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Sommario

Questo articolo ha l'obiettivo di fornire qualche indicazione sul processo di formazione delle previsioni economiche da parte dei cittadini comuni. A questo fine il lavoro propone un'analisi congiunta delle serie storiche rinvenienti da due domande previste nelle indagini sui consumatori italiani - quella sull'andamento economico generale e quella sull'andamento economico personale. Risulta che gli agenti i) danno più peso alle informazioni "personali", ii) sono più in disaccordo sull'andamento del Pil che non riguardo le proprie finanze, iii) il livello di disaccordo tra le previsioni degli agenti, sorprendentemente alto, è una buona proxy del livello di incertezza macro.

Parole chiave: Aspettative, Shock Aggregati, Survey sui consumatori.

Abstract

Exploiting survey data covering two decades, we try to learn how agents forecast. Specifically, we examine the central tendencies (balances) and cross-sectional dispersions (disagreement) of lay consumers' predictions on individual-level and aggregate income dynamics. The joint analysis of expectations on these two different - but linked – fundamentals highlights a number of interesting outcomes for Italy. Agents' predictions on micro and macroeconomic evolutions do not drift apart despite (possibly composite) shocks have permanent effects on expectations. When shocks create a gap between the two expectations, in fact, agents revise only their forecasts about GDP dynamics. These latter overreact to shocks and are more volatile than expectations on personal stances. Unlike what typically assumed in the macroeconomic literature, then, evidence shows that disagreement is persistently high. Astonishingly, when predicting the same fundamental consensus shrinks. Lastly we elaborate a test on whether - and find evidence that – cross sectional disagreement and time series volatility in expectations are equal.

Keywords: Expectations, Aggregate Shocks, Survey Data

1. Introduction

Expectations of future events play a prominent role in economic decision making. Consumers must think about the type of house to buy, the amount of education to pursue, the fraction of income to save, etc. Firms must decide where to locate factories and offices, what products to develop and produce, etc. Despite its crucial role, we are still far from a sufficient understanding of the expectations formation process (EFP). Possibly, this is due to the fact that mainstream behavioral models typically assume, not explain, the way in which expectations are formed.

Another reason is that it is difficult to obtain data on expectations. The standard approach has been to infer expectations from realizations. Some prominent examples are Hall and Mishkin (1982), Skinner (1988), Caballero (1990), and Carroll (1994). This said, Dominitz and Manski (1996) have shown that a researcher seeking to learn expectations from realizations must assume that (s)he knows what information households possess and how they use the available information to form expectations. Moreover, the available data on realizations must be rich enough for the researcher to emulate the assumed processes of expectations formation. Dominitz and Manski conclude that these are strong requirements. As argued by Pesaran (1987), then, inference about the EFP carried out via realizations is conditional on the behavioral model which embodies the expectational variables. Thus, conclusions concerning the EFP will not be invariant to the choice of the underlying behavioral model. Unfortunately, at the moment, there is still no dominant model. Similar convincing caveats can be found in Kapteyn et al. (2009), and in Frydman and Phelps (2013).

One can then resort to direct measures of expectations derived from surveys of households. Bertrand and Mullainathan (2001) argue that doubts about surveys are based on a priori skepticism rather than on evidence that, instead, points to the meaningfulness of surveys. In fact, surveys eliciting agents' expectations have been gaining acceptance and are now well-established in both economics and political circles (Buckle and Meads, 1991; Pesaran and Weale, 2006; De Bruin et al., 2011). A strand of the literature has been seeking the additional information content of survey data beyond what already contained in hard data (Ludvigson, 2004). Other authors have exploited survey expectations to explain the widespread and persistent heterogeneity in agents' predictions (Mankiw et al., 2003; Capistran and Timmermann, 2009).

Against this framework we see our contribution and aim to shed some light on how lay people predict. We do that through the joint analysis of the time series properties of survey expectations on individual-level and aggregate income dynamics. The idea is that examining two different - but linked – fundamentals can help explaining the agents' EFP. As far as we know, this is the first time that the information contained in survey expectations is exploited in this way. Our approach can also offer some hints on the links between forecast uncertainty and disagreement. Though in macroeconomics and monetary policy making it is important to evaluate uncertainty, indeed, this latter is intrinsically unobservable (Zarnowitz and Lambros, 1987; Lahiri and Sheng, 2010). Thus, economists have experimented alternative proxies for forecast uncertainty. One of the more popular measures has been forecast disagreement. Our setting allows elaborating a simple test on the relationship between cross sectional disagreement and time series uncertainty within a vector error correction (VEC) models framework.

To our goals, we compute balances and measures of cross-sectional dispersions of both expectations that we then study via univariate and multivariate - VEC models - analyzes. We interpret changes in expectations as events due to shocks, i.e. to unexpected events leading agents to think that future economic evolutions will be different from what they previously thought. Though there could be shocks leaving expectations unchanged (because, e.g., agents are totally inattentive), it should be clear that this kind of shock is by definition uninformative with respect to our goal. Further, these shocks do not affect our findings that, it is worth repeating, deal with the EFP.

Robust evidence supports some intriguing insights on the expectations formation process. The balance of survey expectations on personal conditions is structurally less volatile than that dealing with GDP dynamics. Both statistics, then, turn out to be very persistent time series. In our sample, indeed, they are I(1) cointegrated processes. In other words, lay consumers' forecasts on micro and macroeconomic evolutions do not drift apart despite (possibly composite) shocks have very persistent effects on agents' expectations. Data also highlights that when shocks create disequilibrium between the two predictions, only expectations on GDP dynamics are revised to close the gap. This can be interpreted as agents systematically putting relatively more weight on expectations on their own situation, no matter the micro or macroeconomic nature of the fundamental to be predicted. It is also in line with the presence of a short-term overshooting in the expectations on aggregate dynamics. Cross sectional disagreement is found to be persistently high, especially – hence astonishingly - for expectations on the same fundamental. While the systematic lack of consensus contrasts with standard macroeconomic models, it gives empirical support to the theoretical literature suggesting the widespread and enduring presence of heterogeneous expectations (Mankiw et al., 2003; Hommes, 2006; Evans and Honkapohja, 2013). Finally, evidence indicates that the level of cross-sectional disagreement is statistically equal to the time-series volatility of Italian consumers' expectations. These findings are confirmed by robustness checks.

The rest of the paper is organized as follows. In the next section we describe the survey data and how the first two moments of the empirical distributions of people's expectations are computed. In Section 3 we report some univariate statistics of the two expectations. Sections 4 and 5 deal, respectively, with the theoretical and empirical multivariate setting. Concluding remarks and robustness checks (Appendixes A and B) close the paper.

2. The Data

For our goal, a unique data set can be obtained from the Business Surveys Unit of the European Commission (European Commission, 2007). Data refer to Italy that we argue to be a good case study because of its declining macroeconomic dynamics over the last two decades (Section 3). In average terms, the annual growth rate of real GDP in Italy has been 1.8% from 1995 to 2000, 1.4% from 2000 to 2005, and -0.4% from 2006 to June 2013. We interpret this gloomy development as the effect of (possibly composite) shocks having had an overall net negative impact in the period under scrutiny.

The data set is based on monthly surveys and covers the period January 1995-July 2013. Each survey is based on two-thousand interviews and it is not a genuine panel, i.e. there are no re-interviews. This said, the survey design is carefully aimed to capture the representative consumer (European Commission, 2007) and, in fact, both economists and practitioners usually compare consecutive surveys reporting no particular caveats. More importantly, we also examine the contemporaneous responses given by the same interviewed.

Though the survey asks several questions, the relevant queries in the present setting are:

"How do you expect the economic situation in your household to change over the next 12 months? It will…".

"How do you expect the general economic situation in the country to develop over the next 12 months? It will…".

Surveyed individuals have six reply options:
LB=…get a lot better;
B=…get a little better;
E=…stay the same;
W=…get a little worse;
LW=…get a lot worse;
N=don't know.

LB, B, E, etc., are the shares of respondents having chosen the corresponding option and they sum up to one. Only these six aggregate shares are available, and only five of them form the basis of this study. Following the usual approach, we have excluded the proportion relative to the option "don't know", rescaling the other shares accordingly. We calculate the first two moments of the distribution of the replies as follows:

$$ {}_{t-h}y_t^e = \alpha(LB_t+0.5*B_t-0.5*W_t-LW_t) \qquad (2.1)$$

$$ {}_{t-h}y_{it}^e = \alpha_i\,(LB_{it}+0.5*B_{it}-0.5*W_{it}-LW_{it}) \qquad (2.1a)$$

$$\sigma_t^e = \frac{K}{K-1}\left(1-\sum_{j=1}^{K} s_{t,j}^2\right) \qquad (2.2)$$

$$\sigma_{it}^e = \frac{K}{K-1}\left(1-\sum_{j=1}^{K} s_{it,j}^2\right) \qquad (2.2a)$$

Henceforth we add the suffix "i" to denote variables referring to personal economic evolutions. Thus, e.g., ${}_{t-h}y_t^e$ and ${}_{t-h}y_{it}^e$ are the statistics relative to expectations formed at date t-h (where h=12 months) on, respectively, general and individual economic dynamics.

Equations (2.1) and (2.1a) define the balance statistic, elaborated by Anderson (1952) and Theil (1952), as modified by the European Commission (2007). The parameters α and α_i serve to convert qualitative survey data in quantitative data that are as close as possible to the underlying economic variable. This choice is arbitrary and it may be misleading (Nardo, 2003). Noting that we compare only qualitative data, we follow the standard procedure and we set $\alpha_i = \alpha_i =1$ (European Commission, 2007). Support for the use of the balance statistics may be found in Driver and Urga (2004) and in Appendix B we offer some robustness check. Clearly the two balances vary between -1 (all agents are very pessimists) and +1 (all agents are very optimists). Alike, a zero central tendency implies that the (weighted) number of optimists and pessimists is equal and that, on average, agents expect no change in the development of the underlying economic fundamental.

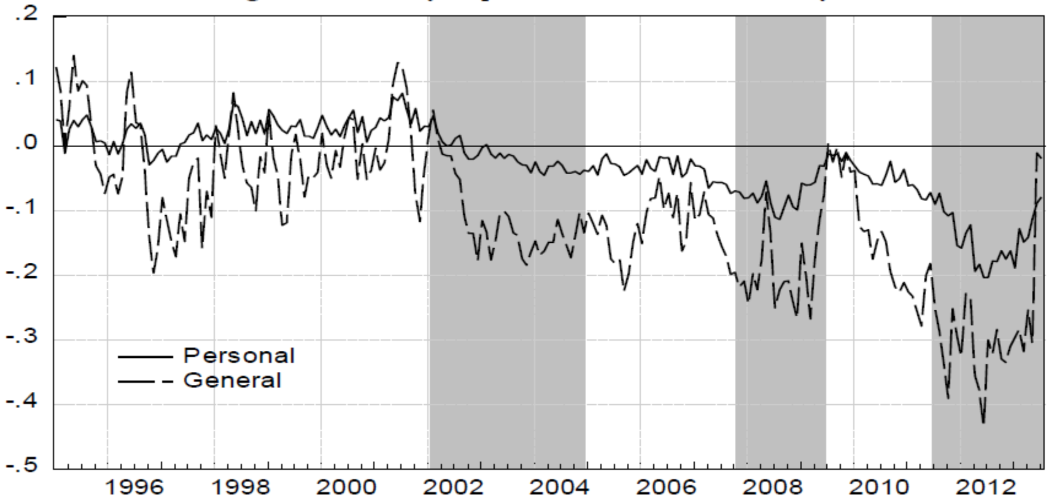
Equations (2.2) and (2.2a) define the cross sectional dispersion in terms of an index of qualitative variation (IQV). We use this index because, according to recent empirical findings (Maag, 2009), it performs better than other possible candidates. Unlike other methods, then, the IQV does not account for the ordered nature of the data and it has not any crucial scaling parameter, thereby increasing the robustness of our results. On the other hand, several authors emphasize reasons to prefer this kind of indicators for quantifying discord across survey beliefs (Lacy, 2006; Badarinza and Buchmann, 2009). In fact, they are the typical choice in the literature (see, e.g., Mankiw et al., 2003; Capistran and Timmermann, 2009). Following our notation, σ_t^e=0 refers to expectations on macro, and σ_{it}^e on microeconomic dynamics. K=5 is the number of option replies and j=LB, B, E, W, LW. The scaling factor merely ensures that $0 \leq \sigma_{it}^e, \sigma_t^e \leq 1$, and $\sigma_{it}^e, \sigma_t^e=0$ means no variation because all cases belong to a single category, that is to say, expectations are totally homogeneous.

In light of the following analyzes, we define shocks as unexpected events leading agents to think that future economic evolutions will be different from what previously expected. Though some shock may leave unaffected expectations (because, e.g., all households are totally inattentive), as it should be clear these events are uninformative by definition with respect to our main research interest. Moreover these (likely rare) events do not affect our results.

3. Univariate analysis

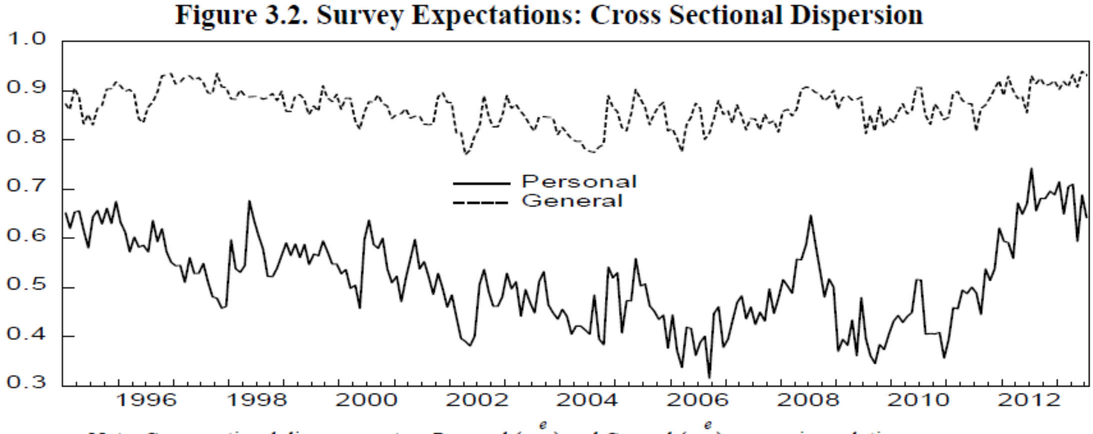
In this section we collect a number of univariate statistics of the two expectations under scrutiny. Figure 3.1 and 3.2 give a visual impression of the evolution of survey expectations in Italy throughout the last two decades.

Figure 3.1. Survey Expectations. Central Tendency



Note. "Personal" (${}_{t-h}y^{e}_{it}$) is the central tendency of the responses to the query "How do you expect the economic situation in your household to change over the next 12 months?" "General" (${}_{t-h}y^{e}_{t}$) is the central tendency of the responses to the query "How do you expect the general economic situation in the country to develop over the next 12 months?" They vary from -1 (all replies are: it will get a lot worse) to +1 (all replies are: it will get a lot better). Shaded area indicates periods of below-full-sample-average GDP annual growth rate.

Figure 3.2. Survey Expectations: Cross Sectional Dispersion



Note: Cross sectional disagreement on Personal (σ^{e}_{it}) and General (σ^{e}_{t}) economic evolutions.
$0 \leq \sigma^{e}_{it}, \sigma^{e}_{t} \leq 1$; and $\sigma^{e}_{it}, \sigma^{e}_{t} = 0$ means totally homogeneous expectations. See also Figure 3.1.

Figure 3.1 show that since 2002 the two balances show no zero crossing and a tendency to stay below zero. We interpret it as reflecting the declining macroeconomic developments in Italy over the last decade and as suggesting that negative shocks have had greater impact than positive ones on both hard data and survey expectations. Data also seems to indicate that ${}_{t-h}y^{e}_{it}$ is less volatile than ${}_{t-h}y_t^e$. Standard deviations confirm the impression: the volatility of ${}_{t-h}y_{it}^e$ is one-half with respect to that of ${}_{t-h}y_t^e$ (respectively, 0.06 and 0.12). One can also observe that ${}_{t-h}y_{it}^e$ is very often above ${}_{t-h}y_t^e$. Both these results are in line with the presence of immanent and widespread psychological biases such as better-than-average effects, illusion of control, overconfidence, and confirmation bias (Tversky and Kahneman, 1974). In fact, these biases impinge specially on individual-level expectations, making these latter rosier and less volatile than ${}_{t-h}y_t^e$ because all of them contribute to maintain or strengthen beliefs in the face of contrary evidence. Note that these psycho-biases are magnified during economic crises - while a recession deteriorates ${}_{t-h}y_t^e$, the illusion of control generates a downward stickiness in expectations on personal perspectives. This, in turn, lessens the cyclical responsiveness of ${}_{t-h}y_{it}^e$. In this sense, Italy is a good case-study to our aims.

Figure 3.2 very clearly shows that, in our sample, the level of disagreement across lay forecasters is persistent. Indeed, σ_{it}^e never goes below 0.3 and it has a sample mean of 0.51. Of course, evidence supporting a sustained cross sectional dispersion of expectations on individual income dynamics is not stunning. Yet, σ_t^e deals with the same fundamental and - at least in the long run - agents' expectations should tend to converge. Instead the average value of σ_t^e, recorded in a sample covering almost two-hundred and thirty months, is as high as 0.87. It is also worth noticing that in our data set agents are clustered in just five categories: it obviously hampers the possibility of wider discord. Thus, these findings are surprising from the standard macroeconomic point of view. They are astonishing not only in absolute terms but, even more, because disagreement about the same fundamental, σ_t^e, is systematically larger than σ_{it}^e. The visual inspection of Figure 3.2 and standard deviations also suggest that σ_{it}^e is more volatile than σ_t^e: in the sample their standard deviations are, respectively, 0.04 and 0.09.

Two considerations are remarkable at this point. In their 2007 paper Mankiw and Reis show that, when forecasting a macroeconomic fundamental, consumers and workers update their information set infrequently but contemporaneously. It can be interpreted as these two types of households being homogeneously inattentive forecasters. Our analysis affords the possibility to add further details on that. A persistently positive σ_t^e implies that the predictions of these household members are likely to be systematically different. In turn, this suggests that consumers' and workers' expectations are possibly conditioned on information sets that are not updated at the same time. This contrasts with the mentioned findings emphasized by the sticky information literature. Second, a high long-lasting value of σ_t^e implies that there is no tendency toward the consensus. It should be considered when studying theoretical beauty-contest games (e.g., Morris and Shin, 2002) or economic systems populated by supposedly identical individuals (which is still standard in macroeconomics).

Table 3.1 collects the autocorrelations and the partial autocorrelations of the two balances at different lags.

Table 3.1. Survey Expectations. Persistence

Lag	${}_{t-h}y^{e}_{it}$ AC	${}_{t-h}y^{e}_{it}$ PAC	${}_{t-h}y^{e}_{t}$ AC	${}_{t-h}y^{e}_{t}$ PAC
1	0.95	0.95	0.87	0.87
2	0.92	0.21	0.77	0.06*
3	0.90	0.09*	0.71	0.10*
...	...	...	...	...
12	0.62	0.06*	0.46	-0.02*
...	...	...	...	...
24	0.35	-0.07*	0.21	0.01*
...	...	...	...	...
36	0.32	0.04*	0.23	0.09*

Note: AC=Autocorrelation, PAC=Partial Autocorrelation, *=Not Significant at the 5% level. See also Figure 3.1

The picture emerging from Table 3.1 shows the enduring memory of expectations, and points to a (though marginal) greater persistence of the forecasts referring to personal economic evolutions. To the extent that the survey expectations we are dealing with refers to income evolutions, the statistics reported in Table 3.1 are unsurprising. In fact the leading view on individual income dynamics (y_{it}) - based on more than two decades of empirical studies - is that a stochastic process comprising a very persistent autoregressive component and transitory component accurately describes the data (Krueger et al., 2010; Guvenen, 2011). As per the aggregate income, the theoretical literature typically assumes that the real GDP growth (y_t) is driven by a similar stochastic process (for empirical evidence on that cfr. Harding and Pagan, 2003). It is easy to see why one must expect two similar stochastic processes: by definition the GDP is the sum of all individual incomes such that their dynamics are obviously connected. This said recall that our data are monthly one-year-ahead predictions: each consecutive survey predicts the same overlapping eleven months (Section 2). As a consequence, survey expectations could display even more long lasting memory than y_{it} and y_t. In view of the results of Table 3.1 and of the VEC analysis of the next sections, we then test whether the balances have unit roots.

Before doing that, two reasons lead to emphasize that ${}_{t-h}y^{e}_{it}$ and ${}_{t-h}y^{e}_{t}$ are both bounded variables. First, conventional unit root tests are potentially unreliable in the presence of bounded variables. The problem is that these latter tend to over-reject the null hypothesis of a unit root, even asymptotically. However, a bounded I(1) process behave as a standard unit root process when it is far away from the bounds. The intuition is that only if the limitations of a bounded process are activated quite often this will bias the standard test results (Granger, 2010; Cavaliere and Xu, 2013). For instance, though GDP level is a bounded variable – because in the beginning of each year it starts from zero - this constraint is hardly ever relevant. Luckily, Figure 3.1 shows that in our sample ${}_{t-h}y^{e}_{it}$ and ${}_{t-h}y^{e}_{t}$ are far from their bounds. Second, the presence of bounds suggests that in unit root tests more reliability should be given to the case with only an intercept: a deterministic trend would imply that our balances hit the upper-barrier with certainty.

The ADF and PP tests have very low power against I(0) alternatives that are close to being I(1). That is, these unit root tests cannot distinguish highly persistent stationary processes from non-stationary processes very well. Since Table 3.1 shows that y and y have first-order autocorrelation coefficients close to one, for maximum power against very persistent alternatives we perform the efficient tests proposed by Elliot et al., (1996) and Ng and Perron (2001). As discussed, we limit the deterministic part of the tests to an intercept. Results collected in Table 3.2 strongly support that the null of unit root cannot be rejected.

The presence of unit root implies that, in our sample, the persistence of both expectations is statistically equal. More importantly for our aim, it calls for a multivariate analysis i) to test whether these two integrated processes do not drift apart and, if so, ii) to find out what is the relative role played by each of the two expectations in their long-run relationship. We perform this kind of analyzes in the following sections.

4. Multivariate Analysis. Theory.

A multivariate analysis allows to assess the connections between the two expectations and, hence, to highlight other interesting aspects of the EFP. In doing that we focus on long-run relationships and, accordingly, we compare the forecasting exercise performed by the same individual on different fundamentals. This further reduces the potential (but marginal) issues stemming from the lack of re-interviews in our survey data.

In Section 3 we have observed that ${}_{t-h}y^{e}_{it}$ and ${}_{t-h}y^{e}_{t}$ are I(1). So, ignoring stationary processes and initial values, we can write (e.g., Hayashi, 2000):

$${}_{t-h}y^{e}_{it} = \sum_{j=1}^{t} \varepsilon_{it} \qquad (4.1)$$

$${}_{t-h}y^{e}_{t} = \sum_{j=1}^{t} \varepsilon_{t} \qquad (4.2)$$

Where ε_{it} and ε_t are white noise processes that, cumulated over time, are two stochastic trends featuring agents' expectations. To examine the joint behavior of these latter a linear combination, z_t, of ${}_{t-h}y^{e}_{it}$ and ${}_{t-h}y^{e}_{t}$ is usually assumed:

$$z_t = {}_{t-h}y^{e}_{it} - \beta\, {}_{t-h}y^{e}_{t} = \sum_{j=1}^{t} \varepsilon_{it} - \beta \sum_{j=1}^{t} \varepsilon_{t} \qquad (4.3)$$

Since they are integrated processes, the two balances must be cointegrated because they cannot drift apart forever. Recall that the fundamentals behind ${}_{t-h}y^{e}_{it}$ and ${}_{t-h}y^{e}_{t}$ are, respectively, personal and general – i.e. aggregate measures of personal - economic dynamics: there must be forces hampering an ever-increasing distance between these two expectations. Moreover, ${}_{t-h}y^{e}_{it}$ is a central tendency that aggregates the forecasts of just five kinds of agents - we are dealing with almost "nation-wide" agents. All in all, it is hard to think of bipolar agents being permanently both optimists on their "macro" situation and pessimists on the macroeconomic system in which they operate (or vice versa). In sum, z_t must be a stationary process. Figure 3.1 (Section 3) gives a first empirical support to this view.

Cointegration requires that the stochastic trends in ${}_{t-h}y^{e}_{it}$ and ${}_{t-h}y^{e}_{t}$ cancel in the linear combination:

$$\sum_{j=1}^{t} \varepsilon_{it} = \beta \sum_{j=1}^{t} \varepsilon_{t} \qquad (4.4)$$

That is to say, the two expectations share a common stochastic trend and their stochastic trends are proportional. On the other hand, as already noted, ${}_{t-h}y^e_{it}$ and ${}_{t-h}y^e_t$ can be thought of as expectations on the future dynamics of individual and aggregate incomes, which are proportional by construction. As will be clear later, it is also useful to consider a regression type formulation:

$$ {}_{t-h}y^e_{it} = \theta + \beta\, {}_{t-h}y^e_t + u_t \qquad (4.5) $$

Where θ is the mean of z_t and the disequilibrium error, u , is a zero-mean stationary process.

Letting the cointegrating relation be [1,-β], we expect β=1 only when dealing with "disagreement corrected" values of the balances (cf. Proposition 4.1).

We also argue that ${}_{t-h}y^e_{it}$ is weakly exogenous with respect to the cointegrating parameter β. In other words we claim that, when u ≠0, only expectations on the macroeconomic fundamental adjust to remove deviations from equilibrium. To see why, it may be better to write the links between ${}_{t-h}y^e_{it}$ and ${}_{t-h}y^e_t$ in VEC model form. Focusing on the error correction term with only a constant=θ, we write:

$$ {}_{t-h}y^e_{it} - {}_{t-h}y^e_{it-1} = \delta_i\, ({}_{t-h}y^e_{it-1} + \beta\, {}_{t-h}y^e_{t-1} + \theta) \qquad (4.6) $$

$$ {}_{t-h}y^e_t - {}_{t-h}y^e_{t-1} = \delta\, ({}_{t-h}y^e_{it-1} + \beta\, {}_{t-h}y^e_{t-1} + \theta) \qquad (4.7) $$

If δ_i=0, then ${}_{t-h}y^e_{it}$ is weakly exogenous. In our settings it means that, in closing the disequilibrium between the two expectations, ${}_{t-h}y^e_t$ is more susceptible to be revised than ${}_{t-h}y^e_{it}$. In fact, δ and δ_i are also referred to as speeds of adjustment. Our zero-speed of adjustment hypothesis can also be interpreted as ${}_{t-h}y^e_{it}$ being the pushing variable: its stochastic trend - i.e. its cumulated (possibly composite) shocks - drives ${}_{t-h}y^e_t$ (see equations 4.1 and 4.2).

We expect δ_i =0 because of the different quantity and quality of information available for agents when forecasting personal versus aggregate incomes. As easily understandable, and in fact as usually maintained in the literature (see, e.g., the imperfect information framework set out by Lucas, 1973), agents have better and more prompt information on their own future situation than on macroeconomic evolutions. Moreover, according to Doms and Morin (2004), news has an effect even at times when the picture of the economy painted by news media is not accurately reflecting underlying fundamentals. It therefore may give rise to overreactions in ${}_{t-h}y^e_t$ that must be reduced later on. In sum, when shocks generate a gap between the two expectations, on the one side, ${}_{t-h}y^e_{it}$ could be less predisposed than ${}_{t-h}y^e_t$ to restore the equilibrium and, on the other side, this latter may suffer from overshooting. It is important to note that the weakly exogeneity of ${}_{t-h}y^e_{it}$ is also consistent with the overconfidence and other better-than-average effects mentioned in Section 3. Finally, the assumption that ${}_{t-h}y^{e}_{it}$ is a pushing variable in the VECM set out in equations 4.6) and 4.7) is also congruent with the following Proposition 4.1.

Proposition 4.1. *If the cointegrating vector between Signal-to-Noise ratios is [1; -1], then cross-sectional disagreement and time-series volatility are equal.*

Before explaining Proposition 4.1 it is worth emphasizing that it enables to shed some light on whether forecast disagreement can proxy forecast uncertainty, which is a very important and still problematic issue (Orphanides and D'Amico, 2008; Lahiri and Sheng, 2010). The basic logic is the following. Since forecast uncertainty is positively linked to the time series volatility of expectations, Proposition 4.1 states a testable condition under which cross sectional disagreement and time series uncertainty in expectations are statistically equal.

In the above mentioned regression type formulation (cfr. Eq. 4.5), when estimating the following equations (abstracting from errors and constants):

$$ {}_{t-h}y^{e}_{t} = \beta\, {}_{t-h}y^{e}_{it} \qquad (4.8) $$

$$ {}_{t-h}y^{e}_{it} = \beta_i\, {}_{t-h}y^{e}_{t} \qquad (4.9) $$

we have that $\beta=\mathrm{cov}({}_{t-h}y^{e}_{it}; {}_{t-h}y^{e}_{t})/\mathrm{var}({}_{t-h}y^{e}_{it})$ and $\beta_i=\mathrm{cov}({}_{t-h}y^{e}_{it}; {}_{t-h}y^{e}_{t})/\mathrm{var}({}_{t-h}y^{e}_{t})$.

If we standardize the central tendency, by construction both these standardized balances have a unitary, hence equal, variance. It turns out that, estimating the system 4.8)-4.9) whereas the two endogenous variables are the above mentioned standardized versions of the two balances, we would obtain, after the usual VECM normalization, $1=\beta_i=\beta$.

Define now the signal to noise ratio (SNR) as central tendency on cross sectional disagreement, i.e. ${}_{t-h}SNR^{e}_{t} = {}_{t-h}y^{e}_{t}/\sigma^{e}_{t}$ and ${}_{t-h}SNR^{e}_{it} = {}_{t-h}y^{e}_{it}/\sigma^{e}_{it}$. Then, assume that the cross sectional disagreement is equal to the time series variance of the central tendency, i.e. $\mathrm{var}({}_{t-h}y^{e}_{it})=\sigma^{e}_{it}$ and $\mathrm{var}({}_{t-h}y^{e}_{t})=\sigma^{e}_{t}$. As seen for the standardized versions of the balances, performing a bivariate VEC model where the two endogenous variables are now the above defined SNRs, we would obtain $\beta_i=\beta$, i.e. the cointegrating vector [1,-1]. QED.

5. Multivariate Analysis. Evidence.

In testing for cointegration between ${}_{t-h}y^{e}_{t}$ and ${}_{t-h}y^{e}_{it}$ we take advantage of the cointegrating Johansen's maximum likelihood methodology (Johansen, 1995). This is a suitable choice in our multivariate setting because Johansen's approach takes into account that cointegration is a system property. Johansen's procedure needs to establish the deterministic terms. Table 5.1 collects the results for cointegration tests based on our preferred long run relationship between ${}_{t-h}y^{e}_{t}$ and ${}_{t-h}y^{e}_{it}$, which has an intercept and no trend (Section 3).

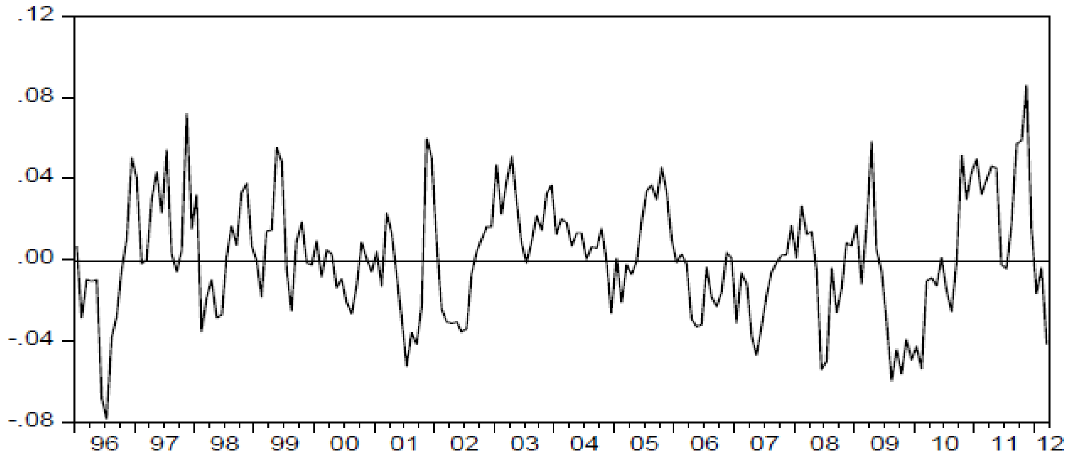
Table 5.1. Central Tendency. Cointegration Test.

Unrestricted Cointegration Rank Test (Trace)°				
Hypothesized N. of CE	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.166020	37.00018	20.26184	0.0001
At most 1	0.010114	1.961929	9.164546	0.7853

CE=Cointegrating Equation. One lag (AIC, SBIC). Sample: 95:01-13:07. Trend assumption: The CE has non zero mean. *denotes rejection of the hypothesis at the 5% level. **MacKinnon-Haug-Michelis (1999) p-values. ° Max. Eigenvalue Tests give almost identical results. See also Figure 3.1

Table 5.1 confirms that ${}_{t-h}y_t^e$ and ${}_{t-h}y_{it}^e$ are cointegrated processes. Focusing as before on long run relationships, we then estimate the VEC model sets out in equations 4.6) and 4.7). Figure 5.1 and Table 5.2 collect the results.

Figure 5.1. Central Tendency. Cointegrating Relation



Note. In the figure is reported the disequilibrium error stemming from the VECM:

${}_{t-h}y_{it}^e - {}_{t-h}y_{it-1}^e = \delta_i\,({}_{t-h}y_{it-1}^e + \beta\,{}_{t-h}y_{t-1}^e + \theta)$; ${}_{t-h}y_t^e - {}_{t-h}y_{t-1}^e = \delta\,({}_{t-h}y_{it-1}^e + \beta\,{}_{t-h}y_{t-1}^e + \theta)$

Table 5.2. Central Tendency. VECM

Speed of adjustment (δ_i)	0.00
Speed of adjustment (δ)	0.61*
Long run parameter (β)	0.58*
Constant (θ)	0.04*
Residuals Correlation	0.68
VEC restriction° (β=1)	0.00

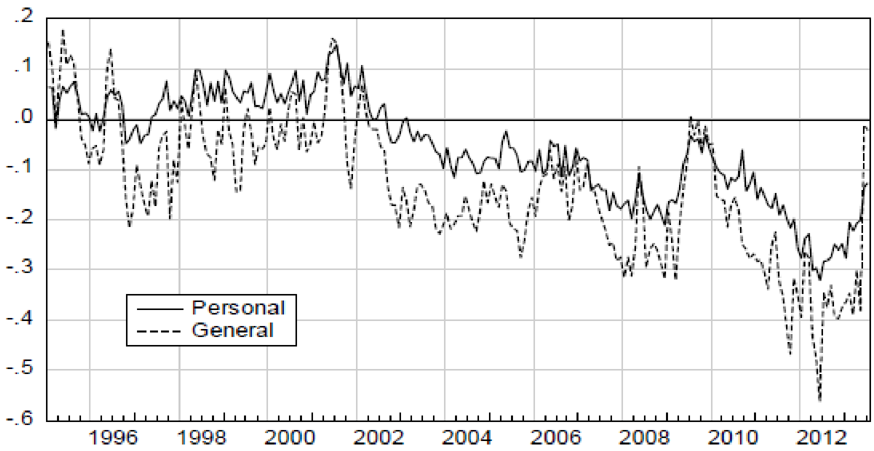
Note: *=significant at the 1% level. Sample: Jan-96 Mar-12
° P-val of the LR test. Residuals are multivariate normal[1]
See also Figure 5.1.

[1] We have limited the sample to obtain multivariate normal residuals. This notwithstanding, the kurtosis still shows a value slightly higher than 3. As argued by Hendry and Juselius (2001), however, leptokurtic residuals are not an issue in context as ours.

Figure 5.1 reassures that the linear combination of the two central tendencies is I(0). Table 5.2 shows then that, as expected, an error correction scheme links the two expectations, with cointegrating vector [1,-0.58]. The speed of adjustment of ${}_{t-h}y^{e}_{t}$, δ, implies that more than one-half (0.61) of the disequilibrium error reported in Figure 5.1 is corrected in just one month. Since δ_i is zero, data also confirms that households modify only ${}_{t-h}y^{e}_{t}$ in order to reduce the divergence with ${}_{t-h}y^{e}_{it}$. Another expected result is the positive correlation between the VECM residuals. This high correlation, 0.68, implies that the presence of (possible composite) shocks in the sample generates contemporaneous feedbacks between the two expectations. Recursive estimations substantially sustain these findings, indicating their remarkable robustness (Appendix A). Estimating the VECM from January 1995 to January 2005 and then adding a month each new estimation, we see that i) the long run parameter β is always significant with marginal variations (it varies between 0.5 and 0.6), that ii) the speed of adjustment relative to ${}_{t-h}y^{e}_{it}$ is invariably statistically zero, and that iii) δ is always significant and it oscillates between 0.6 and 0.9.

Turning the attention to Proposition 4.1, Figure 5.2 reports the historical co-movements of the two signal-to-noise ratios.

Figure 5.2. Survey Expectations: Signal-to-Noise ratios



Note. "Personal" (${}_{t-h}y^{e}_{it}/\sigma^{e}_{it}$) is the signal-to-noise ratio referring to the query "How do you expect the economic situation in your household to change over the next 12 months?" "General" (${}_{t-h}y^{e}_{t}/\sigma^{e}_{t}$) is the signal-to-noise ratio referring to the query "How do you expect the general economic situation in the country to develop over the next 12 months?". See also under Figure 3.1 and 3.2.

Comparing Figure 5.2 to Figures 4.1 and 4.2 it is easily observed that the gap between the two SNRs is much smaller than that featuring their components. As asserted, disagreement-corrected balances are attracted each other more strongly than simple balances are.

More formally, in Table 5.3 we display the results of efficient unit root tests on SNRs:

Table 5.3. Disagreement. Efficient Unit Root Tests

${}_{t-h}y^{e}_{it}/\sigma^{e}_{it}$					${}_{t-h}y^{e}_{t}/\sigma^{e}_{t}$				
ERS	MZa	MZt	MST	MPT	ERS	MZa	MZt	MST	MPT
14.8*	-2.42*	-0.97*	0.40*	9.39*	11.4*	-2.06*	-0.99*	0.48*	11.6*

Note. Exogenous: Constant. Lag length: 3 (Spectral OLS AR based on Modified AIC, maxlag=12. ERS=Elliott et al. (1996); MZa, MZt, MST, MPT=Ng-Perron test statistics (Ng-Perron, 2001). *=cannot reject the null of unit root at 1% level. Sample: January 1995 - July 2013. See also under Figure 5.2.

Verified that our SNRs are integrated processes, we go on testing whether the two ratios are cointegrated (again with an intercept and no trend in the cointegrating equation). Table 5.4 collects the results.

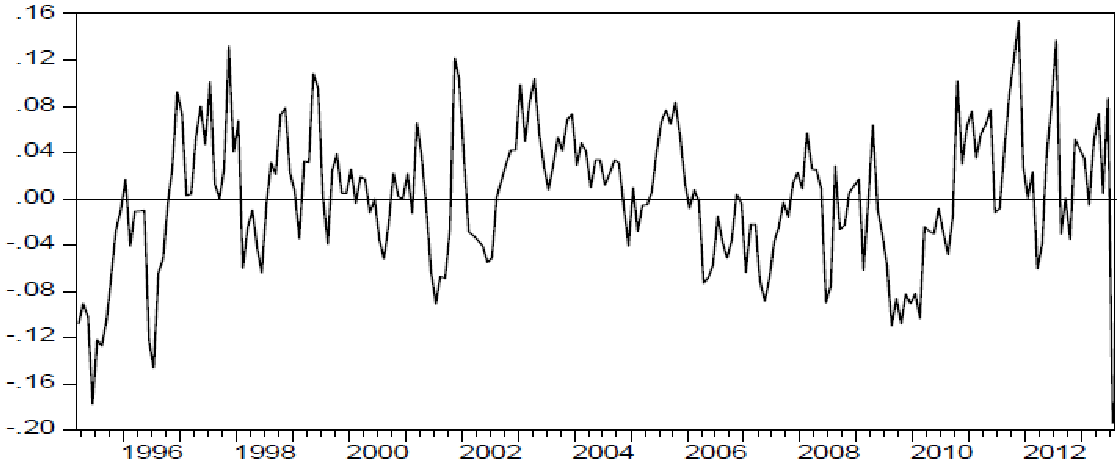
Table 5.4. Signal-to-Noise ratios. Cointegration Test.

Unrestricted Cointegration Rank Test (Trace)°				
Hypothesized N. of CE	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.139668	36.10016	20.26184	0.0002
At most 1	0.012829	2.853637	9.164546	0.6084

Note: CE=Cointegrating Equation. One lag (AIC). Sample: January 1995 - July 2013. Trend assumption: The CE has non zero mean. ° Max. Eigenvalue Tests give almost identical results. *denotes rejection of the hypothesis at the 0.05 level. **MacKinnon-Haug-Michelis (1999) p-values.

Evidence points out that ${}_{t-h}y^{e}_{it}/\sigma^{e}_{it}$ and ${}_{t-h}y^{e}_{t}/\sigma^{e}_{t}$ are cointegrated processes. Thus, we estimate the same VEC model sets out in equations 4.6) and 4.7) whereas, now, the two endogenous variables are the two SNRs. To ease comparisons, we replicate the same format used for the two balances and we report the bivariate SNRs-VECM results in Figure 5.3 and Table 5.5.

Figure 5.3. Signal-to-Noise ratios. Cointegrating Relation



Note. In the figure is reported the disequilibrium error stemming from the VECM:

${}_{t-h}SNR^{e}_{it} - {}_{t-h}SNR^{e}_{it-1} = \delta_i\,({}_{t-h}SNR^{e}_{it-1} + \beta\,{}_{t-h}SNR^{e}_{t-1} + \theta)$; ${}_{t-h}SNR^{e}_{t} - {}_{t-h}SNR^{e}_{t-1} = \delta({}_{t-h}SNR^{e}_{it-1} + \beta\,{}_{t-h}SNR^{e}_{t-1} + \theta)$

Table 5.5. Signal-to-Noise ratios. VECM

Speed of adjustment (δ)	0.39*
Speed of adjustment (δ_i)	0.03
Long run parameter (β)	0.94*
Constant	0.07*
Residual Correlation	0.68
VEC restriction° (β=1)	0.56

Note: *=null rejected at 1% level. Sample Jan-95 Jul-13
Residuals are multivariate normal. ° P-val of the LR test.

Figure 5.3 suggests that the cointegrating relation between the two ratios is a stationary variable with frequent zero-crossing. The last row of Table 5.5 shows that the cointegrating vector is [1,-1], which offers corroborating evidence on Proposition 4.1: Italian lay consumers' expectations are such that their cross sectional disagreement and time series volatility is statistically equal.

As already seen for balances, the recursive estimations reported in Appendix A highlight a remarkable robustness of our outcomes. In Appendix B we compute the first two moments of survey expectations by taking advantage of the Carlson-Parkin method (CP, Carlson and Parkin, 1975) and redo all the statistical analyzes performed in Sections 3 and 5. The CP method is based on different hypotheses with respect to the Anderson-Theil and IQV statistics used so far, in that offering a robustness check to our findings.

6. Concluding Remarks

With the aim to learn the agents' expectations formation process, we have analyzed the time series properties of households' expectations on individual-level and aggregate income dynamics. The idea was that jointly examining beliefs on different - but linked – fundamentals can shed some light on how lay individuals predict. Specifically, we have taken advantage of monthly survey data for Italy to compute balances and cross sectional disagreement statistics of both expectations over two decades.

Robust results show that the two balances are I(1) cointegrated processes. This implies that agents' predictions on micro and macroeconomic evolutions do not drift apart despite (possibly composite) shocks have very persistent effects on expectations. When shocks create disequilibrium between the two predictions, then, only expectations on GDP dynamics adjust to close the gap. It means that in forecasting, lay agents put relatively more weight on what they expect about their own economic conditions than on what they expect about system-wide economic dynamics. This result is confirmed regardless of the micro or macroeconomic nature of the fundamentals to be predicted. It also indicates that, in the short term, i) agents' expectations on aggregate dynamics overreact to shocks and that ii) expectations on personal stances are stickier. Further, unlike what typically maintained in the standard macroeconomic literature, the level of cross sectional disagreement if agents forecasts turns out to be persistently high. Surprisingly, the consensus is even lower for predictions on the same aggregate fundamental. Lastly, our approach allows setting out a simple test on whether the level of cross-sectional disagreement is equal to the time-series volatility/uncertainty in expectations.

Riferimenti bibliografici

Badarinza, C. and Buchmann, M. 2009. “Inflation perceptions and expectations in the euro area - the role of news”, *ECB Working Paper* 1088.

Batchelor, R. A. 1986. “Quantitative v. Qualitative measures of inflation expectations”, *Oxford Bulletin of Economics and Statistics*, 48: 99–120

Batchelor, R.A. and Orr, A.B. 1988. “Inflation Expectations Revisited,” *Economica* 55, 317-331

Baron, J. 2007. *Thinking and deciding*, 4th edition. New York: Cambridge University Press.

Berk, J.M. 1999. Measuring Inflation Expectations: A Survey Data Approach, *Applied Economics* 31, 1467-1480.

Bertrand, M. and Mullainathan, S. 2001. “Do People Mean What They Say? Implications for Subjective Survey Data.” *American Economic Review*, 91(2), 67-72.

Bovi, M. 2009. “Economic versus Psychological Forecasting. Evidence from Consumer Confidence Surveys”, *Journal of Economic Psychology*, 30, 4, pp. 563–574.

Bovi, M. 2013. “Are the Representative Agent’s Beliefs Based on Efficient Econometric Models?”, *Journal of Economic Dynamics and Control*, 37, 633-648.

Buckle, R.A. and C.S. Meads (1991), “How do firms react to surprising changes to demand? A vector autoregressive analysis using business survey data,” *Oxford Bulletin of Economics and Statistics*, 53 (4), 451-466.

Capistrán, C., and Timmermann, A.G. 2009. “Disagreement and Biases in Inflation Expectations” *Journal of Money, Credit and Banking*, 41(2-3), 365-396.

Carlson J. A. and Parkin M. 1975. “Inflation expectations”, *Economica*, 42:123–138.

Carroll, C.D. 1994. “How Does Future Income Affect Current Consumption?,” *The Quarterly Journal of Economics*, 109(1), 111-47

Cavaliere, G. and Xu F. 2013. “Testing for unit roots in bounded time series”, *Journal of Econometrics*, forthcoming.

Caballero, R.J. 1990. “Earnings Uncertainty, Precautionary Savings And Aggregate Wealth Accumulation,” *Columbia University* Discussion Papers, *1990_26*, Department of Economics.

Dasgupta, S. and Lahiri, K. 1992. A Comparative Study of Alternative Methods of Quantifying Qualitative Survey Responses Using NAPM Data, *Journal of Business & Economics Statistics* 10, 391–400.

de Bruin, W.B.; Manski, C.F.; Topa, G., and van der Klaauw, W. 2011. “Measuring consumer uncertainty about future inflation”, *Journal of Applied Econometrics*, 26: 454–478

Dominitz, J. and Manski, C.F. 1996. “Eliciting Student Expectations of the Returns to Schooling,” *Journal of Human Resources*, 31(1), 1-26.

Driver, C. and G. Urga, 2004 “Transforming qualitative survey data: comparisons for the UK”, *Oxford Bulletin of Economics and Statistics*, 66,1, pp. 71-89.

Engle, Robert F. and Granger C.W.J. 1987. “Co-integration and Error Correction: Representation, Estimation, and Testing,” *Econometrica*, 55, 251–276.

European Commission, 2007. The Joint Harmonised EU Programme of Business and Consumer Surveys, User Guide, European Commission. Directorate General for Economic and Financial Affairs.

Elliott, G., Rothenberg, T.J. and Stock J.H. 1996. “Efficient Tests for an Autoregressive Unit Root,” *Econometrica* 64, 813-836.

Evans, G. and Honkapohja, S. 2013. “Learning as a Rational Foundation for Macroeconomics and Finance”, forthcoming in R. Frydman and E. Phelps, Rethinking Expectations: The Way Forward for Macroeconomics.

Frydman R. and E.S. Phelps (2013) Rethinking Expectations: The Way Forward for Macroeconomics, Roman Frydman & Edmund S. Phelps (Eds). Princeton University Press.

Guvenen, F. 2011. “Macroeconomics With Heterogeneity: A Practical Guide”, *NBER Working Paper*, 17622

Hall R.E. and Mishkin F.S. 1982. “The Sensitivity of Consumption to Transitory Income: Estimates from Panel Data on Households,” *Econometrica,* 50(2), 461-81

Hayashi, F. 2000 Econometrics, Princeton University Press.

Hendry, D.F. and Juselius K. 2001. “Explaining Cointegration Analysis: Part II. *Energy Journal*, 22, 75-120.

Hommes, C. 2006. Heterogeneous agent models in economics and finance. In: Judd, K.L., Tesfatsion, L. (Eds.), Handbook of Computational Economics vol. 2; 2006. Agent-Based Computational Economics

Jaimovich, N. and Rebelo, S.T. 2006. “Behavioural Theories of the Business Cycle,” *CEPR Discussion Paper* 5909.

Johansen, S. 1995. *Likelihood-based Inference in Cointegrated Vector Autoregressive Models*, Oxford: Oxford University Press.

Kapteyn, A., K. Kleinjans and A. Van Soest (2009). “Intertemporal consumption with directly measured welfare functions and subjective expectations,” *Journal of Economic Behavior and Organization*, 72(1), 425-437.

Krueger, K., Perri, F., Pistaferri, L. and Violante, G.L. 2010. “Cross Sectional Facts for Macroeconomists,” *Review of Economic Dynamics,* 13(1), 1-14.

Lacy, M.G. 2006. “An explained variation measure for ordinal response models with comparisons to other ordinal R2 measures”, *Sociological Methods and Research*, 34, 469-520.

Lahiri, K. and M. Zaporowski 1987. “More Flexible Use of Survey Data on Expectations in Macroeconomic Models”, *Journal of Business & Economic Statistics*, 5, 1, 69-76.

Lahiri, K. and Sheng, X. 2010. “Measuring forecast uncertainty by disagreement: The missing link”, *Journal of Applied Econometrics*, 25, 514–538

Ludvigson, S. 2004. “Consumer confidence and consumer spending”, *Journal of Economic Perspectives* 18, 29–50.

Maag, T., 2009. “On the Accuracy of the Probability Method for Quantifying Beliefs about Inflation”, Working papers, *KOF Swiss Economic Institute*, ETH Zurich, 09-230.

Mankiw, N. G., J. Wolfers and Reis, R. 2003. “Disagreement about Inflation Expectations” NBER Macroeconomics Annual, 18, 209-248.

Mankiw, N.G. and Reis, R. 2007. “Sticky Information in General Equilibrium,” *Journal of the European Economic Association,* 5(2-3), 603-613.

MacKinnon, J.G., Haug, A. and Michelis, A. 1999. "Numerical Distribution Functions of Likelihood Ratio Tests for Cointegration", *Journal of Applied Econometrics*, 4(5), 563-577.

Nardo, M. 2003. “The Quantification of Qualitative Survey Data: A Critical Assessment,” *Journal of Economic Surveys*, 17: 645–668

Ng, S. and Perron,P. 2001. “Lag Length Selection and the Construction of Unit Root Tests with

Good Size and Power,” *Econometrica*, 69(6), 1519-1554.

Nunes, R. 2009. “On the Epidemiological Microfoundations of Sticky Information”, *Oxford Bulletin of Economics and Statistics*, 71: 643–657

Orphanides, A. and D`Amico, S. 2008. “Uncertainty and disagreement in economic forecasting”, *Finance and Economics Discussion Series*, Board of Governors of the Federal Reserve System.

Pesaran, M.H. 1987. The limits to rational expectations. Basic Blackwell, Oxford, UK.

Pesaran, M. H. and Weale, M. 2006. Survey Expectations. Handbook of Economic Forecasting, Elsevier.

Pohl, R.F. 2004. *Cognitive Illusions: A Handbook on Fallacies and Biases in Thinking, Judgment and Memory*. Hove, UK: Psychology Press.

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

Smith, J., and McAleer, M. 1995. “Alternative Procedures for Converting Qualitative Response Data to Quantitative Expectations: An Application to Australian Manufacturing”, *Journal of Applied Econometrics* 10, 165-185.

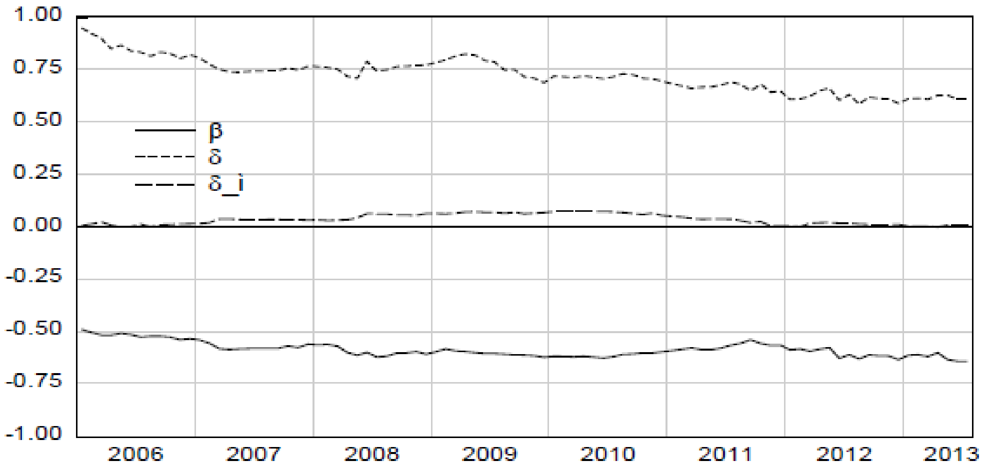
Theil, H. 1952. “On the Shape of Micro-variables and the Munich Business Test”, *Revue de l'Institut International de Statistique* 20, 105-120.

Tversky A., and Kahneman, T. 1974. “Judgment Under Uncertainty: Heuristics and Biases” *Science*, New Series, 185(4157), 1124-1131.

Zarnowitz V, Lambros LA. 1987. “Consensus and uncertainty in economic prediction.” *Journal of Political Economy* 95, pp. 591–621.

Appendix A. Robustness Check: VECM Recursive Estimations.

Figure A1. Recursive VECM coefficients. Central Tendencies.

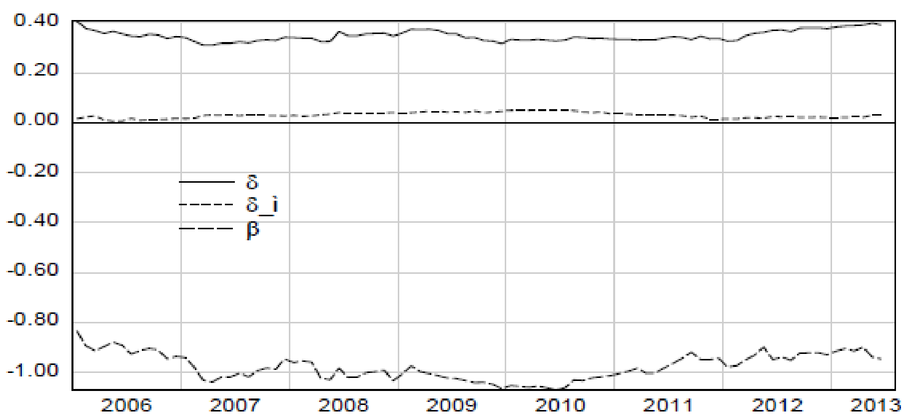


Note. In the figure are reported the recursive coefficients of the VECM:

$${}_{t-h}y^{e}_{it} - {}_{t-h}y^{e}_{it-1} = \delta_i \left({}_{t-h}y^{e}_{it-1} + \beta\, {}_{t-h}y^{e}_{t-1} + \theta \right);$$

$${}_{t-h}y^{e}_{t} - {}_{t-h}y^{e}_{t-1} = \delta \left({}_{t-h}y^{e}_{it-1} + \beta\, {}_{t-h}y^{e}_{t-1} + \theta \right)$$

Figure A2. Recursive VECM coefficients. Signal-to-Noise Ratios.



Note. In the figure are reported the recursive coefficients of the VECM:

$${}_{t-h}SNR^{e}_{it} - {}_{t-h}SNR^{e}_{it-1} = \delta_i \left({}_{t-h}SNR^{e}_{it-1} + \beta\, {}_{t-h}SNR^{e}_{t-1} + \theta \right);$$

$${}_{t-h}SNR^{e}_{t} - {}_{t-h}SNR^{e}_{t-1} = \delta \left({}_{t-h}SNR^{e}_{it-1} + \beta\, {}_{t-h}SNR^{e}_{t-1} + \theta \right)$$

Appendix B. Robustness Check: The Carlson-Parkin Method.

In this Appendix we calculate the first two moments of the distribution of the interviewers' replies with a different approach with respect to that used in the main text. Specifically, we take advantage of the Carlson-Parkin method (CP, Carlson and Parkin, 1975) in the five option replies version of Batchelor (1986), Batchelor and Orr (1988).

The following tables report the same empirical exercises presented in the main text. To ease comparisons we maintain the same table headings of the main text, just adding "B" to the corresponding number of the table.

Table B3.1. Survey Expectations. Persistence

Lag	$y_{it}^{e,CP}$ AC	$y_{it}^{e,CP}$ PAC	$y_{t}^{e,CP}$ AC	$y_{t}^{e,CP}$ PAC
1	0.92	0.92	0.86	0.86
2	0.90	0.32	0.77	0.09*
3	0.87	0.12*	0.71	0.10*
...	...	...	...	...
12	0.63	0.037*	0.46	0.00*
...	...	...	...	...
24	0.37	-0.02*	0.20	0.04*
...	...	...	...	...
36	0.33	0.00*	0.21	0.08*

Note: AC=Autocorrelation, PAC=Partial Autocorrelation, *=Not Significant at 5% level.

Table B3.2. Survey Expectations. Efficient Unit Root Tests

$y_{it}^{e,CP}$					$y_{t}^{e,CP}$				
ERS	MZa	MZt	MST	MPT	ERS	MZa	MZt	MST	MPT
7.53*	-3.72*	-1.25*	0.34*	6.65*	4.84	-6.48**	-1.78**	0.27**	3.85**

Note. Exogenous: Constant. Lag length: 3 (Spectral OLS AR based on Modified AIC, maxlag=12). ERS=Elliott et al. (1996); MZa, MZt, MST, MPT=Ng-Perron test statistics (Ng-Perron, 2001). *=cannot reject the null of unit root at 1% level (** at 10%). Sample: January 1995 - July 2013.

Table B5.1. Central Tendency. Cointegration Test.

Unrestricted Cointegration Rank Test (Trace)°				
Hypothesized N. of CE	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.144469	35.14425	20.26184	0.0002
At most 1	0.012846	2.689363	9.164546	0.6402

CE=Cointegrating Equation. One lag (AIC, SBIC). Sample: 95:01-13:07. Trend assumption: The CE has non zero mean. *denotes rejection of the hypothesis at the 5% level. **MacKinnon-Haug-Michelis (1999) p-values. ° Max. Eigenvalue Tests give almost identical results.

Table B5.2. Central Tendency. VECM

Speed of adjustment (δ_i)	-0.04
Speed of adjustment (δ)	0.49*
Long run parameter (β)	0.73*
Constant (θ)	0.20*
Residuals Correlation	0.59
VEC restriction° (β=1)	0.02

Note: *=significant at the 1% level. Sample: January 1995 - July 2013.
° P-val of the LR test. Residuals are multivariate normal

Table B5.4. Signal-to-Noise ratios. Cointegration Test.

Unrestricted Cointegration Rank Test (Trace)°				
Hypothesized N. of CE	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.137010	32.53731	20.26184	0.0006
At most 1	0.009036	1.887980	9.164546	0.7999

Note: CE=Cointegrating Equation. One lag (AIC). Sample: January 1995 - July 2013. Trend assumption: The CE has non zero mean. ° Max. Eigenvalue Tests give almost identical results. *denotes rejection of the hypothesis at the 5% level. **MacKinnon-Haug-Michelis (1999) p-values.

Table B5.5. Signal-to-Noise ratios. VECM

Speed of adjustment (δ)	-0.03
Speed of adjustment (δ_i)	0.33*
Long run parameter (β)	1.04*
Constant	0.75*
Residual Correlation	0.51
VEC restriction° (β=1)	0.70

Note: *=null rejected at the 1% level. Sample Jan-95 Jul-13
Residuals are multivariate normal. ° P-val of the LR test.