Top-Down versus Bottom-Up Macroeconomics

Paul De Grauwe

CESIFO WORKING PAPER NO. 3020
CATEGORY 6: FISCAL POLICY, MACROECONOMICS AND GROWTH
APRIL 2010

CESifo *Working Paper No. 3020*

Top-Down versus Bottom-Up Macroeconomics

Abstract

I distinguish two types of macroeconomic models. The first type are top-down models in which some or all agents are capable of understanding the whole picture and use this superior information to determine their optimal plans. The second type are bottom-up models in which all agents experience cognitive limitations. As a result, these agents are only capable of understanding and using small bits of information. These are models in which agents use simple rules of behavior. These models are not devoid of rationality. Agents in these models behave rationally in that they are willing to learn from their mistakes.
These two types of models produce a radically different macroeconomic dynamics. I analyze these differences.

JEL-Code: E10, E32, D83.

Keywords: DSGE-model, imperfect information, heuristics, animal spirits.

Paul De Grauwe
University of Leuven
Belgium
paul.degrauwe@econ.kuleuven.be

March 2010
A version of this paper was presented at the CESifo Conference "What's wrong with modern macroeconomics?", Munich, 6-7 November 2009. I am grateful to Yunus Aksoy, Tony Atkinson, Casper de Vries, Stephan Fahr, Daniel Gros, Richard Harrison, Romain Houssa, Gerhard Illing, Pablo Rovira Kaltwasser, Christian Keuschnigg, Alan Kirman, Giovanni Lombardo, Lars Ljungqvist, Patrick Minford, John Muellbauer, Ilbas Pelin, Frank Smets, Leopold von Thadden, David Vines, and Tony Yates for their comments and suggestions.

1. Introduction

In order to understand the nature of different macroeconomic models it is useful to make a distinction between top-down and bottom-up systems. In its most general definition a top-down system is one in which one or more agents fully understand the system. These agents are capable of representing the whole system in a blueprint that they can store in their mind. Depending on their position in the system they can use this blueprint to take over the command, or they can use it to optimize their own private welfare. These are systems in which there is a one to one mapping of the information embedded in the system and the information contained in the brain of one (or more) individuals. An example of such a top-down system is a building that can be represented by a blueprint and is fully understood by the architect.

Bottom-up systems are very different in nature. These are systems in which no individual understands the whole picture. Each individual understands only a very small part of the whole. These systems function as a result of the application of simple rules by the individuals populating the system. Most living systems follow this bottom-up logic (see the beautiful description of the growth of the embryo by Dawkins(2009)). The market system is also a bottom-up system. The best description made of this bottom-up system is still the one made by Hayek(1945). Hayek argued that no individual exists who is capable of understanding the full complexity of a market system. Instead individuals only understand small bits of the total information. The main function of markets consists in aggregating this diverse information. If there were individuals capable of understanding the whole picture, we would not need markets. This was in fact Hayek's criticism of the "socialist" economists who took the view that the central planner understood the whole picture, and would therefore be able to compute the whole set of optimal prices, making the market system superfluous. (For further insightful analysis see Leijonhufvud(1993)).

My contention is that macroeconomic models that use the rational expectations assumption are the intellectual heirs of these central planning models. Not in the sense that individuals in these rational expectations models aim at planning the whole, but in the sense that, as the central planner, they understand the whole picture. Individuals in these rational expectations models are assumed to know and understand the complex structure of the economy and the statistical distribution of all the shocks that will hit the economy. These individuals then use this superior information to obtain the “optimum optimorum” for their own private welfare. In this sense they are top-down models.

In this paper I will contrast the rational expectations top-down model with a bottom-up macroeconomic model. This will be a model in which agents have cognitive limitations and do not understand the whole picture (the underlying model). Instead they only understand small bits and pieces of the whole model and use simple rules to guide their behavior. I will introduce rationality in the model through a selection mechanism in which agents evaluate the performance of the rule they are following and decide to switch or to stick to the rule depending on how well the rule performs relative to other rules.

The modeling approach presented in this paper is not the only possible one to model agents’ behaviour under imperfect information. 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 and Smets(2006), Orphanides and Williams(2004), Milani(2007a), Branch and Evans(2009)). However, I feel that this approach still loads individual agents with too many cognitive skills that they probably do not posses in the real world[1].

The purpose of this paper is to contrast the dynamics of the top-down and the bottom-up models, and to draw some policy conclusions. The paper is very much inspired by the new literature on “agent-based macroeconomic models” (see Howitt(2008), Tesfatsion(2006), LeBaron and Tesfatsion(2008) among others). Section 2 presents the bottom-up model, which will be called “behavioural model”. The next four sections then discuss the different implications the behavioural model has when contrasted with the rational expectations model. Section 7 presents some empirical evidence. The paper is concluded with a discussion of some methodological issues.

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

2. A behavioural macroeconomic model

In this section 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 behavioural 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 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 behavioural model with the DSGE-rational expectations model. However, I will show in section 4 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:

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

Finally the Taylor rule describes the behaviour of the central bank

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

where 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 behaviour is represented by the lagged interest rate in equation (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.

Introducing heuristics in forecasting output

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 forecasting heuristics and apply it to the forecasting rules of future output. I assume two types of forecasting rules. A first rule can be called a "fundamentalist" one. Agents estimate the steady state value of the output gap (which is normalized at 0) and use this to forecast the future output gap. (In a later extension, it will be assumed that agents do not know the steady state output gap with certainty and only have biased estimates of it). A second forecasting rule is an "extrapolative" one. This is a rule that does not presuppose that agents know the steady state output gap. They are agnostic about it. Instead, they extrapolate the previous observed output gap into the future.

The two rules are specified as follows

The fundamentalist rule is defined by $\widetilde{E}_t^f y_{t+1} = 0$ (4)

[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 (3) is equivalent to such a pricing equation (see Gali(2008), Smets and Wouters(2003)).

The extrapolative rule is defined by $\widetilde{E}_t^e y_{t+1} = y_{t-1}$ (5)

This kind of simple heuristic has often been used in the behavioural finance literature where agents are assumed to use fundamentalist and chartist rules (see Brock and Hommes(1997), Branch and Evans(2006), De Grauwe and Grimaldi(2006)). It is probably the simplest possible assumption one can make about how agents, which experience cognitive limitations, use rules that embody limited knowledge to guide their behavior. In this sense they are bottom-up rules. They only require agents to use information they understand, and do not require them to understand the whole picture.

Thus the specification of the heuristics in (4) and (5) should not be interpreted as 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). The use of simple rules 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 their errors by switching from one rule to the other.

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

$$\widetilde{E}_t y_{t+1} = \alpha_{f,t} \widetilde{E}_t^f y_{t+1} + \alpha_{c,t} \widetilde{E}_t^e \tag{6}$$

$$\widetilde{E}_t y_{t+1} = \alpha_{f,t} 0 + \alpha_{c,t} y_{t-1} \tag{7}$$

$$\text{and} \quad \alpha_{f,t} + \alpha_{e,t} = 1 \tag{8}$$

where $\alpha_{f,t}$ and $\alpha_{e,t}$ are the probabilities that agents use a fundamentalist, respectively, an extrapolative rule.

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 behaviour at the micro level and how to aggregate it is too sketchy, however, and I have not tried to do so[3].

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, de Palma, and Thisse, (1992) and Brock & 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:

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

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

where $U_{f,t}$ and $U_{e,t}$ are the forecast performances (utilities) of the fundamentalists and extrapolators, 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 fundamentalist forecasting rule is given by the expression (Anderson, de Palma, and Thisse, (1992) and Brock-Hommes(1997)):

$$\alpha_{f,t} = \frac{\exp(\gamma U_{f,t})}{\exp(\gamma U_{f,t}) + \exp(\gamma U_{e,t})} \tag{11}$$

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

$$\alpha_{e,t} = \frac{\exp(\gamma U_{e,t})}{\exp(\gamma U_{f,t}) + \exp(\gamma U_{e,t})} = 1 - \alpha_{f,t} \tag{12}$$

Equation (11) says that as the past forecast performance of the fundamentalists improves relative to that of the extrapolators agents are more likely to select the fundamentalist rule about the output gap for their future forecasts. As a result the

---

[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. There are some attempts to provide micro-foundations of models with agents experiencing cognitive limitations, though. See e.g. Kirman, (1992), Delli Gatti, et al.(2005).

probability that agents use the fundamentalist rule increases. Equation (12) has a similar interpretation. The parameter γ measures the "intensity of choice". It parametrizes 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 fundamentalist or extrapolator by tossing a coin and the probability to be fundamentalist (or extrapolator) is exactly 0.5. When $\gamma = \infty$ utility is fully deterministic and the probability of using a fundamentalist 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 behaviour that are acceptable. Only those rules that pass the fitness test remain in place. The others are weeded out. 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.

It should also be stressed that although individuals use simple 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, agents avoid making systematic mistakes by constantly being willing to learn from past mistakes and to change their behavior. This also ensures that the market forecasts are unbiased.

The mechanism driving the selection of the rules introduces a self-organizing dynamics in the model. It is a dynamics that is beyond the capacity of any one individual in the model to understand. In this sense it is a bottom-up system. It contrasts with the mainstream macroeconomic models in which it is assumed that some or all agents can take a bird's eye view and understand the whole picture. These agents not only understand the whole picture but also use this whole picture to decide about their optimal behaviour. Thus there is a one-to-one correspondence between the total information embedded in the world and the individual brains.

Introducing heuristics in forecasting inflation

Agents also have to forecast inflation. A similar simple heuristics is used as in the case of output gap forecasting, with one rule that could be called a fundamentalist rule and the other an extrapolative rule. (See Brazier et al. (2006) for a similar setup). The fundamentalist rule is based on the announced inflation target, i.e. agents using this rule have confidence in the credibility of this rule and use it to forecast inflation. The extrapolative rule is used by agents who do not trust the announced inflation target. Instead they extrapolate inflation from the past into the future.

The fundamentalist rule will be called an "inflation targeting" rule. It consists in using the central bank's inflation target to forecast future inflation, i.e.

$$\widetilde{E}_t^{tar} = \pi^* \tag{13}$$

where the inflation target π^* is normalized to be equal to 0

The "extrapolators" are defined by $E_t^{ext}\pi_{t+1} = \pi_{t-1}$ (14)

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

$$\widetilde{E}_t\pi_{t+1} = \beta_{tar,t}\widetilde{E}_t^{tar}\pi_{t+1} + \beta_{ext,t}\widetilde{E}_t^{ext}\pi_{t+1} \tag{15}$$

or

$$E_t\pi_{t+1} = \beta_{tar,t}\pi^* + \beta_{ext,t}\pi_{t-1} \tag{16}$$

$$\text{and} \quad \beta_{tar,t} + \beta_{ext,t} = 1 \tag{17}$$

The same selection mechanism is used as in the case of output forecasting 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.

$$\beta_{tar,t} = \frac{\exp(\gamma U_{tar,t})}{\exp(\gamma U_{tar,t}) + \exp(\gamma U_{ext,t})} \tag{18}$$

$$\beta_{ext,t} = \frac{\exp(\gamma U_{ext,t})}{\exp(\gamma U_{tar,t}) + \exp(\gamma U_{ext,t})} \tag{19}$$

where $U_{tar,t}$ and $U_{ext,t}$ 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 (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 probability 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 solution of the model is found by first substituting (3) into (1) and rewriting in matrix notation. This yields:

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

or

$$\boldsymbol{A}\,\boldsymbol{Z_t} = \boldsymbol{B}\,\boldsymbol{\widetilde{E}_t Z_t} + \boldsymbol{C}\,\boldsymbol{Z_{t-1}} + \boldsymbol{b}\,r_{t-1} + \boldsymbol{v_t} \tag{20}$$

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

$$\boldsymbol{Z_t} = \boldsymbol{A^{-1}}\left[\boldsymbol{B}\,\boldsymbol{\widetilde{E}_t Z_t} + \boldsymbol{C}\,\boldsymbol{Z_{t-1}} + \boldsymbol{b}\,r_{t-1} + \boldsymbol{v_t}\right] \tag{21}$$

The solution exists if the matrix $\boldsymbol{A}$ is non-singular, i.e. if $(1-a_2c_2)a_2b_2c_1 \neq 0$. The system (21) describes the solution for y_t and π_t given the forecasts of y_t and π_t . The latter have been specified in equations (4) to (12) and can be substituted into (21). Finally, the solution for r_t is found by substituting y_t and π_t obtained from (21) into (3).

My research strategy consists in comparing the dynamics of this behavioural 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 equations (1) to (3) can be written in matrix notation as follows:

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

$$\Omega\, Z_t = \Phi\, E_t Z_t + \Lambda\, Z_{t-1} + v_t \qquad (22)$$
$$Z_t = \Omega^{-1}\left[\Phi\, E_t Z_t + \Lambda\, Z_{t-1} + v_t\right] \qquad (23)$$

This model can be solved under rational expectations using the Binder-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. A sensitivity analysis of the main results to changes in the some of the parameters of the model will be presented. The three shocks (demand shocks, supply shocks and interest rate shocks) are i.i.d. with standard deviations of 0.5%.

3. Animal spirits, learning and forgetfulness

In this section simulations of the behavioural model in the time domain are presented and interpreted. The upper panel of Figure 1 shows the time pattern of output produced by the behavioural model. A strong cyclical movement in the output gap can be observed. The lower panel of Figure 1 shows a variable called "animal spirits"[4]. It represents the evolution of the fractions of the agents who extrapolate a positive output gap. Thus when the curve reaches +1 all agents are extrapolating a positive output gap; when the curve reaches 0 no agents are extrapolating a positive output gap. In fact in that case they all extrapolate a negative output gap. Thus the curve shows the degree of optimism and pessimism of agents who make forecasts of the output gap.

Combining the information of the two panels in figure 1 it can be seen that the model generates endogenous waves of optimism and pessimism. During some periods optimists (i.e. agents who extrapolate positive output gaps) dominate and this translates into above average output growth. These optimistic periods are followed by pessimistic ones when pessimists (i.e. agents who extrapolate negative output gaps) dominate and the growth rate of output is below average. These waves of optimism

[4] See Mario Nuti (2009)on the different interpretations of "Animal Spirits". The locus classicus is Keynes(1936). See also Farmer(2006) and the recent book of Akerlof and Shiller(2009).

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 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 extrapolating one, delivers a higher payoff, i.e. a lower mean squared forecast error (MSFE). This attracts agents that were using the fundamentalist rule. If the successful extrapolation happens to be a positive extrapolation, more agents will start extrapolating the positive output gap. The "contagion-effect" leads to an increasing use of the optimistic extrapolation of 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. Fundamentalist forecasts may become attractive again, but it is equally possible that pessimistic extrapolation becomes attractive and therefore fashionable again. The economy turns around.

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 (e.g. optimistic extrapolations or pessimistic extrapolations). 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.

The results concerning the time path of inflation are shown in figure 2. First concentrate on the lower panel of figure 2. 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 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. We will return to the question of how the central can reduce this loss of credibility.

Figure 1: Output gap in behavioural model

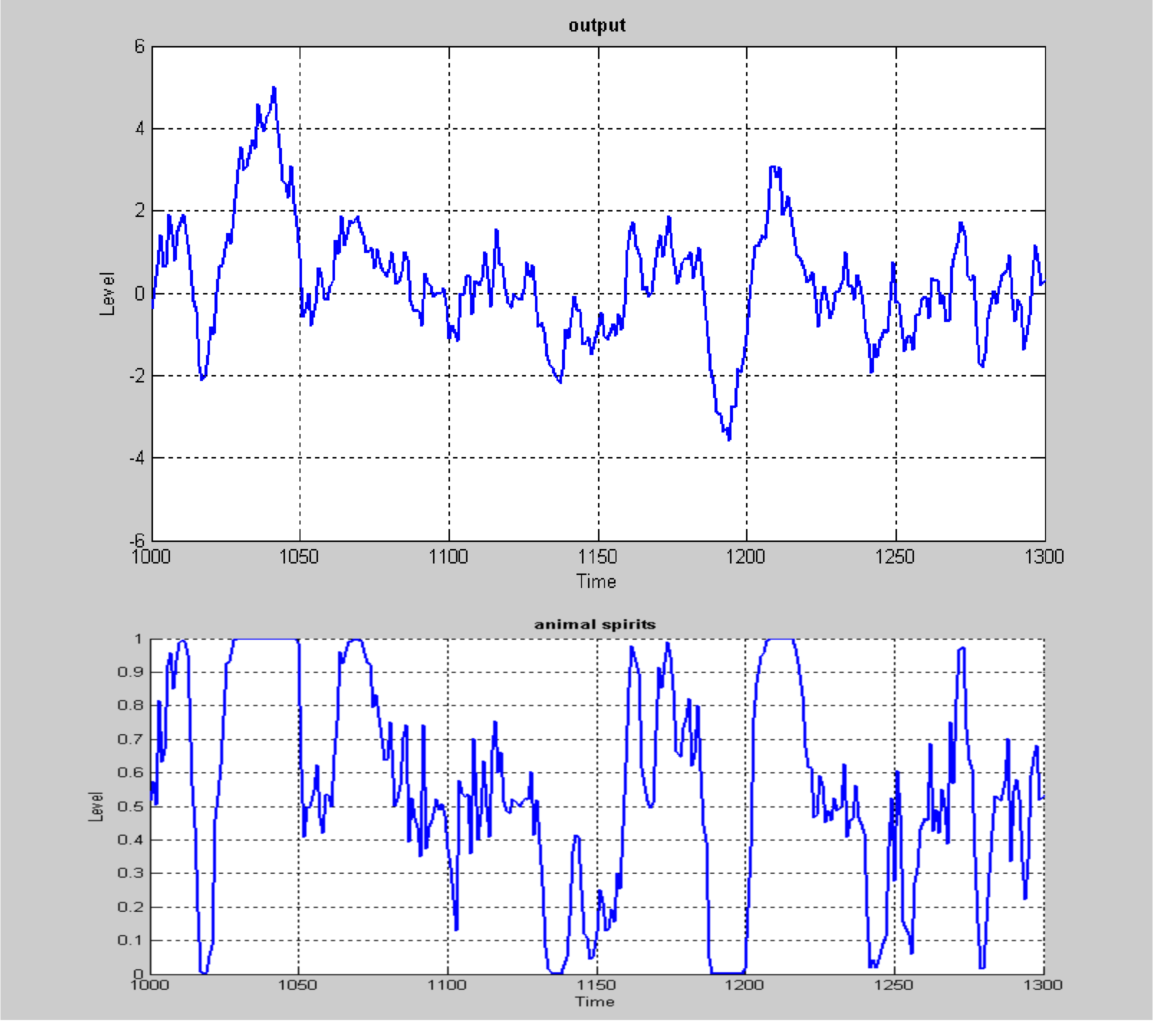
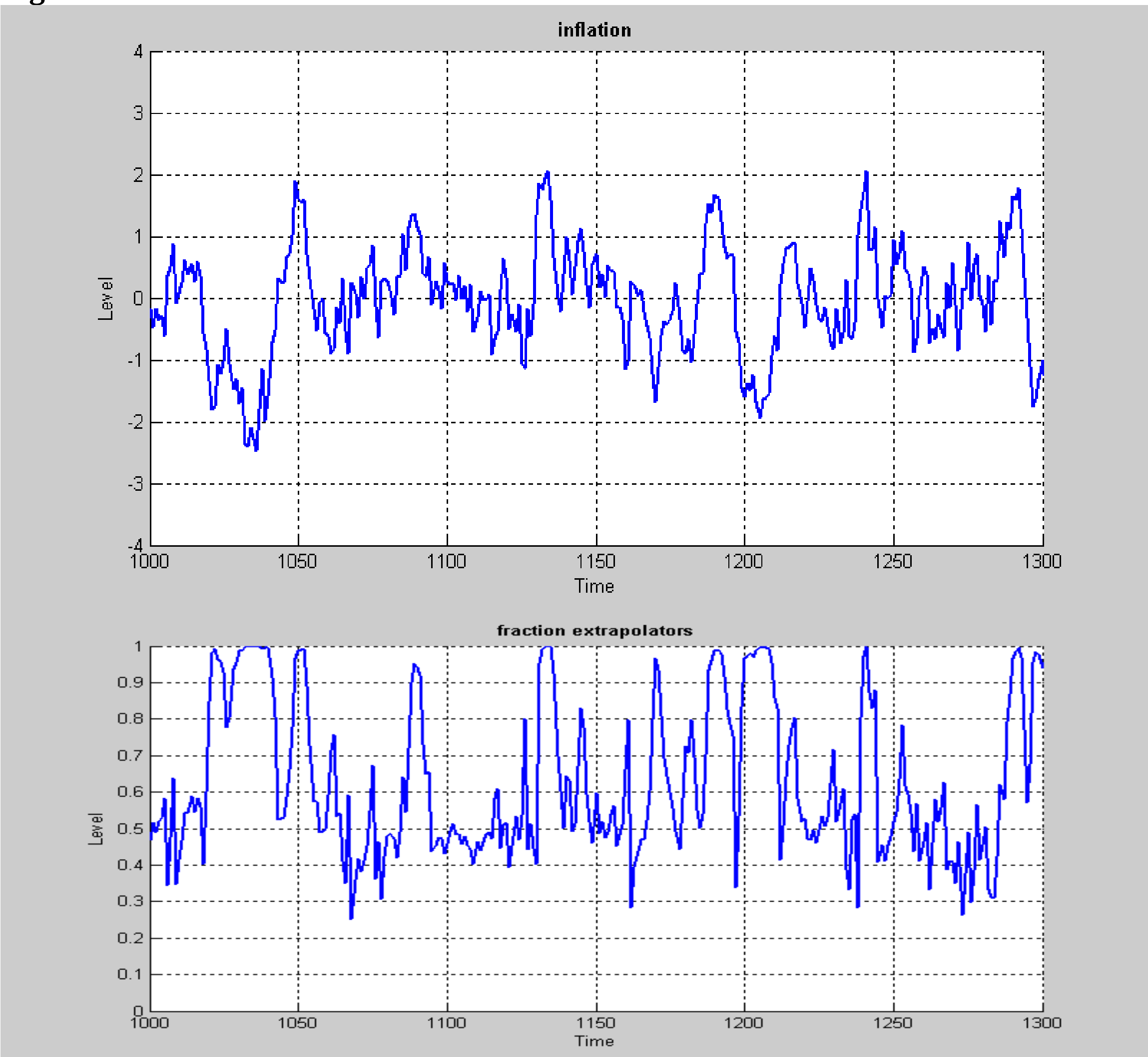


Figure 2 Inflation in behavioural model



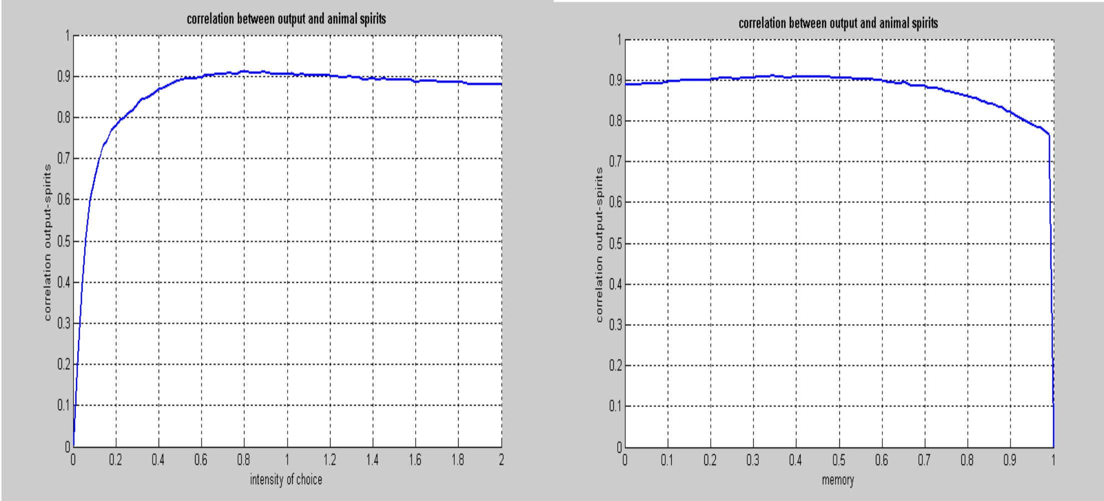
The simulations reported in the previous section assumed a given set of numerical values of the parameters of the model. It was found that for this set of parameter values animal spirits (measured by the movements in the fraction of optimistic extrapolators) emerge and affect the fluctuations of the output gap. The correlation coefficient between the fraction of optimists and the output gap in the simulation reported in figure 1 is 0.86. One would like to know how this correlation evolves when one changes the parameter values of the model. I concentrate on two parameter values here, the intensity of choice parameter, γ, and the memory agents have when calculating the performance of their forecasting. The latter is represented by the parameter ω_k in equations (9)-(10) and is a series of declining weights attached to past forecast errors. I define $\omega_k = (1-\rho)\rho^k$ (and $0 \le \rho \le 1$). 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 figure 3. The left hand panel shows the correlation between the output gap and the fraction of optimistic extrapolators (animal spirits) 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 figure 3 that this is achieved with relatively low levels of γ.

The right hand 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 0.98 the correlations between output and animal spirits are quite high.

Having presented the main features of the behavioural (bottom up) model I now proceed to show how this model leads to a view of macroeconomic dynamics that contrasts greatly with the view obtained from the rational expectations (top down) macroeconomic models . I concentrate on three areas. The first one has to do with the business cycle theories implicit in the behavioural and the rational expectations models. The second one focuses on the nature of the uncertainty in the two models and the third one on the implications for monetary policies.

Figure 3 Correlations between output gap and fraction of optimists



4. Two different business cycle theories

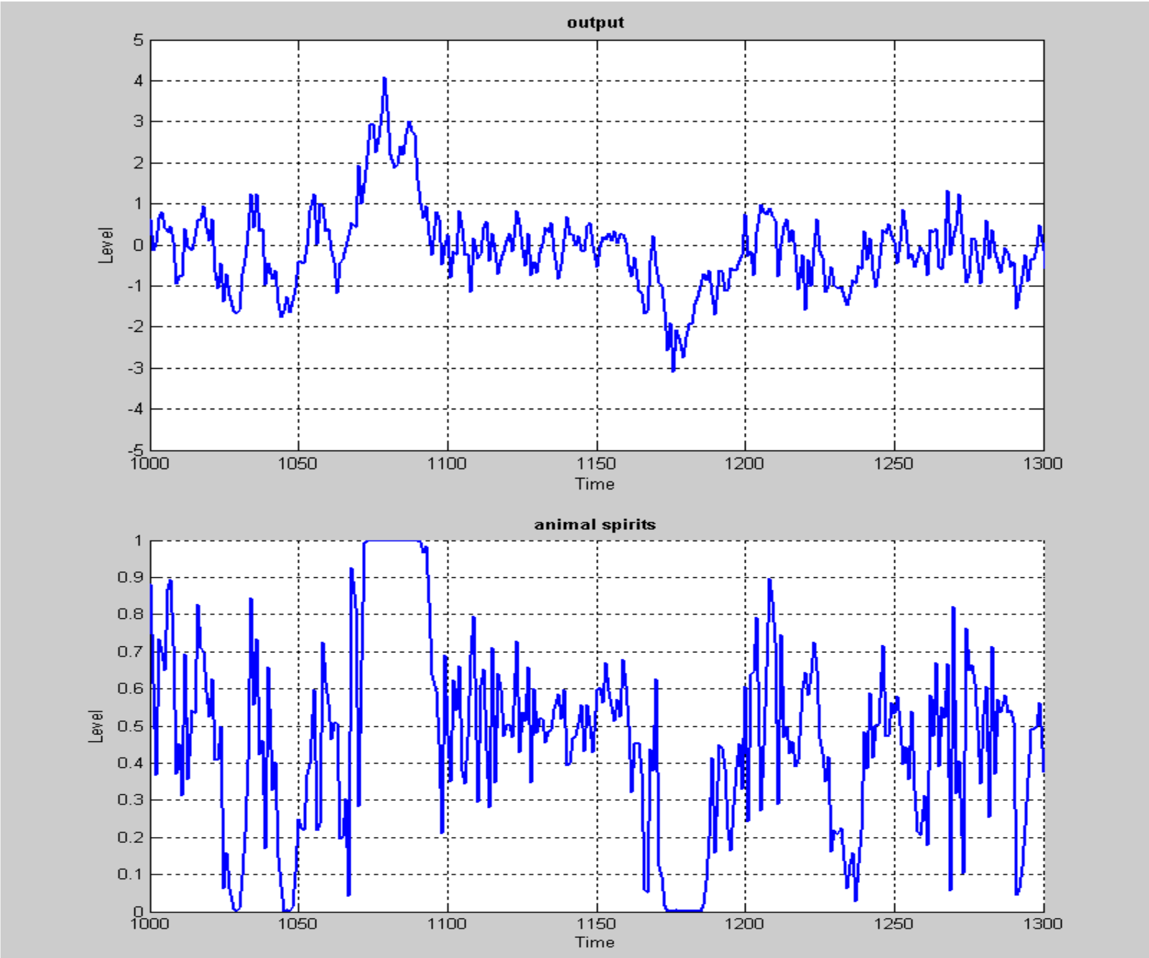
The behavioural and rational expectations macroeconomic models lead to very different views on the nature of business cycle. Business cycle movements in the rational expectations (DSGE) models arise as a result of exogenous shocks (in productivity and preferences) and lags in the transmission of these 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[5].

In contrast, the behavioural model presented here is capable of generating inertia (and business cycles) without imposing lags in the transmission process. This could be called endogenous inertia. I show this by presenting simulations of output and animal spirits 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 equation (1) and $b_1 = 1$ in equation (2). The results are shown in figure 4. We observe similar business cycle movements in output that are highly correlated to

[5] In a way it can be said that the lags in the transmission mechanism introduce an exogenous, some may say an ad-hoc, element into the logic of the DSGE-model. To give an example, Calvo pricing in which firms are constrained to adjust prices instantaneously (Christiano, Eichenbaum and Evans (2001)) is routinely imposed in DSGE models. It is clear, however, that such a restriction comes from outside the logic of the model. In a world where everybody understands the model and each other's rationality, which is at the core of the DSGE-models, agents would want to go immediately to the optimal plan using the optimal price. They would not want to accept such a restriction.

animal spirits as in figure 1. The correlation between output and animal spirits now is 0.71, which is somewhat lower than when lags in the transmission process were assumed (figure 1). This correlation, however, remains significant and is the main driving force behind the output fluctuations.

Figure 4



The inertia obtained in the behavioural model could also be called informational inertia. In contrast to the rational expectations model, agents in the behavioural 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[6]

[6] Critics of the heuristic model presented here may argue that the comparison between the rational and the behavioural 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

The different natures of the business cycles in the DSGE-models and the behavioural model also have policy implications. In the DSGE-models now favoured by central banks, business cycle movements in output and prices originate from price and wage stickiness. In order to reduce this kind of volatility more flexibility in prices and wages is required. That is why many central banks call for more flexibility. 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 behavioural 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 at the risk of reducing price stability.

5. The nature of uncertainty in the two models

The behavioural and the rational expectations models produce a different view about the nature of uncertainty. We illustrate this feature by presenting 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.

The peculiarity of the behavioural 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 5 shows the mean impulse responses to an interest rate shock. These were constructed by simulating the model 10,000 times with 10,000 different realizations

---

reason why the behavioural 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 behavioural 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.

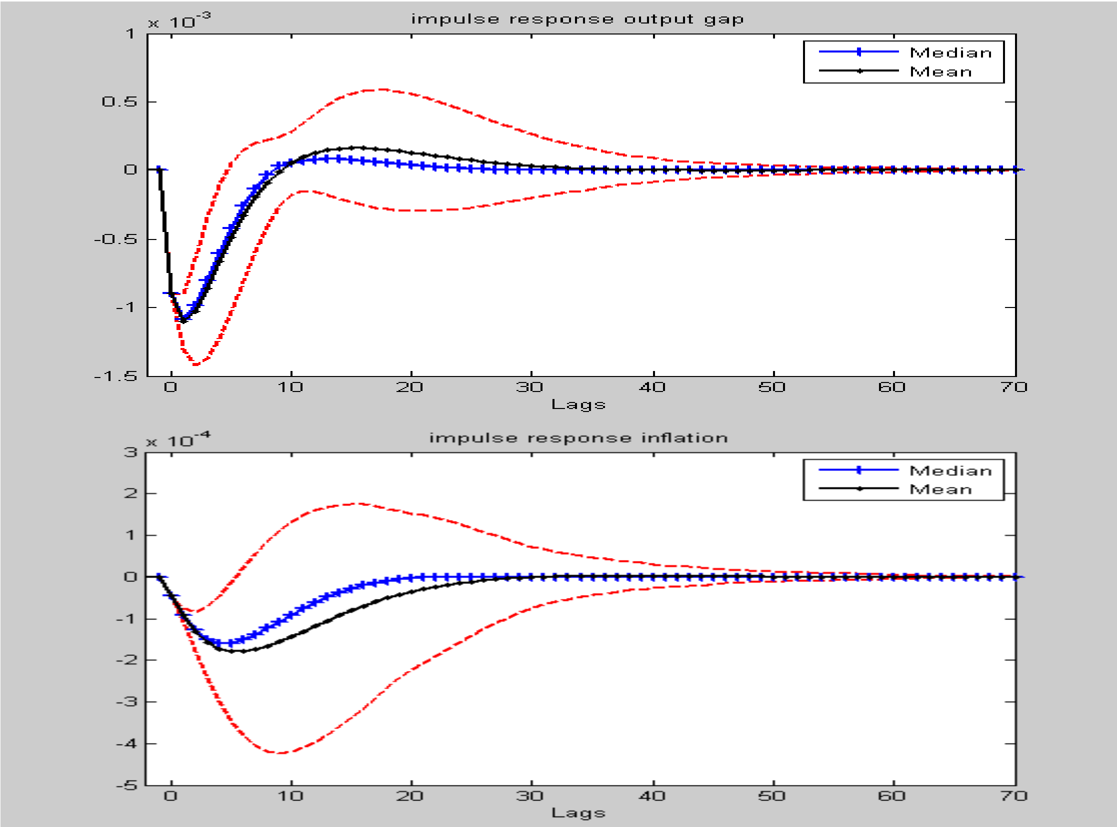
of the shocks. The mean and median responses together with the standard deviations were then computed. Figure 5 shows the mean and median response (the dotted lines are + and – 2 standard deviations from the mean response), exhibiting the standard result of an interest rate shock on output and inflation. However, the uncertainty surrounding this result is considerable at least in the short run. This contrasts with the rational expectations model which does not show such uncertainty (see figure 6).

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 behavioural 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 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.

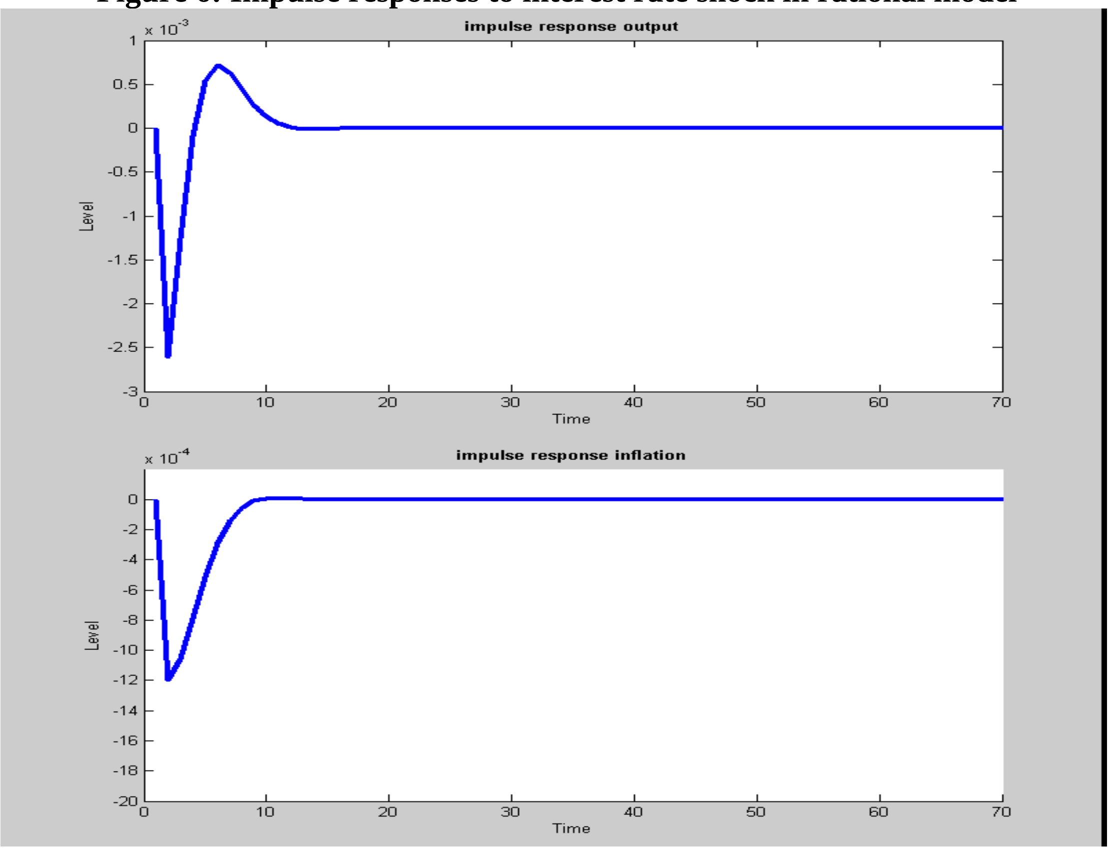
The previous discussion leads to the conclusion that the nature of the uncertainty in the two models is very different. In the top down structure of the rational expectations models, agents capable of overseeing the whole picture, compute with great precision how these shocks are transmitted. The question that arises here is whether the precision obtained in this model does not create an illusion among the practitioners of these models about what one can know in economics.

Figure 5: Mean impulse responses to interest rate shock in the behavioural model



Note: The dotted lines represent the impulse responses with +/- 2 standard deviations

Figure 6: Impulse responses to interest rate shock in rational model



The contrast with the behavioural model is great. The bottom up structure of this model is one in which agents have only limited information. These agents with limited and heterogeneous information, follow rules of behaviour that when interacting with other rules lead to great complexity and a great amount of uncertainty about how an interest rate shock is transmitted. In fact our results suggest that even if one knows the parameters of the model with certainty, it will not be possible to predict how a given shock in the interest rate applied at a particular time will be transmitted in the economy.

6. The nature of uncertainty: some further results.

In this section I discuss some further results illustrating the nature of the uncertainty in the behavioral model. I ask the question of how the transmission of the interest rate shock is influenced by the market sentiments (animal spirits). The way I proceed is as follows. From the impulse response function I extract the short-term output and inflation responses to the interest rate shock. I define short-term to mean after five periods. Then I computed the mean animal spirits index (as defined in section 3 and figure 1) during the periods up to period 5 after the interest rate shock. I repeat this exercise 500 times. This yields 500 observations of the short-term response and the mean animal spirits that prevailed up to the period when I measure the short-term response. The results are shown in figures 7 and 8. On the horizontal axis the animal spirits index is shown. As before it varies between 0 and 1. When the index is zero all agents are extrapolating a negative output gap, i.e. pessimism is at the highest level. When the index is one alls agents extrapolate a positive output gap. Optimism is at its peak. When the index is equal to 0.5 few agents are in fact extrapolating, and most are following a fundamentalists rule, i.e. they expect the output gap to return to zero (its steady state value. On the vertical axis of figure 7 the short-term output effect of an interest rate increase is shown; on the vertical axis of figure 8 the short-term inflation effect of an interest rate increase is shown. I have expressed these effects as "multipliers", i.e. I devide the output and inflation effects by the interest rate shock (which is one standard deviation of the error term in the Taylor equation).

The results of figures 7 and 8 lend themselves to the following interpretation. First, animal spirits have a strong impact on the short-term output effect of the same interest rate shock. In general, I find that the stronger the animal spirits, i.e. the stronger optimism and pessimism are, the greater is the short term impact of the interest rate shock on output. In contrast, when animal spirits are weak (the index is close to 0.5) the impact is weakest. Thus, when the market is dominated by either optimism or pessimism, the monetary authorities' interest rate instrument has the greatest impact on output (in the short run). These effects, however, tend to disappear in the long run.

Second, the animal spirits have a much lower impact on the effectiveness of monetary policy to move inflation. This is made clear from figure 7, which shows a low sensitivity of animal spirits on the impact of an interest rate shock on inflation.

Figure 6

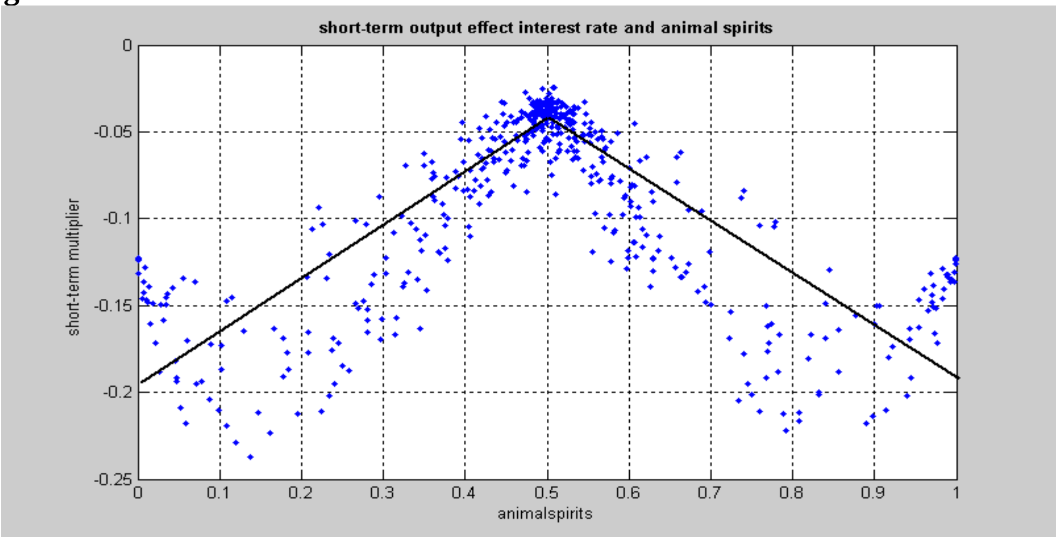
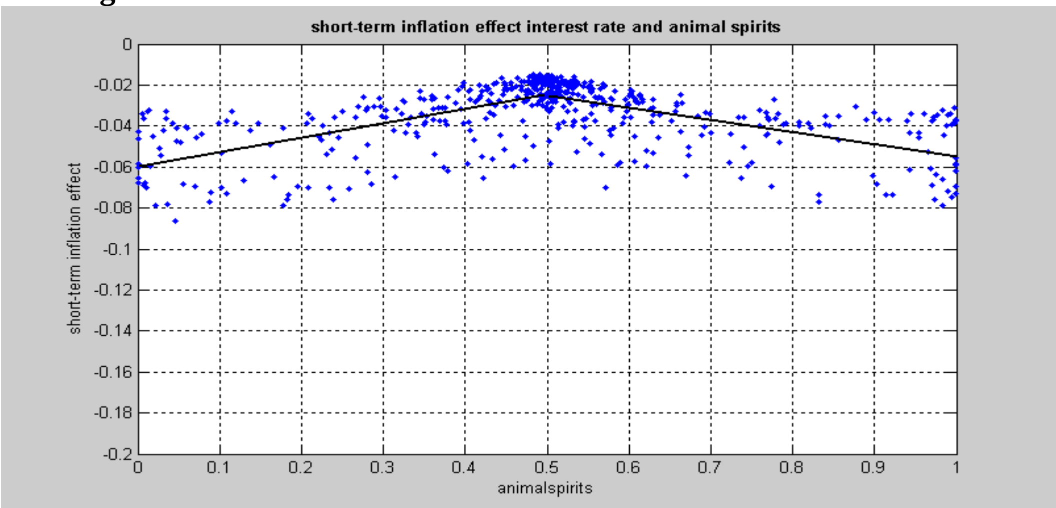


Figure 7



7. Animal Spirits: theory and empirics

The concept of animal spirits, i.e. waves of optimism and pessimism, has played a central role in the behavioural macroeconomic model presented in the previous sections. Is there an empirical counterpart for this concept? There is one, and it is widely used in day-to-day macroeconomic analysis. Many countries use survey based consumer and/or business sentiment indicators as a tool of analyzing the business cycle and as a predictive instrument.

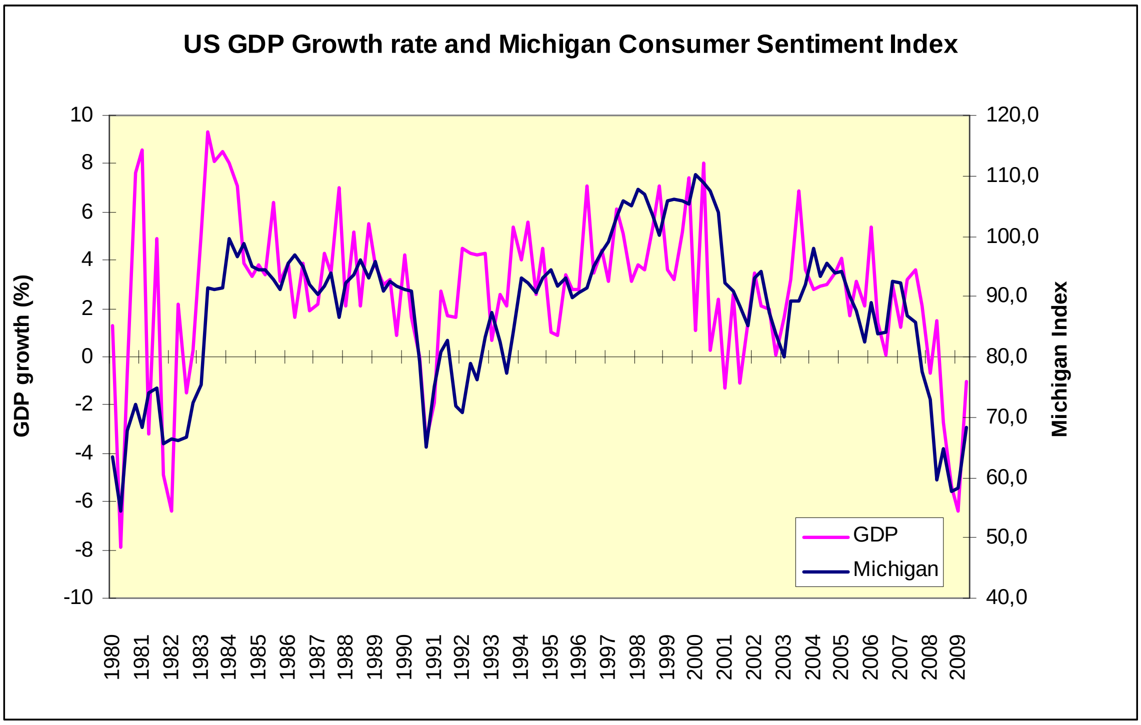
The best-known sentiment indicator in the US is the Michigan Consumer Confidence indicator which has been in use since the 1950s. The first measures of consumer confidence were developed by George Katona in the late 1940s (see Katona(1951)). Since then similar indicators have been implemented in a large number of countries (see Curtin(2007) for an evaluation). Typically, sentiment indicators are constructed on the basis of a number of questions of how the individual perceives the present and the future economic conditions. Thus, these surveys produce two indices, one concerning present conditions, and one about future economic conditions. I will concentrate on the latter here, because this comes closest to the concept of optimism and pessimism used in this paper, which is forward looking. The structure of these questions usually presents the individual with a discrete choice between good-bad-neutral. An example from the Michigan indicator is the question: "Do you think that during the next twelve months, we'll have good times financially or bad times or what? [good times/uncertain/bad times]". The answers are then transformed into an index by computing the divergence between "good times" and "bad times" answers.

The question that is addressed in this section is to what extent these sentiment indicators behave in a way that is consistent with our behavioural macroeconomic model. In figure 12 the Michigan Consumer Confidence indicator is shown, together with the growth rate of US GDP (quarterly data) during 1980-2009. The correlated movements of the sentiment index and the growth rates of GDP are striking. The correlation coefficient was found to be 0.56. Note that in the simulations reported in the previous sections the correlation coefficient between the output gap and the fraction of optimists was typically around 0.85. The lower correlation observed in reality is related to the fact that the survey based sentiment indicators have a lot of noise. Also in figure 8 the consumer sentiment is compared to the growth of GDP, while in the theory sentiments and realizations relate to the same variable, output gap.

In both cases, though, there is a similar pattern of contemporaneous correlation between sentiments and observed economic growth.

A typical feature of this correlation in the theoretical model is that the causality goes both ways, i.e. animal spirits affect output and output feeds back on animal spirits. We illustrated this by performing a Granger causality test on the simulated output gaps and the fractions of optimists (see table 2). It showed that one cannot reject the hypotheses that animal spirits Granger cause the output gap and that the output gap Granger causes the animal spirits. Can one find the same structure in the relation between the observed GDP growth rates and the Michigan Consumer Confidence indicator? The answer is provided in table 3. It shows that one cannot reject the hypothesis that the Michigan Consumer Confidence indicator Granger causes US GDP. The reverse is less clear-cut: there is some evidence that GDP Granger causes the Michigan Confidence indicator, but the level of significance is a borderline case. Curtin(2007) has shown that in a sample of more than 50 countries in a majority of these countries one finds two-way causality between the confidence indicator and GDP growth (or another proxy for the business cycle).

Figure 8



Source: US Department of Commerce, Bureau of Economic Analysis, and University of Michigan: Consumer Sentiment Index.

Table 4: Pairwise Granger Causality Tests

Null Hypothesis:	Obs	F-Statistic	Probability
MICHIGAN does not Granger Cause GDP	118	11.2085	0.001
GDP does not Granger Cause MICHIGAN		2.33769	0.129

8. Conclusion

Macroeconomic models based on rational expectations assume extraordinary cognitive capabilities of individual agents. The latter are assumed to be capable of understanding the whole picture. This feature makes them top-down models. 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 behaviour.

I have used these new insights to develop a macroeconomic model in which the cognitive limitations of agents take center stage. I have called this a bottom-up model. 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 behavioural model produces a number of results that distinguishes it from the rational expectations models. First, the behavioural 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, the bottom-up behavioural model produces a degree of uncertainty about the transmission of monetary policy shocks that is different from the uncertainty obtained in rational expectations (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 behavioural 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. This is an insight not found in mainstream top-down models. In fact these models produce results whose precision is made possible because some agents are assumed to have unlimited cognitive abilities. Models with such features carry the risk of luring economists in believing that the transmission of shocks can be predicted with great confidence.

Finally, the behavioural model provides for a very different theory of the business cycle as compared to the business cycle theory implicit in the rational expectations (DSGE) models. In the DSGE-models, business cycle movements in output and prices 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.

In contrast to the rational expectations model, agents in the behavioural model 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 the inertia in output and prices. Thus a very different 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 is 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 behavioural 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 behavioural model proposed in this paper can be criticised 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-hocquerie”, 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. In contrast, there is no secret in how the superbly informed individuals in the rational expectations top down world process information. They understand the model, and therefore there is only one way to write down how they form their expectations. This feature may give the model builder intellectual satisfaction, but it is unclear whether such a model is useful to understand a world in which agents’ cognitive capacities are severely restricted.

In addition, the current DSGE-models have attached many ad-hoc features aimed at improving the empirical fit which they fail to produce without these additions. All these ad-hoc additions (Calvo-pricing and other ad-hoc lags, rule of thumb consumers) constitute departures from rational behaviour. As a result, it is unclear how much of the dynamics of these models is produced by these ad-hoc additions rather than by the micro-founded rational behaviour.

The research presented in this paper should be considered to be preliminary. Although, some empirical evidence was provided suggesting that the behavioural macroeconomic model has some plausibility, a more rigorous empirical evaluation of the model will be necessary. 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, although remains relatively small in this paper. Thus necessitates to broaden the menu of possible rules so that the selection of the “fittest” rules can occur using a wider pool of rules.

References:

Adjemian, S., Darracq Pariès, M., Moyen, S., (2007), Optimal Monetary Policy in an Estimated DSGE-Model for the Euro Area, Working Paper, no. 803, European Central Bank.

Akerlof, G., and Shiller, R., (2009), *Animal Spirits. How Human Psychology Drives the Economy and Why It Matters for Global Capitalism*, Princeton University Press, 230pp.

Anagnostopoulos, A., Licandro, O., Bove, I., Schlag, K., (2007), An evolutionary theory of inflation inertia, *Journal of the European Economic Association*, 5, 433-443.

Anderson, S., de Palma, A., Thisse, J.-F., 1992, Discrete Choice Theory of Product Differentiation, MIT Press, Cambridge, Mass.

Anufriev, M;, Assenza, T., Hommes, C., Massaro, D., (2009), Interest Rate Rules and Macroeconomic Stability under Heterogeneous Expectations, CeNDEF, University of Amsterdam.

Binder, M., and M.H. Pesaran, (1996), Multivariate Rational Expectations Models and Macroeconomic Modeling: A Review and Some Results, in M.H. Pesaran and M. Wickens, eds., Handbook of Applied Econometrics: Macroeconomics.

Branch, W., and Evans, G., (2006), Intrinsic heterogeneity in expectation formation, *Journal of Economic theory*, 127, 264-95.

Branch, W., and Evans, G. (2009), Monetary Policy with Heterogeneous Expectations, mimeo, Stanford University.

Brazier, A., Harrison, R., King, M., and Yates, T;, (2006), The danger of inflating expectations of macroeconomic stability: heuristic switching in an overlapping generations monetary model, Working Paper no. 303, Bank of England, August.

Brock, W., and Hommes, C., 1997, A Rational Route to Randomness, Econometrica, 65, 1059-1095

Camerer, C., Loewenstein, G., Prelec, D., (2005), Neuroeconomics: How neurosciencecan inform economics, *Journal of Economic Literature*, 63(1), 9-64.

Chari, V., Kehoe, P., McGrattan, E., (2009), New Keynesian Models: Not Yet Useful for Policy Analysis, *American Economic Journal: Macroeconomics*, 1:1, p. 242-266.

Christiano, L., Eichenbaum, M., and Evans, C., (2001), Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy, NBER Working Paper, no. 8403, July.

Christiano, L., Motto, R., Rostagno, M., (2007), Shocks, Structures or Monetary Policies, Working Paper, no. 774, European Central Bank.

Clarida, R., Gali, J., Gertler, M., (1999), The Science of Monetary Policy, A New Keynesian Perspective, *Journal of Economic Literature*, 37, 1661-1707.

Curtin, R., (2007), Consumer Sentiment Surveys: Worldwide Review and Assessment, *Journal of Business Cycle Measurement and Analysis*, 1-37

De Grauwe, P., and Grimaldi, M., (2006), The Exchange Rate in a Behavioural Finance Framework, Princeton University Press.

Della Vigna, S., (2007, Psychology and Economics: Evidence from the Field, NBER Working Paper, no. 13420.

Delli Gatti, D., Di Guilmi, C;, Gaffeo, E., Giuloni, G., Gallegati, M., Palestrini, A., (2005), A new approach to business fluctuations: heterogenous interacting agents, scaling laws and financial fragility, *Journal of Economic Behavior and Organization*, vol. 56, 489-512

De Long, J., Bradford, B., Schleiffer and Summers, L., 1990, "Noise Trader Risk in Financial Markets", *Journal of Political Economy*.

Estrella, A., and Furher, J., Dynamic Inconsistencies: Counterfactual Implications of a Class of Rational Expectations Models, *American Economic Review*, 92(4), Sept., 1013-1028.

Evans, G., and Honkapohja, S., 2001, Learning and Expectations in Macroeconomics, Princeton University Press, 421pp.

Farmer, Roger, E.A., (2006), Animal Spirits, *Palgrave Dictionary of Economics.*

Galí, J., López-Salido, D., Vallés, J., (2004), Rule of Thumb Consumers and the Design of Interest Rate Rules, *Journal of Money Credit and Banking*, 36, no. 4, 739-764.

Galí, J., (2008), Monetary Policy, Inflation and the Business Cycle, Princeton University Press, 203pp.

Gaspar, V., Smets, F., Vestin, D., (2006), Adaptive Learning, Persistence and Optimal Monetary Policy, Working Paper Series, no. 644, European Central Bank.

Gigerenzer, G., and P.M. Todd.1999. *Simple Heuristics That Make Us Smart*. New York: Oxford University Press.

Goodhart, C., (2007), The Continuing Muddles of Monetary Theory: A Steadfast Refusal to Face Facts,(mimeo), Financial Markets Group, London School of Economics

Hayek, F., (1945), The Use of Knowledge in Society, *American Economic Review*, XXXV, no. 4, 519-530..

Howitt, P., (2008), Macroeconomics with Intelligent Autonomous Agents, In *Macroeconomics in the Small and the Large: Essays on Microfoundations, Macroeconomic Applications and Economic History in Honor of Axel Leijonhufvud*, edited by Roger Farmer. Cheltenham: Edward Elgar..

Kahneman, D., and Tversky, A., 1973, Prospect Theory: An analysis of decisions under risk, *Econometrica*, 47, 313-327

Kahneman, D., and Tversky, A., 2000, Choices, Values and Frames, New York: Cambridge University Press.

Kahneman, D., 2002, Maps of Bounded Rationality: A Perspective on Intuitive Judgment and Choice, Nobel Prize Lecture, December 8, Stockholm

Kahneman, D., and Thaler, R., 2006, Utility Maximization and Experienced Utility, *Journal of Economic Perspectives*, 20, 221-234

Katona, George. 1951. *Psychological analysis of economic behavior*. New York: McGraw-Hill

Keynes, J. M. (1936): The General Theory of Employment, Interest and Money. MacMillan and Co.

Kirman, A., (1993), Ants, Rationality and Recruitment, *Quarterly Journal of Economics,* 108: 137-156.

LeBaron,B., and Tesfatsion, L., (2008), "Modeling Macroeconomies as Open-Ended Dynamic Systems of Interacting Agents", *American Economic Review (Papers & Proceedings)*, Volume 98, No. 2, pp. 246-250

Leijonhufvud, A., (1993), Towards a Not-Too-Rational Macroeconomics, *Southern Economic Journal*, Vol. 1, no. 1, July.

Ludvigson, S., (2004), Consumer Confidence and Consumer Spending, *Journal of Economic Perspectives,* 18:2, Spring

Mankiw, N. Gregory and Ricardo Reis (2002). "Sticky Information versus Sticky Prices: A Proposal to Replace the New Keynesian Phillips Curve." *Quarterly Journal of Economics,* 117 (4), 1295-1328.

Mankiw, N. Gregory and Ricardo Reis (2006) "Pervasive Stickiness." *American Economic Review,* 96 (2), 164-169..

Milani, F., (2007a), Learning and Time-Varying Macroeconomic Volatility, mimeo, University of California, Irvine.

Milani, F., (2007b), Expectations, Learning and Macroeconomic Persistence, *Journal of Monetary Economics*, 54, 2065-2082.

Nelson, E., (1998), Sluggish Inflation and Optimizing Models of the Business Cycle, *Journal of Monetary Economics,* 42(2), Oct., 303-322.

Orphanides, A., and Williams, J., (2004), Robust Monetary Policy with Imperfect Information, Board of Governors of the Federal Reserve System.

Sargent, T. 1993. *Bounded Rationality in Macroeconomics*. Oxford University Press.

Sims, C., (2005), Rational Inattention: A Research Agenda, Discussion Paper, no. 34/2005, Deutsche Bundesbank.

Smets, F. and Wouters, R., (2003), An Estimated Dynamic Stochastic General Equilibrium Model, *Journal of the European Economic Association*, 1, 1123-1175.

Smets, F., and Wouters, R., (2007), Shocks and Frictions in Us Business Cycles, Working Paper, no. 722, European Central Bank.

Stanovich, K., and West, R., 2000, Individual differences in reasoning: Implications for the rationality debate, *Behavioural and Brain Sciences*, 23, 645--665.

Svensson, L., (1997), Inflation Forecast Targeting: Implementing and Monitoring Inflation Targets, *European Economic Review,* 41: 111-46.

Tesfatsion, L;, (2006), Agent-Based Computational Economics: A Constructive Approach to Economic Theory, pp. 831-880 in Leigh Tesfatsion and Kenneth L. Judd (eds.), Handbook of Computational Economics, Volume 2: Agent-Based Computational Economics, Handbooks in Economics Series, North-Holland/Elsevier, the Netherlands, Spring 2006.

Thaler, R., 1994, Quasi Rational Economics, Russell Sage Foundation, New York.

Tversky, A., and Kahneman, D., 1981, The framing of decisions and the psychology of choice, Science, 211, 453-458.

Walsh, C., (2003), Monetary Theory and Policy, MIT-Press, 612 pp.

Woodford, M., (2003), Interest and Prices: Foundations of a Theory of Monetary Policy, Princeton University Press.

Woodford, M., (2009), Convergence in Macroeconomics: Elements of the New Synthesis, *American Economic Journal: Macroeconomics*, Vol. 1, no. 1, January, 267-97.

Appendix : parameter values of the calibrated model

Heuristic model

pstar = 0;	% the central bank's inflation target
a1 = 0.5;	%coefficient of expected output in output equation
a2 = -0.2;	%a is the interest elasticity of output demand
b1 = 0.5;	%b1 is coefficient of expected inflation in inflation equation
b2 = 0.05;	%b2 is coefficient of output in inflation equation
c1 = 1.5;	%c1 is coefficient of inflation in Taylor equation
c2 = 0.5;	%c2 is coefficient of output in Taylor equation
c3 = 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
sigma1 = 0.5;	%standard deviation shocks output
sigma2 = 0.5;	%standard deviation shocks inflation
sigma3 = 0.5;	%standard deviation shocks Taylor
rho=0.5;	%rho measures the speed of declining weights in mean squares errors (memory parameter)

Rational model

pstar = 0;	% the central bank's inflation target
a1 = 0.5;	%coefficient of expected output in output equation
a2 = -0.2;	%a is the interest elasticity of output demand
b1 = 0.5;	%b1 is coefficient of expected inflation in inflation equation
b2 = 0.05;	%b2 is coefficient of output in inflation equation
c1 = 1.5;	%c1 is coefficient of inflation in Taylor equation
c2 = 0.5;	%c2 is coefficient of output in Taylor equation
c3 = 0.5;	%interest smoothing parameter in Taylor equation
sigma1 = 0.5;	%standard deviation shocks output
sigma2 = 0.5;	%standard deviation shocks inflation
sigma3 = 0.5;	%standard deviation shocks Taylor

CESifo Working Paper Series

for full list see www.cesifo-group.org/wp
(address: Poschingerstr. 5, 81679 Munich, Germany, office@cesifo.de)

2953 Roland Strausz, The Political Economy of Regulatory Risk, February 2010

2954 Sanjay Jain, Sumon Majumdar and Sharun W. Mukand, Workers without Borders? Culture, Migration and the Political Limits to Globalization, February 2010

2955 Andreas Irmen, Steady-State Growth and the Elasticity of Substitution, February 2010

2956 Bengt-Arne Wickström, The Optimal Babel – An Economic Framework for the Analysis of Dynamic Language Rights, February 2010

2957 Stefan Bauernschuster and Helmut Rainer, From Politics to the Family: How Sex-Role Attitudes Keep on Diverging in Reunified Germany, February 2010

2958 Patricia Funk and Christina Gathmann, How do Electoral Systems Affect Fiscal Policy? Evidence from State and Local Governments, 1890 to 2005, February 2010

2959 Betsey Stevenson, Beyond the Classroom: Using Title IX to Measure the Return to High School Sports, February 2010

2960 R. Quentin Grafton, Tom Kompas and Ngo Van Long, Biofuels Subsidies and the Green Paradox, February 2010

2961 Oliver Falck, Stephan Heblich, Alfred Lameli and Jens Suedekum, Dialects, Cultural Identity, and Economic Exchange, February 2010

2962 Bård Harstad, The Dynamics of Climate Agreements, February 2010

2963 Frederick van der Ploeg and Cees Withagen, Is There Really a Green Paradox?, February 2010

2964 Ingo Vogelsang, Incentive Regulation, Investments and Technological Change, February 2010

2965 Jan C. van Ours and Lenny Stoeldraijer, Age, Wage and Productivity, February 2010

2966 Michael Hoel, Climate Change and Carbon Tax Expectations, February 2010

2967 Tommaso Nannicini and Roberto Ricciuti, Autocratic Transitions and Growth, February 2010

2968 Sebastian Brauer and Frank Westermann, A Note on the Time Series Measure of Conservatism, February 2010

2969 Wolfram F. Richter, Efficient Education Policy – A Second-Order Elasticity Rule, February 2010

2970 Tomer Blumkin, Yoram Margalioth and Efraim Sadka, Taxing Children: The Re-distributive Role of Child Benefits – Revisited, February 2010

2971 Chang Woon Nam and Georg Wamser, Application of Regionally Varying Additionality Degrees in the Practice of EU Cohesion Policy, February 2010

2972 Ali Bayar, Frédéric Dramais, Cristina Mohora, Masudi Opese and Bram Smeets, Modeling Russia for Climate Change Issues, February 2010

2973 Magnus Söderberg, Informal Benchmarks as a Source of Regulatory Threat in Unregulated Utility Sectors, March 2010

2974 Piotr Wdowiński and Marta Malecka, Asymmetry in Volatility: A Comparison of Developed and Transition Stock Markets, March 2010

2975 Frans van Winden, Michal Krawczyk and Astrid Hopfensitz, Investment, Resolution of Risk, and the Role of Affect, March 2010

2976 Hyun-Ju Koh and Nadine Riedel, Do Governments Tax Agglomeration Rents?, March 2010

2977 Johann K. Brunner and Susanne Pech, Optimum Taxation of Bequests in a Model with Initial Wealth, March 2010

2978 Guglielmo Maria Caporale and Nicola Spagnolo, Stock Market Integration between three CEECs, Russia and the UK, March 2010

2979 Florian Englmaier, Ales Filipi and Ravi Singh, Incentives, Reputation and the Allocation of Authority, March 2010

2980 Konstantinos Angelopoulos, George Economides and Apostolis Philippopoulos, What is the Best Environmental Policy? Taxes, Permits and Rules under Economic and Environmental Uncertainty, March 2010

2981 Frederick van der Ploeg, Rapacious Resource Depletion, Excessive Investment and Insecure Property Rights, March 2010

2982 Wolfram F. Richter and Christoph Braun, Efficient Subsidization of Human Capital Accumulation with Overlapping Generations and Endogenous Growth, March 2010

2983 Francesco Cinnirella, Marc Piopiunik and Joachim Winter, Why Does Height Matter for Educational Attainment? Evidence from German Pre-Teen Children, March 2010

2984 Bernard Van Praag, Well-being Inequality and Reference Groups – An Agenda for New Research, March 2010

2985 Francesca Barion, Raffaele Miniaci, Paolo M. Panteghini and Maria Laura Parisi, Profit Shifting by Debt Financing in Europe, March 2010

2986 Alexander Haupt and Magdalena Stadejek, The Choice of Environmental Policy Instruments: Energy Efficiency and Redistribution, March 2010

2987 John Komlos and Marek Brabec, The Trend of BMI Values among US Adults, March 2010

2988 Emanuele Massetti and Lea Nicita, The Optimal Climate Policy Portfolio when Knowledge Spills across Sectors, March 2010

2989 Helmut Rainer and Thomas Siedler, Family Location and Caregiving Patterns from an International Perspective, March 2010

2990 Toru Kikuchi and Ngo Van Long, A Simple Model of Service Offshoring with Time Zone Differences, March 2010

2991 Assaf Razin, Efraim Sadka and Benjarong Suwankiri, Migration and the Welfare State: Dynamic Political-Economy Theory, March 2010

2992 Bård Harstad, Buy Coal! Deposit Markets Prevent Carbon Leakage, March 2010

2993 Axel Dreher, Stephan Klasen, James Raymond Vreeland and Eric Werker, The Costs of Favoritism: Is Politically-driven Aid less Effective?, March 2010

2994 Sven Neelsen and Thomas Stratmann, Effects of Prenatal and Early Life Malnutrition: Evidence from the Greek Famine, March 2010

2995 Claude Hillinger and Bernd Süssmuth, The Quantity Theory of Money: An Assessment of its Real Linchpin Prediction, March 2010

2996 Matthew M. Chingos and Martin R. West, Do More Effective Teachers Earn More Outside of the Classroom?, March 2010

2997 Laurence Jacquet and Dirk Van de gaer, A Comparison of Optimal Tax Policies when Compensation or Responsibility Matter, March 2010

2998 Valentina Bosetti, Carlo Carraro, Romain Duval and Massimo Tavoni, What Should we Expect from Innovation? A Model-Based Assessment of the Environmental and Mitigation Cost Implications of Climate-Related R&D, March 2010

2999 Scott Alan Carson, Nineteenth Century Stature and Family Size: Binding Constraint or Productive Labor Force?, March 2010

3000 Jukka Pirttilä and Ilpo Suoniemi, Public Provision, Commodity Demand and Hours of Work: An Empirical Analysis, March 2010

3001 Bertrand Candelon and Franz C. Palm, Banking and Debt Crises in Europe: The Dangerous Liaisons?, March 2010

3002 Joan Costa-i-Font and Marin Gemmill-Toyama, Does Cost Sharing really Reduce Inappropriate Prescriptions?, March 2010

3003 Scott Barrett, Climate Treaties and Backstop Technologies, March 2010

3004 Hans Jarle Kind, Tore Nilssen and Lars Sørgard, Price Coordination in Two-Sided Markets: Competition in the TV Industry, March 2010

3005 Jay Pil Choi and Heiko Gerlach, Global Cartels, Leniency Programs and International Antitrust Cooperation, March 2010

3006 Aneta Hryckiewicz and Oskar Kowalewski, Why do Foreign Banks Withdraw from other Countries? A Panel Data Analysis, March 2010

3007 Eric A. Hanushek and Ludger Woessmann, Sample Selectivity and the Validity of International Student Achievement Tests in Economic Research, March 2010

3008 Dennis Novy, International Trade and Monopolistic Competition without CES: Estimating Translog Gravity, April 2010

3009 Yin-Wong Cheung, Guonan Ma and Robert N. McCauley, Renminbising China's Foreign Assets, April 2010

3010 Michel Beine and Sara Salomone, Migration and Networks: Does Education Matter more than Gender?, April 2010

3011 Friedrich Schneider, Tilman Brück and Daniel Meierrieks, The Economics of Terrorism and Counter-Terrorism: A Survey (Part I), April 2010

3012 Friedrich Schneider, Tilman Brück and Daniel Meierrieks, The Economics of Terrorism and Counter-Terrorism: A Survey (Part II), April 2010

3013 Frederick van der Ploeg and Steven Poelhekke, The Pungent Smell of "Red Herrings": Subsoil Assets, Rents, Volatility and the Resource Curse, April 2010

3014 Vjollca Sadiraj, Jan Tuinstra and Frans van Winden, Identification of Voters with Interest Groups Improves the Electoral Chances of the Challenger, April 2010

3015 Guglielmo Maria Caporale, Davide Ciferri and Alessandro Girardi, Time-Varying Spot and Futures Oil Price Dynamics, April 2010

3016 Scott Alan Carson, Racial Differences in Body-Mass Indices for Men Imprisoned in 19th Century US Prisons: A Multinomial Approach, April 2010

3017 Alessandro Fedele, Paolo M. Panteghini and Sergio Vergalli, Optimal Investment and Financial Strategies under Tax Rate Uncertainty, April 2010

3018 Laurence Jacquet, Take it or Leave it: Take-up, Optimal Transfer Programs, and Monitoring, April 2010

3019 Wilhelm Kohler and Jens Wrona, Offshoring Tasks, yet Creating Jobs?, April 2010

3020 Paul De Grauwe, Top-Down versus Bottom-Up Macroeconomics, April 2010