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The scientific foundation of dynamic stochastic general equilibrium (DSGE) models

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Abstract DSGE-models provide a coherent framework of analysis. This coherence is brought about by restricting acceptable behavior of agents to dynamic utility maximization and rational expectations. 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. In addition, these models need a lot of ad-hoc assumptions to make them fit the data. I argue that we need models that take into account the limited cognitive abilities of agents. One can introduce rationality in such models by assuming "trial and error" learning. I propose such a model and I analyze its implications.

Keywords Behavioral macroeconomics · DGSE models · Inflation · Methodology of macroeconomics · Output gap

JEL Classification E13 · E17 · E30

1 Introduction

One of the surprising developments in macroeconomics is the systematic incorporation of the paradigm of the utility maximizing forward looking and fully informed agent into macroeconomic models. This development started with the rational expectations revolution of the 1970s, which taught us that macroeconomic models can be accepted only if agents' expectations are consistent with the underlying model structure. The real business cycle theory (RBC) introduced the idea that macroeconomic models should be "micro-founded", i.e., should be based on dynamic utility maximization. While RBC models had no place for price rigidities and other inertia, the New Keynesian School systematically introduced rigidities of all kinds into similar micro-founded models. These developments occurred in the ivory towers of academia for several decades until in recent years these models were implemented empirically in such a way that they have now become tools of analysis in the boardrooms of

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central banks. The most successful implementation of these developments are to be found in the Dynamic Stochastic General Equilibrium models (DSGE-models) that are increasingly used in central banks for policy analysis (see Smets and Wouters 2003, 2007; Christiano et al. 2007; Adjemian et al. 2007).

These developments are surprising for several reasons. First, while macroeconomic theory enthusiastically embraced the view that agents fully understand the structure of the underlying models in which they operate, other sciences like psychology and neurology increasingly uncovered the cognitive limitations of individuals (see e.g. Stanovich and West 2000; Damasio 2003; Kahneman 2002; Camerer et al. 2005). We learn from these sciences that agents understand only small bits and pieces of the world in which they live, and instead of maximizing continuously taking all available information into account, agents use simple rules (heuristics) in guiding their behavior and their forecasts about the future. This raises the question of whether the micro-founded macro-economic theory that has become the standard is well-grounded scientifically.

A second source of surprise in the development of macroeconomic modeling in general and the DSGE-models in particular is that other branches of economics, like game theory and experimental economics have increasingly recognized the need to incorporate the limitations agents face in understanding the world. This has led to models that depart from the rational expectations paradigm (see e.g. Thaler 1994).

Standard macroeconomics has been immune for these developments. True, under the impulse of Sargent (1993) and Evans and Honkapohja (2001) there has been an attempt to introduce the notion in macroeconomic models that agents should not be assumed to be cleverer than econometricians and that therefore they should be modeled as agents who learn about the underlying model as time passes. This has led to learning in macroeconomics. The incorporation of learning in macroeconomics, however, has up to now left few traces in standard macroeconomic models and in the DSGE-models.

In the first part of this paper we subject the DSGE-models to a methodological analysis using the main insights we have obtained from other disciplines. We will ask the question of whether these models are scientifically well founded. In a second part, we develop an alternative stylized version of a macroeconomic model that incorporates the idea that agents use simple rules (heuristics) in forecasting and we contrast the results of this "behavioral model" with a stylized version of the DSGE-model, which will be labeled the "rational model".

2 The scientific foundation of the DSGE-models

The DSGE-models embody the two central tenets of modern macroeconomics. The first one is that a macroeconomic model should be based ("micro founded") on dynamic utility maximization of a representative agent. The second one is that expectations should be model-consistent which implies that agents make forecasts based on the information embedded in the model. This idea in turn implies that agents have a full understanding of the structure of the underlying model.

There can be no doubt that this approach to macroeconomics has important advantages compared to previous macroeconomic models. The main advantage is that it provides for a coherent and self-contained framework of analysis. This has great intellectual appeal. There is no need to invoke ad-hoc assumptions about how agents behave and how they make forecasts. Rational expectations and utility maximization introduce discipline in modeling the behavior of agents.

The scientific validity of a model should not be based on its logical coherence or on its intellectual appeal, however. It can be judged only on its capacity of making empirical predictions that are not rejected by the data. If it fails to do so, coherent and intellectually appealing models should be discarded. Before turning our attention to the empirical validation of models based on dynamic utility maximization and rational expectations, of which the DSGE-models are now the most prominent examples, we analyze the plausibility of the underlying assumptions about human behavior in these models.

There is a very large literature documenting deviations from the paradigm of the utility maximizing agent who understands the nature of the underlying economic model. For recent surveys, see Kahneman and Thaler (2006) and Della Vigna (2007). This literature has followed two tracks. One was to question the idea of utility maximization as a description of agents' behavior (see Kirchgässner 2008 for an illuminating analysis of how this idea has influenced social sciences). Many deviations have been found. A well-known one is the framing effect. Agents are often influenced by the way a choice is framed in making their decisions (see Tversky and Kahneman 1981). Another well-known deviation from the standard model is the fact that agents do not appear to attach the same utility value to gains and losses. This led Kahneman and Tversky (1973) to formulate prospect theory as an alternative to the standard utility maximization under uncertainty.

We will not deal with deviations from the standard utility maximization model here, mainly because many (but not all) of these anomalies can be taken care of by suitably specifying alternative utility functions. Instead, we will focus on the plausibility of the rational expectations assumption and its logical implication, i.e., that agents understand the nature of the underlying model.

It is no exaggeration to say that there is now overwhelming evidence that individual agents suffer from deep cognitive problems limiting their capacity to understand and to process the complexity of the information they receive.

Many anomalies that challenge the rational expectations assumption were discovered (see Thaler 1994 for spirited discussions of these anomalies; see also (Camerer et al. 2005; Della Vigna 2007). We just mention "anchoring" effects here, whereby agents who do not fully understand the world in which they live are highly selective in the way they use information and concentrate on the information they understand or the information that is fresh in their minds. This anchoring effect explains why agents often extrapolate recent movements in prices.

In general the cognitive problem which agents face leads them to use simple rules ("heuristics") to guide their behavior (see Gabaix 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. The challenge when we try to model heuristics will be to introduce discipline in the selection of rules so as to avoid that "everything becomes possible".

One important implication of the assumption that agents know the underlying model's structure is that all agents are the same. They all use the same information set including the information embedded in the underlying model. As a result, DSGE-models routinely restrict the analysis to a representative agent to fully describe how all agents in the model process information. There is no heterogeneity in the use and the processing of information in these models. This strips models based on rational expectations from much of their interest in analyzing short-term and medium-term macroeconomic problems which is about the dynamics of aggregating heterogeneous behavior and beliefs (see Colander et al. 2008).[1]

It is fair to conclude that the accumulated scientific evidence casts doubts about the plausibility of the main assumption concerning the behavior of individual agents in DSGE-models, i.e., that they are capable of understanding the economic model in which they operate and of processing the complex information distilled from this model. Instead the scientific evidence suggests that individual agents are not capable of doing so, and that they rely on rules that use only small parts of the available information.

One could object here and argue that a model should not be judged by the plausibility of its assumptions but rather by its ability to make powerful empirical predictions. Thus, despite the apparent implausibility of its informational assumption, the macroeconomic model based on rational expectations could still be a powerful one if it makes the right predictions. This argument, which was often stressed by Milton Friedman, is entirely correct. It leads us to the question of the empirical validity of the rational macromodels in general and the DSGE-models in particular.

The main problem of the "pure" micro-founded macro-model with forward looking agents appears to be that it underestimates the degree of inertia in wages and prices. For example, it predicts that when new information reaches the market rational agents will immediately change their optimal plans, leading to instantaneous price changes. This prediction flies in the face of empirical evidence that shows quite universally that prices have a strong inertial component and react sluggishly to shocks (see Nelson 1998; Estrella and Furher 1992 for empirical evidence; see also Walsh 2003).

Thus, right from the start, the micro-founded macroeconomic models had to be sent back to the repair shop. Once in the repair shop, macro theorists diluted their ambition to "micro-found" the macro-theory by introducing ad-hoc assumptions about why agents do not adjust their plans instantaneously and why prices are rigid. The pure micro-founded model received a "New Keynesian" treatment (see e.g. Clarida et al. 1999; Woodford 2003). The main characteristics of this "repair shop treatment" were to add lags into the model so as to create the necessary inertia observed in the data. This was done in several ways.

First, consumers were modeled as agents subject to habit formation. This trick allowed one to introduce lagged consumption in the utility function and added welcome inertia. Few theorists, however, bothered about the inconsistency of assuming super-rational agents that can continuously optimize using the latest available information and yet are prone to strange habits that prevent them from acting according to the optimal plan and from using all available information.

A second popular way to introduce inertia in the model has been to invoke Calvo pricing in which firms are constrained in adjusting prices instantaneously (Christiano et al. 2001). Again the inconsistency was brushed under the carpet. Why is it that in a world where everybody understands the model and each other's rationality, agents would not want to go immediately to the optimal plan using the optimal price?

The use of Calvo-pricing rules is often justified by invoking institutional restrictions that limit the freedom of action of individual firms. But again the question arises here why rational and perfectly informed agents would accept institutions that limit their freedom to set optimal plans. After all, it is against their own interest to accept such limitations. It is not

[1] There have been attempts to model heterogeneity of information processing in rational expectations models. These have been developed mainly in asset market models. Typically, it is assumed in these models that some agents are fully informed (rational) while others, the noise traders, are not. See e.g. De Long et al. (1990).

only against the interests of the firms, but also of consumers and workers, who in the rational macroeconomic models are agents who perfectly understand the world and their own interests and will always want to maximize their utilities. Any limitation on their optimizing behavior reduces their welfare. Thus in the context of DSGE-models these limitations should not be invoked. If they exist in the real world, it is proof that this should be interpreted as evidence against DSGE-models. We are forced to conclude that Calvo pricing is an ad hoc assumption forced unto the model to create enough inertia so that it would fit the data better.

Other limitations on optimizing behavior (e.g., rule of thumb consumers) have been introduced that can be interpreted in a similar way.

Thus, when the models came out of the repair shops, they were changed fundamentally by the addition of features that have no micro-foundations. These changes were not just innocent ones. They were crucial in making the model fit the data. In a way it can be said that habit formation, Calvo-pricing, and rule of thumb consumers have been ways to introduce heuristics into the DSGE-models through the back door.

The issue then is how much is left over from the paradigm of the fully informed rational agent in the existing DSGE-models? How important have the heuristics become in generating the dynamics in these models? Since the heuristics has been added in an ad-hoc and haphazard way it is difficult to answer this question. The suspicion exists that the heuristics may drive most of the dynamics in the DSGE models (see Chari et al. 2009). We return to this issue in Sect. 4.

This leads to the question of whether it is not preferable to admit that agents' behavior is guided by heuristics, and to incorporate these heuristics into the model from the start, rather than to pretend that agents are fully rational but to rely in a nontransparent way on heuristics to improve the fit of the model. That is what we plan to do in the next section.

3 A behavioral model

In this part of the paper we describe how an alternative modeling strategy could be developed. We do this 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 a selection mechanism. Put differently, agents endogenously select the forecasting rules that have delivered the greatest 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 we also obtain heterogeneity. This, as will be shown, creates endogenous business cycles.

We will contrast the behavior of this model with a similar model that incorporates rational expectations and that we interpret as a stylized version of DSGE-models. This comparison will also allow us to focus on some crucial differences in the transmission of shocks, in particular of monetary policy shocks.

Obviously, the approach presented here is not the only possible one. In fact, a large literature has emerged attempting to introduce imperfect information 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 2004; Milani 2007). However, we feel that this approach still loads individual agents with too many cognitive skills that they probably do not possess in the real world. A similar criticism can be developed against another approach to modeling imperfect information based on "rational inattention" (see Mackowiak and Wiederholt 2005; Sims 2005).

Our approach is also not the first attempt to introduce heuristics into macroeconomic models. Recently, Brazier et al. (2006) have done so in the context of an overlapping generations model (see also Branch and Evans 2006). 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 their behavior and forecasting (see Brock and Hommes 1997; De Grauwe and Grimaldi 2006).

3.1 The model

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

The aggregate demand equation can be derived from dynamic utility maximization. This produces an Euler equation in the same vein as in DSGE-models. We obtain

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

where 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. We will specify this process subsequently. We follow the procedure introduced in DSGE-models of adding lagged output in the demand equation. This is usually justified by invoking habit formation. We criticized this approach for being an ad-hoc departure from the assumption of rational forward-looking agents. In a model where agents cannot fully understand the world it is a more reasonable assumption to make. In addition, given that we want to compare the behavioral model with the DSGE-rational expectations model we follow the same procedure as in the latter. Finally, we will show in Sect. 4 that we do not really need these inertia-building devices to generate inertia in the endogenous variables.

The aggregate supply equation can be derived from profit maximization of individual producers. We assume as in DSGE-models a Calvo pricing rule, which leads to a lagged inflation variable in the equation.[2] The supply curve can also be interpreted as a New Keynesian Philips curve. We obtain:

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

Finally the Taylor rule describes the behavior of the central bank

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

where π_t^* is the inflation target which for the sake of convenience will be set equal to 0. Note that we assume, as is commonly done, that the central bank smoothes the interest rate. This smoothing behavior is represented by the lagged interest rate in (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. We have not done so here in order to maintain simplicity in the model.

[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 maximization in a world of imperfect competition. It allows introducing more detail into the model and makes it possible to specify productivity shocks better. It also allows for analyzing how shocks in markups affect the economy. We have not tried to introduce this feature here (see Gali 2008; Smets and Wouters 2003).

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

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

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

where $g > 0$ expresses the degree of bias in estimating the output gap. We will interpret $2g$ to express the divergence in beliefs among agents about the output gap.

Note that we do not consider this assumption of a simple bias to be a realistic representation of how agents forecast. Rather is it a parsimonious representation of a world where agents do not know the "Truth" (i.e., the underlying model). As a result of their cognitive limitations the rule they use is biased. This does not mean that the agents are "dumb" and that they do not want to learn from their errors. We 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.,

$$\tilde{E}_t y_{t+1} = \alpha_{\text{opt},t} \tilde{E}_t^{\text{opt}} y_{t+1} + \alpha_{\text{pes},t} \tilde{E}_t^{\text{pes}} y_{t+1} \tag{6}$$

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

$$\text{and } \alpha_{\text{opt},t} + \alpha_{\text{pes},t} = 1 \tag{8}$$

where $\alpha_{\text{opt},t}$ and $\alpha_{\text{pes},t}$ are the weights of optimists, receptively, pessimists in the market.

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[3] and how to aggregate it is too sketchy, however, and we have not tried to do so.

As indicated earlier, agents are rational in the sense that they continuously evaluate performances of their forecasts. We 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 the forecast performance of the different heuristics as follows:

$$U_{\text{opt},t} = -\sum_{k=1}^{\infty} \omega_k [y_{t-k} - \tilde{E}_{\text{opt},t-k-1} y_{t-k}]^2 \tag{9}$$

[3]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.

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

where $U_{\mathrm{opt},t}$ and $U_{\mathrm{pes},t}$ are the forecast performances 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).

$$\alpha_{\mathrm{opt},t} = \frac{\exp(\gamma U_{\mathrm{opt},t})}{\exp(\gamma U_{\mathrm{opt},t}) + \exp(\gamma U_{\mathrm{pes},t})} \tag{11}$$

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

$$\alpha_{\mathrm{pes},t} = \frac{\exp(\gamma U_{\mathrm{pes},t})}{\exp(\gamma U_{\mathrm{opt},t}) + \exp(\gamma U_{\mathrm{pes},t})} = 1 - \alpha_{\mathrm{opt},t} \tag{12}$$

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 the probability of being an 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.

Note that this selection mechanism is the disciplining device introduced in this model on the kind of rules of behavior that are acceptable. Only those rules that pass the fitness test remain in place. The others are weeded out. In contrast to 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.

It should also be stressed that although individuals use biased rules in forecasting the future, this does not mean that they fail to learn. On the contrary, the fitness test is a learning mechanism based on "trial and error". When observing that the rule they use performs less well than the alternative rule, they are willing to switch to the better performing rule. Put differently, the rules are biased because agents have a poor understanding of the underlying model. But these agents are not "dumb". They avoid making systematic mistakes by constantly being willing to learn from past mistakes and to change their behavior. This "trial and error" learning mechanism ensures that the market forecasts are unbiased.

Agents also make forecasts of inflation in this model. At this stage of the analysis we will simply assume that all agents perceive the central bank's announced inflation target π_t^* to be fully credible. They use this value as their forecast of future inflation, i.e., $\tilde{E}_t \pi_{t+1} = \pi_t^*$ (where for the sake of simplicity we assume the inflation target to be equal to 0). We will extend this simple inflation forecasting process in a later section when we will also assume that there is heterogeneity of beliefs in the inflation forecasting process. We 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 (3) into (1) and rewriting in matrix notation. This yields

$$\begin{bmatrix} 1 & -b_2 \\ -a_2 c_1 & 1 - a_2 c_2 \end{bmatrix} \begin{bmatrix} \pi_t \\ y_t \end{bmatrix} = \begin{bmatrix} b_1 & 0 \\ -a_2 & a_1 \end{bmatrix} \begin{bmatrix} \tilde{E}_t \pi_{t+1} \\ \tilde{E}_t y_{t+1} \end{bmatrix} + \begin{bmatrix} 1 - b_1 & 0 \\ 0 & 1 - a_1 \end{bmatrix} \begin{bmatrix} \pi_{t-1} \\ y_{t-1} \end{bmatrix}$$

$$+\begin{bmatrix} 0 \\ a_2 c_3 \end{bmatrix} r_{t-1} + \begin{bmatrix} \eta_t \\ a_2 u_t + \varepsilon_t \end{bmatrix}$$

or

$$\boldsymbol{A}\boldsymbol{Z}_t = \boldsymbol{B}\tilde{\boldsymbol{E}}_t \boldsymbol{Z}_{t+1} + \boldsymbol{C}\boldsymbol{Z}_{t-1} + \boldsymbol{b} r_{t-1} + \boldsymbol{v}_t \tag{13}$$

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

$$\boldsymbol{Z}_t = \boldsymbol{A}^{-1}\left[\boldsymbol{B}\tilde{\boldsymbol{E}}_t \boldsymbol{Z}_{t+1} + \boldsymbol{C}\boldsymbol{Z}_{t-1} + \boldsymbol{b} r_{t-1} + \boldsymbol{v}_t\right] \tag{14}$$

The solution exists if the matrix $\boldsymbol{A}$ is non-singular, i.e., if $(1 - a_2 c_2) - a_2 b_2 c_1 \neq 0$. The system (14) describes the solution for y_t and π_t given the forecasts of y_t and π_t . The latter have been specified in (4) to (12) and can be substituted into (14). Finally, the solution for r_t is found by substituting y_t and π_t obtained from (14) into (3).

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

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

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

$$\Omega Z_t = \Phi E_t Z_{t+1} + \Lambda Z_{t-1} + v_t \tag{15}$$

$$Z_t = \Omega^{-1}\left[\Phi E_t Z_{t+1} + \Lambda Z_{t-1} + v_t\right] \tag{16}$$

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

3.2 Calibrating the behavioral and the rational model

We proceed by calibrating the model. In Appendix A we present the parameters used in the calibration exercise. We have calibrated the model in such a way that the time units can be considered to be months. In Sect. 7 we present a sensitivity analysis of the main results to changes in the main parameters of the model.

We show the results of a simulation exercise in which the three shocks (demand shocks, supply shocks and interest rate shocks) are i.i.d. with standard deviations of 0.5%.

We first present a simulation in the time domain. Figure 1 shows the time pattern of output and inflation produced by the behavioral model. We observe a strong cyclical movement in the output gap. The source of these cyclical movements is seen to be the weight 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 periods 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.

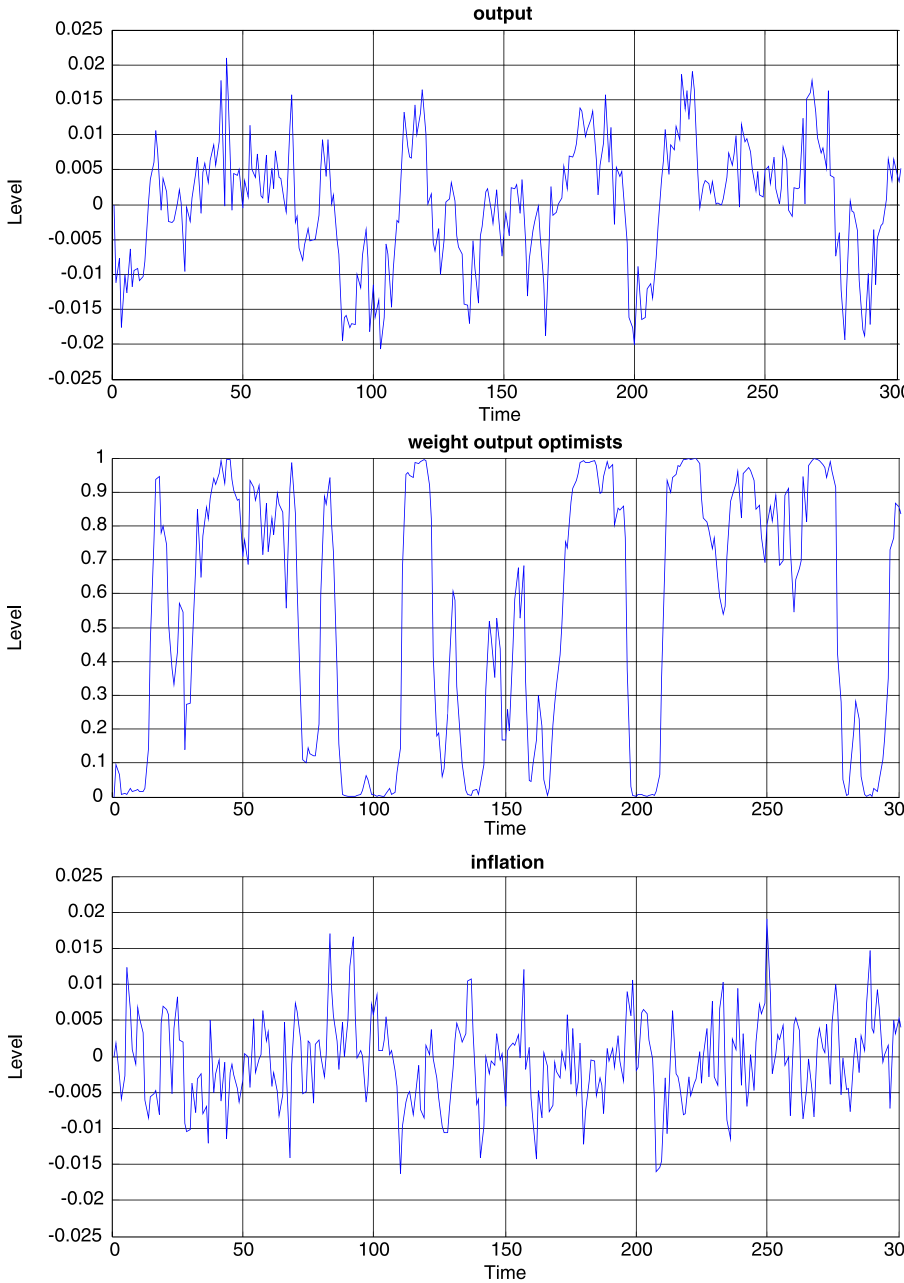


Fig. 1 Output gap and inflation in behavioral model

These endogenously generated cycles in output are reminiscent of what Keynes called "animal spirits". In our model these animal spirits are created by a 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 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, either because of negative stochastic shocks or because during a boom the central bank raises the interest rate (using the Taylor rule, (3)) a dent in the MSFE of the optimistic forecasts is made. The pessimistic belief becomes attractive and therefore fashionable again. The economy turns around.

From Fig. 1 (third panel) we observe 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 our assumption that agents are homogeneous in giving full credibility to the inflation target of the central bank. We will return to this when we introduce heterogeneity among agents in their perception of the credibility of the central bank's inflation target.

We contrast these results with those obtained using the model under rational expectations. We 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 i.i.d. structure.

We show the results in Fig. 2. Two differences stand out. First the 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. Thus our results illustrate that the cycles produced in the DSGE models come to a large extent from outside the model. We return to this issue in Sect. 4 where we analyze the degree of inertia produced by the two models.

Second, output and inflation are more volatile in the rational expectations model compared to the behavioral model. This can also be seen from Table 1 where we show the standard deviations of the output gap and inflation in the two models. Again this has to do with the minimal inertia assumed in the underlying structural model. Much of the attempt to fit the rational expectations model (DSGE-models) has consisted in adding additional lags so as to produce more persistence and less short-term volatility.

3.3 Impulse responses in the behavioral and the rational model

The next step in the analysis is to compute the impulse responses to shocks. Here we focus on the impulse responses to an interest rate shock, defined as plus one standard deviation of the shock in the Taylor equation.

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).

Figure 3 shows the mean impulse responses to an interest rate shock. We constructed the mean response by simulating the model 100 times with 100 different realizations of the shocks. We then computed the mean response together with the standard deviations. 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 100 periods). We obtain 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.

Where does this uncertainty come from? Not from parameter uncertainty. We use the same parameters in constructing all our impulse responses. The answer is that in this be-

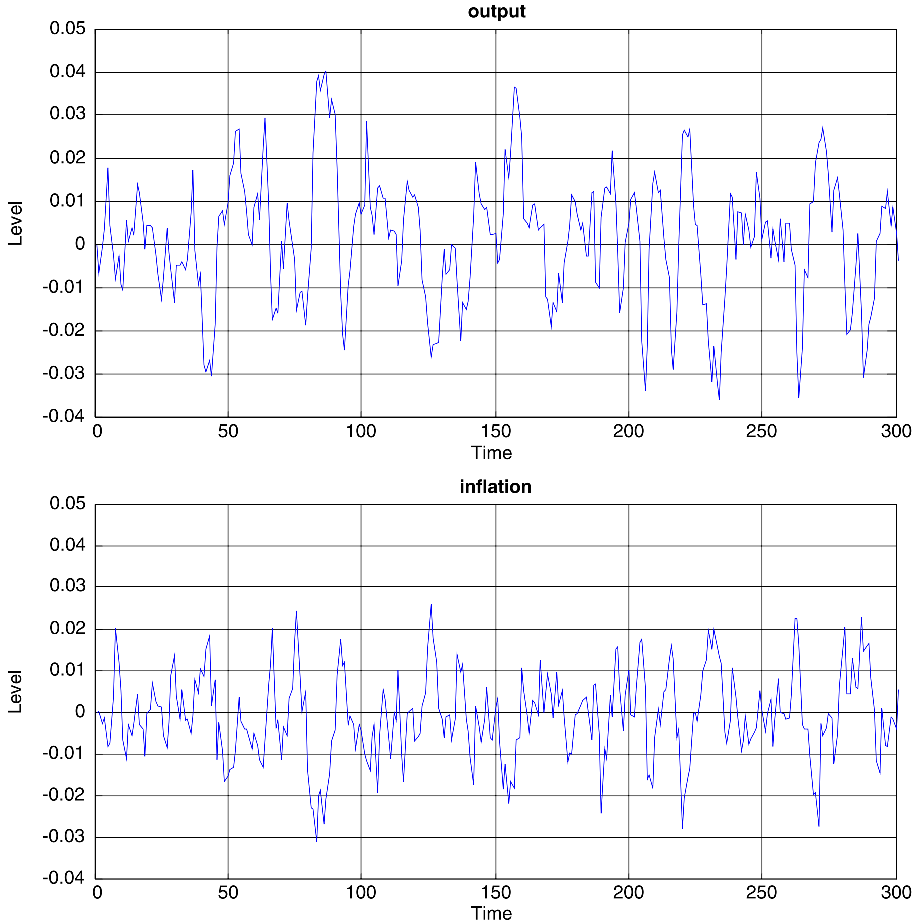


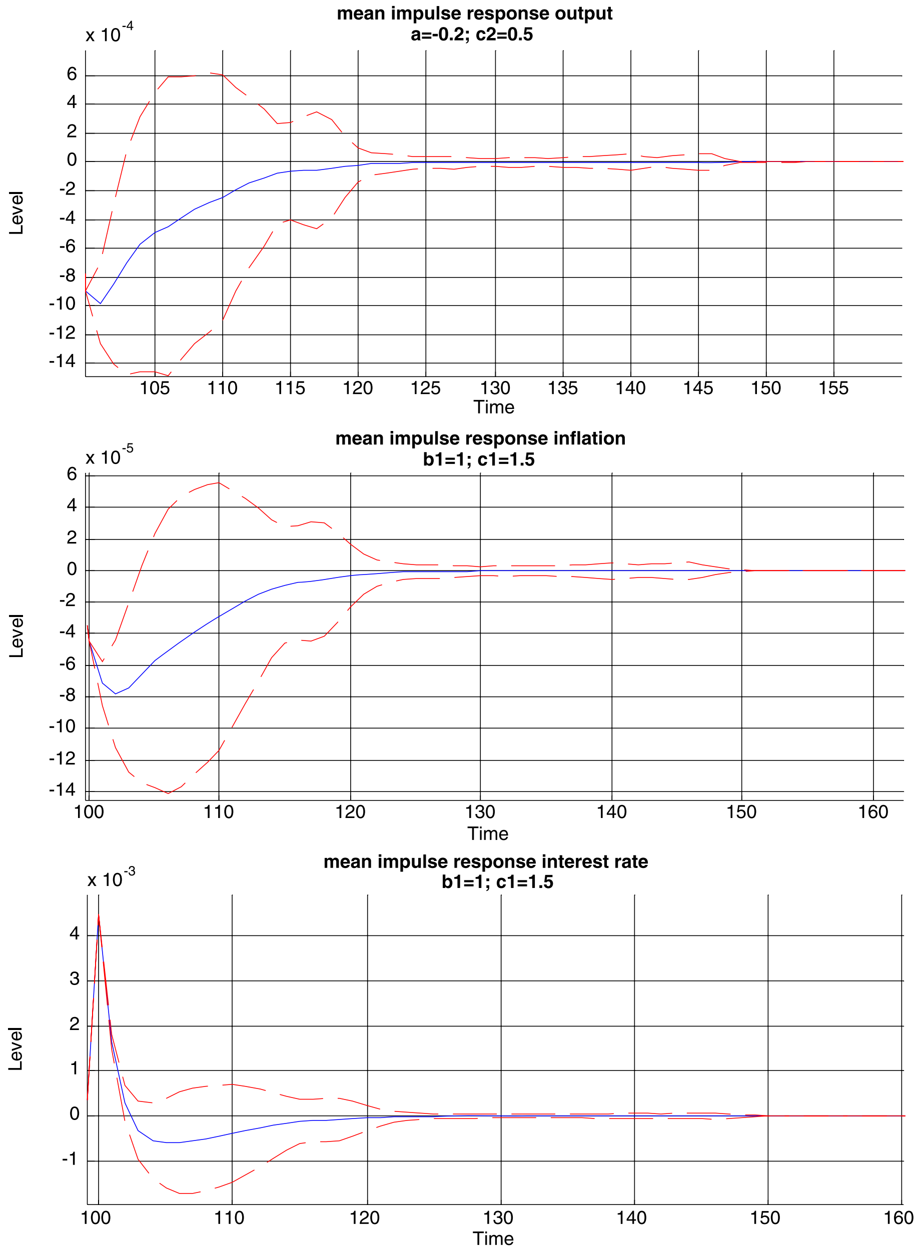
Fig. 2 Output gap and inflation in the rational model

Table 1 Standard deviations of output gap and inflation

	Behavioral model	Rational model
Output gap	0.86	1.35
Inflation	0.56	0.89

Note: these standard deviations are the averages obtained from simulating the model 1000 times, each time over 1000 periods

havioral model each realization of the shocks creates different waves of optimism and pessimism. We could also call this "market sentiments". Thus a shock that occurs in period 100 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.



Note: The dotted lines represent the impulse responses with ± 2 standard deviations.

Fig. 3 Mean impulse responses to interest rate shock in the behavioral model

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. This contrasts with what rational expectations models tell us. In a rational expectations world the timing of the shock does not matter. In this sense the rational expectations model is a-historic.[4]

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 heuristic 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. This is done for the sake of mathematical simplicity. It leads to a problem though. If the microfoundation of the model leads to a non-linear model, it is important to know how this non-linearity (which is part of the micro-foundation) affects the dynamics generated by the model. Eliminating these non-linearities amounts to destroying information that is relevant to predict the transmission of shocks. This may not matter much for the long run, but since the DSGE-models have the ambition of forecasting the transmission process, it is of significant importance.

3.4 The extended behavioral model

In this section we extend the behavioral model by allowing the inflation forecasters to be heterogeneous. We follow Brazier et al. (2006) 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., $\tilde{E}_t^{\text{tar}}\pi_{t+1} = \pi_t^*$, where as before we set the inflation target $\pi_t^* = 0$.

The "extrapolators" are defined by $\tilde{E}_t^{\text{ext}}\pi_{t+1} = \pi_{t-1}$.

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

$$\tilde{E}_t\pi_{t+1} = \beta_{\text{tar},t}\tilde{E}_t^{\text{tar}}\pi_{t+1} + \beta_{\text{ext},t}\tilde{E}_t^{\text{ext}}\pi_{t+1} \tag{17}$$

or

$$E_t\pi_{t+1} = \beta_{\text{tar},t}\pi_t^* + \beta_{\text{ext},t}\pi_{t-1} \tag{18}$$

and

$$\beta_{\text{tar},t} + \beta_{\text{ext},t} = 1 \tag{19}$$

We use the same selection mechanism as in the previous section based on the mean squared forecasting errors produced by the two rules to determine the proportions of agents trusting the inflation target and those who do not trust it and revert to extrapolation of past inflation, i.e.,

$$\beta_{\text{tar},t} = \frac{\exp(\gamma U_{\text{tar},t})}{\exp(\gamma U_{\text{tar},t}) + \exp(\gamma U_{\text{ext},t})} \tag{20}$$

[4]Michael Woodford has claimed that rational expectations models of the kind analyzed here have an element of historic dependence. This follows from the fact the existence of lags in the model. The historic dependence we are talking about here is of another nature.

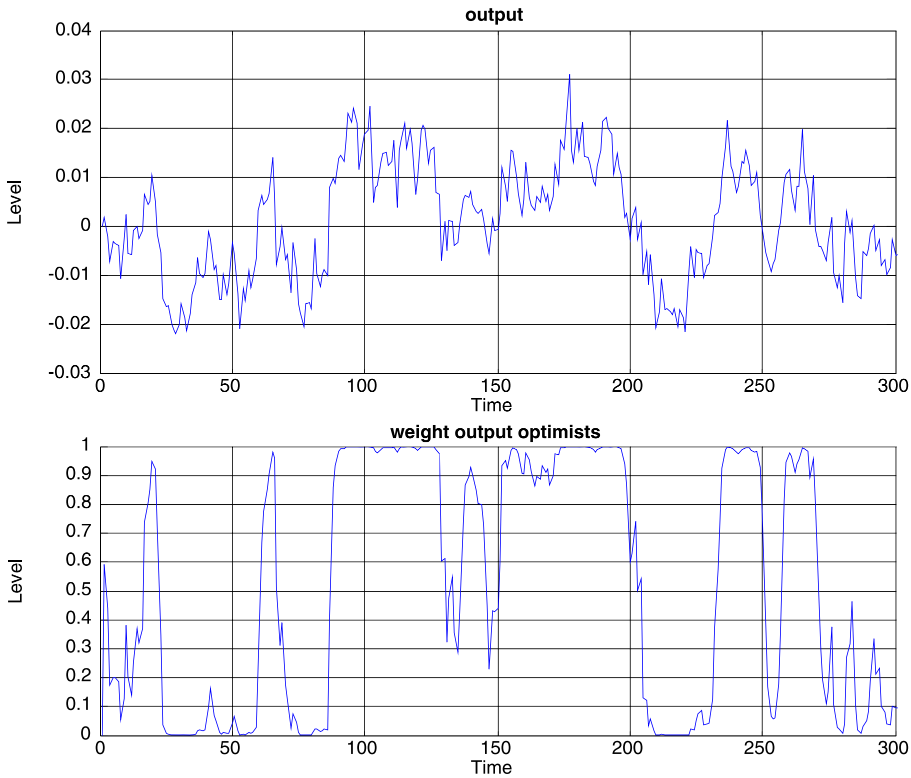


Fig. 4 Output gap in the extended behavioral model

$$\beta_{\text{ext},t} = \frac{\exp(\gamma U_{\text{ext},t})}{\exp(\gamma U_{\text{tar},t}) + \exp(\gamma U_{\text{ext},t})} \tag{21}$$

where U_{tar_t} and $U_{\text{ext},t}$ are the weighted averages of past squared forecast errors using targeter and extrapolator rules, respectively. These are defined in the same way as in (9) and (10).

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 proportion of agents relying on the inflation target will be large. If on the other hand the inflation target does not produce good forecasts (compared to a simple extrapolation rule) it will not be used much and therefore the proportion of agents using it will be small.

We calibrated the model using the same parameters as in the previous section. We first show the results in the time domain and then discuss the impulse response functions.

Figure 4 presents the results for the output gap in the time domain. We find the same cycles in the output gap as in the previous section. Again these cycles are related to the waves of optimism and pessimism in the forecasting (second panel in Fig. 4).

The results concerning the time path of inflation are shown in Fig. 5. We first concentrate on the second panel of Fig. 5. This shows the proportion of "extrapolators", i.e., the agents who do not trust the inflation target of the central bank. We can identify two regimes. There is a regime in which the proportion of extrapolators fluctuates around 50% which also implies that the proportion of forecasters using the inflation target as their guide (the

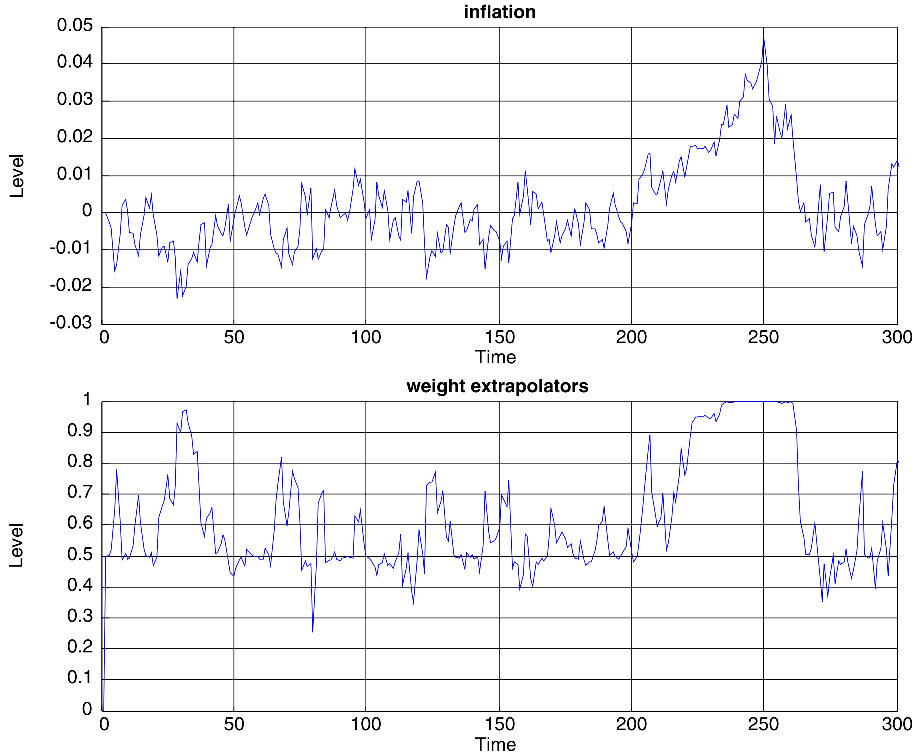


Fig. 5 Inflation in the extended behavioral model

"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 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.

How can the central bank strengthen the inflation targeting regime? The previous simulations assumed an inflation coefficient of 1.5 in the Taylor equation. This is a value often found in empirical work. As an alternative the central bank could apply a larger inflation coefficient, implying that it reacts more strongly to changes in inflation from its target. We show the results of a simulation when the central bank sets this coefficient equal to 2.5 in Fig. 6. We now observe that this stricter inflation targeting policy has the effect of keeping the rate of inflation within the narrow band of ±1% most of the time. There are occasional "dérapages" into the second more turbulent regime but these are less frequent and less persistent. This has all to do with the fact that a sufficiently large proportion of agents continue to trust the central bank's inflation target as a guide in forecasting.

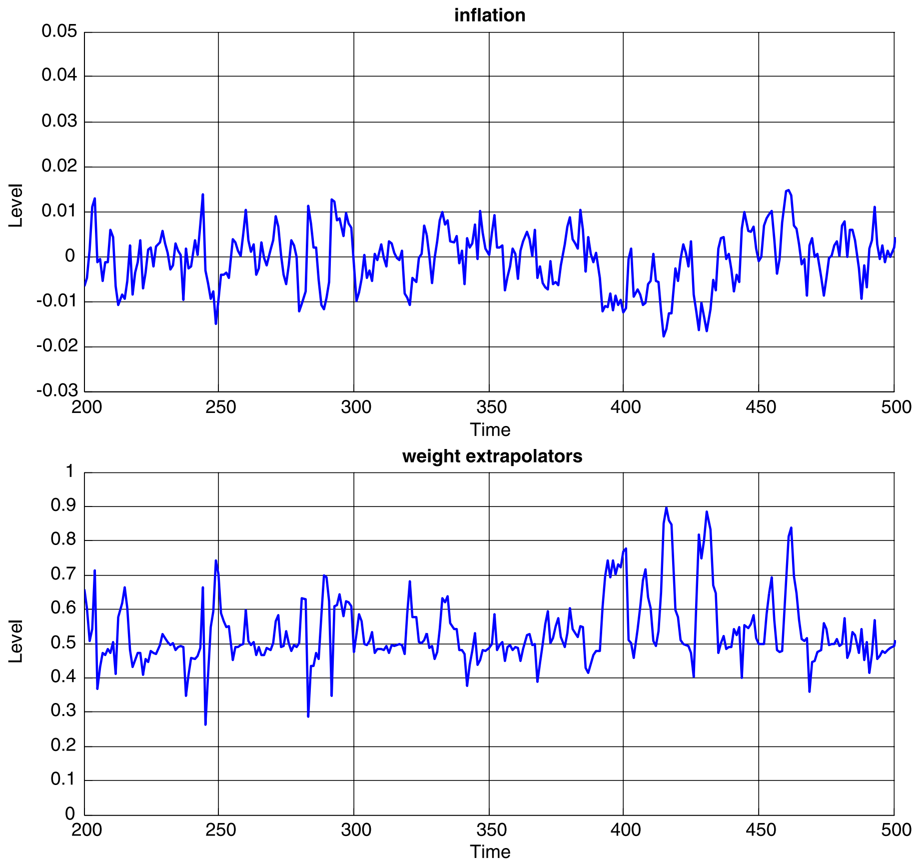


Fig. 6 Inflation in the extended behavioral model with stricter inflation targeting

3.5 Impulse responses in the extended behavioral model

In this section we present the impulse responses to a positive interest rate shock of one standard deviation (Fig. 7). Two results stand out. First the uncertainty surrounding the effects of interest rate shocks is greater and lasts longer than in the simple behavioral model with homogeneous inflation forecasting. 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.[5]

3.6 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

[5] A similar result was obtained by Anagnostopoulos et al. (2007).

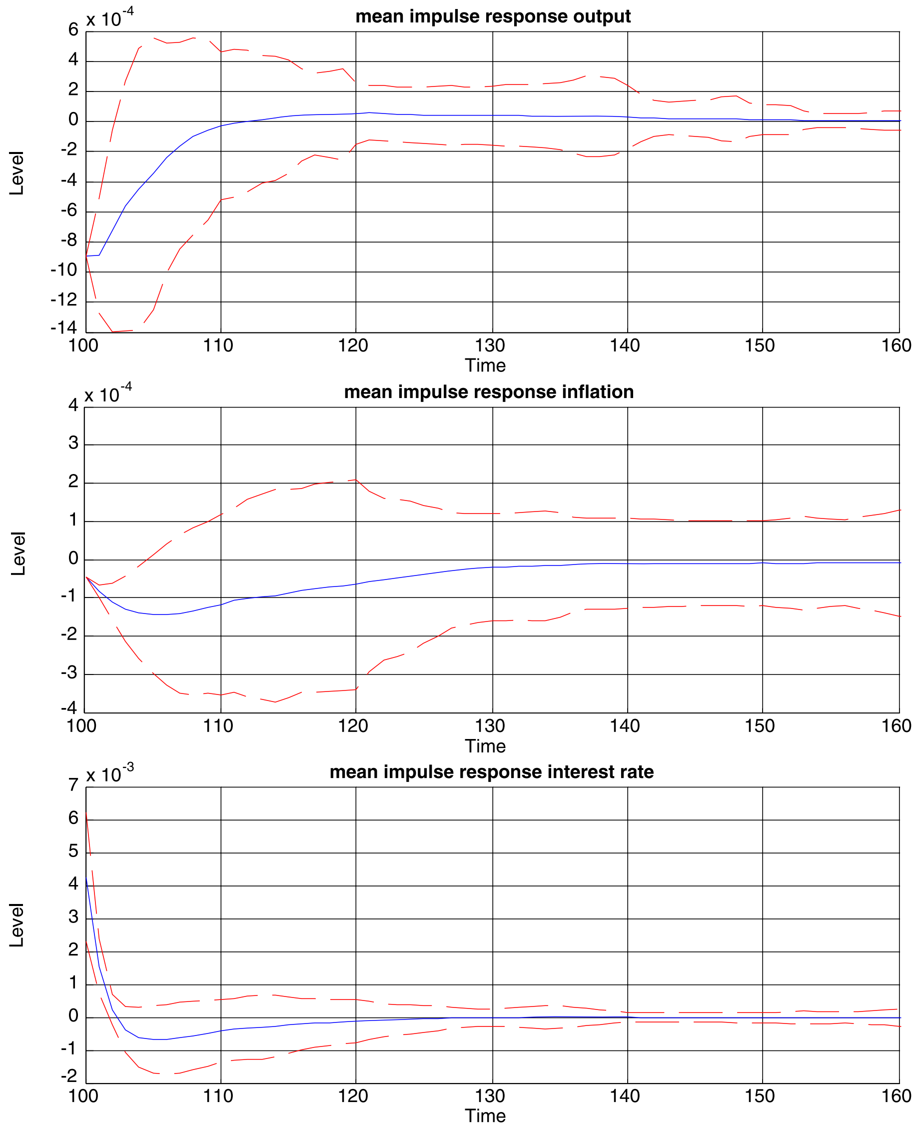


Fig. 7 Mean impulse responses to an interest rate shock in the extended behavioral model

(even by chance) use an unbiased rule. In this section we analyze the question of how the model is affected if we allow for a third, unbiased, forecasting rule. We implement this idea by defining a third forecasting rule to be

$$\tilde{E}_t^{\mathrm{un}} y_{t+1} = 0 \tag{22}$$

where $\tilde{E}_t^{\mathrm{un}} y_{t+1}$ is the unbiased forecasting rule.

We now assume as before a switching rule, whereby agents can switch between the three rules. This implies first that agents compute the performance (utility) of using these rules as in (9) and (10) for the optimistic and pessimistic rules. For the unbiased rule this becomes

$$U_{\mathrm{un},t} = -\sum_{k=1}^{\infty} \omega_k [y_{t-k} - \tilde{E}_{\mathrm{un},t-k-1} y_{t-k}]^2 \tag{23}$$

The corresponding probabilities of using the three rules now become:

$$\alpha_{\mathrm{opt},t} = \frac{\exp(\gamma U_{\mathrm{opt},t})}{\exp(\gamma U_{\mathrm{opt},t}) + \exp(\gamma U_{\mathrm{pes},t}) + \exp(\gamma U_{\mathrm{un},t})} \tag{24}$$

$$\alpha_{\mathrm{pes},t} = \frac{\exp(\gamma U_{\mathrm{pes},t})}{\exp(\gamma U_{\mathrm{opt},t}) + \exp(\gamma U_{\mathrm{pes},t}) + \exp(\gamma U_{\mathrm{un},t})} \tag{25}$$

$$\alpha_{\mathrm{un},t} = \frac{\exp(\gamma U_{\mathrm{un},t})}{\exp(\gamma U_{\mathrm{opt},t}) + \exp(\gamma U_{\mathrm{pes},t}) + \exp(\gamma U_{\mathrm{un},t})} \tag{26}$$

We simulated the model in the time domain using the same calibration as in Sects. 3.4 and 3.5 (the extended behavioral model). We show the results in Fig. 8. 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).

We obtain rather interesting results. We find that the existence of unbiased predictors does not eliminate the occurrence of waves of optimism and pessimism. As one can see from the bottom half of Fig. 8, 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. Note also that the unbiased rules do not vary much and fluctuate around 1/3 of the market. As a result, they have only a limited impact on the movements of the output gap.

In order to find out how important animal spirits are in shaping fluctuations in the output gap we correlated the simulated output gap with the fraction of optimists in the market. We did this both for the three-agent model and for the two-agent model of the previous sections. We find an average correlation coefficient of 0.83 in the three-agent model and one of 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, our main results that waves of optimism and pessimism (animal spirits) can emerge, is maintained even in a world where agents have access to unbiased forecasts.

4 Trade-offs between inflation and output variability

The business of central banks is to make choices which arise from the existence of trade-offs. We analyze these trade-offs both in the behavioral and the rational expectations models. We return to the two-agent model used earlier.

Figure 9 presents the trade-offs. These are obtained by varying the output coefficient in the Taylor rule (c_2) from 0 to 1 and computing the inflation and output variability for each of these values. These variabilities in inflation and output are set out on the vertical and horizontal axes of Fig. 9. The trade-offs we obtain shows that a central bank applying more output stabilization (by increasing c_2) manages to reduce output variability at the expense

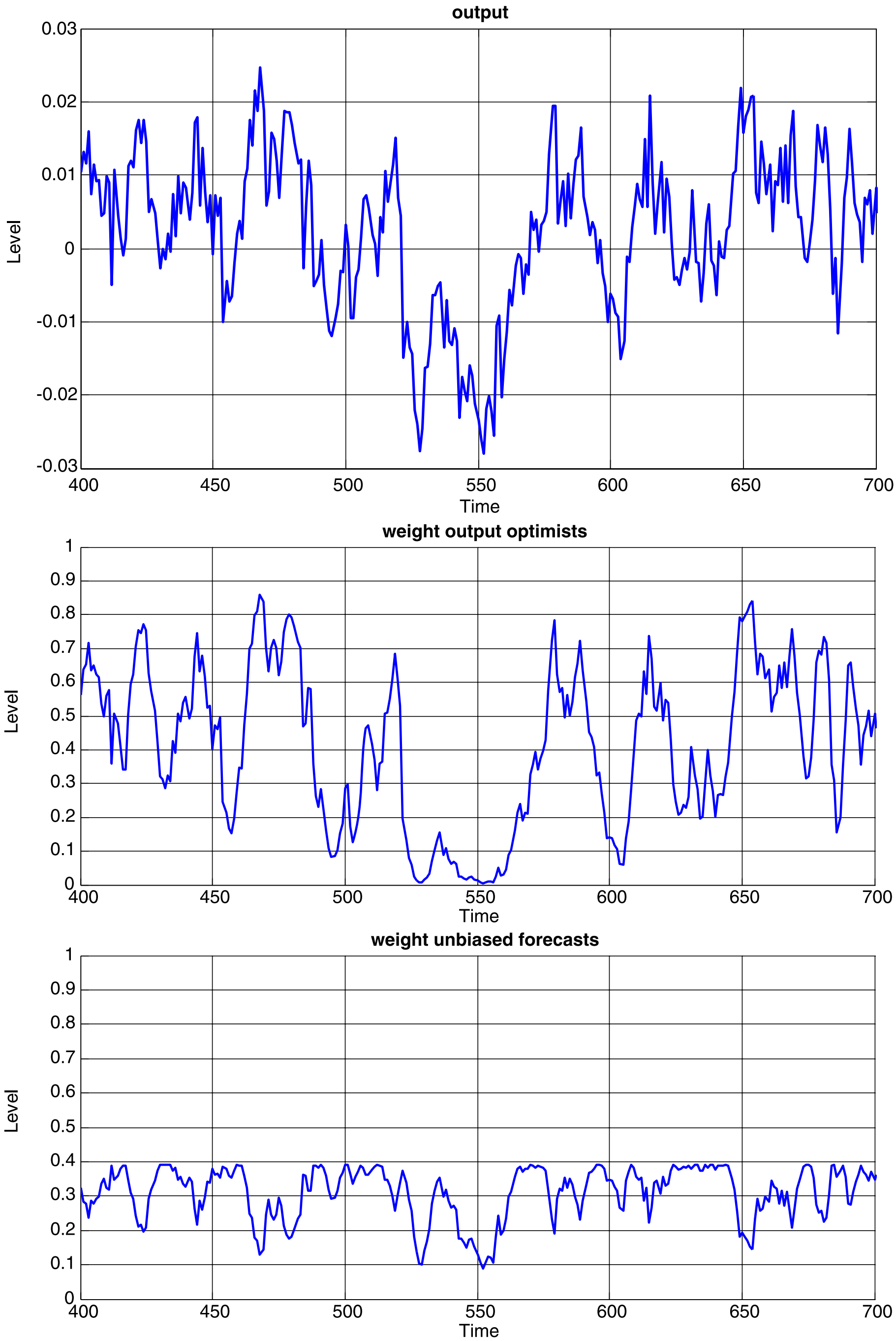


Fig. 8 Output gap and animal spirits in a three-agent model

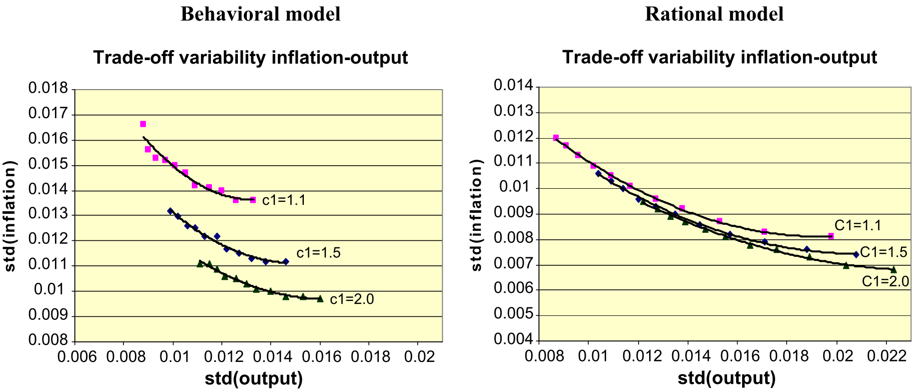


Fig. 9 Trade-offs between inflation and output variability

of more inflation variability. We obtain this result in both the behavioral and the rational model. We also note that the trade-off improves when c_1 increases, i.e., when the central bank reacts more forcefully to an inflation upsurge, it can achieve both lower inflation and output variability.

We observe one major difference in the trade-offs of the behavioral and the rational models. We find that the value of c_1 has a significantly lesser effect on improving the trade-off in the rational expectations model as compared to the behavioral model. Put differently, in a rational expectations world a more forceful reaction of the central bank to an inflation surge (a higher c_1) does not improve the trade-off significantly. It does in our behavioral model. The reason is that a more credible inflation targeting regime also reduces the intensity of the waves of optimism and pessimism, thereby reducing both inflation and output variability.

5 Endogenous and exogenous inertia

In the previous sections we contended that the rational model introduces inertia by imposing a lag structure on the transmission mechanism, the logic of which comes from outside the model. We could call this an exogenously created inertia. In contrast, the behavioral model is capable of generating inertia without introducing lags in the transmission process. This could be called endogenous inertia. We illustrate this difference by analyzing the behavioral and the rational model in the absence of lags in the transmission process in the demand and the supply equations. We achieve this by setting $a_1 = 1$ in (1) and $b_1 = 1$ in (2). We then applied the same i.i.d. shocks in both the heuristic and the rational model and computed the autocorrelation coefficients of the simulated series of output gaps and inflation. We show the results in Table 2. We observe 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. Our rational model produces no inertia in the output gap and in inflation.

Table 2 then shows the autocorrelation coefficients obtained in models that assume lags in the transmission. These coefficients are obtained when we set $a_1 = 0.5$ in (1) and $b_1 = 0.5$ in (2). These are also the numerical values assumed in all the simulations reported in the previous sections. We now observe that inertia in the output gap and in inflation increases in both models.

Table 2 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
Lags in transmission and autoregressive shocks		
Output gap	0.99	0.98
Inflation	0.98	0.97

Note: the autocorrelation coefficients are the averages obtained from simulating the model 1000 times, each time over 1000 periods

Finally we simulate the models assuming both lags in the transmission process and an autoregressive pattern in the error terms. We assumed a first order autocorrelation of the error terms of 0.8 in both models. We now observe that the autocorrelation coefficients of output and inflation converge to the same high values in both models. From this exercise, it can be concluded that most of the inertia obtained in the rational model is the result of lags in the transmission process and autoregressive errors. This is not the case in the behavioral model that produces a significant level of endogenous inertia that is independent of the transmission process and the autoregressive nature of the shocks.

This difference between the two models is quite fundamental. In the rational model there is no uncertainty about how the shock is transmitted in the model. Thus in the absence of lags in transmission, agents immediately find the optimal levels of output and inflation. In order to produce the required inertia (and the business cycle movements), lags in transmission preventing instantaneous adjustment to the optimal plan, are necessary together with autoregressive shocks. In the behavioral model, agents do not fully understand how the shock will be transmitted. As a result they follow a procedure (heuristics together with a selection mechanism) that functions as a "trial and error" learning mechanism aimed at revealing information about shocks and the transmission process. This is a slow process that also uses backward evaluation processes. It generates an endogenous inertia (and business cycle) into the model.

The inertia obtained in our 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 we obtain very different theories of the business cycles in the two models.

Critics of the behavioral model presented here may argue that the comparison between the rational and the behavioral model is unfair for the rational model. For the behavioral model generates inertia because the evaluation process of the different heuristics is backward looking. This is the reason why the behavioral model does not need lags in the transmission process to generate inertia. This latter is correct. However, we claim that this evaluation process can only be backward, and as a result, the lags that are present in the behavioral model are completely within the logic of that model. This contrasts with the lags introduced in the rational model: they come from outside the logic of the model.

6 Sensitivity analysis

In this section we 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 our model. First, there is the divergence between the optimists' and pessimists' beliefs. We will call this the divergence parameter, which we define as $2g$ (remember that g is the bias of the optimists and $-g$ is the bias of the pessimists).

Second, there is the memory agents have when calculating the performance of their forecasting. This was represented by the parameter ω_k in (9)–(10) and is a series of declining weights attached to past forecast errors. We define $\omega_k = (1-\rho)\rho^k$ (and $0 \leq \rho \leq 1$). The parameter ρ can 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.

Finally, there is the parameter γ which measures the intensity with which agents are willing to switch to a better performing rule (see (11)–(12)).

We discuss the sensitivity of the results with respect to these parameters by showing how they affect the volatility and the degree of inertia (autocorrelation) of inflation and output.

6.1 Sensitivity to divergence in beliefs

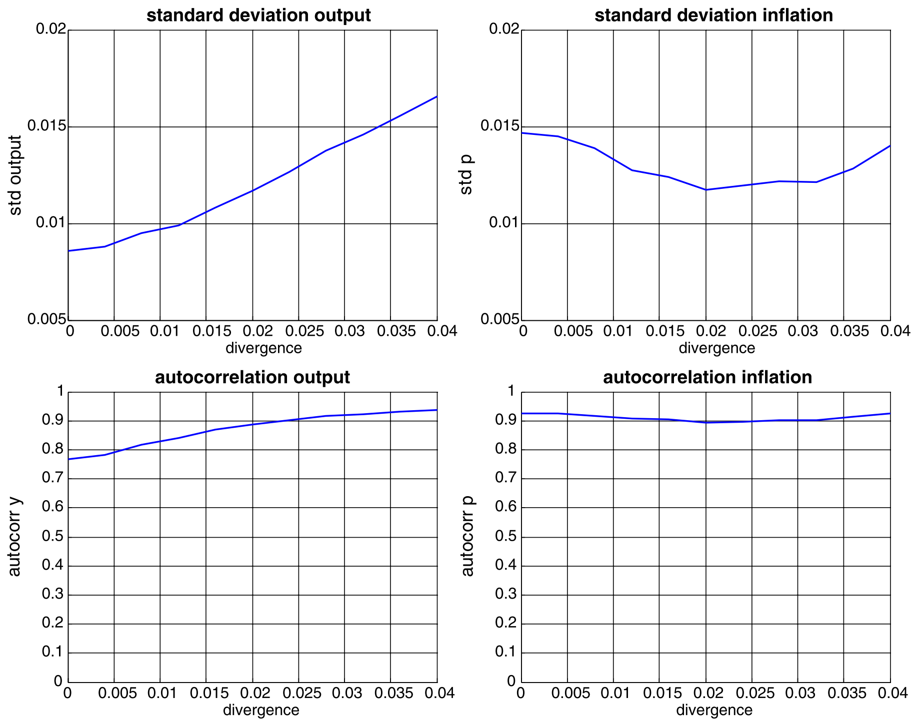
The upper panels of Fig. 9 show how the volatility of output and inflation depends on the degree of divergence in beliefs in forecasting output. We observe that when divergence increases the volatility of output increases substantially. No such increase occurs with inflation which is not surprising as the divergence parameter relates to differences in beliefs about future output.

The lower panels of Fig. 10 indicate that increasing divergence tends to increase inertia in output (autocorrelation), with little effect on inflation inertia.

6.2 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. 11. 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 longer 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 the previous sections we set $\rho = 0.5$. 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).

We obtain similar results 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. We conclude that long memory tends to stabilize output and inflation and to reduce inertia in these variables.



Note: the standard deviations and autocorrelation coefficients are the averages obtained from simulating the model 1000 times, each time over 1000 periods.

Fig. 10 Standard deviation and autocorrelation of output gap and inflation (divergence)

6.3 Sensitivity to intensity of choice

The intensity of choice parameter controls the degree with which agents switch from one rule to the other when the performances of the forecasting rules change. In general we find that, as this parameter increases, volatility and inertia tend to increase. This is illustrated in Fig. 12. The upper panel shows the volatility of output and inflation as a function of the intensity of choice parameter. We observe a clear positive relation. The lower panel shows how the autocorrelation coefficients increase when intensity of choice is increased.

We conclude that as agents react more forcefully to changes in performance of their forecasting rules, the volatility of output and inflation and their inertia increases. The intuition for this result is the following. With a low intensity of choice parameter agents do not let their decision to switch depend much on past performance. The switching behavior is then mostly driven by chance. Waves of optimism and pessimism cannot then come off the ground easily, leading to output changes that come close to i.i.d. changes. As the intensity of choice parameter increases in value, agents react more forcefully to performance. This sets in motion the endogenous waves of optimism and pessimism. As a result, both the volatility and the autoregressive pattern increase (Fig. 13).

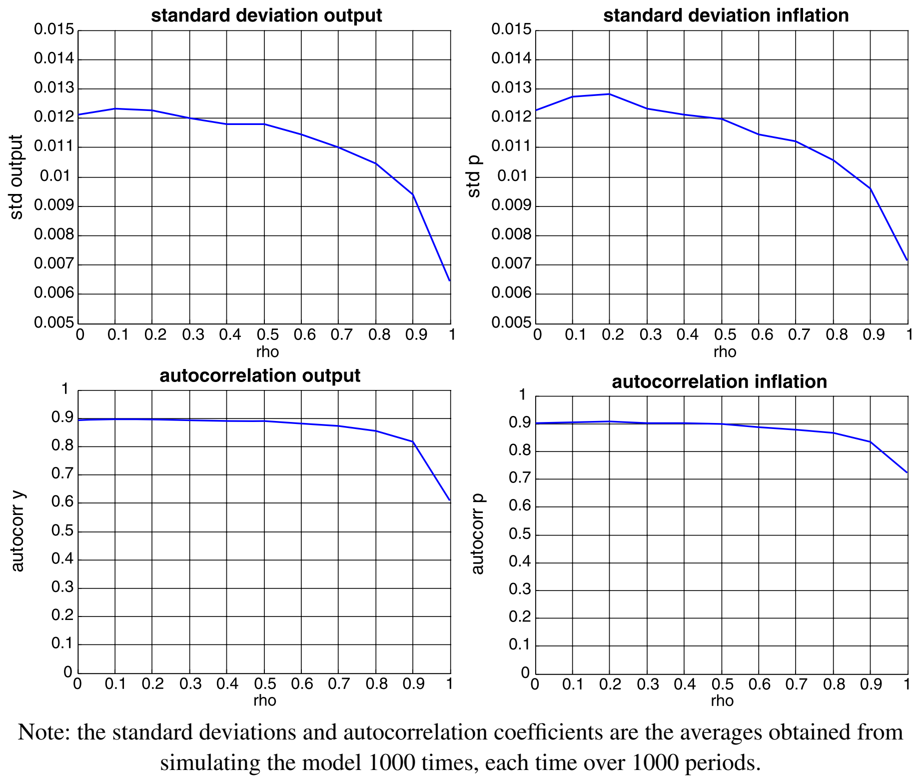


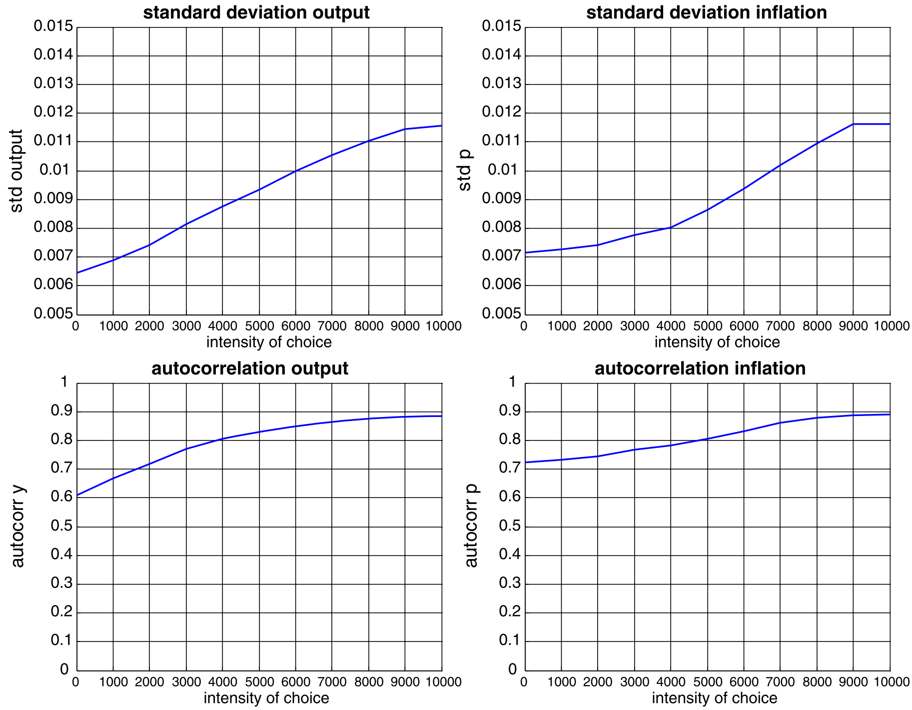
Fig. 11 Standard deviation and autocorrelation of output gap and inflation (memory)

7 Conclusion

DSGE-models provide a coherent framework of analysis. This coherence is brought about by restricting the acceptable behavior of agents to dynamic utility maximization and rational expectations. These features explain the intellectual appeal of these models and their recent success in academic circles and among policymakers.

The problem of the DSGE-models (and more generally of rational expectations macroeconomic models) is that they assume extraordinary cognitive capabilities of individual agents. Recent developments in other disciplines including psychology and brain science overwhelmingly 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.

The fact that the assumption of rational expectations is implausible does not necessarily mean that models using such an assumption cannot be powerful tools in making empirical predictions. The problem, however, is that rational expectations macroeconomic model make systematically wrong predictions, in particular about the speed with which prices adjust. This empirical failure could have led the profession of macroeconomists to drop the model and to look for another one. Instead, macroeconomists decided to stick to the rational expectations model but to load it with a series of ad-hoc repairs that were motivated by a desire to improve its fit. These repair operations most often involved adding lags to the models so as to create sufficient inertia in variables. These operations were successful



Note: the standard deviations and autocorrelation coefficients are the averages obtained from simulating the model 1000 times, each time over 1000 periods.

Fig. 12 Standard deviation and autocorrelation of output gap and inflation (intensity of choice)

in the sense that the fit was significantly improved. In another sense, however, they were failures because the inertia building tricks are really departures from rationality. As a result, the present DSGE-models create a dynamics the largest part of which is the result of the ad-hoc repair operations. These have nothing to do with optimizing behavior and rationality of expectations. In a way it can be said that these ad-hoc repairs introduced heuristics in the model through the back door.

We argued that if it is necessary to introduce heuristics into the model in order to make it empirically palatable, one might as well introduce these heuristics explicitly and right from the start. That is what we did in this paper. The advantage of this approach is that one can also specify explicitly what kind of heuristics is acceptable. We did this by introducing a selection mechanism guiding the use of heuristics.

The ensuing "behavioral model" produces a number of results that distinguishes it from the rational expectations models. First, the behavioral model is capable of generating endogenous cycles based on waves of optimism and pessimism. This dynamics is akin to what Keynes called animal spirits. Second, in contrast to the DSGE-models the inertia in output and prices is generated within the model, instead of being "imported". Third, the behavioral model produces a degree of uncertainty about the transmission of monetary policy shocks that is very different from the uncertainty obtained in DSGE-models. In the latter models, uncertainty about the effects of monetary policy shocks arises 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 very different effects depending on what we have called market conditions, i.e., the degree of optimism and pessimism agents have about the future.

The success of the DSGE-model has much to do with the story it tells about how the macroeconomy functions. This is a story in which rationality of superbly informed and identical agents reigns. Shocks from the outside occur continuously forcing these agents to re-optimize repeatedly, which they are eager to do. Unfortunately and inexplicably, the outside world imposes restrictions on this behavior creating distortions and departures from optimality. It also generates cycles in output and inflation. This in turn creates a stabilizing responsibility for the central bank.

We have questioned this story by presenting an alternative one. This is a story in which agents do not understand the model well, and use a trial and error learning strategy to discover its underlying logic. Such a model generates cycles endogenously. Thus in contrast with the DSGE-world where the shocks come from outside, in the behavioral world some shocks are generated within the model. As a result, the degree of uncertainty about how monetary policy is transmitted is of a higher order of magnitude.

There is another dimension in the difference between the two models. In his famous AER article Hayek (1945) stressed that individuals have only very small parts of the available information in their brains. No individual can ever hope to understand and to process the full complexity of the world in which he lives. That's why markets are so important. They are institutions that efficiently aggregate the diverse bits of information stored in individual brains. The socialist economists at the time in contrast assumed that there was one individual, "the planner", who understood the whole picture. By giving him all the power this all-knowing individual could compute all the relevant prices and so force the optimum on the system. Markets were not necessary in this view.

Paradoxically, the rational expectations revolution that was so much influenced by the Chicago School created a model that, like in the socialist models of the past, assumes an all-knowing individual, who can compute the optimal plans and set the optimal prices. In such a world, markets are indeed not necessary to coordinate the actions of heterogeneous individuals. The representative agent does it all in his mind. In the behavioral model presented here, we go back to the old Hayekian idea that we need markets to aggregate the information that is spread out in tiny little bits in individuals' brains. It is this aggregation process that creates macroeconomic fluctuations.

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Appendix A: parameter values of the calibrated model

A.1 Behavioral model

pstar = 0;	% the central bank's inflation target
$a_1 = 0.5$;	% coefficient of expected output in output equation
$a_2 = -0.2$;	% a is the interest elasticity of output demand
$b_1 = 0.5$;	% b_1 is coefficient of expected inflation in inflation equation
$b_2 = 0.05$;	% b_2 is coefficient of output in inflation equation
$c_1 = 1.5$;	%c_1 is coefficient of inflation in Taylor equation
$c_2 = 0.5$;	% c_2 is coefficient of output in Taylor equation
$c_3 = 0.5$;	% interest smoothing parameter in Taylor equation
$g = 0.01$;	% output forecasts optimists
gamma = 10,000;	% switching parameter gamma in Brock Hommes
$\text{sigma}_1 = 0.005$;	% standard deviation shocks output
$\text{sigma}_2 = 0.005$;	% standard deviation shocks inflation
$\text{sigma}_3 = 0.005$;	% standard deviation shocks Taylor
rho = 0.5;	% rho measures the speed of declining weights omega in mean squares errors

A.2 Rational model

pstar = 0;	% the central bank's inflation target
$a_1 = 0.9$;	% coefficient of expected output in output equation
$a_2 = -0.2$;	% a is the interest elasticity of output demand
$b_1 = 0.5$;	% b_1 is coefficient of expected inflation in inflation equation
$b_2 = 0.05$;	% b_2 is coefficient of output in inflation equation
$c_1 = 1.5$;	% c_1 is coefficient of inflation in Taylor equation
$c_2 = 0.5$;	% c_2 is coefficient of output in Taylor equation
$c_3 = 0.5$;	% interest smoothing parameter in Taylor equation
$\text{sigma}_1 = 0.005$;	% standard deviation shocks output
$\text{sigma}_2 = 0.005$;	% standard deviation shocks inflation
$\text{sigma}_3 = 0.005$;	% standard deviation shocks Taylor

Appendix B

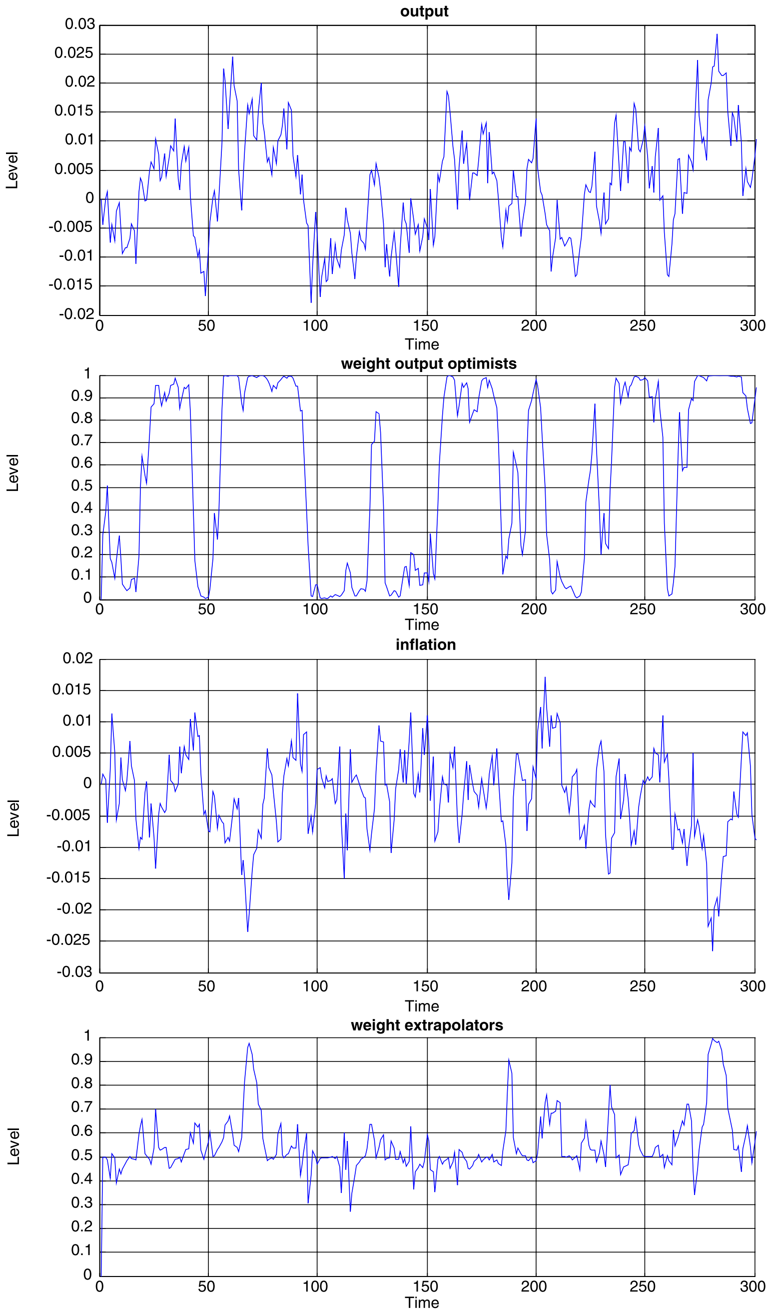

Fig. 13 Output gap and inflation in behavioral model: additional silulations

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