Business Cycle Fluctuations in High- and Low-Information Regimes: An Empirical Investigation

Luca Gambetti*
Universitat Autònoma de Barcelona, BSE,
Università di Torino and Collegio Carlo Alberto

Abstract

Consumers' information about current macroeconomic conditions varies over time. Fluctuations in information significantly influence macroeconomic dynamics. In a high-information regime the main business cycle shock generates (i) larger business cycle fluctuations in GDP and consumption, and (ii) greater volatility in consumers' expectations, GDP and consumption than in a low-information regime. The evidence is obtained using frequency-domain techniques in a Threshold SVAR estimated on US data, where the state variable is a novel measure of consumers' information constructed from the Michigan Survey of Consumers. Results are in line with the predictions of limited-information models with time-varying degree of information frictions.

JEL classification: C32, E32.

Keywords: Business Cycles, Consumers' Information, Consumers' Expectations, Asymmetric Business Cycles, Threshold SVAR, Information Cycles, Imperfect Information, Main Business Cycle Shock.

*I acknowledge the financial support from the Spanish Ministry of Science and Innovation, through the Severo Ochoa Programme for Centres of Excellence in R&D (CEX2019-000915-S), the financial support of the Spanish Ministry of Science, Innovation and Universities through grant PGC2018-094364-B-I00, and the Barcelona Graduate School Research Network.

1 Introduction

In modern macroeconomics, agents' expectations play a key role for macroeconomic dynamics and the transmission of macroeconomic shocks. Expectations are formed on the basis of the available information about current and future economic developments. This establishes a direct and potentially important link between information and macroeconomic dynamics. The *primum movens* of this research is the consideration that if, as I will document, information is not constant but rather varies over time, then also the response of macroeconomic variables to economic shocks can potentially change. In other words, information can act as a mechanism that amplifies or dampens economic fluctuations.

Time varying information sets are simply excluded by assumption under the Full Information Rational Expectations (FIRE) paradigm (see the seminal contribution by Muth, 1961). A growing number of works have departed from the FIRE framework because of its limited capability of accounting for several empirical phenomena (see Pesaran and Weale, 2006), and have explored other theoretical settings where information is limited, like models with sticky and noisy information.[1] In the former, see Mankiw and Reis (2002), only a fraction of agents update their information set at every point in time. As a consequence, information flows become more sluggish and the average expectation of future variables turns out to be a combination of past rational expectation forecasts with weights that depend on the proportion of agents updating their information. Under noisy information, see Woodford (2001) and Lorenzoni (2009, 2010), agents still use rational expectations but their information set is limited in the sense that they do not perfectly observe current economic shocks.[2] Agents might be able to learn the true value of the shock only in the future.[3] From an empirical point of view, several papers have tested the predictions of models of imperfect information and found evidence supporting those predictions.[4]

[1] There are other alternative theoretical frameworks to model limited information. For instance, under rational inattentions, see, among others, Mackowiak and Wiederholt (2009), Paciello and Wiederholt (2014) and Sims (2003), agents are constrained in their ability of processing information and have to select which information to acquire. Under learning, see among others Evans and Honkapohja (2012), Adam, Marcet and Nicolini (2016), agents learn about features of the models and model parameters.

[2] See also Blanchard L'Huillier and Lorenzoni (2013) among others.

[3] Several papers have provided the micro-foundations of imperfect information models mostly relying on the cost of acquiring information, see, among others, Reis, (2006a, 2006a) Sims (2003), Matějka, (2016) and Matějka and McKay (2012). Other papers have studied the policy implications of imperfect information (see among others Reis, 2009).

[4] Using survey data Coibion and Gorodnichenko (2012, 2015) and Andrade and Le Bihan (2013) find that forecast errors are predictable, an implication which is ad odds with FIRE models. Other papers,

In models with information frictions, both the magnitude and the persistence of the responses of expectations, and thus consequently of macroeconomic variables, depend on the degree of frictions, i.e. on the speed of the expectations adjustment process and the level of the signal to noise ratio. The specific way agents react to shocks will depend on their preferences and other modeling assumptions.

When one embraces the idea that information is imperfect, there is no compelling reason to exclude the possibility that the amount of information held by economic agents, or the degree of information frictions, can change over time. The empirical evidence, including the one provided in this paper, suggests that information is countercyclical. In Cheremukhin and Tutino (2016) this is due to the fact that firms optimally allocate more attention to economic conditions in recession than in expansion. Other papers point out that recessions receive a larger news coverage than expansions, either because of the existence of a media bias (Soroka, 2006) or simply because bad shocks might have larger effects on macroeconomic variables. If information varies over time, then the dynamics of macroeconomic variables generated by agents' expectations can also vary. Thus, information can acts as a channel amplifying or dampening economic fluctuations. The aim of the paper is to empirically assess this role.

The starting point of my analysis is to derive measures of consumers' information. I rely on the Michigan Survey of Consumers. The main information measure I use is based on Question A6 of the questionnaire, which asks: *"During the last few months, have you heard of any favorable or unfavorable changes in business conditions?"*. Respondents can answer either *"Yes"* or *"No, haven't heard"*. I take the percentage of respondents answering ''Yes" as a proxy for consumers' information. The variable reflects the fraction of informed consumers as well as, presumably, the fraction of agents of agents updating their expectations. In an extension of the baseline model, I develop two measures of pervasiveness of information, defined as the extent to which individuals agree about whether the news received are favorable or unfavorable. If a responds ''Yes" to A6, then a second question, A6b, is asked: ''What did you hear? (Have you heard of any other favorable or unfavorable changes in business conditions?)''. The survey classifies responses either ''positive" or ''negative". The two measures are the following: (1) the absolute value of the difference between the proportion of favorable minus unfavorable; (2) the entropy associated to the responses.

The three measures display ''information cycles", i.e. protracted periods of low in-

see Mankiw, Reis and Wolfers (2004), Dovern et al. (2012) and Andrade et al. (2016), have used survey data disagreement and dispersion to assess the empirical support of imperfect information models.

formation followed by periods of high information. These cycles tend to be negatively correlated with the business cycle, with information typically declining during economic booms and rising during recessions.

To assess the effects of information as an amplifying mechanism of economic fluctuations, I employ a Threshold Structural Vector Autoregression (TSVAR) with the information variable as the state variable. A key challenge is that information variables are correlated with the business cycle, so any observed asymmetries could reflect differences in agents' response during expansions versus recessions, rather difference is the information sets. To address this issue I first filter the information variable to remove the component driven by changes in economic conditions. A define a high-information when the filtered measure is above its median, and a low-information when the variable is below the median. The model includes two consumers' expectation variables –the Michigan Confidence Index and the expected buying conditions for large household goods (DUR)– and two macroeconomic variables –GDP and consumption growth.

I perform two types of analysis. First, I analyze the model-based unconditional spectral densities of the four variables in the two information regimes. Second, I identify the main business cycle shock in the two regimes along the line of Angeletos et al. (2020) and Forni et al. (2024), and I investigate the conditional spectral densities constructed using the impulse response functions of the identified shock.

The main finding are as follows. The main business cycle shock generates (i) larger business cycle fluctuations in consumption and GDP; (ii) more volatile expectations, consumption and GDP than in a low-information regime; (iii) conditional spectra of consumption and GDP with a higher mass concentrated at the business cycle frequencies. Similar findings also emerge for the unconditional spectral densities. The evidence point to information as an important amplifier mechanism of economic shocks.

Using a simple theoretical framework with sticky and limited information, I show that the empirical findings are consistent with the model's predictions. More specifically i show that the larger estimated variance of macroeconomic variables in the high-information regime can be attributed to both a larger probability of updating expectations and a larger signal-top noise ratio. By contrast, only the former appears to play a key role in amplifying business cycle fluctuations.

When frictions are low both the variance of expectations and consumption and the business cycle fluctuations of consumption are higher than when the frictions are high.

The paper is closely related, in terms of the methodology, to Ricco, Callegari and Cimadomo (2016). The authors study the effects of fiscal policy shocks in period of low and high disagreement among US professional forecasters. They find that fiscal policy shocks are much more effective for GDP and investment in periods of low disagreement than in periods of high disagreement, reaching a conclusion similar to mine: information matters.

The remainder of the paper is organized as follows. Section 2 discusses the econometric approach. Section 3 presents the main results. Section 4 presents a very stylized theoretical framework of imperfect information. Section 5 concludes.

2 Econometric approach

In this section I discuss the econometric approach, the empirical measure of consumers' information, the macroeconomic data and the model specification.

2.1 The model

I employ a Threshold Vector Autoregression model, see Tong (1983) and Tsay (1998).[5] The model is a state-dependent model with two observed states: high-information and low-information. More formally, let y_t be a n-dimensional covariance stationary time series vector which is assumed to follow

$$y_t = F(z_t)(\mu_H + A_H(L)y_{t-1} + S_H u_t) + (1 - F(z_t))(\mu_L + A_L(L)y_{t-1} + S_L u_t), \qquad (1)$$

where L is the lag operator, $F(z_t)$ is a dummy variable taking value 1 in the high information regime and 0 in the low information regime and z_t is the underlying information variable (see next subsection for details), $A_H(L) = A_{H1} + A_{H2}L + ... + A_{Hp}L^{p-1}$ and $A_L(L) = A_{L1} + A_{L2}L + ... + A_{Lp}L^{p-1}$ are the VAR polynomial matrices in the high- and low-information regime respectively, μ_H and μ_L are the constant terms in the two regimes and $u_t \sim WN(0, I)$. The matrix S_H is the Cholesky factor of Σ_H, the covariance matrix of the innovation in the high information regime $\varepsilon_{Ht} = S_H u_t$. The matrix S_L is the Cholesky factor of Σ_L, the covariance matrix of the innovation in the low information regime $\varepsilon_{Lt} = \Sigma_L u_t$.

The model can be rewritten as

$$y_t = F(z_t)\Psi_H(L)u_t + (1 - F(z_t))\Psi_L(L)_t, \qquad (2)$$

[5]This modeling approach has been extensively used to study the state-dependent effects on fiscal policy shocks, see Ricco, Callegari and Cimadomo (2016), Caggiano et al. (2015) and Owyang, Ramey and Zubairy (2013) among others.

where $\Psi_H(L) = (I - A_H(L)L)^{-1}S_H$, are the impulse response functions in the high-information regime, while $\Psi_L(L) = (I - A_L(L)L)^{-1}S_L$ are those in the low-information regime. The impulse response functions of this representation do not have any structural meaning since the Cholesky representation is simply used as a statistical representation of the data which is particularly useful to define the spectra as below.

The unconditional dynamics of y_t are studied using frequency domain analysis. When $F(z_t) = 1$ the spectral density of y_t at frequency $\omega = 0, ..., \pi$ is

$$\mathcal{S}_H(\omega) = (2\pi)^{-1}\Psi_H(e^{-i\omega})\Psi_H(e^{i\omega})',$$

while when $F(z_t) = 0$ the spectral density is

$$\mathcal{S}_L(\omega) = (2\pi)^{-1}\Psi_L(e^{-i\omega})\Psi_L(e^{i\omega})'.$$

Finally, I define $s_H(\omega)$ the vector containing the diagonal elements of $\mathcal{S}_H(\omega)$ (the spectra of the n variables in the high information regime) and $s_L(\omega)$ the vector containing the diagonal elements of $\mathcal{S}_L(\omega)$ (the spectra of the n variables in the low information regime).

Model estimation is done as follows. The matrices of coefficients $A_H(L)$ and $A_L(L)$ are estimated with OLS. The covariance matrices of the two regimes are estimated as $\hat{\Sigma}_H = \bar{\tau}^{-1}\sum_{t\in\tau_H}\hat{\varepsilon}_{Ht}\hat{\varepsilon}'_{Ht}$, where $\hat{\varepsilon}_{Ht}$ is the vector of residuals in the high information regime ($\bar{\tau}$ is the number of periods of high information regime and τ_H the set of time periods in the high information regime), and $\hat{\Sigma}_L = \underline{\tau}^{-1}\sum_{t\in\tau_L}\hat{\varepsilon}_{Lt}\hat{\varepsilon}'_{Lt}$, where $\hat{\varepsilon}_{Lt}$ is the vector of residuals in the high information regime ($\underline{\tau}$ is the number of periods of high information regime and τ_L the set of time periods in the low information regime). Confidence bands are constructed using bootstrap.

2.2 Identification

To better understand the business cycle properties of the macroeconomic variables in the two regimes, I identify the main business cycle shock in the two regimes and then study its impulse response functions and the implied spectral densities. The shock, in the spirit of Angeletos et al. (2020) and Forni et al. (2025), is defined as the one that maximizes the variance at the business cycle frequencies of both consumption and GDP. The implementation is done as in Forni et al. (2025). Let h_H and h_L the unit-norm column vectors obtained from the maximization of the cyclical variance in the high- and low-information regime respectively. The impulse response functions of the main business cycle shock are $\psi_H(L) = \Psi_H(L)h_H$ and $\psi_L(L) = \Psi_L(L)h_L$ in the two regimes respectively.

The spectral densities generated by the main business cycle shocks are

$$\mathcal{C}_H(\omega) = (2\pi)^{-1}\psi_H(e^{-i\omega})\psi_H(e^{i\omega})'$$

in the high-information regime ($F(z_t) = 1$), and

$$\mathcal{C}_L(\omega) = (2\pi)^{-1}\psi_L(e^{-i\omega})\psi_L(e^{i\omega})'$$

in the low-information regime ($F(z_t) = 0$).

Let $c_H(\omega)$ be the vector containing containing the spectra of the n variables (the diagonal elements of $\mathcal{C}_H(\omega)$) in the high-information regime generated by the main business cycle shock, and let $c_L(\omega)$ be the vector containing containing the spectra of the n variables (the diagonal elements of $\mathcal{C}_L(\omega)$) in the low-information regime generated by the main business cycle shock. As in Angeletos et al. (2020), the main business cycle shock does not have any structural interpretation. This however is not a drawback since the aim is to understand what are the maximal fluctuation at the business cycle frequencies that can be attained in the two regime and assessing whether they are different.

2.3 Empirical measures of consumers' information

I construct a consumers' information measure using the Michigan Survey of Consumers. Question A6 of the Michigan Survey questionnaire asks: *"During the last few months, have you heard of any favorable or unfavorable changes in business conditions?"*. There are two possible answers: *"Yes"* and *"No, haven't heard"*. My main information variable X_{1t} is the proportion of individuals responding ''Yes". The left panel of the first row of Figure 1 plots the information variable (red solid line). For sake of comparison, the unemployment rate is also reported (dashed black line).

The percentage of informed individuals varies over time. In particular, a persistent information cycle, a sequence of protracted high-information periods followed by a sequence of protracted low-information periods, emerges. It is remarkable that a sizable amount of individuals do not hear any news about current economic conditions. This information cycle is negatively correlated with the business cycle: agents tend to be more informed in recessionary periods than in expansions, the correlation coefficient between X_{1t} and the unemployment rate being 0.4.

As I will discuss in section 4, X_{1t} can be interpreted as a proxy for information frictions. On the one hand, the variable reveals the percentage of individuals updating their expectations as long as individuals exposed to new information actually revise their expectations, as it seems plausible to think. On the other hand the variable proxies also the information content conveyed by the signal about economic outcomes the agents receive at every point in time. The number of informed individuals is higher when the signal they receive is more informative.

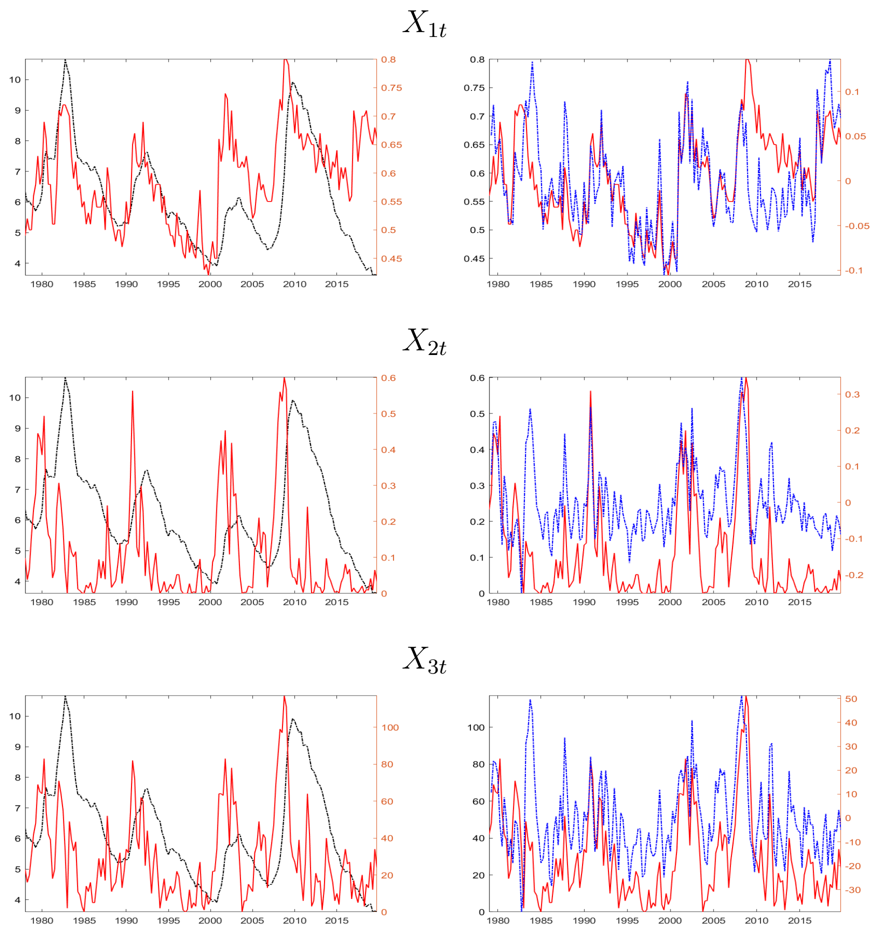

Figure 1: Left column: news variable (red solid lines) and unemployment rate (black dotted lines). Right column: news variables (red solid lines) and purged news variables (blue dotted lines).

The threshold variable, z_t, I employ is a cleaned version of X_{1t} where the component driven by business cycle fluctuations is removed. The main reason of this treatment is that, as seen before, the information variable is strongly countercyclical and without such a preliminary cleaning, one might attribute asymmetries to different information sets while they could simply arise because agents' response to economic shocks is different in recessions and expansions. To clean the news variable from the component attributable by business cycle fluctuations, I regress the news variable onto the current value and four lags of log GDP and the unemployment rate. I then set z_t equal to the residual of this regression. The purged variable thus represents the changes in information which are orthogonal to current and past values of unemployment rate and GDP. I define the high-information regime $F(z_t) = 1$ when $z_t \geq Med(z_t)$, i.e. larger than the median, and the low-information regime $F(z_t) = 0$ when $z_t < Med(z_t)$.[6]

The right panel of the first row of Figure 1 plots the original series (red solid line) together with its purged version (dashed-dotted blue line). The purging, as expected, seems to play an important role since fluctuations in the purged version are substantially mitigated, especially in correspondence of the Great Recession. Nonetheless, large and relatively persistent swings still remain even after removing the effects attributable to the business cycle.

I also derive two other measures of information. These two measures are related to the pervasiveness of information, where by pervasiveness I mean the extent to which agents agree about the sign of the news received, i.e. whether news are favorable or unfavorable. Conditional on answering ‘’Yes” in question A6, a second question, A6b, is asked: ‘’What did you hear?”. The answers to this question are classified by the survey conductor as ‘’favorable” or ‘’unfavorable”. A first measure is simply

$$X_{2t} = |F_t - U_t|$$

where F_t is the number of responses ‘’Favorable” and U_t the number of responses ‘’Unfavorable”. Pervasiveness is maximal when all the agents response either ‘’favorable” or ‘’unfavorable” and minimal when the responses are split in an equal proportion.

A second measure is base on the concept of entropy in information theory. Let $f_t = \frac{F_t}{F_t+U_t}$. The measure is the following

$$X_{3t} = 1 + E_t,$$

where $E_t = -f_t \log_2(f_t) - (1 - f) \log_2(1 - f_t)$ is the entropy.[7] Pervasiveness is maximal when entropy is zero (all the individuals agree on the type of news heard, favorable or unfavorable) which occurs when $f_t = 1$ or $f_t = 0$ and minimal when $f_t = 1/2$.

The second and third row of Figure 1 depicts the two pervasiveness measures. The left panels plot the information variable (red solid line) and the unemployment rate (dashed black line). Similarly to X_{1t}, pervasiveness tends to be countercyclical. During recessions, agents generally exhibit greater agreement about economic outcomes. One possible explanation is that recessions dominate the headlines, whereas expansions receive less media

[6]Using the mean does alter the results.

[7]When $f_t = 0$, the standard convention $-f_t \log_2(f_t) = 0$ is used.

coverage. The right panels plot the original series (red solid line) alongside its purged version (dashed-dotted blue line). Once again, purging the variable appears to be important confirming that a substantial portion of the variable is endogenous and can be explained by business cycles indicators.

2.4 Data and model specification

I use US quarterly data spanning 1978:Q1-2019:Q4. I start the sample in 1978 because of the availability of the information variable. Vector y_t includes the following variables: the Michigan Confidence Index (ICS, Michigan survey mnemonic), buying conditions for large household goods (DUR, Michigan survey mnemonic),[8] the growth rate of total real personal consumption expenditures and the growth rate of GDP. The first two variables are taken as measures of consumers' expectations, the last two are the macroeconomic variables of interest. The number of lags is set equal to three. I choose a parsimonious specification because of the relatively short sample available and the relatively high number of parameters of the model.

3 Evidence

This section reports the main empirical results. First I discuss the unconditional spectra, then I present the results obtained for the main business cycle shock.

3.1 Unconditional spectral densities

Figure 2 reports the unconditional spectra of the four variables, i.e. $s_H(\omega)$ and $s_L(\omega)$. The first column reports the spectra in the high information (blue solid line) and low information (dotted red) regimes, gray areas represents the business cycle frequencies; column two reports the normalized spectra (the spectra normalized by the sum of the spectra at all frequencies), gray areas represents the business cycle frequencies; column three reports the confidence bands (light gray 95% and dark gray 68%) of the difference between the spectrum in high information and the spectrum in low information regime. I report, for sake of clarity only the spectra at frequency in the interval $[0, 1.54]$, which

[8] The question was: About the big things people buy for their homes - such as furniture, a refrigerator, stove, television, etc. Generally speaking, do you think now is a good or a bad time for people to buy major household items? The variable is the difference between the number of responses ''Good time to buy" and ''Bad time to buy"

include the low and business cycle frequencies (the plots do not report the very high frequency being the spectra quite flat at those frequencies).

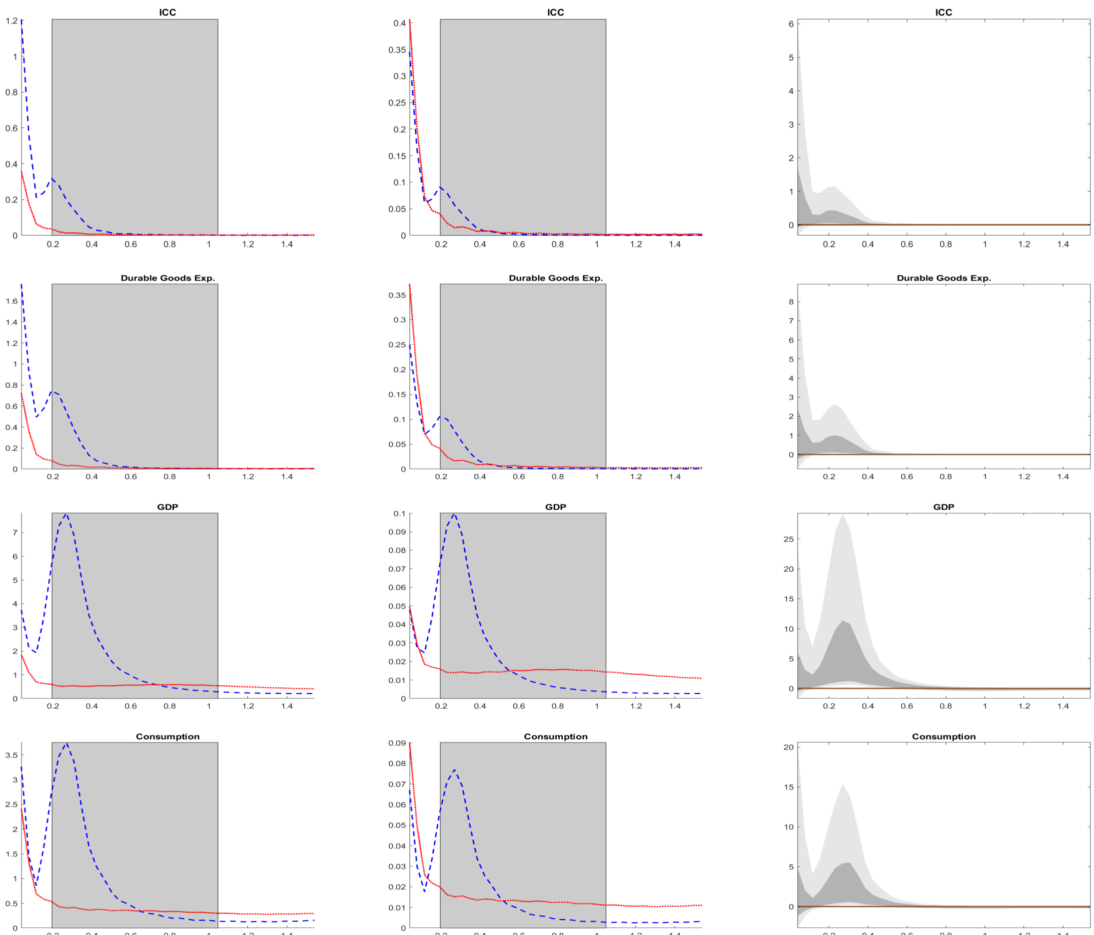

Figure 2: Spectra: column one reports the spectra in the high information (blue solid line) and low information (dotted red) regimes; column two reports the normalized spectra; column three reports the confidence bands of the difference between the spectrum in high information and the spectrum in low information regime, light gray 95%, dark gray 68%.

A few results stand out. First, cyclical fluctuations in consumption and GDP are much larger in the high information case. Indeed, the spectrum of the two variables at the business cycle frequencies in the high information regime is substantially higher than in the low information regime, where the spectral densities peak at the very low frequencies (see column one). The differences are significant (see column three). Second, the same result emerges for the the normalized spectra (column two): the normalized spectra of GDP and consumption growth have a a much larger proportion of variance concentrated at the business cycle frequencies. Third, the variance (the sum of the spectra over all frequencies) of the four variables in the high information regime is higher that in the low information regime. Indeed the blue dashed lines are above the dotted red lines almost everywhere.

In the high-information regime, business cycle fluctuations of macroeconomic variables are larger and the series are more volatile that a low information economy, where low frequency movements play the major role.

The analysis employs the exogenous component of information, the component which is orthogonal to current and past values of macroeconomic variables. This is motivated by the fact the main goal is to isolate the ''pure" information effects on macroeconomic dynamics. However, information, as discussed above, is, to a large extent, countercyclical. This implies that information acts as an endogenous mechanism that amplifies the negative effects of recessions and dampens the positive effects of booms.

3.2 Main business cycle shock

I identify the main business cycle shock in the two regimes as discussed in section 2.4. Figure 3 reports the spectra associated to the main business cycle shock, i.e. $c_H(\omega)$, and $c_L(\omega)$. Column one reports the spectra in the high information (blue solid line) and low information (solid red) regimes, gray areas represents the business cycle frequencies; column two reports the normalized spectra (the spectra rescaled by the sum of the spectra at all frequencies), gray areas represents the business cycle frequencies; column three reports the confidence bands of the difference between the spectrum in high information and the spectrum in low information regime, light gray 95%, dark gray 68%. Again, I report only the spectra at frequency in the interval $[0, 1.54]$.

A few remarks are in order. First, the main business cycle shock generates much larger business cycle fluctuations for all the variables in the high information regime. This can be seen in column one, where the blued dashed line is much above than the red line at the business cycle frequencies. The difference are significant, as it can be seen in column three. Second, not only the cyclical variance is higher, but also the proportion of business cycle variance is higher when information is high (see second column). Third, the component of the four variables generated by the shock is much more volatile in the high information regime than in the low information regime (it is clear from visual inspection that the sum of the blue lines is larger than the sum of the red lines).

Table 1 reports the variance decomposition for the main business cycle shock. In both regimes the shock explain, as imposed, the highest portion of the cyclical variance of consumption and GDP. However two differences emerge. First, the explained cyclical variance of expectations is substantially higher in the high information regime. Second, the shock explains a much larger portion of the long run variance of consumption ad GDP in the low frequency regime than in the high information regime. This means that in the low information regime the cyclical shock is also the long run shock, while in the high information regime there is a sort of disconnection between business cycle and long run.

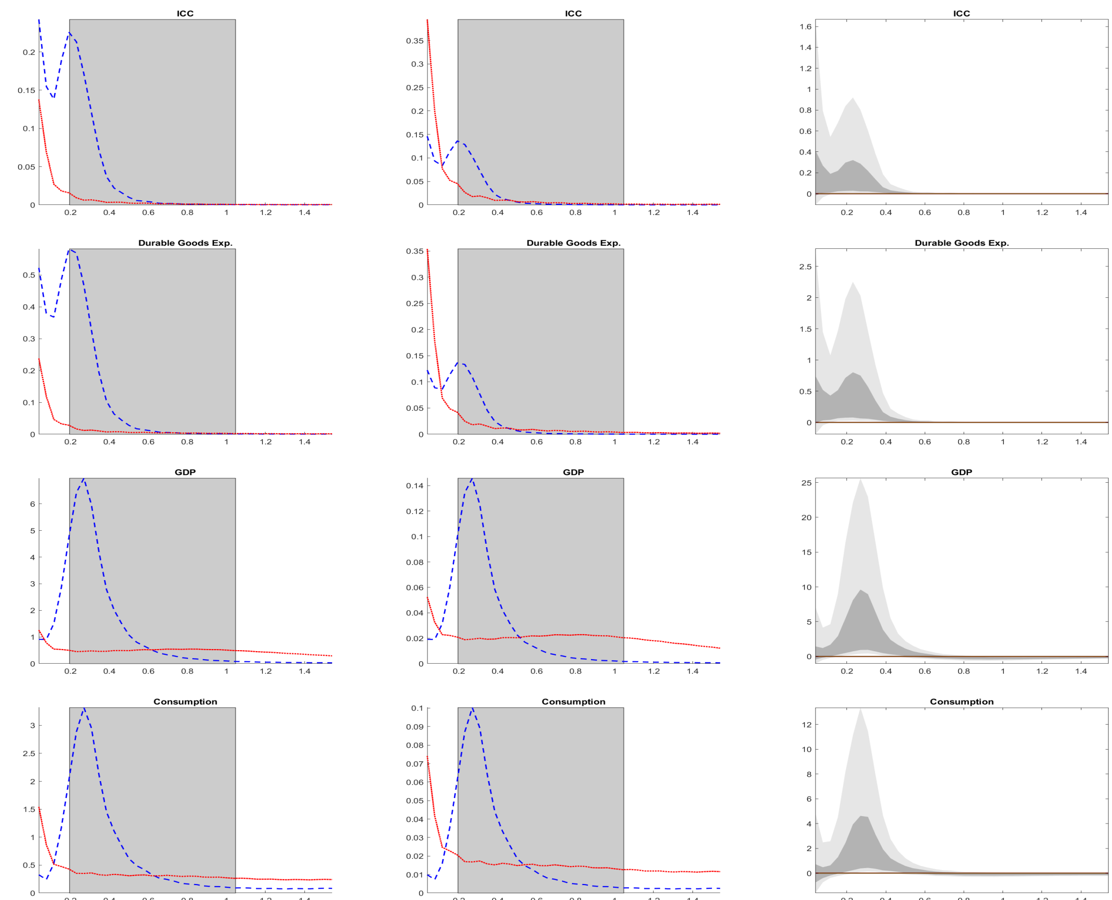

Figure 3: Spectra: column on spectra in the high information (blue solid line) and low information (solid red) regimes; column two normalized spectra; column confidence bands of the difference of the spectrum in high information minus the spectrum in low information regime, light gray 95%, dark gray 68%.

Figure 4 plots the impulse response functions in the two regimes. Left column reports the impulse response functions in the high information regime. Solid lines are the point estimates, gray areas are 68% confidence bands and the dotted red line is the point estimate response in the low information regime. Right column reports the responses

	Total Variance		Business cycle		Long run	
	High	Low	High	Low	High	Low
ICC	47.5	39.6	78.1	47.1	22.5	38.7
Durables Exp.	60.3	34.5	80.7	42.2	33.4	32.8
GDP	61.1	64.2	77.9	91.7	31.0	69.0
Consumption	67.9	77.8	85.3	88.2	12.0	64.5

Table 1: Variance decomposition of the main business cycle shock.

in the low information regime. Solid lines are the point estimates, gray areas are 68% confidence bands. The shapes of the responses in the two regimes are very different. Responses in high information tend to be much more humped shaped than in the low information regime where the transition to the long run level is much smoother. The hump-shaped pattern reflects the higher variance of the series concentrated at the business cycle frequencies.

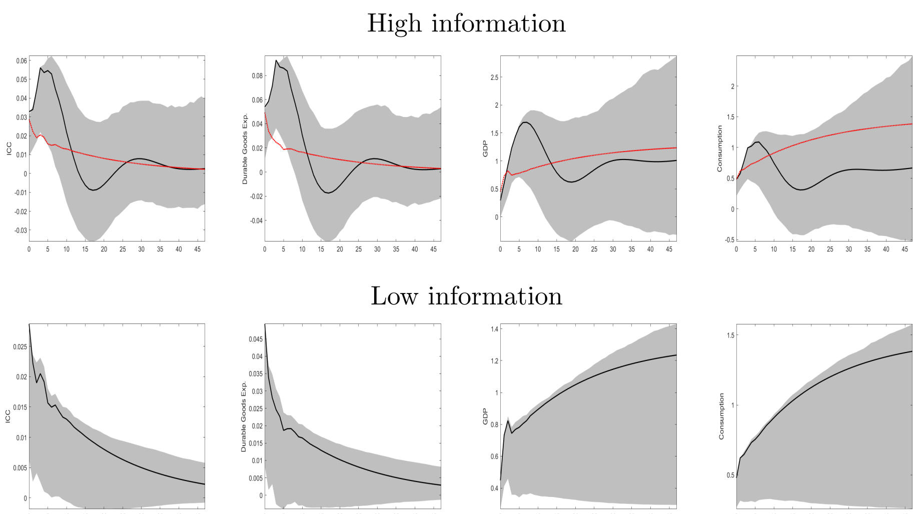

Figure 4: Impulse response functions of the main business cycle shock. Left column reports the impulse response functions in the high information regime. Right column reports the responses in the low information regime. Solid lines are the point estimates, gray areas are 68% confidence bands and the dotted red line in the panels in the left column represents the point estimate response in the low information regime.

To sum up, the main business cycle shock generate different dynamics in the two regimes. Business cycle fluctuations of consumption and GDP are much larger in the high information regime and the variables are more volatile. The shock seems to be much less important for the long run than in the low information regime.

3.3 Pervasiveness of information

Using the purged version of X_{2t} and X_{3t} in place of X_{1t} I perform the same analysis: first I compute the unconditional spectra spectra, then we identify the main business cycle shock and estimate the conditional spectra.

Figure 6 and 7 in the Appendix report the unconditional spectra and the spectra generated by the main business cycle shock obtained using X_{2t}. Figure 8 and 9 report the unconditional spectra and the spectra generated by the main business cycle shock obtained using X_{3t}. The results are similar to those obtained in the baseline specification and the main conclusions are unchanged using these other two measures. In the high information regime variables are more volatile and business cycle fluctuations larger than in the low-information regime than in low-information regime both unconditionally and conditionally.

4 An interpretative framework

I use an extremely stylized theoretical framework to interpret the above empirical findings. In particular I will play with model parameters to understand whether different degrees of information frictions can explain the empirical differences documented above. I focus on two types of frictions which have become popular during the last years: sticky information and imperfect information.

4.1 Information frictions

To begin with, I assume that the fundamental of the economy evolves as an invertible MA process

$$a_t = \theta(L)\eta_t \tag{3}$$

where $\theta(L) = \theta_0 + \theta_1 L + ...$, with $\theta_j > 0$ for all j, and $\eta_t \sim N(0, \sigma_\eta^2)$ is a structural shock. Let E_{it} denote the rational expectation of individual i conditional on the information available at time t. Following Coibion and Gorodnichenko (2012) and Mankiw and Reis (2006), let us assume that at each point in time an individual updates its expectation with probability $1 - \lambda$ and with probability λ does not. Thus, the value of λ determines how fast is the updating process. When updating expectations, the agent uses rational expectations. At time t the mean (across agents) k-step ahead expectation of a_t, $F_t a_{t+k}$, is given by

$$F_t a_{t+k} = (1-\lambda)\bar{E}_t a_{t+k} + \lambda F_{t-1} a_{t+k}, \tag{4}$$

where $\bar{E}_t a_{t+k}$ denotes the average (across agents) rational expectations E_{ti}. The solution to (4) is

$$F_t a_{t+k} = (1-\lambda)\sum_{j=0}^{\infty} \lambda^j \bar{E}_{t-j} a_{t+k}. \tag{5}$$

Furthermore, I assume that agents, when forming expectations, have imperfect information. More specifically, I assume that a_t becomes available only in $t+1$ (we can think of a first release of the variable) and agents, at each point in time, only receive an individual noisy signal of the shock

$$s_{it} = \eta_t + v_{it}$$

where $v_{it} \sim N(0, \sigma_v^2)$ is an individual noise independent of η_t.

Two remarks are in order. First, being (3) invertible means that η_t is known in $t+1$. The reason is that a_t is observed in $t+1$ and, by invertibility, η_t can be obtained as a combination of a_{t+1-j} with $j = 0, 1, ...$ Second, the agent's best forecast of η_t, given its information set, is $E_{it}(\eta_t) = \gamma s_{it}$, where $\gamma = \frac{\sigma_\eta^2}{\sigma_\eta^2 + \sigma_v^2}$. The parameter can be interpreted as the strength of the economic shock in the individual signal. The higher γ, the more informative about the economic shock is the signal.

Using (3), the k-step ahead individual rational expectation for $j = 0, 1, ...$ is

$$E_{it-j} a_{t+k} \;=\; \gamma\theta_{j+k}\eta_{t-j} + \gamma\theta_{j+k} v_{it-j} + \sum_{i=1}^{\infty} \theta_{j+k+i}\eta_{t-j-i}$$

By aggregating, the individual noise vanishes and the cross-sectional mean expectation is

$$\int E_{it-j} a_{t+k} di = \bar{E}_{t-j} a_{t+k} = \gamma\theta_{j+k}\eta_{t-j} + \sum_{i=1}^{\infty} \theta_{j+k+i}\eta_{t-j-i}. \tag{6}$$

Replacing (6) in (5), the following expression for the dynamics of average expectations is obtained:

$$F_t a_{t+k} \;=\; \alpha(L)\tilde{\eta}_t,$$

where $\alpha(L) = \sum_{j=0}^{\infty} \alpha_J L^j$, with $\alpha_j = [1 - \lambda^j(1-\gamma(1-\lambda))]\theta_{j+k}\sigma_\eta$ and $\tilde{\eta}_t = \sigma_\eta^{-1}\eta_t$ is a unit variance shock.

The way rigidities affect other macroeconomic variables will depend on the specific features of the model, consumer's preferences etc., see Tutino (2013). Here, I consider a simple consumption framework based on Carroll et al. (2020). The fraction of individuals which update their expectations set consumption equal to $c_{it} = E_{it} a_{t+k}$; the fraction of individuals who do not receive news and do not update their expectations keep consumption at the same level of the previous period, $c_{it} = c_{it-1}$. The cross sectional mean consumption c_t is

$$\int c_{it} di = c_t = (1-\lambda)\bar{E}_t a_{t+k} + \lambda c_{t-1}.$$

Solving backward

$$c_t = (1-\lambda)\sum_{j=0}^{\infty} \lambda^j \bar{E}_{t-j} a_{t+k-j},$$

so we can rewrite it as

$$c_t = \pi(L)\tilde{\eta}_t, \tag{7}$$

where $\pi(L) = \sum_{j=0}^{\infty} \pi_j L^j$, $\pi_0 = (1-\lambda)\gamma\theta_k\sigma_\eta$, $\pi_j = (1-\lambda)\left(\sum_{i=0}^{j-1} \lambda^i \theta_{j+k-i}\sigma_\eta + \lambda^j \gamma\theta_k\sigma_\eta\right)$ for $j = 1, 2, ...$

4.2 Impulse response functions

The polynomials $\alpha(L)$ and $\pi(L)$ represent the impulse response functions of expectations and consumption to the unit-variance economic shock $\tilde{\eta}_t$. In a frictionless economy ($\lambda = 0$ and $\gamma = 1$) the coefficients of the impulse response functions of expectations and consumption are $\alpha_j = \pi_j = \theta_{j+k}\sigma_\eta$.

Now consider the case where frictions are present ($\gamma < 1$ and $\lambda > 0$). The presence of frictions modify the impulse response functions. More specifically the following results hold:

$$\begin{aligned}
\frac{\partial \alpha_j}{\partial \gamma} &= (1-\lambda)\lambda^j \theta_{j+k}\sigma_\eta > 0, \;\; j = 0, 1, ... \\
\frac{\partial \alpha_j}{\partial \lambda} &= -[j\lambda^{j-1}(1-\gamma) + (j+1)\lambda^j \gamma]\theta_{j+k}\sigma_\eta < 0, \;\; j = 0, 1, ... \\
\frac{\partial \pi_j}{\partial \gamma} &= (1-\lambda)\lambda^j \theta_{j+k}\sigma_\eta > 0 \\
\frac{\partial \pi_0}{\partial \lambda} &= -\gamma\theta_k\sigma_\eta < 0. \\
\frac{\partial \pi_j/\pi_0}{\partial \lambda} &= \frac{1}{\gamma}\sum_{i=0}^{j-1} i\lambda^{i-1} + j\lambda^{j-1} > 0 \;\; j = 1, 2, ...
\end{aligned}$$

An increase in γ, a stronger signal, increases the parameters of the impulse response functions of both expectations and consumption at all horizons, giving rise to more volatile consumption and expectations. A reduction in λ, a faster expectations update, increases both the response of expectations at all the horizons, making expectations more volatile, and the impact effect of consumption.

At longer horizons, the sign of the derivative $\partial\pi_j/\partial\lambda$ depends on model parameters. However the effect on the parameters normalized by the impact effect π_j/π_0 are positive. This means that a lower frequency of updating increases the persistence of aggregate consumption. The impulse response becomes more delayed, reducing the importance of short-run movements and shifting the response toward longer-run dynamics. In frequency-domain terms, higher information frictions shift the mass of the response from high to low frequencies. This suggests that, at least to some extent, the empirical finding that a larger share of the spectral density is concentrated at business-cycle frequencies in the high-information regime may reflect faster updating. We discuss this mechanism in more detail in the next subsection.

Of course, if information frictions vary over time, the resulting impulse response functions will vary accordingly. Developing a model with time-varying information frictions would be extremely interesting, but is beyond the scope of this paper. Instead, I use a simple comparative-statics simulation to examine how different degree of frictions affect the spectra of expectations and consumption. The aim of the simulation is to understand whether whether the changes in the dynamics of expectations and consumption documented in the previous section can be rationalized by different degrees of information frictions.

4.3 Simulations

In what follows I study the relationship between the theoretical spectra of $F_t a_{t+k}$ and c_t and the degree of information frictions, i.e. different values of the parameters γ and λ. I focus on the unconditional spectral density since there is only one shock in the model. The spectral density of $F_t a_{t+k}$ is

$$\mathcal{D}_F(\omega) = \alpha(e^{i\omega})\alpha(e^{-i\omega}) \tag{8}$$

and the spectral density of consumption is

$$\mathcal{D}_c(\omega) = \pi(e^{i\omega})\pi(e^{-i\omega}). \tag{9}$$

I construct the spectral densities of $F_t a_{t+k}$ and c_t using equation (8) and (9) for different values of the parameters λ and γ. First, I set $\sigma_\eta = 1$. Second, to calibrate the MA parameters θ_j I proceed as follows. I identify a standard technology shock as the first Cholesky shock in a VAR estimated using TFP, log GDP, and log real personal consumption. Then I set θ_j equal to the response of TFP to the technology shock j-period ahead. Finally, I consider the following range of values for the friction parameters: $\lambda = 0.05, 0.1, ..., 0.95$ and $\gamma = 0.05, 0.1, ..., 0.95$ (implying a value of σ_v^2 ranging from 0.05 to 39). For each combination of the two parameters γ and λ, I compute $\mathcal{D}_F(\omega)$ and $\mathcal{D}_c(\omega)$. The sum of the spectrum across frequencies is proportional to the variance of the series and I refer to it as total variance.

Panel (a) of Figure 5 reports the total variance of expectations and Panel (c) the total variance of consumption for different values of γ (x-axis) and $1-\lambda$ (y-axis). The variance of expectations is monotonically increasing with both γ and $1-\lambda$. The smaller is the degree of information frictions, the higher is the variance of expectations. For consumption, the picture is slightly different as the relationship is non-monotonic. However when both $1-\lambda$ and γ are both large – say larger than 0.5– the variance of consumption is much larger than when both $1-\lambda$ and γ are below 0.5.[9] Thus, the variance of consumption is higher when both frictions are relatively low. This result is a well known result, discussed in several papers, see Mankiw and Reis (2002), Mankiw, Reis, and Wolfers (2004) Woodford, (2003) and Sims, (2003). More frequent expectations updating or stronger signals lead to faster and stronger adjustments of expectations and, consequently, to higher expectation volatility.

Panel (c) of Figure 5 plots the spectra of consumption for $\lambda = 0.85$ (black dotted lines, low probability of updating expectations), $\lambda = 0.5$ (red solid lines, medium probability of updating expectations) and $\lambda = 0.15$ (blue dashed lines, high probability of updating expectations) and all the values of $\gamma = 0.05, 01, ..., 0.95$. Each line corresponds to a given value the two parameters. Panel (e) reports the normalized spectra (the spectra of Panel (c) divided by the sum of the spectra over all frequencies). From Panel (c) it clearly emerges that as λ reduces (the probability of updating expectations increases), the variance of the series at the business cycle frequencies increases. Indeed both the red and blue lines are much larger than the black lines in correspondence of the gray areas. An increase in the speed of the expectation updating process generate larger business cycle fluctuations. Also, as λ reduces, independently on the value of γ, the spectra tend to have a larger mass concentrated at business cycle frequencies and a smaller mass concentrated at low frequencies, see Panel (e).

[9] In the model λ and γ are independent parameters. However it is plausible to think that the two could be related. When the signal is informative, then it is likely to believe that the fraction of individual updating is larger.

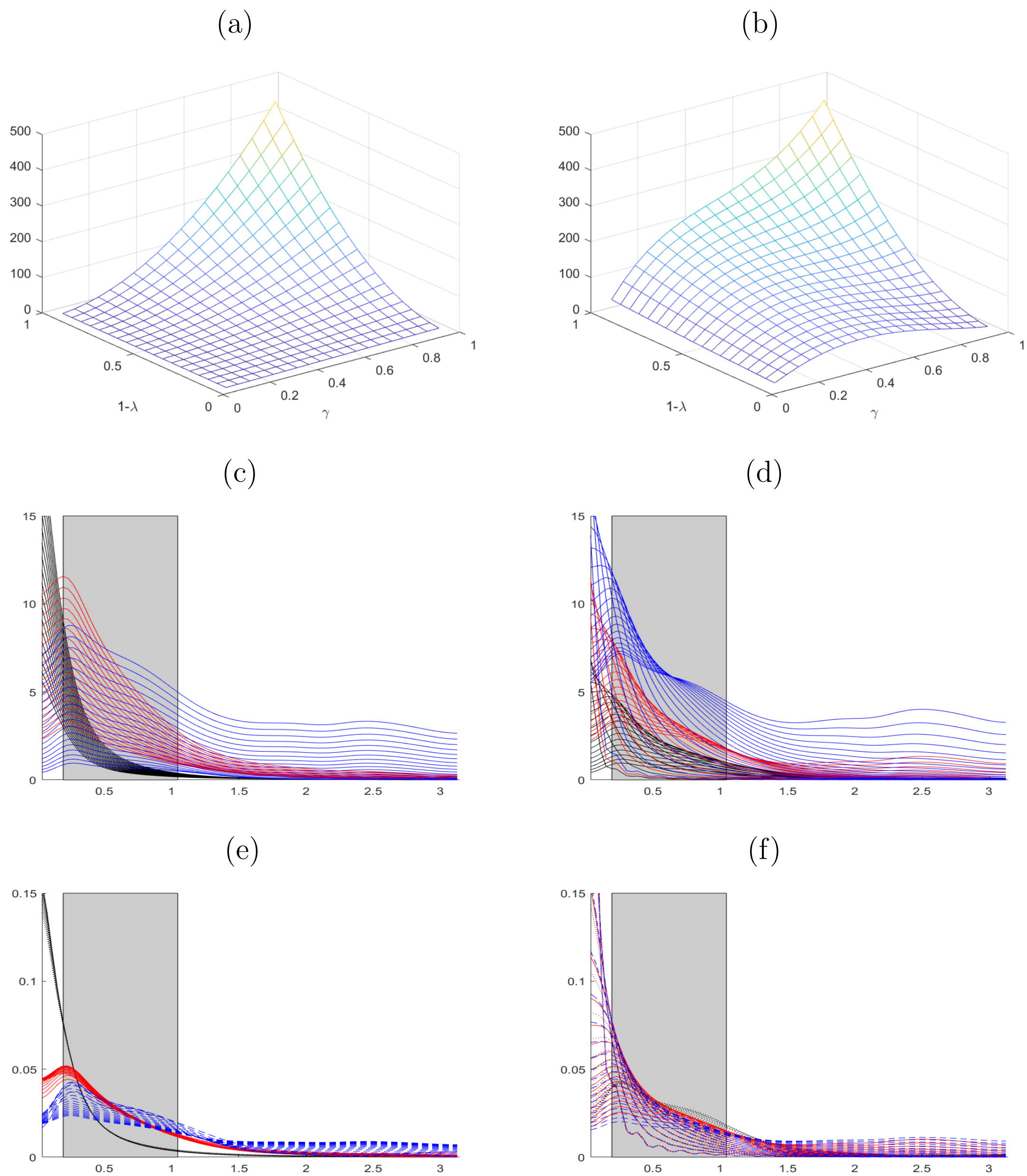

Figure 5: Panel (a): total variance of expectations. Panel (b): total variance of consumption. γ is on the x-axis and $1-\lambda$ on the y-axis. Panel (c): spectra of consumption for $\lambda = 0.85$ (black dotted lines), $\lambda = 0.5$ (red solid lines), $\lambda = 0.15$ (blue dashed), and γ in the interval $[0.0.5, 0.95]$. Panel (e) normalized spectral density of Panel (c). Panel (d): spectra of consumption for $\gamma = 0.15$ (black dotted lines), $\gamma = 0.5$ (red solid lines), $\gamma = 0.85$ (blue dashed), and λ in the interval $[0.0.5, 0.95]$. Panel (f) normalized spectral density of Panel (d).

Panel (d) of Figure 5 plots the spectra of consumption for $\gamma = 0.15$ (black dotted lines, low signal to noise ratio), $\gamma = 0.5$ (red solid lines, medium signal to noise ratio), $\gamma = 0.85$ (blue dashed lines, high signal to noise ratio) and all the values of $\lambda = 0.05, 01, ..., 0.95$. Each line corresponds to a given value the two parameters. Panel (f) reports the normalized spectra (the spectra of Panel (d) divided by the sum of the spectra over all frequencies). A stronger signal (an increase in γ) generates an upward shift of the spectra at all frequencies, i.e. a more volatile consumption at all frequencies and does not produce a shift in the mass at business cycle frequencies. Indeed the lines in Panel (f) are all over the place depending on the different values of λ but without a clear pattern for different values of γ.

While the implications of information frictions for volatility have been extensively studied, there is no clear theoretical result explicitly linking the degree of frictions to the size of business cycle fluctuations. This simulation provides some insights. More frequent updating of expectations shifts a sizable portion of the spectral density of both expectations and consumption from long-run to business-cycle frequencies. By contrast, an increase in the strength of the signal does not produce a similar effect.

To sum up, in the model: (i) a reduction in both the degree of information frictions (higher values of γ and $1 - \lambda$) produces more volatile expectations and consumption; (ii) a higher speed of adjustment of expectations (a higher value of $1 - \lambda$), implies larger business cycle fluctuations of consumption and a shift of the spectra densities towards business cycle frequencies.

4.4 Interpreting the empirical evidence

Our empirical results can be interpreted through the lens of this simple theoretical framework. Note that our empirical measure can be viewed as a proxy for $1-\lambda$ and γ: the lower the degree of frictions, the higher the value of the empirical information measure. This interpretation holds, for instance, if (a) informed individuals update their expectations, and (b) the share of informed individuals depends on the variance of the fundamental shock or the strength of the signal. This is a plausible and reasonable case since large economic events (i.e. high values of σ_η^2) are likely to receive a wider news coverage and, as a consequence, increase the number of informed individuals.

Consequently, a high-information regime can be interpreted as a low-friction regime, whereas a low-information regime can be interpreted as a high-friction regime. Under this interpretation, and in the light of the theoretical model implications, the larger estimated variance of macroeconomic variables in the high-information regime can be attributed to both a larger probability of updating expectations and a larger signal-top noise ratio.

By contrast, only the former appears to play a key role in amplifying business cycle fluctuations.

Information frictions in this simple framework are considered exogenous. In reality, however, they are likely to depend on macroeconomic conditions themselves. For instance they could depend on the size of macroeconomic shocks, i.e. on σ_η^2. When this is the case, large shocks might reduce frictions and this, in turn, tend to amplify fluctuations in macroeconomic variables. Allowing for endogenous frictions is beyond the scope of this paper but seems a promising line of research.

5 Conclusions

This paper empirically highlights the role of agents' information as a mechanism that both amplifies and dampens the effects of economic shocks. Using measures of information obtained from the Michigan Survey of Consumers, I show that in a high-information regime (i) business cycle fluctuations in GDP and consumption are larger, (ii) expectations, GDP and consumption growth are more volatile, and (iii) the main business cycle shock generate larger business cycles fluctuations than in a low-information regime.

Using a simple theoretical framework with sticky and imperfect information, I show that these empirical findings can be rationalized by different degree of information frictions. The larger estimated variance of macroeconomic variables in the high-information regime can be attributed to both a larger probability of updating expectations and a larger signal-top noise ratio. By contrast, only the former appears to play a key role in amplifying business cycle fluctuations.

The model is intentionally parsimonious, particularly in its treatment of the information signal. An important direction for future research is to explore how richer signal structures and more complex information dynamics affect these results. Another promising avenue is to study the role of information in the transmission of monetary policy.

Appendix

Additional empirical results

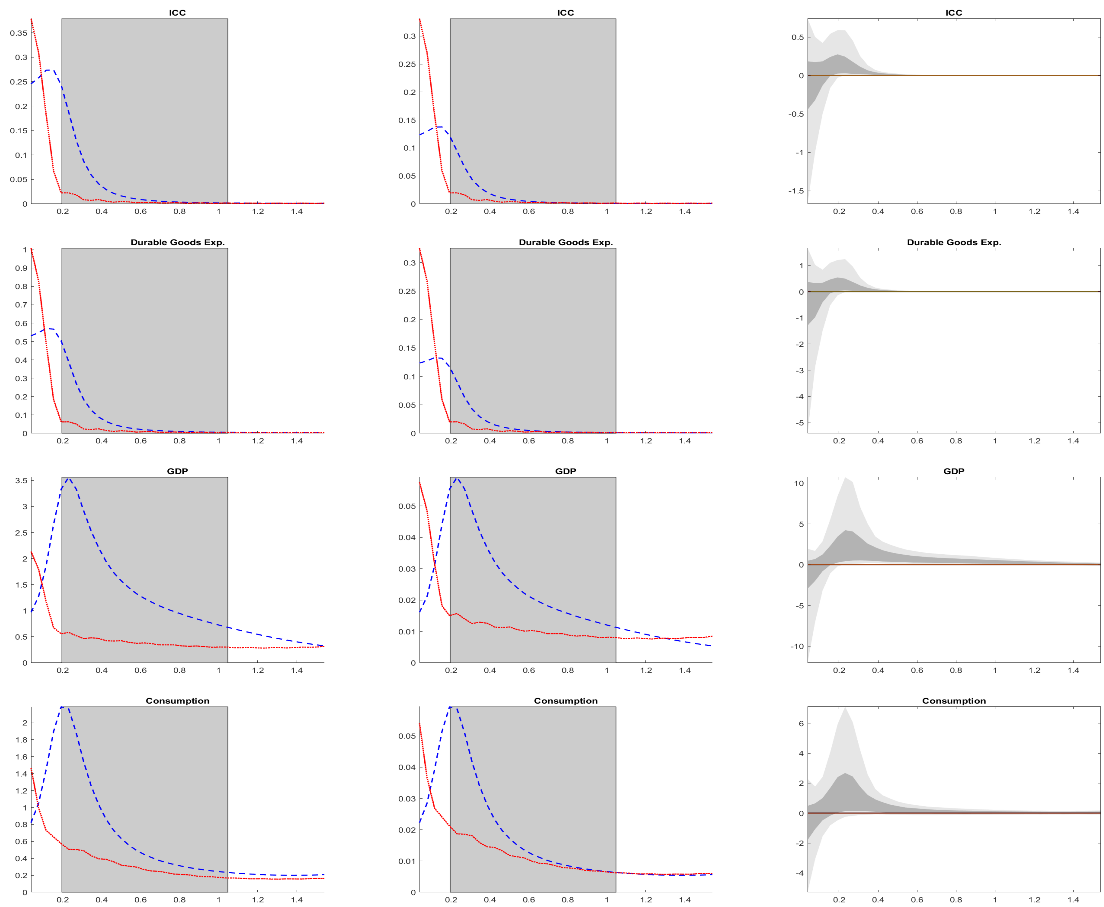

Figure 6: Unconditional spectra using X_{2t}: column on spectra in the high information (blue solid line) and low information (solid red) regimes; column two normalized spectra; column confidence bands of the difference of the spectrum in high information minus the spectrum in low information regime, light gray 95%, dark gray 68%.

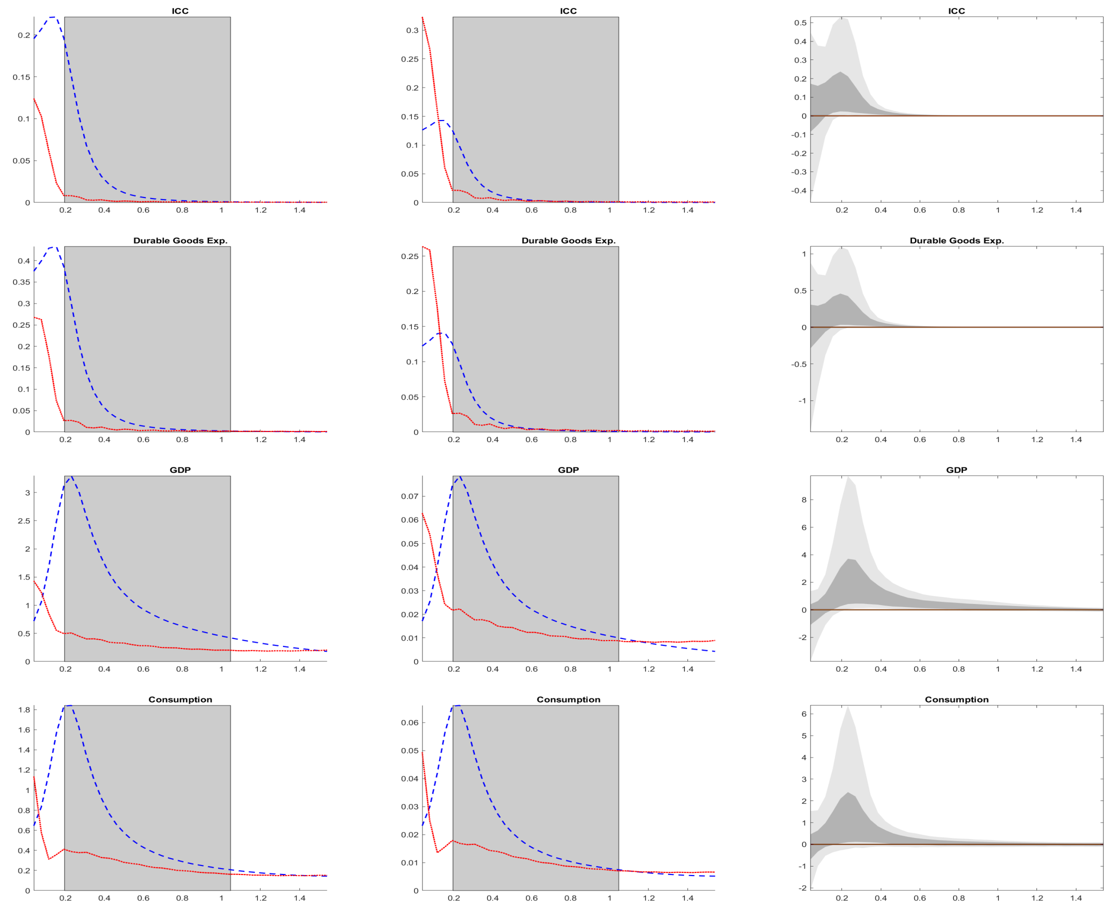

Figure 7: Spectra of the main business cycle shock X_{2t}: column on spectra in the high information (blue solid line) and low information (solid red) regimes; column two normalized spectra; column confidence bands of the difference of the spectrum in high information minus the spectrum in low information regime, light gray 95%, dark grey 68%.

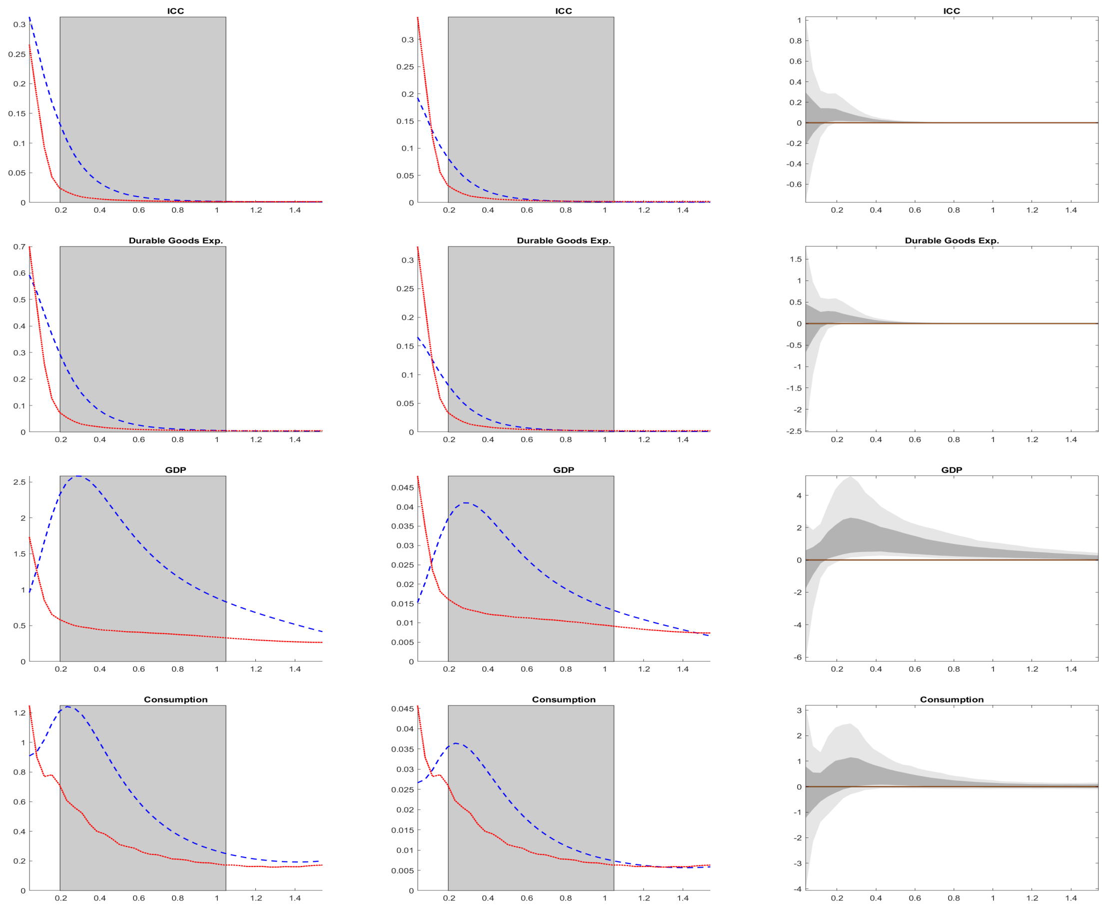

Figure 8: Unconditional spectra X_{3t}: column on spectra in the high information (blue solid line) and low information (solid red) regimes; column two normalized spectra; column confidence bands of the difference of the spectrum in high information minus the spectrum in low information regime, light gray 95%, dark gray 68%.

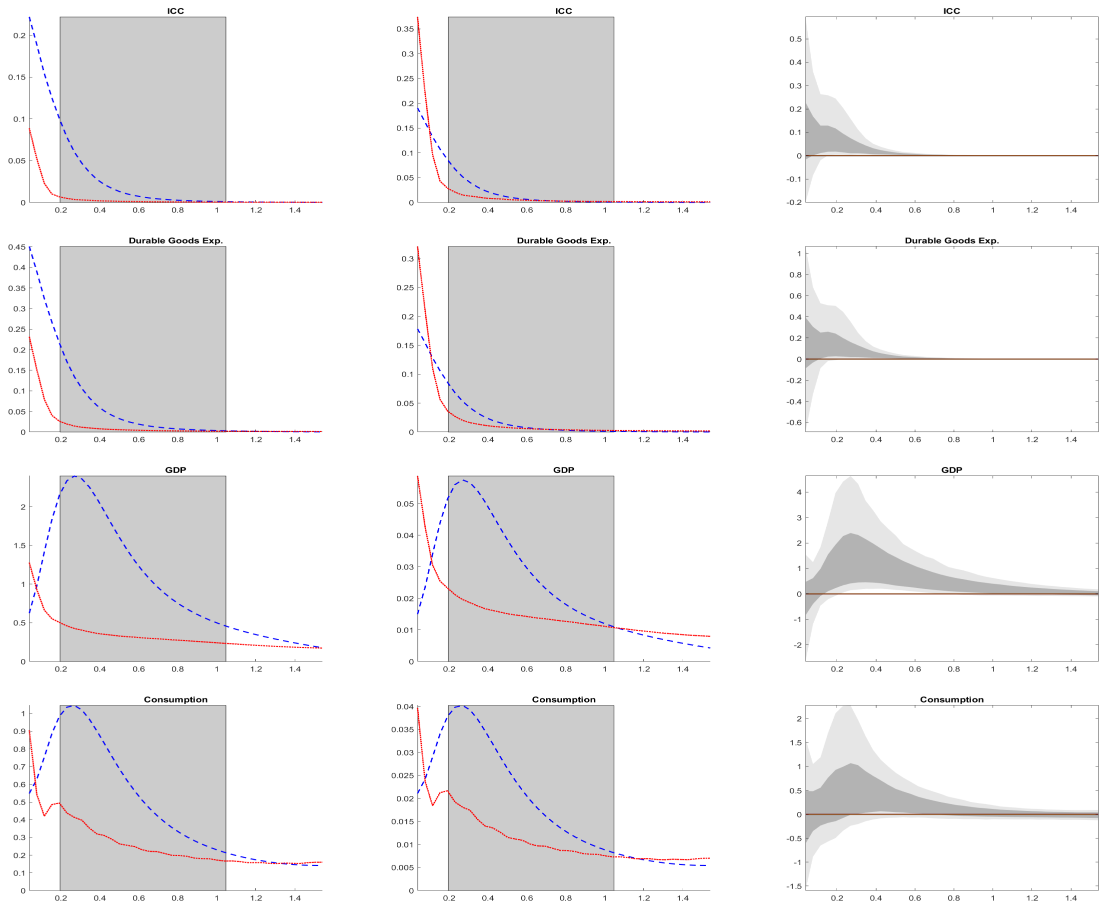

Figure 9: Spectra of the main business cycle shock X_{3t}: column on spectra in the high information (blue solid line) and low information (solid red) regimes; column two normalized spectra; column confidence bands of the difference of the spectrum in high information minus the spectrum in low information regime, light gray 95%, dark grey 68%.

References

[1] Adam K., A. Marcet and J.P. Nicolini (2016), ''Stock Market Volatility and Learning" Journal of Finance, 71(1):33-82.

[2] Andrade P. and H. Le Bihan, (2013), "Inattentive professional forecasters", Journal of Monetary Economics, 60(8): 967-982.

[3] Angeletos G., M. and J. La'O (2010), "Noisy Business Cycles", NBER Macroeconomics Annual 24, pp. 319-378.

[4] Angeletos, G., M., C. Fabrice and H. Dellas. (2020), "Business-Cycle Anatomy." American Economic Review 110 (10): 3030–70.

[5] Barsky, R. and E. Sims (2011), "News shocks and business cycles", Journal of Monetary Economics 58, 273-289.

[6] Barsky, R. and E. Sims (2012), "Information, Animal Spirits, and the Meaning of Innovations in Consumer Confidence", American Economic Review 102, 1343-77.

[7] Beaudry, P. and F. Portier (2006), "Stock Prices, News, and Economic Fluctuations", American Economic Review 96, 1293-1307.

[8] Beaudry, P. and F. Portier (2014), "The News View of Business Cycles: Insights and Challenges", Journal of Economic Literature, 52(4):993-1074.

[9] Blanchard O.J., G. Lorenzoni and J.P. L'Huillier (2013), "News, Noise, and Fluctuations: An Empirical Exploration", American Economic Review, vol. 103(7), pp. 3045-70.

[10] Caggiano, G., E. Castelnuovo, V. Colombo and G. Nodari (2015)''Estimating Fiscal Multipliers: News From A Non-linear World", 125(584): 746-776

[11] Carro, C.D. (2003), "Macroeconomic Expectations of Households and Professional Forecasters", Quarterly Journal of Economics, 118(1): 269-298

[12] Carroll, C.D., E. Crawley, J. Slacalek, K. Tokuoka, and M.N. White. (2020) "Sticky Expectations and Consumption Dynamics." American Economic Journal: Macroeconomics 12 (3): 40–76.

[13] Chahrour, R. and R. Ulbricht, (2019) '' Information-driven business cycles: A primal approach." Available at SSRN 3135375

[14] Cheremukhin, A. and A. Tutino (2016), “Information Rigidities and Asymmetric Business Cycles,” Journal of Economic Dynamics & Control, 73: 142-158.

[15] Coibion, O. and Y. Gorodnicenko (2012), ”What can survey forecasts tell us about informational rigidities?”, Journal of Political Economy 120, pp. 116-159.

[16] Coibion, O. and Y. Gorodnicenko (2015) , “Information Rigidity and the Expectations Formation Process: A Simple Framework and New Facts”, American Economic Review, 105(8): 2644-2678.

[17] Evans G. W. and S. Honkapohja (2012), ‘’Learning and Expectations in Macroeconomics”, Princeton University Press.

[18] Forni, M., L. Gambetti, M. Lippi and L. Sala (2017),“Noise bubbles”, The Economic Journal, Vol. 127(604), pp. 1940-1976.

[19] Forni, M., L. Gambetti and L. Sala (2014), “No news in business cycles”, The Economic Journal, Vol. 124(581), pp. 1168-1191.

[20] Forni, M., L. Gambetti, A. Granese, L. Sala and S. Soccorsi (2025) ”An American Macroeconomic Picture: Supply and Demand Shocks in the Frequency Domain”, American Economic Journal: Macroeconomics, 17(3): 311–41.

[21] Hubert, P., and G. Ricco (2018), ‘’ Imperfect Information in Macroeconomics” Revue de l’OFCE , 157:181-196.

of Representativeness”, Cognitive Psychology, 3(3): 430-454.

[22] Kurmann, A., and C. Otrok (2013), “News Shocks and the Slope of the Term Structure of Interest Rates”, American Economic Review 103(6): 2612-32.

[23] Lorenzoni, G., (2009), “A theory of demand shocks”, American Economic Review, 99, 2050-84.

[24] Lorenzoni, G. (2010). “Optimal Monetary Policy with Uncertain Fundamentals and Dispersed Information”, Review of Economic Studies 77, pp. 305-338.

[25] Lucas, R.E., Jr. (1972), “Expectations and the Neutrality of Money”, Journal of Economic Theory 4, 103-124.

[26] Maćkowiak B. and M. Wiederholt, (2009), “Optimal Sticky Prices under Rational Inattention”, American Economic Review, 99(3): 769-803.

[27] Mankiw G. N. and R. Reis (2002), "Sticky information versus sticky prices: a proposal to replace the New Keynesian Phillips curve", Quarterly Journal of Economics 117, 1295-1328.

[28] Mankiw and Reis (2002), "Sticky Information versus Sticky Prices: A Proposal to Replace the New Keynesian Phillips Curve", Quarterly Journal of Economics, 117(4): 1295-1328.

[29] Mankiw N.G. and R. Reis (2010), ''Imperfect Information and Aggregate Supply", Handbook of Monetary Economics Volume 3, 2010, Pages 183-229

[30] Mankiw N. G., R. Reis and J. Wolfers (2004), "Disagreement about Inflation Expectations", NBER Chapters, in: NBER Macroeconomics Annual 2003, 18: 209-270.

[31] Matějka F., (2016), "Rationally Inattentive Seller: Sales and Discrete Pricing", Review of Economic Studies, Oxford University Press, 83(3): 1125-1155.

[32] Matějka F. and A. McKay, (2012), "Simple Market Equilibria with Rationally Inattentive Consumers", American Economic Review, American Economic Association, 102(3): 24-29, May

[33] Muth J., (1961), "Rational Expectations and the Theory of Price Movements", Econometrica, 29(3): 315-335.

[34] Nimark, K.P., (2014) ''Man-bites-dog business cycles", American Economic Review 104:2320–2367.

[35] Owyang M.T, V.A. Ramey and S.Zubairy (2013), '' Are Government Spending Multipliers Greater during Periods of Slack? Evidence from Twentieth-Century Historical Data" American Economic review, 103(3): 129-34.

[36] Paciello and Wiederholt (2014), "Disagreement about Inflation Expectations", NBER Chapters, in: NBER Macroeconomics Annual 2003, 18: 209-270.

[37] Pesaran H. and M. Weale, 2006, "Survey expectations", Handbook of economic forecasting, 1: 715-776.

[38] Reis (2006a), "Inattentive Producers", Review of Economic Studies, 73(3): 793-821.

[39] Reis (2006b), "Inattentive consumers", Journal of Monetary Economics, 53(8) : 1761-1800

[40] Reis R. (2009), ''Optimal Monetary Policy Rules in an Estimated Sticky-Information Model American Economic Journal: Macroeconomics 1(2): 1-28.

[41] Ricco G., G. Callegari and J. Cimadomo, (2016), "Signals from the government: Policy disagreement and the transmission of fiscal shocks", Journal of Monetary Economics, 82(C): 107-118.

[42] Schmitt-Grohé, S. and Uribe, M. (2012), "What's news in business cycles", Econometrica 80: pp. 2733-2764.

[43] Shannon, C.E. (1948) "A Mathematical Theory of Communication", The Bell System Technical Journal 27: 379–423, 623–656.

[44] Sims, C. A. (2003), "Implications of Rational Inattention", Journal of Monetary Economics 50, 665-690.

[45] Soroka, S. N. (2006). Good news and bad news: asymmetric responses to economic information. The Journal of Politics, 68(2): pp. 372-385.

[46] Soroka, S. N. (2012). The gatekeeping function: distributions of information in media and the real world. The Journal of Politics, 74(2): pp. 514-528.

[47] Tsay, R. S., (1998), ''Testing and modeling multivariate threshold models". Journal of 561 the American Statistical Association 93: 1188–1202.

[48] Tutino, A. (2013), ''Rationally inattentive consumption choices". Review of Economic Dynamics, 16 (3): 421-439.

[49] Woodford M. (2002), "Imperfect Common Knowledge and the Effects of Monetary Policy." in P. Aghion, R. Frydman, J. Stiglitz, and M. Woodford, eds., Knowledge, Information, and Expectations in Modern Macroeconomics: In Honor of Edmund S. Phelps, Princeton: Princeton University Press.

[50] Tsay, R. S., 1998. Testing and modeling multivariate threshold models. Journal of the American Statistical Association 93, 1188–1202.