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

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Abstract

We present a common-source infection model for explaining the formation of expectations by households. Starting from the framework of "Macroeconomic expectations of household and professional forecasters" (C.D. Carroll, *The Quarterly Journal of Economics*, 2003), we augment 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 selected group of European countries (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 with the level of uncertainty spread by newspapers and conveyed by Internet.

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

<div align="right">Jurado et al. (2015)</div>

1 Introduction

Expectations matter in the macroeconomy. Changes in expectations may lead to changes in economic activity, both at the individual level (i.e. firms and consumers) and at the aggregate level. For example, interest rates expectations enter into investment decisions of firms (Neumeyer and Perri, 2005), portfolio decisions of investors (Friedman and Roley, 1979), and 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 through their impact on consumption expenditure. Carroll and Dunn (1997) proxy income uncertainty, due to unemployment risk, with 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 emphasizes the role of perceived unemployment risk in amplifying business cycles;[1] see Ravn et al. (2012) and Beaudry et al. (2017).

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

Even though the FIRE approach is an useful and theoretically strong starting point (Friedman, 1953; Muth, 1961), its actual empirical soundness has been repeatedly discussed in the last decades, as summarized in Curtin (2010). 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) the presence of which makes expectations not so likely to be formed in a fully rational way. Actually, Roberts (1998) and Tortorice (2012) report that surveys reflect only an intermediate degree of rationality, and Ball (2000) proposes near-rationality in inflation expectations as a possible solution.

One of the main weaknesses of the FIRE is the assumption that all individuals have access to the same, complete set of information used to form expectations. Moreover, even

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[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).

if individuals have access to all information, not all of them may have the capacity and/or the willingness to absorb all the information available. If there are positive costs associated to collect and process information, the agents may find optimal 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). "Sticky Information" (SI) models assume that agents are rational, but the presence of fixed costs in both updating and processing information induces agents to update their information set infrequently. Once they update, they acquire the 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 the 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, differently from SI, the weight put on 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 across people as the result of an "infection" process 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 like a virus. 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 modelize the expectations lies in the possibility for less informed agents to revise their expectations. While in Branch (2004, 2007), Woodford (2003) and Sims (2003) all agents revise their expectations, Mankiw and Reis (2002) and Carroll (2003) assume that only informed agents change their expectations. The uninformed (inattentive) group, instead, maintains the previous expectation. The hypothesis that inattentive agents do not revise at all their previous opinion may appear quite strong in practice. Even the more

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

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

"discouraged" agents may take an effort to build an expectation.[4]

Starting from Carroll (2003),[5] we develop a common-source-infection (CSI) model applied to expected changes in the unemployment rate for a selected group of European countries, namely Germany, France, Italy, and UK.[6] This work is innovative in the framework of Carroll (2003) in three ways. First, we generalize 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 in detail, 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 to produce 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 a small effort in terms of time and resources. Second, we allow the key parameter measuring the probability of being infected to be time-varying, while Carroll (2003) estimates are based upon the assumption of a constant probability.[7] Third, we find a (negative) link between the time-varying infection probability and the level of uncertainty, both the one diffused by newspapers (proxied by the index introduced by Baker et al., 2016) and the one represented by web searches on economic uncertainty (proxied by Google searches on the topic).

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

The paper is organized as follows. Section 2 presents further empirical evidence on the importance of unemployment expectations at the macroeconomic level. Section 3 presents the theoretical framework. Sections 4 highlights the role of uncertainty in the CSI

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

[5]The term "epidemiology" has different meanings in several different streams of literature. Carroll (2003) defines this as an epidemiological framework because the information is considered such as 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) no possibility of contagion among agents; (iii) 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, throughout the paper we prefer to label the model as "common-source-infection" model.

[6]The model is designed in terms of unemployment rates variations (i.e. in first-differences) since the formulation of survey question on unemployment expectations goes in this direction.

[7]In a different setup, a similar time-varying estimate is present also in Coibion and Gorodnichenko (2015). Anyway, considering the different aim of our work, our time-varying approach is totally model-based. We make this choice in order to avoid spurious correlation with the "news-based" indexes.

framework. Section 5 presents the estimation strategy and Section 6 the related output. Section 7 concludes.

2 On the role of expectations on consumption

Before introducing the common-source-infection model, we shortly present further evidence on the role of unemployment expectations at the macroeconomic level. Expectations shape households behaviour. Very briefly, Carroll (1997) has shown that an agent which is both prudent and impatient may be induced to build up a "buffer stock" of savings to face periods of potentially low income (or, equivalently, potentially high expenses). The level of this "buffer" targeted by the household depends on his expectations about the future: the higher the uncertainty and the lower the income he expects,[8] the more he accumulates savings, thereby reducing current consumption levels. As examined in depth in Carroll and Dunn (1997), unemployment expectations are theoretically and empirically relevant, since they can be viewed as a proxy for the (perceived) probability of having no labour income, and a deterioration of these expectations depresses the consumption level. In a recent paper, Carroll et al. (2012) analyse the US saving rate and find a positive effect of households expectations on the aggregate saving rate.

We run a very stylized macro VAR model – consumption, disposable income,[9], inflation and households unemployment expectations – on the set of countries studied in this paper. As expected, a generalized impulse-response analysis highlights a common negative effect of unemployment expectations on consumption decisions. We take into consideration France and Germany, the two leading economies for the Euro area, Italy, one of the biggest countries among the ones suffering of low growth, and an important non-Euro country like the United Kingdom. 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. These results give support to the idea of an important role of unemployment expectations on consumption/saving decisions.[10]

# 3 Theoretical framework

3.1 Carrol's CSI framework

Carroll (2003, 2006) introduced a CSI model to formalize households expectations. In this framework, the information propagates through the economy as a virus and each agent has

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

[9]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.

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

Figure 1: Impulse Response graph of disposable income per capita, consumption per capita and inflation to unemployment expectations (1991Q1-2016Q4).
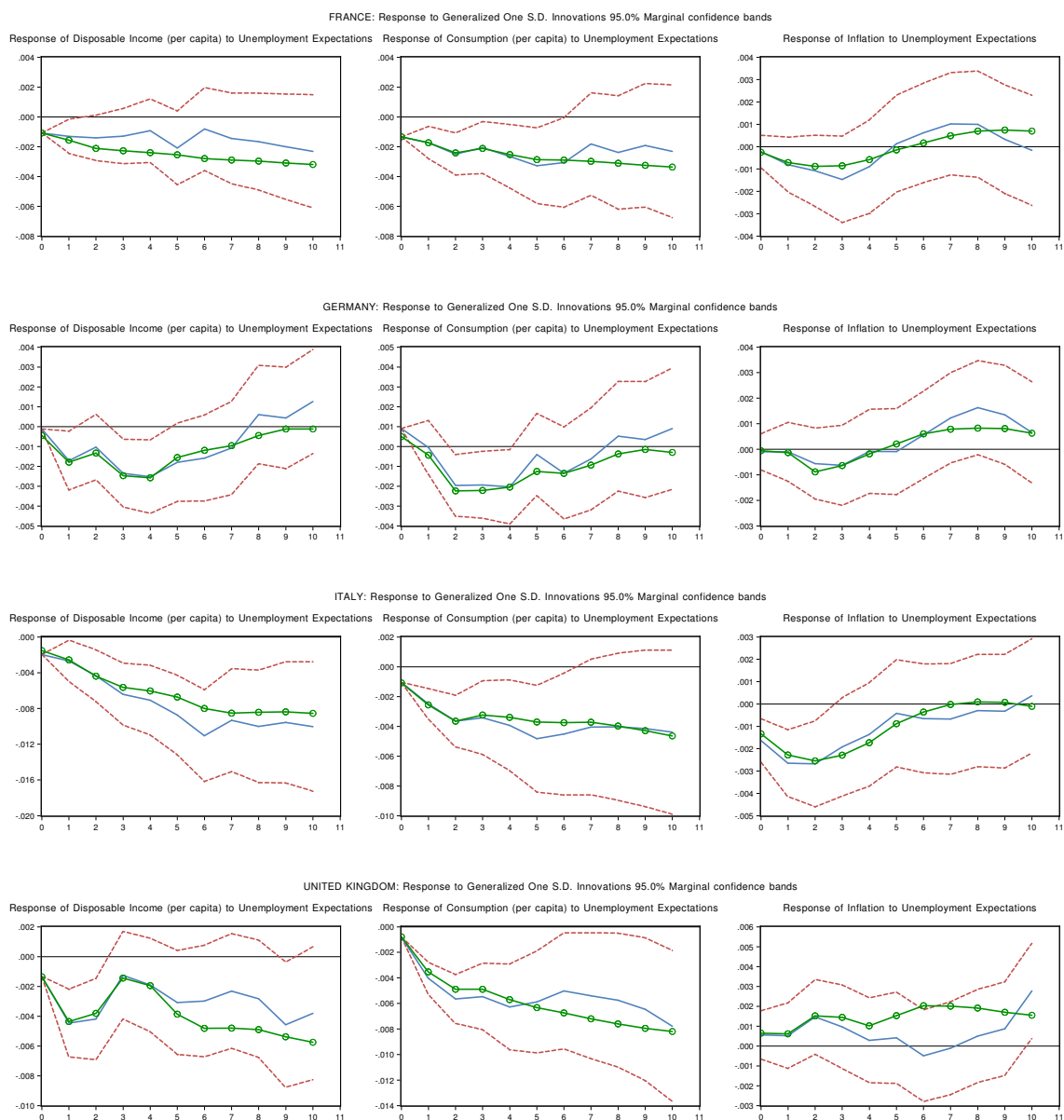
Notes: Impulse response (blue) and confidence bands (red) are estimated according to the local projection method (Jordà et al., 2005; Jordà, 2009). Standard VAR estimates are in green.

a given probability to be infected. Denoting with x the variable of interest, the following points characterize Carroll (2003, 2006)'s model:[11]

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 exactly x_{t+1}^*, so that the prediction of x_{t+1} corresponds to

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

where $N_t\left[x_{t+1}\right]$ indicates the professional forecasts prediction. In other words, the innovation η_{t+1} is always observed by expert agents in period t.[12].

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.[13]

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

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

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

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

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

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

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[11]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 kind of economic variables such as GDP, disposable income, consumption, and unemployment.

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

[13]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 $t-1$).

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

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

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:

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

Thus Eq. (7) can be expressed as:

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

or

$$[1-(1-\lambda)L]\,M_t[x_{t+1}] = \lambda N_t[x_{t+1}] \qquad (10)$$

which corresponds to

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

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:

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

where $M_t[x_{t+4}]$ now indicates the population-mean value of expectations on x made in t over the quarter $t+4$ and $N_t[x_{t+4}]$ 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 after 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 high degree of "stickyness" in aggregate expectations, with important macroeconomic consequences.

One of the central implication in 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

(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} requires a costly activity (in terms of time and money spent to study how the economy works) for a typical person. Since news reports provide forecasts for free, an individual prefers to dedicate time to other activities such as work, family, hobbies, etc.

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

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

I' The typical person believes that x_t behaves like a *stationary stochastic model*:[14]

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

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

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. Now, typical agents may form and change expectations by themselves, from one period to another, 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 from the expectation for x_{t+j+1} ($\forall j \neq 0$).[15]

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:

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

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[14]From a mathematical point of view, a stationary process could be obtained with $-1 < \beta < 1$. Anyway, if β were negative, a fundamental shock η would imply an oscillatory pattern of the fundamental value of the variable of interest. Oscillatory pattern which has no confirmation on empirical data of the macroeconomic variables we are going to study and, more in general, to macroeconomic variables for which this model could be applied. The assumption on the autoregressive nature of the variable has been made also, in a different setup, by the "noisy information" model of Woodford (2003).

[15]Furthermore, on the one hand, under the random walk hypothesis of Eq. (2) informed agents have superior information also concerning the long-run horizon: in period t, the best guess for $x_\infty^* = x_{t+1}^* = x_t^* + \eta_{t+1}$. So, 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 even more, periods before. On the other hand, there is no long-period advantage under the stationary process of (14), since $x_\infty^* = \frac{\alpha}{1-\beta}$: 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 "infected" at time t, then Eq. (15) is equal to

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

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:

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\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 expectation 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 (2003) model to 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: 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; second, the characteristics of the statistical process of the variable under investigation.[16] The first point allows us to identify how the variable is measured (i.e. level or growth rates). The second point is crucial to understand if the process is better described by:

1. a random walk, like inflation in 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 for 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. First, it is clear that the survey question refers to a change in unemployment in the next year: i.e. the future number of unemployed people less the current one. Second, it is important to understand which kind of unemployment data the 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 terms of a change in 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 usually newspapers and newscasts, communicating economic data, report data on unemployment expressed as a percentage of the labour force (i.e., the unemployment rate), we guess that agents have in mind this kind of data. A visual inspection between 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 households unemployment expectations. The time series of unemployment expectations are expressed by the European

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

Commission as a balance index. The balance values range from -100 (all respondents choose the most positive option) to +100 (all respondents choose the most negative option).[17] For our purposes, this balance is firstly converted in quarterly time series and then,[18] following Carroll (2003), converted in the same unit of measure of the unemployment rate using the following auxiliary regression:[19]

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

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 $U_{t+4} - U_t = \phi_0 + \phi_1 EU_t^U + \epsilon_t$ (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***

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 represented by Eqs. (1)-(2) or as represented by Eqs. (13)-(14)?

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) of Dickey and Fuller (1979)) and (2) a test with a trend-stationary null (the Kwiatkowsky-Phillips-Schmidt-Shin (KPSS) test of Kwiatkowski et al. (1992)). 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 a strong evidence in favour of a stationary process of ΔU_t for all countries.

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[17]For further details on aggregation and weighting of consumer surveys answers see European Commission (2016).

[18]More in details, 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. Full description of data is given in Appendix D.

[19]This auxiliary regression is known in the literature as the "regression approach" to qualitative surveys Pesaran (1984, 1987). 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).

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.

A more sophisticated alternative way to shed light on the above-mentioned dilemma consists in estimating the process of ΔU_t via univariate unobserved component (UC) model. A UC allows us to decompose the change of the unemployment rate in a persistent component (ΔU_t^*) and shocks elements (ϵ_t and η_t). The goal in this empirical exercise is to investigate the persistence of the fundamental value ΔU_t^*.[20] 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 and the Wald test confirms this statistically. The unobserved component estimates allow

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[20]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.

us to check the central hypothesis of the CSI model, that changes in the unemployment rate move around a fundamental value proxied by the expert unemployment expectations. A correlation-based analysis in Appendix C confirms this evidence giving an important support for this crucial assumption.

Following unit root and UC estimates, we assume households have some intuition that, in absence of new information, the best possible guess 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 is that with a persistent (but stationary) fundamental value 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.

4 CSI model and "news-based" uncertainty

The idea of using survey data to measure uncertainty is not new in the literature, and has been mainly focused on business surveys. Two recent examples are 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, and the two measures turn out to be strongly correlated. Girardi and Reuter (2016) extend the work of Bachmann et al. (2013), adding as a further measure the inter-question dispersion, since uncertainty may impact differently the expectations on the various macroeconomic indicators. Moreover, they also consider consumer surveys.

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

In general, non-expert agents adapt the level of attention they put on professional forecasters estimates in response to changes in the 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 Gorod-nichenko, 2015; Reis, 2006). Anyway, it is not the only effect involved. For example Moscarini (2004) presents a model in which agents update their information set infrequently, but absorbing information is more challenging (hence, more costly) when the environment is more uncertain.[21]. This higher cost of collecting/processing information

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[21]"For example, reading the Wall Street Journal every day in recent times of stock market turbolence is

mitigates, and possibly outweighs, the hunger for state-of-the-art information.

Furthermore, "noisy information" models (Sims, 2003; Woodford, 2003) emphasize that the weight agents put on the signal they receive depends on the level of noisiness of that signal. Similarly, in 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". There is strong evidence in experimental studies that people under uncertainty tend to use heuristics or intuitions deviating from full rationality (see, for example, Kahneman et al. (1974)). In our framework, this implies that uncertainty influences (negatively) the decisions of non-expert agents to look for information by reading newspapers, surfing the web and watching newscasts. In other words, agents, in presence of sustained uncertainty, are less confident on the capacity of experts to predict the future (actual) values of unemployment and may decide to use the rule of thumb updating expectation rule (i.e. Eq. (17) according to the CSI framework) instead of spending time to read 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 in the CSI framework this does not mean that agents may decide to "forget" and not to use the professional forecasts they are aware of;[22] conversely, they may not put a particular effort in capturing 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 transmission channel of the virus. Generally speaking, an agent may be infected through the "traditional" channel (print journalism and broadcast news) and the Internet channel (online versions of newspapers, plus online news blogs and social media). Whether the 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 clue about which can be considered as the main channel of transmission of the virus. Obviously, it may happen that both channels influence agents decision to intercept the professional predictions.

As we describe more in detail in the data appendix (Appendix D), the use of "news-based" indexes like the well-known Baker et al. (2016) Economic Policy Uncertainty Index (EPU), which is based upon newspaper articles content, and an index of uncertainty based on online search engines data from Google Trends (Google Uncertainty Index, GUI) may help to proxy 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 upon journalists' feeling about uncertainty,[23] the GUI focuses on the agents

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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)

[22]Remember that in the model if you are infected you cannot recover from the infection (Assumption 4 in Section 3.1).

[23]Quoting from the methodology part of the EPU website `http://www.policyuncertainty.com/methodology.html`, "We count the number of newspaper articles containing the terms uncertain or un-

perception of uncertainty counting the volume of searches for words containing the terms uncertain or uncertainty, economic or economy. 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.

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 the uncertainty in the economy (as explained in Section 4). In particular, the second point requires the adoption of a time-varying approach in estimating the parameters for comparing λ with the uncertainty index measure over time. The easiest way to satisfy the two point is to estimate equation (23) via a state-space approach. Equation (23) can be easily expressed as follows:

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

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 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.[24]

In addition to the state-space model, as a robustness check, we run a GMM estimate of equation (23).[25] The choice of GMM, specifically IV, instead of OLS[26] lies in the presence of potential measurement errors in the non-expert agents expectations variable. These

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certainty, economic or economy, and one or more policy-relevant terms".

[24]Alternatively, 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). Anyway, the main aim of our paper is instead first to investigate the time-varying proportion of people reading newspapers, then studying a relationship with uncertainty. For this reason, we prefer to avoid the approach suggested by the SDM (State Dependent Models) literature of considering volatility or uncertainty indexes as explanatory variables, since we would force a correlation and weaken our conclusions.

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

[26]The measurement error may produce a downward bias in the estimated coefficients. Actually, OLS estimation produces estimates of λ which are much closer to zero and not significant at all:

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

potential errors are due to the transformation needed to convert EU_t^U (Non-expert expectations expressed in balance terms) in the same metric of changes in the unemployment rate 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 variables in the relationship. For our purposes we use (lagged) international variables and financial variables as instruments, which satisfy the requirement of Sargan (1958).

6   Results

Figure 2: Time-varying estimates of λ obtained via state space model (1986Q1-2016Q4)
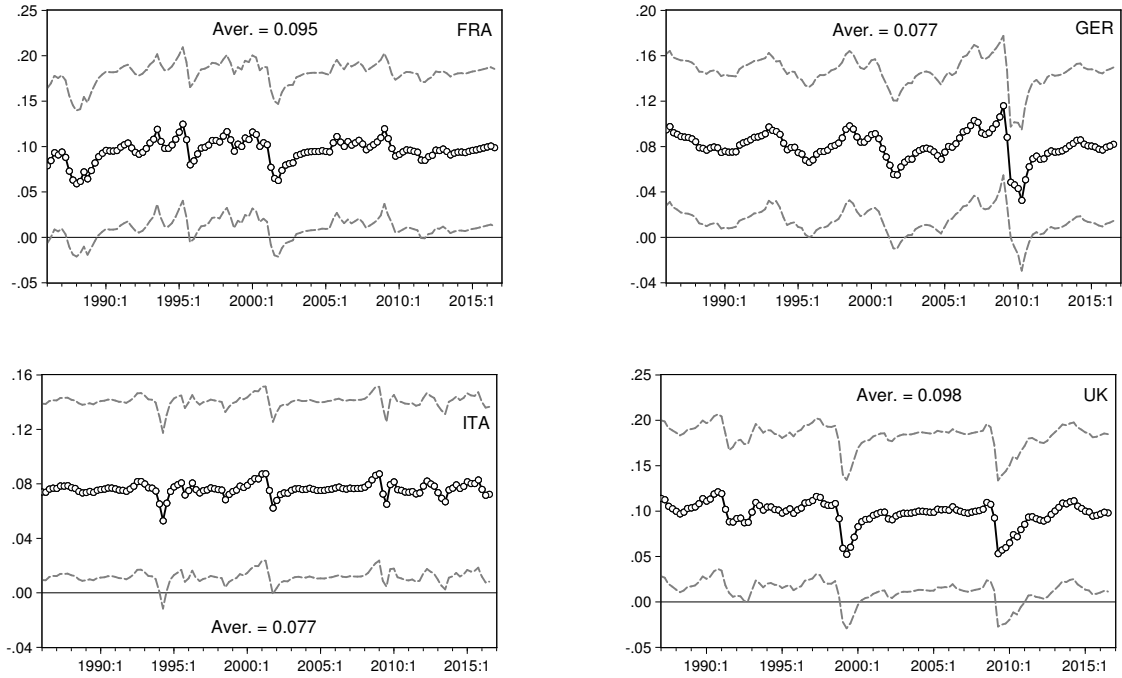
The time-varying parameters pattern of state-space model (24) is plotted in Figure 2 and Figure 3. In particular, in Figure 2 we plot the evolution of λ_t, whereas in Figure 3 we plot the dynamic of aggregate $(1 - \lambda_t)\beta_t$. From Figure 2 it emerges that in all countries λ fluctuates around an average value between 0.07 and 0.1. The dynamics are very similar for all countries. An important drop in the value of λ occurred in Germany and the UK in correspondence to the economic crisis. This drop is less evident instead in Italy and France. Concerning Figure 3, the evolution of $(1 - \lambda_t)\beta_t$ appears smoother for all countries. As a further consideration, the average values are smaller than unit as expected.

Figure 3: Time-varying estimates of $(1 - \lambda)\beta$ obtained via state space model (1986Q1-2016Q4)
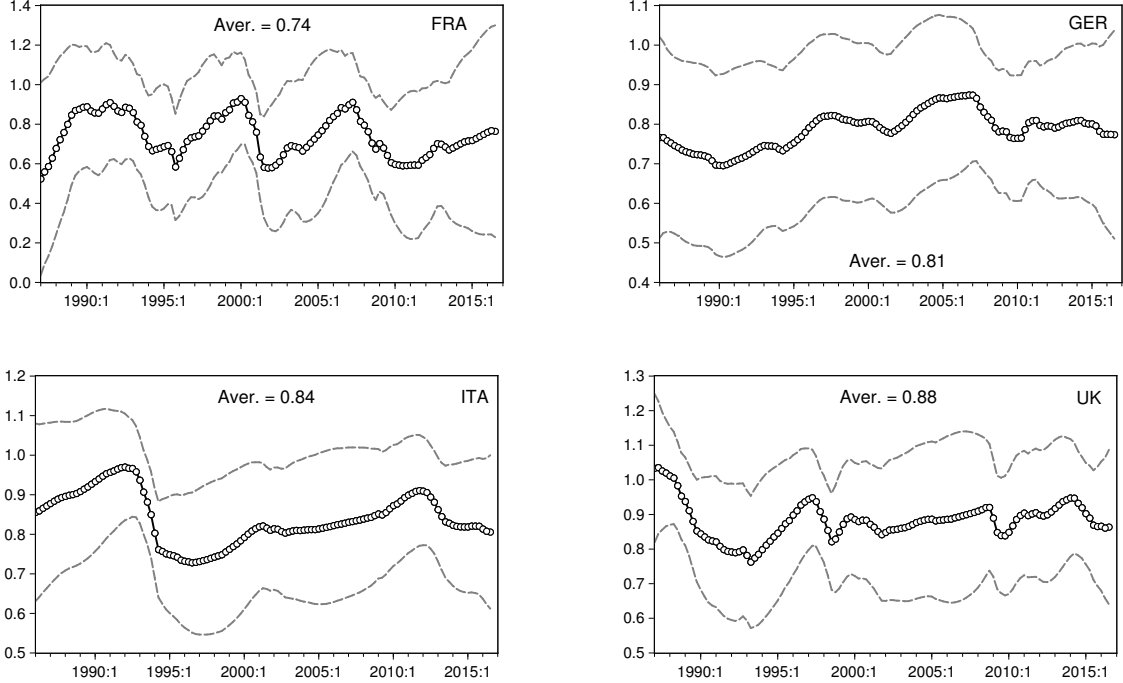
The GMM estimates of Equation (23) are in Table 4. The values of the parameters are in line with the average values obtained via time-varying state-space model. In particular, France and the UK exhibit higher values of λ with respect to the other countries in accordance with the state-space estimates. More importantly, using the values of λ and β obtained from GMM, we obtain values very similar to the average values of $(1 - \lambda_t)\beta_t$ in the state-space model.[27] Given the similarities of GMM and state-space model estimates, we can confirm the robustness of our results.

Figure 4 compares the estimates of λ of various countries with the EPU of Baker et al. (2016). The λ seems to move clearly in opposite direction with respect to the EPU index for France and Italy;[28] for these two countries the correlation over the two series for the whole period (1997Q1-2016Q3) is -0.31 for France and -0.38 for Italy. 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 values of correlation may suggest that a typical agent in Germany and the UK does not use print journalism and similar traditional media as source of information (and then contagion). Figure 5 shows the dynamics of λ with respect to the GUI obtained via Google trends. Plots for Germany and the UK show high

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

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

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

Model: $\widehat{M_t}\left[\Delta_4 U_{t+4}\right] = \lambda N_t\left[\Delta_4 U_{t+4}\right] + (1-\lambda)\left(\alpha + \beta\widehat{M_{t-1}}\left[\Delta_4 U_{t+3}\right]\right)$			
	$\alpha(1-\lambda)$	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: $\Delta_4 ln(sp)_{t-1}$, $\sum_{j=0}^{2}\Delta_4 ln(oil)_{t-1}$, $\sum_{j=1}^{3}\Delta_4 ln(hp^{USA})_{t-j}$, $\sum_{j=0}^{1}\Delta_4 i_{t-j}$, $\sum_{j=0}^{1} spread_{t-j}$. $\widehat{M}\left[\bullet\right]$ 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.

negative correlation with the GUI, equal to -0.44 and -0.40, respectively. These results are supported by other studies conducted on households habits in European countries. In particular, the Eurobarometer survey data[29] shows that British agents have a poor opinion about the quality and usefulness of the press. 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. From Figure 6 it emerges clearly that UK agents are very skeptical about the reliability of information disseminated by press. Conversely, the French, Germans and Italians have a better consideration of press information content. This evidence may suggest that agents in the UK use as source of information other media such as blogs and social media. Figure 5 on the relation between λ and the GUI confirms 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 like if Internet is complementing print journalism as a source of contagion. This insight is worth some future research.

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

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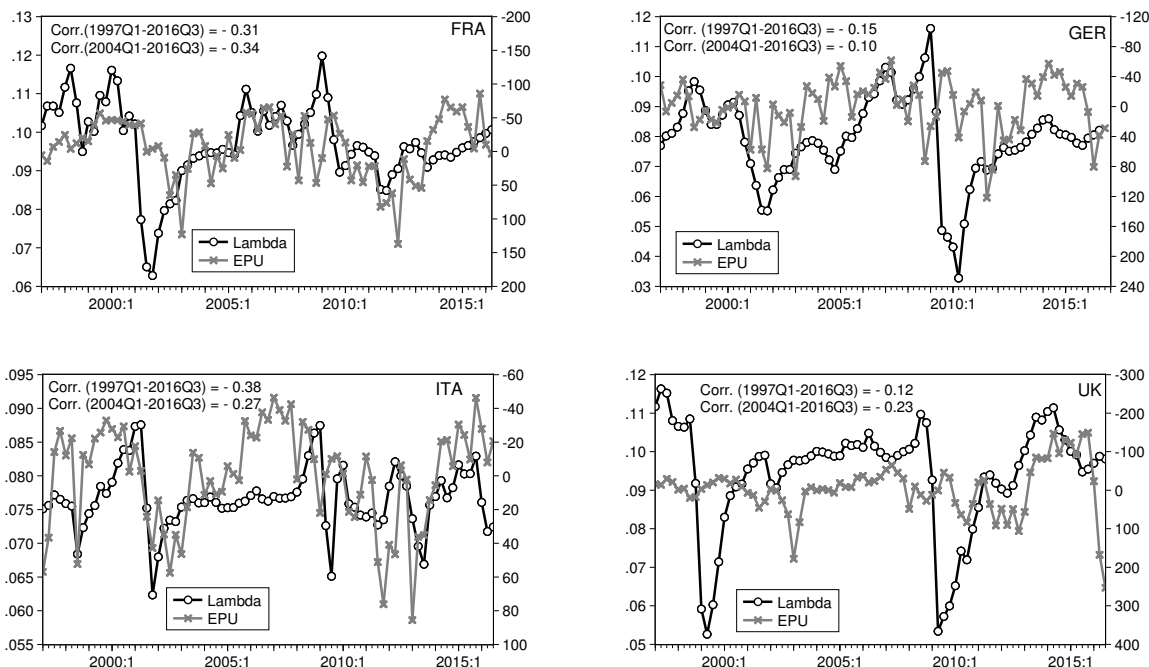
7   Conclusions

In the present work, we extend the "common-source-infection" (CSI) framework of Carroll (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 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 remaining individuals behave as naive econometricians, updating their expectation using outdated information. Moreover, expectations seem to be related to the level of perceived uncertainty, proxied by newspaper coverage on economic uncertainty and by web searches on the topic: in periods of higher uncertainty, agents absorb new information less frequently.

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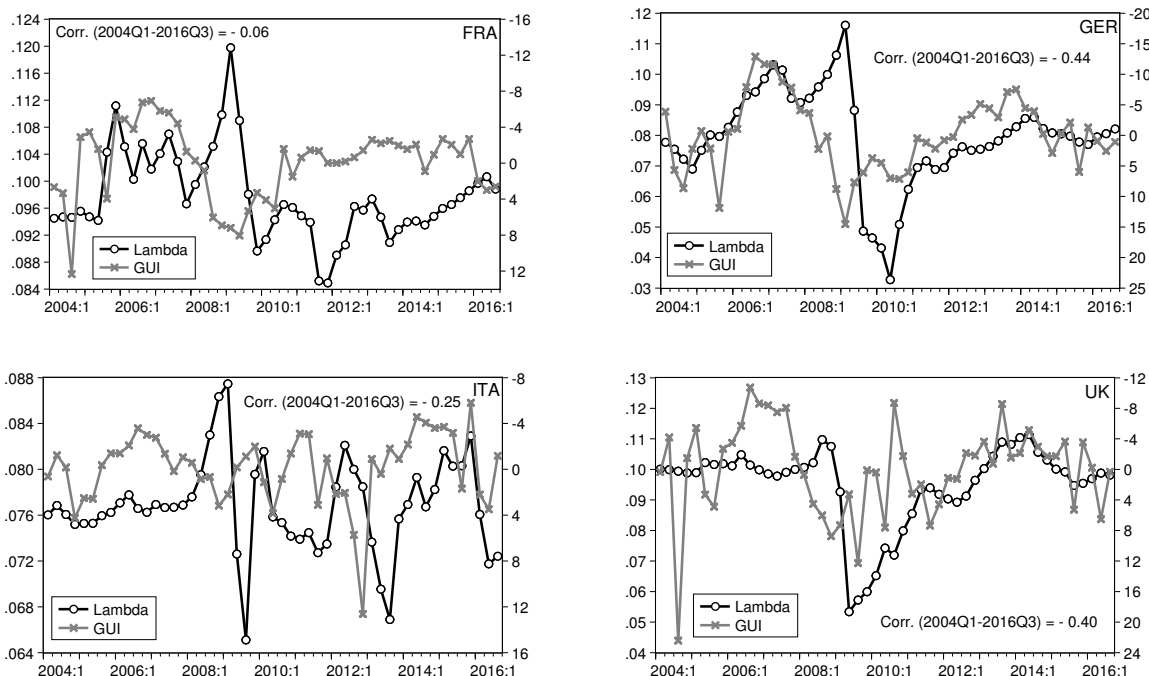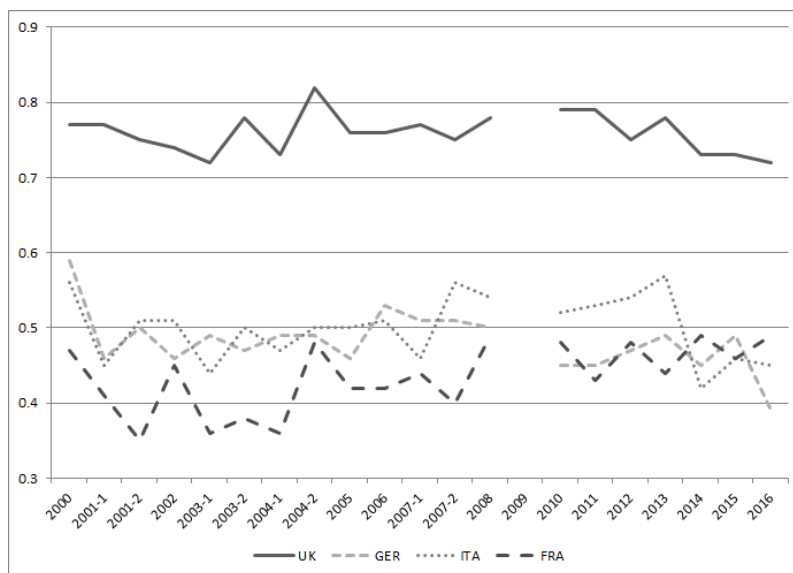

Figure 6: Confidence in the press, 2000-2016

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/`).

Acknowledgements

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

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

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 $N_t[\bullet]$ 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:

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

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

$$E_t^i[x_{t+4}] = N_t[x_{t+4}]. \tag{29}$$

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

$$E_t^i[x_{t+4}] = N_{t-1}[x_{t+4}] = N_{t-1}[x_{t+3}]. \tag{30}$$

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

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

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

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

A.2   Derivation of Equation (19)

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

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

Thus Eq. (18) can be expressed as:

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

or

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

which corresponds to (19)

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

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:

$$N_t\left[x_{t+4}\right] = x^*_{t,t+4} = \alpha + \beta x^*_{t-1,t+3} + \eta_{t+4}.^{30} \tag{37}$$

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:

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

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

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

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[30] 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 $N_t\left[\bullet\right]$ 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).
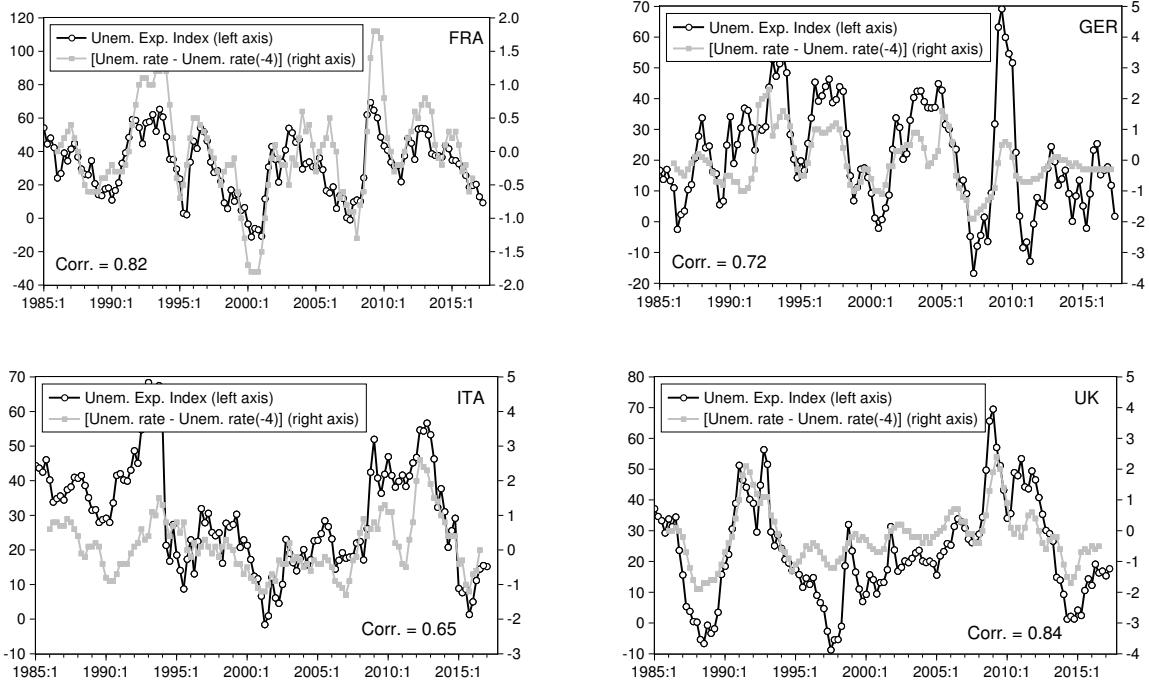

C Stylized facts: expert forecasts and (unobserved) long-run determinant of change in unemployment rate

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 ($N_{t-4}\left[\Delta U_t\right]$) and long-run component of change in unemployment rate (ΔU_t) for each country.[31] 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.

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

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).
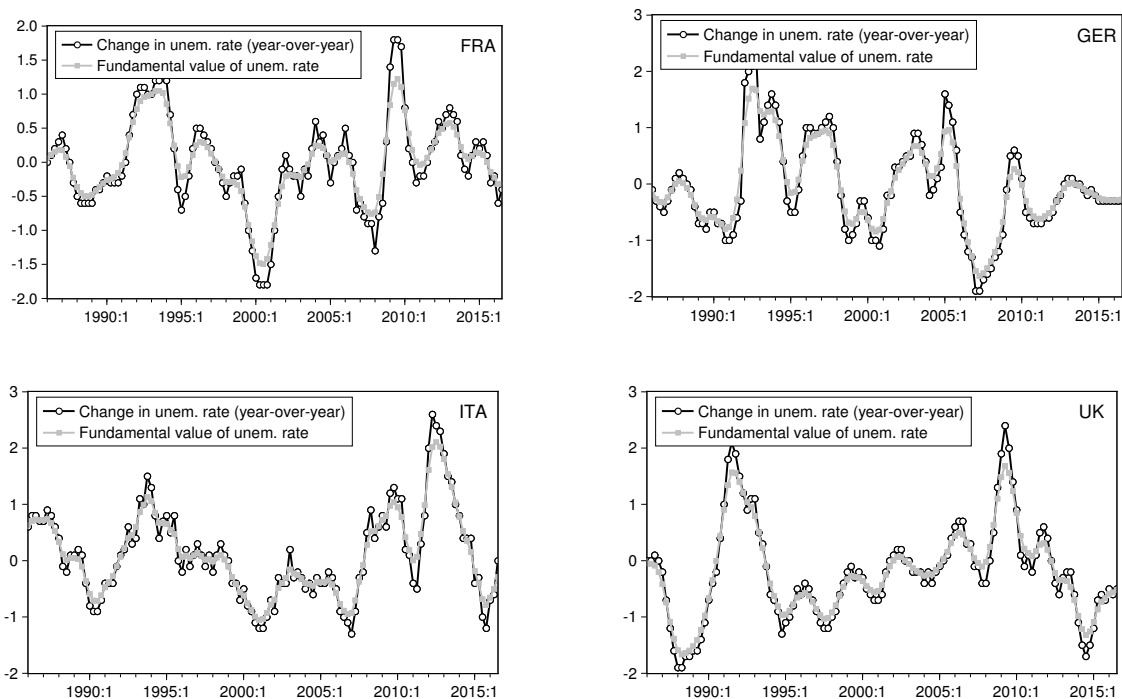
These results confirm that, excluding for some anomalous predictions that may occur, the hypothesis that professional forecasters time series proxy the long-run component of change in unemployment rate is supported by data.

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   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 6.

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).

Figure 9: Professional forecasts (`Prof.  For`) *vs* (unobserved) long-run determinant of change in unemployment rate (`Long-run Unob.  Comp.`) (1986Q1-2016Q3)
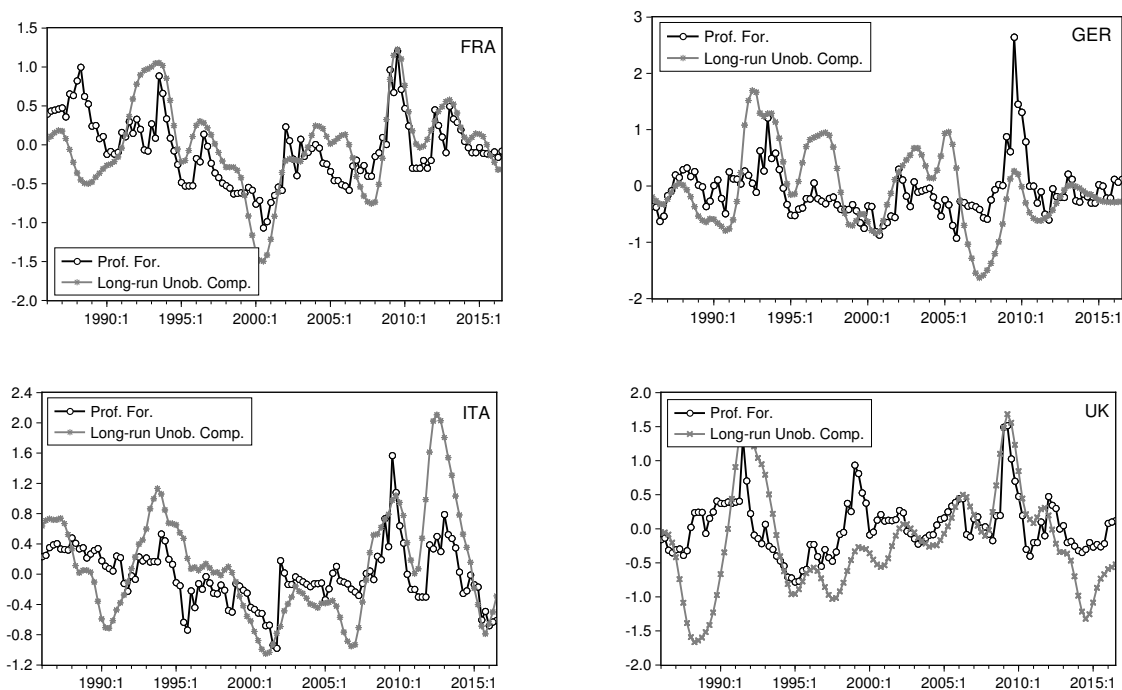
The non-expert unemployment expectations are the expectations on unemployment rate changes in the next 12 months taken from European Commission's Joint Harmonised EU Programme of Consumer Surveys. These expectations series are expressed as a balance index and are seasonally adjusted. Data are available 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.[32]. 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 web searches

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[32]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".

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.

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Table 6: 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
$M_t[\Delta_4 u_{t+4}]$	Non-expert unemployment rate expectations*	Year-over-year change	Yes	1986q1-2016q4	EU Commission
$N_t[\Delta_4 u_{t+4}]$	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