Expectations and uncertainty: A common-source infection model for selected European countries

Luca Gerotto[*] Antonio Paradiso[†]

May 22, 2018

Abstract

We present a common-source infection model to explain how households form their expectations. Starting from the theoretical framework of "Macroeconomic expectations of households and professional forecasters" (C.D. Carroll, *The Quarterly Journal of Economics*, 2003), we expand the original model assuming that also uninformed individuals are able to update expectations according to a naive econometric process. In this novel framework, a key role is played by the parameter measuring the probability of being informed: the dynamics of this factor over time capture the level of uncertainty perceived by households. This new framework is applied to study unemployment expectations for a select group of European countries, namely, France, Germany, Italy and the UK. Our results show that: (*i*) the novel framework is supported by data on unemployment expectations; and (*ii*) the probability of being informed is (negatively) correlated to the level of uncertainty spread by newspapers and communicated on the Internet.

JEL CODES: D84, E24

Key Words: Expectations, Unemployment

[*]Department of Economics, Ca' Foscari University, Cannaregio 873, Fondamenta San Giobbe, 30121, Venice, Italy luca.gerotto@unive.it

[†]Corresponding author, Department of Economics, Ca' Foscari University, Cannaregio 873, Fondamenta San Giobbe, 30121, Venice, Italy antonio.paradiso@unive.it

At a general level, uncertainty is typically defined as the conditional volatility of a disturbance that is unforecastable from the perspective of economic agents.

Jurado et al. (2015)

1 Introduction

Expectations matter in the macroeconomy and changes in expectations may lead to further changes in economic activity, both at an individual (i.e. firms and consumers) and at an aggregate level. For example, interest-rate expectations enter into the investment decisions of firms (Neumeyer and Perri, 2005), the portfolio decisions of investors (Friedman and Roley, 1979) and the bond issues of companies (Baker et al., 2003). Similarly, inflation expectations may impact on consumption behavior (D'Acunto et al., 2015; Duca et al., 2016), whereas stock price and output expectations may influence investment decisions (Lamont, 2000). Expectations concerning unemployment are another important source of business fluctuations given their impact on consumption expenditure. Carroll and Dunn (1997) use as proxy for income uncertainty, due to unemployment risk, unemployment expectations. The authors find that unemployment expectations - the proxy of unemployment risk? are strongly correlated with consumer expenditure. Moreover, Carroll and Dunn (1997) show that the deterioration in unemployment expectations played an important role in explaining the 1990-1991 recession and recent theoretical models emphasize the role of perceived unemployment risk in amplifying business cycles (Sterk and Ravn, 2017; Beaudry et al., 2017).[1]

Although the recognized importance of unemployment expectations in generating business fluctuations, the way expectations are formed in macroeconomics still remains an open issue. In general, most empirical and theoretical models assume Full Information Rational Expectations (FIRE). Under FIRE agents have access to all the available information, know the true model and use it to form predictions.

Even though the FIRE approach is a useful and theoretically strong starting point (Friedman, 1953; Muth, 1961), its actual empirical soundness has been repeatedly discussed in recent decades as summarized in Curtin (2010). Further, Simon (1959, 1978, 1979) casts doubts on the ability of theories based upon the rationality assumption to explain observed phenomena. Classical papers in behavioural economics have identified several cognitive biases (Kahneman et al., 1982; Earl, 1990; Thaler, 1994; Rabin and Schrag, 1999; Thaler, 2012) that undermine the formation of rational expectations. Furthermore, Roberts (1998) and Tortorice (2012) report that surveys only reflect an intermediate degree of rationality, and Ball (2000) proposes near-rationality in inflation expectations as a possible solution.

One of the main weaknesses of FIRE is the assumption that all individuals have access to the same complete set of information used to form expectations. Moreover, even assuming individuals have access to all the available information, not all of them may have the capacity and/or the willingness to absorb all the data. If there are positive costs

[1] For a more general analysis of the role of psychological factors and "less-than-fully-rational" shifts in expectations on business cycles, see Milani (2011).

associated to collecting and processing information, the agents may find it best to formulate less accurate expectations. Examples in the direction of information rigidities are the "Sticky Information" (Mankiw and Reis, 2002) and "Noisy Information" models (Sims, 2003; Bacchetta and Van Wincoop, 2005; Woodford, 2003) where "Sticky Information" (SI) models assume that agents are rational, but the presence of fixed costs in both updating and processing information induce agents to rarely update their information set. Once they update, they acquire FIRE. Conversely, "Noisy Information" (NI) models assume that agents update information every period,[2] but they are able to observe only one of many noisy signals rather than the true state. Being unable to disentangle true innovation from the noise, they do not fully "trust" that signal. Rather, their new expectation is a weighted average of the signal and their prior belief.

Despite the different underlying theoretical assumptions,[3] both SI and NI imply the same level of stickiness in aggregate expectations (Coibion and Gorodnichenko, 2015). For this reason, tests on aggregate empirical data cannot discriminate between NI and SI. Coibion and Gorodnichenko (2015) also point out that for NI, as opposed to SI, the weight attributed to the signal depends on (*i*) the persistence of the variable under consideration, and (*ii*) the noisiness of the signal: the higher the variance of the noise, the less agents take the signal into consideration.

Similarly to SI, Branch (2004, 2007) assumes that agents are rational and are able to use sophisticated models to resolve uncertainty. However, sophisticated models are costly (in terms of both time and resources) and, for this reason, some agents may prefer to form their expectations using adaptive or naive models. Carroll (2003) has, instead, modelled the disagreement among people as the result of an "infectious" process deriving from a common source. He assumes that only a small fraction of agents (professional forecasters) form their own expectations. These professional opinions then spread across the population via news media much like virus do. In any given period, each agent has a given probability of hearing the latest "official" forecast through newscasts. If this happens, he equalizes his expectation to this "professional" forecast, otherwise he maintains his previous expectation.

Whatever the cause generating disagreement across agents and staggered changes in expectations, one of the main differences between the above-mentioned approaches to model the expectations lies in the possibility for less informed agents to revise their expectations. According to Branch (2004, 2007), Woodford (2003) and Sims (2003) all agents revise their expectations, while Mankiw and Reis (2002) and Carroll (2003) assume that only the informed ones do. The uninformed (inattentive) group, instead, maintains the previous expectation. The hypothesis that inattentive agents do not revise their previous opinion at all may appear quite bold in practice. Even the more "discouraged" agents may make an effort to build an expectation.[4]

[2] In standard NI models, the underlying macroeconomic variable subject of expectations is formalized as an autoregressive process.

[3] According to SI, cross-sectional disagreement across people reflects different choices with regards to updating information, while in NI it is the result of the different signals they observe.

[4] Easaw and Golinelli (2012) remove the assumption of fixed expectations by inattentive agents in Carroll's framework (2003) by using the particular structure of UK survey. The authors assume that a

Starting from Carroll (2003),[5] we developed a common-source-infection (CSI) model applied to expected changes in the unemployment rate for a select group of European countries, namely Germany, France, Italy, and the UK.[6] This work is innovative with respect to Carroll's framework (2003) in three ways. First, we generalized the CSI framework, introducing the possibility that also the fraction of uninformed agents may change their expectations. In this regard, we assume that inattentive agents act as "naive" econometricians. More specifically, the idea is that the formulation of "sophisticated" expectations requires an investment of time and resources that only professional forecasters may sustain: non-professional agents rationally prefer not to spend time and resources in producing state-of-the-art forecasting models. As a consequence, if agents are "infected" by news, they embody professional expectations; otherwise, if agents are not "infected", they exploit the old information to build expectations using simple naive models, with little effort in terms of time and resources. Second, we allowed the key parameter measuring the probability of being infected to be time-varying. Carroll's (2003) estimates, on the other hand, are based on the assumption of a constant probability.[7] And, third, we found a (negative) link between the time-varying infection probability and the level of uncertainty, both as diffused by newspapers (using as proxy the index introduced by Baker et al., 2016) and as represented by Internet searches on economic uncertainty (using as proxy the volume of Google searches on the topic).

Our main results are as follows. First of all, we found that CSI model predictions track the survey balances for unemployment expectations well. Secondly, it appears that households less frequently spend time to learn professional expectations when they perceive heightened uncertainty: the exact future value of unemployment becomes harder to forecast, even for professional forecasters. In this situation, it is highly likely that non-expert agents care less about expert opinions.

The remainder of this paper is structured as follows: Section 2 presents some theoretical and empirical evidence on the importance of unemployment expectations at the macroeconomic level. Section 3 presents the theoretical framework and section 4 highlights the

fraction of uninformed agents use forecasts made in the previous period but over the same horizon (i.e. a multi-period ahead survey-based forecasts) and the remaining fraction is anchored to the previous forecast.

[5] The term "epidemiology" has different meanings in several diverse streams of literature. Carroll (2003) defines this as an epidemiological framework because the information is considered in terms of a virus spreading through the population. In order to obtain an estimable-closed-form solution of the model, the author assumes that: (*i*) only an unique common source of infection exists; (*ii*) there is no possible contagion among agents; and, (*iii*) there is no recovery from the virus. The above-mentioned assumptions deprive the model from characteristics which are considered as crucial for an epidemiological model in other streams of literature. In order to avoid any confusion in the reader, we prefer to label the model as "common-source-infection" model throughout the paper.

[6] The model is designed in terms of unemployment rate variations (i.e. in first-differences) since the formulation of the question on unemployment expectations, both in the Eurostat (for Europe) and in the Michigan (for US) surveys of households, goes in this direction.

[7] Coibion and Gorodnichenko (2015) also offer a similar time-varying estimate, however, this refers to different circumstances. In any case, our time-varying approach is totally model-based in consideration of the different aim of our work. This choice has been made in order to avoid a spurious correlation with the "news-based" indexes.

role of uncertainty in the CSI framework. Section 5 presents the estimation strategy and Section 6 the related output. Section 7 concludes the paper.

2 The effect of expectations on consumption: theoretical and empirical facts

Before introducing the common-source-infection model, in what follows we present further evidence of the specific implications of household unemployment expectations at the macroeconomic level, implicitly highlighting the importance of studying the related formation process.

Several theoretical and empirical papers have dealt with the issue of household behaviour and precautionary savings under uncertainty, especially with regard to income uncertainty (Skinner, 1988; Kimball, 1990; Deaton, 1991; Carroll et al., 1992; Carroll, 1997). A large fraction of US households has reported that they do not save to prepare for retirement, but to be prepared for emergencies (Carroll, 1997). For example, according to the Buffer-Stock Theory (Carroll et al., 1992; Carroll, 1997) an agent which is both prudent and impatient may be induced to build a "buffer stock" of savings to face periods of potentially low income or, equivalently, periods of potentially high expenditure. The level of this "buffer" targeted by the household depends on his expectations: the higher the uncertainty and the lower the income expected,[8] the more savings are accumulated thereby reducing current consumption levels. In such a theoretical framework unemployment expectations are of striking relevance since they can be viewed as the (perceived) probability of having no labour income. A deterioration of these expectations should depress the consumption level. Examples of articles that have shed light on the empirical relationship between unemployment expectations and consumption-saving choices of US households can be found in Carroll and Dunn (1997) for consumption and Carroll et al. (2012) for the saving rate. Recently,Carroll et al. (2014) has extended the analysis to empirical data for European households, finding that their behaviour is more in line with the logic of the buffer-stock saving than with the standard life-cycle model.[9]

In the spirit of Lettau et al. (2002), Wu (2003) and Marcellino (2006), we estimate a small macro VAR model to give support to the importance of unemployment expectations on consumption decisions. The model includes household consumption (durables and non-durables, as a logarithm) along with the following three variables that are central in investigating household spending decisions: disposable income,[10] unemployment expectations and the inflation rate.[11] This model can be used to construct impulse response

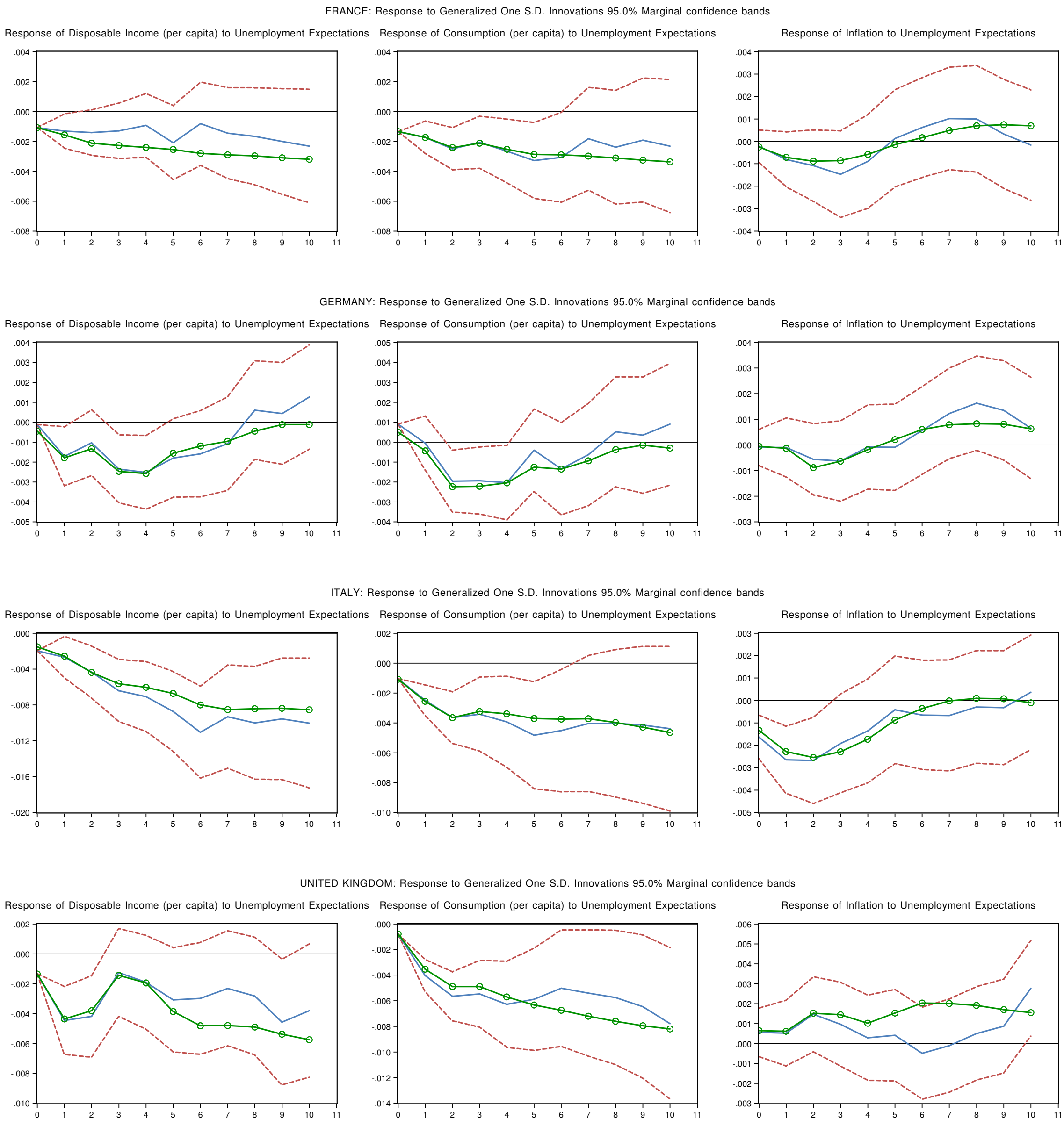
[8] Or, equivalently, the higher the expenses he expects to face.

[9] Carroll et al. (2014) does not make any explicit reference to unemployment expectations.

[10] Disposable income does not include only labour income but also the other sources of income which could be promptly spent, like interest and dividend payments from financial assets, and rents and net profits from businesses. As for consumption, in is expressed in logarithm.

[11] The inflation rate may intercept additional effects such as monetary policy interventions, or the relative price illusion (Deaton, 1977).

Figure 1: Impulse Response graph of disposable income per capita, consumption per capita and inflation to unemployment expectations (1991Q1-2016Q4).



Notes: Impulse response (blue) and confidence bands (red) are estimated according to the local projection method (Jordà, 2005, 2009). Standard VAR estimates are in green.

functions showing the dynamic response of consumption expenditure when a shock in unemployment expectations occurs. We employ two alternative impulse response functions (IFRs) to exemplify this. The first approach is the Generalized Impulse Responses (GIRF) of Pesaran and Shin (1998). The GIRF approach is quite general because it does not vary according to how variables are ordered in VAR. Furthermore, following Jordà (2005, 2009) we use local projections. This approach is robust against misspecification and can accomodate nonlinear and flexible specifications. In VAR analysis we consider France and Germany, the two leading economies for the Euro area, Italy, one of the biggest countries among those suffering from low growth, and an important non-Euro country like the United Kingdom. As expected, a generalized impulse-response analysis highlights a common negative effect of unemployment expectations on consumption decisions. According to the results plotted in Figure 1, it appears that the more households are pessimistic, the less they choose to consume. This effect is highly negative and statistically significant for the above-mentioned countries. Further, these results lend support to the idea of an important role played by unemployment expectations on European household consumption and saving decisions.[12]

3 Theoretical framework

3.1 Carrol's CSI framework

Carroll (2003, 2006) introduces a CSI model to formalize household expectations. In this framework, information propagates through the economy as a virus and each agent has a given probability of being infected. Denoting with x the variable under scrutiny, the following points characterize Carroll's model:[13]

I The typical person believes that x_t behaves like a *non-stationary stochastic model*:

$$x_t = x_t^* + \epsilon_t \tag{1}$$

$$x_{t+1}^* = x_t^* + \eta_{t+1}, \tag{2}$$

where x_t^* represents the "fundamental value" of x_t, and the disturbance ϵ_t and the innovation η_t are Gaussian independent processes.

II Only professional forecasters, a group of expert agents, are able to form expectations on x_{t+1}. These groups of experts have the ability to observe x_{t+1}^* exactly, so that the prediction concerning x_{t+1} corresponds to:

$$N_t\left[x_{t+1}\right] = x_{t+1}^* = x_t^* + \eta_{t+1}, \tag{3}$$

[12]Possibly with the exception of Germany, where the effect is a bit weaker.

[13]Carroll (2003, 2006) used these assumptions to develop a model describing the formation of inflation expectations. The framework introduced in Carroll (2003, 2006) is general enough to be extended to other kinds of economic variables such as GDP, disposable income, consumption, and unemployment.

where $N_t[x_{t+1}]$ indicates the professional forecast prediction. In other words, the innovation η_{t+1} is always observed by expert agents in period t.[14]

III Professional forecasters expectations spread in the economy via news media (i.e., the so-called "common source of infection"). In each period, an agent i has a probability λ of being infected by the information and, then, to revise the expectation incorporating the professional forecasters prediction.[15]

IV $N_{t+k}[x_{t+k+1}]$ is a different "virus" with respect to $N_{t+k+h}[x_{t+k+h+1}]$ $\forall k \geq 0, h > 0$. The individual infected at a generic time t never recovers from the "virus"; in other words, agents who acquire $N_{t+k}[x_{t+k+1}]$ never forget this information.

Under this set of assumptions, the expectation of x at time $t+1$ by a generic non-expert agent i can be written as:

$$E_t^i[x_{t+1}] = E_t^i\left[x_{t+1}^*\right] + \underbrace{E_t^i[\epsilon_{t+1}]}_{=0}. \tag{4}$$

If agent i is "infected" at time t, then Eq. (4) can be written as:

$$E_t^i[x_{t+1}] = N_t[x_{t+1}] = x_{t+1}^*. \tag{5}$$

If agent i is not infected in t, but was instead infected at time $t-1$, Eq. (4) is equal to

$$E_t^i[x_{t+1}] = N_{t-1}[x_{t+1}] = N_{t-1}[x_t] = E_{t-1}^i[x_t] = x_t^*. \tag{6}$$

According to these rules, the average expectation of x at time $t+1$ can be represented as:

$$M_t[x_{t+1}] = \lambda N_t[x_{t+1}] + (1-\lambda)\{\lambda N_{t-1}[x_t] + (1-\lambda)(\lambda N_{t-2}[x_{t-1}]\ldots)\}, \tag{7}$$

where $M_t[x_{t+1}]$ denotes the population-mean value of expectations of x_{t+1} made in t, $N_t[x_{t+1}]$ represents the professional forecasters expectation as reported by news media in t, and λ is the proportion of informed agents infected by news media.

Given the property of the lag polynomial (L), the right-hand side of (7) can be rewritten as:

$$\begin{aligned} \lambda N_t[x_{t+1}] + (1-\lambda)\{\lambda N_{t-1}[x_t] + (1-\lambda)(\lambda N_{t-2}[x_{t-1}]\ldots)\} &= \\ \{1 + (1-\lambda)L + (1-\lambda)^2 L^2 + \ldots\}\lambda N_t[x_{t+1}] &= \\ \frac{1}{1-(1-\lambda)L}\lambda N_t[x_{t+1}]. \end{aligned} \tag{8}$$

[14] It is important to note that future values of η beyond $t+1$ are unobservable for expert agents in period t.

[15] In terms of equation (3), this means that non-expert agents, if infected for example at time t, are able to observe directly the fundamental value x_{t+1}^*, without the ability to disentagle x_t^* from η_{t+1} (unless they have been infected also in period $t-1$).

Thus Eq. (7) can be expressed as:

$$M_t\left[x_{t+1}\right] = \frac{1}{1-(1-\lambda)L}\lambda N_t\left[x_{t+1}\right] \tag{9}$$

or

$$\left[1-(1-\lambda)L\right] M_t\left[x_{t+1}\right] = \lambda N_t\left[x_{t+1}\right] \tag{10}$$

which corresponds to

$$M_t\left[x_{t+1}\right] = \lambda N_t\left[x_{t+1}\right] + (1-\lambda)\, M_{t-1}\left[x_t\right]. \tag{11}$$

When the time is expressed in quarters and forecasts are made over the following year (i.e. from t to $t+4$), Eq. (11) can be written as:

$$M_t\left[x_{t+4}\right] = \lambda N_t\left[x_{t+4}\right] + (1-\lambda)\, M_{t-1}\left[x_{t+3}\right], \tag{12}$$

where $M_t\left[x_{t+4}\right]$ now indicates the population-mean value of expectations on x made in t over the quarter $t+4$ and $N_t\left[x_{t+4}\right]$ are the professional forecasters expectation as published by the news reports in t. More details on the derivation of (12) are reported in Appendix A.1.

Carroll (2003, 2006) uses Eq. (12) to investigate the evolution of inflation and unemployment expectations in the US for the period following the second half of 1970s. The results show that people only occasionally pay attention to news reports: the fraction of updaters is, on average, equal to 0.25. This inattention generates a high degree of "stickiness" in aggregate expectations, with important macroeconomic consequences.

One of the central implications of Carroll's model is the inability of inattentive agents to change expectations. This point is the result of the particular process assumed for x_t and x_t^* (point I) and of the assumption that η_{t+1} is predictable only by professional forecasters (point II). The justification for point (II) is that observing η_{t+1} is a costly activity (in terms of time and money spent to study how the economy works) for the typical person. Since news reports provide forecasts for free, an individual prefers to dedicate time to other activities such as work, family, hobbies, and so on.

3.2 A new CSI framework allowing for changes of inattentive agents predictions

With respect to Carroll's model (2003, 2006), we modify point (I) as follows:

I' The typical person believes that x_t behaves as a stationary stochastic model:[16]

$$x_t = x_t^* + \epsilon_t \tag{13}$$

$$x_{t+1}^* = \alpha + \beta x_t^* + \eta_{t+1},\ 0 \leq \beta < 1 \tag{14}$$

where β represents the autoregressive coefficient of the fundamental value process, α is a constant term and the disturbance ϵ_t and the innovation η_t are Gaussian independent processes.

This assumption introduces an important change with respect to Carroll's version. Here, typical agents may form and change expectations from one period to another by themselves without relying on state-of-the-art professional forecasters' estimates. A crucial implication is that, given the information set available, the expectation by a non-expert agent for x_{t+j} is different to that for x_{t+j+1} $(\forall j \neq 0)$.[17]

An example similar to that presented in subsection 3.1 helps to clarify the different implications. Under the new assumption (I') and maintaining points II-IV discussed in subsection 3.1, the expectation of x at time t + 1 by a generic non-expert agent i can be written as:

$$E_t^i\left[x_{t+1}\right] = E_t^i\left[x_{t+1}^*\right] + \underbrace{E_t^i\left[\epsilon_{t+1}\right]}_{=0}. \tag{15}$$

If agent i is "infected" at time t, then Eq. (15) is equal to

$$E_t^i\left[x_{t+1}\right] = N_t\left[x_{t+1}\right] = x_{t+1}^*. \tag{16}$$

[16] From a mathematical point of view, a stationary process could be obtained with $-1 < \beta < 1$. Still, if β were negative, a fundamental shock η would imply an oscillatory pattern of the fundamental value of the variable of interest. This oscillatory pattern is not confirmed by the empirical data supplied by the macroeconomic variables we are going to study and, for this reason, we ignore this possibility in our analysis. The assumption on the autoregressive nature of the variable has also been made, in a different setup, by Woodford's "noisy information" model (2003).

[17] Furthermore, concering long-run expectations, informed agents also have superior information concerning the long-run horizon under the random walk hypothesis of Eq. (2): in period t, the best guess for $x_\infty^* = x_{t+1}^* = x_t^* + \eta_{t+1}$. As a result, individuals who have learned about x_{t+1}^* (and implicitly about η_{t+1}) have more precise short and long-run expectations with respect to individuals who have read professional forecasts only one or more periods before. Conversely, there is no long-period advantage under the stationary process of (14) since $x_\infty^* = \alpha/(1-\beta)$: informed agents have a more precise short-run expectation, while the expectations of all agents (informed and uninformed) concerning the long-run horizon converge to the same steady level x_∞^*.

If agent i is not infected in t, but was instead infected at time $t-1$, he does not know the innovation η_{t+1} but, except for the disturbances, he is aware of the process, so Eq. (15) is equal to

$$E_t^i[x_{t+1}] = N_{t-1}[x_{t+1}] = \alpha + \beta N_{t-1}[x_t] = \alpha + \beta x_t^*. \tag{17}$$

According to these rules, the population-mean expectation of x at time $t+1$ can be represented as:

$$\begin{aligned}
M_t[x_{t+1}] &= \lambda N_t[x_{t+1}] + (1-\lambda)\{\lambda N_{t-1}[x_{t+1}] + (1-\lambda)(\lambda N_{t-2}[x_{t+1}] + (1-\lambda)(\lambda N_{t-3}[x_{t+1}]\ldots)\} \\
&= \lambda N_t[x_{t+1}] + (1-\lambda)\{\lambda[\alpha + \beta N_{t-1}[x_t]] + (1-\lambda)(\lambda[\alpha + \beta N_{t-2}[x_t]] \\
&\quad + (1-\lambda)(\lambda[\alpha + \beta N_{t-3}[x_t]]\ldots)\} \\
&= \lambda N_t[x_{t+1}] + (1-\lambda)\{\lambda[\alpha + \beta N_{t-1}[x_t]] + (1-\lambda)(\lambda[\alpha + \beta[\alpha + \beta N_{t-2}[x_{t-1}]]] \\
&\quad + (1-\lambda)(\lambda[\alpha + \beta[\alpha + \beta N_{t-3}[x_{t-1}]]]\ldots)\} \\
&= \lambda N_t[x_{t+1}] + (1-\lambda)\{\lambda[\alpha + \beta N_{t-1}[x_t]] + (1-\lambda)(\lambda[\alpha + \beta[\alpha + \beta N_{t-2}[x_{t-1}]]] \\
&\quad + (1-\lambda)(\lambda[\alpha + \beta[\alpha + \beta[\alpha + \beta N_{t-3}[x_{t-2}]]]]\ldots)\}
\end{aligned} \tag{18}$$

where $M_t[x_{t+1}]$ denotes the population-mean value of expectations of x_{t+1} made in t, $N_t[x_{t+1}]$ represents the professional forecasters expectations as reported by news media in t, and λ is the proportion of informed agents infected by news media. Using the property of lag polynomials and rearranging terms as shown in Appendix A.2, (18) corresponds to

$$M_t[x_{t+1}] = \lambda N_t[x_{t+1}] + (1-\lambda)(\alpha + \beta M_{t-1}[x_t]). \tag{19}$$

If the time is expressed in quarters and the forecast is over the next year (i.e. from t to $t+4$), Eq. (19) can be written as:

$$M_t[x_{t+4}] = \lambda N_t[x_{t+4}] + (1-\lambda)(\alpha + \beta M_{t-1}[x_{t+3}]). \tag{20}$$

Appendix A.3 contains details on the derivation of Eq. (20).

While Eq. (20) may appear as a simple generalization of Eq. (12) (actually if $\alpha = 0$ and $\beta = 1$, (20) corresponds to (12)), it has very different implications. Hence, rather than a generalization, it has to be considered as an extension of Carroll's model (2003) to examine variables which are characterized by a persistent, maybe even highly persistent, but not unit root process. Therefore, the question is, which version is applicable to a given variable? Our answer is that it depends on the statistical process of the variable under investigation.

3.3 Application of the CSI framework to unemployment expectations

Applying the CSI model to unemployment expectations requires us to study two important issues: first, the formulation of the question concerning unemployment expectations in the survey of households; and, second, the characteristics of the statistical process of the variable under investigation.[18] The first point allows us to identify how the variable is measured (i.e. level or growth rates). The second point is crucial in understanding if the process is better described by:

1. a random walk, like inflation in the US (Carroll, 2003), supporting the hypothesis that households do not change expectations if they do not learn about the innovation, leading to Eq. (12), or
2. a stationary autoregressive process, supporting the hypothesis that households may naively update their expectation multiplying the previous period value by a constant factor (and eventually adding another constant value), leading to Eq. (20).

In our analysis of France, Germany, Italy, and the UK, we consider survey data on unemployment expectations obtained from the European Commission's Joint Harmonised EU Programme of Consumer Surveys. The formulation of the question concerning unemployment expectations (Q7) is as follows:

Q7: How do you expect the number of people unemployed in this country to change over the next 12 months?
The number will: (++) increase sharply; (+) increase slightly; (=) remain the same; (−) fall slightly; (−−) fall sharply; (N) don't know.

Two aspects emerge analyzing the above question. The first is that the survey question clearly refers to a change in unemployment in the next year, that is, the future number of unemployed people less the current one. Secondly, it is important to understand what kind of unemployment data respondents have in mind: level or rate? In other words, do they reply to question Q7 in terms of a change in the level of unemployment or in the unemployment rate? As a necessary premise, it has to be highlighted that both the number of unemployed people and the unemployment rate are very highly correlated, both in levels and in first differences. Furthermore, since newspapers and newscasts usually report data on unemployment expressed as a percentage of the labour force (i.e., the unemployment rate), we presume that agents have this kind of data in mind. A visual inspection of year-over-year change in the unemployment rate (i.e., a change in the unemployment rate with respect to the same period of the previous year) and survey data on unemployment expectations for all the countries under investigation confirm our view; see Figure 7 in Appendix B.

Another important point concerns the unit used to measure household unemployment expectations. The European Commission expresses the time series of unemployment ex-

[18] The order of investigation is important, since we are able to study the statistical process only after having identified how to measure the expectation variable.

pectations as a balance index, where the balance values range from -100 (all respondents choose the most positive option) to +100 (all respondents choose the most negative option).[19] For our purposes, this balance is first converted in quarterly time series and then,[20] following Carroll (2003), converted into the same unit of measure of the unemployment rate using the following auxiliary regression:[21]

$$U_{t+4} - U_t = \phi_0 + \phi_1 EU_t^U + \xi_t, \tag{21}$$

where U_{t+4} is the unemployment rate at time $t+4$, U_t is the unemployment rate at time t, and EU_t^U is the EU index of unemployment expectations. Using estimated values $\{\hat{\phi}_0, \hat{\phi}_1\}$, the forecast for the next year unemployment rates change can be constructed as:

$$\widehat{M}_t \left[\Delta_4 U_{t+4}\right] = \hat{U}_{t+4} - \hat{U}_t = \hat{\phi}_0 + \hat{\phi}_1 EU_t^U. \tag{22}$$

Table 1: Auxiliary regression $U_{t+4} - U_t = \phi_0 + \phi_1 EU_t^U + \xi_t$ (1981q1-2016q3)

	ϕ_0	ϕ_1
FRA	-0.5855***	0.0177***
GER	-0.3932***	0.0142***
ITA	-0.7320***	0.0283***
UK	-0.8291***	0.0267***

Notes: The estimation sample is 1991q1-2016q1 for Germany, whereas for the United Kingdom is 1986q1-2015q4. The Lagrange multiplier test for autocorrelation rejects the hypothesis of no serial correlation for all countries up to order four.

Having identified the variable under investigation, the second relevant point concerns the investigation of its statistical process. Does the year-over-year change in unemployment rate follow a process such as that represented by Eqs. (1)-(2) or as represented by Eqs. (13)-(14)?

[19]For further details on the aggregation and weighting of consumer survey answers see the European Commission (2016).

[20]Survey data are published every month and are transformed in quarterly data (taking a simple average of the months) to fit with the frequency of the survey of professional forecasters. A full description of data is given in Appendix E.

[21]This auxiliary regression is known in literature as the "regression approach" to qualitative surveys, introduced by Pesaran (1984, 1987). More specifically, Pesaran (1984, 1987) uses the judgments on the current situation and the current values of the variable under investigation as an yardstick to quantify the expectations; unfortunately, judgments about unemployment are not present neither in the Eurostat consumer survey, nor in the Michigan consumer survey adopted by Carroll (2003). The absence of data on consumers' judgments demands an approach that uses only data on expectations with the actual change in the unemployment rate. This kind of approach may suffer from measurement errors since it regresses ex-post actual change in the unemployment rate (x_t) with ex-ante expectations of the fundamental value x_t^*, which could be ex-post wrong due to the disturbance ϵ_t. Measurement errors cause attenuation bias in the estimated coefficients. In order to mitigate the possible attenuation bias problem we use IV instead of OLS (Sargan, 1958; Farmer et al., 2009).

The usual way to clarify this dilemma consists in testing for a unit root in the year-over-year change of unemployment rate (i.e. $U_t - U_{t-4} \equiv \Delta_4 U_t$) for the countries under investigation. We apply two types of tests: (1) a test with a unit root null (the Augmented Dickey-Fuller (ADF), Dickey and Fuller (1979)) and (2) a test with a trend-stationary null (the Kwiatkowsky-Phillips-Schmidt-Shin (KPSS) test, Kwiatkowski et al. (1992)). The results are reported in Table 2. We find that, for all countries under investigation, the ADF test rejects the null while the KPSS test fails to reject the null. This implies that there is strong evidence in favour of a stationary process of ΔU_t for all countries.

Table 2: Unit root tests results (1981q1-2016q3)

	ADF		KPSS	
	Statistic	Lag	Statistic	k
$(\Delta_4 U_t)_{FRA}$	-2.963**	5	0.095	8
$(\Delta_4 U_t)_{GER}$	-3.896***	6	0.197	8
$(\Delta_4 U_t)_{ITA}$	-3.027**	6	0.135	8
$(\Delta_4 U_t)_{UK}$	-3.122**	5	0.109	8
Critical values	1%	-3.487		0.739
Critical values	5%	-2.886		0.463
Critical values	10%	-2.580		0.347

Notes: $U_t - U_{t-4} \equiv \Delta_4 U_t$. Since observed data does not exhibit an increasing or decreasing trend, in test equations only an intercept is considered as deterministic term. The H_0 in ADF is that the variable is I(1). The H_0 in KPSS is that the variable is I(0). The lag length in ADF is chosen using SIC. k is the bandwidth for the Newey-West HACC estimator with Bartlett weights. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

Table 3: Unobserved component model estimation of $\Delta_4 U_t$ (1986q1-2016q3)

Model: $\Delta_4 U_t = \Delta_4 {U_t}^* + \epsilon_t$, $\epsilon_t \sim NID(0, \sigma_\epsilon^2)$
$\Delta_4 {U_{t+1}}^* = \alpha + \beta \Delta_4 {U_t}^* + \eta_{t+1}$, $\eta_t \sim NID(0, \sigma_\eta^2)$
(disturbances are uncorrelated)

	α	β	$\Delta_4 {U_t}^*$	Wald Test $\beta = 1$	$\sigma_\epsilon / \sigma_\eta$
FRA	-0.003	0.873***	(See Fig. 8)	p-value=0.009	1.72
GER	-0.010	0.874***	(See Fig. 8)	p-value=0.007	1.39
ITA	0.010	0.913***	(See Fig. 8)	p-value=0.022	1.38
UK	-0.020	0.908***	(See Fig. 8)	p-value=0.016	1.52

Notes: The estimation method is the Maximum Likelihood (ML) with BFGS optimization procedure with Marquardt step. The standard errors are computed using the negative inverse Hessian after convergence.*** indicates 1% significance level.

An alternative and more sophisticated way to shed light on the above-mentioned dilemma consists in estimating the process of $\Delta_4 U_t$ via a univariate unobserved component (UC) model. A UC allows us to disentangle the persistent change of the unemployment rate ($\Delta_4 U_t^*$) from shock elements (ϵ_t and η_t). The goal in this empirical exercise is to investigate the persistence of the fundamental value Δ_4Ut*.[22] The results of this estimation for France, Germany, Italy, and the UK are reported in Table 3. For all countries, the coefficient β, that measures the persistence of the fundamental component, is smaller than unity. The Wald test statistically confirms that $\beta < 1$. The unobserved component estimates allow us to check the central hypothesis of the CSI model that changes in the unemployment rate move around a fundamental value, approximated by expert unemployment expectations. A correlation-based analysis in Appendix C confirms this evidence supporting this crucial assumption significantly.

Following unit root and UC estimates, we assume households have some intuitions that, in the absence of new information, the best possible supposition is that unemployment change is less-than-proportional to the previous one. On this basis, we can affirm that the most plausible version of the CSI model to examine unemployment expectation is the one with a persistent (but stationary) fundamental value as described in section 3.2. The final equation representing the aggregate change in unemployment expectation is the following:

$$M_t\left[\Delta_4 U_{t+4}\right] = \lambda N_t\left[\Delta_4 U_{t+4}\right] + (1-\lambda)\left(\alpha + \beta M_{t-1}\left[\Delta_4 U_{t+3}\right]\right), \tag{23}$$

which corresponds to the four-quarter unemployment rate change ($\Delta_4 u_t$) version of Eq. (20) described in section 3.2 for a generic macroeconomic or financial variable x.

[22]For a visual inspection of the dynamics between the fundamental value and the actual change in the unemployment rate, see Figure 8 in Appendix B.

4 CSI model and "news-based" uncertainty

The idea of using survey data to measure uncertainty is not new in literature and has focused mainly on business surveys. Two recent examples are offered by Bachmann et al. (2013) and Girardi and Reuter (2016). Bachmann et al. (2013) measure business-level uncertainty from business survey data for Germany and the United States. They construct measures based both on dispersion in ex-ante forecasts and dispersion in ex-post forecast errors, where the two measures prove to be strongly correlated. Girardi and Reuter (2016) extend the work of Bachmann et al. (2013), adding the inter-question dispersion as a further measure, since uncertainty may impact expectations for the various macroeconomic indicators differently. Moreover, they also consider consumer surveys.

In Carroll (2003, 2006), the parameter λ indicates the probability of being infected by opinions diffused by news media and, in this way, determines the aggregate expectation of the variable of interest. Given the relevance of household beliefs in influencing the pattern of economies, as presented in Section 2, it is important to understand which factors may influence λ and how the virus is transmitted (i.e. through the professional forecasters expectations).

In general, non-expert agents adapt the level of attention they place on professional forecaster estimates in response to changes to environmental conditions.

The very first intuition is that a more uncertain environment should induce economic agents to collect more information in order to avoid wrong decisions (Coibion and Gorodnichenko, 2015; Reis, 2006). Similarly, according to Akerlof et al. (2000), price and wage setters may safely ignore inflation when it is low, but need to be properly informed and take inflation into account when it is high. Nevertheless, it is not the only effect involved. Moscarini (2004), for example, presents a model in which agents update their information set infrequently, but absorbing the information is more challenging (hence, more costly) when the environment is more uncertain.[23] The higher cost of collecting/processing information mitigates, and possibly outweights, the hunger for state-of-the-art information.

Furthermore, "noisy information" models (Sims, 2003; Woodford, 2003) emphasize that the weight agents place on the signal they receive depends on that signal's level of noisiness. Similarly, within the CSI framework it is reasonable to assume that the level of economy-wide uncertainty perceived by non-expert agents may affect their decision to spend time in exploiting news media to "capture" the predictions of professional forecasters. For example, Heiner (1989), Beckert (1996), and Dequech (1999) claim that in moments of high uncertainty people adopt "rule of thumbs". Experimental studies offer strong evidence that people in situations of uncertainty tend to deviate from full rationality and use heuristics or intuitions (see, for example, Kahneman et al. (1974)). In our framework, this implies that uncertainty (negatively) influences the decisions of non-expert agents to look for information by reading newspapers, surfing the Internet or watching newscasts. In other words, agents, in the presence of sustained uncertainty, are less confident of the ability of

[23] "For example, reading the Wall Street Journal every day in recent times of stock market turbolence is more time- and capacity-consuming because the quantity of information transmitted is higher for the given daily frequency, and less capacity is left for reading novels or thinking about dinner" Moscarini (2004).

experts to predict the future (actual) values of unemployment and may decide to use a rule of thumb updating the expectation rule (i.e. Eq. (17) according to the CSI framework) instead of spending time in reading newspapers. Hence, it would not be so surprising to observe a drop in parameter λ in periods of high uncertainty. It is important to emphasize that, within the CSI framework, this does not mean that agents may decide to "forget" and not use the professional forecasts they are aware of.[24] Conversely, they may not put particular effort in paying attention to new forecasts. In a nutshell, this could imply that a typical agent continues to read newspapers but he may decide not to care about the financial section, which reports the updated forecasts.

The mechanism described above is important because it helps to understand the channel by which the virus is transmitted. Generally speaking, an agent may be infected via a "traditional" channel (print journalism and broadcast news) or the Internet channel (online versions of newspapers, plus online news blogs and social media). Whether parameter λ is more sensitive to the level of uncertainty conveyed by the "traditional" press or to the one conveyed by the Internet, it is a relevant indication of what can be considered as the main channel of transmission of the virus. Obviously, it may happen that both channels influence an agents' decision to collect professional predictions.

As we describe more in detail in the data appendix (Appendix E), "news-based" indexes like the well-known Baker et al. (2016) Economic Policy Uncertainty Index (EPU), based on the content of newspaper articles, and an uncertainty index based on online search engine data from Google Trends (Google Uncertainty Index, GUI) may be good proxies of the level of uncertainty spread out by the two transmission channels. One relevant difference between the two approaches is that while the traditional uncertainty index is based on journalists' feelings of uncertainty,[25] the GUI focuses on agents' perception of uncertainty by counting the volume of searches for words containing the terms "uncertain" or "uncertainty" and "economic" or "economy". The intensity of Internet searches, which is related to the above-mentioned keywords, should reflect (i.e. be a proxy for) a high level of uncertainty perceived among non-expert agents.

5 Estimation strategy

We are interested in (i) estimating equation (23) together with the need to (ii) investigate the relationship between the parameter λ and uncertainty in the economy (as explained in section 4). In particular, the second point requires adopting a time-varying approach in estimating the parameters, in order to compare λ_t with the uncertainty index measured over time. The easiest way to satisfy the two points is to estimate equation (23) via a state-space approach. Equation (23) can be easily expressed as follows:

[24] Remember that the model foresees that once infected you cannot recover from the infection (Assumption IV in Section 3.1).

[25] Quoting the EPU website `http://www.policyuncertainty.com/methodology.html` regarding methodology, "We count the number of newspaper articles containing the terms uncertain or uncertainty, economic or economy, and one or more policy-relevant terms".

$$\begin{cases} \widehat{M_t}[\bullet] = \alpha_0 + \theta_t N_t[\bullet] + \varphi_t \widehat{M}_{t-1}[\bullet] + \epsilon_t^M \\ \theta_{t+1} = \omega_\theta \theta_t + \epsilon_{t+1}^\theta \sim NID(0, \sigma_\theta^2) \\ \varphi_{t+1} = \omega_\varphi \varphi_t + \epsilon_{t+1}^\varphi \sim NID(0, \sigma_\varphi^2) \end{cases} \tag{24}$$

where $\theta_t \equiv \lambda_t$ and $\varphi_t \equiv (1 - \lambda_t)\,\beta_t$. The key parameter λ and the product of parameters $(1 - \lambda)\,\beta$ are now expressed as AR(1) processes in order to study their evolution over time. With respect to a simple rolling window estimation, a state-space with time-varying coefficients has the advantage of not losing observations.[26]

In addition to the state-space model, we run a GMM estimate of equation (23) as a robustness check.[27] The choice of GMM, specifically IV, instead of OLS lies in the presence of potential measurement errors in the non-expert agent expectations variable.[28] These potential errors are due to the transformation needed to convert EUUt (Non-expert expectations expressed in balance terms) in the same metric of unemployment rate changes of $N_t[\bullet]$ (see Eq. (21) and Eq. (22)). In particular, as Sargan (1958) stressed, variables used for constructing the instrument need to be independent from the ones involved in the second-stage regression. This requirement excludes the use of the unemployment rate and lags of dependent and independent variables. For our purposes we use (lagged) international variables and financial variables as instruments, which satisfy Sargan's requirement (1958).

6 Results

The time-varying parameter pattern of the state-space model (24) is plotted in Figure 2 and Figure 3. In particular, we plot the evolution of λ_t in Figure 2, whereas we plot the dynamic of aggregate $\beta_t\,(1 - \lambda_t)$ in Figure 3. As emerges from Figure 2, λ fluctuates around an average value that ranges from 0.07 to 0.1 in every country. The dynamics for all countries appear to be similar and turn out to be very smooth, without many sharp changes; this result is coherent with our framework, since agents infrequently updating their information are also likely to slowly change their expectation formation process. An

[26] As an alternative, it is possible to model the time-varying coefficient λ to be a function of exogenous factors related to uncertainty, such as NBER recessions (Coibion and Gorodnichenko, 2015) or uncertainty indexes (Easaw et al., 2017). Still, the main aim of our paper is to first investigate the time-varying proportion of people reading newspapers and, then, to study the relationship with uncertainty. For this reason, we prefer to avoid the approach suggested by SDM (State Dependent Models) literature and, that is, to consider volatility or uncertainty indexes as explanatory variables since this would force a correlation and weaken our conclusions.

[27] As argued by Geary (1948) and Sargan (1958), and more recently by Fuller (2009, p.273), instrumental variables is a suitable estimation technique in cases where the variables in the relationship are measured with errors.

[28] Measurement error may produce a downward bias in the estimated coefficients. In fact, OLS estimation produces estimates of λ which are much closer to zero and not significant at all. OLS results are presented in Appendix D.

Figure 2: Time-varying estimates of λ obtained via state space model (1986Q1-2016Q4)

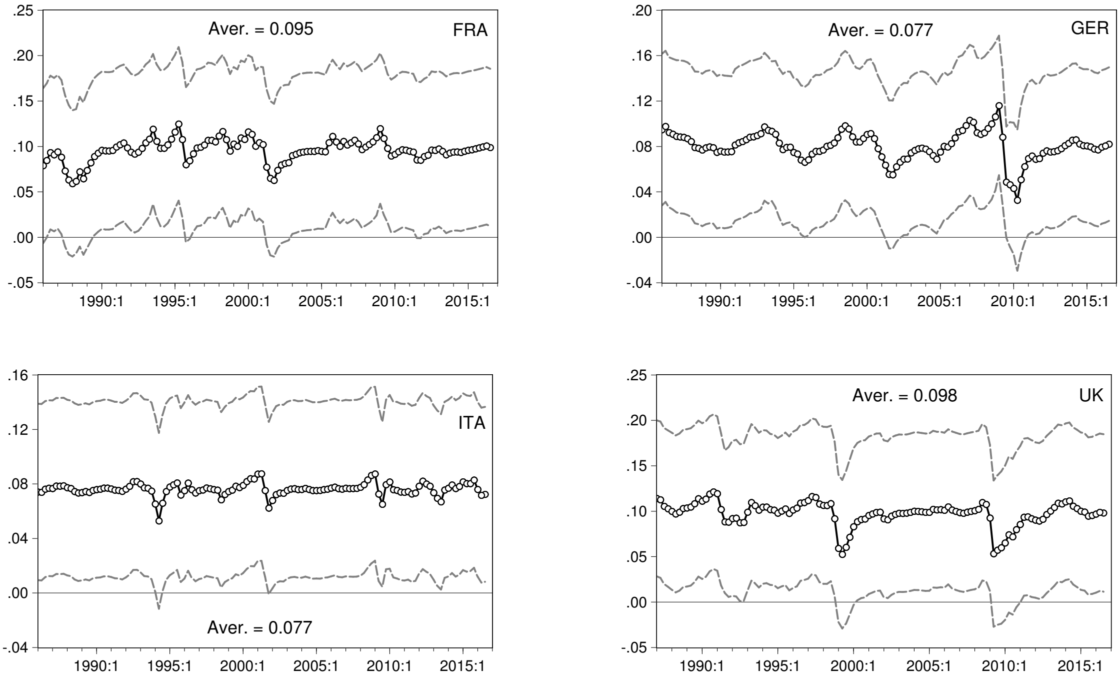
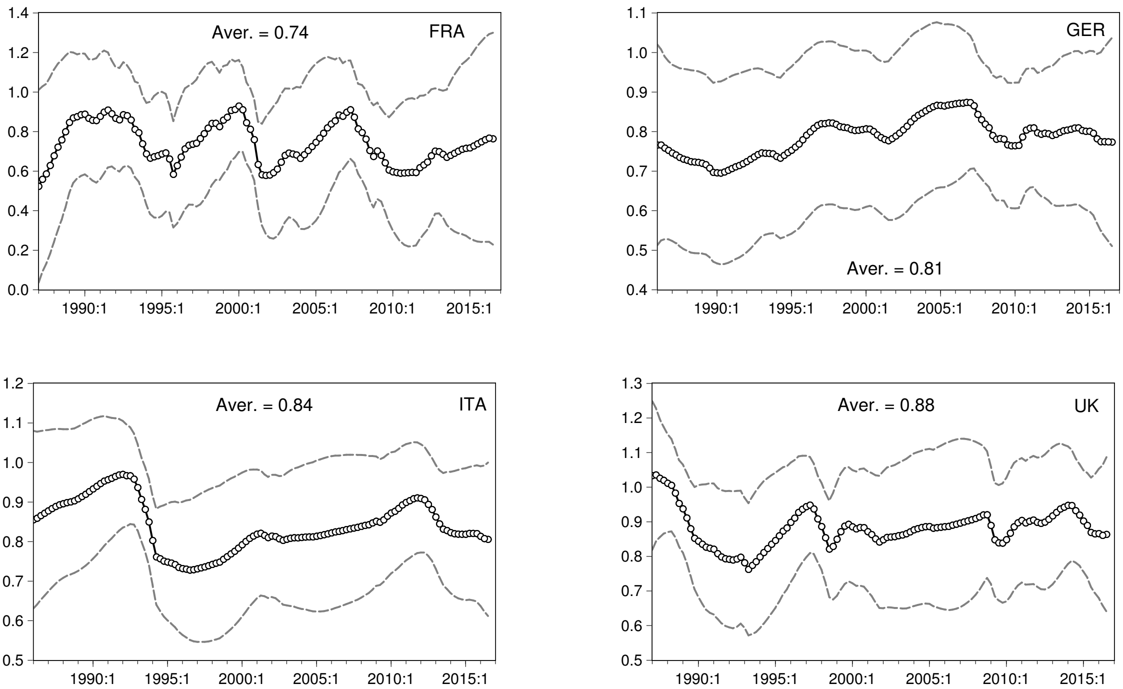


Figure 3: Time-varying estimates of $(1-\lambda)\beta$ obtained via state space model (1986Q1-2016Q4)



important exception is the drop in the value of λ in correspondence to the economic crisis.[29] Concerning Figure 3, the evolution of $(1-\lambda_t)\,\beta_t$ appears even smoother for all countries. As a further consideration, the average values are smaller than unit as expected.

The GMM estimates of Equation (23) are reported in Table 4. The values of the parameters are in line with the average values obtained via the time-varying state-space model. In particular, France and the UK exhibit higher values of λ with respect to the other countries in accordance with the state-space estimates. More importantly, using the values of λ and β obtained from GMM, we obtain values that are very similar to the average values of λ_t and $(1-\lambda_t)\,\beta_t$ in the state-space model.[30] Given the similarities of GMM and state-space model estimates, we can confirm the robustness of our results.

Table 4: GMM estimates of Eq. (23) (1987q2-2016q4)

Model: $\widehat{M_t}\,[\Delta_4 U_{t+4}] = \lambda N_t\,[\Delta_4 U_{t+4}] + (1-\lambda)\,(\alpha + \beta \widehat{M_{t-1}}\,[\Delta_4 U_{t+3}]$				
	$\alpha(1-\lambda)$	λ	β	Prob (J-stat)
FRA	-0.014	0.135*	0.962***	0.448
	(0.015)	(0.077)	(0.071)	
GER	-0.003	0.080*	0.924***	0.378
	(0.009)	(0.042)	(0.058)	
ITA	0.011	0.093*	0.955***	0.810
	(0.007)	(0.050)	(0.037)	
UK	-0.052**	0.127**	0.962***	0.542
	(0.024)	(0.056)	(0.053)	

Notes: List of instruments used (in addition to the constant): FRA: $\sum_{j=1}^{4} \Delta_4 ln(y^{USA})_{t-j}$, $\sum_{j=1}^{2} \Delta_4 ln(sp)_{t-j}$, $\sum_{j=0}^{1} \Delta_4 ln(oil)_{t-1}$, $\sum_{j=0}^{1} \Delta_4 i_{t-j}$, $\sum_{j=1}^{3} \Delta_4 ln(hp^{USA})_{t-j}$; GER: $\sum_{j=1}^{2} \Delta_4 ln(y^{USA})_{t-j}$, $\sum_{j=0}^{1} \Delta_4 i_{t-j}$, $\sum_{j=1}^{2} \Delta_4 ln(sp)_{t-j}$, $\sum_{j=1}^{3} \Delta_4 ln(hp)_{t-j}$; ITA: $\sum_{j=1}^{2} \Delta_4 ln(y^{USA})_{t-j}$, $\Delta_4 ln(sp)_{t-1}$, $\sum_{j=0}^{2} \Delta_4 ln(oil)_{t-j}$, $\sum_{j=1}^{2} \Delta_4 ln(hp)_{t-j}$; UK: $\Delta_4 ln(sp)_{t-1}$, $\sum_{j=0}^{2} \Delta_4 ln(oil)_{t-1}$, $\sum_{j=1}^{3} \Delta_4 ln(hp^{USA})_{t-j}$, $\sum_{j=0}^{1} \Delta_4 i_{t-j}$, $\sum_{j=0}^{1} spread_{t-j}$. $\widehat{M}\,[\bullet]$ indicates that the average non-expert agents expectation is built using the auxiliary regression estimates (22). Newey-West (HAC) standard errors are reported in parentheses. J-stat is the Sargan's J statistical test.

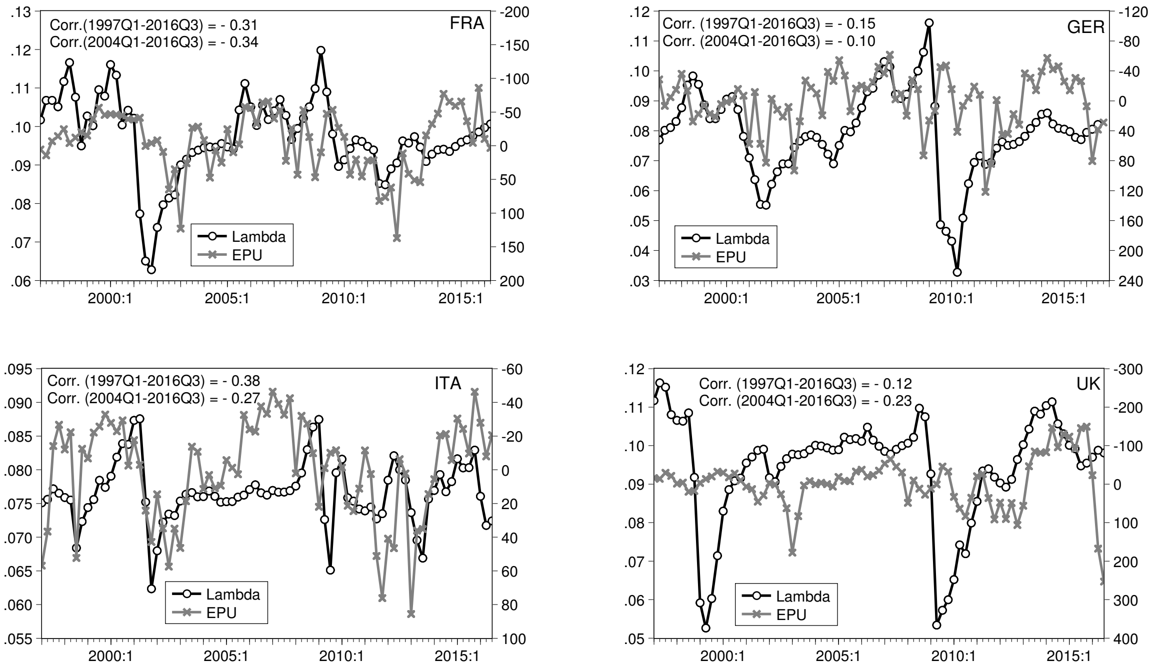
Figure 4 compares the estimates of λ in various countries with the EPU of Baker et al. (2016). Parameter λ seems to move clearly in the opposite direction with respect to the EPU index for France and Italy where the correlation over the two series for the whole period (1997Q1-2016Q3) is -0.31 and -0.38, respectively.[31] The comovement of λ and the EPU is less clear for Germany and the UK; the correlation value is very low for both countries. These low correlation values may suggest that a typical agent in Germany and the UK does not use print journalism and similar traditional media as main source of information (and then contagion). Figure 5 shows the dynamics of λ with respect to

[29] The drop is more relevant for Germany and the UK, while it is less evident for France and Italy.

[30] In detail, the average values are: $[(1-\lambda)\,\beta]^{FRA} = 0.83$; $[(1-\lambda)\,\beta]^{GER} = 0.85$; $[(1-\lambda)\,\beta]^{ITA} = 0.87$; $[(1-\lambda)\,\beta]^{UK} = 0.84$.

[31] Note that in Figure 4 the uncertainty index is plotted on the right axis with inverted scale.

Figure 4: Time-varying estimates of λ *vs* Policy Uncertainty Index (`EPU`, inverted scale) (1997Q1-2016Q3)



the GUI obtained via Google trends. Plots for Germany and the UK show high negative correlation with the GUI, equal to -0.44 and -0.40, respectively. These results are supported by other studies conducted on household habits in European countries. In particular, Eurobarometer survey data show that British agents have a poor opinion of the quality and usefulness of the press.[32] The value is among the lowest in Europe.

Figure 6 plots the percentage of people who do not trust the press for the period 2000-2016. It clearly emerges that British agents are very skeptical about the reliability of information disseminated by the press. Conversely, the French, the Germans and the Italians have a better consideration of press information content. This evidence may suggest that agents in the UK use other media such as blogs and social media as sources of information. The relation between λ and the GUI supports this hypothesis. Similarly for Germany, λ is more correlated with the GUI than with the EPU; conversely, for France λ is almost uncorrelated with the GUI. The case of Italy, finally, is curious: it is the country with the highest correlation between λ and the EPU but, if we focus on the subperiod for which we have data for both the EPU and the GUI (i.e. since 2004), this correlation decreases and is almost equal to the one between λ and the GUI. It is as if the Internet is complementing print journalism as a source of contagion. This insight is worthy of future research.

[32] Data are available at `http://ec.europa.eu/commfrontoffice/publicopinion/index.cfm`.

Figure 5: Time-varying estimates of λ *vs* Google Uncertainty Index (`GUI`, inverted scale) (2004Q1-2016Q3)

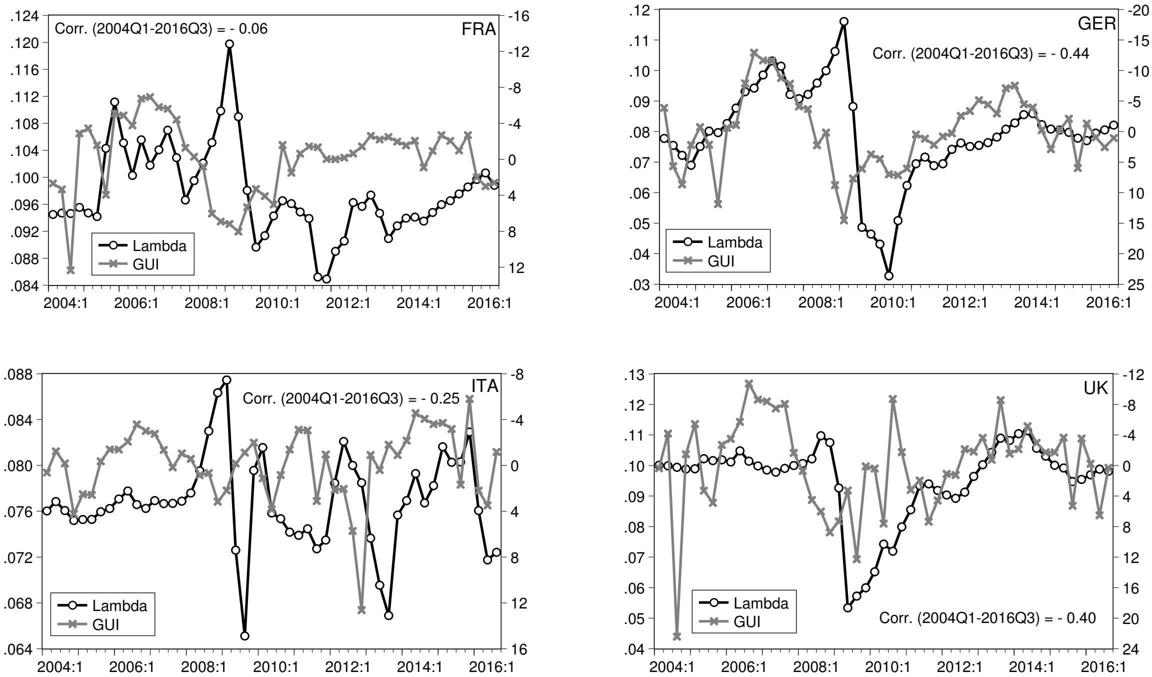
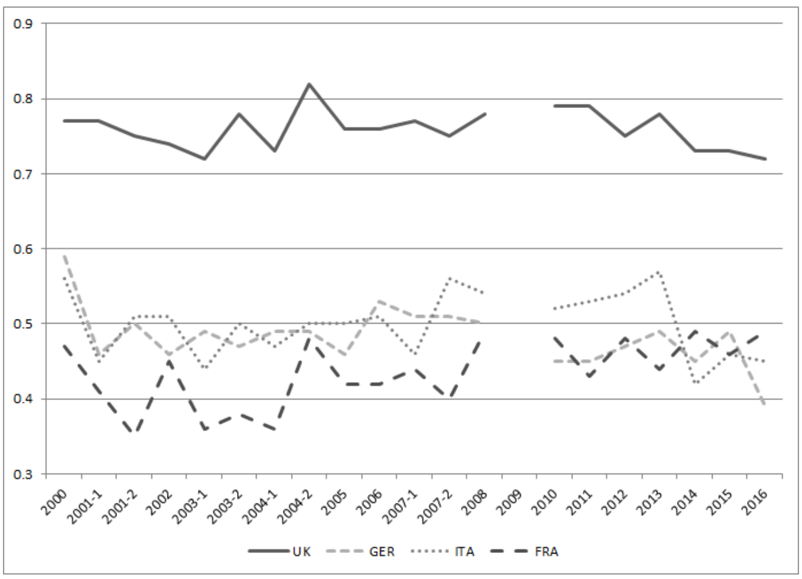


Figure 6: Confidence in the press, 2000-2016



Confidence in the press indicates the percentage of people who tend not to trust the press. Source: Eurobarometer survey (`http://ec.europa.eu/commfrontoffice/publicopinion/index.cfm/`).

7 Conclusions

In the present work, we extend Carroll's "common-source-infection" (CSI) framework (2003). This new formulation may allow researchers to apply the common-source-infection model to the study of macroeconomic and financial variables which are not governed by an unit root or quasi-unit root process. In particular, we have studied unemployment expectations from household surveys from a number of selected European countries (France, Germany, Italy and the UK). Econometric results have shown that a properly formulated CSI model, despite being relatively simple, is able to capture the main features of non-expert expectations. Data are compatible with a situation where agents are boundedly rational. Among boundedly rational individuals, about one tenth of the population absorbs and processes new information (expert forecasts) in each quarter, whereas the remainder behave as naive econometricians, updating their expectation using outdated information. Moreover, expectations seem to be related to the level of perceived uncertainty, using as proxies newspaper coverage on economic uncertainty and Internet searches on the topic: in periods of higher uncertainty, agents absorb new information less frequently.

Acknowledgements

We thank for useful comments and helpful discussion Thomas Bassetti, Pietro Dindo, Roberto Golinelli, Andrea Giovannetti, Luca Rossini, Gabriele Tedeschi, Friederike Wall and the participants to XXI and XXII WEHIA, held in Universidad Jaume I of Castellon de la Plana in June 2016 and Catholic University of Milan in June 2017, respectively, and the participants to the BoMoPaV Meeting 2018. In particular, Luca Gerotto is highly indebted to Christopher Carroll for helpful comments and discussion, and to the Johns Hopkins University for having hosted him during some visiting period.

Appendix

A Technical Appendix

A.1 Derivation of Equation (12)

Under the hypothesis that data frequency is quarterly and the forecast horizon is one year (i.e. from t to $t+4$), the evolution of the variable x that people have in mind – in the case of Carroll (2003)'s CSI model – can be represented in the following way:

I"

$$x_t = x^*_{t-4,t} + \epsilon_t, \tag{25}$$

where $x^*_{t-4,t}$ denotes that fundamental value in period t, which is perfectly forecastable four periods in advance $(t-4)$ by professional forecasters.
In each period the fundamental value of the variable evolves according to the following process:

$$x^*_{t,t+4} = x^*_{t-1,t+3} + \eta_{t+4}. \tag{26}$$

II" The professional forecasters expectation of the variable x at time $t+4$ corresponds to

$$N_t\left[x_{t+4}\right] = x^*_{t,t+4} = x^*_{t-1,t+3} + \eta_{t+4}, \tag{27}$$

where the subscript t is omitted from the notation since we are assuming from the beginning that the forecast horizon is of one year and it is already clear from the expectation operator $N_t\left[\bullet\right]$ that the starting period of forecasting is t.

Under the new assumptions (I" $-$ II"), and maintaining the points $III - IV$ discussed in Section 3.1, the expectation of x at time $t+4$ by a generic non-expert agent i can be written as:

$$E^i_t\left[x_{t+4}\right] = E^i_t\left[x^*_{t+4}\right] + \underbrace{E^i_t\left[\epsilon_{t+4}\right]}_{=0}. \tag{28}$$

If agent i is "infected" at time t, then Eq. (28) can be written as:

$$E^i_t\left[x_{t+4}\right] = N_t\left[x_{t+4}\right]. \tag{29}$$

If agent i is not infected in t, but was instead infected at time $t-1$, Eq. (29) is equal to

$$E^i_t\left[x_{t+4}\right] = N_{t-1}\left[x_{t+4}\right] = N_{t-1}\left[x_{t+3}\right]. \tag{30}$$

According to these rules, the average expectation of x at time $t+4$ can be represented as:

$$M_t\left[x_{t+4}\right] = \lambda N_t\left[x_{t+4}\right] + (1-\lambda)\left\{\lambda N_{t-1}\left[x_{t+3}\right] + (1-\lambda)\left(\lambda N_{t-2}\left[x_{t+2}\right]\ldots\right)\right\}. \tag{31}$$

Given the property of the lag polynomial, repeating the same arrangements described in section 3.1, it is easy to arrive at Eq. (12):

$$M_t\left[x_{t+4}\right] = \lambda N_t\left[x_{t+4}\right] + (1-\lambda)\, M_{t-1}\left[x_{t+3}\right].$$

A.2 Derivation of Equation (19)

Using the property of the lag polynomial, the right-hand side of (18) can be rewritten as:

$$\begin{aligned}
&= \lambda\{N_t[x_{t+1}] + (1-\lambda)\beta N_{t-1}[x_t] + (1-\lambda)^2\beta^2 N_{t-2}[x_{t-1}] + \dots\} \\
&+ \lambda(1-\lambda)\alpha\{[1+(1-\lambda)+(1-\lambda)^2+\dots] + (1-\lambda)\beta[1+(1-\lambda)+\dots] + (1-\lambda)^2\beta^2[1+\dots]\} \\
&= \lambda N_t[x_{t+1}]\{1+(1-\lambda)\beta L + (1-\lambda)^2\beta^2L^2+\dots\} \\
&+ \lambda(1-\lambda)\alpha\{1+(1-\lambda)\beta+(1-\lambda)^2\beta^2+\dots\}\{1+(1-\lambda)+(1-\lambda)^2+\dots\} \qquad (32) \\
&= \frac{1}{1-(1-\lambda)\beta L}\lambda N_t[x_{t+1}] + \frac{1}{1-(1-\lambda)\beta}\frac{1}{1-(1-\lambda)}\lambda(1-\lambda)\alpha \\
&= \frac{1}{1-(1-\lambda)\beta L}\lambda N_t[x_{t+1}] + \frac{1}{1-(1-\lambda)\beta}(1-\lambda)\alpha
\end{aligned}$$

Thus Eq. (18) can be expressed as:

$$M_t\left[x_{t+1}\right] = \frac{1}{1-(1-\lambda)\beta L}\lambda N_t[x_{t+1}] + \frac{1}{1-(1-\lambda)\beta}(1-\lambda)\alpha \tag{33}$$

or

$$[1-(1-\lambda)\beta L]M_t\left[x_{t+1}\right] = \lambda N_t[x_{t+1}] + \frac{1-(1-\lambda)\beta L}{1-(1-\lambda)\beta}(1-\lambda)\alpha \tag{34}$$

which corresponds to (19)

$$M_t\left[x_{t+1}\right] = \lambda N_t\left[x_{t+1}\right] + (1-\lambda)\left(\alpha + \beta M_{t-1}\left[x_t\right]\right).$$

A.3 Derivation of Equation (20)

Respect to the case presented in Appendix A.1, point I" changes as follows:

$I"'$. The typical person believes that x_t behaves like a *stationary stochastic model*. In quarterly terms, this means that we have:

$$x_t = x^*_{t-4,t} + \epsilon_t, \tag{35}$$

where the fundamental value of the variable evolves according to the following stationary process:

$$x^*_{t,t+4} = \alpha + \beta x^*_{t-1,t+3} + \eta_{t+4},\ 0 \le \beta < 1, \tag{36}$$

where β represents the autoregressive coefficient of the fundamental value process, α is a constant term, and ϵ_t and η_t are Gaussian independent disturbances.

$II^{"'}$. The professional forecasters expectation of the variable x at time $t+4$ corresponds to:

$$N_t\left[x_{t+4}\right] = x^*_{t,t+4} = \alpha + \beta x^*_{t-1,t+3} + \eta_{t+4}.^{33} \tag{37}$$

Under the new assumptions $(I^{"'})$ – $(II^{"'})$, and maintaining points (III) – (IV) discussed in Subsection 3.1, the expectation of x at time $t+4$ by a generic non-expert agent i can be written as:

$$E^i_t\left[x_{t+4}\right] = E^i_t\left[x^*_{t+4}\right] + \underbrace{E^i_t\left[\epsilon_{t+4}\right]}_{=0}. \tag{38}$$

If agent i is "infected" at time t, then Eq. (38) is equal to

$$E^i_t\left[x_{t+4}\right] = N_t\left[x_{t+4}\right]. \tag{39}$$

If agent i is not infected in t, but was instead infected at time $t-1$:

$$E^i_t\left[x_{t+4}\right] = N_{t-1}\left[x_{t+4}\right] = \alpha + \beta N_{t-1}\left[x_{t+3}\right]. \tag{40}$$

According to these rules, the average expectation of x at time $t+4$ can be represented as:

$$M_t[x_{t+4}] = \lambda N_t[x_{t+4}] + (1-\lambda)\{\lambda N_{t-1}[x_{t+4}] + (1-\lambda)(\lambda N_{t-2}[x_{t+4}] + (1-\lambda)(\lambda N_{t-3}[x_{t+4}]\ldots)\} \tag{41}$$

Given the property of the lag polynomial, repeating the same arrangements described in Appendix A.2, it is easy to arrive at Eq. (20):

$$M_t\left[x_{t+4}\right] = \lambda N_t\left[x_{t+4}\right] + (1-\lambda)\left(\alpha + \beta M_{t-1}\left[x_{t+3}\right]\right).$$

[33]The subscript t is omitted from the notation since we are assuming from the beginning that forecast horizon is of one year and it is already clear from the expectation operator $N_t[\bullet]$ that the starting period of forecasting is t.

B Additional Figures

Figure 7: Non-expert unemployment expectations index (`Unemp. Exp. Index`$=EU_t^U$) *vs* actual past unemployment change (`Unem. rate - Unem. rate(-4)`$=\Delta_4 u_t$) (1986Q1-2016Q3).

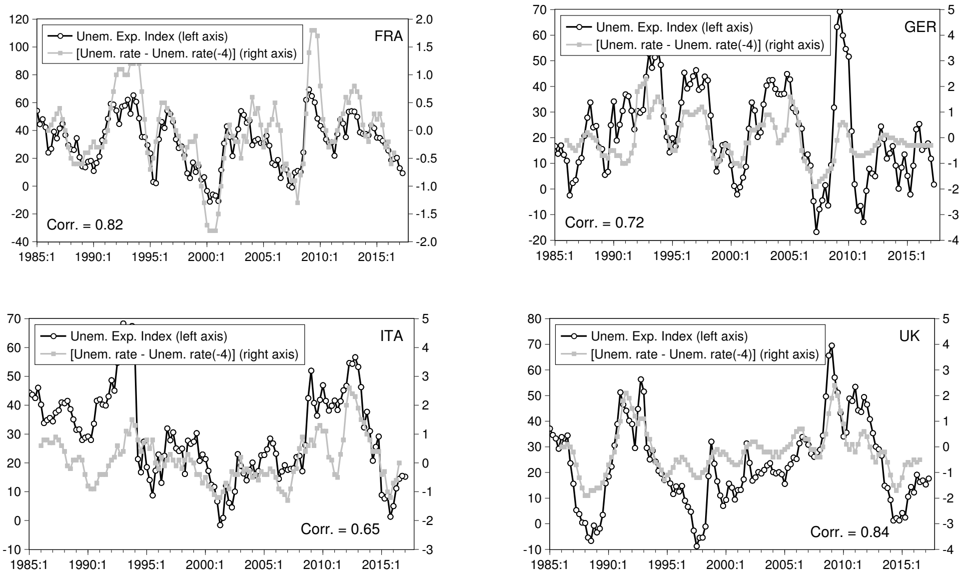
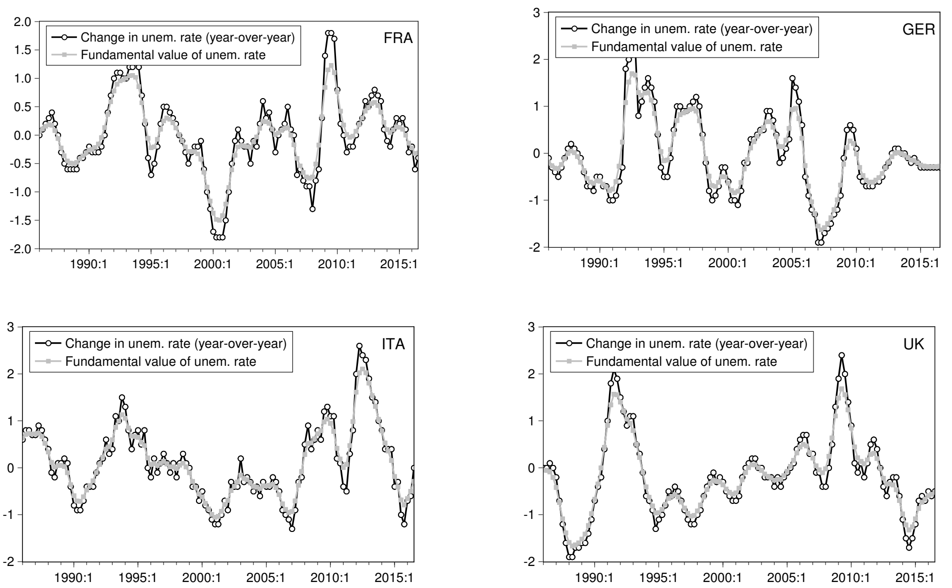


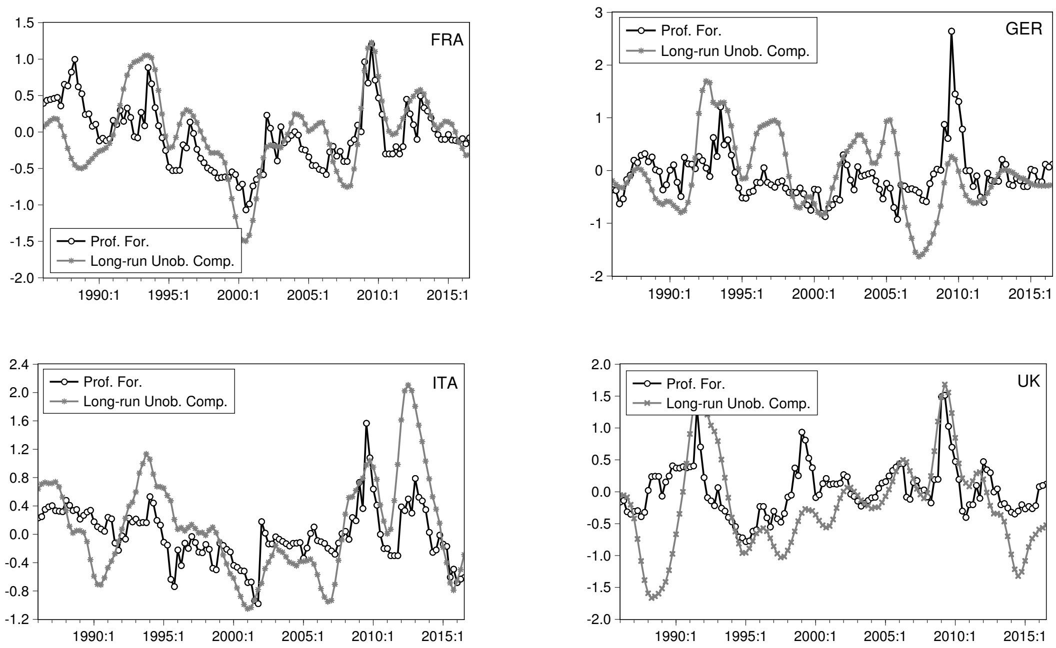
Figure 8: Fundamental value of change in unemployment rate ($\Delta_4 U_t{}^*$) *vs* actual change in unemployment rate ($\Delta_4 U_t$) (1986Q1-2016Q3).



C Stylized facts: expert forecasts and (unobserved) long-run determinant of change in unemployment rate

This Appendix presents a comparison between professional forecasts and the long-run component of change in unemployment rate $\Delta_4 {u_t}^*$, as estimated through Table 3. Figure 9 gives a visual inspection of the relation. The two series seem to move together over time. To give a statistical measure of this co-movement, we calculate the correlations, over the period 1986Q1-2016q3, between four lagged periods of professional forecasters ($N_{t-4}[\Delta U_t]$) and long-run component of change in unemployment rate (ΔU_t) for each country.[34] Results are reported in the Table 5. It is important to emphasize that for all countries, the correlation is above 0.30. The exception is Germany, where the correlation is 0.15. The reason lies in the huge "outlier" observed in the professional forecasters predictions for the period 2009Q3-2010Q1. If these extreme values are excluded, the correlation is 0.30. These results confirm that, excluding for some anomalous predictions that may occur, the hypothesis that professional forecasters time series proxy the long-run component of change in unemployment rate is supported by data.

Figure 9: Professional forecasts (`Prof. For`) *vs* (unobserved) long-run determinant of change in unemployment rate (`Long-run Unob. Comp.`) (1986Q1-2016Q3)



[34] Remember that professional forecasts predict the future value of change in unemployment rate at time $t+4$.

Table 5: Correlation of OECD forecasts and fundamental rate change (1986Q1-2016Q3)

$Corr. = (N_{t-4}[\Delta U_t], \Delta U_t)$			
Fra	Ger	Ita	Uk
0.34	0.15	0.31	0.50

D OLS estimation of Eq. (23)

Table 6: OLS estimates of Eq. (23) (1985q2-2016q4)

	$\alpha(1-\lambda)$	λ	β
FRA	-0.004	0.071	0.861***
	(0.016)	(0.045)	(0.046)
GER	-0.001	0.011	0.868***
	(0.014)	(0.034)	(0.038)
ITA	0.006	0.054	0.918***
	(0.016)	(0.052)	(0.051)
UK	-0.024	0.047	0.951***
	(0.020)	(0.049)	(0.042)

E Data description

This appendix describes the data used in the empirical analysis for France, Germany, Italy, and the UK. All time series have quarterly frequency and cover different time periods according to their availability. All details are summarized in Table 7.

Data on the unemployment rate are expressed as year-over-year change (i.e. change respect to the same quarter of the previous year). Data are seasonally adjusted and are recovered from OECD and Federal Reserve Economic Data (FRED).

The non-expert unemployment expectations are the expectations on unemployment rate changes in the next 12 months taken from European Commission's Joint Harmonised EU Programme of Consumer Surveys. These expectations series are expressed as a balance index and are seasonally adjusted. Data are available at monthly frequency and are transformed in quarterly series taking the average of the corresponding monthly observations. Finally, the quarterly series are converted in the same unit of measure of the unemployment rate using an auxiliary regression. See Section 3.3 for more details.

The expert unemployment expectations are proxied by forecasts contained in the OECD Economic Outlook. The predictions refer to the seasonally adjusted unemployment rate in the next year. In our analysis we use the change in the unemployment rate expectations measured as the difference between the forecasted unemployment rate in the next four quarters and the unemployment rate of the current quarter.

The Economic Policy "news-based" Uncertainty index (EPU) is constructed counting the number of articles related to uncertainty and economy reported by the press.[35]. The time series is then detrended using a quadratic trend. The source is Baker et al. (2016).

The Google Uncertainty Index (GUI) is built counting the volume of Google searches containing the terms uncertain or uncertainty, economic or economy. The source is the website Google Trends. We consider searches both in the native language of the country and in English. The intensity of Internet searches, which are related to the above mentioned keywords, should reflect (proxy) a high level of uncertainty perceived among non-expert agents. In this regard, Bontempi et al. (2017), in introducing a similar index based on Google Trends for US, presents a list of conditions necessary to make sure that online searches reflect perceived uncertainty and not mere general interest. First of all, there must be "a careful selection of the list of the specific search terms potentially related to uncertainty"; that is, it must be understood if there is an uncertainty-related common driver that leads to an increase or a decrease of these searches, while searches related to general interest can be considered as noise. The second condition is that this list "must be long enough to exploit the statistical averaging effect across many different queries". As an application of these two conditions, we opted for the keywords of Baker et al. (2016), while dropping the further very specific policy-related terms, since for our selected European countries there are too few data for several very specific searches, hindering the possibility to elaborate the related time series from Google Trends. The series are seasonally adjusted, converted in quarterly data (taking the average of montlhy observations), and detrended (using a quadratic trend).

In the GMM estimates we use as instruments the following exogenous variables: oil price changes, equity returns, housing price changes, short-run interest rate changes, spread between long-term and short-term interest rates, and US real GDP growth. All these data are recovered from the Federal Reserve website, with the exclusion of oil price which is taken from the OECD database.

[35] Quoting from the methodology part of the EPU website, "We count the number of newspaper articles containing the terms uncertain or uncertainty, economic or economy, and one or more policy-relevant terms".

Table 7: Data description and sources for France, Germany, Italy and the United Kingdom

Label	Description	Data measurement	Seas. Adj.	Period	Source
C_t	Household per capita consumption	Level	Yes	1991q1-2016q4	OECD, Eurostat (UK), Istat (ITA)
Y_t	Household per capita income	Level	Yes	1991q1-2016q4	OECD, Eurostat (UK), Dallas FED and Istat (ITA*)
π_t	Yearly inflation rate (Private Consumption Expenditure deflator)	Rate	Yes	1991q1-2016q4	Dallas FED
EU_t^U	Non-expert unemployment rate expectations	Balance Index	Yes	1986q1-2016q4	EU Commission
$\Delta_4 u_{t+4}$	Harmonised unemployment rate	Year-over-year change	Yes	1981q1-2016q3	OECD and FRED
$M_t\left[\Delta_4 u_{t+4}\right]$	Non-expert unemployment rate expectations*	Year-over-year change	Yes	1986q1-2016q4	EU Commission
$N_t\left[\Delta_4 u_{t+4}\right]$	Expert unemployment rate expectations	Year-over-year change	Yes	1986q1-2016q4	OECD Economic Outlook
EPU_t	"News-based" Economic Policy Uncertainty index	De-trended using quadratic trend	Yes	1997q1-2016q3	Baker et al. (2016)
GUI_t	"Internet-based" Google Uncertainty index	De-trended using quadratic trend	Yes†	2004q1-2016q3	Google Trends
$\Delta_4 oil_t{}^\ddagger$	Oil price (US $)	year-over-year percentage change	NA	1987q1-2016q4	FRED
$\Delta_4 y_t^{USA\ddagger}$	US real GDP	year-over-year percentage change	Yes	1984q1-2016q4	FRED
$\Delta_4 hp_t^{USA\ddagger}$	US Real housing price	year-over-year percentage change	Yes	1984q1-2016q4	Dallas FED
$\Delta_4 i_t{}^\ddagger$	Short-term interest rate	year-over-year change	NA	1984q1-2016q4	OECD
$spread_t{}^\ddagger$	Spread between long-term and short-term interest rates	Percentage points difference	NA	1984q1-2016q4	OECD

Note: NA= Not Applicable. *Data expressed as a balance index and converted in the same unit of measure of unemployment rate (see Section 3.3 and Eqs (21) and (22)). * FED of Dallas (1991Q1-1998Q4); ISTAT (1999Q1-2017Q1). † The Internet-based uncertainty Index is seasonally adjusted by authors using X13-ARIMA procedure. ‡ Data used as instruments in GMM estimation

References

Akerlof, G. A., Dickens, W. T., Perry, G. L., Bewley, T. F., and Blinder, A. S. (2000). Near-rational wage and price setting and the long-run phillips curve. *Brookings papers on economic activity*, 2000(1):1–60.

Bacchetta, P. and Van Wincoop, E. (2005). Rational inattention: A solution to the forward discount puzzle. NBER Working Paper 11633, National Bureau of Economic Research.

Bachmann, R., Elstner, S., and Sims, E. R. (2013). Uncertainty and economic activity: Evidence from business survey data. *American Economic Journal: Macroeconomics*, 5(2):217–249.

Baker, M., Greenwood, R., and Wurgler, J. (2003). The maturity of debt issues and predictable variation in bond returns. *Journal of Financial Economics*, 70(2):261–291.

Baker, S. R., Bloom, N., and Davis, S. J. (2016). Measuring economic policy uncertainty. *The Quarterly Journal of Economics*, 131(4):1593–1636.

Ball, L. (2000). Near-rationality and inflation in two monetary regimes. NBER Working Paper 7988, Cambridge, MA: National Bureau of Economic Research.

Beaudry, P., Galizia, D., and Portier, F. (2017). Reconciling Hayek's and Keynes Views of Recessions. *Review of Economic Studies*, *forthcoming*:1–38.

Beckert, J. (1996). What is sociological about economic sociology? Uncertainty and the embeddedness of economic action. *Theory and Society*, 25(6):803–840.

Bontempi, M. E., Golinelli, R., and Squadrani, M. (2017). A New Index of Uncertainty Based on Internet Searches: A Friend or Foe of Other Indicators? Mimeo, Department of Economics, University of Bologna.

Branch, W. A. (2004). The theory of rationally heterogeneous expectations: evidence from survey data on inflation expectations. *The Economic Journal*, 114(497):592–621.

Branch, W. A. (2007). Sticky information and model uncertainty in survey data on inflation expectations. *Journal of Economic Dynamics and Control*, 31(1):245–276.

Carroll, C., Slacalek, J., and Sommer, M. (2012). Dissecting saving dynamics: measuring credit, wealth and precautionary effects. *Available at: http://www. econ2. jhu. edu/people/ccarroll/papers/cssUSSaving. pdf.*

Carroll, C. D. (1997). Buffer-stock saving and the life cycle/permanent income hypothesis. *The Quarterly journal of economics*, 112(1):1–55.

Carroll, C. D. (2003). Macroeconomic expectations of households and professional forecasters. *The Quarterly Journal of Economics*, 118(1):269–298.

Carroll, C. D. (2006). The Epidemiology of Macroeconomic Expectations. In Blume, L. E. and Durlauf, S. N., editors, *The Economy as an Evolving Complex System, III: Current Perspectives and Future Directions*, pages 5–29. Oxford University Press, Oxford, New York.

Carroll, C. D. and Dunn, W. E. (1997). Unemployment expectations, jumping (S, s) triggers, and household balance sheets. *NBER macroeconomics annual*, 12:165–217.

Carroll, C. D., Hall, R. E., and Zeldes, S. P. (1992). The buffer-stock theory of saving: Some macroeconomic evidence. *Brookings papers on economic activity*, 1992(2):61–156.

Carroll, C. D., Slacalek, J., and Tokuoka, K. (2014). The distribution of wealth and the mpc: implications of new european data. *American Economic Review*, 104(5):107–11.

Coibion, O. and Gorodnichenko, Y. (2015). Information rigidity and the expectations formation process: A simple framework and new facts. *The American Economic Review*, 105(8):2644–2678.

Curtin, R. (2010). Inflation expectations and empirical tests. *Inflation Expectations*, 56:34.

D'Acunto, F., Hoang, D., and Weber, M. (2015). Inflation expectations and consumption expenditure. *Unpublished manuscript, University of Chicago*.

Deaton, A. (1977). Involuntary saving through unanticipated inflation. *The American Economic Review*, 67(5):899–910.

Deaton, A. (1991). Saving and liquidity constraints. *Econometrica: Journal of the Econometric Society*, pages 1221–1248.

Dequech, D. (1999). Expectations and confidence under uncertainty. *Journal of Post Keynesian Economics*, 21(3):415–430.

Dickey, D. A. and Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association*, 74(366a):427–431.

Duca, I. A., Kenny, G., and Reuter, A. (2016). How do inflation expectations impact consumer behaviour? *Unpublished manuscript, European Central Bank*.

Earl, P. E. (1990). Economics and psychology: a survey. *The Economic Journal*, 100(402):718–755.

Easaw, J. and Golinelli, R. (2012). Household Inflation Expectations: Information gathering, Inattentive or 'Stubborn'? Working Paper 853, University of Bologna, Department of Economics.

Easaw, J. Z., Golinelli, R., and Heravi, S. (2017). Inflation forecasts, Inattentiveness and Uncertainty. Mimeo, Cardiff University Business School, Cardiff, UK.

European Commission (2016). The joint harmonised EU programme of business and consumer surveys: User guide. Technical report, European Commission: Directorate-General for Economic and Financial Affairs.

Farmer, R. E., Waggoner, D. F., and Zha, T. (2009). Understanding Markov-switching rational expectations models. *Journal of Economic theory*, 144(5):1849–1867.

Friedman, B. M. and Roley, V. V. (1979). Investors' Portfolio Behavior Under Alternative Models of Long-Term Interest Rate Expectations: Unitary, Rational or Autoregressive. *Econometrica*, 47(6):1475–1497.

Friedman, M. (1953). *Essays in positive economics*. University of Chicago Press.

Fuller, W. A. (2009). *Introduction to statistical time series*, volume 428. John Wiley & Sons.

Geary, R. C. (1948). Studies in relations between economic time series. *Journal of the Royal Statistical Society. Series B (Methodological)*, 10(1):140–158.

Girardi, A. and Reuter, A. (2016). New uncertainty measures for the euro area using survey data. *Oxford Economic Papers*, 69(1):278–300.

Heiner, R. A. (1989). The origin of predictable dynamic behavior. *Journal of Economic Behavior & Organization*, 12(2):233–257.

Jordà, Ò. (2005). Estimation and inference of impulse responses by local projections. *American Economic Review*, 95(1):161–182.

Jordà, Ò. (2009). Simultaneous confidence regions for impulse responses. *The Review of Economics and Statistics*, 91(3):629–647.

Jurado, K., Ludvigson, S. C., and Ng, S. (2015). Measuring uncertainty. *The American Economic Review*, 105(3):1177–1216.

Kahneman, D., Slovic, P., and Tversky, A. (1974). Judgment under uncertainty: Heuristics and biases. *Science*, 185(4157):1124–1131.

Kahneman, D., Slovic, P., and Tversky, A. (1982). Judgments under uncertainty. *Heuristics and Biases, Cambridge*.

Kimball, M. S. (1990). Precautionary saving in the small and in the large. *Econometrica: Journal of the Econometric Society*, pages 53–73.

Kwiatkowski, D., Phillips, P. C., Schmidt, P., and Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root? *Journal of Econometrics*, 54(1-3):159–178.

Lamont, O. A. (2000). Investment plans and stock returns. *The Journal of Finance*, 55(6):2719–2745.

Lettau, M., Ludvigson, S., and Steindel, C. (2002). Monetary policy transmission through the consumption-wealth channel. *FRBNY Economic Policy Review*, 5:117–133.

Mankiw, N. G. and Reis, R. (2002). Sticky information versus sticky prices: a proposal to replace the New Keynesian Phillips curve. *The Quarterly Journal of Economics*, 117(4):1295–1328.

Marcellino, M. (2006). Some stylized facts on non-systematic fiscal policy in the euro area. *Journal of Macroeconomics*, 28(3):461–479.

Milani, F. (2011). Expectation shocks and learning as drivers of the business cycle. *The Economic Journal*, 121(552):379–401.

Moscarini, G. (2004). Limited information capacity as a source of inertia. *Journal of Economic Dynamics and control*, 28(10):2003–2035.

Muth, J. F. (1961). Rational expectations and the theory of price movements. *Econometrica: Journal of the Econometric Society*, 29(3):315–335.

Neumeyer, P. A. and Perri, F. (2005). Business cycles in emerging economies: the role of interest rates. *Journal of monetary Economics*, 52(2):345–380.

Pesaran, H. H. and Shin, Y. (1998). Generalized impulse response analysis in linear multivariate models. *Economics letters*, 58(1):17–29.

Pesaran, M. (1984). Expectations formation and macroeconomic modelling', in (P. Malgrange and P. Muet, eds.) Contemporary Macroeconomic Modelling.

Pesaran, M. H. (1987). *The limits to rational expectations*. Blackwell Oxford.

Rabin, M. and Schrag, J. L. (1999). First impressions matter: A model of confirmatory bias. *The Quarterly Journal of Economics*, 114(1):37–82.

Reis, R. (2006). Inattentive producers. *The Review of Economic Studies*, 73(3):793–821.

Roberts, J. M. (1998). Inflation expectations and the transmission of monetary policy. Discussion Paper 1998-43, Federal Reserve FEDS.

Sargan, J. D. (1958). The estimation of economic relationships using instrumental variables. *Econometrica: Journal of the Econometric Society*, pages 393–415.

Simon, H. A. (1959). Theories of decision-making in economics and behavioral science. *The American economic review*, 49(3):253–283.

Simon, H. A. (1978). Rationality as process and as product of thought. *The American economic review*, pages 1–16.

Simon, H. A. (1979). Rational decision making in business organizations. *The American economic review*, 69(4):493–513.

Sims, C. A. (2003). Implications of rational inattention. *Journal of monetary Economics*, 50(3):665–690.

Skinner, J. (1988). Risky income, life cycle consumption, and precautionary savings. *Journal of Monetary Economics*, 22(2):237–255.

Sterk, V. and Ravn, M. (2017). Job uncertainty and deep recessions. *Journal of Monetary Economics*.

Thaler, R. (2012). *The winner's curse: Paradoxes and anomalies of economic life*. Simon and Schuster.

Thaler, R. H. (1994). *Quasi rational economics*. Russell Sage Foundation.

Tortorice, D. L. (2012). Unemployment expectations and the business cycle. *B.E. Journal of Macroeconomics*, 12:1–47.

Woodford, M. (2003). Imperfect Common Knowledge and the Effects of Monetary Policy. *Knowledge, Information, and Expectations in Modern Macroeconomics: In Honor of Edmund S. Phelps*, pages 25–58.

Wu, T. (2003). Stylized facts on nominal term structure and business cycles: an empirical VAR study. *Applied Economics*, 35(8):901–906.