency	✓	✓	✓

Under full and partial transparency, the PLM is given by:

$$Z_t = b_t Z_{t-1} + c_t u_{t-1} + d_t r^n_{t-1} + e_t$$

where:

$$c_t = \begin{pmatrix} c^\pi_t \\ c^x_t \\ 0 \end{pmatrix}; \quad d_t = \begin{pmatrix} d^i_t \\ d^x_t \\ 0 \end{pmatrix}$$

- $Z_t = \{\pi_t, x_t, i_t\}'$.
- a_t, b^i_t, c^i_t, c^i_t are not estimated.
- $\bar{b}^i$ is assumed to be equal to the coefficients estimated for the Taylor rule under rational expectations.

Appendix B

Details on the Complete Data Set from the MSC

This appendix shows the descriptive statistics and outcome distribution for the MSC complete database after depurating it by the availability of information in the variables of interest. This information set comprises 192,233 observations, and it serves as a base to take the random sample of 70,000 observations used in the estimation presented in section 2.4.

Variable	**Mean**	**S.D.**	**Min.**	**Max.**
Age	48.673	17.026	18	97
Gender	0.509	0.500	0	1
College	0.452	0.498	0	1
Real income	34,977	31,677	0.6817	448,830
Unemployment rate	5.867	1.774	3.300	15.700
Inflation rate	0.212	0.355	-2.200	1.500

Table B.1: Descriptive statistics of covariates.

The distribution of inflation expectations implies that 82.04%, 14.57%, and 3.38% of the observations are in categories 3, 2, and 1, respectively.

Response	**Observations**
1: Deflation	6,507
2: No inflation	28,013
3: Inflation	157,713

Table B.2: Distribution of survey responses on inflation expectations.

Appendix C

Details on the MCMC Algorithm

In this section, the algorithm followed for estimation is described jointly with all the complete posterior conditionals.

1. Sample β_g from $\beta_g|z, G, \sigma_g^2$ for g = 1,2.

   Within each latent class, or state of nature, the coefficients for the covariates in the ordinal probit model, β_g, are sampled from their full conditional distributions:

   $$\beta_s \sim N(\hat{\beta}_g, \hat{B}_g), \text{ with } \hat{B}_g = \left(B_{0,g}^{-1} + \frac{X_g' X_g}{\sigma_g^2}\right)^{-1} \text{ and } \hat{\beta}_g = \hat{B}_g\left(B_{0,g}^{-1}\beta_{0,g} + \frac{X_g' z_g}{\sigma_g^2}\right).$$

   where X_g and z_g refer to the subvectors of the covariates in the ordinal probit model, X, and the continuous latent variable, z, for class g.

2. Sample σ_g^2 from $\sigma_g^2|\beta_g, z, G$ for g = 1,2.

   Similarly, the variances of the ordered probit are sampled for each class from their conditionals given by:

   $$\sigma_g^2 \sim \mathcal{IG}(\hat{\nu}, \hat{d}), \text{ with } \hat{\nu} = \left(\frac{\nu + n_g}{2}\right) \text{ and } \hat{d} = \left(\frac{d + (z_g - X_g\beta_g)'(z_g - X_g\beta_g)}{2}\right).$$

   where n_g is the number of observations in class g.

3. a. Sample α from $\alpha|\beta, \sigma^2, y$ where $\beta = \{\beta_1, \beta_2\}$, $\sigma^2 = \{\sigma_1^2, \sigma_2^2\}$.

The class membership model coefficients, α, are sampled from their full conditional distributions:

$$\alpha \sim N(\hat{\alpha}, \hat{A}), \text{ with } \hat{A} = (A_0^{-1} + W'W)^{-1} \text{ and } \hat{\alpha} = \hat{A}(A_0^{-1}\alpha_0 + W'l).$$

b. Sample l_i from $l_i|\alpha, g$ for i = 1,2,...,n.

Following Albert and Chib (1993), the continuous latent variable in the membership model, l, is sampled from:

$$l_i \sim \mathcal{TN}_{B_i}(W_i'\alpha, 1),$$

$$with \quad B_i = \begin{cases} (0, \infty), & \text{if } g_i = 2 \\ (-\infty, 0], & \text{if } g_i = 1 \end{cases}$$

4. Sample g_i' from $g_i'|\alpha, \beta, \sigma^2, y$ for i = 1,2,...,n.

   The class indicator, g_i, is transformed into a binary variable $g_i' = g_i - 1$, so it can be easily sampled from a Bernoulli distribution:

   $$g_i' \sim Bernoulli(K_i), \text{ with } K_i = \left(\frac{\Phi(W_i'\alpha)P_{y_i|2}}{[1-\Phi(W_i'\alpha)]+P_{y_i|1}\Phi(W_i'\alpha)P_{y_i|2}}\right)$$

   where $P_{y_i|g} = \Phi\left(\frac{\gamma_{y_i,g} - x_i'\beta_g}{\sigma_g}\right) - \Phi\left(\frac{\gamma_{y_{i-1},g} - x_i'\beta_g}{\sigma_g}\right)$, g = 1, 2, is derived from the ordinal probit model by substituting into $P_{ij|g}$ the realization of y_i.

5. Sample z_{i,g_i} from $z_{i,g_i}|\beta, \sigma^2, y, G$ for i = 1,2,...,n.

   Once again, taking advantage of the data augmentation method proposed by Albert and Chib (1993), the continuous latent variable in the ordered probit model, z, is sampled from:

   $$z_{i,g} \sim \mathcal{TN}_{\gamma_{y_i-1},\gamma_{y_i}}(x_i'\beta_{g_t}, \sigma_{g_i}^2),$$

   where γ_{y_i} is the cut-point for the realization of y_i.

Appendix D

Ordinal Probit Model Results

	Posterior mean	**90% credible interval**
Latent class 1		
Age	0.031	[0.013, 0.049]
Gender	-0.020	[-0.053, 0.014]
College	-0.118	[-0.157, -0.080]
Income	0.037	[0.021, 0.053]
σ_1^2	0.760	[0.576, 0.876]
Latent class 2		
Age	-0.096	[-0.127, -0.065]
Gender	-0.083	[-0.139, -0.026]
College	0.049	[-0.013, 0.113]
Income	0.064	[0.035, 0.091]
σ_1^2	1.177	[1.058, 1.306]
Class membership		
Regional u rate	0.377	[0.331, 0.424]
Regional π rate	-0.225	[-0.260, -0.192]

Table D.1: Posterior means for the ordinal probit model parameters.

	Deflation	**No inflation**	**Inflation**
Latent class 1			
Age	0	0.001	-0.006
Gender	0	-0.001	0.004
College	0	-0.003	0.021
Income	0	0.001	-0.007
Latent class 2			
Age	-0.001	-0.003	0.034
Gender	-0.001	-0.002	0.024
College	0	0.001	-0.014
Income	0	0.002	-0.018

Table D.2: Covariate effects of the ordinal probit model.

Appendix E

Label-Switching Correction

Label-switching is a common identification problem in mixture models. This occurs because the distribution of the parameters of interest remains unchanged if the group labels are permuted. For example, in the present latent class model, if we interchange the label indicators $g_i = 1$ and $g_i = 2$, and replace K_i with $1 - K_i$, the likelihood of the data will remain the same.

There are multiple solutions to eliminate this issue. In this paper, following Papastamoulis (2016), I considered the following three methods:

- Ordering constraint on the intercept in both classes $\beta_{0,1} < \beta_{0,2}$.
- Stephens method.
- Equivalence Classes Representatives (ECR).

However, in the end, the estimation of the latent class ordinal probit model using simulated data and survey data from the MSC does not present label-switching issues. Therefore, correcting of the results by the methods described in Papastamoulis (2016) is not necessary.

Appendix F

Data Details

F.1 Expectations Data

Expectation data are extracted from the Survey of Professional Forecasters conducted quarterly by the Federal Reserve Bank of Philadelphia since 1990:Q2. However, SPF data are available from 1968:Q4 and onwards as it was previously implemented by the American Statistical Association (ASA) and the National Bureau of Economic Research (NBER). This survey is applied each quarter, just after the release of the Bureau of Economic Analysis's (BEA) advance report of the national income and product accounts (NIPA) which is published at the end of the first month of each quarter. In addition, responders have as deadline to submit their forecasts at late in the second to third week of the middle month of each quarter.[1] The Federal Reserve Bank of Philadelphia appends recent historical relevant data to its survey questionnaires. Therefore, it is safe to assume that projections from professional forecasters incorporate all available data, that is, information up to period $t-1$.

At each quarter, forecasters provide their projections for the current and next four quarters, plus

[1] The timing of surveys prior to the Philadelphia Fed take-over in 1990:Q2 Survey is not clear. However, in the official documentation of the survey, the Fed expresses: "We think that, in broad terms, the timing was similar to that adopted by the Philadelphia Fed."

forecasts for the end of the current and next years are also available. All survey forecasts are seasonally adjusted and reflect the quarterly level of the relevant variable being projected. Additionally, certain forecasts are available for longer horizons. Unfortunately, this is not the case for forecast of relevant variables used in this study. This leads to truncation in the estimation of the model at j=4.

Taking all available information, survey data are exploited to extract expectations on inflation, output, and nominal interest rate formed with different information sets. For instance, expectations are constructed with information updated up to t-j with $j = \{1, 2, 3, 4\}$, as required by the proposed model and allowed by the truncation level.

Inflation expectations. Inflation expectations of the form $E_{t-j}\pi_{t+1}$ enters directly the model, where j reflect the lag agents have on their information sets. Thus, these expectations are the ones extract from the SPF database.

In this paper, inflation expectations are derived using the nowcast and one-period-ahead forecasts for the chain-weighted GDP price index, label as "PGDP" in the survey.

In specific, inflation expectations are computed as 100 times the log of the expected one-quarter-ahead PGDP minus the log of the expected current quarter PGDP and using information up to t-j to account for the assumption of inattentive agents:

$$E_{t-j}(\pi_{t+1}) = 100(ln(E_{t-j}(PGDP_{t+1})) - ln(E_{t-j}(PGDP_t))) \tag{F.1}$$

Output expectations. Output gap expectations for the current and next-quarter play a role in the model, $E_{t-j}x_t$ and $E_{t-j}x_{t+1}$. Again, j reflects the lag on the information set of available to agents. However, the SPF reports only information about GDP expectations. Thus, I exploit this data to construct output growth expectations, denoted here as $E_{t-j}\Delta y_{t+1}$ and $E_{t-j}\Delta y_t$, as follows. First, I divide the expected nominal GDP, labeled as "NGDP", by the GDP price index projection, "PGDP", to construct real GDP expectations. Next, I compute growth rates of expected real GDP between $t-j$ and $t+1$ and among $t-j$ and t, as required by the model.

$$E_{t-j}(\Delta y_{t+1}) = ln\left(\frac{E_{t-j}(RGDP_{t+1})}{E_{t-j}(RGDP_{t-1})}\right) \tag{F.2}$$

$$E_{t-j}(\Delta y_{t}) = ln\left(\frac{E_{t-j}(RGDP_{t})}{E_{t-j}(RGDP_{t-1})}\right) \tag{F.3}$$

where:

$$E_{t-j}(RGDP_{t+1}) = 100ln\left(\frac{E_{t-j}(NGDP_{t+1})}{E_{t-j}(PGDP_{t+1})}\right) \tag{F.4}$$

$$E_{t-j}(RGDP_{t}) = 100ln\left(\frac{E_{t-j}(NGDP_{t})}{E_{t-j}(PGDP_{t})}\right) \tag{F.5}$$

$$\tag{F.6}$$

In the estimation, these expectations about growth rates of real GDP are mapped into output gap growth expectations in the measurement equation.

Interest rate expectations. Finally, $E_{t-1}i_t$ also enters the model directly. I could take these expectations from the SPF, as the survey reports information for the present-period nominal interest rate expectations. However, they are only available from 1981:Q3. Alternatively, I estimate them using the expectations theory of the term structure, as Milani (2011), and data for the three and six-month Treasury bill rate.[2] In particular, expectations theory of the term structure implies that:

$$i_t^{6M} = \left(\frac{i_t^{3M} - E_t i_{t+1}^{3M}}{2}\right) + \zeta \tag{F.7}$$

$$E_{t-1}i_t^{3M} = 2i_t^{6M} - i_t^{3M} - \zeta \tag{F.8}$$

where ζ is the constant risk premium, assumed here equal to 0.

[2] This decision is mainly due to the fact that data on TBILL expectations are available on the SPF.

F.2 Real-Time Data

As counterpart of survey expectations, I use real-time quarterly data from 1969-Q3 to 2006-Q1. This information is unrevised data available to economic agents at the time of the survey was applied. According to the Federal Reserve Bank of Philadelphia, forecasters information set is updated up to period t-1 when answering questionnaires for period t: *"The survey's timing is geared to the release of the Bureau of Economic Analysis's (BEA) advance report of the national income and product accounts (NIPA). This report is released at the end of the first month of each quarter. It contains the first estimate of GDP (and components) for the previous quarter. We send our survey questionnaires after this report is released to the public. The survey's questionnaires report recent historical values of the data from the BEA's advance report and the most recent reports of other government statistical agencies. Thus, in submitting their projections, our panelists' information sets include the data reported in the advance report."* All data are extracted from the Federal Reserve Bank of Philadelphia and processed as follows.

Inflation is constructed as 100 times the log difference of the real-time price index for GDP, labeled as "PQvQd" in the Real-Time Data Set for Macroeconomists.[3]

$$\pi_t = 100(ln(PQvQd_t) - ln(PQvQd_{t-1})) \tag{F.9}$$

Output is measured as real GDP and is computed dividing the real-time Nominal GDP, denoted "NOUTPUT" in the Real-Time Data Set for Macroeconomists, and the real-time GDP price index. While potential output is taken from the CBO's estimate.

For interest rate, I use the three-month Treasury bill (expressed on a quarterly basis) as the SPF includes data on T-bill expectations is available on the SPF. As a proxy for real-time data on three-month T-bill, I used one-period lagged revised information since, unfortunately, the Philadelphia Fed does not release for real-time data information before 1981-Q3.

[3]For more details on this data set, see Croushore and Stark (2001).

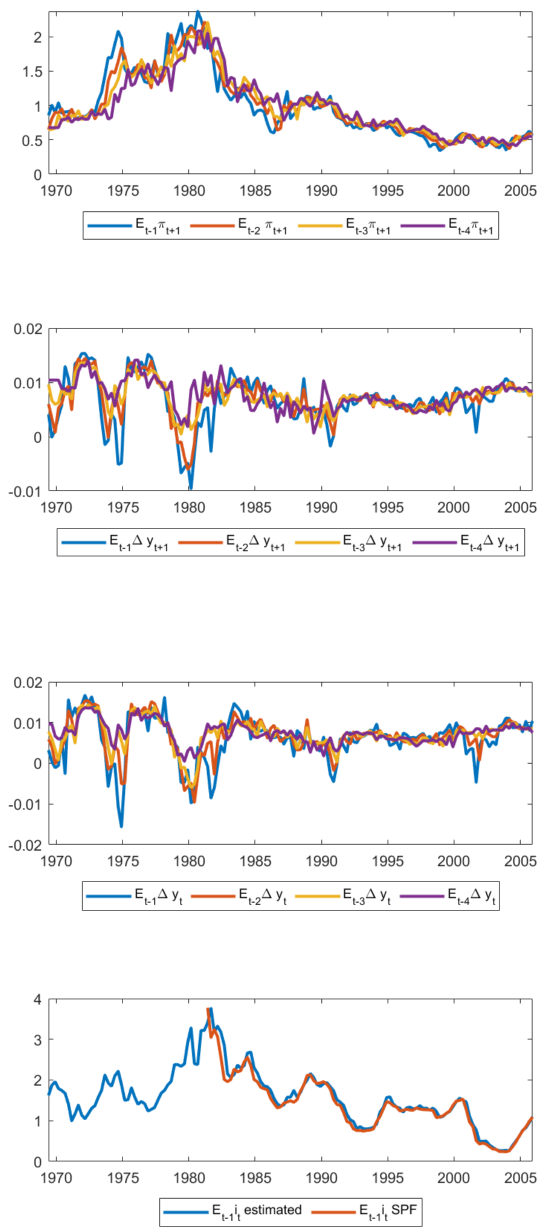

Figure F.1: SPF and market expectations.

Appendix G

Additional Figures and Tables

	Posterior means			
	1969Q3-2006Q1	**1969Q3-1980Q4**	**1981Q1-2006Q1**	**1969Q3-2019Q4**
α_p	0.557	0.553	0.599	0.524
ρ	0.832	0.767	0.745	0.878
ϕ_π	1.236	1.191	1.232	1.418
ϕ_x	0.060	0.066	0.019	0.031
λ_p	0.163	0.491	0.202	0.100
ρ_p	0.747	0.625	0.744	0.774
ρ_x	0.500	0.518	0.613	0.597
ρ_i	0.365	0.460	0.616	0.371
σ_p	9.281	7.903	7.794	11.685
σ_x	1.831	2.403	0.989	1.423
σ_i	0.200	0.285	0.133	0.179
g	0.002	0.006	0.003	0.001
Log. Marginal L.	-1,066.597	-640.295	-394.546	-1,190.110

Table G.1: Posterior estimates for different samples, survey expectations and real-time data model.

	Posterior mean	95% Credible interval
$\rho_{e^{\pi},1}$	0.470	[0.356, 0.598]
$\rho_{e^{\pi},2}$	0.846	[0.788, 0.901]
$\rho_{e^{\pi},3}$	0.851	[0.794, 0.905]
$\rho_{e^{\pi},4}$	0.888	[0.842, 0.932]
$\rho_{e^{i}}$	0.821	[0.758, 0.882]
$\rho_{e^{x_0},1}$	0.861	[0.789, 0.925]
$\rho_{e^{x_0},2}$	0.336	[0.167, 0.528]
$\rho_{e^{x_0},3}$	0.407	[0.268, 0.626]
$\rho_{e^{x_0},4}$	0.535	[0.328, 0.733]
$\rho_{e^{x_{01},1}}$	0.046	[-0.033, 0.132]
$\rho_{e^{x_{01},2}}$	0.422	[0.266, 0.564]
$\rho_{e^{x_{01},3}}$	0.418	[0.227, 0.551]
$\rho_{e^{x_{01},4}}$	0.332	[0.149 0.519]
$\rho_{e^{x_1},1}$	0.741	[0.627, 0.845]
$\rho_{e^{x_1},2}$	0.797	[0.648, 0.913]
$\rho_{e^{x_1},3}$	0.753	[587, 0.900]
$\rho_{e^{x_1},4}$	0.697	[0.519, 0.851]
$\rho_{e^{x_{10},1}}$	0.100	[-0.024, 0.223]
$\rho_{e^{x_{10},2}}$	0.066	[-0.104, 0.270]
$\rho_{e^{x_{10},3}}$	0.152	[-0.024, 0.358]
$\rho_{e^{x_{10},4}}$	0.244	[0.057, 0.451]
$\sigma_{e^{\pi},1}$	0.202	[0.184, 0.223]
$\sigma_{e^{\pi},2}$	0.160	[0.145, 0.176]
$\sigma_{e^{\pi},3}$	0.141	[0.128, 0.1556]
$\sigma_{e^{\pi},4}$	0.135	[0.123, 0.148]
$\sigma_{e^{i}}$	0.086	[0.078, 0.095]
$\sigma_{e^{x_0},1}$	0.406	[0.369, 0.447]
$\sigma_{e^{x_0},2}$	0.535	[0.484, 0.591]
$\sigma_{e^{x_0},3}$	0.636	[0.578, 0.701]
$\sigma_{e^{x_0},4}$	0.692	[0.627, 0.763]
$\sigma_{e^{x_1},1}$	0.566	[0.514, 0.624]
$\sigma_{e^{x_1},2}$	0.660	[0.599, 0.728]
$\sigma_{e^{x_1},3}$	0.702	[0.638, 0.774]
$\sigma_{e^{x_1},4}$	0.728	[0.660, 0.802]

Table G.2: Posterior estimates for expectational shocks parameters, survey expectations and real-time data model.

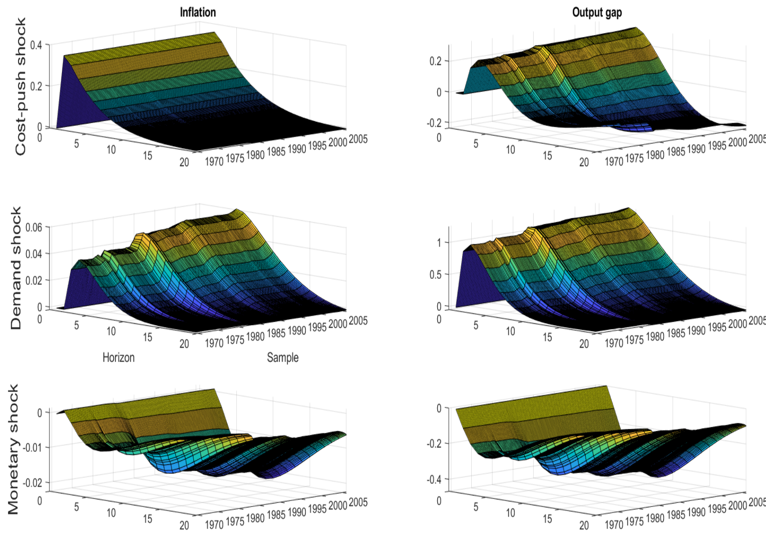

Figure G.1: 3-Dimensional impulse response functions to a one standard deviation positive cost-push, demand and monetary shock, survey expectations and real-time data model.
Note: Impulse response function are estimated as an average of the last 5,000 draws from the Metropolis-Hastings algorithm.

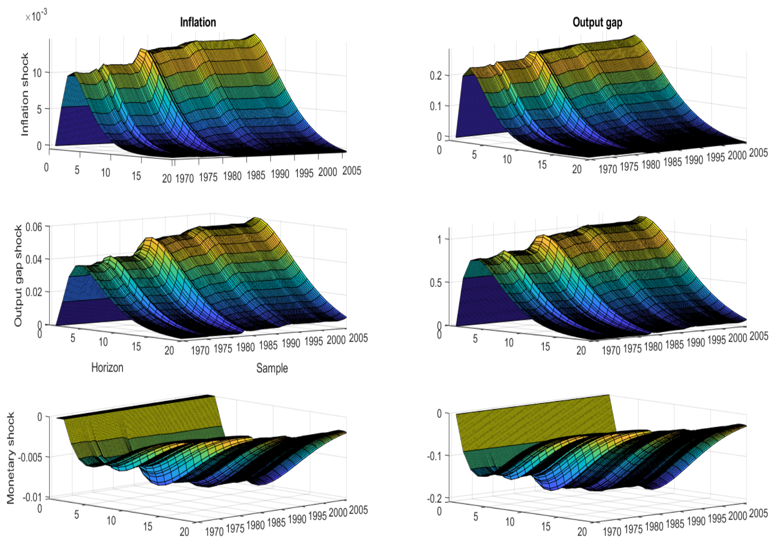

Figure G.2: 3-Dimensional impulse response functions to a one standard deviation positive expectational shock, survey expectations and real-time data model.
Note: Impulse response function are estimated as an average of the last 5,000 draws from the Metropolis-Hastings algorithm.

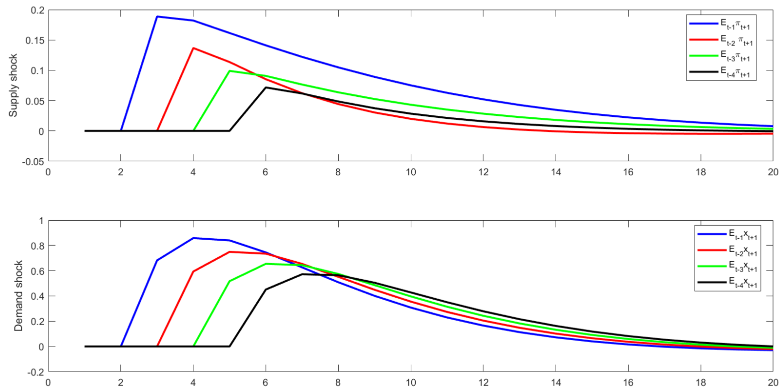

Figure G.3: Average impulse response functions of future expectations, formed with different information sets, to a one standard deviation positive supply and demand shocks, survey expectations and real-time data model.

Note: Impulse response function are estimated as an average of the last 5,000 draws from the Metropolis-Hastings algorithm.