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SYMPOSIUM

Animal spirits and monetary policy

Paul De Grauwe

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Abstract I develop a behavioral macroeconomic model in which agents have cognitive limitations. As a result, they use simple but biased rules (heuristics) to forecast future output and inflation. Although the rules are biased, agents learn from their mistakes in an adaptive way. This model produces endogenous waves of optimism and pessimism ("animal spirits") that are generated by the correlation of biased beliefs. I identify the conditions under which animal spirits arise. I contrast the dynamics of this model with a stylized DSGE-version of the model and I study the implications for monetary policies. I find that strict inflation targeting is suboptimal because it gives more scope for waves of optimism and pessimism to emerge thereby destabilizing output and inflation.

Keywords Animal spirits · Heuristics · Behavioral macroeconomics · Rational expectations

JEL Classification E10 · E32 · D83

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P. De Grauwe (✉)
Department of Economics, University of Leuven, Naamsestraat 69, 3000 Leuven, Belgium
e-mail: paul.degrauwe@econ.kuleuven.be

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1 Introduction

The idea that "animal spirits" drive the business cycle has been at the core of the macroeconomic dynamics described by Keynes. These "animal spirits" are defined as waves of optimism and pessimism gripping investors and consumers, and by having self-fulfilling properties, influencing output and investment. Although elusive as a concept, it has maintained a great popularity in analyses of the business cycle outside academia.

As a result of the systematic incorporation of rational expectations in macroeconomic models, the concept of "animal spirits" plays almost no role in mainstream macroeconomic theory. In the currently fashionable DSGE models that incorporate the rational expectations hypothesis together with a new Keynesian framework of wage and price rigidities, there is no room for waves of optimism and pessimism to exert an independent influence on economic activity. In these models, all fluctuations in investment and output are the result of exogenous shocks in preferences, endowments and technologies that are slowly transmitted into the economy. This combination of exogenous shocks and slow transmission (inertia) creates cyclical movements in these models. In this sense the cyclical movements in output and prices in DSGE-models are created exogenously.

There have been serious attempts to incorporate the notion of "animal spirits" in dynamic general equilibrium models. This literature started with Azariadis (1981) and was further extended by Farmer and Guo (1994), and Benhabib and Farmer (1994). These authors aim at developing rigorous models of the business cycle in which expectations are rational and aggregate fluctuations are driven by animal spirits. Typically these models produce multiple equilibria (sunspots). Together with random shocks they are capable of generating endogenous business cycles. It must be admitted though that these models have not become a part of mainstream macroeconomic thinking.

In this paper, an alternative approach to modeling animal spirits is presented. This is done because the notions of "animal spirits" and rational expectations do not mix well. The assumption of rational expectations implies that agents understand the underlying model structure and the distribution of the shocks. It also means that agents use the same information set, and can, therefore, be represented by one individual, the representative agent, who understands the "truth". In such a framework, it is difficult to see how agents could be gripped by collective waves of optimism and pessimism.

The notion of animal spirits as understood in this paper is based on the fact that individuals do not understand the "truth". Individuals only understand small parts of the total information set, and they are not capable of describing the statistical distribution of economic shocks. The cognitive limitations of individuals have now been abundantly documented by psychologists and brain scientists (For recent surveys, see Kahneman and Thaler 2006; Della Vigna 2007; Thaler 1994; Clarida et al. 1999; Read and van Leeuwen 1998). As a result of these cognitive limitations, there is also heterogeneity in the use of information (see also the classic analysis of Hayek 1945).

It is now also generally recognized that the cognitive limitations of individuals in understanding and processing information leads them to use simple rules ("heuristics") to guide their behavior (see Gaspar et al. 2006). They do this not because they are irrational, but rather because the complexity of the world is overwhelming. In a way it can be said that using heuristics is a rational response of agents who are aware of their limited capacity to understand the world. Because agents have limited cognitive abilities, these rules will also typically be biased. The challenge when we try to model such heuristics is twofold. First, we have to introduce discipline in the selection of rules so as to avoid that "everything becomes possible". We will achieve this discipline by subjecting the selection of rules to a "fitness" criterion. Second, we want to use a selection mechanism that allows agents to learn from their mistakes (their biases). We will use a "trial and error" (adaptive) learning mechanism to achieve this. Thus our concept of rationality is one in which agents are aware of the fact that their beliefs are biased but are willing to learn from the mistakes these biases produce.

The modeling approach presented in this paper is not the only possible one to model agents' behavior under bounded rationality. In fact, a large literature has emerged attempting to introduce bounded rationality into macroeconomic models. These attempts have been based mainly on the statistical learning approach pioneered by Sargent (1993) and Evans and Honkapohja (2001). This literature leads to important new insights (see e.g., Gaspar et al. 2006; Orphanides and Williams 2005; Milani 2007a; Branch and Evans 2009). However, we feel that this approach still loads individual agents with too many cognitive skills that they probably do not posses in the real world.[1]

A similar criticism can be leveled against another approach at modeling imperfect information which is based on the notion of "rational inattention" (see Mackowiak and Wiederholt 2005; Sims 2005; Ball et al. 2005). In these models, the processing of information is costly. As a result, the use of new information is slowed down, leading to inertia in prices. After the passage of time, however, agents are able to use all available information, so that they then have conventional rational expectations. Imperfect information, in our model, is different in nature. Agents never acquire the cognitive skills to understand the full complexity of the underlying model. The heuristics agents use and the switching process between different heuristics is a learning process by which these agents try to understand the world, the complexity of which, however, they never fully grasp. This view contrasts with both the "rational inattention" and the "statistical learning" literatures which are fundamentally optimistic about the capacity of individuals to find out the ultimate "truth". Ours is a less optimistic view, although agents never stop trying to understand.

Our approach is also not the first attempt to introduce heuristics into macroeconomic models. Recently, Brazier et al. (2008) have done so in the context of an overlapping generations model. Branch and Evans (2006) have developed models in which agents must choose between misspecified models. Thus, although agents may have full information, for a variety of reasons, such as concerns about degrees of freedom, they may be fitting overly parsimonious models (see also Anufriev et al. 2009). Kurz (1994) and Kurz and Motolose (2007) use models in which agents develop "rational beliefs". In addition, there is a large literature of behavioral finance models that now incorporate the view that agents are limited in their cognitive skills and use heuristics to guide

[1] See the fascinating book of Gigerenzer and Todd (1999) on the use of simple heuristics as compared to statistical (regression) learning.

their behavior and forecasting (see Kirman 1993; Brock and Hommes 1997; Lux and Marchesi 2000; De Grauwe and Grimaldi 2006).

In this paper, a parsimonious model capable of generating endogenous and self-fulfilling waves of optimism and pessimism (animal spirits) in an otherwise standard setup is developed. Parsimony makes it possible to find out what the simplest possible model is needed to generate such cycles. As will become clear extremely simple rules are capable of generating a very complex dynamics.

2 A behavioral macroeconomic model

In this the modeling strategy is described. This is done by presenting a standard aggregate–demand–aggregate supply model augmented with a Taylor rule. The novel feature of the model is that agents use simple rules, heuristics, to forecast the future. These rules are subjected to an adaptive learning mechanism, i.e., agents endogenously select the forecasting rules that have delivered the highest performance ("fitness") in the past. This selection mechanism acts as a disciplining device on the kind of rules that are acceptable. Since agents use different heuristics one obtains heterogeneity. This, as will be shown, creates endogenous business cycles.

This behavioral model is contrasted with a similar model that incorporates rational expectations, and that is interpreted as a stylized version of DSGE-models. This comparison will make it possible to focus on some crucial differences in the transmission of shocks, in particular of monetary policy shocks.

2.1 The model

The model consists of an aggregate demand equation, an aggregate supply equation and a Taylor rule.

The aggregate demand equation is specified in the standard way, i.e.,

$$y_t = a_1 \tilde{E}_t y_{t+1} + (1 - a_1) y_{t-1} + a_2 (r_t - \tilde{E}_t \pi_{t+1}) + \varepsilon_t \tag{1}$$

where $0 \le a_1 \le 1, a_2 < 0$, y_t is the output gap in period t, r_t is the nominal interest rate, π_t is the rate of inflation, and ε_t is a white noise disturbance term. $\tilde{E}_t$ is the expectations operator where the tilde above E refers to expectations that are not formed rationally. This process will be specified subsequently. I follow the procedure introduced in DSGE-models of adding a lagged output in the demand equation. This is usually justified by invoking habit formation. I keep this assumption here as I want to compare the behavioral model with the DSGE-rational expectations model. However, I will show in Sect. 3 that I do not really need this inertia-building device to generate inertia in the endogenous variables.

The aggregate supply equation can be derived from profit maximization of individual producers. As in DSGE-models a Calvo pricing rule and some indexation rule used in adjusting prices is assumed. This leads to a lagged inflation variable in the equation.[2] The supply curve can also be interpreted as a New Keynesian Philips curve:

$$\pi_t = b_1 \tilde{E}_t \pi_{t+1} + (1 - b_1)\pi_{t-1} + b_2 y_t + \eta_t \tag{2}$$

where $0 \leq b_1 \leq 1$ and $b_2 > 0$.

Finally, the Taylor rule describes the behavior of the central bank

$$r_t = c_1(\pi_t - \pi^*) + c_2 y_t + c_3 r_{t-1} + u_t \tag{3}$$

where $c_1, c_2 > 0, 0 \leq c_3 \leq 1$ and π^* is the inflation target which for the sake of convenience will be set equal to 0. Note that, as is commonly done, the central bank is assumed to smooth the interest rate. This smoothing behavior is represented by the lagged interest rate in Eq. (3). Ideally, the Taylor rule should be formulated using a forward looking inflation variable, i.e., central banks set the interest rate on the basis of their forecasts about the rate of inflation. This was not done here in order to maintain simplicity in the model.

Agents are assumed to use simple rules (heuristics) to forecast the future output and inflation. The way I proceed is as follows. I start with a very simple heuristics for forecasting and apply it to the forecasting rules of future output. Because agents do not fully understand how the output gap is determined, their forecasts are assumed to be biased. Some agents are optimistic and systematically bias the output gap upwards, others are pessimistic and systematically bias the output gap downwards.

$$\text{The optimists are defined by } \tilde{E}_t^{\text{opt}} y_{t+1} = g_t \tag{4}$$

$$\text{The pessimists are defined by } \tilde{E}_t^{\text{pes}} y_{t+1} = -g_t \tag{5}$$

where $g_t > 0$ expresses the degree of bias in estimating the output gap. The expression $d_t = 2g_t$ can be interpreted as the divergence in beliefs among agents about the output gap. This divergence in beliefs is assumed to be a function of the volatility of the output gap. Thus

$$d_t = \beta + \delta\sigma(y_t) \tag{6}$$

where $\beta \geq 0, \delta \geq 0$ and $\sigma(y_t)$ is the unconditional standard deviation of the output gap (computed over a fixed window of past observations[3]). The logic is that when the volatility of the output gap increases, the uncertainty surrounding the movements of the output gap increases, leading the agents' beliefs about the true output gap to diverge more. However, the special case where $\delta = 0$, i.e., the divergence in beliefs is constant and equal to β, will also be analyzed. In that case g_t in Eqs. (4) and (5) is constant and equal to $\frac{\beta}{2}$.

[2] It is now standard in DSGE-models to use a pricing equation in which marginal costs enter on the right hand side. Such an equation is derived from profit maximisation in a world of imperfect competition. It can be shown that under certain conditions the aggregate supply equation (2) is equivalent to such a pricing equation (see Galí 2008; Smets and Wouters 2003).

[3] In the numerical implementation this window is set at 50 periods.

The forecasting rule used here may appear ad hoc. Indeed it is when one assumes that agents know the underlying model and the statistical distribution of shocks. There would then be no reason for these agents not to use that information. This is not so, however, in a world where uncertainty, i.e., non-quantifiable risk reigns. In such an uncertain world there is no scientific basis for making predictions. All that is left over is beliefs about the future. In this paper we assume the simplest possible set of beliefs, i.e., optimistic and pessimistic beliefs. Clearly, this set of beliefs can be extended (we perform such an extensions in Sect. 5).

The rule agents use is biased. This does not mean that the agents are "dumb" and that they do not want to learn from their errors. I will specify a learning mechanism later in this section in which these agents continuously try to correct for the bias by switching from one rule to the other.

The market forecast is obtained as a weighted average of these two forecasts, i.e.,

$$\tilde{E}_t y_{t+1} = \alpha_{\text{opt},t} \tilde{E}_t^{\text{opt}} y_{t+1} + \alpha_{\text{pes},t} \tilde{E}_t^{\text{pes}} y_{t+1} \tag{7}$$

$$\tilde{E}_t y_{t+1} = \alpha_{\text{opt},t} g_t - \alpha_{\text{pes},t} g_t \tag{8}$$

and

$$\alpha_{\text{opt},t} + \alpha_{\text{pes},t} = 1 \tag{9}$$

where $\alpha_{\text{opt},t}$ and $\alpha_{\text{pes},t}$ are the probabilities that agents use an optimistic, respectively, a pessimistic rule. As will be made clear later, this market forecast will turn out to be unbiased on average.

A methodological issue arises here. The forecasting rules (heuristics) introduced here are not derived at the micro level and then aggregated. Instead, they are imposed ex post, on the demand and supply equations. This has also been the approach in the learning literature pioneered by Evans and Honkapohja (2001). Ideally one would like to derive the heuristics from the micro-level in an environment in which agents experience cognitive problems. Our knowledge about how to model this behavior at the micro level[4] and how to aggregate it is too sketchy, however, and I have not tried to do so.

As indicated earlier, agents are rational in the sense that they continuously evaluate their forecast performance. I apply notions of discrete choice theory (see Anderson et al. 1992; Brock and Hommes 1997) in specifying the procedure agents follow in this evaluation process. Discrete choice theory analyzes how agents decide between different alternatives. The theory takes the view that agents are boundedly rational, i.e., utility has a deterministic component and a random component. Agents compute

4 Psychologists and brains scientists struggle to understand how our brain processes information. There is as yet no generally accepted model we could use to model the micro-foundations of information processing.

the forecast performance of the different heuristics as follows:

$$U_{\text{opt},t} = -\sum_{k=1}^{\infty} \omega_k \left[y_{t-k} - \tilde{E}_{\text{opt},t-k-1} y_{t-k} \right]^2 \tag{10}$$

$$U_{\text{pes},t} = -\sum_{k=1}^{\infty} \omega_k \left[y_{t-k} - \tilde{E}_{\text{pes},t-k-1} y_{t-k} \right]^2 \tag{11}$$

where $U_{\text{opt},t}$ and $U_{\text{pes},t}$ are the forecast performances (utilities) of the optimists and pessimists, respectively. These are defined as the mean squared forecasting errors (MSFEs) of the optimistic and pessimistic forecasting rules; ω_k are geometrically declining weights.

Applying discrete choice theory the probability that an agent will use the optimistic forecasting rule is given by the expression (Anderson et al. 1992; Brock and Hommes 1997):

$$\alpha_{\text{opt},t} = \frac{\exp\left(\gamma U_{\text{opt},t}\right)}{\exp(\gamma U_{\text{opt},t}) + \exp(\gamma U_{\text{pes},t})} \tag{12}$$

Similarly the probability that an agent will use the pessimistic forecasting rule is given by:

$$\alpha_{\text{pes},t} = \frac{\exp\left(\gamma U_{\text{pes},t}\right)}{\exp(\gamma U_{\text{opt},t}) + \exp(\gamma U_{\text{pes},t})} = 1 - \alpha_{\text{opt},t} \tag{13}$$

Equation (12) says that as the past forecast performance of the optimists improves relative to that of the pessimists agents are more likely to select the optimistic belief about the output gap for their future forecasts. As a result the fraction of agents using the optimistic rule increases. Equation (13) has a similar interpretation. The parameter γ measures the "intensity of choice". It parameterizes the extent to which the deterministic component of utility determines actual choice. When $\gamma = 0$, utility is purely stochastic. In that case agents decide to be optimist or pessimist by tossing a coin and the probability to be optimist (or pessimist) is exactly 0.5. When $\gamma = \infty$, utility is fully deterministic and the probability of using an optimistic rule is either 1 or 0. The parameter γ can also be interpreted as expressing a willingness to learn from past performance. When $\gamma = 0$ this willingness is zero; it increases with the size of γ.

Note that this selection mechanism is the disciplining device introduced in this model on the kind of rules of behavior that are acceptable. Rules that perform better (are fitter) are used more; those that perform less well are used less.[5] In contrast with the disciplining device implicit in rational expectations models which implies that agents have superior cognitive capacities, we do not have to make such an assumption here.

[5] The rule used here contrasts with replicator dynamics, in which poorly performing rules are gradually weeded out. For a paper that compares the two dynamics, see Branch and McGough (2008).

It should also be stressed that although individuals use biased rules in forecasting the future, this does not mean that they fail to learn. In fact the fitness criterion used should be interpreted as a learning mechanism based on "trial and error". When observing that the rule they use performs less well than the alternative rule, agents are willing to switch to the more performing rule. Put differently, the rules may be biased, but agents reduce this bias by constantly being willing to learn from past mistakes and to change their behavior.

Agents also make forecasts of inflation in this model. At this stage of the analysis I will simply assume that all agents perceive the central bank's announced inflation target π^* to be fully credible. They use this value as their forecast of future inflation, i.e., $\tilde{E}_t\pi_{t+1} = \pi^*$ (where for the sake of simplicity we assume the inflation target to be equal to 0). I will extend this simple inflation forecasting process in a later section when I will also assume that there is heterogeneity of beliefs in the inflation forecasting process. I keep homogeneity of beliefs here to focus on the impact of heterogeneity in the forecasting of future output gaps.

The solution of the model is found by first substituting Eq. (3) into Eq. (1) and rewriting in matrix notation. This yields:

$$\begin{aligned}\begin{bmatrix} 1 & -b_2 \\ -a_2c_1 & 1-a_2c_2 \end{bmatrix}\begin{bmatrix} \pi_t \\ y_t \end{bmatrix} &= \begin{bmatrix} b_1 & 0 \\ -a_2 & a_1 \end{bmatrix}\begin{bmatrix} \tilde{E}_t\pi_{t+1} \\ \tilde{E}_t y_{t+1} \end{bmatrix} \\ &\quad + \begin{bmatrix} 1-b_1 & 0 \\ 0 & 1-a_1 \end{bmatrix}\begin{bmatrix} \pi_{t-1} \\ y_{t-1} \end{bmatrix} \\ &\quad + \begin{bmatrix} 0 \\ a_2c_3 \end{bmatrix} r_{t-1} + \begin{bmatrix} \eta_t \\ a_2u_t + \varepsilon_t \end{bmatrix}\end{aligned}$$

or

$$\boldsymbol{AZ_t} = \boldsymbol{B\tilde{E}_tZ_{t+1}} + \boldsymbol{CZ_{t-1}} + \boldsymbol{b}r_{t-1} + \boldsymbol{V_t} \tag{14}$$

where bold characters refer to matrices and vectors. The solution for $\boldsymbol{Z}_t$ is given by

$$\boldsymbol{Z_t} = \boldsymbol{A}^{-1}\left[\boldsymbol{B\tilde{E}_tZ_{t+1}} + \boldsymbol{CZ_{t-1}} + \boldsymbol{b}r_{t-1} + \boldsymbol{V_t}\right] \tag{15}$$

The solution exists if the matrix $\boldsymbol{A}$ is non-singular, i.e., if $(1 - a_2c_2)a_2b_2c_1 \neq 0$ which is satisfied given the conditions imposed on the parameters in Eqs. (1)–(3). The system (15) describes the solution for y_t and π_t given the forecasts of y_{t+1} and π_{t+1}. The latter have been specified in Eqs. (4)–(13) and can be substituted into Eq. (15). Finally, the solution for r_t is found by substituting y_t and π_t obtained from Eq. (15) into Eq. (3).

My research strategy consists in comparing the dynamics of this heuristic model with the same structural model [aggregate demand equation (1), aggregate supply equation (2) and Taylor rule equation (3)] under rational expectations which we interpret as a stylized DSGE-model.

The model consisting of Eqs. (1)–(3) can be written in matrix notation as follows:

$$\begin{bmatrix} 1 & -b_2 & 0 \\ 0 & 1 & -a_2 \\ -c_1 & -c_2 & 1 \end{bmatrix} \begin{bmatrix} \pi_t \\ y_t \\ r_t \end{bmatrix} = \begin{bmatrix} b_1 & 0 & 0 \\ -a_2 & a_1 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} E_t \pi_{t+1} \\ E_t y_{t+1} \\ E_t r_{t+1} \end{bmatrix} + \begin{bmatrix} 1-b_1 & 0 & 0 \\ 0 & 1-a_1 & 0 \\ 0 & 0 & a_3 \end{bmatrix} \begin{bmatrix} \pi_{t-1} \\ y_{t-1} \\ r_{t-1} \end{bmatrix} + \begin{bmatrix} \eta_t \\ \varepsilon_t \\ u_t \end{bmatrix}$$

$$\boldsymbol{\Omega Z_t = \Phi E_t Z_{t+1} + \Lambda Z_{t-1} + V_t} \tag{16}$$

$$\boldsymbol{Z_t = \Omega^{-1} \left[\Phi E_t Z_{t+1} + \Lambda Z_{t-1} + V_t\right]} \tag{17}$$

This model can be solved under rational expectations using the Binder and Pesaran (1996) procedure.

2.2 Calibrating the model

I proceed by calibrating the model. In Appendix A, the parameters used in the calibration exercise are presented. The model was calibrated in such a way that the time units can be considered to be months. I find that the model is determinate under rational expectations. In Sect. 2.5, a sensitivity analysis of the main results to changes in the main parameters of the model is presented. The three shocks (demand shocks, supply shocks and interest rate shocks) are i.i.d. with standard deviations of 0.5%.

First simulations in the time domain are presented. Figure 1 shows the time pattern of output and inflation produced by the behavioral model. A strong cyclical movement in the output gap can be observed. The source of these cyclical movements is seen to be the fractions of optimists and pessimists in the market (see second panel of Fig. 1). The model in fact generates endogenous waves of optimism and pessimism. During some periods pessimists dominate and this translates into below average output growth. These pessimistic periods are followed by optimistic ones when optimistic forecasts tend to dominate and the growth rate of output is above average. These waves of optimism and pessimism are essentially unpredictable. Other realizations of the shocks produce different cycles with the same general characteristics.

These endogenously generated cycles in output are made possible by a partially self-fulfilling mechanism that can be described as follows. A series of random shocks creates the possibility that one of the two forecasting rules, say the optimistic one, delivers a higher payoff, i.e., a lower mean squared forecast error (MSFE). This attracts agents that were using the pessimistic rule. The "contagion-effect" leads to an increasing use of the optimistic belief to forecast the output-gap, which in turn stimulates aggregate demand. Optimism is therefore self-fulfilling. A boom is created. At some point, negative stochastic shocks and/or the reaction of the central bank through the Taylor rule make a dent in the MSFE of the optimistic forecasts. The pessimistic belief becomes attractive and therefore fashionable again. The economy turns around.

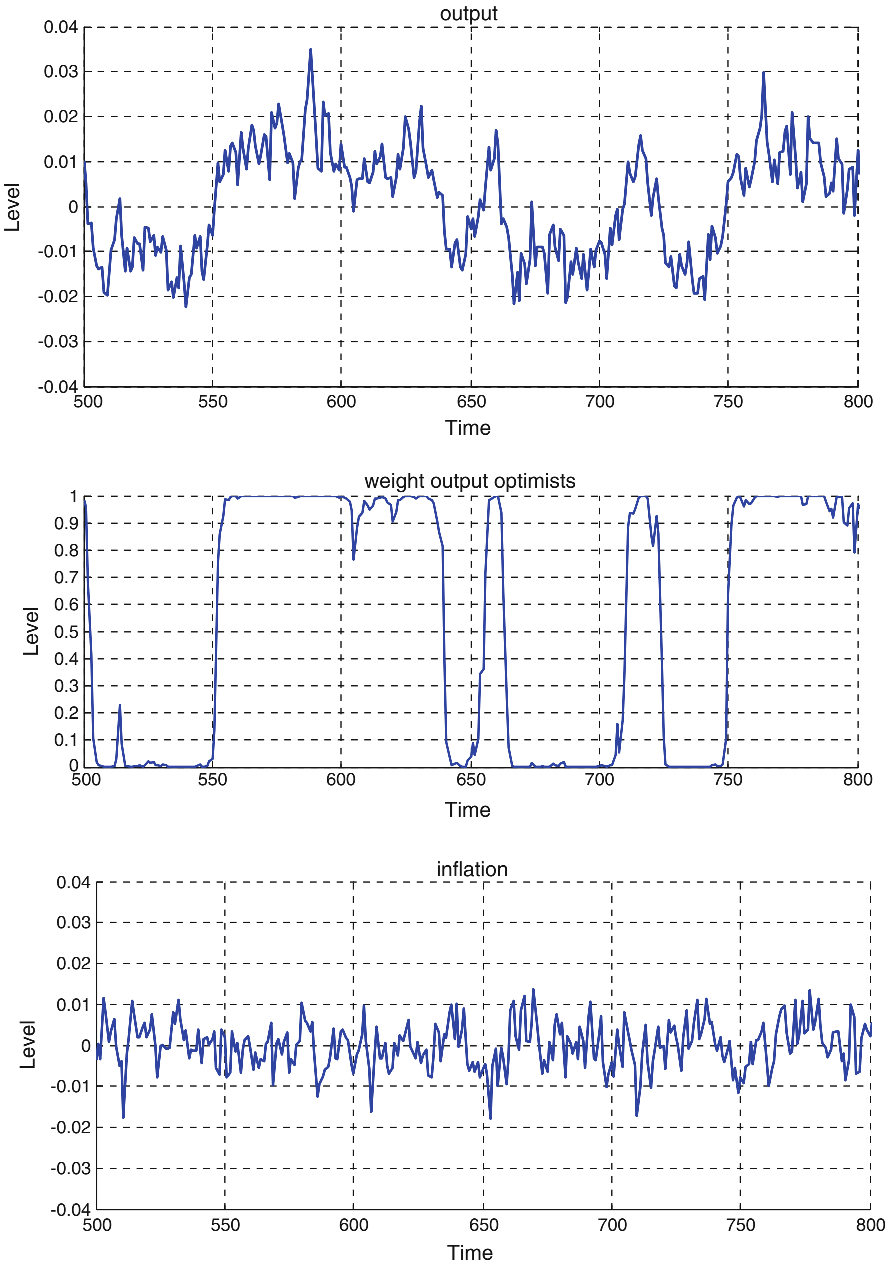

Fig. 1 Output gap and inflation in behavioral model

These waves of optimism and pessimism can be understood to be searching (learning) mechanisms of agents who do not fully understand the underlying model but are continuously searching for the truth. An essential characteristic of this searching mechanism is that it leads to systematic correlation in beliefs (either optimistic or pessimistic ones). This systematic correlation is at the core of the booms and busts created in the model. Note, however, that when computed over a significantly large period of time the average error in the forecasting goes to zero. In this sense, the forecast bias tends to disappear asymptotically.[6]

From Fig. 1 (third panel), one observes that inflation is relatively stable and fluctuates around the target (set at 0) in a relatively narrow band. This result has everything to do with the assumption that agents are homogeneous in giving full credibility to the inflation target of the central bank. I will return to this when I introduce heterogeneity among agents in their perception of the credibility of the central bank's inflation target.

These results can be contrasted with those obtained using the model under rational expectations. I use the same structural model with the same parameter values for the aggregate demand, supply and Taylor equations. In addition, the shocks are the same with the same iid structure. The results are shown in Fig. 2. (Note that with the chosen parameters the RE-model is determinate). Comparing this figure with Fig. 1 one observes that rational expectations model does not produce clear cyclical movements in the output gap. In a way this is not surprising: the shocks are white noise and the transmission mechanism exhibits a minimal degree of inertia. In full-fledged DSGE-models the inertia is more complex and the shocks typically exhibit autoregressive patterns that are important in producing cyclical movements in output (see Chari et al. 2009 who argue that most of the movements of output and inflation in standard DSGE-models come from the shocks). Thus the results confirm that the cycles produced in the DSGE models come to a large extent from outside the model. This issue will be analyzed further in Sect. 3.

One could argue that the comparison of the behavioral model with the stylized version of the DSGE-model is not entirely fair. DSGE-models have been extended not only by introducing more transmission lags and autoregressive shocks but also by adding credit amplification effects that can generate booms and busts. But these can also be added to the behavioral model. The attractive feature of the behavioral model is that one does not need these additional complexities to generate business cycle movements.

2.3 Impulse responses in the behavioral and the rational model

The next step in the analysis is to compute the impulse responses to shocks. Here I focus on the impulse responses to an interest rate shock, defined as plus one standard deviation of the shock in the Taylor equation. Since this is a non-linear model, during the post-shock period I continue to allow for random disturbances. Thus the impulse response measures the response to the interest rate shock in an environment in which the random disturbances are the same for the series with and without the interest rate shock.

[6] This is not an artefact arising from the symmetry assumption that the positive and negative bias are equal as implied in Eqs. (4) and (5). In a model with asymmetric beliefs the bias also disappears asymptotically because the fractions of optimists endogenously adjust to the potential bias introduced by asymmetric beliefs.

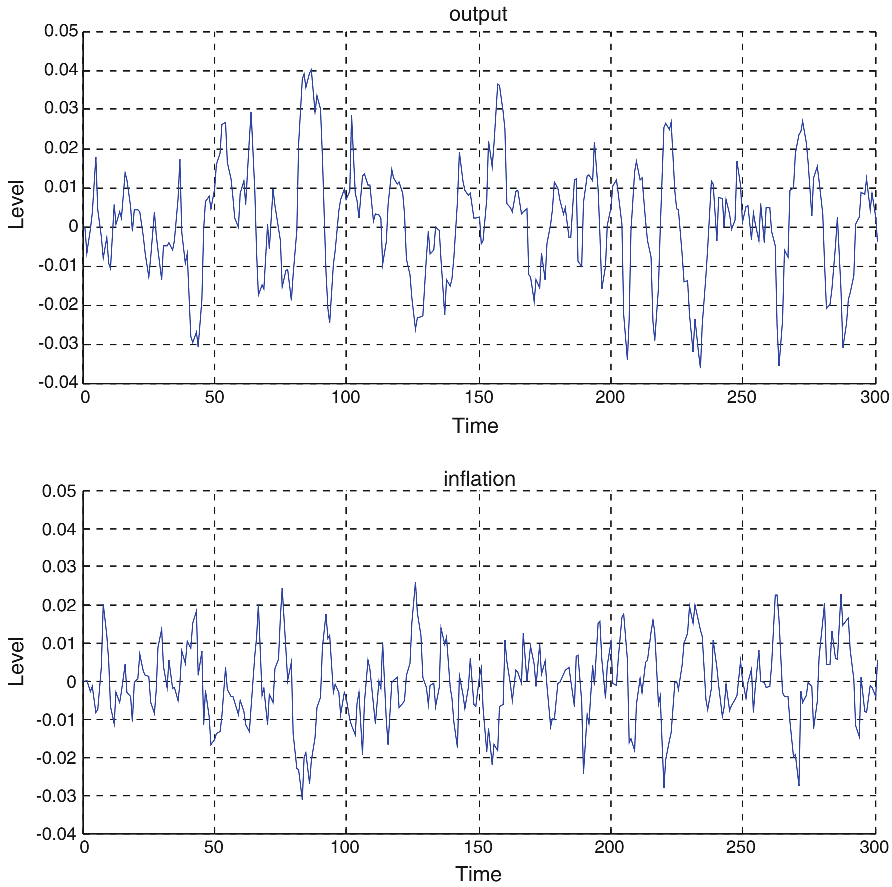

Fig. 2 Output gap and inflation in the rational model

The peculiarity of the behavioral model is that for the same parameters of the model the impulse responses are different for each realization of the stochastic shocks. This contrasts with the rational expectations model where the impulse response functions are not sensitive to the realization of the stochastic shocks (keeping the parameters unchanged). I will return to this difference and give it an interpretation.

Figure 3 shows the mean impulse responses to an interest rate shock. These were constructed by simulating the model 100 times with 100 different realizations of the shocks. The mean response together with the standard deviations were then computed. Figure 3 shows the mean response (the dotted lines are the mean response + and -2 standard deviations; note also that we introduced the shock after 150 periods[7]), exhibiting the standard result of an interest rate shock on output and inflation. However, the uncertainty surrounding this result is considerable at least in the short run.

[7] Actually the impulse response analysis is started after letting the program run 1,000 initial periods to make sure that the system has converged to its ergodic distribution.

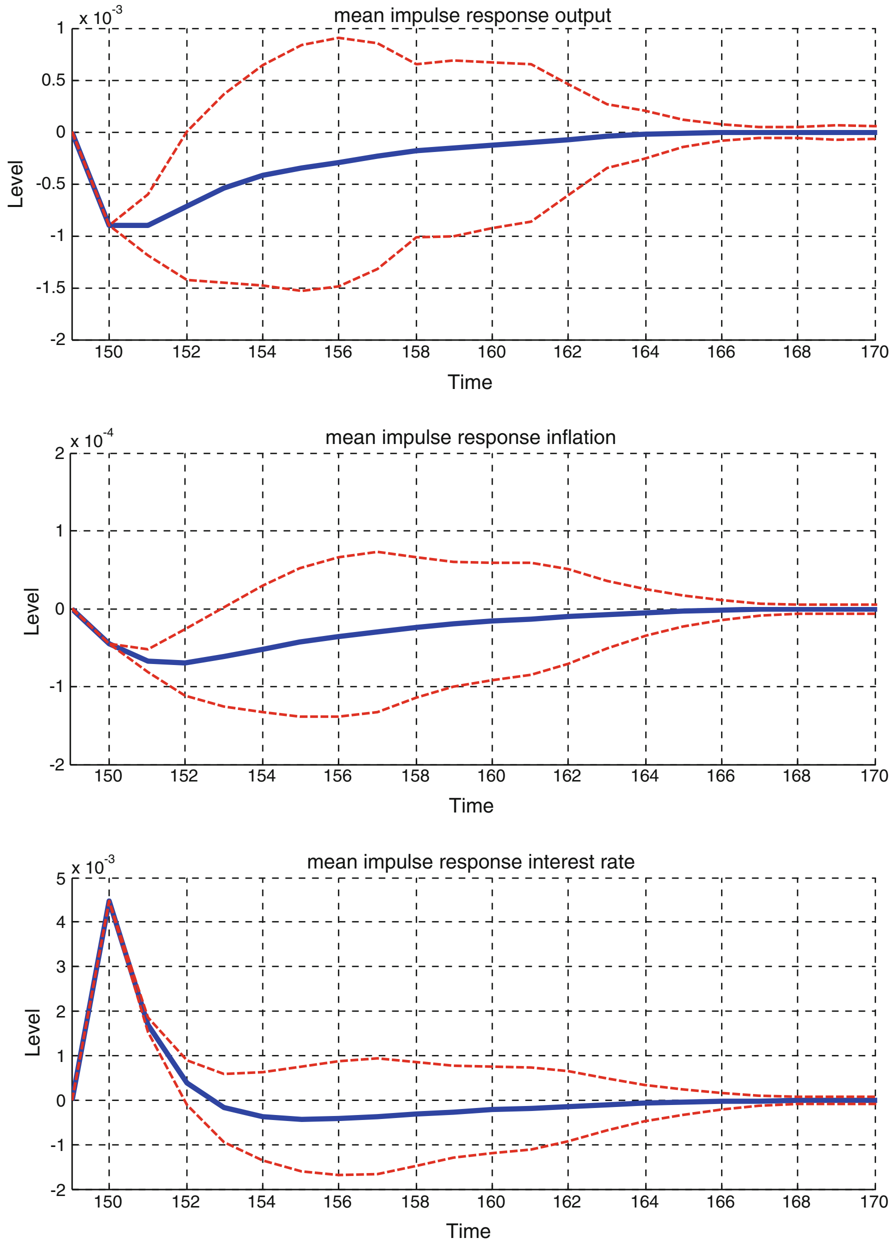

Fig. 3 Mean impulse responses to interest rate shock in the behavioral model. *Dotted lines* represent the impulse responses with ±2 standard deviations

Where does this uncertainty come from? Not from parameter uncertainty. The same parameters are used in constructing all our impulse responses. The answer is that in this behavioral model each realization of the shocks creates different waves of optimism and pessimism (animal spirits). One could also call these "market sentiments". Thus a shock that occurs in period 150 in one simulation happens in a different market sentiment than the same shock in another simulation. In addition, the shock itself affects market sentiments. As a result, the short-term effects of the same interest rate shock become very hard to predict.

Another way to interpret this result is to say that the timing of the shock is important. The same shocks applied at different times can have very different short-term effects on inflation and output. In other words, history matters. Note that the uncertainty about the impulse responses tends to disappear in the long run, as the effect of short-term differences in market sentiments disappears.

This difference in the nature of uncertainty in a behavioral and a rational expectations model has everything to do with the fact that the former has non-linear features while the latter is linear. Thus the additional uncertainty produced by the behavioral model, i.e., the dependence of the impulse response functions on the state of the economy is the outcome of its non-linearity. Rational expectations models including the DSGE-models traditionally impose some linearization procedure. It would be valuable to extend the approach of this paper to DSGE-models that retain their nonlinear structure (See Benhabib et al. 2001; Evans et al. 2008).

2.4 The extended behavioral model

In this section, the behavioral model is extended by allowing the inflation forecasters to be heterogeneous. I follow Brazier et al. (2008) in allowing for two inflation forecasting rules. One rule is based on the announced inflation target (as in the previous section); the other rule extrapolates inflation from the past into the future. One may argue that this is quite a different pair of heuristics than in the case of output forecasting. The difference between inflation forecasting and output forecasting is that in the former case there is a central bank that announces a particular inflation target. This target works as an anchor for the forecasts of agents. Such an anchor is absent in the case of output forecasting.

The "inflation targeters" use the central bank's inflation target to forecast future inflation, i.e.,

$$\tilde{E}_t^{\text{tar}} \pi_{t+1} = \pi^* \tag{18}$$

where as before the inflation target $\pi^* = 0$

$$\text{The "extrapolators" are defined by } E_t^{\text{ext}} \pi_{t+1} = \pi_{t-1} \tag{19}$$

The market forecast is a weighted average of these two forecasts, i.e.,

$$\tilde{E}_t \pi_{t+1} = \beta_{\text{tar},t} \tilde{E}_t^{\text{tar}} \pi_{t+1} + \beta_{\text{ext},t} \tilde{E}_t^{\text{ext}} \pi_{t+1} \tag{20}$$

or

$$E_t \pi_{t+1} = \beta_{\text{tar},t} \pi^* + \beta_{\text{ext},t} \pi_{t-1} \tag{21}$$

and

$$\beta_{\text{tar},t} + \beta_{\text{ext},t} = 1 \tag{22}$$

The same selection mechanism is used as in the previous section to determine the probabilities of agents trusting the inflation target and those who do not trust it and revert to extrapolation of past inflation, i.e.,

$$\beta_{\text{tar},t} = \frac{\exp\left(\gamma U_{\text{tar},t}\right)}{\exp(\gamma U_{\text{tar},t}) + \exp(\gamma U_{\text{ext},t})} \tag{23}$$

$$\beta_{\text{ext},t} = \frac{\exp\left(\gamma U_{\text{ext},t}\right)}{\exp(\gamma U_{\text{tar},t}) + \exp(\gamma U_{\text{ext},t})} \tag{24}$$

where $U_{\text{tar},t}$ and $U_{\text{ext},t}$ are the weighted averages of past squared forecast errors of using targeter and extrapolator rules, respectively. These are defined in the same way as in Eqs. (10) and (11).

This inflation forecasting heuristics can be interpreted as a procedure of agents to find out how credible the central bank's inflation targeting is. If this is very credible, using the announced inflation target will produce good forecasts and as a result, the probabilities that agents will rely on the inflation target will be high. If on the other hand the inflation target does not produce good forecasts (compared to a simple extrapolation rule) the probability that agents will use it will be small.

The model is calibrated using the same parameters as in the previous section. First the results in the time domain are shown and then the impulse response functions are discussed.

Figure 4a presents the results for the output gap in the time domain. The same cycles in the output gap are found as in the previous section. Again these cycles are related to the waves of optimism and pessimism in the forecasting (second panel in Fig. 4a). In this particular simulation, the correlation coefficient between the fraction of optimists and the output gap is 0.86.

The results concerning the time path of inflation are shown in Fig. 4b. First concentrate on the second panel of Fig. 4b. This shows the fraction of agents using the extrapolator heuristics, i.e., the agents who do not trust the inflation target of the central bank. One can identify two regimes. There is a regime in which the fraction of extrapolators fluctuates around 50% which also implies that the fraction of forecasters using the inflation target as their guide (the "inflation targeters") is around 50%. This is sufficient to maintain the rate of inflation within a narrow band of approximately + and −1% around the central bank's inflation target. There is a second regime though which occurs when the extrapolators are dominant. During this regime the rate of inflation fluctuates significantly more. Thus the inflation targeting of the central bank is fragile. It can be undermined when forecasters decide that relying on past inflation

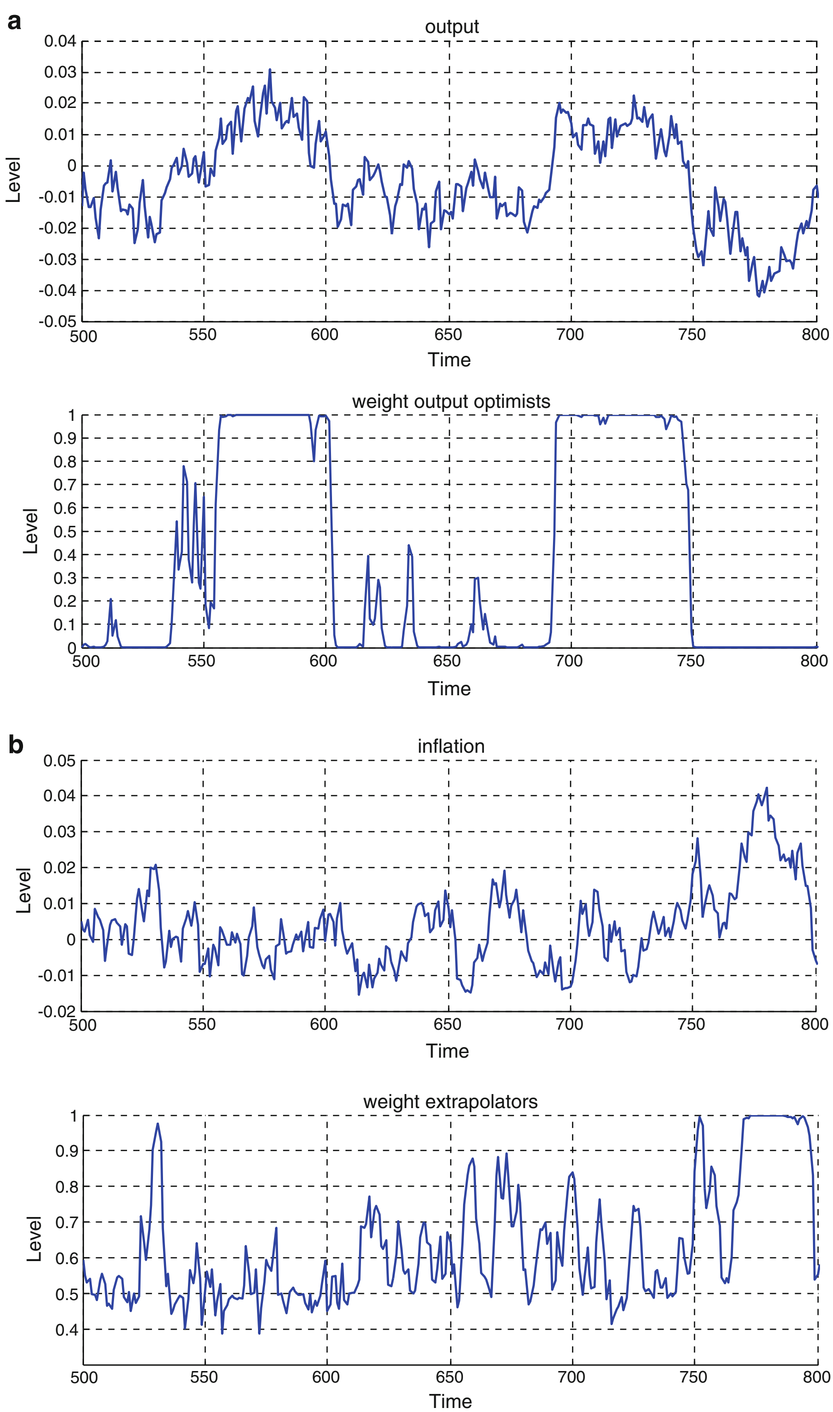

Fig. 4 **a** Output gap in the extended behavioral model, **b** inflation in the extended behavioral model

movements produces better forecast performances than relying on the central bank's inflation target. This can occur quite unpredictably as a result of stochastic shocks in supply and/or demand.

How can the central bank strengthen the inflation targeting regime? This issue is taken up in Sect. 4 where the tradeoffs between output and inflation variability are analyzed.

2.5 Animal spirits, learning and forgetfulness

The simulations reported in the previous section assumed a given set of numerical values of the parameters of the model. It was found that for this set of parameter values animal spirits (measured by the movements in the fraction of optimists) emerge and affect the fluctuations of the output gap. The correlation coefficient between the fraction of optimists and the output gap in the simulation reported in Fig. 4 is 0.86. One would like to know how this correlation evolves when one changes the parameter values of the model. I concentrate on three parameter values here,[8] the intensity of choice parameter (γ), the sensitivity of divergence in beliefs to the volatility of the output gap (δ), and the memory agents have when calculating the performance of their forecasting. The latter is represented by the parameter ω_k in Eqs. (9)–(10) and is a series of declining weights attached to past forecast errors. I define $\omega_k = (1-\rho)\rho^k$ (and $0 \leq \rho \leq 1$). The parameter ρ can then be interpreted as a measure of the memory of agents. When $\rho = 0$ there is no memory; i.e., only last period's performance matters in evaluating a forecasting rule; when $\rho = 1$ there is infinite memory, i.e., all past errors, however far in the past, obtain the same weight.

The results of the sensitivity analysis are shown in Fig. 5. The upper left hand panel shows the correlation between the output gap and the fraction of optimists for increasing values of the intensity of choice parameter, γ. It can be seen that when γ is zero (i.e., the switching mechanism is purely stochastic), this correlation is zero. The interpretation is that in an environment in which agents decide purely randomly, i.e., they do not react to the performance of their forecasting rule, there are no systematic waves of optimism and pessimism (animal spirits) that can influence the business cycle. When γ increases, the correlation increases sharply. Thus in an environment in which agents learn from their mistakes, animal spirits arise. Thus one needs a minimum level of rationality (in the sense of a willingness to learn) for animal spirits to emerge and to influence the business cycle. It appears from Fig. 5 that this is achieved with relatively low levels of γ.

The upper right panel shows the correlation between output gap and the fraction of optimists for increasing values of the parameter δ. We observe that this correlation is relatively little affected by δ. It is significant to note that when $\delta = 0$ (i.e., the divergence of beliefs is constant and unaffected by the uncertainty surrounding the movements of the output gap), the correlation is high. This means that the emergence of animal spirits does not depend on the value of δ.

[8] In appendix, I shows the results of more extensive sensitivity analyses.

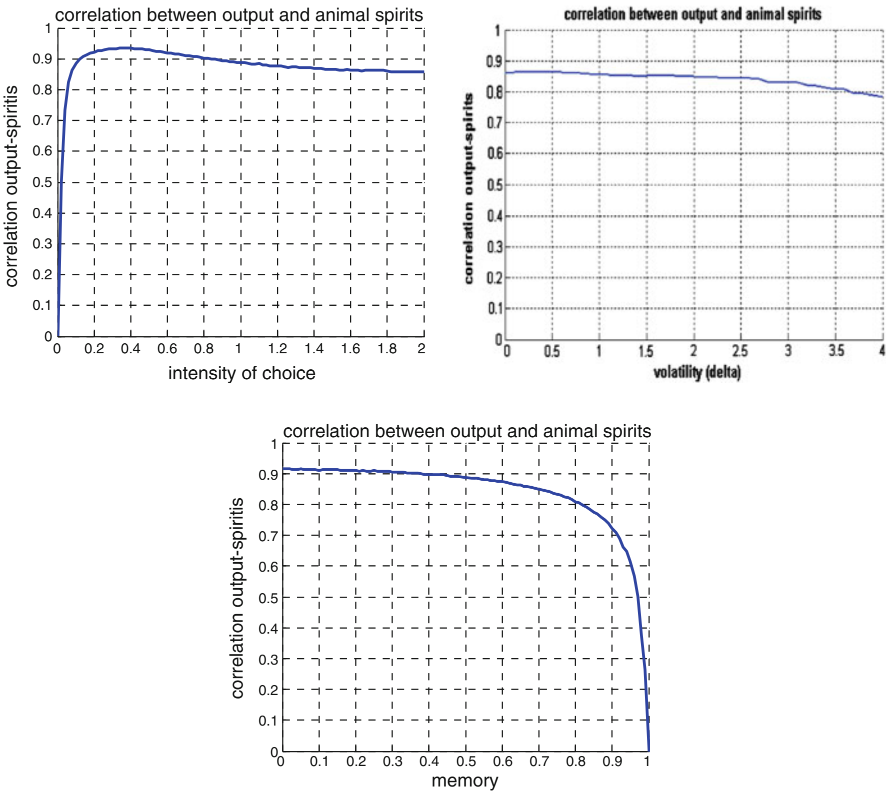

Fig. 5 Correlations between output gap and fraction of optimists

The lower panel shows the correlation between the output gap and the fraction of optimists for increasing values of the memory parameter ρ. It can be seen that when $\rho = 1$ the correlation is zero. This is the case where agents attach the same weight to all past observations, however, far in the past they occur. Put differently, when agents have infinite memory; they forget nothing. In that case animal spirits do not occur. Thus one needs some forgetfulness (which is a cognitive limitation) to produce animal spirits. Note that the degree of forgetfulness does not have to be large. For values of ρ below 0.9 the correlations between output and animal spirits are quite high.[9]

2.6 Impulse responses in the extended behavioral model

In this section, the impulse responses to a positive interest rate shock of one standard deviation are presented. Two results stand out (see Fig. 6). First the uncertainty surrounding the effects of interest rate shocks is greater and lasts longer than in the simple

[9] The importance of the degree of forgetting is also emphasized by Branch and Evans (2006). They find that the most interesting time-series dynamics arise when the "gain" under dynamic predictor selection (their term for the degree of forgetting) is not too small.

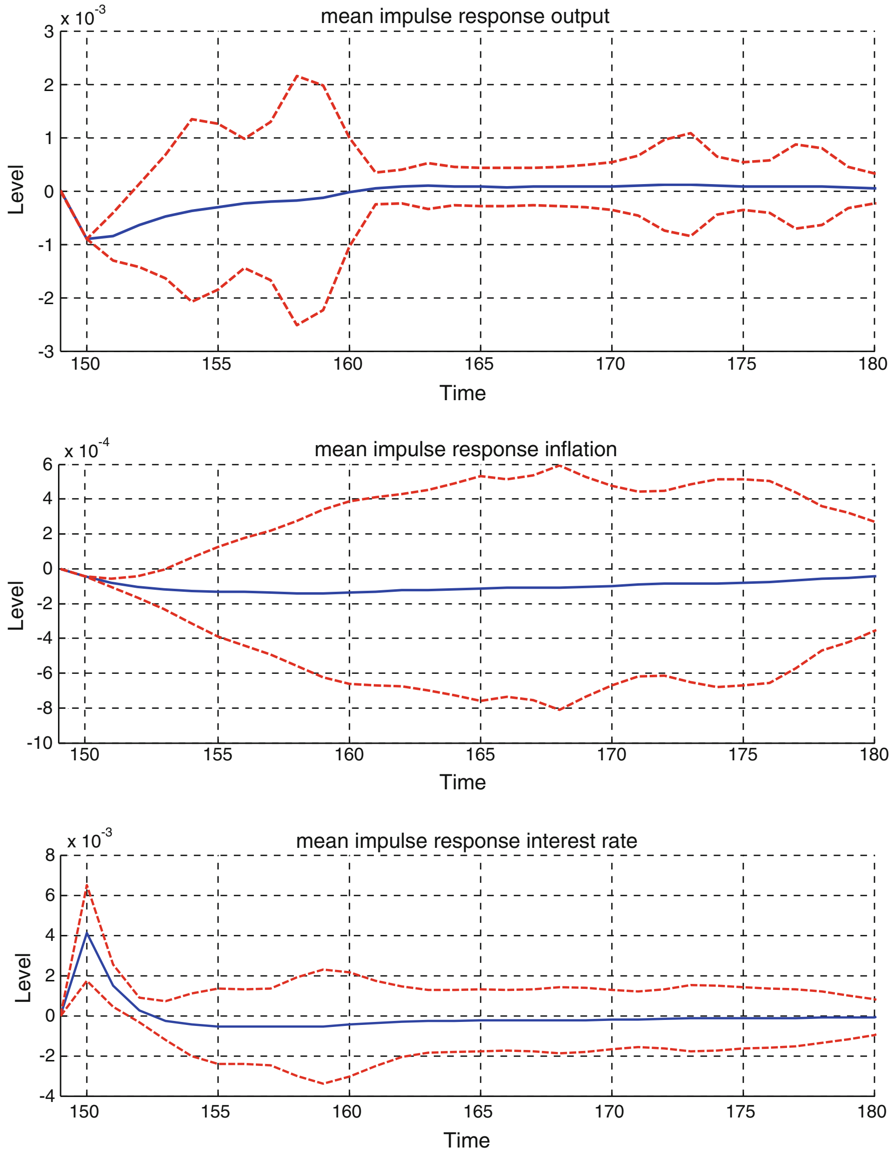

Fig. 6 Mean impulse responses to an interest rate shock in the extended behavioral model

behavioral model with homogenous inflation forecasting based on full credibility of the announced inflation target. Second, there is in this extended model considerably more inertia in inflation adjustment than in output adjustment following the interest rate shock. This feature whereby there is more inertia in inflation adjustment than in output adjustment after a shock is routinely found in VAR estimates of interest rate surprises. The inertia generated by the model finds its origin in the evolutionary process inherent in the fitness criterion guiding the selection of forecasting rules.[10]

3 Endogenous and exogenous inertia

Business cycle movements in the DSGE-models arise as a result of exogenous shocks (in productivity and preferences) and lags in the transmission of these shocks to output and inflation. Thus inertia in output and inflation are the result of the lagged transmission of exogenous shocks.

One could call the inertia (and the business cycles) introduced in the DSGE-model exogenously created phenomena. In contrast, the behavioral model presented here is capable of generating inertia (and business cycles) without imposing lags in the transmission process. This could be called endogenous inertia. This difference is illustrated by analyzing the behavioral and the rational models in the absence of lags in the transmission process in the demand and the supply equations. This is achieved by setting the parameters of the forward looking variables $a_1 = 1$ in Eq. (1) and $b_1 = 1$ in Eq. (2). The same i.i.d. shocks are then applied in both the behavioral and the rational models and the autocorrelation coefficients of the simulated series of output gaps and inflation are computed. The results are shown in Table 1. It can be seen that the behavioral model produces inertia (positive autocorrelation) in the output gap and in inflation even if there are no lags in the transmission of shocks. The rational model produces no inertia in the output gap and in inflation.

Table 1 also shows the autocorrelation coefficients obtained in models that assume lags in the transmission. These coefficients are obtained when $a_1 = 0.5$ in Eq. (1) and $b_1 = 0.5$ in Eq. (2). These are also the numerical values assumed in all the simulations reported in the previous sections. One now observes that inertia in the output gap and in inflation increases in both models. However, it can be concluded that all of the inertia obtained in the rational model is the result of the lags in the transmission process. This is not the case in the behavioral model where most of the inertia is produced endogenously.

Table 1 Autocorrelation coefficients in output gap and inflation

	Behavioral model	Rational model
No lags in transmission		
Output gap	0.77	0.07
Inflation	0.69	−0.02
Lags in transmission		
Output gap	0.89	0.79
Inflation	0.90	0.61

The autocorrelation coefficients are the averages obtained from simulating the model 1,000 times, each time over 1,000 periods

[10] A similar result was obtained by Anagastopoulos et al. (2006).

The inertia obtained in the behavioral model could also be called informational inertia. In contrast to the rational expectations model, agents in the behavioral model experience an informational problem. They do not fully understand the nature of the shock nor its transmission. They try to understand it by applying a trial and error learning rule, but they never succeed in fully understanding the complexity of the world. This cognitive problem then creates the inertia in output and prices. Thus one obtains very different theories of the business cycles in the two models.[11]

Mankiw and Reis (2002, 2006) have introduced a similar concept which they call "sticky information". In their model information inertia arises because agents find it costly to gather and make use of information. As a result, agents update their information sets infrequently. Thus, firms form expectations that are rational, given their information set, but in any given period most firms do not update their information set. This has the effect that the economy never reaches a full information rational expectations equilibrium.

4 Trade-offs between inflation and output variability

In this section the tradeoff between output and inflation variability is analyzed in the context of the extended behavioral model.

The tradeoffs are constructed as follows. Figure 7 shows how output variability (Fig. 7a) and inflation variability (Fig. 7b) change as the output coefficient (c_2) in the Taylor rule increases from 0 to 1. Each line represents the outcome for different values of the inflation coefficient (c_1) in the Taylor rule.

Figure 7a showing the evolution of output variability exhibits the expected result, i.e., as the output coefficient increases (inflation targeting becomes less strict) output variability tends to decrease. One would now expect that this decline in output variability resulting from more active stabilization comes at the cost of more inflation variability. This, however, is not found in Fig. 7b. One observes that the relationship is non-linear. As the output parameter is increased from zero, inflation variability first declines. Only when the output parameter increases beyond a certain value (in a range 0.6–0.8) inflation variability starts increasing. Thus the central bank can reduce both output and inflation variability when it moves away from strict inflation targeting ($c_2 = 0$) and engages in some output stabilization, not too much though. Too much output stabilization turns around the relationship and increases inflation variability.

Figure 7 allows us to construct the tradeoffs between output and inflation variability. These are shown in Fig. 8 for different values of the inflation parameter c_1. Take the tradeoff AB. This is the one obtained for $c_1 = 1$. Start from point A on the tradeoff.

[11] Critics of the heuristic model presented here may argue that the comparison between the rational and the heuristic model is unfair for the rational model. Indeed the heuristic model generates inertia because the evaluation and selection process of the different heuristics is backward looking. This is the reason why the heuristic model does not need lags in the transmission process to generate inertia. However, it can be argued that this evaluation and selection process can only be backward looking, and as a result, the lags that are present in the heuristic model are within the logic of that model. This contrasts with the lags introduced in the rational model: they come from outside the model. See Milani (2007b) who makes a similar point contrasting rational expectations models with learning models.

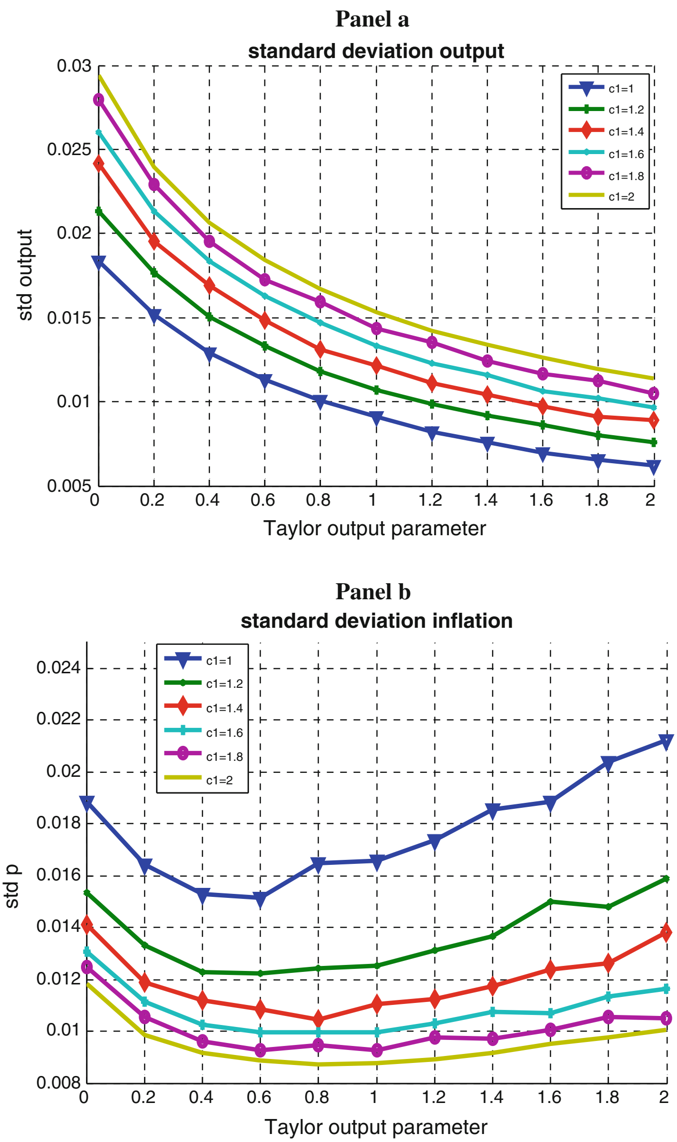

Fig. 7 Output and inflation variability

In point A, the output parameter $c_2 = 0$ (strict inflation targeting). As output stabilization increases we first move downwards. Thus increased output stabilization by the central bank reduces output and inflation variability. The relation is non-linear, however. At some point, with too high an output stabilization parameter, the tradeoff curve starts increasing, becoming a "normal" tradeoff, i.e., a lower output variability is obtained at the cost of increased inflation variability.

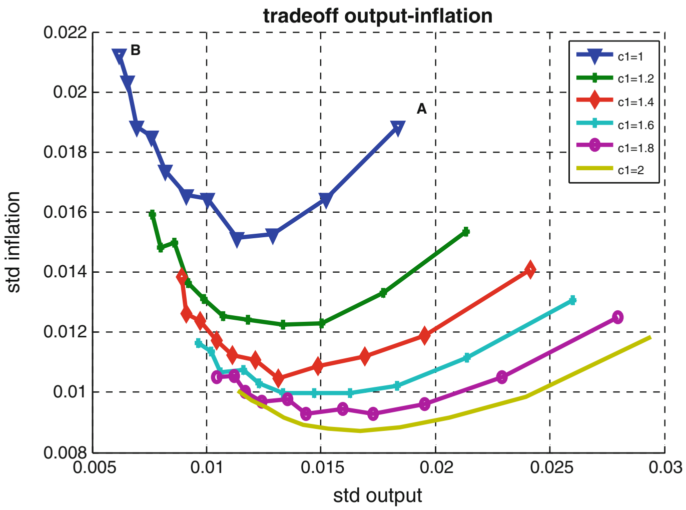

Fig. 8 Trade-offs in the extended behavioral model

How can we interpret these results? Let us start from the case of strict inflation targeting, i.e., the authorities set $c_2 = 0$. There is no attempt at stabilizing output at all. The ensuing output variability intensifies the waves of optimism and pessimism (Animal spirits). These larges waves lead to higher inflation variability. Thus, some output stabilization is good; it reduces both output and inflation variability by preventing too large swings in animal spirits. With no output stabilization at all ($c_2 = 0$) the forces of animal spirits are so high that the high output variability also increases inflation volatility through the effect of the output gap on inflation (supply equation). Too much output stabilization, however, reduces the stabilization bonus provided by a credible inflation target. When the central bank attaches too much importance to output stabilization it creates more scope for better forecasting performance of the inflation extrapolators, leading to more inflation variability.

Figure 8 also tells us something important about inflation targeting. We note that increasing the inflation parameter in the Taylor rule (c_1) has the effect of shifting the tradeoffs downwards, i.e., the central bank can improve the tradeoffs by reacting more strongly to changes in inflation.[12] The central bank achieves this improvement in the tradeoff because by reacting more intensely to changes in inflation it reduces the probability that inflation extrapolators will tend to dominate the market, and as a result it reduces the probability that inflation targeting looses credibility. Such a loss of credibility destabilizes both inflation and output. Thus maintaining credibility of inflation targeting is an important source of macroeconomic stability in our behavioral model.

[12] A similar result on the importance of strict inflation is also found in Orphanides and Williams (2005), and Gaspar et al. (2006) who use a macroeconomic model with least squares learning. Our paper stresses that in addition to setting a sufficiently high value for the inflation parameter in the Taylor rule, it also matters to set a sufficiently high value for the output parameter.

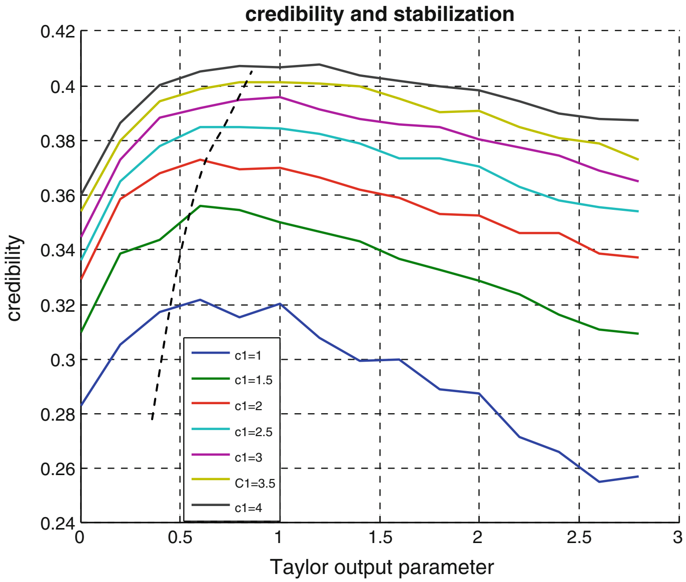

Fig. 9 Credibility and stabilization

The previous results suggest that there is a relationship between the parameters c_1 and c_2 in the Taylor equation and the credibility of the inflation target. This relationship can be analyzed in more detail. Inflation credibility can be given a precise definition in the model. It can be defined as the fraction of agents who use the inflation target to forecast inflation ("inflation targeters"). Thus when more agents use the announced inflation target to forecast inflation, credibility increases. Figure 9 presents the relationship between inflation credibility and the parameters c_1 and c_2. On the horizontal axis, the parameter c_2 (output parameter) is set out; on the vertical axis the inflation credibility. The latter is obtained by simulating the model 200 times and computing the mean fraction of inflation targeters for different values of the c_1 and c_2. Each curve represents the relation between credibility and the output parameter (c_2) for different values of the inflation parameter (c_1). It has a non-linear feature, i.e., when the output parameter c_2 increases this has the effect of first increasing inflation credibility until a maximum is reached. Then credibility starts declining when c_2 increases further. This non-linear feature is found for all values of c_1. Note that the maximum points obtained in Fig. 10 correspond to the minimum point of the tradeoffs in Fig. 8.

These results have the following interpretation. When the central bank increases its effort to stabilize output this has at first a positive effect on the credibility of its inflation target. The reason, as was discussed earlier, is that by stabilizing output, the central bank also reduces the amplitude of the animal spirits thereby stabilizing output and inflation.

Finally, Fig. 9 shows that for increasing values of c_1 the credibility curves increase. Thus a central bank can improve its inflation credibility by reacting more strongly to changes in inflation. This feature then underlies the result found in Fig. 8 that higher values of c_1 improve the tradeoff between inflation and output variability.

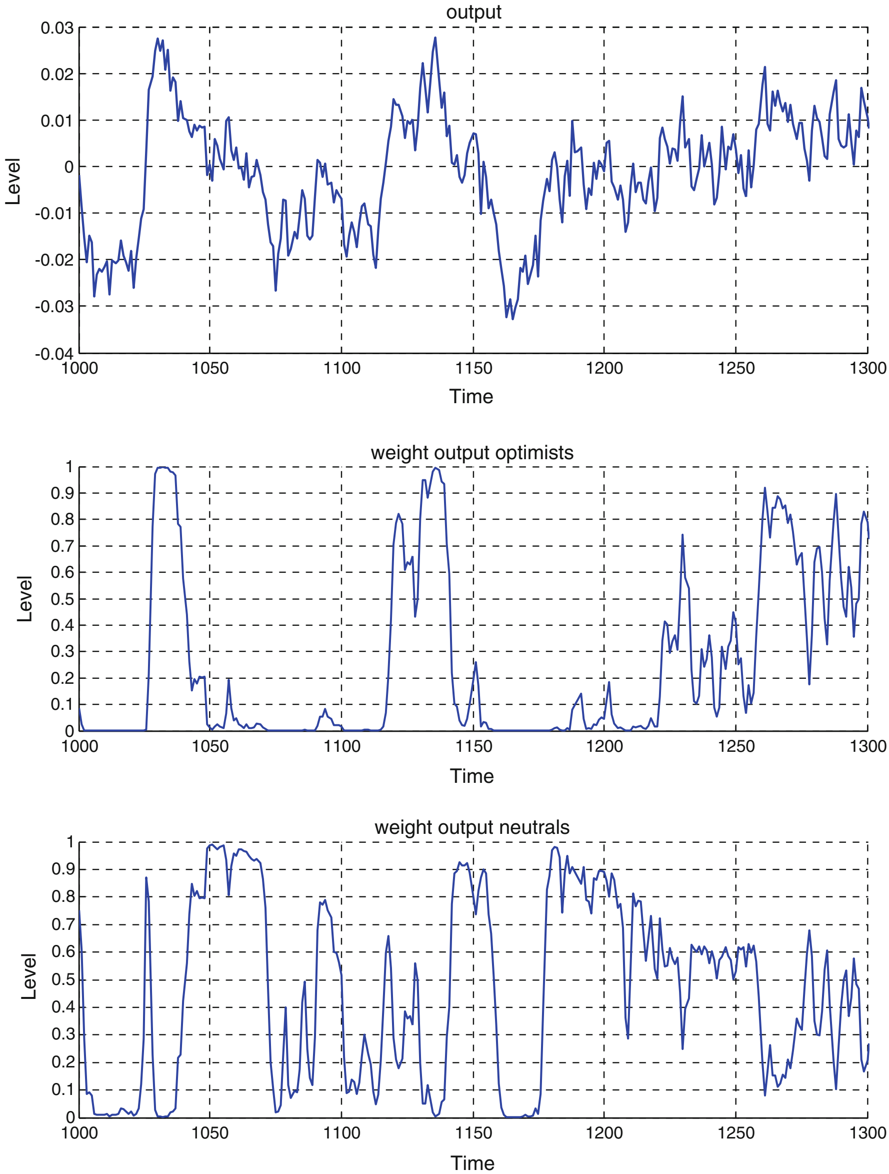

Fig. 10 Output gap and animal spirits in a three-agent model

5 A further extension: a three-agent model

The heuristics used in the forecasting of the output gap assumes that agents are biased either in the positive or in the negative sense. It does not allow for the possibility that agents may (even by chance) use an unbiased rule. In this section, the question is analyzed of how the model is affected if we allow for a third, unbiased, forecasting rule. This idea is implemented by defining a third forecasting rule to be

$$\tilde{E}_t^{\mathrm{un}} y_{t+1} = 0 \tag{25}$$

where $\tilde{E}_t^{\mathrm{un}} y_{t+1}$ is the unbiased forecasting rule.
As before a selection mechanism is assumed, whereby agents can switch between the three rules. This implies first that agents compute the performance (utility) of using these rules as in Eqs. (10) and (11) for the optimistic and pessimistic rules. For the unbiased rule this becomes

$$U_{\mathrm{un},t} = -\sum_{k=1}^{\infty} \omega_k \left[y_{t-k} - \tilde{E}_{\mathrm{un},t-k-1} y_{t-k} \right]^2 \tag{26}$$

The corresponding probabilities of using the three rules now are:

$$\alpha_{\mathrm{opt},t} = \frac{\exp\left(\gamma U_{\mathrm{opt},t}\right)}{\exp(\gamma U_{\mathrm{opt},t}) + \exp(\gamma U_{\mathrm{pes},t}) + \exp(\gamma U_{\mathrm{un},t})} \tag{27}$$

$$\alpha_{\mathrm{pes},t} = \frac{\exp\left(\gamma U_{\mathrm{pes},t}\right)}{\exp(\gamma U_{\mathrm{opt},t}) + \exp(\gamma U_{\mathrm{pes},t}) + \exp(\gamma U_{\mathrm{un},t})} \tag{28}$$

$$\alpha_{\mathrm{un},t} = \frac{\exp\left(\gamma U_{\mathrm{un},t}\right)}{\exp(\gamma U_{\mathrm{opt},t}) + \exp(\gamma U_{\mathrm{pes},t}) + \exp(\gamma U_{\mathrm{un},t})} \tag{29}$$

The model was simulated in the time domain using the same calibration as in Sect. 2.4 (the extended behavioral model). The results are shown in Fig. 10. The top panel shows the output gap in the time domain; the middle panel shows the fractions (probabilities) of the agents using the optimistic forecasting rule; and the bottom panel shows the fractions using the unbiased rule. (Note that the pessimistic fractions are equal to 1 minus the previous two fractions).

The results are rather interesting. The existence of unbiased predictors does not eliminate the occurrence of waves of optimism and pessimism. As one can see from the center panel of Fig. 10, there are regularly periods during which the market is dominated by optimism, despite the fact that there are agents that use the unbiased forecasts. Similarly, there are periods where the market is dominated by pessimistic forecasts. These waves of optimism then affect output in a self-fulfilling way.

In order to find out how important animal spirits are in shaping fluctuations in the output gap the simulated output gap was correlated with the fraction of optimists in the market. This was done both for the three-agent model and for the two-agent model of the previous sections. The average correlation coefficient is 0.84 in the three-agent model and 0.86 in the two-agent model. This means that the addition of a third unbiased rule does not reduce the correlation of the output gap and the "animal spirits" in a significant way. Thus, one of the main results of this paper, i.e., that waves of optimism and pessimism (animal spirits) can emerge, is maintained even in a world where agents have access to unbiased forecasts.

6 Animal spirits in the macroeconomic literature

As mentioned in the introduction our model is not the first one to formalize the idea of animal spirits, i.e., expectations driven business cycle movements. In fact there is a very large literature that has done so in various ways. In this section we compare our approach to these different strands of the literature.

There is a first important strand of literature producing models with sunspot-equilibria. This literature started with Shell (1977) and Azariadis (1981), and includes Azariadis and Guesnerie (1986). Models with sunspot equilibria are found both in the RBC-framework (see Benhabib and Farmer 1994 and Farmer and Guo 1994 as in the New-Keynesian framework Clarida et al. 2000). In these models there are multiple REE solutions, which include "self-fulfilling" solutions that depend on extraneous variables ("sunspots"). These models provide for a fully rational way to model animal spirits, implementing the basic insights of Keynes.

A very similar strand of literature is provided by models generating global indeterminacies. Howitt and McAfee (1992), Evans et al. (1998), and Evans and Honkapohja (2001) develop models with externalities that lead to multiple steady states. These papers exhibit equilibria with random switching between high and low activity steady states (or, in the Evans et al. (1998) paper, between high and low growth rates). The rational expectations solutions in these models depend on an exogenous two-state Markov variable that acts to coordinate expectations and triggers the shifts between high (optimistic) and low (pessimistic) states.[13]

The common characteristics of these multiple equilibria models is an exogenous process that leads to switches between these different equilibria. The model presented in the present paper differs from these multiple equilibria models in that it does not rely on extraneous "sunspots." The economic fluctuations are driven instead by the intrinsic random shocks of the model.

The latter is also the case in Evans and Honkapohja (2001, ch. 14), in which the fluctuations are driven by productivity shocks, with the learning rule leading to occasional shifts between equilibria. However, our model differs from this and the previous models in that it does not have multiple equilibria under Rational Expectations. Instead, the multiplicity is the result of the restricted list of forecast rules from which the agents can choose.

Our model comes closest to Branch and Evans (2007) who also use a discrete choice framework inside a simple monetary model and who find regime-switching behavior driven by the shocks in the model. The shifts in expectations, as agents occasionally move from pooling on one forecast rule to pooling on the other rule, is a kind of self-fulfilling phenomenon. The similarity with our model is that in the Branch and Evans (2007) model there is a unique equilibrium under Rational Expectations, but because agents must choose between two misspecified models, there are multiple equilibria (of a type that the authors carefully define). Under real-time updating of the discrete-choice type, this leads to regime-switching behavior over time. However, in Branch and Evans (2007), the switching is between high and low volatility regimes, whereas

13 It should be noted that in each of these models fluctuations can also arise as the outcome of a boundedly rational learning process.

in our paper it is also between high and low activity states, generating business cycle effects that are of first order. Although the two set-ups differ in a number of other details, the critical one is that in our paper the choice of the two forecast rules is between two "biased" rules, i.e., between an optimistic forecast rule and a pessimistic one. The tendency for agents at any moment to pool on one of the forecast rules then leads to the results.

7 Conclusion

The idea that the business cycle is driven by waves of optimism and pessimism has a long tradition. It was made popular by Keynes who called these waves "animal spirits". Outside academia, this idea continues to enjoy a wide acceptability in explaining movements in economic activity. Only recently has it obtained some academic respectability again (see Akerlof and Shiller 2009).

As a result of the systematic incorporation of rational expectations in macroeconomic theory the idea that waves of optimism and pessimism can have an independent influence on economic activity has been discarded from mainstream academic thinking. The DSGE-models which have now achieved a near monopoly in macroeconomics, view business cycles as the result of a combination of exogenous shocks and slow transmission of these shocks into output and prices. In these models there is no place for endogenously generated business cycles.

The problem of the DSGE-models (and more generally of macroeconomic models based on rational expectations) is that they assume extraordinary cognitive capabilities of individual agents. Recent developments in other disciplines including psychology and brain science document that individual agents struggle with limited cognitive abilities, restricting their capacity to understand the world. As a result, individual agents use small bits of information and simple rules to guide their behavior.

I have used these new insights to develop a macroeconomic model in which the cognitive limitations of agents take center stage. Once one moves into a world of cognitive limitations one faces the problem that agents use simple and biased rules to forecast output and inflation. In order to provide discipline in the use of these rules a learning mechanism was introduced that allows for the selection of those rules that are more profitable than others. This learning mechanism ensures that although agents use biased rules the market forecasts are unbiased.

The ensuing "behavioral model" produces a number of results that distinguishes it from the rational expectations models. First, the behavioral model creates correlations in beliefs which in turn generate waves of optimism and pessimism. The latter produce endogenous cycles which are akin to the Keynesian "animal spirits". These animal spirits are found to become more important when agents are willing to learn from the errors produced by biased beliefs. But, at the same time, there must be some forgetfulness about errors made long ago for animal spirits to emerge and to influence the business cycle.

Second, due to its non-linearity, the behavioral model produces a degree of uncertainty about the transmission of monetary policy shocks that is different from the uncertainty obtained in DSGE-models. In the latter linear models, uncertainty about the effects of monetary policy shocks arises only because of the lack of precision in the estimation of the structural parameters of the model. In the behavioral model there is an additional dimension to uncertainty. This is that the same policy shock can have different effects depending on the state of the economy, including the degree of optimism and pessimism agents have about the future. As a result, the transmission of policy shocks depends on the timing of these shocks.

A third result is that the inflation targeting regime turns out to be of great importance to stabilize the economy in a behavioral model. In a regime in which inflation targeting is credible, inflation and output variability are greatly reduced. The reason is that credibility also helps to reduce correlations in beliefs and the ensuing self-fulfilling waves of optimism and pessimism. In a regime of imperfect credibility, these waves are more pronounced.

However, and fourth, strict inflation targeting is not an optimal policy. Some output stabilization (given a credible inflation target) also helps in reducing the correlation of biased beliefs thereby reducing the scope for waves of optimism and pessimism to emerge and to destabilize output and inflation.

Finally, the behavioral model provides for a very different theory of the business cycle as compared to the business cycle theory implicit in the DSGE-models. In the DSGE-models, business cycle movements in output and prices only arise because rational agents cannot adjust their optimal plans instantaneously after an exogenous disturbance. Price and wage stickiness prevent such instantaneous adjustment. As a result, these exogenous shocks produce inertia and business cycle movements.

Agents in the behavioral model not only cannot instantaneously adjust their prices but they also experience an informational problem. They do not fully understand the nature of the shock nor its transmission. They use a trial and error learning process aimed at distilling information. This cognitive problem then creates inertia in output and prices in addition to the price inertia originating from the fact that contracts cannot be changed instantaneously. Thus, a richer theory of the business cycles is obtained.

These differences also have policy implications. In order to reduce output volatility in the DSGE-models more flexibility in prices and wages is required. That's why many central banks call for more flexibility of wages and prices. In a more flexible world, central banks will not be called upon so often to stabilize output, and thereby set price stability at risk.

In the behavioral model, business cycle movements in output arise from informational inertia. Thus, even if prices and wages become more flexible, this will not necessarily reduce the business cycle movements in output. As a result, society's desire to stabilize output will not be reduced. And central banks that inevitably respond to these desires will face the need to stabilize output.

The behavioral model proposed in this paper can be criticized for being "ad hoc". There is no doubt that the model has ad hoc features, i.e., assumptions that cannot be grounded on some deeper principle, and therefore have to be taken for granted. In defence of this "ad hoc querie", the following should be stressed. Once we leave the comfortable world of agents who experience no limits to their cognitive abilities, ad hoc assumptions are inevitable. This is due to the fact that we do not fully comprehend the way individuals with cognitive limitations process information.

The research presented in this paper should be considered to be preliminary. In order to be convincing as an alternative modeling strategy, the predictions of the model will have to be confronted more systematically with the data. In addition, the menu of heuristics which is extremely small in this paper, will have to be broadened so that the selection of the "fittest" rules can occur using a wider pool of possible rules.

Appendix A: Parameter values of the calibrated model

Heuristic model

$\pi^* = 0$ %the central bank's inflation target,
$a_1 = 0.5$ %coefficient of expected output in output equation,
$a_2 = -0.2$ %interest elasticity of output demand,
$b_1 = 0.5$ %coefficient of expected inflation in inflation equation,
$b_2 = 0.05$ %coefficient of output in inflation equation,
$c_1 = 1.5$ %coefficient of inflation in Taylor equation,
$c_2 = 0.5$ %coefficient of output in Taylor equation,
$c_3 = 0.5$ %interest smoothing parameter in Taylor equation,
$\beta = 1$ %fixed divergence in beliefs,
$\delta = 2$ %variable component in divergence of beliefs,
$\gamma = 1$ %intensity of choice parameter,
$\rho = 0.5$ %ρ measures the speed of declining weights in mean squares errors (memory parameter),
sigma1 = 0.5 %standard deviation shocks output gap.
sigma2 = 0.5 %standard deviation shocks inflation,
sigma3 = 0.5 %standard deviation shocks Taylor.

Rational model

This uses the same parameter values as in the heuristic model.

Appendix B: Sensitivity analysis

In this Appendix, I analyze how sensitive the results are to different numerical values of the "learning parameters" in the model. These are the parameters describing how agents use and select forecasting rules. There are three such parameters in the model. First, there is the divergence between the optimists' and pessimists' beliefs. I analyze the sensitivity to the coefficient β in Eq. (6) which measures the sensitivity of the divergence of beliefs to output uncertainty.

Second, there is the memory agents have when calculating the performance of their forecasting, as represented by the parameter ρ.

Finally, there is the parameter γ which measures the intensity with which agents are willing to switch to a better performing rule [see Eqs. (12)–(13)].

The sensitivity of the results with respect to these parameters are discussed by showing how these parameters affect the volatility of inflation and output, and the degree of inertia (autocorrelation) in these variables.

B.1 Sensitivity to uncertainty

The upper panels of Fig. 11 show how the volatility of output and inflation depends on the degree to which the divergence in beliefs depends on output volatility (uncertainty). One observes that when uncertainty increases, the volatility of output and inflation increases substantially. The lower panels of Fig. 11 indicate that increasing uncertainty tends to increase inertia in output (autocorrelation), with little effect on inflation inertia.

B.2 Sensitivity to memory

The memory agents use when they evaluate their past performance, plays an important role in the dynamics of the model. This is illustrated by Fig. 12. The upper part shows the volatility of output and inflation for different values of the memory parameter (ρ). It is striking to find that with increasing memory the volatility of these variables declines significantly. Note however that the relationship is non-linear. One needs a large value of ρ for the volatility to start declining. In the simulations presented in

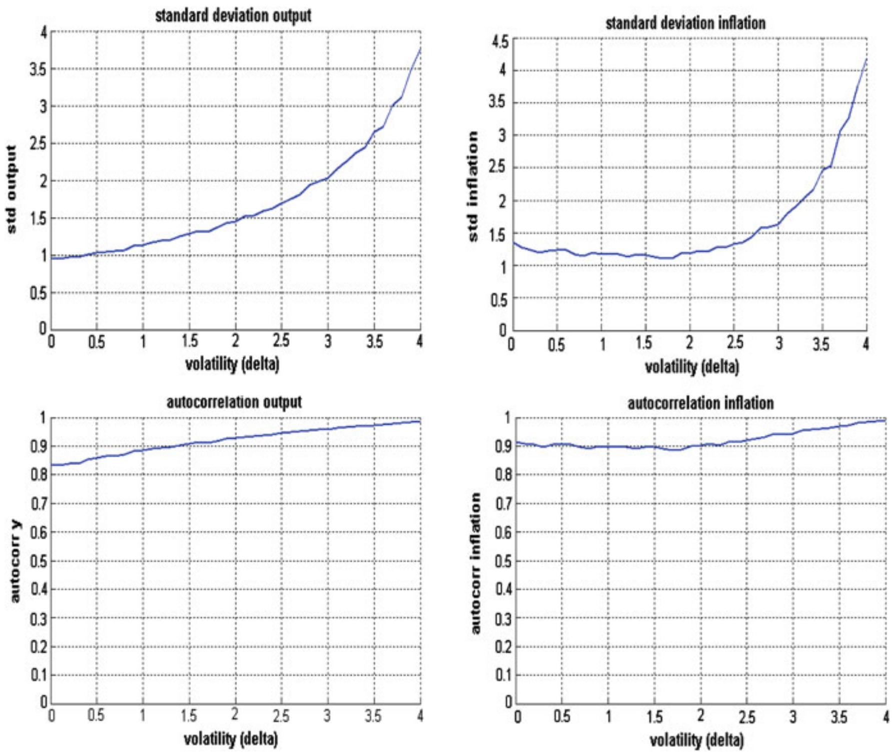

Fig. 11 Standard deviation and autocorrelation of output gap and inflation. The standard deviations and autocorrelation coefficients are the averages obtained from simulating the model 1,000 times, each time over 1,000 periods

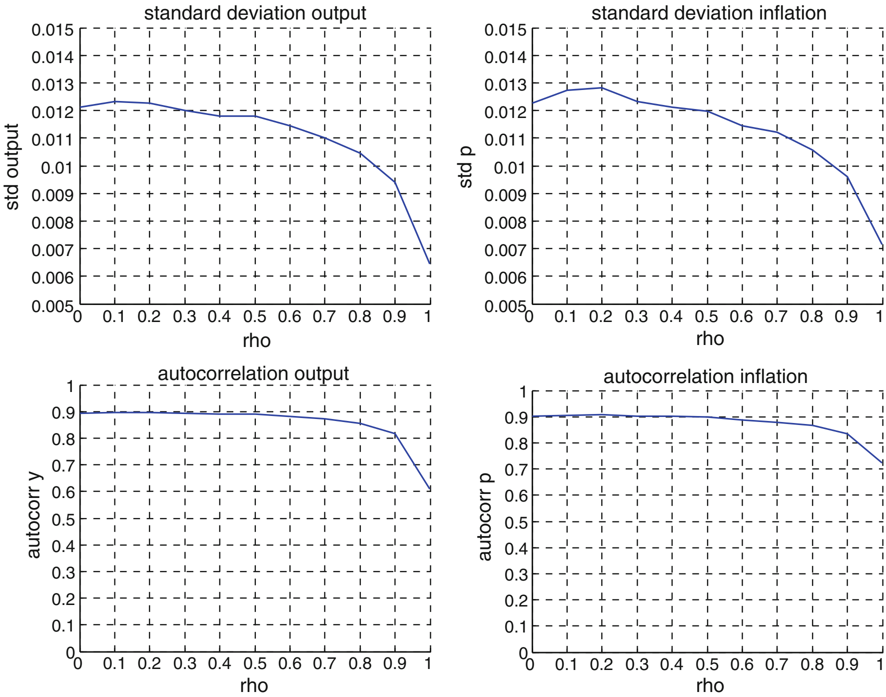

Fig. 12 Standard deviation and autocorrelation of output gap and inflation. The standard deviations and autocorrelation coefficients are the averages obtained from simulating the model 1,000 times, each time over 1,000 periods

the previous sections $\rho = 0.5$. The volatility obtained for this parameter value is very close to the volatility obtained when $\rho = 0$ (i.e., when agents have no memory and only the performance of the last period matters).

Similar results are obtained with the autocorrelation coefficients of output and inflation. For low and medium values of ρ the autocorrelation coefficients are relatively constant. One needs a sufficiently large value of the memory parameter to reduce the autocorrelation coefficients significantly. Thus long memory tends to stabilize output and inflation and to reduce inertia in these variables.

B.3 Sensitivity to intensity of choice

The intensity of choice parameter γ parametrizes the extent to which the deterministic component of utility determines actual choice. When $\gamma = 0$ utility is purely stochastic. In that case the probability to be optimist (or pessimist) is constant and exactly 0.5. When $\gamma = \infty$ utility is fully deterministic and the probability of using an optimistic rule is either 1 or 0 depending on whether the optimistic rule outperforms the pessimistic one or not.

Figure 13 shows that an increase in γ raises volatility and inertia. The upper panel shows the volatility of output and inflation as a function of γ. A clear positive relation

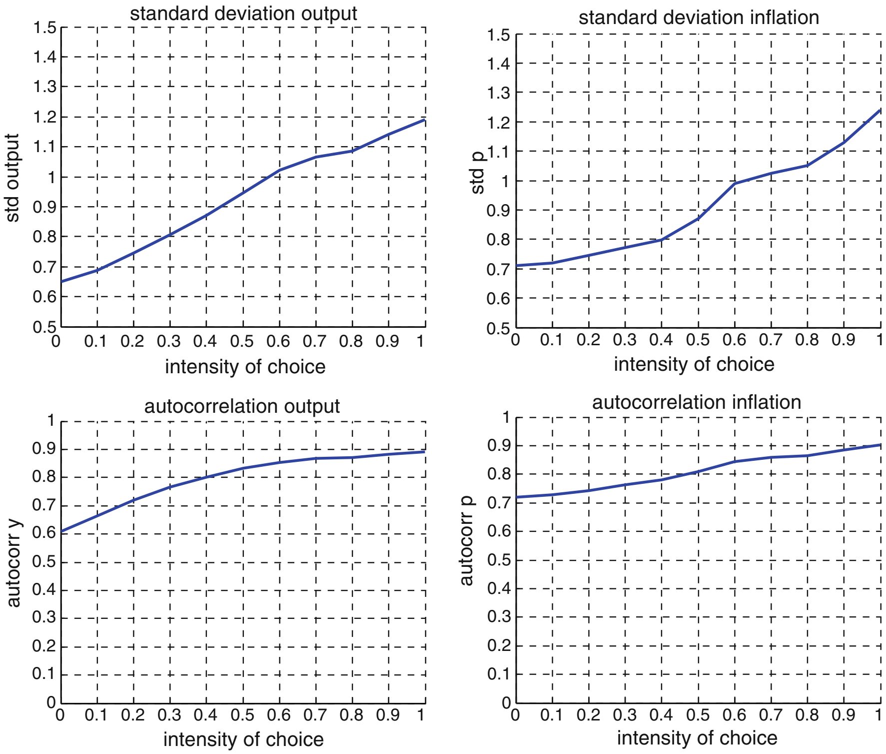

Fig. 13 Standard deviation and autocorrelation of output gap and inflation. The standard deviations and autocorrelation coefficients are the averages obtained from simulating the model 1,000 times, each time over 1,000 periods

can be observed. The lower panel shows how the autocorrelation coefficients increase when intensity of choice is increased.

It can be concluded that as utility becomes more deterministic, i.e., agents come closer to rational behavior (in the sense of increasing willingness to learn), the volatility of output and inflation and their inertia increase.

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