Information Cycles and Asymmetric Fluctuations

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Abstract

Agents' information, measured with survey variables, varies over time displaying persistent cycles. Agents' expectations and consumption respond more to economic shocks in periods where information is high, giving origin to asymmetric economic fluctuations. A high-information economy generates, on average, a much more volatile consumption than a low-information economy. Had information been low during the Great Recession, the fall in consumption would have been milder. In the aftermath of the crisis, had information been high, the recovery in consumption would have been faster. Results are obtained by estimating a Threshold SVAR with US data using consumers' information measures as state variables. The findings are in line with the predictions of a simple theoretical interpretative framework of information frictions.

JEL classification: C32, E32.

Keywords: News, Agents' Information, Agents' Expectations, Business Cycles, SVAR.

*I am thankful to Nicolò Maffei and Sarah Zoi for their great research assistance. 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

Agents' expectations about current and future economic developments are formed on the basis of their available information and represent one of the key determinant of the agents' decision-making process. 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 should change accordingly. In other words, shocks are predicted to generate state-dependent dynamics related to the degree of agents' information. In this regard, information plays the role of a mechanism that amplifies and dampens economic fluctuations.

Time varying information sets are simply excluded by assumption under the Full Information Rational Expectations (FIRE) paradigm (see the seminal contribution of 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 wth 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), agents still use rational expectations but their information set is limited in the sense that they observe current economic shocks with noise. They might be able to learn the true value of the shock only in the future.[2] From an empirical point of view, several papers have tested the predictions of models of imperfect information and found evidence supporting those predictions.[3]

[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]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).

[3]Using survey data Coibion and Gorodnichenko (2012, 2015) and Andrade and Le Bihan (2013) find that

In models with information frictions, both the magnitude and the persistence of the responses of macroeconomic variables depend on the degree of frictions, i.e. on the speed of the expectations adjustment process and the size of the signal to noise ratio. In particular, the smaller the frictions, the higher the persistence and the smaller the magnitude of the response of macro variables to economic shocks. The reason is that under noisy information consumers become more cautious and react less to the shock until uncertainty is dissipated delaying consumption decisions. Under sticky information, expectations become more sluggish and this is translated into agents' decisions.

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, is constant over time. There is some evidence that bad economic events receive more coverage than good events, either because of the existence of a media bias (Soroka, 2006) or simply because bad shocks have larger effects on macroeconomic variables (Gambetti et al., 2020). If information varies over time, then the dynamics generated by agents expectations will also vary. So, 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 first measure is obtained from Question A6 of the questionnaire. The question 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"*. I take as a proxy for consumers' information the percentage of respondents answering ''Yes". The variable is revealing of the percentage of informed consumers or the speed of expectation updating process. A second variable is associated with the uncertainty of the information. If an individual answers ''Yes" in 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 answers to this question are classified by the survey conductor as ''positive" and ''negative". As a proxy of the information uncertainty I use the Shannon's (1948) entropy associated to the answers to question A6b. Finally, I propose an overall measure that combines both variables. Information measures display ''information cycles", i.e. protracted periods of low information followed by periods of high information. These cycles tend to be negatively correlated with the business cycles,

forecast errors are predictable, an implication which is ad odds with FIRE models. Other papers, 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.

information having the tendency of reducing in booms and increasing in recessions.

To assess the effects of information cycles on macroeconomic fluctuations I use a Threshold Structural VAR where the threshold variable is the part of the information proxies generated by shocks which are orthogonal to current and past changes in industrial production, stock prices and the unemployment rate. Since information variables are correlated with the business cycle, this preliminary cleaning step is important in order not to mix effects attributable to information with effects attributable to the fact that agents might respond differently in expansions and recessions. I focus on the effects of an innovation to consumers' current confidence index. The shock lacks of a precise structural interpretation but has the important advantage of being an important shock to agents' expectation since it explains a large portion of the variance.

The main finding is that the response of both expectations and consumption is significantly larger in magnitude when information is high. A larger response of consumption, in turn, implies more volatile consumption in periods of high information relative to periods of low information. Indeed, by means of a counterfactual experiment, I document that the variance of consumption fluctuations in a high-information economy is a few times larger than the variance of the consumption fluctuations in a low-information economy. Again, using counterfactual experiments, I find that had information been low during the Great Recession, the fall in consumption would have been milder. On the contrary, in the aftermath of the end of the recession, had information been high, the recovery in consumption would have been faster. Because of its counter-cyclical nature, information becomes an important channel that amplifies the effects of recessionary shocks.

The paper is closely related, in spirit, to Ricco, Callegari and Cimadomo, (2016), although the topic is different. The authors study the effects of fiscal policy shocks in period of low and high disagreement among US professional forecasters. They find, in line with my findings, that expansionary fiscal policy shocks are much more effective in affecting GDP and investment in periods of low disagreement than in periods of high disagreement.

The remainder of the paper is organized as follows. Section 2 discusses empirical measures of information. Section 3 discusses some implications of a very stylized framework of imperfect information. Section 4 presents the econometric model. Section 5 presents the results. Section 6 concludes.

2 Empirical measures of consumers' information

In this section I discuss three variables, derived from the Michigan Survey of Consumers, that can be interpreted as proxies for consumers' information. The first variable is informative about the amount of informed individuals, the second about the degree of information dispersion, and the third combines the first two.

2.1 News level

The first variable is a direct measure of the percentage of informed individuals. Question A6 of the 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"*. The variable, call it X_{1t}, is simply the proportion of individuals responding ''Yes". Besides being a direct measure of the percentage of informed individuals, the variable can also be interpreted as a proxy for the proportion of individuals updating their expectations at each point in time, since presumably having access to new information lead agents to modify their expectations. I further discuss this point in the next section.[4]

The first panel of column (a) of Figure 1 plots X_{1t}. For sake of comparison, the unemployment rate is also reported. A couple of remarks are in order. First, for long periods of time, a sizable amount of individuals do not hear any news about current economic conditions. This lends strong support to the presence of information frictions and goes against the assumption of full information. Second, information is time-varying. In particular a persistent information cycle, a sequence of high-information and low-information periods, emerges. This cycle is negatively correlated with the business cycle: agents tend to be more informed in recessionary periods than in expansions, the correlation between X_{1t} and and the unemployment rate being 0.4.

2.2 News accuracy

The second variable I derive is a measure of information dispersion. 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 ''positive" or ''negative". Intuitively, the closer are the percentages of positive and negative news, the higher is information dispersion or information uncertainty, since agents tend to disagree about the sign

[4]The variable is also used in Gambetti et al. (2020).

of the news. A natural measure of information dispersion is represented by the Shannon's (1948) entropy. Let p_t be the proportion of answers ‘positive" at time t conditional on having having answered ‘'Yes" in question A6. The entropy associated to the answer to question A6b is[5]

$$H_t = -p_t \log_2(p_t) - (1 - p_t)\log_2(1 - p_t).$$

Entropy takes value in the interval $[0, 1]$: it is maximal at $p_t = 0.5$ and minimal at $p_t = 1$ or $p_t = 0$. In general, entropy is a measure of uncertainty associated with the set of possible outcomes. In this specific case the variable measures the degree of agents' uncertainty or disagreement about economic news. When $p = 1$ or $p = 0$, uncertainty is zero and all of the agents agree upon one of the two outcomes. When $p = 0.5$, disagreement is maximal since half of the individuals have heard good news, half have heard bad news. The second information variable, interpreted as news accuracy or agreement across respondents, is $X_{2t} = 1 - H_t$.

The second panel of column (a) of Figure 1 plots this measure. Again, information cycles clearly emerge, although with some differences compared to the previous variable. Indeed agreement tends to be low and stable for long period of time with short sudden jumps. As before, the sudden increases in agreement tend to coincide with recessionary periods suggesting, as before, that agents tend to be more informed in recessions than in expansions.

2.3 Overall information

The two variables described above provide insights about connected but distinct features of agents' information set: the level and the accuracy of the information. Here I develop a third variable which puts them together and can be interpreted as an overall measure of information. To do so, first of all I make the assumption that, conditional on answering *"No, haven't heard"* to question A6, uncertainty about positive or negative news, is maximal, i.e. entropy equal to 1. The reason is that when a consumer has no news, answering to A6b is just like tossing a coin.[6] Under this assumption, a way of combining X_{1t} and X_{2t} in a

[5]Let V and W be two random variables with support sets $\mathcal{V}$ and $\mathcal{W}$. The entropy of V conditional to $W = w$ is

$$H(V|W = w) = -\sum_{v\in\mathcal{V}} p(V = v, W = w) log(p(V = v, W = w)$$

. The conditional entropy is

$$H(V|W) = -\sum_{w\in\mathcal{W}} p(W = w)H(V|W = w)$$

.

[6]Strictly speaking, the conditional entropy could not be computed since question A6b is asked only if the answer to question A6 is ‘'Yes". For this reason I have to make the assumption that entropy is equal to 1

meaningful way is through the conditional entropy (see footnote 4):

$$H_t^C = X_{1t}H_t + (1 - X_{1t}).$$

Notice that conditional entropy is simply a weighted average of the two entropy, H_t and 1, with weights equal to the proportion of informed and non-informed agents. The variable which summarizes the overall information is then $X_{3t} = 1 - H_t^C$. By substituting H_t the variable reduces to the product of the two variables: $X_{3t} = X_{1t}X_{2t}$. Let us consider the properties of this variable. Again it takes values in the interval $[0, 1]$. When $X_{2t} = 0$, i.e. maximal uncertainty, or $X_{1t} = 0$, no news heard by anyone, then $X_{3t} = 0$ and overall information is minimal. On the contrary, the variable is maximal when both $X_{1t} = 1$ and $X_{2t} = 1$, either all of the respondents have heard positive news, or all of the respondents have heard negative news. In between these two extreme cases, the variable increases as the uncertainty reduces and the proportion of informed individuals increases and viceversa.

The third panel of column (a) in 1 plots overall information. The variable looks similar to X_{2t}: long periods of low information followed by abrupt increases in the information held by the agents.

From the above analysis two main conclusions can be drawn. First, information is far from being perfect. Indeed a sizable portion of population have no information for long periods of time. Second, information is time-varying. In the next section I investigate through the lens of a stylized theoretical framework what are the implications in terms of the response to economic shocks of time-varying information sets.

3 An illustrative framework

Evolving information can play an important role for macroeconomic dynamics. More specifically, different information sets can imply very different responses of economic agents to economic shocks. In this section I study this relationship by means of a simple but illustrative theoretical set-up of imperfect information. I focus on two types of frictions which have become popular during the last years: sticky information and imperfect information. The model employed is extremely stylized but it allows to show my main point in a clear and simple way.

when the response is "No, haven't heard". The assumption however seems to be reasonable since in case of no information the answer can be thought as tossing a coin.

First of all, I study the implications for the response of consumers' expectations and consumption of a change in the degree of information frictions. Second, I show that the variables presented earlier can be considered as proxies for information frictions.

3.1 Information frictions

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

$$a_t = \theta(L)\omega_t \tag{1}$$

where $\theta(L) = \theta_0 + \theta_1 L + ...$, with $\omega_t \sim N(0, \sigma^2)$. Let E_t^i denote the rational expectation of individual i conditional on the information available at time t. Following 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. Thum, the value of λ determines how fast is the updating process. When updating expectations, the agent uses rational expectations. At time t the average (across agents) of the k-step ahead expectation F_t is given by

$$F_t a_{t+k} = (1-\lambda)\bar{E}_t a_{t+k} + \lambda F_{t-1} a_{t+k}, \tag{2}$$

where $\bar{E}_t a_{t+k}$ denotes the average (across agents) rational expectations E_{it}. A solution to (2) is

$$F_t a_{t+k} = (1-\lambda)\sum_{j=0}^{\infty} \lambda^j \bar{E}_{t-j} a_{t+k}. \tag{3}$$

Furthermore, we assume that agents, when forming expectations, have imperfect information. More specifically, we 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 $s_{it} = \omega_t + v_{it}$, where the noise $v_t \sim N(0, \sigma_v^2)$ is independent on ω_t. The ratio $\frac{\sigma_\omega^2}{\sigma_v^2}$ represents a measure of how informative is the signal about the economic shock. The larger of the variance of the economic shock relative to that of the noise, the more informative will be the signal. Two additional remarks are in order. First, being (1) invertible means that ω_t is known in $t+1$. The reason is that a_t is observed in $t+1$ and, by invertibility, ω_t can be obtained as a combination of current and (infinitely many) past values of a_t. Second, the agent's best forecast of ω_t, given its information set, is γs_t, where the projection parameter $\gamma = \frac{1}{1+\frac{\sigma_v^2}{\sigma_\omega^2}}$ negatively depends on the ratio $\frac{\sigma_v^2}{\sigma_\omega^2}$. The higher is the informational content of the signal, the larger is the weight associated to the signal, γ. Thus, using (1) we have that the

k-step ahead individual rational expectation for $j = 0, 1, ...$ is

$$\begin{aligned} E_{it-j} a_{t+k} &= \gamma \theta_{j+k} s_{it-j} + \sum_{i=1}^{\infty} \theta_{j+k+i} \omega_{t-j-i} \\ &= \gamma \theta_{j+k} v_{it-j} + \gamma \theta_{j+k} \omega_{t-j} + \sum_{i=1}^{\infty} \theta_{j+k+i} \omega_{t-j-i} \end{aligned}$$

By averaging across a sufficiently large number of individuals updating expectations in t, the individual noise vanishes and average expectation is

$$\bar{E}_{t-j} a_{t+k} = \theta_{j+k} \gamma \omega_{t-j} + \sum_{i=1}^{\infty} \theta_{j+k+i} \omega_{t-j-i}. \tag{4}$$

Replacing (4) in (3), I obtain

$$F_t a_{t+k} = \sum_{j=0}^{\infty} [1 - \lambda^j (1 - \gamma(1-\lambda))] \theta_{j+k} L^j \omega_t. \tag{5}$$

Now, as long as consumption depends on expectations, these dynamics will be translated to consumption as well. Let us consider a simple example. Let us assume that individual consumption is trivially proportional to the individual expectation of the one-period ahead economic fundamental a_{t+1}.[7] Aggregate per-capita consumption is therefore $c_t = \alpha F_t a_{t+1}$. By replacing (5), consumption simply becomes

$$c_t = \alpha \sum_{j=0}^{\infty} [1 - \lambda^j (1 - \gamma(1-\lambda))] \theta_{j+1} L^j \omega_t. \tag{6}$$

Notice that the model nests a pure sticky information model, when $\gamma = 1$, and a pure imperfect information model, when $\lambda = 0$.

3.2 Implications

Let us now discuss the link between agents' responses to the economic shock and the degree of frictions, i.e. the value of the parameters γ and λ.

Implication #1

The partial derivative of the MA coefficients in (5) and (6) with respect to λ is negative: the faster is the updating process the larger is the reaction of consumption and consumers' expectations.

[7] one could take longer expectations, the algebra would become more involved but the main implications would remain unchanged.

Implication #2

The partial derivative of the MA coefficients in (5) and (6) with respect to γ is positive. The parameter γ, in turn, depends on the ratio $\sigma_v^2/\sigma_\omega^2$. Recall that this ratio simply represents a measure of the inverse of the strength of the economic shock relative to the noise. Thus, the higher is the information about the economic shock held by the agents, the larger is γ and consequently the larger the effects on expectations (and consumption).

Panel (a) of Figure 2 plots the response of expectations above for different values of λ and γ. Colors refer to different values of λ, styles corresponds to different values of γ. The two implications can be clearly seen. The lower are information frictions, the higher tend to be the responses to the economic shock and the faster the maximal response is reached.

Implication #3

Next, I derive an implication in terms of agents' uncertainty about news, i.e. uncertainty about the sign of s_{it}. In addition, I also consider uncertainty about the sign of expected economic conditions (better or worse expected economic conditions). I rely on uncertainty (or disagreement) about qualitative outcomes since this is directly related to the empirical measure of information accuracy discussed in the previous section. I perform two simulations with the goal of better understanding how information frictions and news uncertainty interact on the one hand, and, on the other hand, assessing whether news uncertainty can be considered a good proxy for information frictions. As before, I use Shannon's (1948) entropy to measure uncertainty and disagreement.[8] Let p the proportion of positive news, i.e. $s_{it} > 0$, or positive expectations and $1-p$ the proportion of negative news or negative expectations. The entropy is $-p\log_2(p) - (1-p)\log_2(1-p)$. As mentioned before, if 100% of the individuals agree that the sign of the news is positive (or negative), i.e. zero disagreement, the associated entropy will be minimal. Entropy is maximal, and so is disagreement, when 50% of the individuals say positive and 50% say negative.

In the first simulation, I focus on uncertainty about news, i.e. the variable s_{it}. The simulation works as follows. I fix $\sigma_\omega^2 = 1$, I set $\omega_t = 0.1, 0.5, 0.9$ and $\sigma_v^2 = 0, 0.01, 0.02, ..., 2$. For each of the 603 different parametrizations I generate $N = 10^6$ individual signals s_{it}. Uncertainty is measured with the entropy associated to the sign of the individual signals. Panel (b) of Figure 2 plots news entropy as a function of σ_v^2. Each line corresponds to a value of the shock ω_t. The higher is the noise variance, the lower is the information content

[8]Disagreement, in case of continuous variables like individual forecasts, can also be measured using dispersion measures.

of the signal about the economic shock and the higher is uncertainty. When $\sigma_v^2 = 0$, the signal is perfectly informative and uncertainty is zero: all of the agents agree upon the sign of the signal. Notice that, since a lower noise variance implies a higher value of γ, a direct link between the degree of friction and news uncertainty arises: the higher is γ the lower is news uncertainty.

In the second simulation I focus on disagreement among agents in terms of sign of expected economic outcomes. Again I set $\sigma_\omega^2 = 1$ and consider a set of values for parameters γ and λ in the range [0.2 0.8]. I assume that the economic a_t follows and AR(1) with parameters 0.25, the values obtained by fitting an AR(1) to industrial production growth. For each combination of the two parameters I generate $N = 5000$ individuals expectations about current economic outcomes, a_t, of length $T = 300$ periods. In each period I construct the associated entropy using p_1 as the proportion of individuals expecting worse economic conditions. I then average over the T periods. Panel (c) of Figure 2 plots the value of entropy for each combination of the parameters. Disagreement increases with information frictions, lower values of the parameter γ and higher values of the parameter λ are associated with high disagreement. Expectation uncertainty increases with the degree of information frictions.

The two simulations lead to the third implication. The larger is the parameters γ and the smaller is the parameter λ, i.e. the smaller is the degree of frictions, the smaller is news uncertainty and the more agents agree on the sign of the signal s_t and the sign of the expectations of the economic variable.

From the above analysis, it can be noticed that the three empirical measures presented in the previous section can be interpreted as proxies for the degree of information frictions. I use these three empirical measures in the next section in order to assess empirically the role of information for economic fluctuations.

4 Econometric approach

In this section I empirically assess the role of information as a mechanism generating asymmetric fluctuations. More specifically, I investigate whether the response of consumption and agents' expectations are higher in high-information periods relative to low-information periods as implied by the theoretical framework discusses above.

4.1 The model

I employ a Threshold Vector Autoregression model, see Tsay (1998).[9] The model is a state dependent model with two states: high information and low information. First I describe the model and then I discuss the state variable in detail. Let y_t be a n-dimensional time series vector assumed to follow

$$y_t = (1 - F(z_t))(c + A(L)y_{t-1} + Gu_t) + F(z_t)(d + B(L)y_{t-1} + Hw_t), \tag{7}$$

where $u_t \sim WN(0, I)$, $w_t \sim WN(0, I)$ (I being the identity matrix), $A(L) = A_0 + A_1 L + ... + A_p L^p$, $B(L) = B_0 + B_1 L + ... + B_p L^p$ (L being the lag operator). The matrices G and H are such that $GG' = \Sigma$ and $HH' = \Omega$ where Σ is the covariance matrix of $\varepsilon_t = Gu_t$ and Ω is the covariance matrix of $\eta_t = Hw_t$.

I specify the model as follows. The vector y_t includes the following variables. Two consumer expectation variables: the current Michigan Confidence Index, the expected Michigan Confidence Index. Three consumption aggregates: (log) total consumption, (log) durable consumption, and (log) non-durable consumption. The specification is motivated by the fact that the main goal is to investigate the effects of information both on consumers' expectations and consumption decisions.

The threshold variable I employ is a cleaned version of X_{1t}, X_{2t} and X_{3t} (used in three separate models), where the component attributable to business cycle fluctuations is removed (see the next subsection for the details of this preliminary treatment). The main reason of this treatment is that, as seen before, information variables are counter-cyclical. Without this preliminary cleaning, one might interpret possible asymmetries as due to different information sets while they could simply arise because agents' response to economic shocks is different in recessions and expansions. I call the purged variable N_t. I then set $z_t = N_{t-1}$ and define a low-information regime $F(z_t) = 1$ if $z_t < Med(N_{t-1})$, i.e. smaller than the median, and a high-information regime $F(z_t) = 0$ if $z_t \geq Med(N_{t-1})$.[10] Taking the lag ensures that the variable is exogenous with respect to the variables at time t.

The coefficient $A(L)$ and G are therefore the coefficients of the high information regime, while $B(L)$ and H are the coefficients of the low information regime. The impulse response

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

[10] Using the mean does alter the results.

function in the high information regime are $(I - A(L)L)^{-1}G$, while those in the low information regime are $(I - ABL)L)^{-1}H$.

Model estimation is straightforward. Notice that the above model can be written as

$$y_t = (1 - F(z_t))(c + A(L)y_{t-1}) + F(z_t)(d + B(L)y_{t-1}) + \xi_t \tag{8}$$

where $\xi_t = \varepsilon_t + \eta_t$. I specify six lags. The matrices of coefficients $A(L)$ and $B(L)$ are estimated with OLS. The covariance matrices of the two regimes are estimated as $\hat{\Sigma} = \overline{\tau}^{-1} \sum_{t \in \overline{\tau}} \hat{\varepsilon}_t$ ($\overline{\tau}$ being the number of periods of high information regime) with $\hat{\varepsilon}_t = (1 - F(z_t))\hat{\xi}_t$, and $\hat{\Omega} = \underline{\tau}^{-1} \sum_{t \in \underline{\tau}} \hat{\eta}$ ($\underline{\tau}$ being the number of periods in the low information regime), with $\hat{\eta}_t = F(z_t)\hat{\xi}_t$, where ξ_t is the residual in (8) . Finally I set G equal to the Cholesky factor of Σ and H equal to the Cholesky factor of Ω.

To assess the information channel, I perform both a conditional analysis, i.e. conditional on a certain shock, and an unconditional analysis, i.e. unconditional statistics of the the economic variables generated under the two regimes.

My story unfolds as follows. Agents' expectations depend of the degree of information frictions. Different information sets will generate different expectation dynamics. These changes will be then reflected into the response of consumption. Thus, in order to assess these potential differences a shock which plays an important role for consumers' expectations has be considered. The shock which maximizes the explained short run variance of expectations is simply its innovation. Given that the current conditions confidence index, the first variable in vector y_t is an average of two expectation variables[11] the first element in u_t and w_t represents such an innovation which is orthogonal to all the remaining in the vector u_t and w_t.[12] Of course, the shock lacks of a clear structural interpretation. This, however, should not be seen as a limitation since the information-driven asymmetry should apply to any shock affecting agents' expectations on impact, particularly to the innovation whose effect on the expectation is maximal on impact.

[11]The current index is constructed as $ICC = \frac{Z_1 + Z_2}{2.6424} + 2$ where Z_1 is the difference between positive and negative answers (in percentage terms) to the question "We are interested in how people are getting along financially these days. Would you say that you (and your family living there) are better off or worse off financially than you were a year ago?". The variable Z_2 is the difference between positive and negative answers (in percentage terms) "About the big things people buy for their homes–such as furniture, a refrigerator, stove, television, and things like that. Generally speaking, do you think now is a good or bad time for people to buy major household items?"

[12]The innovation explains more than 50% of the variance of the two confidence indexes.

4.2 Preliminary treatment of the information variable

To clean the news variable I proceed as follows. Let x_t be a vector including the log industrial production, log stock prices, the unemployment rate and the information variable (X_{it}, $i = 1, 2, 3$) ordered last.[13] I estimate model (7) for x_t using unemployment as state variables (larger or smaller than the mdeian) and applying a Cholesky decomposition. The choice of using a non-linear model even in this preliminary step depends on the fact that there is evidence that agents' information is more responsive to bad economic events than good events, see Soroka (2012) and Gambetti et al. (2020). This is captured by allowing the dynamics of to be dependent on the unemployment rate. A linear VAR however would yield similar results qualitatively. The cleaned version of the news variable is the component driven by the shock which is orthogonal to current and past values of industrial production and the unemployment rate, i.e. the third shock of the Cholesky representation. I call this variable N_t.

Column (b) of Figure 1 plots the original series X_{it} (dashed-dotted line) together with their purged version (solid lines). The purging, as expected, seems to play an important role since fluctuations in the purged version are mitigated, especially in the pre-2000 period. Nonetheless, large and relatively persistent swings still remain even after removing the effects attributable to the business cycle.

5 Results

In this section I will present the main results of my analysis. First, I will discuss the impulse response functions, second, I will discuss the findings obtained using a counterfactual experiment.

5.1 Asymmetric impulse response functions

Figure 3 plots the impulse response functions in the two regimes using the three proxies (corresponding to the three columns). The blue line is the point estimate of the low-information regime and the blue areas the associated 68% confidence bands. The red line is the response in the the high-information regime. Within the first two years after the shock, the high-information regime response is always larger in magnitude than the low-information regime response, laying outside the low-information bands in the short and medium run. Although

[13] Using the growth rates of industrial production and stock prices yields very similar results.

the model just represents an interpretative framework and a formal quantitative assessment of it is far beyond the scope of this paper, still it can be noted that the empirical responses of the two expectations are qualitatively similar to the parametrizations ($\lambda = 0.2, \gamma = 0.8$) and ($\lambda = 0.5, \gamma = 0.8$). Qualitatively, the results are similar across the three information variables. However there are a few quantitative differences. Indeed for the disagreement variables the differences between the two regimes appear to be much larger.

Overall the results are very much in line with the implications of the above theoretical framework: when information frictions are lower the responses of expectations and consumption tend to be larger in magnitude. The evidence supports the idea that information acts as an asymmetric propagator of the effects of the shock giving origin to a more volatile consumption in high-information regimes.

5.2 Counterfactuals

The above analysis was conditional to an innovation to the consumer confidence index. Here I extend the analysis and perform an unconditional assessment of the role of information as an asymmetric amplifier. I perform the following counterfactual experiment. Using the estimated orthogonal shocks $\hat{u}_t$ and $\hat{w}_t$ and the estimated parameters, I generate new artificial series from the following two models [14]

$$y_t^{High} = \hat{A}(L)y_{t-1}^{High} + \hat{G}(\hat{u}_t + \hat{w}_t) \tag{9}$$

$$y_t^{Low} = \hat{B}(L)y_{t-1}^{Low} + \hat{H}(\hat{u}_t + \hat{w}_t) \tag{10}$$

The first is a model where the coefficients are set constant and equal to the values estimated for the high-information regime, while the second is a model where the coefficients are set constant and equal to the values estimated for the low-information regime. By abstracting from the constant the generated series con be interpreted as the fluctuations in (log) consumption generated by the shocks under the two different parametrizations. Using the counterfactual series I then compute the yearly growth rate of total consumption, durables consumption, and non-durables consumption in order to be able to compute variances and other statistics. Notice that, given that the shocks are identical in the two models, all the differences in the two counterfactual series are attributable to the differences in the model coefficients.

Table 1 reports the results in terms of volatility of the two variables (column 1 and 2) and in terms of average difference between the absolute value of the estimated series /column

[14] Notice that I abstract from the constant term.

3). The two are measures of the amplitude of the fluctuations associated to the two regimes. Fluctuations in the high-information regime are substantially larger than those obtained in the low-information regime. The variances, as well as the average absolute effects differences, are much larger for all of the five variables. To get an idea, the average absolute effect differences for consumption are around 0.5-0.7%, 2-2.6% and 0.7-1% for the three models. As far as volatility is concerned, in model the low-information regime variances of consumption are about 60-70% smaller than the high-information regime in the three models.

I perform two other counterfactual exercises in order to assess the role of information during the Great Recession and its aftermath. The first works as follows. According to the estimates the period 2007M12-2009M5 is a period of high-information. The idea is to generate a counterfactual series for the recession period from the low-information regime parameters and compare the two series. The difference between the two series represents the effect of information. To do so I use the estimated orthogonal shocks $\hat{u}_t$ and $\hat{w}_t$ and the estimated parameters. First I generate a series from the model

$$y_t^{Asy} = (1 - F(z_t))(\hat{A}(L)y_{t-1}^{Asy} + \hat{G}\hat{u}_t) + F(z_t)(\hat{B}(L)y_{t-1}^{Asy} + \hat{H}\hat{w}_t). \tag{11}$$

Then I generate a second series is generated using (11) until 2007M11, the month previous to the official beginning of the recession, and (10) for the 12 months after. Thus, the two series are identical until to onset of the Great Recession and differ afterwards since the second is generated using low-information regime parameters.

The black solid line is the path of consumption generated using (11) and can be interpreted (with a difference in the constant term) as actual consumption. The dashed red line is the counterfactual consumption obtained in the low information regime. Actual confidence and consumption is always larger in absolute value than counterfactual consumption, and the differences in terms of magnitudes are sizable, see column 4 of Table 1. In the X_{3t} specification actual consumption (total, durable and non-durable) is -1.2, -5.2 and -1.2 percent smaller than counterfactual consumption. In the X_{1t} and X_{2t} specifications the differences are similar. In the former the differences are -0.7, -3.4 and -1. In the latter -1.4, -6.1 and -1.5. So, had information been low the fall in consumption during the great recession would have been milder.

The second counterfactual works as follows. First I generate a series (series 1) from the model (11). Second, I generate a second series (series 2) using (11) until July 2009 (the official end of the recession) and using (10) afterward. I also generate a third series (series 2) from (11) until July 2009 and from ((9)) afterwards. The goal of the exercise is to understand how would have been the recovery had information always been high or always low. The results are displayed in Figure 5. The solid black line is series 1. The dashed-dotted blue line is series 2 and the dotted red line is series 3. Using X_{2t} and X_{3t} a very interesting finding emerge. According to the estimates, had information always been higher after the end of the recession, the recovery in terms of consumption would have been much faster (the blue line). At the beginning of 2010 consumption growth would have been at a level comparable to the pre-recession period 2005-2006. The result hold for the three types of consumption. The increase would have been remarkably faster for durable consumption. A similar fast recovery is also found for the confidence indexes. The finding does not emerge however when considering X_{1t}. An possible explanation is that X_{1t} does not proxy the quality of the information and consumers' agreement which might play an important role.

6 Conclusions

Information is at the root of the agents' decision process. I have shown empirically that agents' information set is time-varying displaying persistent cycles. Time-variations creates asymmetries in economic fluctuations since, consistently with the predictions of a very stylized framework of information frictions, agents react more to shocks in a high-information regime than a low-information regime. As a result, a high-information regime give rise to a more volatile consumption.

The findings open a very intriguing question: why do agents acquire information cyclically? There is a growing evidence that media news cover economic events in an asymmetric fashion giving more importance to bad events rather than good events. However it could also be due to asymmetries in the agents' optimal decision process itself. For instance the existence of loss aversion or other features. I leave this question for future research.

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Tables

	X_{1t}			
	$Var(\Delta c_t^{High})$	$Var(\Delta c_t^{Low})$	$\|\Delta c_t^{High}\| - \|\Delta c_t^{Low}\|$	$\Delta c_t^{Asy} - \Delta c_t^{Low}$
ICC	287.66	71.80	6.94	-5.64
ICE	271.54	90.49	5.74	-4.85
Total Cons.	3.62	1.26	0.66	-0.74
Durable	48.31	18.80	2.26	-3.45
Non-durable	5.29	1.29	1.00	-0.96
	X_{2t}			
	$Var(\Delta c_t^{High})$	$Var(\Delta c_t^{Low})$	$\|\Delta c_t^{High}\| - \|\Delta c_t^{Low}\|$	$\Delta c_t^{Asy} - \Delta c_t^{Low}$
ICC	180.28	42.78	5.51	-9.59
ICE	172.62	63.83	4.04	-9.30
Total Cons.	3.08	1.06	0.51	-1.44
Durable	43.81	15.45	1.98	-6.11
Non-durable	3.59	0.96	0.68	-1.47
	X_{3t}			
	$Var(\Delta c_t^{High})$	$Var(\Delta c_t^{Low})$	$\|\Delta c_t^{High}\| - \|\Delta c_t^{Low}\|$	$\Delta c_t^{Asy} - \Delta c_t^{Low}$
ICC	250.27	45.76	7.39	-9.49
ICE	228.83	63.87	5.85	-9.10
Total Cons.	3.62	1.04	0.69	-1.18
Durable	49.89	14.66	2.61	-5.24
Non-durable	4.30	1.14	0.77	-1.25

Table 1: Countefactuals experiment. First column: variance of annual consumption growth rate in the high information regime. Second column: variance of annual consumption growth rate in the low information regime. Third column: average of the difference of the absolute effects in high and low information regime. Fourth column: difference between average consumption growth and average counterfactual consumption growth obtained in the low information regime during the Great Recession

Figures

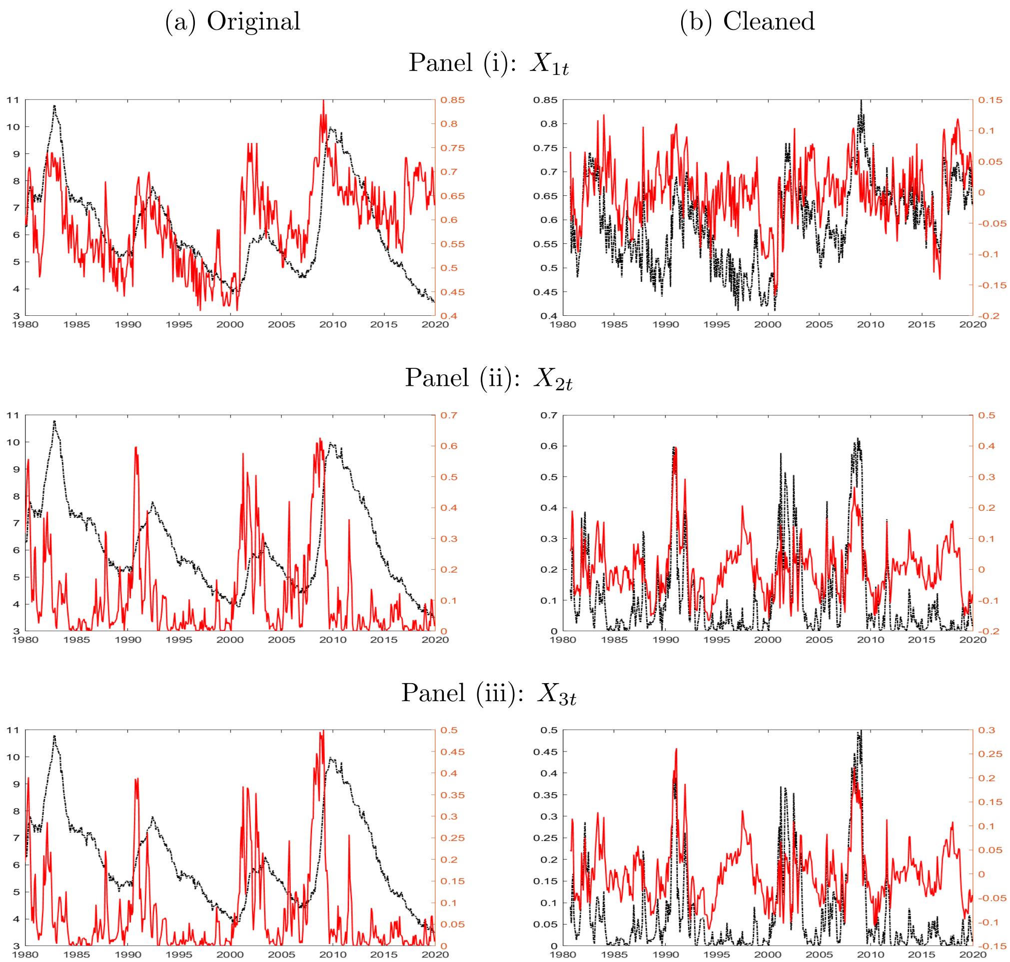

Figure 1: News variables X_{it}, $i = 1, 2, 3$.. Left column: news variables (red solid lines) and unemployment rate (black dotted lines). Right column: news variables (black dotted lines) and purged news variables (red solid lines).

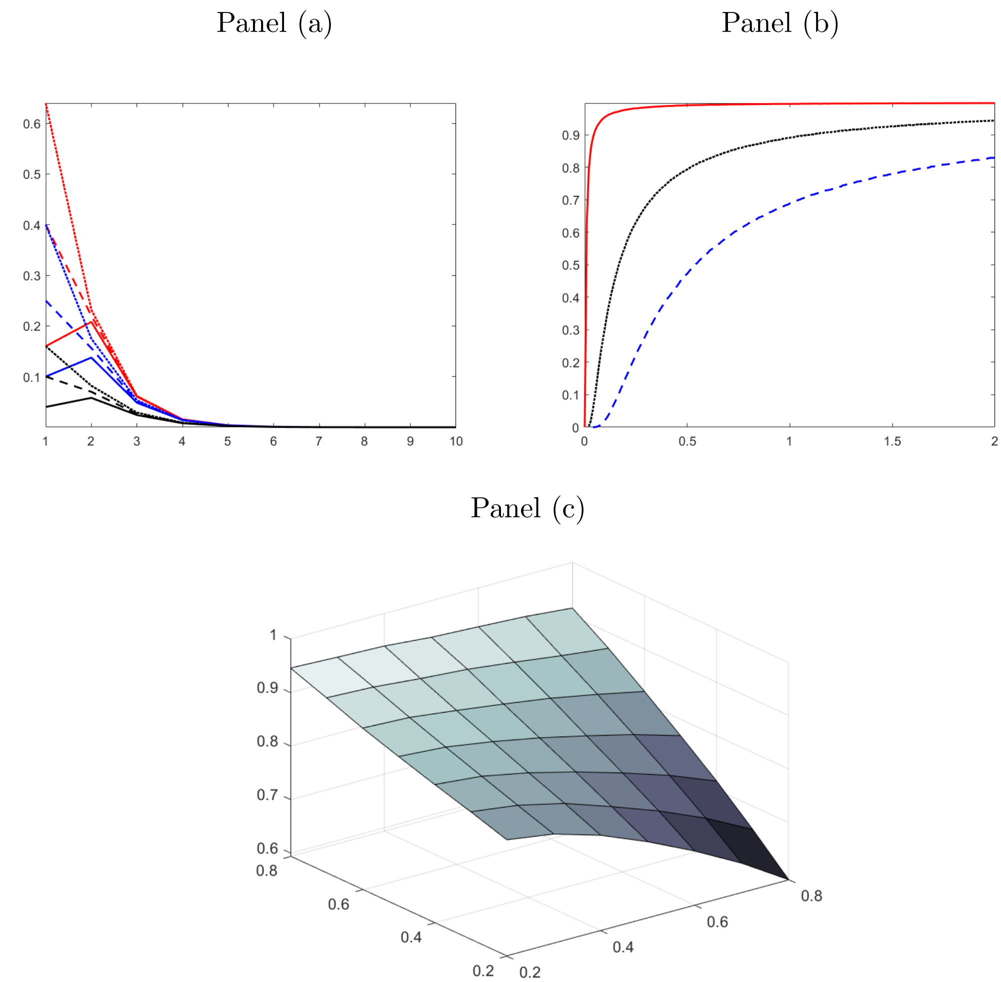

Figure 2: Panel (a), theoretical impulse response functions. Red lines $\lambda = 0.2$. Blue lines $\lambda = 0.5$. Black lines $\lambda = 0.8$. Solid lines $\gamma = 0.2$. Dashed lines $\gamma = 0.5$. Dotted lines $\gamma = 0.8$. Panel (b) entropy. Red solid line $\omega_t = 0.1$. Black dotted line $\omega_t = 0.5$. Blue dashed $\omega_t = 0.9$. x-axis is σ_v^2. Panel (c). x-axis γ, y-axis λ, z-axis entropy.

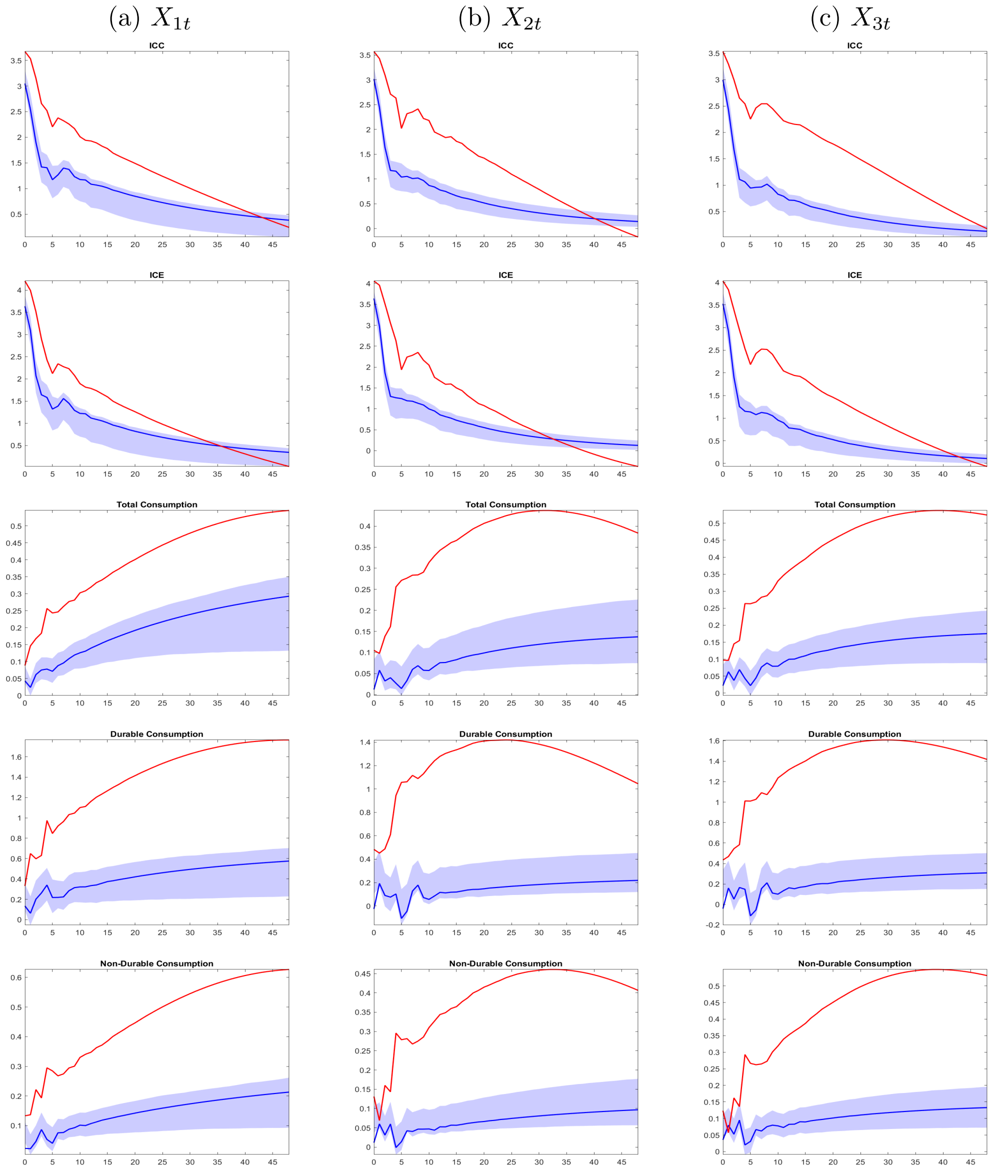

Figure 3: Impulse response functions in the three models using different X_{it}. The blue line is the point estimate of the low-information regime and the blue areas the associated 68% confidence bands. The red line is the response in the the high-information regime.

(a) X_{1t} (b) X_{2t} (c) X_{3t}

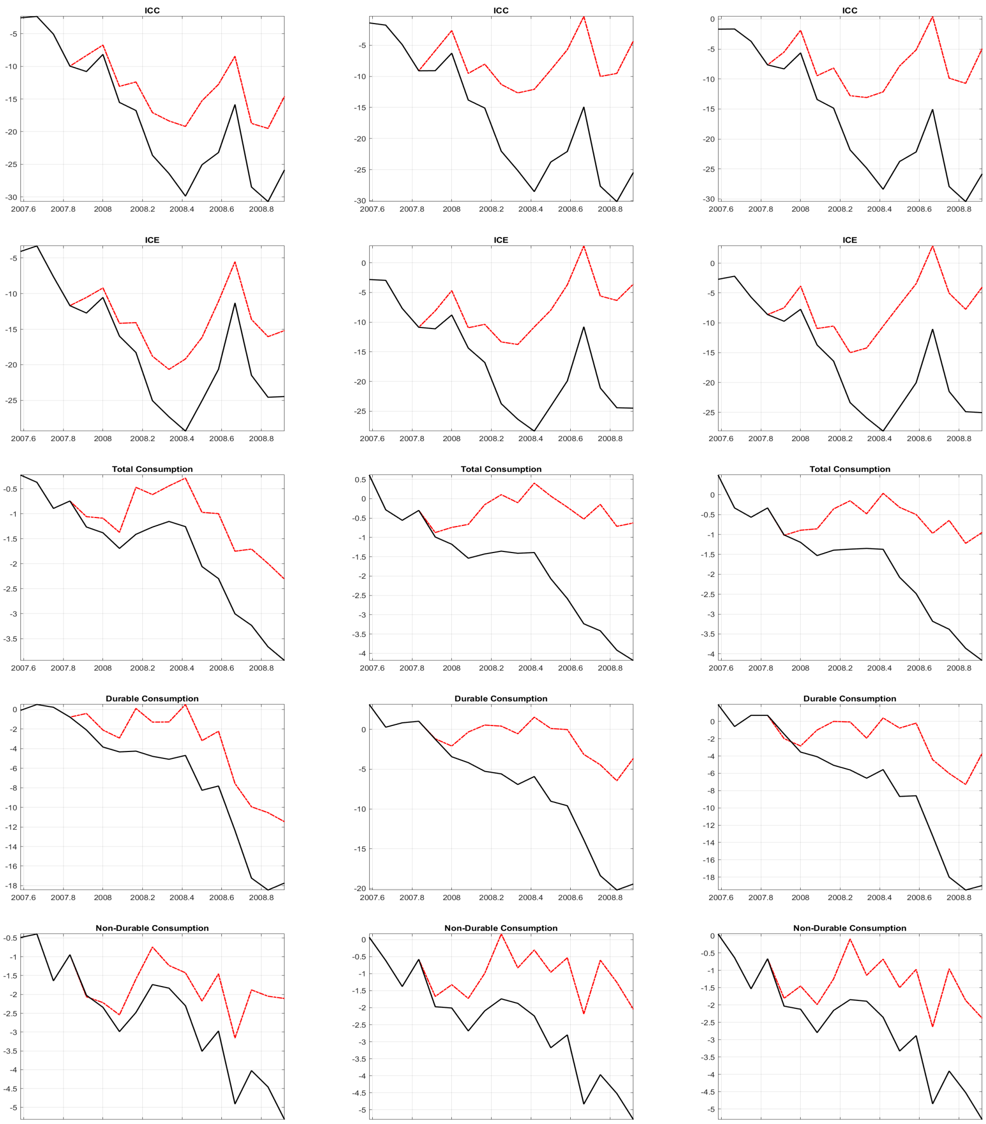

Figure 4: Counterfactual 1. Black solid lines consumption generated using y_t^{Asy}. Red dashed lines, consumption generated using y_t^{Low}.

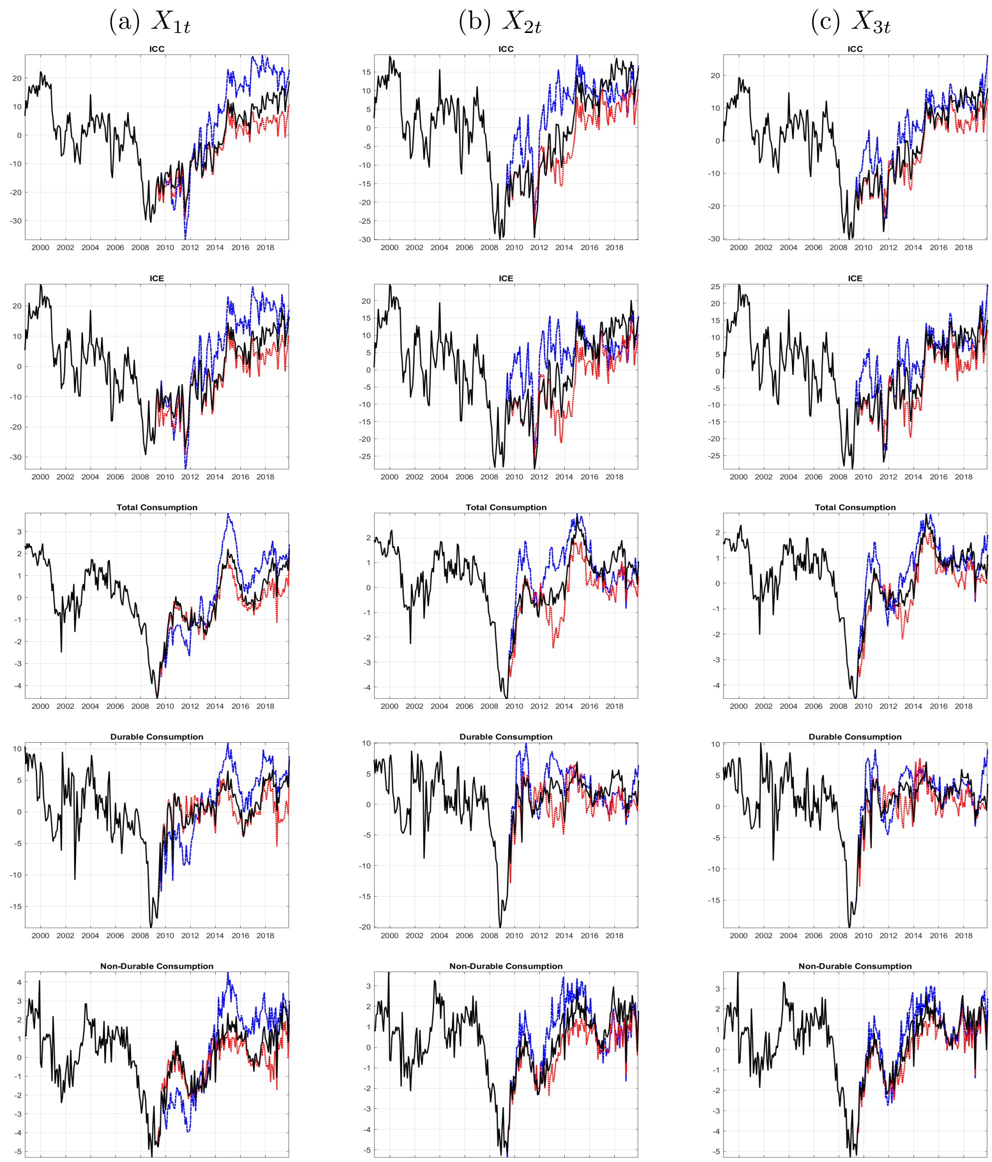

Figure 5: Counterfactual 2. Black solid lines consumption generated using y_t^{Asy}. Red dotted lines, consumption generated using y_t^{Low}. Blue dashed lines, consumption generated using y_t^{High}.