Shocks and the Expectations Formation Process. A Tale of Two Expectations.

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Abstract

Studying shocks and survey expectations we try to learn the expectations formation process of lay consumers. Standard assumptions and stylized facts lead to advance a battery of testable propositions on the effects of shocks on the time series properties of expectations. Survey expectations allow performing univariate and VECM analyzes to test our theoretical hypotheses. Specifically, we examine central tendencies (balances) and cross-sectional dispersions (disagreement) in agents' predictions on individual-level and aggregate income dynamics. The joint analysis of expectations on two different - but linked - fundamentals, highlights a number of interesting empirical outcomes that are in line with our theoretical framework. Agents' predictions on micro and macroeconomic evolutions do not drift apart despite shocks have permanent effects on expectations. When shocks create a gap between the two expectations, 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, there is even less consensus when the fundamental to be predicted is the same. Lastly, we elaborate a test on whether - and find evidence that – cross sectional disagreement and time series volatility in expectations are equal.

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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.

Shocks can be defined as unexpected events leading agents to revise their expectations. As we discuss later, in our setting the absence of (the effects of) shocks implies that all agents would predict “no change” and, hence, that expectations would be totally homogeneous. Shocks can be by and large collected according to the features of their effects or sources. There are permanent or transitory shocks, aggregate or idiosyncratic shocks. Policy makers may generate demand shocks; technology may cause supply shocks; “animal spirits” may spur confidence shocks. Obviously, in practice shocks may have several combinations of these features: one may well observe aggregate transitory demand shocks or the like. Nonetheless, the literature has ruled out some of these combinations. For instance, it has been suggested that only supply-side shocks can have permanent effects (Blanchard and Quah, 1989; Galì, 1999).

Expectations and shocks are strictly linked. On the one hand, since Pigou (1927) a huge amount of work has been devoted to examine the role of expectations in the propagation of shocks (recent instances are Lorenzoni, 2009; Blanchard et al., 2012; Beaudry and Portier, 2013). On the other hand, as noted, shocks may cause shifts in agents’ expectations. This latter topic is less explored, and we will focus on it.

To address the relationships between shocks and expectations, one should have reliable data on both phenomena. Obtaining data on expectations is difficult and, typically, the literature has been inferring 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. 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. Recently, in fact, surveys eliciting agents' expectations have gained acceptance and are now well-established (Pesaran and Weale, 2006; De Bruin et al., 2011). In fact, these surveys are one of the most watched tools in financial, economic and political circles all over the world. Finally, as argued by Pesaran (1987), inference about the expectations formation process carried out via realizations is conditional on the behavioral model which embodies the expectational variables. Thus, conclusions concerning the expectations formation process will not be invariant to the choice of the underlying behavioral model (see also Evans and Honkapohjia, 2003; Kapteyn et al., 2009; Coibion and Gorodnichenko, 2012). Unfortunately, at the moment, there is still no dominant model.

As per shocks, the presence of overlapping effects of different types of shocks is an inexorable trait of economic systems that makes it hard to analyze them separately. SVAR and DSGE models are widespread tools employed to identify shocks and to study how expectations propagate the effects of different kinds of shocks (e.g., Lorenzoni, 2012). While we are aware that to study the role of expectations in the propagation of shocks is very important, as mentioned we are more interested in the expectations formation process.

Specifically, we see our contribution and novelty to examine how (possibly composite) shocks shape the time series properties of expectations. To this end we offer some theoretical propositions not based on a particular behavioral model and mainly thought to be easily testable. Model-free does not mean without discipline: it would be very hard to justify theoretical relations contrasting ours. This is because the hypotheses we advance *i)* stem from - and obey to - very few realistic assumptions typically maintained in the literature, *ii)* take into account - and are congruent with -

some undisputed stylized facts, *iii)* depict an internally consistent setting. Last but not least, *iv)* our hypotheses are easily testable and evidence robustly support them.

Beyond the lack of a dominant model another, crucial, reason behind our choice to search for model-free results, lies in the fact that we examine expectations on both micro and macro fundamentals. One of the most salient advantage of examining our survey data, indeed, is that they gather monthly predictions on both individual-level and aggregate fundamentals over two decades. As we argue later the joint analysis of these two expectations can be very informative with respect to our goal. However, dealing with individual-level stances has some drawback. Empirically, the length and frequency of the available "hard data" do not allow to adequately investigating expectations relative to micro-level situations over time. Theoretically, standard macroeconomic models analyze homogeneous agents, which hampers the understanding of intriguing features of real-world economic systems. In a recent survey on macroeconomics and heterogeneity, Guvenen (2011) argues that the implications of representative-agent models are "boring".

To sum up, the model-free joint analysis of our two expectations allows exploring in an unusual way the relationships between shocks and expectations, providing some useful insights into how expectations react to shocks and into the way they are formed.

From the empirical point of view, we test our theoretical hypotheses by performing univariate and multivariate - vector error correction (VEC) models - analyzes. Specifically, we compute balances and measures of cross-sectional dispersions in survey expectations on individual-level and aggregate income dynamics in Italy over the last twenty years. As we clarify later, the peculiar economic development in Italy offers a good case study for our goal. In light of our model-free approach it is important to note that our theoretical setting suggests to test whether cross sectional disagreement and time series volatility in expectations are statistically equal. We elaborate a simple test on that within a VECM framework.

Robust evidence supports the proposed framework, pointing out some intriguing outcomes. 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 forecasted. It may also indicate a short-term overshooting in the expectations on aggregate dynamics. All this is coherent with the hypothesized relatively lower volatility of expectations on personal conditions. Cross sectional disagreement is found to be persistently high, especially 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 (Kirman, 1992; Hommes, 2006; Evans and Honkapohja, 2013). Finally, evidence indicates that the level of cross-sectional disagreement is statistically equal to the time-series volatility in Italian consumers' expectations. These findings are confirmed by robustness checks.

Our results should be seen as complementary to those of the existing literature on the links between expectations and shocks (Jaimovich and Rebelo, 2006; Lorenzoni, 2009; Blanchard et al., 2012; Beaudry and Portier, 2013). We also believe that this paper may shed some light on heterogeneity, volatility and uncertainty in expectations and on their connections (Mankiw and Reis, 2002; Mankiw et al., 2003; D'Amico and Orphanides, 2008; Doven et al., 2009; Lahiri and Sheng, 2010; De Bruin et al., 2011; Bloom, et al. 2012; Bovi, 2013). Finally, our findings may be of some help in evaluating the information content of survey expectations (Lahiri and Zaporowski, 1987; Bertrand and Mullainathan, 2001; Ludvigson, 2004; Weale and Pesaran, 2006; De Bruin et al., 2011).

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 carry out a theoretical discussion to highlight a number of testable propositions on some univariate characteristics of expectations. In Section 4 we search evidence on these hypotheses. Analogously, but in a multivariate setting, Section 5 advances, and Section 6 tests, other theoretical hypotheses. 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). We focus on Italy because Italian GDP has experienced, over the last two decades, declining dynamics. 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 (see Fig. 4.1). We interpret this gloomy development as the effect of several shocks having had an overall net negative impact in the period under scrutiny. It is important because, as we argue later, negative shocks have more clear-cut effects on lay consumers' expectations, allowing to find out more easily evidence on the theoretical propositions presented in Sections 3 and 5. In sum, Italy seems to be a suitable case-study for our aims.

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”,[1] rescaling the other shares accordingly. We calculate the first two moments of the distribution of the replies as follows:

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

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

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

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

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.

[1] Possibly, it is a “non response”, i.e. it is not the outcome of an explicit elaboration but, rather, a declaration of no information. In this regard, the European Commission Users’ Manual (2007, p. 18) states that: “(…) there are six reply options: five “real” ones and a ‘do not know’ option”.

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 $\alpha=\alpha_i=1$ (European Commission, 2007). In Appendix B we offer some robustness check. It should be clear that the two balances vary between -1 (all agents are very pessimists) and +1 (all agents are very optimists). 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.[2] 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 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.

We define shocks as unexpected events leading to a change in survey expectations. In our framework, therefore, in periods without (the effects of) shocks we would observe $E_t=1$ at any time. In other words expectations, lacking shocks, would lie in a steady state whereas every agent expects economic conditions to "stay the same". Hence, in steady state totally homogeneous

[2] For robustness check in Appendix B we use another procedure to compute the dispersion in expectations.

expectations would emerge:[3] ${}_{t-h}y^e_{it} = {}_{t-h}y^e_t = \sigma^e_{it} = \sigma^e_t = 0$. In this sense, shocks shape the time series properties of households' expectations. If agents are Muth-rational shocks would be unforeseeable, and not just unexpected, events. We use the adjective "unexpected" because expectations here need not be Muth-rational. For instance, expectations could be conditioned on outdated information (as argued, e.g., in Mankiw and Reis, 2002). On that, one should bear in mind that household surveys elicit expectations from lay individuals.

3 Univariate Analysis. Testable Propositions

The theoretical approach to expectations that we present in this Section and in Section 5 is behavioral-model-free and aimed to point out easily testable propositions. In doing that we can afford to search for complementary information with respect to the existing literature on the time connections between shocks and expectations. The discipline in our framework lies *i)* in its inner coherence and *ii)* in the fact that the advanced propositions stem from - and obey to - few assumptions typically maintained in the literature as well as from some hard to dispute stylized facts. Then, and importantly, *iii)* the proposed propositions are testable. Since we want to offer testable propositions, we ponder the nature of the available data. For instance, we have five option replies so that we can observe only five kinds of agent. Due to this "semi-aggregate" nature of the data set, we assume that survey expectations shift only because of the impact of aggregate shocks. That is, we hypothesize that purely idiosyncratic shocks do not affect our data. If not otherwise stated, thus, in the following we will write "shocks" to refer to "aggregate shocks". To clear the matter more neatly we assume, as in standard approaches (Blanchard and Quah, 1989; Galì, 1999), that demand-side shocks have temporary effects only while supply-side shocks have also permanent effects. Also, henceforth, we assume that the fundamentals closest to what people have in mind when thinking of "personal" and "general" economic evolutions are, respectively, individual

[3] Note that one may have ${}_{t-h}y^e_{it} = {}_{t-h}y^e_t = 0$ even for $E_t < 1$. It is so when the (weighted) number of optimists and pessimists is equal. Yet, in this case, $\sigma^e_{it}, \sigma^e_t \neq 0$.

income (y_{it}) and GDP (y_t) dynamics. This correspondence it is not strictly necessary in our setting, but it enables to give a more precise economic interpretation to survey data. As we will see, moreover, evidence supports it.[4] Noticing that the following univariate analysis must be read as an important first step for the multivariate analysis of Sections 5 and 6, we are finally in a position to formulate our testable propositions.

Proposition 3.1. ${}_{t-h}y_{it}^{e}$ **is less volatile than** ${}_{t-h}y_{t}^{e}$**. Both balances are long-memory processes.**

The basic logic of the first statement is that demand shocks produce offsetting effects on ${}_{t-h}y_{t}^{e}$ and more homogeneous reactions on ${}_{t-h}y_{t}^{e}$. Instead, other kinds of shocks (supply-side, confidence) do not affect the relative volatility of the two expectations. Therefore the difference in volatility is only due to demand shocks.

Suppose that a positive demand shock hits the economy, say a monetary expansion. According to the sticky information literature (Mankiw and Reis, 2002 and 2007; Mankiw et al., 2003), only some agent quickly review her expectations on GDP dynamics. Even under this assumption, yet, the net effect of a positive shock on ${}_{t-h}y_{t}^{e}$ in the short run must be strictly positive: no agent should worsen her forecasts. The variation in ${}_{t-h}y_{it}^{e}$, instead, will be surely smaller due to the different consequences of this kind of shock on individual situations that, of course, are known with no delay. Under the realistic assumption that the degree of indexation is less than 100% (an assumption maintained, inter alia, by the sticky information proponents too), in fact, reduced interest rates and increasing inflation shrink the disposable income of net creditors leading them to revise their expectations downward. By the same token, net debtors gain and become more optimists on their economic future. Moreover, a transfer of wealth from creditors to debtors may lead to an increase in aggregate demand (and, possibly, in ${}_{t-h}y_{t}^{e}$), because it is well-known that borrowing-constrained debtors have a higher propensity to consume than creditors (see Eggertsson and Krugman, 2012, for a recent application of this very old idea). All in all, thus, the monetary shock impinges more

[4] Bovi (2013) reports some evidence and hints on the reliability of this correspondence.

strongly on balances dealing with aggregate than with individual-level expectations. Accordingly, ${}_{t-h}y^{e}_{it}$ is less volatile than ${}_{t-h}y^{e}_{t}$. This conclusion holds, mutatis mutandis, even in the occurrence of a negative monetary shock. Analogously, it is easy to think of fiscal shocks (e.g. an unexpected intervention on taxation or public outlays) leading to rather different changes in the two balances once one considers the immanent presence of disparate individual economic situations. In fact, fiscal policies very seldom do not affect income distribution in the economic system (Uhlig, 2010; Drautzburg and Uhlig, 2011). Again, the net impact of a demand shock on ${}_{t-h}y^{e}_{it}$ will be smaller, leading it to be less volatile than ${}_{t-h}y^{e}_{t}$. As we argue later, in the case of negative shock the relative reaction of ${}_{t-h}y^{e}_{t}$ should be even larger.

Suppose now that a positive supply shock hits the economy, say a technology or productivity shock. It is clearly unrealistic to think of such a shock impinging on all incomes immediately. In fact, several authors argue that permanent shocks influence economic systems smoothly (e.g., Blanchard et al., 2012). In the short term, thus, the shock increases the income of a fraction of agents only. These, possibly few, individuals observe the new situation and surely become more confident on their own as well as, likely, on GDP dynamics. All the remaining agents do not observe an immediate improvement in their own situation and, hence, they may wait before updating their expectations on ${}_{t-h}y^{e}_{it}$ and ${}_{t-h}y^{e}_{t}$. It may be worth recalling that these latter deal with one-year-ahead predictions which, moreover, are collected monthly – due to its gradual diffusion a supply shock hardly can impact quickly on such forecasts. In any case, the main point is that individuals become more optimists on both personal and general stances such that there are no short run variations in the *relative* time series pattern of the two expectations. Similar considerations holds for negative supply shocks but, as above said, with a clarification. Regardless the demand- or supply-side nature of the shock, in fact, in the aftermath of a negative shock the situation is different and more clear-cut. In particular, negative shocks lead expectations on GDP dynamics to drop faster and more uniformly across agents than those on personal incomes. The logic behind is that the worsened economic perspectives abruptly become common knowledge. In turn, this is so *i)* because of the stylized fact that media coverage of bad news is wider with respect to that of good news (Blendon et al., 1997; Wu et al., 2002; Doms and Morin, 2004), and *ii)* because of a larger share of agent becomes more sensitive to economic information in times of economic emergency (Akerlof et al., 2000; Santoro and Pfajfar, 2006). The first gives the occasion - it is less costly to be informed - and the second the motivation - it is more costly to be uninformed - for agents to be more informed. In addition, an adverse supply shock usually shows up faster than a positive one.[5] Think about a natural calamity versus a technical innovation such as the internet.

To sum up, it is very likely that in the short run ${}_{t-h}y_{it}^{e}$ responds less than ${}_{t-h}y_{t}^{e}$. Even more so in periods whereas negative shocks have stronger and/or more prolonged effects than positive ones. As recalled, this is the situation in Italy throughout the last two decades (Sections 2 and 4).

As time passes the effects of a transitory shock fade out and ${}_{t-h}y_{t}^{e}$ needs to trace back relatively more than ${}_{t-h}y_{it}^{e}$. Again, this latter must therefore be stickier than ${}_{t-h}y_{t}^{e}$. In the case of permanent shock, irrespective of its sign, the innovation slowly starts diffusing across the economy and an ever-growing number of agents experience the new macroeconomic environment. To the extent that in the short term ${}_{t-h}y_{it}^{e}$ reacts less than ${}_{t-h}y_{t}^{e}$, in the presence of permanent shocks its adjustment could be lengthier. Accordingly, a permanent shock could have more enduring effects on ${}_{t-h}y_{it}^{e}$ than on ${}_{t-h}y_{t}^{e}$. Yet, if in the short term ${}_{t-h}y_{t}^{e}$ overreacts to shocks different dynamics may be in order. In any case, both balances are persistent processes. We add more considerations on these issues in the next proposition and, especially regarding the long-run time connections between ${}_{t-h}y_{it}^{e}$ and ${}_{t-h}y_{t}^{e}$, in the multivariate analyzes of Sections 5 and 6.

[5] Note that since Keynes (1936) a well-known stylized fact is that the arrival of a recession is quite prompt while the recovery is more drawn out.

Suppose, finally, that a confidence shock shows up. In our context the shift in expectations due to confidence may derive from autonomous (with respect to fundamentals) "animal spirits" (Barsky and Sims, 2012) as well as news shocks, i.e. today agents have information on tomorrow economic needs and speculate accordingly (Beaudry and Portier, 2013). In any case, we argue that confidence shocks modify ${}_{t-h}y^{e}_{it}$ and ${}_{t-h}y^{e}_{t}$ in a similar way, leaving their relative patterns unchanged. In this respect their effects on expectations are similar to those of a positive supply shock. Unlike this latter here the logic is that if one feels more optimist/pessimist, (s)he must be "exuberant/gloomy" on both personal and general evolutions.[6] In the short run, thus, the relative time series patterns of ${}_{t-h}y^{e}_{it}$ and ${}_{t-h}y^{e}_{t}$ should remain unaffected by confidence shocks. This holds no matter the sign or the (likely temporary) duration of the shock.

All considered, we can safely conclude that (possibly composite) shocks lead ${}_{t-h}y^{e}_{it}$ to be less volatile than ${}_{t-h}y^{e}_{t}$: the opposite situation is much less likely. Once one resort to animal spirits useful insights may be searched in the psychological literature,[7] which can add even more on the coherence and realism of our framework. Specifically, we must expect a lower volatility of ${}_{t-h}y^{e}_{it}$ with respect to ${}_{t-h}y^{e}_{t}$ because of the presence of immanent and widespread psychological biases (Tversky and Kahneman, 1974). Undisputed instances of these latter are better-than-average effects, illusion of control, overconfidence, and confirmation bias. Note that these biases are so widespread and unquestionable to seriously challenge the general validity of behavioral models contrasting them (Pohl, 2004; Baron, 2007; Della Vigna, 2009). This said, they impinge specially on individual-level expectations, making these latter less volatile because all of them contribute to maintain or strengthen beliefs in the face of contrary evidence.[8] Once again, it is important to note that these psycho-biases are magnified during economic crises - while a recession deteriorates ${}_{t-h}y^{e}_{t}$, the illusion of control generates a downward stickiness in expectations on personal

[6] In Sections 5 and 6 we argue that expectations on personal and general conditions cannot diverge systematically.
[7] An analysis of subjective expectations in light of psychology can be found in Bovi (2009) and Gouret and Hollard (2011).
[8] A recent strand of the macroeconomic literature is working on that (e.g. Jaimovich and Rebelo, 2006).

perspectives. This, in turn, lessens the cyclical responsiveness of ${}_{t-h}y^{e}_{it}$ (Bovi, 2009). All that contributes to justify what stated so far, reinforcing the inner coherence of the theoretical setting behind our propositions.

Lastly, and importantly, it must be emphasized that all the studied shocks affect the cross sectional dispersion of expectations. The analysis of the second moments of survey expectations turns out to be paramount. In the following proposition we advance some basic hints on this.

Proposition 3.2. σ^{e}_{it},σ^{e}_{t}>0 for $\forall$ t; σ^{e}_{it} is smaller and more volatile than σ^{e}_{t}.

The level of cross sectional disagreement on expected personal economic evolutions (σ^{e}_{it}) mirrors different individual-level dynamics. Since in the previous proposition we have asserted that shocks may affect differently individual incomes, it turns out that shocks may amplify the cross sectional dispersion of expectations. Of course, shocks are an immanent trait of real-life economic systems and their (persistent or temporary) effects very likely overlap. Hence, individual-level income dynamics are disparate and, accordingly, σ^{e}_{it} must be systematically greater than zero. Moreover, overwhelming evidence shows that, over the last three decades, many countries experienced substantial increases in wages and earnings inequality (Krueger, et al., 2010). All these considerations make the persistent presence of strictly positive values of σ^{e}_{it} hard-to-challenge.

Though the representative agent still populates mainstream macroeconomic models, some strands of literature[9] - not to mention the observation of the real world - suggest several potential causes behind the widespread and persistent disagreement in agents' forecasts on aggregate fundamentals (σ^{e}_{t}). Well-known instances are: sticky information (Mankiw and Reis, 2002; Reis 2006), different predictors (Brock and Hommes, 1997), noisy information (Sims, 2003), structural changes (Evans and Honkapoja, 2013). In line with the mentioned caveats raised by Pesaran (1987) about behavioral-models conditioned results (see Introduction), Coibion and Gorodnichenko (2012) show

[9]A throughout discussion of the weakness of assuming the presence of a representative agent can be found in Kirman (1992).

that theoretical frameworks on informational rigidities point to different implications and, moreover, both challenge those of rational expectations models.[10] Finally, Acemoglu, et al. (2006) show that, under reasonable assumptions, even Bayesian agents maintain divergent forecasts. Thus, there are several strong reasons to believe that both σ_{it}^{e} and σ_{t}^{e} are significantly positive.

Perhaps more importantly, we also argue that the dispersion of expectations on GDP dynamics is greater than that on individual income evolutions. Though prima facie astonishing in model-based frameworks, this proposition can be easily reached in our approach via a two-fold logic. On the one side, cross sectional disagreement and time series volatility/uncertainty in forecasts are surely positively connected (D'Amico and Orphanides, 2008; Capistràn and Timmermann, 2009; Lahiri and Sheng, 2010). On the other side, in Proposition 3.1 we have showed that ${}_{t-h}y_{it}^{e}$ is less volatile than ${}_{t-h}y_{t}^{e}$. Considering the two sides together, a solid message emerges: $\sigma_{it}^{e} < \sigma_{t}^{e}$. In Section 5 we will say more on volatility and disagreement in expectations, and in Section 6 we test whether they are interchangeable in our sample.

We finally claim that the level of disagreement on individual conditions should be relatively more volatile than σ_{t}^{e}. This is because shocks impinge on σ_{it}^{e} relatively more than on σ_{t}^{e}. As usual in our setting, it can be more easily seen in periods whereas negative shocks are more frequent/greater than positive ones. Negative shocks increase inequality among non-affluent[11] individuals because only a fraction of these agents lose their (possibly unique) income source. E.g., some individual is fired and becomes promptly more pessimist on her own economic future. Even due to the psychological biases that make rigid expectations on personal stances (Proposition 3.1), instead,

[10] Coibion and Gorodnichenko (2012) show that under sticky information, disagreement among agents should rise after any economic shock, whereas in noisy information models the amount of disagreement is independent of shocks. Moreover, these authors show that all of these models make a common prediction (the average forecast across agents should respond more gradually to a shock than the variable being forecasted) which is in direct contrast to the prediction under full-information rational expectations models.

[11] A stylized fact reported by several authors suggests the strong counter-cyclicality of earnings inequality (Krueger, et al., 2010; Bloom Raskin, 2013; Saez, 2013). It is hardly surprising. Intuitively, low- middle-income households are more vulnerable to shocks than rich ones because they have fewer options to diversify and insure their income sources. Note that surveys collect the expectations of the representative consumer's which, of course, is not rich.

people who do not lose job leave unchanged their expectations. Thus, shocks have large effects on σ_{it}^{e} and, accordingly, the volatility of this latter is high.

As per σ_{t}^{e} it is likely to be cyclical as well because shocks increase both aggregate volatility and disagreement (Capistran and Timmermann, 2009). As claimed in Proposition 3.1, however, agents are more informed amid economic crises and, consequently, they form relatively less heterogeneous predictions. Thus, on the one side, higher GDP volatility makes forecasting exercises more difficult, in that raising the cyclical response of σ_{t}^{e}. On the other side, greater information makes more likely to form similar forecasts, in that decreasing the cyclical response of σ_{t}^{e}. Especially in bad times, therefore, there are counter balancing effects leading to expect that σ_{t}^{e} is less volatile than σ_{it}^{e}.

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.[12] It can be interpreted as 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.[13] 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).

4. Univariate Analysis. Evidence

[12] Mankiw and Reis (2007) find that about a fifth of workers and consumers update their information sets every quarter, so the mean information lag for both household members is approximately five quarters. By contrast, firms are estimated to be much better informed when setting prices: About two-thirds update their information set every quarter.

[13] In fact, consumers and workers might be homogeneously inattentive if their replies are distributed in peculiar, but unlikely, ways in the surveys.

The theoretical propositions of Section 3 have pointed out some effects of shocks on expectations. Survey data afford to test them and to offer a quantitative view of the topic. Figure 4.1 and 4.2 give a visual impression of the evolution of survey expectations in Italy throughout the last two decades.

Figure 4.1. and 4.2 about here

Figure 4.1 shows 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 the persistent presence of (possibly composite) negative shocks. It also seems to support that ${}_{t-h}y_{it}^{e}$ is actually 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 note that ${}_{t-h}y_{it}^{e}$ is very often above ${}_{t-h}y_{t}^{e}$. An explanation can be found in the better-than-average effects featuring personal perspectives recalled in the previous section.

Figure 4.2 deals with Proposition 3.2. It very clearly shows that, in our sample, the disagreement across lay forecasters is persistent. Specifically, 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 (see footnote 10). 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}. Our analysis emphasizes an internally coherent framework whereas it must be that *i)* both levels of discord are significantly positive and *ii)* $\sigma_t^e > \sigma_{it}^e$. Then, Proposition 3.2 points out that σ_{it}^e must be more volatile than σ_t^e. The visual inspection of Figure 4.2 and standard deviations offer empirical support: in the sample the standard deviations of σ_t^e and σ_{it}^e are, respectively, 0.04 and 0.09.

As per the relative persistence of expectations, Table 4.1 collects the autocorrelations and the partial autocorrelations of the two balances at different lags.

Table 4.1. about here

The picture emerging from Table 4.1 clearly 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 4.1 are unsurprising. The leading view on individual income dynamics, 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 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 so that their dynamics are obviously connected.

So, well-established stylized facts suggest that y_{it} and y_t follow persistent processes. These latter may be clearly mirrored in survey expectations on economic conditions. Further, our data are monthly one-year-ahead predictions: each consecutive survey predicts the same 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 4.1 and of the VECM 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 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 behaves 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 4.1 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 4.1 shows that ${}_{t-h}y^{e}_{it}$ and ${}_{t-h}y^{e}_{t}$ 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 4.2 strongly support that the null of unit root cannot be rejected.

Table 4.2. about here

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.

5. Multivariate Analysis. Testable Propositions

A multivariate analysis allows studying more deeply and explicitly the foregoing shocks-driven connections between expectations on micro and macroeconomic dynamics. For instance in Section 3 we have pointed out, although somewhat implicitly, that the contemporaneous correlation between ${}_{t-h}y^e_{it}$ and ${}_{t-h}y^e_t$ should be positive. Alike, as we argue below, establishing the role of pushing or pulling variable in a VECM analysis offers additional evidence and hints on the framework set out in Section 3. We will focus on long-run relationships and, in doing that, in Section 6 we compare the forecasting exercise performed by the same individual on different fundamentals. It further shrinks the potential (but marginal) issues stemming from the lack of re-interviews in our survey data.

Proposition 5.1. ${}_{t-h}y^e_{it}$ and ${}_{t-h}y^e_t$ are cointegrated; ${}_{t-h}y^e_{it}$ is weakly exogenous.

In Section 4 we have found 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 (Hayashi, 2000):

$$ {}_{t-h}y^e_{it} = \sum\nolimits_{j=1}^{t} \varepsilon_{it} \tag{5.1} $$

$$ {}_{t-h}y^e_{t} = \sum\nolimits_{j=1}^{t} \varepsilon_{t} \tag{5.2} $$

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:

$$ z_t = {}_{t-h}y^e_{it} - \beta\, {}_{t-h}y^e_{t} = \sum\nolimits_{j=1}^{t} \varepsilon_{it} - \beta \sum\nolimits_{j=1}^{t} \varepsilon_{t} \tag{5.3} $$

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 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. All in all, it is hard to think of (semi-macro) "bipolar" agents being permanently both optimists on their situation and pessimists on the economic system in which they operate (or vice versa). In Sections 3 we have suggested that ${}_{t-h}y^{e}_{it}$ and ${}_{t-h}y^{e}_{t}$ must be linked in different, more palatable, ways. In sum, z_t must be a stationary process. Figure 4.1 (Section 4) 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:

$$\sum_{j=1}^{t} \varepsilon_{it} = \beta \sum_{j=1}^{t} \varepsilon_{t} \tag{5.4}$$

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 incomes and GDP, which are proportional by construction. It is also useful to consider a regression type formulation (see Proposition 5.2):

$$ {}_{t-h}y^{e}_{it} = \theta + \beta\, {}_{t-h}y^{e}_{t} + u_t \tag{5.5}$$

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

We expect a cointegrating relation [1,-β] and, for reasons that we will clarify in Proposition 5.2, we also expect β=1 only when dealing with "disagreement corrected" values of the balances.

Finally, we argue that ${}_{t-h}y^{e}_{it}$ should be weakly exogenous with respect to the cointegrating parameter β. In other words we claim that, when $u_t \neq 0$, only expectations on the macroeconomic fundamental adjust to remove deviations from equilibrium. To see why, it may be better to write the links between ${}_{t-h}y_t^e$ and ${}_{t-h}y_{it}^e$ in VECM form.[14] Focusing on the error correction term with only a constant=θ, we write:

$${}_{t-h}y_{it}^e - {}_{t-h}y_{it-1}^e = \delta_i\,({}_{t-h}y_{it-1}^e + \beta\,{}_{t-h}y_{t-1}^e + \theta) \tag{5.6}$$

$${}_{t-h}y_t^e - {}_{t-h}y_{t-1}^e = \delta\,({}_{t-h}y_{it-1}^e + \beta\,{}_{t-h}y_{t-1}^e + \theta) \tag{5.7}$$

If $\delta_i = 0$, then ${}_{t-h}y_{it}^e$ is weakly exogenous. In our settings it means that, in closing the disequilibrium between the two expectations, ${}_{t-h}y_t^e$ is more susceptible to be revised than ${}_{t-h}y_{it}^e$. 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 ${}_{t-h}y_{it}^e$ being the pushing variable: its stochastic trend - i.e. its cumulated (possibly composite) shocks - drives ${}_{t-h}y_t^e$ (see equations 5.1 and 5.2). We expect $\delta_i = 0$ because of the different quantity and quality of information available for agents when forecasting personal versus aggregate incomes. As usual we condition our assumptions on hard-to-question facts. 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 ${}_{t-h}y_t^e$ that must be reduced later on. In sum, when shocks generate a gap between the two expectations, on the one side, ${}_{t-h}y_{it}^e$ could be less predisposed than ${}_{t-h}y_t^e$ to restore the equilibrium and, on the other side, this latter may suffer from overshooting. In light of the inner coherence of our framework, we underline that the weakly exogeneity of ${}_{t-h}y_{it}^e$ is also consistent

[14] Basically, the Engle and Granger' s representation theorem (Engle and Granger, 1987) states that, provided that two time series are cointegrated, the short-term disequilibrium relationship between them can always be expressed in the error correction form. In Section 4 we have explained why we add only a constant in the cointegrating equations 5.6) and 5.7).

with overconfidence and other better-than-average effects, which affect individual-level expectations more than aggregate ones and that make the former less volatile than the latter. Moreover, the assumption that ${}_{t-h}y^{e}_{it}$ is a pushing variable in the VECM set out in equations 5.6) and 5.7) is also congruent with both Proposition 3.1 and what follows.

Proposition 5.2. If cross-sectional disagreement and time-series volatility are equal, then the cointegrating vector between Signal-to-Noise ratios is [1; -1].

In the univariate analysis we have argued that cross sectional dispersion and time series volatility in expectations must be related. Our approach enables to work out a simple way to test whether the time series volatility of expectations is statistically equal to the level of cross sectional disagreement in expectations. In the regression type formulation, estimating the following equations (abstracting from errors and constants):

$$ {}_{t-h}y^{e}_{t} = \beta\, {}_{t-h}y^{e}_{it} \tag{5.8} $$

$$ {}_{t-h}y^{e}_{it} = \beta_{i}\ {}_{t-h}y^{e}_{t} \tag{5.9} $$

we have β=cov(${}_{t-h}y^{e}_{it}$; ${}_{t-h}y^{e}_{t}$)/var(${}_{t-h}y^{e}_{it}$), β_{i} =cov(${}_{t-h}y^{e}_{it}$; ${}_{t-h}y^{e}_{t}$)/var(${}_{t-h}y^{e}_{t}$).

If we standardize the central tendency, i.e. ${}_{t-h}y^{e}_{t}$/stdev(${}_{t-h}y^{e}_{t}$) and ${}_{t-h}y^{e}_{it}$/stdev(${}_{t-h}y^{e}_{it}$), by construction both these standardized balances have a unitary, hence equal, variance. It turns out that, estimating the system 5.8)-5.9) whereas the two endogenous variables are the above mentioned standardized versions of the two balances, one would obtain $1=\beta=\beta_{i}$.

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. var(${}_{t-h}y^{e}_{it}$)=σ^{e}_{it} and var(${}_{t-h}y^{e}_{t}$)=σ^{e}_{t}. As seen for the standardized versions of the balances, performing a bivariate VECM where the two endogenous variables are now the above defined SNRs, we would obtain $\beta=\beta_i$, i.e. a cointegrating vector [1,-1]. QED. It also suggests that the reason behind a non-unitary long run parameter linking ${}_{t-h}y_t^e$ and ${}_{t-h}y_{it}^e$ is that their time series volatility is different. In equations 5.8) and 5.9), in fact, $\beta=\beta_i=1$ would imply that stdev(${}_{t-h}y_{it}^e$)=stdev(${}_{t-h}y_t^e$). But this contrasts with Proposition 3.2 and the evidence collected in Section 4.

Following the logic of this paper, we recall what previously said to add some consideration on the role of shocks in increasing the proportionality between the two disagreement-corrected balances (namely, the two SNRs). Suppose, as in our case-study, a negative shock hits the economy. As suggested in Proposition 3.2, income inequality and, consequently σ_{it}^e, rises. On the other hand, σ_t^e shrinks because of more information-sensitive forecasters and wider media coverage. Offsetting effects are in order for the numerators of the two disagreement-corrected balances. As explained in Proposition 4.1, in fact, a negative shock reduces ${}_{t-h}y_t^e$ more than ${}_{t-h}y_{it}^e$. In sum, the two SNRs are relatively closer each other than the two simple balances because expectations respond to shocks such a way that *i)* ${}_{t-h}y_{it}^e$ is less volatile than ${}_{t-h}y_t^e$, and *ii)* σ_{it}^e is more volatile than σ_t^e. As it should be clear at this point, it holds especially when the net overall effect of shocks is negative.

6. Multivariate Analysis. Evidence

In testing for cointegration between ${}_{t-h}y_{it}^e$ and ${}_{t-h}y_t^e$ 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 6.1 collects the results for cointegration tests based on our preferred long run relationship between ${}_{t-h}y_{it}^e$ and ${}_{t-h}y_t^e$, which has an intercept and no trend (Section 4).

Table 6.1. about here

Table 6.1 confirms that ${}_{t-h}y^{e}_{it}$ and ${}_{t-h}y^{e}_{t}$ are cointegrated processes. Focusing as before on long run relationships, we estimate the VEC model sets out in equations 5.6) and 5.7). Figure 6.1 and Table 6.2 collect the results.

Figure 6.1. about here

Table 6.2. about here

Figure 6.1 reassures that the linear combination of the two central tendencies is I(0). Table 6.2 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 6.1 is corrected in just one month. Since δ_i is zero, data also confirms that households only modify ${}_{t-h}y^{e}_{t}$ 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,[15] which is congruent with our framework. 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 ${}_{t-h}y^{e}_{it}$, δ_i, is invariably statistically zero, and that *iii)* δ is always significant and it oscillates between 0.6 and 0.9. In fact, evidence points out that δ is uniformly decreasing in the sample, suggesting that ${}_{t-h}y^{e}_{t}$ is less and less prompt to do the job of closing the gap with ${}_{t-h}y^{e}_{it}$.

[15] We have performed the Geweke's instantaneous feedback test and we have verified that, unsurprisingly, the VECM residual correlation matrix is not diagonal. Results are available upon request.

Turning the attention to Proposition 5.2, Figure 6.2 reports the historical co-movements of the two signal-to-noise ratios.

Figure 6.2. about here

Comparing Figure 6.2 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 6.3 we display the results of efficient unit root tests on SNRs:

Table 6.3. about here

Verified that our SNRs are integrated processes, as before we go on testing whether the two ratios are cointegrated (again with an intercept and no trend in the cointegrating equation). Table 6.4 collects the results.

Table 6.4. about here

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 VECM sets out in equations 5.6) and 5.7) 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 6.3 and Table 6.5.

Figure 6.3. about here

Table 6.5. about here

Figure 6.3 suggests that the cointegrating relation between the two ratios is a stationary variable with frequent zero-crossing. The last row of Table 6.5 shows that the cointegrating vector is [1,-1], which offers corroborating evidence on Proposition 5.2: Italian lay consumers' expectations are such that their cross sectional disagreement and time series volatility are 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 4 and 6. 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.

7. Concluding Remarks

The expectations feedback system (EFS) can be defined as a circuit whereas the connections between information acquisition/processing, expectations formation, economic decision-making and realizations take place. Shocks play a crucial role in this setting, likely affecting all the EFS elements. With the aim of shedding some light on the agents' expectations formation process, we have addressed the limited question of how shocks shape the time series properties of expectations.

Specifically, we have jointly analyzed households' expectations on individual-level and macroeconomic dynamics, i.e., beliefs on different - but linked - fundamentals. Searching for easy-to-test propositions, we have not conditioned these latter on a given behavioral model. Our hypotheses stem from both palatable assumptions typically maintained in the literature, and a number of hard to dispute stylized facts within an internally congruent framework. Lacking a dominant model, the idea was to offer some insight into our aim offering a different and complementary standpoint with respect to the existing literature. Moreover, ours is a relatively unexplored question in the potential relations between shocks and expectations.

Working with survey expectations, we have computed balance and cross sectional disagreement statistics to test our hypotheses. We have done that in a poor performing economic environment, which we have argued to be a good case study for our aim.

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 evolutions than on what they expect about system-wide economic dynamics. It is so regardless the micro or macroeconomic nature of the fundamental to be predicted. It also indicates that, in the short term, *i)* agents' expectations on aggregate dynamics overreact to shocks and that *ii)* those on personal stances are stickier. Further, unlike what typically maintained in the standard macroeconomic literature, the level of cross sectional disagreement turns out to be persistently high. Especially - hence even more surprisingly - for predictions on the same aggregate fundamental. Lastly, our approach calls for and allows setting out a simple test on whether the level of cross-sectional disagreement is equal to the time-series volatility in expectations. Evidence for Italy suggests that it is the case.

We believe that our findings may help researchers interested in heterogeneity, uncertainty and volatility of beliefs, in the relationships between shocks and expectations, and in the information content of survey expectations.

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Appendix A. Robustness Check. VECM Recursive Estimations.

We re-write here the long-run relationships shown in Section 5 for two generic variables, $x_{i,t}$ and x_t:

$$x_{it} - x_{it-1} = \delta_i \,(x_{it-1} + \beta\, x_{t-1} + \theta) \qquad \text{(A5.6)}$$

$$x_t - x_{t-1} = \delta\,(x_{it-1} + \beta\, x_{t-1} + \theta) \qquad \text{(A5.7)}$$

Figure A1 collects the recursive coefficients of equations A5.6) and A5.7) referring to the central tendencies, i.e. whereas $x_{it} = {}_{t-h}y^{e}_{it}$ and $x_t = {}_{t-h}y^{e}_{t}$. Alike, Figure A2 reports the recursive coefficients of equations A5.6) and A5.7) referring to the two signal to noise ratios, i.e. whereas $x_{it} = {}_{t-h}y^{e}_{it} / \sigma^{e}_{it}$ and $x_t = {}_{t-h}y^{e}_{t} / \sigma^{e}_{t}$.

Figure A1 and A2 about here

Figures A1 and A2 point to a remarkable robustness of the findings of the main text.

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 and Orr (1988). Essentially, the method interprets the share of respondents as maximum likelihood estimates of areas under the density function of aggregate expectations, that is, as probabilities. More formally, the first two moments are:

$$y_t^{e,CP} = - y_t^r \left(\frac{z_t^3 + z_t^4}{(z_t^1 + z_t^2 - z_t^3 - z_t^4)} \right) \qquad \text{(B1)}$$

$$\sigma_t^{e,CP} = y_t^r \left(\frac{2}{(z_t^1 + z_t^2 - z_t^3 - z_t^4)} \right) \qquad \text{(B2)}$$

where:

y_t^r = agent's reference GDP growth rate;

$z_t^1 = N^{-1}[1\text{-}LB_t]$; $z_t^2 = N^{-1}[1\text{-}LB_t\text{-}B_t]$; $z_t^3 = N^{-1}[1\text{-}LB_t\text{-}B_t\text{-}E_t]$; $z_t^4 = N^{-1}[LW_t]$;

$N^{-1}[]$=inverse of the cumulative normal distribution.[16]

As done in the main text, we add the suffix "i" to refer to individual-level conditions. Thus, mutatis mutandis and applying the formulae B1 and B2 to the data referring to expectations on personal stances, we obtain the first, $y_{it}^{e,CP}$, and the second moment, $\sigma_{it}^{e,CP}$, of expectations on personal stances. Analogously to what said about the parameters α and α_i in the Anderson-Theil measures (Section 2), y_t^r and y_{it}^r can be chosen to ensure that the CP-statistics have the same average value as the (perceived) underlying income process in the sample period. As before, it is a critical choice.[17]

[16] Dasgupta and Lahiri (1992), Smith and McAleer (1995), and Berk (1999) find that the accuracy of the quantified series does not significantly vary between any of the common parametric distributions.

[17] Cfr. Pesaran and Weale, 2006.

To increase the comparability of the outcomes, we set $y_t^r = y_{it}^r$ = 1 as done for the parameters α and α_i in the balance statistics. This said, it is worth noticing that *i)* our aim is not the quantification of survey expectations, that *ii)* we just match survey data and that, more importantly, *iii)* this issue disappears when working with CP-signal-to-noise ratios.

Confirming Proposition 3.1, the standard deviation of $y_{it}^{e,CP}$ and $y_t^{e,CP}$ is, respectively, 0.07 and 0.11. As per Proposition 3.2, the sample mean of $\sigma_{it}^{e,CP}$ and $\sigma_t^{e,CP}$ is, respectively, 0.28 and 0.43, while the standard deviation of $\sigma_{it}^{e,CP}$ and $\sigma_t^{e,CP}$ is, respectively, 0.02 and 0.05. As we will see, this latter is the sole evidence not conforming to our theoretical framework. A possible explanation is that, as found in the literature (Maag, 2009), the Carlson-Parkin method captures less precisely the cross sectional disagreement than the index of qualitative variation. On the other hand, several authors emphasize reasons to prefer this latter kind of indicator for quantifying discord across survey beliefs (Lacy, 2006; Badarinza and Buchmann, 2009). In fact, the use of similar indicators it is the typical choice in the literature (Mankiw *et al.*, 2003; Capistran and Timmermann, 2009).

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” in the corresponding number of the table.

Table B4.1 and B4.2 about here

Table B4.1 shows that the persistence of the two central tendencies is practically unchanged irrespective of the method used to compute them. Table B4.2 informs that the unit-root tests for $y_t^{e,CP}$ cannot reject the null of I(1) only at the 10% level.[18] We therefore go on with Johansen’s cointegration tests. Since two series with different orders of integration cannot be cointegrated, the cointegration test may offer further evidence on whether both central tendencies are I(1) processes.

[18] In fact, the ERS test rejects even at the 10% level. In the presence of MA terms, as in the present case (cfr. Tab 4.1), the NG-Perron tests are superior to the ERS test (Ng and Perron, 2001).

Table B6.1 about here

Table B6.1 reassures that the two statistics are cointegrated.

Working with the equations A5.6) and A5.7) presented in Appendix A, we estimate another VECM whereas x_{it} and x_t are now the two CP-central tendencies. We collect the results in the following Table B6.2.

Table B6.2 about here

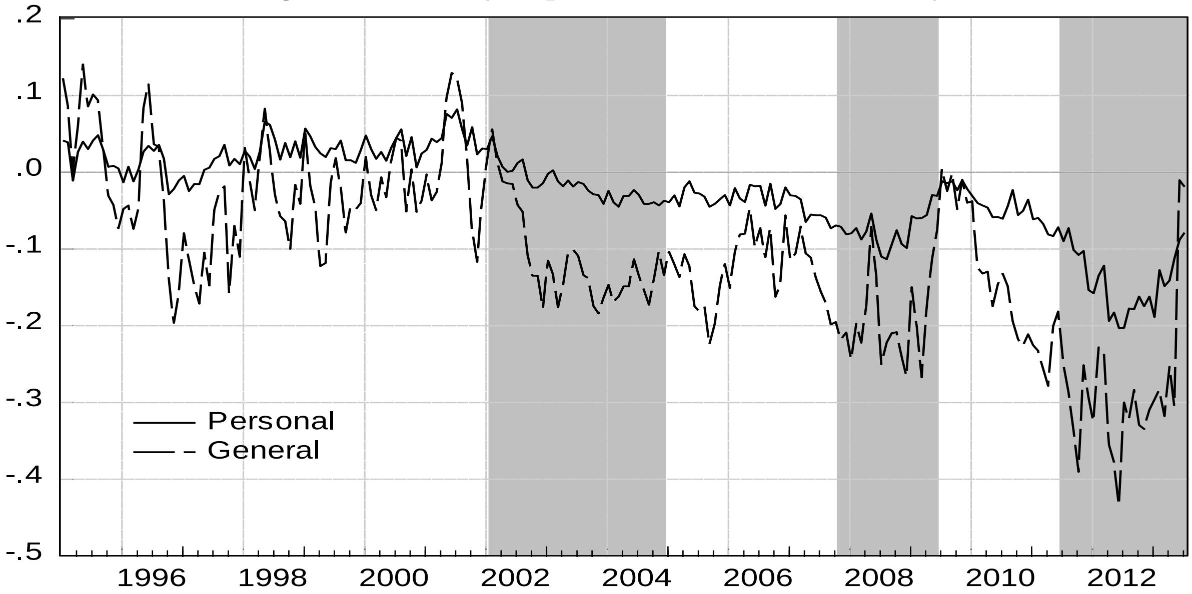
Once again, the results of the main text are substantially validated.

Finally, using the two above mentioned CP statistics, define the signal to noise ratio (CP-SNR) as central tendency on cross sectional disagreement, i.e. ${}_{t-h}SNR_t^{e,CP} = y_t^{e,CP} / \sigma_t^{e,CP}$ and ${}_{t-h}SNR_{it}^{e,CP} = y_{it}^{e,CP} / \sigma_{it}^{e,CP}$. Similarly to what done for the two CP-central tendencies, Table B6.4 collects the results of Johansen's cointegration tests and Table B6.5 those of the bivariate VECM sets out in equations A5.6) and A5.7) (Appendix A) relative to the two CP-SNRs

Table B6.4 and B6.5 about here

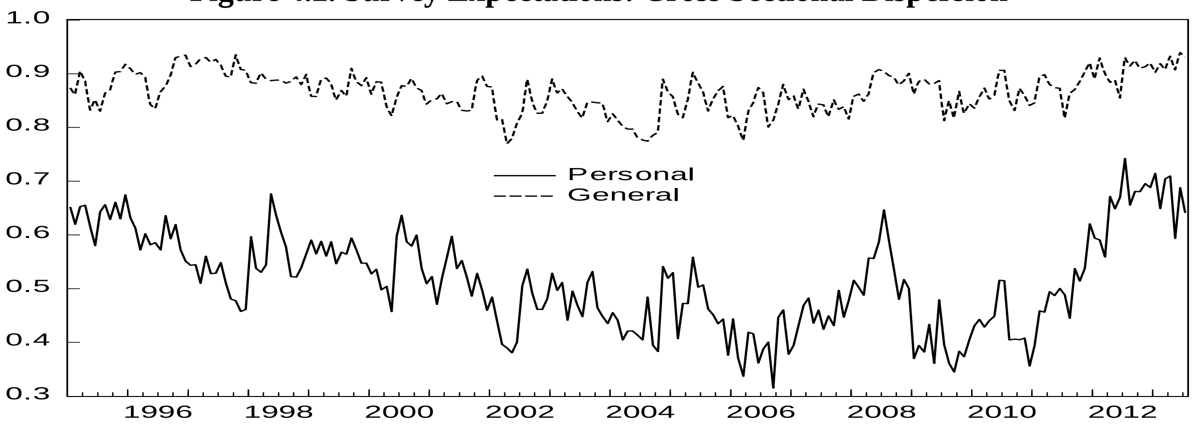
All in all, the evidence obtained using the Carlson-Parkin method is substantially reassuring about the high degree of robustness of the outcomes reported in the main text.

Figure 4.1. 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.

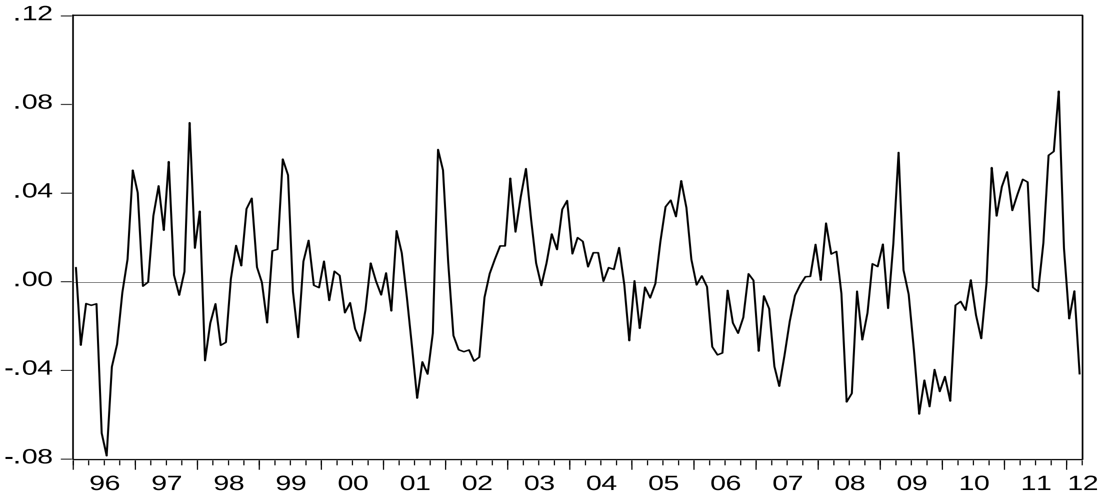
Figure 4.2. Survey Expectations: Cross Sectional Dispersion



Note: Cross sectional disagreement on Personal (σ^{e}_{it}) and General (σ^{e}_{t}) economic evolutions.

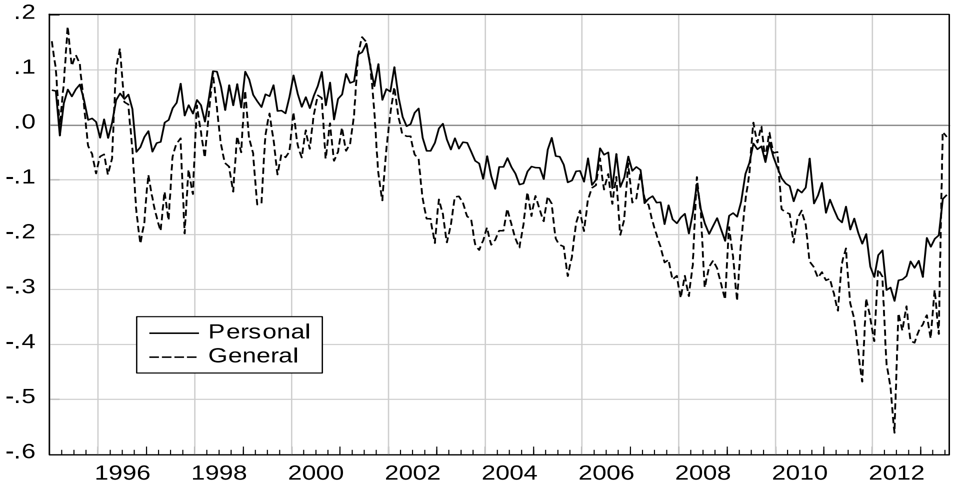
$0 \leq \sigma^{e}_{it}, \sigma^{e}_{t} \leq 1$; and $\sigma^{e}_{it}, \sigma^{e}_{t} = 0$ means totally homogeneous expectations. See also Figure 4.1.

Figure 6.1. Central Tendency. Cointegrating Relation



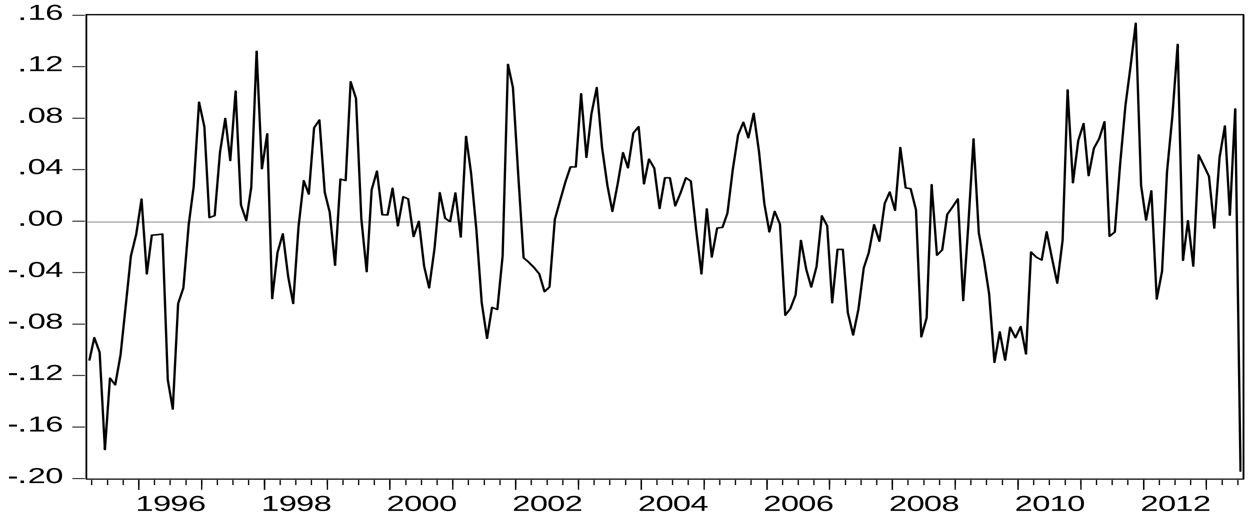
Note. In the figure is reported the disequilibrium error stemming from the VECM:
${}_{t-h}y^{e}_{it} - {}_{t-h}y^{e}_{it-1} = \delta_i \,({}_{t-h}y^{e}_{it-1} + \beta\,{}_{t-h}y^{e}_{t-1} + \theta)$; ${}_{t-h}y^{e}_{t} - {}_{t-h}y^{e}_{t-1} = \delta\,({}_{t-h}y^{e}_{it-1} + \beta\,{}_{t-h}y^{e}_{t-1} + \theta)$

Figure 6.2. 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 4.1 and 4.2.

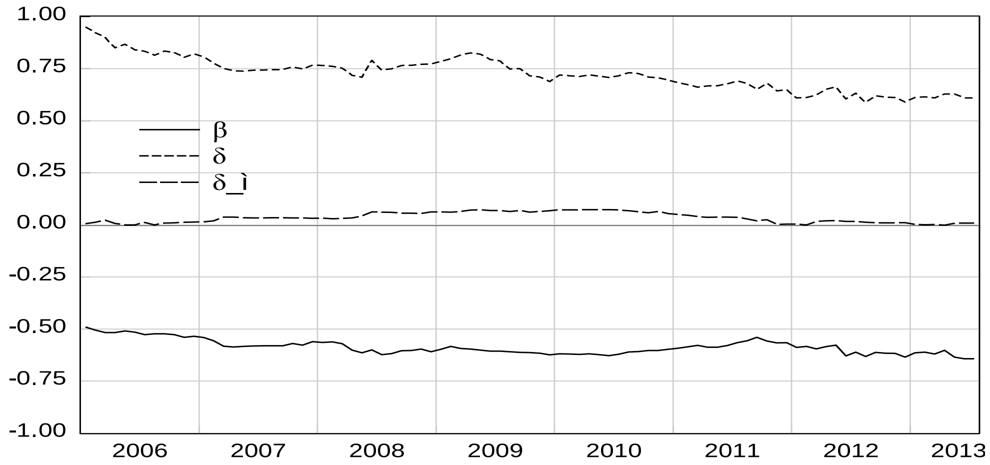
Figure 6.3. Signal-to-Noise ratios. Cointegrating Relation



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

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

Figure A1. Recursive VECM coefficients. Central Tendencies.

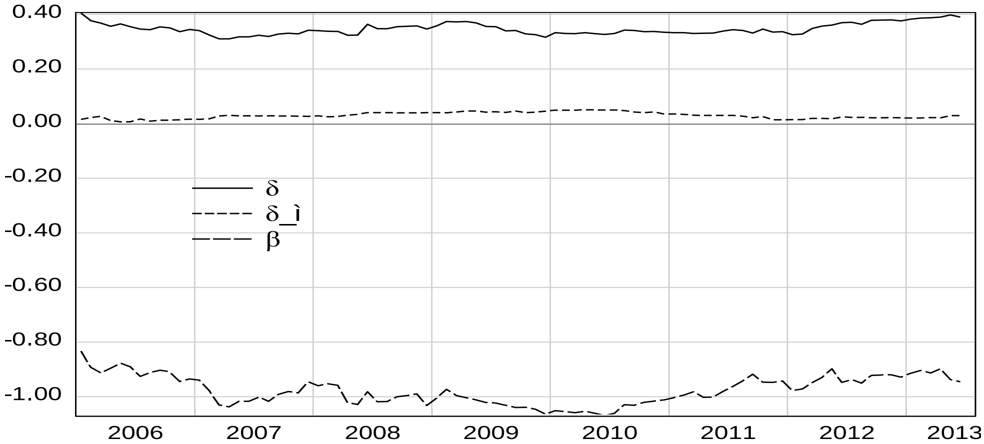


Note. In the figure are reported the recursive coefficients of the VECM:

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

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

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



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

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

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

Table 4.1. 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 4.1

Table 4.2. Survey Expectations. Efficient Unit Root Tests

${}_{t-h}y^{e}_{it}$					${}_{t-h}y^{e}_{t}$				
ERS	MZa	MZt	MST	MPT	ERS	MZa	MZt	MST	MPT
14.2*	-2.52*	-0.97*	0.38*	9.02*	11.2*	-2.10*	-1.00*	0.48*	11.4*

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 the 1% level. Sample: January 1995 - July 2013. See also Figure 4.1

Table 6.1. 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 4.1

Table 6.2. 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[19]
See also Figure 6.1.

[19] 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.

Table 6.3. 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 6.2.

Table 6.4. 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.

Table 6.5. 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.

Table B4.1. Survey Expectations. Persistence

Lag	$y^{e,CP}_{it}$ AC	$y^{e,CP}_{it}$ PAC	$y^{e,CP}_{t}$ AC	$y^{e,CP}_{t}$ 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 B4.2. 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 B6.1. 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 B6.2. 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: Jan-96 Mar-12
° P-val of the LR test. Residuals are multivariate normal

Table B6.4. 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 B6.5. 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.
See equation 5.6a) and 5.7a).