1

A Behavioral Macroeconomic Model

1.1 Introduction

Capitalism is characterized by booms and busts, by periods of strong growth in output followed by periods of declines in economic growth. Every macroeconomic theory should attempt at explaining these endemic business cycle movements.

Before developing the behavioral model it is useful to present some stylized facts about the cyclical movements of output. In figure 1.1 I show the strong cyclical movements of the output gap in the United States since 1960. These cyclical movements imply that there is strong autocorrelation in the output gap numbers, i.e., the output gap in period t is strongly correlated with the output gap in period $t-1$. The intuition is that if there are cyclical movements we will observe clustering of good and bad times. A positive (negative) output gap is likely to be followed by a positive (negative) output gap in the next period. This is what we find for the U.S. output gap over the period 1960–2009: the autocorrelation coefficient is 0.94. Similar autocorrelation coefficients are found in other countries.

A second stylized fact about the movements in the output gap is that these are not normally distributed. The evidence for the U.S. is shown in figure 1.2. We find, first, that there is excess kurtosis (kurtosis = 3.62), which means that there is too much concentration of observations around the mean to be consistent with a normal distribution. Second, we find that there are fat tails, i.e., there are more large movements in the output gap than is compatible with the normal distribution. This implies that the business cycle movements are characterized by periods of tranquility interrupted by large positive and negative movements in output, in other words, booms and busts. This also means that if we were basing our forecasts on the normal distribution we would underestimate the probability that in any one period a large increase or decrease in the output gap can occur. Finally, the Jarque–Bera test leads to a formal rejection of normality of the movements in the U.S. output gap series.

The same empirical features have been found in other OECD countries (see Fagiolo et al. 2008, 2009). These authors also confirm that output *growth rates* in most OECD countries are nonnormally distributed, with tails that are much fatter than

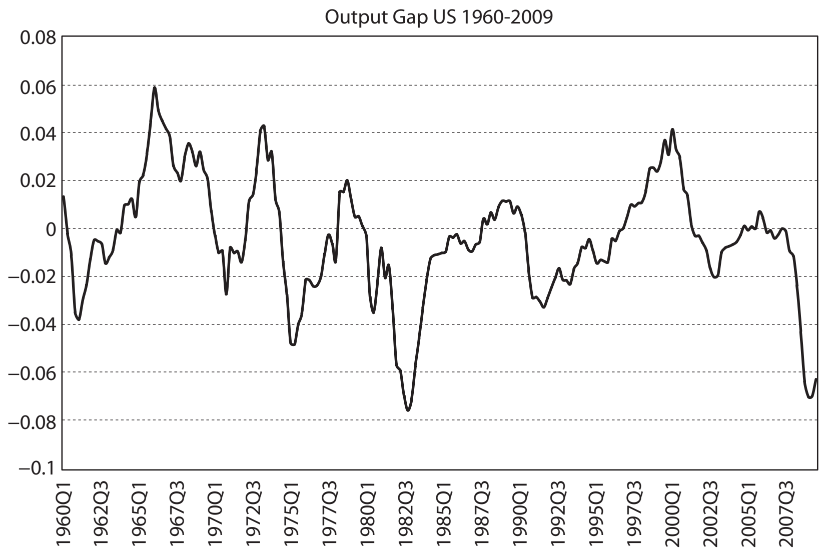

Figure 1.1. *Source:* U.S. Department of Commerce and Congressional Budget Office.

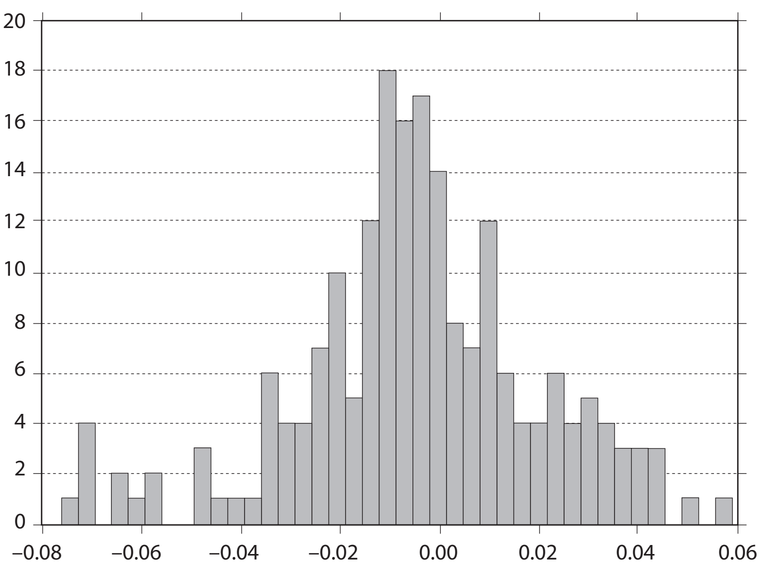

Figure 1.2. Frequency distribution of U.S. output gap (1960–2009): kurtosis, 3.61; Jarque–Bera, 7.17 with p-value = 0.027. *Source:* U.S. Department of Commerce and Congressional Budget Office.

those in a normal distribution. In the empirical chapter 8 additional evidence is provided for other industrialized countries illustrating the same empirical regularities observed for the United States.

One of the purposes of this chapter is to explain this boom and bust characteristic of movements of the business cycle. We will also want to contrast the explanation provided by the behavioral model with the one provided by the mainstream macroeconomic model, which is based on rational expectations.

1.2 The Model

I will use a standard macroeconomic model that in its basic structure is the same as the mainstream new Keynesian model as described in, for example, Galí (2008). In this section I describe this model. In the next I introduce the behavioral assumptions underlying the way agents make forecasts.

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.,

$$y_t = a_1 \tilde{E}_t y_{t+1} + (1 - a_1) y_{t-1} + a_2 (r_t - \tilde{E}_t \pi_{t+1}) + \varepsilon_t, \tag{1.1}$$

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 symbol refers to expectations that are not formed rationally. This process will be specified subsequently. I follow the procedure introduced in new Keynesian macroeconomic models of adding a lagged output in the demand equation (see Galí 2008; Woodford 2003). This is usually justified by invoking habit formation. I keep this assumption here as I want to compare the behavioral model with the new Keynesian rational expectations model. However, I will later show that I do not really need this inertia-building device to generate inertia in the endogenous variables.

The aggregate demand equation has a very simple interpretation. Utility-maximizing agents will want to spend more on goods and services today when they expect future income (output gap) to increase and to spend less when the real interest rate increases.

The aggregate supply equation is derived from profit maximization of individual producers (see Galí 2008, chapter 3). In addition, it is assumed that producers cannot adjust their prices instantaneously. Instead, for institutional reasons, they have to wait to adjust their prices. The most popular specification of this price-adjustment mechanism is the Calvo pricing mechanism (Calvo 1983; for a criticism see McCallum 2005). This assumes that in period t a fraction of prices remains unchanged. Under those conditions the aggregate supply equation (which is often referred to as the new Keynesian Philips curve) can be derived as

$$\pi_t = b_1 \tilde{E}_t \pi_{t+1} + (1 - b_1) \pi_{t-1} + b_2 y_t + \eta_t. \tag{1.2}$$

The previous two equations determine the two endogenous variables—inflation and output gap—given the nominal interest rate. The model has to be closed by specifying the way the nominal interest rate is determined. The most popular way to do this has been to invoke the Taylor rule (see Taylor 1993). This rule describes the behavior of the central bank. It is usually written as follows:

$$r_t = c_1(\pi_t - \pi^*) + c_2 y_t + c_3 r_{t-1} + u_t, \tag{1.3}$$

where π^* is the inflation target. Thus the central bank is assumed to raise the interest rate when the observed inflation rate increases relative to the announced inflation target. The intensity with which it does this is measured by the coefficient c_1. Similarly, when the output gap increases the central bank is assumed to raise the interest rate. The intensity with which it does this is measured by c_2. The latter parameter then also tells us something about the ambitions the central bank has to stabilize output. A central bank that does not care about output stabilization sets $c_2 = 0$. We say that this central bank applies strict inflation targeting. Finally, note that, as is commonly done, the central bank is assumed to smooth the interest rate. This smoothing behavior is represented by the lagged interest rate in equation (1.3).

The parameter c_1 is important. It has been shown (see Woodford 2003, chapter 4; Galí 2008) that it must exceed 1 for the model to be stable. This is also sometimes called the "Taylor principle."

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 is not done here in order to maintain simplicity in the model (again see Woodford 2003, p. 257).[1]

It should also be mentioned that another approach to describing the monetary policy of the central bank is to start from a minimization of the loss function and to derive the optimal response of the central bank from this minimization process (see Woodford 2003). This has not been attempted here.

We have added error terms in each of the three equations. These error terms describe the nature of the different shocks that can hit the economy. There are demand shocks, ε_t, supply shocks, η_t, and interest rate shocks, υ_t. We will generally assume that these shocks are normally distributed with mean zero and a constant standard deviation. Agents with rational expectations are assumed to know the distribution of these shocks. It will turn out that this is quite a crucial assumption.

The model consisting of equations (1.1)–(1.3) can be solved under rational expectations. This will be done in Section 1.9. I will call this new Keynesian model with rational expectations the "mainstream model" to contrast it with our behavioral model. I will also occasionally refer to the DSGE model, i.e., the dynamic stochastic general equilibrium model, which has the same features, i.e., new Keynesian wage and price rigidities coupled to rational expectations. In the following sections

[1] As is shown in Woodford (2003), forward-looking Taylor rules may not lead to a determinate solution even if the Taylor principle is satisfied.

I specify the assumptions that underlie the forecasting of output and inflation in the behavioral model.

1.3 Introducing Heuristics in Forecasting Output

In the world of rational expectations that forms the basis of the mainstream model, agents are assumed to understand the complexities of the world. In contrast, we take the view that agents have cognitive limitations. They only understand tiny little bits of the world. In such a world agents are likely to use simple rules, heuristics, to forecast the future (see, for example, Damasio 2003; Kahneman 2002; Camerer et al. 2005). In this chapter, a simple heuristic will be assumed. In a later chapter (chapter 5) other rules are introduced. This will be done to study how more complexity in the heuristics affects the results.

Agents who use simple rules of behavior are no fools. They use simple rules only because the real world is too complex to understand, but they are willing to learn from their mistakes, i.e., they regularly subject the rules they use to some criterion of success. There are essentially two ways this can be done. The first one is called statistical learning. It has been pioneered by Sargent (1993) and Evans and Honkapohja (2001). It consists in assuming that agents learn like econometricians do. They estimate a regression equation explaining the variable to be forecasted by a number of exogenous variables. This equation is then used to make forecasts. When new data become available the equation is re-estimated. Thus each time new information becomes available the forecasting rule is updated. The statistical learning literature leads to important new insights (see, for example, Bullard and Mitra 2002; Gaspar et al. 2006; Orphanides and Williams 2004; Milani 2007a; Branch and Evans 2011). However, this approach loads individual agents with a lot of cognitive skills that they may or may not have.[2] I will instead use another learning strategy that can be called "trial-and-error" learning. It is also often labeled "adaptive learning." I will use both labels as synonyms.

Oh gosh… adaptive learning here doesn't refer to adaptive learning…

Adaptive learning is a procedure whereby agents use simple forecasting rules and then subject these rules to a "fitness" test, i.e., agents endogenously select the forecasting rules that have delivered the highest performance (fitness) in the past. Thus, an agent will start using one particular rule. She will regularly evaluate this rule against the alternative rules. If the former rule performs well, she keeps it. If not, she switches to another rule. In this sense the rule can be called a trial-and-error rule.

refers to Branch's RPE

This trial-and-error selection mechanism acts as a disciplining device on the kind of rules that are acceptable. Not every rule is acceptable. It has to perform well. What that means will be made clear later. It is important to have such a

[2] See the book of Gigerenzer and Todd (1999), which argues that individual agents experience great difficulties in using statistical learning techniques. It has a fascinating analysis on the use of simple heuristics as compared with statistical (regression) learning.

disciplining device, otherwise everything becomes possible. The need to discipline the forecasting rule was also one of the basic justifications underlying rational expectations. By imposing the condition that forecasts must be consistent with the underlying model, the model builder severely limits the rules that agents can use to make forecasts. The adaptive selection mechanism used here plays a similar disciplining role.

sic!

There is another important implication of using trial-and-error rules that contrasts a great deal with the rational expectations forecasting rule. Rational expectations implies that agents understand the complex structure of the underlying model. Since there is only one underlying model (there is only one "Truth"), agents understand the same "Truth." They all make exactly the same forecast. This allows builders of rational expectations models to focus on just one "representative agent." In the adaptive learning mechanism that will be used here, this will not be possible because agents can use different forecasting rules. Thus there will be heterogeneity among agents. This is an important feature of the model because, as will be seen, this heterogeneity creates interactions between agents. These interactions ensure that agents influence each other, leading to a dynamics that is absent from rational expectations models.

Agents are assumed to use simple rules (heuristics) to forecast the future output and inflation. The way I proceed is as follows. 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 in chapter 7, 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.

(i) The fundamentalist rule is defined by

$$\tilde{E}_t^{\mathrm{f}} y_{t+1} = 0. \tag{1.4}$$

(ii) The extrapolative rule is defined by

$$\tilde{E}_t^{\mathrm{e}} y_{t+1} = y_{t-1}. \tag{1.5}$$

This kind of simple heuristic has often been used in the behavioral 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). The rules are simple in the sense that they only require agents to use information they understand, and do not require them to understand the whole picture. Some experimental evidence in support of the two rules (1.4) and (1.5) for inflation forecasts in a new Keynesian model can be found in a paper by Pfajfar and Zakelj (2009).

Thus the specification of the heuristics in (1.4) and (1.5) 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 continually 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.,

$$\tilde{E}_t y_{t+1} = \alpha_{\mathrm{f},t} \tilde{E}_t^{\mathrm{f}} y_{t+1} + \alpha_{\mathrm{e},t} \tilde{E}_t^{\mathrm{f}}, \tag{1.6}$$

$$\tilde{E}_t y_{t+1} = \alpha_{\mathrm{f},t} 0 + \alpha_{\mathrm{e},t} y_{t-1}, \tag{1.7}$$

and

$$\alpha_{\mathrm{f},t} + \alpha_{\mathrm{e},t} = 1, \tag{1.8}$$

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

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 and how to aggregate it is too sketchy, however. Psychologists and neuroscientists struggle to understand how our brains process information. There is as yet no generally accepted model we could use to model the micro-foundations of information processing in a world in which agents experience cognitive limitations. I have not tried to do so.[3] In the appendix I return to some of the issues related to micro-founding of macroeconomic models.

Selecting the Forecasting Rules

As indicated earlier, agents in our model are not fools. They are willing to learn, i.e., they continually evaluate their forecast performance. This willingness to learn and to change one's behavior is the most fundamental definition of rational behavior. Thus our agents in the model *are* rational, just not in the sense of having rational

[3] There are some attempts to provide micro-foundations of models with agents experiencing cognitive limitations, though (see, for example, Kirman 1992; Delli Gatti et al. 2005; Branch and Evans 2011; Branch and McGough 2008).

expectations. We do not use this assumption here because it is an implausible assumption to make about the capacity of individuals to understand the world. Instead our agents are rational in the sense that they learn from their mistakes. The concept of "bounded rationality" is often used to characterize this behavior.

The first step in the analysis then consists in defining a criterion of success. This will be the forecast performance of a particular rule. Thus in this first step, agents compute the forecast performance of the two different forecasting rules as follows:

$$U_{\mathrm{f},t} = -\sum_{k=0}^{\infty} \omega_k [y_{t-k-1} - \tilde{E}_{\mathrm{f},t-k-2} y_{t-k-1}]^2, \tag{1.9}$$

$$U_{\mathrm{e},t} = -\sum_{k=0}^{\infty} \omega_k [y_{t-k-1} - \tilde{E}_{\mathrm{e},t-k-2} y_{t-k-1}]^2, \tag{1.10}$$

where $U_{\mathrm{f},t}$ and $U_{\mathrm{e},t}$ are the forecast performances (utilities) of the fundamentalist and extrapolating rules, respectively. These are defined as the mean squared forecasting errors (MSFEs) of the forecasting rules; ω_k are geometrically declining weights. We make these weights declining because we assume that agents tend to forget. Put differently, they give a lower weight to errors made far in the past as compared with errors made recently. The degree of forgetting will turn out to play a major role in our model.

The next step consists in evaluating these forecast performances (utilities). I apply discrete choice theory (see Anderson et al. (1992) for a thorough analysis of discrete choice theory and Brock and Hommes (1997) for the first application in finance) in specifying the procedure agents follow in this evaluation process. If agents were purely rational they would just compare $U_{\mathrm{f},t}$ and $U_{\mathrm{e},t}$ in (1.9) and (1.10) and choose the rule that produces the highest value. Thus under pure rationality, agents would choose the fundamentalist rule if $U_{\mathrm{f},t} > U_{\mathrm{e},t}$, and vice versa. However, things are not so simple. Psychologists have found out that when we have to choose among alternatives we are also influenced by our state of mind. The latter is to a large extent unpredictable. It can be influenced by many things, the weather, recent emotional experiences, etc. One way to formalize this is that the utilities of the two alternatives have a deterministic component (these are $U_{\mathrm{f},t}$ and $U_{\mathrm{e},t}$ in (1.9) and (1.10)) and a random component $\varepsilon_{\mathrm{f},t}$ and $\varepsilon_{\mathrm{e},t}$. The probability of choosing the fundamentalist rule is then given by

$$\alpha_{\mathrm{f},t} = P[U_{\mathrm{f},t} + \varepsilon_{\mathrm{f},t} > (U_{\mathrm{e},t} + \varepsilon_{\mathrm{e},t})]. \tag{1.11}$$

In words, this means that the probability of selecting the fundamentalist rule is equal to the probability that the stochastic utility associated with using the fundamentalist rule exceeds the stochastic utility of using an extrapolative rule. In order to derive a more precise expression one has to specify the distribution of the random variables $\varepsilon_{\mathrm{f},t}$ and $\varepsilon_{\mathrm{e},t}$. It is customary in the discrete choice literature to assume that these random variables are logistically distributed (see Anderson et al. 1992, p. 35). One then obtains the following expressions for the probability of choosing the fundamentalist rule:

$$\alpha_{\mathrm{f},t} = \frac{\exp(\gamma U_{\mathrm{f},t})}{\exp(\gamma U_{\mathrm{f},t}) + \exp(\gamma U_{\mathrm{e},t})}. \tag{1.12}$$

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

$$\alpha_{\mathrm{e},t} = \frac{\exp(\gamma U_{\mathrm{e},t})}{\exp(\gamma U_{\mathrm{f},t}) + \exp(\gamma U_{\mathrm{e},t})} = 1 - \alpha_{\mathrm{f},t}. \tag{1.13}$$

Equation (1.12) says that as the past forecast performance of the fundamentalist rule improves relative to that of the extrapolative rule, agents are more likely to select the fundamentalist rule for their forecasts of the output gap. Equation (1.13) has a similar interpretation. The parameter γ measures the "intensity of choice." It is related to the variance of the random components $\varepsilon_{\mathrm{f},t}$ and $\varepsilon_{\mathrm{e},t}$. If the variance is very high, γ approaches 0. 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 $\gamma = \infty$ the variance of the random components is zero (utility is then 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.

It should be mentioned here that the probabilities $\alpha_{\mathrm{f},t}$ and $\alpha_{\mathrm{e},t}$ can also be interpreted as the fractions of agents that use a fundamentalist and extrapolative forecasting rule, respectively. This can be seen as follows. Suppose the number of agents is N. Then, if the probability that an agent uses a fundamentalist rule is $\alpha_{\mathrm{f},t}$ on average $\alpha_{\mathrm{f},t}N$ agents will use this rule. Thus the fraction of the total number of agents using this rule is $\alpha_{\mathrm{f},t}N/N = \alpha_{\mathrm{f},t}$. The same holds for $\alpha_{\mathrm{e},t}$. These fractions are determined by the rules (1.12) and (1.13) and are time dependent. This illustrates an important feature of the model, i.e., the heterogeneity of beliefs and their shifting nature over time.

Note also 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 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.

As argued earlier, the selection mechanism 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 behavior.

Finally, it is worth mentioning that the selection of the forecasting rules is done according to a standard reinforcement learning model (see, for example, Sutton and Barto 1998). There is a lot of experimental evidence in support of such reinforcement learning models (see, for example, Duffy 2007).

1.4 Heuristics and Selection Mechanism 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. (2008) for a similar setup.) We assume an institutional setup in which the central bank announces an explicit inflation target. The fundamentalist rule is then based on this announced inflation target, i.e., agents using this rule have confidence in the credibility of this rule and use it to forecast inflation. Agents who do not trust the announced inflation target use the extrapolative rule, which consists in extrapolating 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.,

$$\tilde{E}_t^{\text{tar}}\pi_{t+1} = \pi^*, \tag{1.14}$$

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

The "extrapolators" are defined by

$$E_t^{\text{ext}}\pi_{t+1} = \pi_{t-1}. \tag{1.15}$$

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

$$\tilde{E}_t\pi_{t+1} = \beta_{\text{tar},t}\tilde{E}_t^{\text{tar}}\pi_{t+1} + \beta_{\text{ext},t}\tilde{E}_t^{\text{ext}}\pi_{t+1} \tag{1.16}$$

or

$$\tilde{E}_t\pi_{t+1} = \beta_{\text{tar},t}\pi^* + \beta_{\text{ext},t}\pi_{t-1} \tag{1.17}$$

and

$$\beta_{\text{tar},t} + \beta_{\text{ext},t} = 1. \tag{1.18}$$

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.,

$$\beta_{\text{tar},t} = \frac{\exp(\gamma U_{\text{tar},t})}{\exp(\gamma U_{\text{tar},t}) + \exp(\gamma U_{\text{ext},t})}, \tag{1.19}$$

$$\beta_{\text{ext},t} = \frac{\exp(\gamma U_{\text{ext},t})}{\exp(\gamma U_{\text{tar},t}) + \exp(\gamma U_{\text{ext},t})}, \tag{1.20}$$

where $U_{\text{tar},t}$ and $U_{\text{ext},t}$ are the forecast performances (utilities) associated with the use of the fundamentalist and extrapolative rules. These are defined in the same way as in (1.9) and (1.10), i.e., they are the negatives of the weighted averages of past squared forecast errors of using fundamentalist (inflation targeting) and extrapolative rules, respectively.

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 with a simple extrapolation rule), the probability that agents will use it will be small.

1.5 Solving the Model

The solution of the model is found by first substituting (1.3) into (1.1) and rewriting in matrix notation. This yields

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

or

$$\boldsymbol{A}\boldsymbol{Z}_t = \boldsymbol{B}\tilde{\boldsymbol{E}}_t\boldsymbol{Z}_{t+1} + \boldsymbol{C}\boldsymbol{Z}_{t-1} + \boldsymbol{b}r_{t-1} + \boldsymbol{v}_t, \tag{1.21}$$

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

$$\boldsymbol{Z}_t = \boldsymbol{A}^{-1}[\boldsymbol{B}\tilde{\boldsymbol{E}}_t\boldsymbol{Z}_{t+1} + \boldsymbol{C}\boldsymbol{Z}_{t-1} + \boldsymbol{b}r_{t-1} + \boldsymbol{v}_t]. \tag{1.22}$$

The solution exists if the matrix $\boldsymbol{A}$ is nonsingular, i.e., if $(1 - a_2c_2) - a_2b_2c_1 \neq 0$. The system (1.22) 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 (1.7)–(1.17) and can be substituted into (1.22). Finally, the solution for r_t is found by substituting y_t and π_t obtained from (1.22) into (1.3).

The model has nonlinear features making it difficult to arrive at analytical solutions.[4] That is why we will use numerical methods to analyze its dynamics. In order to do so, we have to calibrate the model, i.e., to select numerical values for the parameters of the model. In Appendix A the parameters used in the calibration exercise are presented. They are based on Galí (2008). 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 some of the parameters of the model will be presented. The three shocks (demand shocks, supply shocks and interest rate shocks) are independently and identically distributed (i.i.d.) with standard deviations of 0.5%. The Matlab code used for the numerical analysis is also provided in the appendix.

1.6 Animal Spirits, Learning, and Forgetfulness

In this section simulations of the behavioral model in the time domain are presented and interpreted. The upper panel of figure 1.3 shows the time pattern of output produced by the behavioral model given a particular realization of the stochastic i.i.d. shocks. A strong cyclical movement in the output gap can be observed. The autocorrelation coefficient of the output gap is 0.95 (which is very close to 0.94, i.e., the autocorrelation of the output gap that was found in the United States during 1960–2009). The lower panel of figure 1.3 shows a variable called "animal spirits." It represents the evolution of the probabilities that agents extrapolate a positive output gap. As shown earlier, these probabilities can also be interpreted as the fraction of agents using a positive extrapolation rule. Thus, when the probability that agents extrapolate a positive output gap is 1, we will say that the fraction of agents using this rule is 1. When in figure 1.3 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 that case they all extrapolate a negative output gap. Thus the curve can also be interpreted as showing the degree of optimism and pessimism of agents who make forecasts of the output gap.

The concept of animal spirits was introduced by Keynes (1936). Keynes defined these as waves of optimism and pessimism of investors that have a self-fulfilling property and that drive the movements of investment and output.[5] As a result of

[4] In a way it is paradoxical that it is more difficult to solve the behavioral model than the rational expectations counterpart model. This of course has to do with the fact that the latter is a linear model while the former is nonlinear. This difference in complexity is also related to the fact that the rational expectations model assumes a representative consumer and producer. Solving such a model is then relatively easy because it disregards the complexity that arises from the fact that there is heterogeneity in beliefs.

[5] See Akerlof and Shiller (2009) on the different interpretations of animal spirits. See also Farmer (2006).

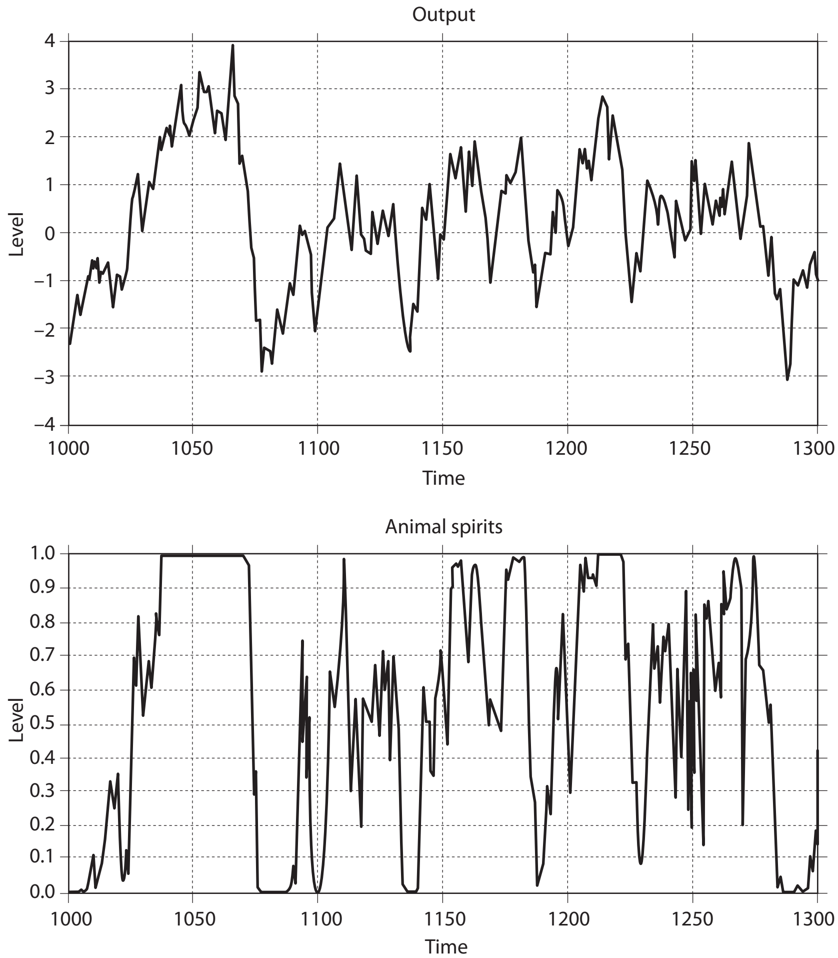

Figure 1.3. Output gap in behavioral model.

the rational expectations revolution, the notion that business cycle movements can be driven by independent waves of optimism and pessimism was discarded from mainstream macroeconomic thinking. Recently, it was given a renewed academic respectability by Akerlof and Shiller (2009).[6] Our model gives a precise definition of these animal spirits. We now show how important these animal spirits are in shaping movements in the business cycle.

[6] There is an older literature, which will be discussed in section 1.13, that tried to introduce the notion of animal spirits in macroeconomic models. The idea of animal spirits can also be found in Brock and Hommes (1997).

Combining the information of the two panels in figure 1.3, it can be seen that the model generates endogenous waves of optimism and pessimism (animal spirits). 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 and pessimism are essentially unpredictable. Other realizations of the shocks (the stochastic terms in equations (1.1)–(1.3)) 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, has a higher performance (utility), 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.

How does a turnaround arise? There are two mechanisms at work. First, there are negative stochastic shocks that may trigger the turnaround. Second, there is the application of the Taylor rule by the central bank. During a boom, the output gap becomes positive and inflation overshoots its target. This leads the central bank to raise the interest rate, thereby setting in motion a reverse movement in output gap and inflation. This dynamics tends to make a dent in the performance of the optimistic extrapolative 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 continually 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 1.4. First concentrate on the lower panel of figure 1.4. 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

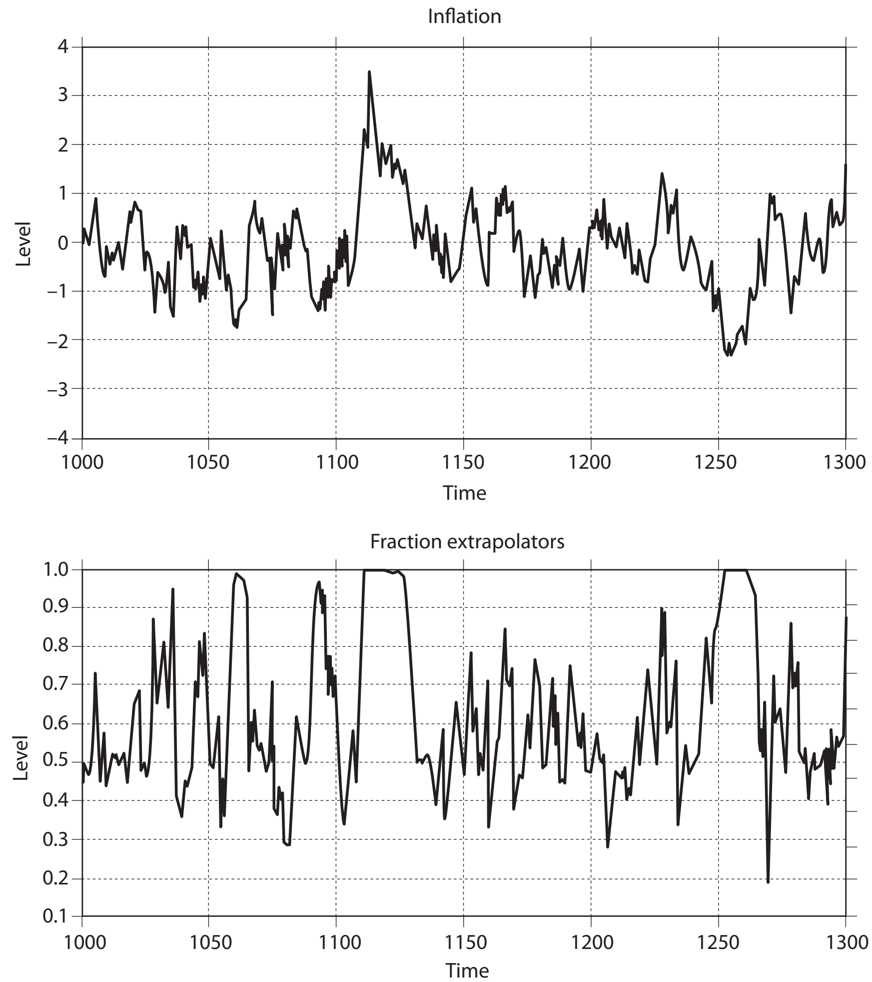

Figure 1.4. Inflation in behavioral model.

around 50%. This is sufficient to maintain the rate of inflation within a narrow band of approximately $\pm 1\%$ around the central bank's inflation target. There is a second regime, however, 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 bank can reduce this loss of credibility in chapter 3.

1.7 Conditions for Animal Spirits to Arise

The simulations reported in the previous section assumed a given set of numerical values of the parameters of the model (see the appendix). 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 1.3 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. This sensitivity analysis will allow us to detect under what conditions animal spirits can arise.

A Willingness to Learn

We first concentrate on the intensity of choice parameter, γ. As will be remembered this is the parameter that determines the intensity with which agents switch from one rule to the other when the performances of these rules change. This parameter is in turn related to the importance of the stochastic component in the utility function of agents. When γ is zero the switching mechanism is purely stochastic. In that case, agents decide about which rule to apply by tossing a coin. They learn nothing from past mistakes. As γ increases they are increasingly sensitive to past performance of the rule they use and are therefore increasingly willing to learn from past errors.

To check the importance of this parameter γ in creating animal spirits we simulated the model for consecutive values of γ starting from zero. For each value of γ we computed the correlation between the animal spirits and the output gap. We show the results of this exercise in figure 1.5 On the horizontal axis the consecutive values of γ (intensity of choice) are presented. On the vertical axis the correlation coefficient between output gap and animal spirits is shown. We obtain a very interesting result. 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. In other words, 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 1.5 that this is achieved with relatively low levels of γ. Thus, surprisingly, animal spirits arise not because agents are irrational. On the contrary, animal spirits can only emerge if agents are sufficiently rational.

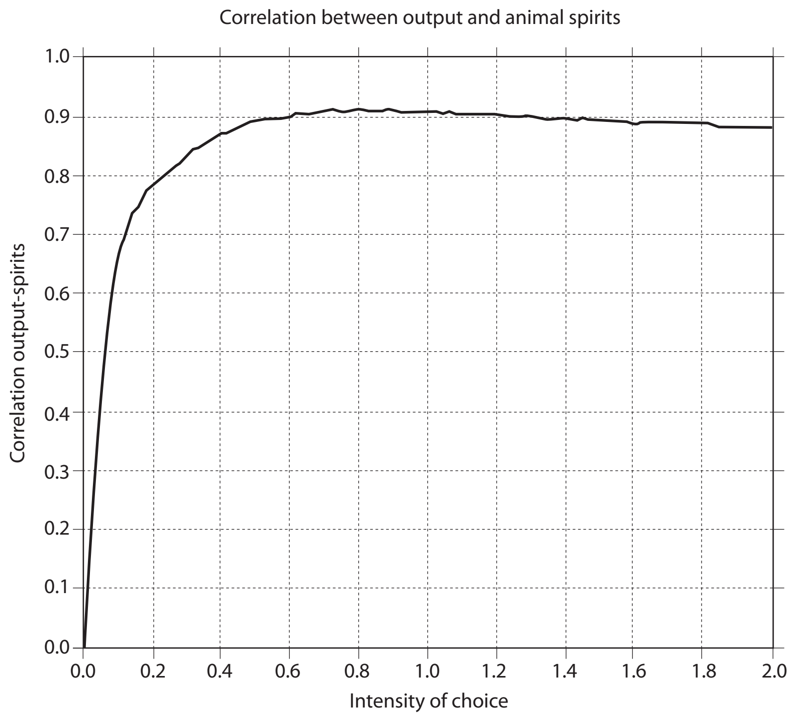

Figure 1.5. Animal spirits and learning.

A Capacity to Forget

When agents test the performance of the forecasting rules they compute past forecasting errors. In doing so, they apply weights to these past forecast errors. These weights are represented by the parameter ω_k in equations (1.9) and (1.10). We assume that these weights decline as the past recedes. In addition, we assume that these weights decline exponentially. Let us define $\omega_k = (1-\rho)\rho^k$ (and $0 \leqslant \rho \leqslant 1$). We can then rewrite equations (1.9) and (1.10) as follows (if you do not see this, try the reverse, i.e., start from (1.23) and (1.24), do repeated substitutions of $U_{\mathrm{f},t-1}$, $U_{\mathrm{f},t-2}$, etc., and you then find (1.9) and (1.10)):

$$U_{\mathrm{f},t} = \rho U_{\mathrm{f},t-1} - (1-\rho)[y_{t-1} - \tilde{E}_{\mathrm{f},t-2} y_{t-1}]^2, \tag{1.23}$$

$$U_{\mathrm{e},t} = \rho U_{\mathrm{e},t-1} - (1-\rho)[y_{t-1} - \tilde{E}_{\mathrm{e},t-2} y_{t-1}]^2. \tag{1.24}$$

We can now interpret ρ 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. Since in this case there are infinitely many periods to remember, each period receives the same 0 weight. Values of ρ between 0 and 1 reflect some but imperfect memory. Take as an example $\rho = 0.6$. This number

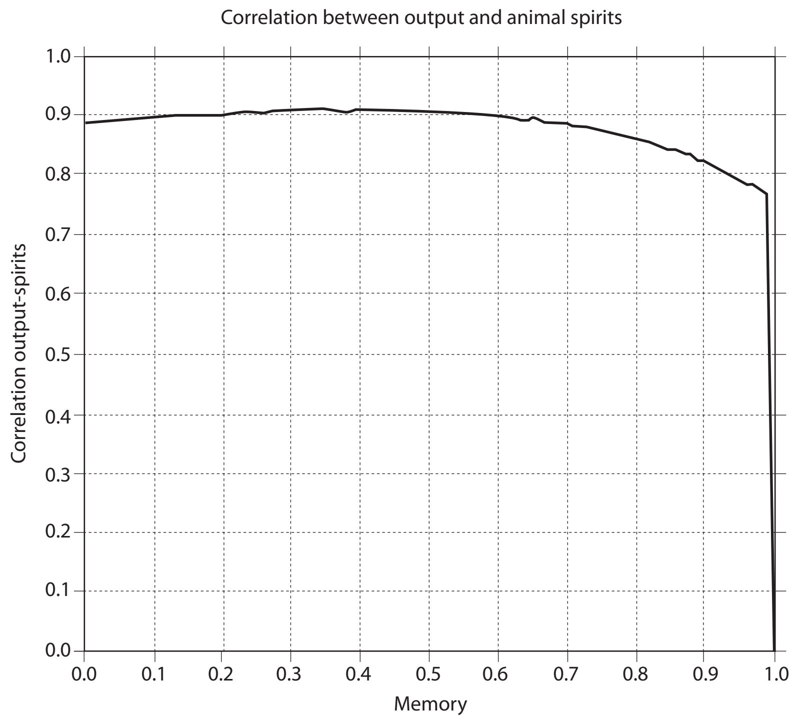

Figure 1.6. Animal spirits and forgetting.

implies that agents give a weight of 0.4 to the last observed error (in period $t-1$) and a weight of 0.6 to all the errors made in periods beyond the last period.

We performed the same exercise as in the previous section and computed the correlation between animal spirits and the output gap for consecutive values of ρ. The results are shown in figure 1.6. 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. Paradoxically, they then also learn nothing from new information. 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.[7]

This and the previous results lead to an interesting insight. Animal spirits emerge when agents behave rationally (in the sense of a willingness to learn from mistakes)

[7] Note that it appears from figure 1.6 that a discontinuity occurs close to $\rho = 1$. This, however, is due to the fact that the figure shows insufficient detail close to $\rho = 1$. The correlation drops to 0 in a continuous manner but this happens at values very close to 1.

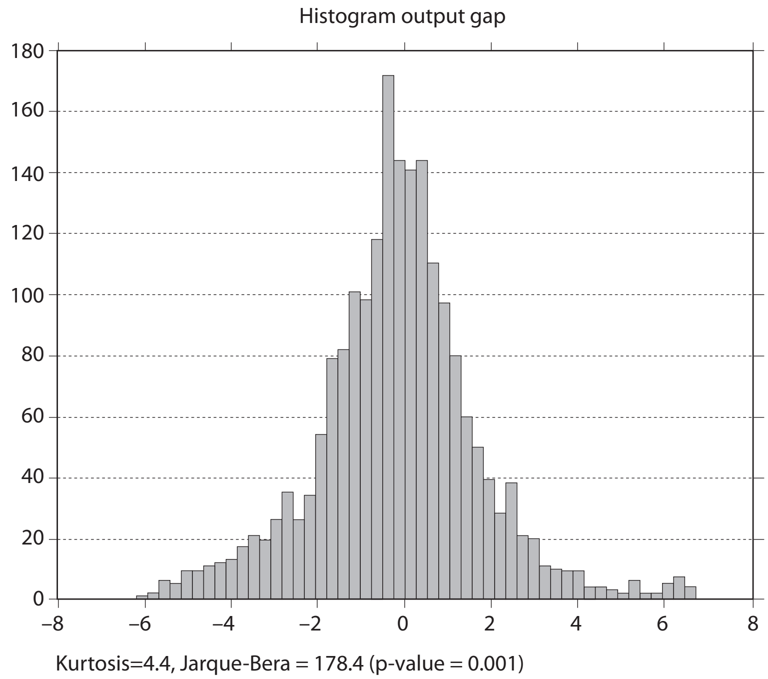

Figure 1.7. Frequency distribution of simulated output gap.

and when they experience cognitive limitations. They do not emerge in a world of either super-rationality or irrationality.

1.8 Two Different Business Cycle Theories: Behavioral Model

How well is our behavioral model capable of mimicking the empirical regularities in the business cycle that we identified in the introduction? This question is answered in this section. In the next section we ask the question of how the mainstream new Keynesian model based on rational expectations (the DSGE model) performs.

Figure 1.3 presented a typical simulation of the output gap obtained in the behavioral model. The autocorrelation coefficient of the output gap obtained in figure 1.3 is 0.95, which is very close to 0.94, i.e., the autocorrelation of the output gap in the United States during 1960–2009 (see the introduction). In addition, our behavioral macroeconomic model produces movements of output that are very different from the normal distribution. We show this by presenting the histogram of the output gaps obtained from figure 1.3. The result is presented in figure 1.7. The frequency distribution of the output gap deviates significantly from a normal distribution. There is excess kurtosis (kurtosis = 4.4), i.e., there is too much concentration of observations around the mean for the distribution to be normal. In addition, there are fat tails. This means that there are too many observations that are very small or very large to be compatible with a normal distribution. We also applied a more formal test of normality, the Jarque–Bera test, which rejected normality. Note that the nonnormality of the distribution of the output gap is produced endogenously by the model, as we feed the model with normally distributed shocks.

This result is not without implications. It implies that when we use the assumption of normality in macroeconomic models we underestimate the probability of large changes. In this particular case, assuming normal distributions tends to underestimate the probability that intense recessions or booms occur. The same is true in finance models that assume normality. These models seriously underestimate the probability of extremely large asset price changes. In other words they underestimate the probability of large bubbles and crashes. To use the metaphor introduced by Nassim Taleb, there are many more black swans than theoretical models based on the normality assumption predict.

It is fine to observe this phenomenon. It is even better to have an explanation for it. Our model provides such an explanation. It is based on the particular dynamics of "animal spirits." We illustrate this in figure 1.8. This shows the frequency distribution of the animal spirits index (defined earlier) which is associated with the frequency distribution of the output gap obtained in figure 1.7. From figure 1.8 we observe that there is a concentration of the animal spirits at the extreme values of 0 and 1 and also in the middle of the distribution (but more spread out). This feature provides the key explanation of the nonnormality of the movements of the output gap.

When the animal spirits index clusters in the middle of the distribution we have tranquil periods. There is no particular optimism or pessimism, and agents use a fundamentalist rule to forecast the output gap. At irregular intervals, however, the economy is gripped by either a wave of optimism or of pessimism. The nature of these waves is that beliefs get correlated. Optimism breeds optimism; pessimism breeds pessimism. This can lead to situations where everybody has become either optimist of pessimist. These periods are characterized by extreme positive of negative movements in the output gap (booms and busts).

From the previous discussion it follows that our behavioral macroeconomic model makes a strong prediction about how the movements of the output gap are distributed. These movements should be nonnormal. This is also what one observes in reality. We come back to the empirical issues in chapter 8.

1.9 Two Different Business Cycle Theories: New Keynesian Model

How well does the new Keynesian rational expectations (DSGE) model perform in mimicking the empirical regularities of the business cycle? In order to answer this question, I used the same model consisting of the aggregate demand equation (1.1), the aggregate supply equation (1.2), and the Taylor rule equation (1.3). The model was solved under rational expectations. This was done as follows.

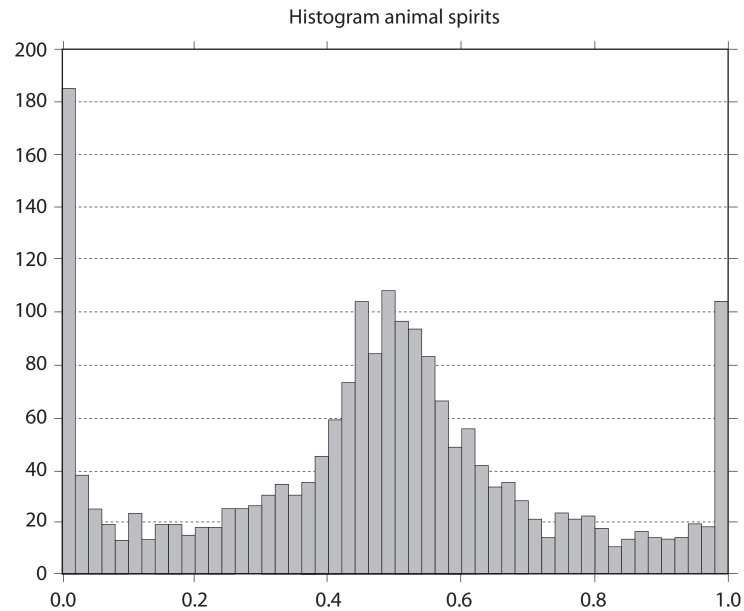

Figure 1.8. Frequency distribution of simulated animal spirits.

The model consisting of equations (1.1)–(1.3) can be written in matrix notation as follows:

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

$$\Omega \boldsymbol{Z}_t = \Phi \boldsymbol{E}_t \boldsymbol{Z}_{t+1} + \boldsymbol{v}_t, \tag{1.25}$$

$$\boldsymbol{Z}_t = \Omega^{-1}[\Phi \boldsymbol{E}_t \boldsymbol{Z}_{t+1} + \boldsymbol{v}_t]. \tag{1.26}$$

There are several ways one can solve for rational expectations (see Minford and Peel 1983; Walsh 2003). Here I will use numerical methods to solve the system mainly because the behavioral model that was used earlier is highly nonlinear (in contrast with the rational expectations version of the model, which is linear) necessitating the use of numerical solution techniques. I use the Binder–Pesaran procedure (Binder and Pesaran 1996). The Matlab code is provided in appendix. The numerical values of the parameters are the same as those used for the behavioral model (see appendix). They are based on values commonly used in these models (see Galí 2008, p. 52).

I show the movements of the simulated output gap in figure 1.9. The upper panel shows the output gap in the time domain and the lower panel in the frequency domain. The autocorrelation in the output gap is 0.77, which is significantly lower than in the observed data (for the United States we found 0.94). In addition, these

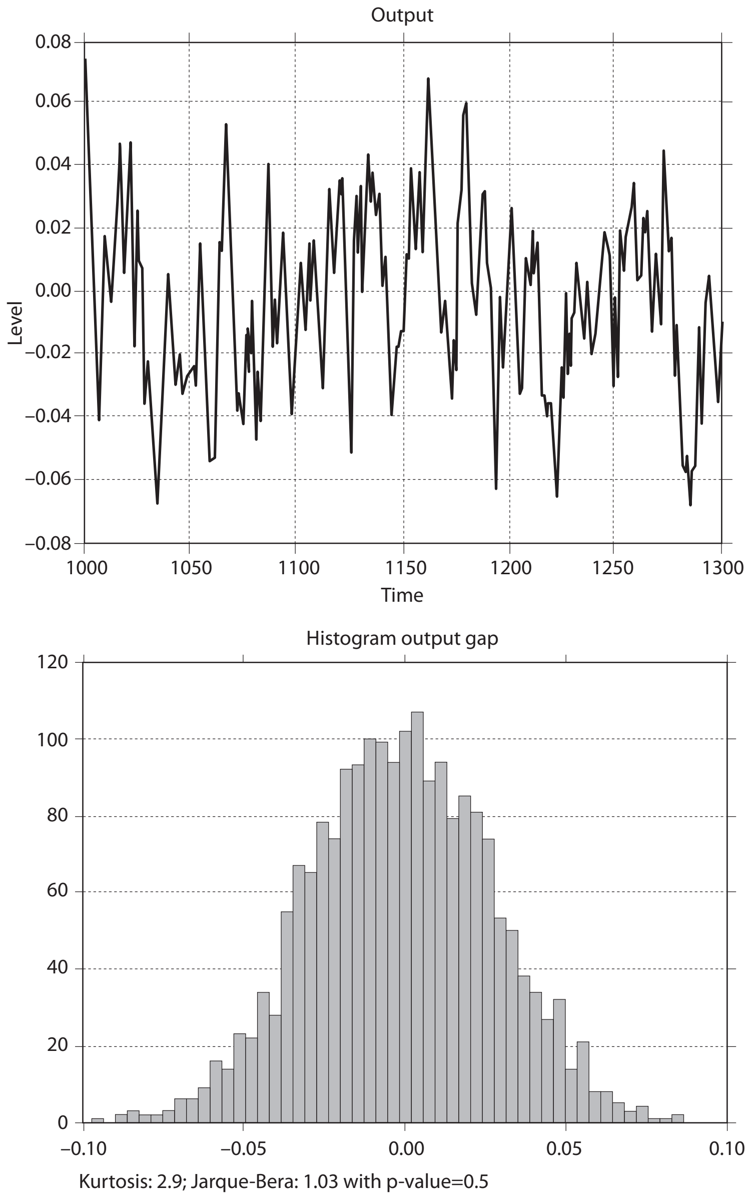

Figure 1.9. Simulated output gap in extended new Keynesian model.

output gap movements are normally distributed (see lower panel). We could not reject that the distribution is normal. Thus, it appears that the simple new Keynesian rational expectations model which is fed with random disturbances is not capable of representing two important empirical features. These are the cyclical nature of output gap movements and nonnormality of its distribution.

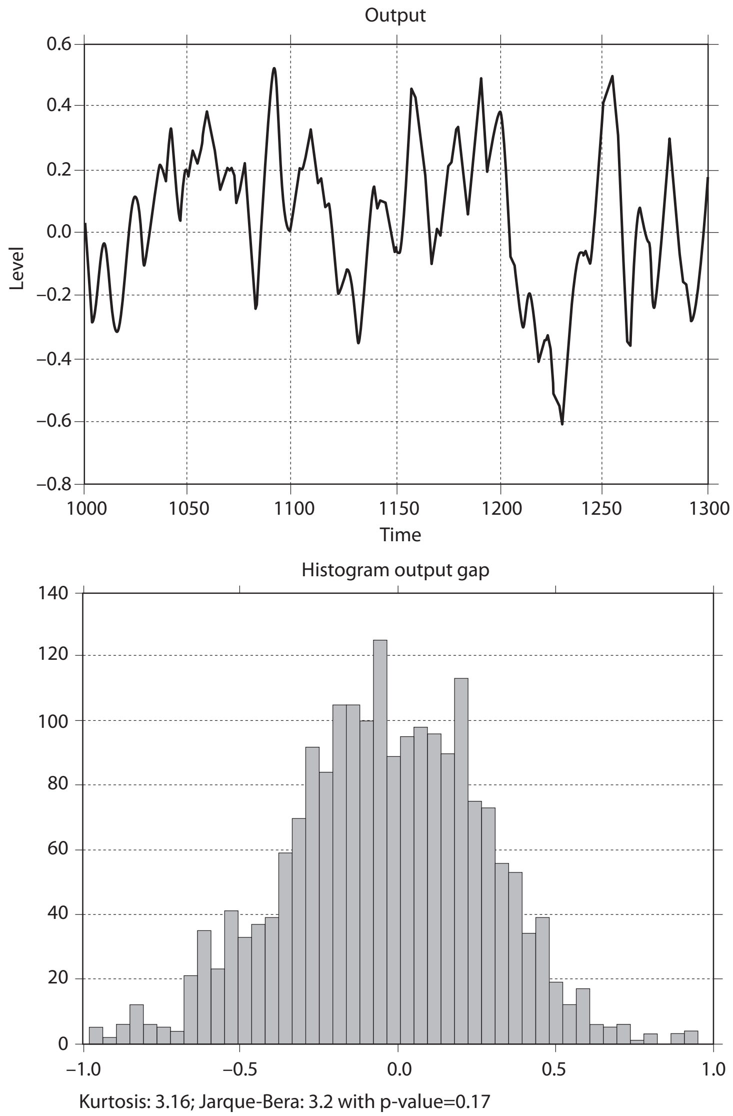

Figure 1.10. Simulated output gap in extended new Keynesian model and autocorrelated errors.

The next step in making this model more empirically relevant has consisted in adding autocorrelation in the error terms. This is now the standard procedure in DSGE models (see Smets and Wouters 2003). We do the same with our version of the new Keynesian rational expectations model and assume that the autocorrelation of the error terms in the equations (1.1)–(1.3) is equal to 0.9. The result of this assumption is shown in the simulations of the output gap in figure 1.10. We now obtain movements of the output gap that resemble real-life movements. The autocorrelation of the output gap is now 0.98, which is very close to the observed number of 0.94 in the postwar U.S. output gap. We still cannot reject normality though (see the Jarque–Bera test). This is a problem that DSGE models have not been able to solve.

Thus, in order to mimic business cycle movements, the new Keynesian rational expectations (DSGE) model builders have had recourse to introducing autocorrelation in the error terms (the shocks that hit the economy). This trick has allowed DSGE models to closely fit observed data (see Smets and Wouters 2003). This success has been limited to the first and second moments of the movements of output, but not to the higher moments (kurtosis, fat tails). The latter failure has the implication that in order to explain a large movement in output (e.g., a deep recession or a strong boom) DSGE models have to rely on large unpredictable shocks.

There are two problems with this theory of the business cycle implicit in the DSGE models.

First, business cycles are not the result of an endogenous dynamics. They occur as a result of exogenous shocks and slow transmission of these shocks (because of wage and price rigidities). Put differently, the DSGE models picture a world populated by rational agents who are fully informed. In such a world there would never be business cycles. The latter arise because of exogenous disturbances and of constraints on agents' ability to react instantaneously to these shocks. Thus a given shock will produce ripple effects in the economy, i.e., cyclical movements.

Thus, the DSGE models explain the large booms and busts that are regularly observed in capitalist economies by large outside shocks. The macroeconomy is a peaceful world in which agents continually optimize. However, sometimes this peaceful world is hit by large exogenous disturbances that are then transmitted into the macroeconomy.

This is not a very satisfactory theory of the business cycle.[8] It leads to the question of why the world outside the macroeconomy is characterized by nonnormally distributed shocks, while the macroeconomy itself does not produce such shocks. The macroeconomist in the mainstream world is therefore condemned to ask other scientists why these large shocks occur. He has no theory capable of explaining these.

A second problem is methodological. When the new Keynesian model is tested empirically, the researcher finds that there is a lot of the output dynamics that is not predicted by the model. This unexplained dynamics is then to be found in the error term. So far so good. The next step taken by DSGE modelers is to conclude that these errors (typically autocorrelated) should be considered to be exogenous shocks.

[8] There is a long tradition in economics of developing endogenous business cycle theories (e.g., Hicks 1950; Goodwin 1951). This has been completely abandoned in modern macroeconomics.

The problem with this approach is that it is scientifically questionable. When the DSGE modeler finds a dynamics not predicted by the model, he decides that the new Keynesian rational expectations model must nevertheless be right (because there can be no doubt that individual agents are rational) and that thus the deviation between the observed dynamics and the one predicted by the model must come from outside the model.

1.10 Uncertainty and Risk

Frank Knight, a famous professor of economics at the University of Chicago before World War II, introduced the distinction between risk and uncertainty in his book *Risk, Uncertainty and Profits*, published in 1921. Risk according to Knight is quantifiable. It has to do with events that have a probability of occurrence that can be represented by a statistical distribution. As a result, we can compute the probability that these events occur with great precision. The reason we can do this is that there is some regularity in the occurrence of these events and lots of data to detect this regularity. In contrast, uncertainty does not allow for such quantification because of a lack of regularity and/or an insufficiency of data to detect these regularities.

The mainstream macroeconomic models based on rational expectations (including the DSGE models) only allow for risk. In these models agents are capable of making probabilistic statements about all future shocks based on quantifiable statistical distributions obtained from the past. Thus in the DSGE models agents know, for example, that in any period there is a probability of, say, 10% that a negative supply shock of −5% will occur. In fact, they can tabulate the probability of all possible supply shocks, and all possible demand shocks. This is certainly an extraordinary assumption.

The frequency distribution of the output gap presented in figure 1.7 suggests that although the distribution is nonnormal, there is enough regularity in the distribution for individual agents to use in order to make probabilistic predictions. This regularity, however, appears only because of a large amount of periods (2000) in the simulation exercise. Assuming that one period corresponds to one month, we can see that the frequency distribution is obtained using 170 years of observations. In most developed countries today the maximum number of years for which we have output gap data is about 40–50, a quarter of the number of observations used to construct the frequency distribution in figure 1.7.

The question that then arises is, how reliable are frequency distributions of the output gap obtained from much shorter periods? In order to answer this question we ran simulations of the behavioral model over short periods (400, corresponding to approximately 40 years). For each 400-period simulation we computed the frequency distribution of the output gap. The result is presented in figure 1.11. We observe that the frequency distributions of the output gap obtained in different 400-period simulations look very different. All exhibit excess kurtosis but the degree of

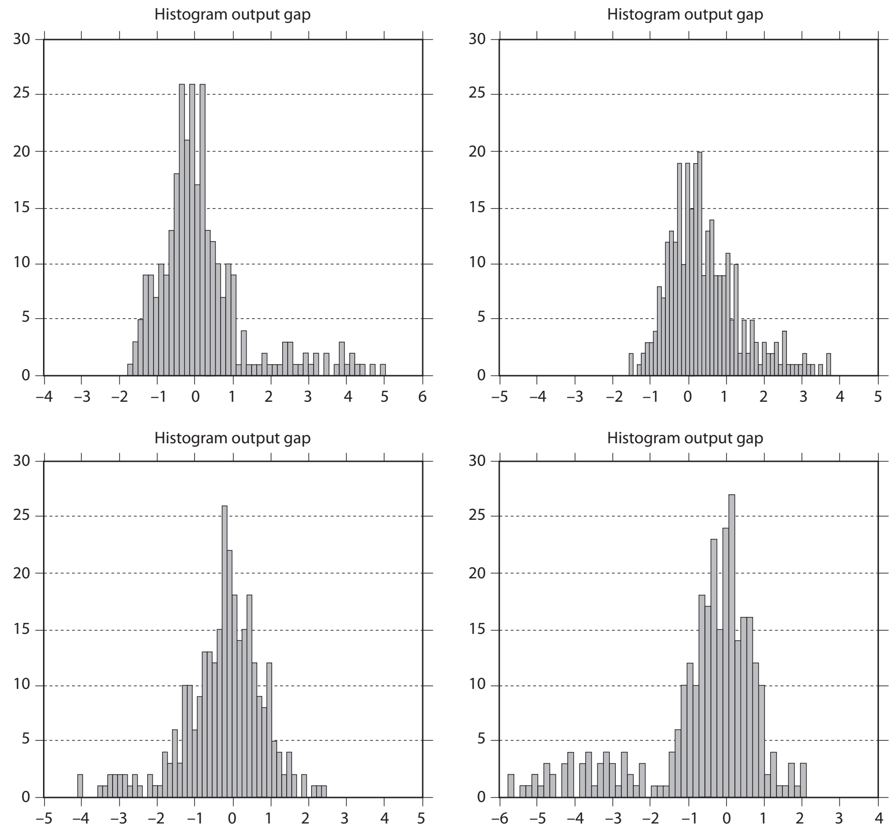

Figure 1.11. Frequency distribution of output gap in 400-period simulations.

excess kurtosis varies a great deal. In all cases there is evidence of fat tails, but the exact shape varies a lot. In some 400-period simulations there are only positive fat tails, in others only negative fat tails. In still other simulations fat tails appear on both sides of the distributions.

This suggests that if our model of animal spirits is the right representation of the real world, observations over periods of approximately 40 years are by far insufficient to detect regularities in the statistical distributions of important variables as the output gap that can be used to make probabilistic statements about this variable. Thus, our behavioral model comes close to representing a world in which uncertainty rather than risk prevails at the macroeconomic level. This contrasts with the standard rational expectations macroeconomic models in which there is only risk and no uncertainty.

Our simulations using the behavioral model suggest that over 40-year periods we should see different frequency distributions for the output gap. But given our limited historical sample (just one historical frequency distribution), it is difficult to test for this result. Put differently, how do we know that uncertainty is more relevant than risk in macroeconomic modeling? We will come back to this question in the empirical chapter. There it will be shown that using evidence of more than one country, the empirically observed frequency distributions obtained for relatively short periods have very different shapes and forms, making it difficult to draw statistical inferences. Thus, as will be shown, the empirical evidence suggests that it is uncertainty rather than risk that prevails in macroeconomic reality. That is also what our behavioral model tells us.

One could also argue that the difference we have detected here between uncertainty and risk is a matter of degree rather than of essence. In our model uncertainty is transformed into measurable risk if the number of observations becomes large enough. This criticism is undoubtedly true. In fact there has always been a dual interpretation of the difference between uncertainty and risk. The first one is more narrow and is also found in our model: uncertainty arises because we lack sufficient data to make statistical inferences. The second one considers the difference to be qualitative in nature, i.e., the increase in data points does not improve the capacity for making statistical inferences, because some phenomena do not lend themselves to measurement (at least with our present state of understanding of these phenomena). Our model gives substance to the first interpretation of the difference between uncertainty and risk. It does not do justice to the second interpretation.

1.11 Credibility of Inflation Targeting and Animal Spirits

In the previous sections we identified the conditions in which animal spirits, i.e., self-fulfilling waves of optimism and pessimism, can arise. We argued that when animal spirits prevail, uncertainty in Frank Knight's sense is created. Our implicit assumption was that the inflation target announced by the central bank is not 100% credible. This imperfect credibility leads agents to be skeptical and to continually test the resolve of the central bank. We showed that in such an environment animal spirits can arise.

In this section we ask the following question. Suppose the inflation target can be made 100% credible. What does such a regime imply for the emergence of animal spirits? We ask this question not because we believe that such a perfect credibility can be achieved, but rather to analyze the conditions under which animal spirits can arise.

We analyze this question in the following way. Equations (1.14) and (1.15) define the forecasting rules agents use in an environment of imperfect credibility. In such an environment, agents will occasionally be skeptical about the announced inflation target. In that case they cease to use the inflation target to forecast inflation and revert to an extrapolative rule. In a perfectly credible inflation targeting regime, agents have no reason to be skeptical and will therefore always use the announced target as the basis for their forecast. Thus in a perfectly credible regime, agents only use rule (1.14) and there is no switching. The market forecast of inflation (equation (1.17)) now simplifies to

$$\tilde{E}_t \pi_{t+1} = \pi^*$$

and the switching equations (1.19) and (1.20) disappear. The rest of the model is unchanged.

We simulated this version of the model using the same techniques as in the previous sections. We show some of the results in figure 1.12 and compare them with the results obtained in the regime of imperfect credibility of inflation targeting analyzed in the previous section.

The contrast in the results is quite striking. When inflation targeting is perfectly credible, animal spirits are weak. This can be seen from the fact that the animal spirits index does not show a concentration of observations at the extreme values of 1 (extreme optimism) and 0 (extreme pessimism). This contrasts very much with the imperfect credibility case. This difference in occurrence of animal spirits has the effect of eliminating the fat tails in the frequency distribution of the output gap and of inflation. In fact both distributions are now normal with a kurtosis around 3. The Jarque–Bera test cannot reject the hypothesis that the distributions of output gap and inflation are normal in the perfect credibility case. The contrast with the distributions obtained in the imperfect credibility case is striking: these exhibit fat tails and excess kurtosis.

Thus when inflation targeting is perfectly credible, periods of intense booms and busts produced by the existence of animal spirits do not occur. In addition, Knightian uncertainty is absent. The normal distribution of output gap and inflation allows agents to make reliable probabilistic statements about these variables. Where does this result come from? The answer is that when inflation targeting is perfectly credible, the central bank does not have to care about inflation because inflation remains close to the target most of the time. As a result, the interest rate instrument can be used to stabilize output most of the time. Thus when animal spirits are optimistic and tend to create a boom, the central bank can kill the boom by raising the interest rate. It can do the opposite when animal spirits are pessimistic. Put differently, in the case of perfect credibility the central bank is not put into a position where it has to choose between inflation and output stabilization. Inflation stability is achieved automatically. As a result, it can concentrate its attention on stabilizing output. This then "kills" the animal spirits.

A fully credible inflation-targeting regime produces wonderfully stabilizing results on output and inflation movements. How can a central bank achieve such a regime of full credibility of its announced inflation target? A spontaneous answer is that this could be achieved more easily by a central bank that only focuses on stabilizing the rate of inflation and stops worrying about stabilizing output. Thus by following a strict inflation targeting regime a central bank is, so one may think,

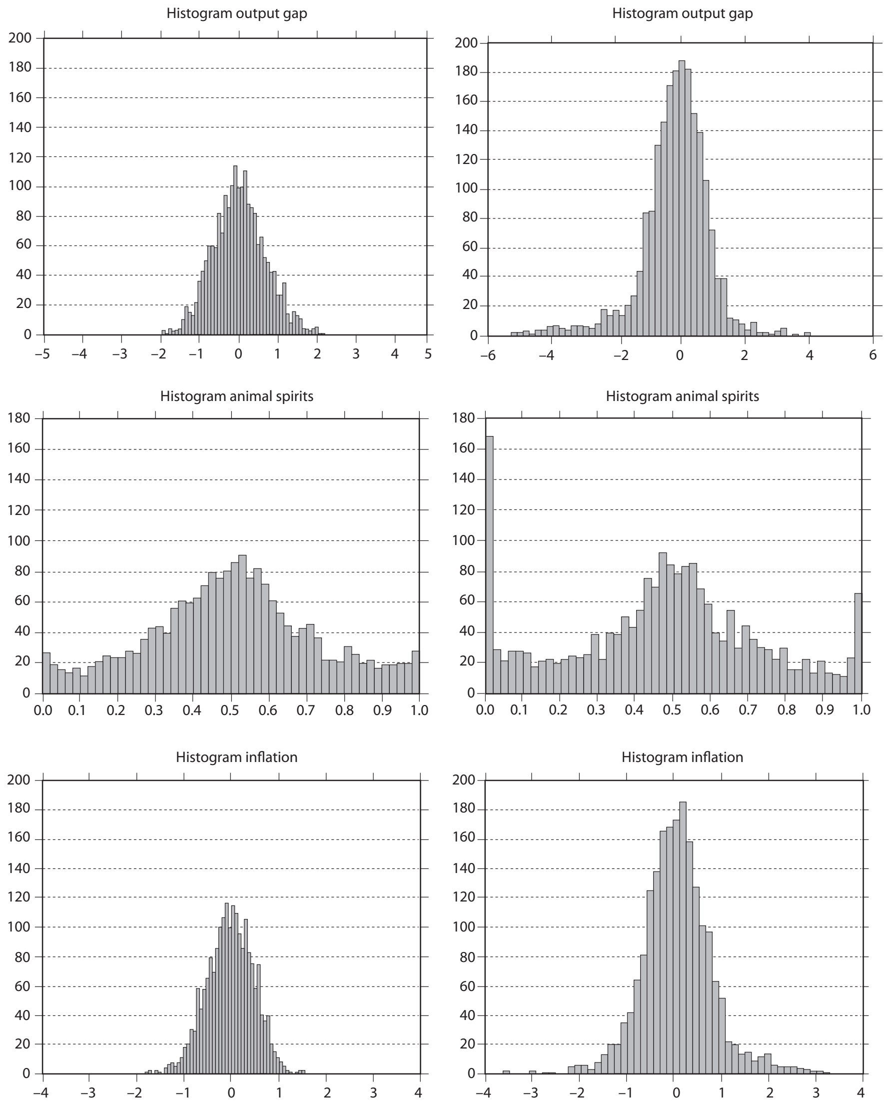

Figure 1.12. Frequency distribution of output gap, inflation, and animal spirits.

more likely to reach full credibility. We checked whether this conclusion is correct in the following way. We simulated the model assuming that the central bank sets the output coefficient in the Taylor rule equal to zero. Thus this central bank does not care at all about output stabilization and only focuses on the inflation target. Will such a central bank, applying strict inflation targeting, come close to full credibility? We show the result of simulating the model under strict inflation targeting in figure 1.13. The answer is immediately evident. The frequency distribution of

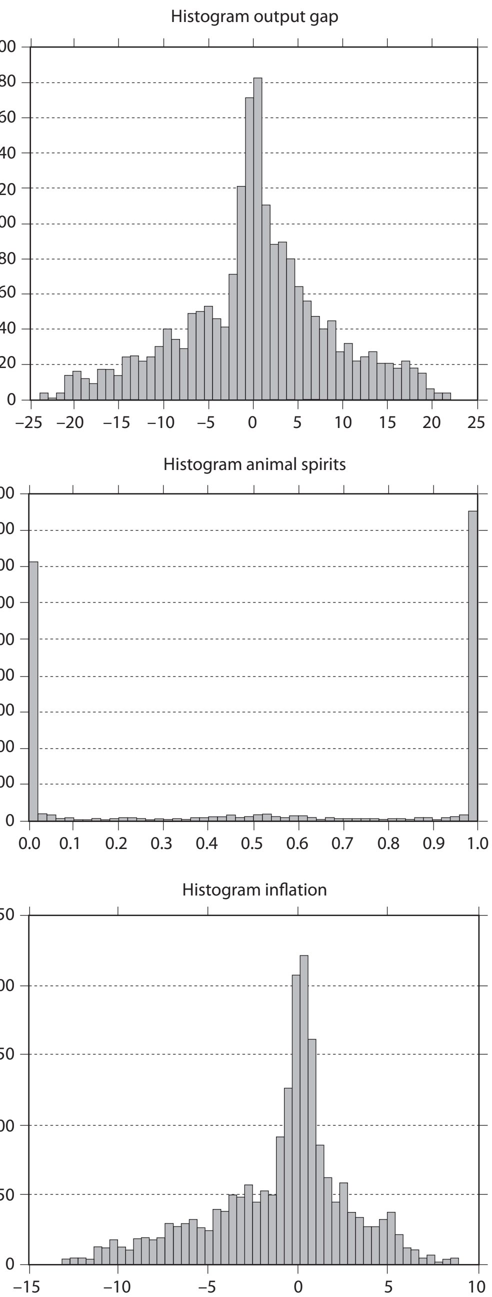

Figure 1.13. Frequency distribution of output gap, animal spirits, and inflation with strict inflation targeting.

output gap shows extreme deviations from the normal distribution with very fat tails, suggesting large booms and busts. Even more remarkably, we find the same feature in the frequency distribution of the rate of inflation that now shows large deviations from the target (normalized at 0).

Thus strict inflation targeting dramatically fails to bring us closer to full inflation credibility. The reason why this is so, is that the power of the animal spirits is enhanced. This can be seen by the middle graph in figure 1.13. We now see that most of the time the economy is gripped by either extreme optimism or extreme pessimism. This tends to destabilize not only the output gap but also the rate of inflation. Thus, strict inflation targeting instead of bringing us closer to the nirvana of perfect credibility moves us away from it. We will come back to this issue in chapter 3, where we analyze the trade-offs between inflation and output variability in a behavioral macroeconomic model.

This result stands in stark contrast with the results obtained in the mainstream rational expectations model (Woodford 2003; Galí 2008). In these models strict inflation targeting, while generally not optimal because of the existence of wage and price inertia, has important stabilizing features. As a result, strict inflation targeting pretty much approximates the optimal policy in the standard model (see Galí 2008, p. 11).

1.12 Different Types of Inertia

The behavioral 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, preferences, policy regime) 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. In addition, as was pointed out in Section 1.9, DSGE modelers have routinely added autoregressive exogenous shocks, thereby importing a dynamics that is not explained by the model. As a result, one could call the business cycles introduced in the DSGE model exogenously created phenomena.

In contrast, the behavioral model presented here is capable of generating inertia, and business cycles, without imposing lags in the transmission process and without the need to impose autocorrelation in the error terms. This could be called endogenous inertia.[9] This is shown 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 (1.1) and $b_1 = 1$ in equation (1.2). The results are presented in figure 1.14. We observe similar business cycle movements in output

[9] A similar informational inertia is found in Ball et al. (2005) and Mankiw and Reis (2002).

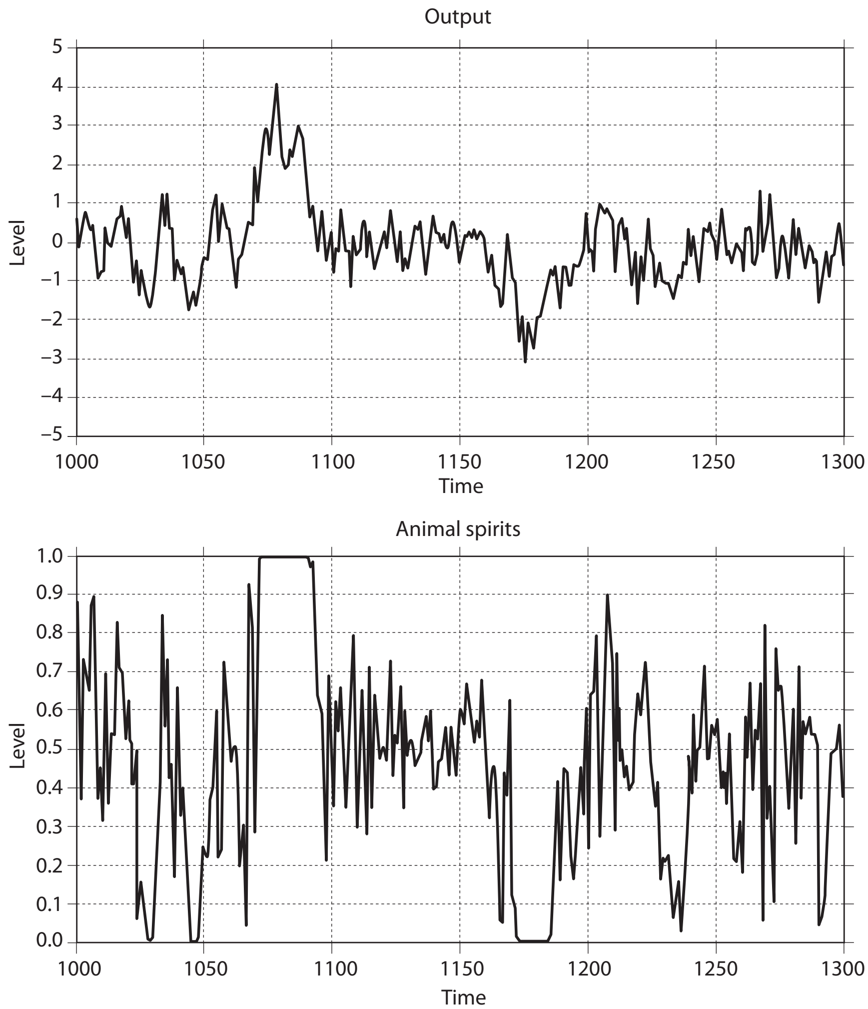

Figure 1.14. Output gap and animal spirits in model without lags.

that are highly correlated to animal spirits as in figure 1.3. 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 1.3). This correlation, however, remains significant and is the main driving force behind the output fluctuations.

The inertia obtained in the behavioral model could also be called informational inertia. In contrast to the rational expectations model, agents in the behavioral model experience an informational problem. They do not fully understand the nature neither of the shock nor of 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.[10]

1.13 Animal Spirits in the Macroeconomic Literature

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

First, there is an important strand of literature producing models with sunspot equilibria. This literature started with Shell (1977) and Azariadis (1981), and includes Azariadis and Guesnerie (1986). Models with sunspot equilibria are found both in the RBC framework (see Benhabib and Farmer 1994; Farmer and Guo 1994) as in the new Keynesian framework (Clarida et al. 1999). In these models there are multiple RE solutions, which include "self-fulfilling" solutions that depend on extraneous variables ("sunspots"). These models provide for a fully rational way to model animal spirits, implementing the basic insights of Keynes (1936).

A very similar strand of literature is provided by models generating global indeterminacies. Howitt and McAfee (1992), Evans et al. (1998), and Evans and Honkapohja (2001) develop models with externalities that lead to multiple steady states. These papers exhibit equilibria with random switching between high and low activity steady states (or, in the Evans–Honkapohja–Romer paper, between high and low growth rates). The rational expectations solutions in these models depend on an exogenous two-state Markov variable that acts to coordinate expectations and triggers the shifts between high (optimistic) and low (pessimistic) states.[11]

The common characteristics of these multiple equilibria models is an exogenous process that leads to switches between these different equilibria. Thus, when "animal spirits" arise in these models, they are exogenously driven. The model presented in the present chapter differs from these multiple equilibria models in that it does not rely on extraneous "sunspots." The economic fluctuations are driven instead by the intrinsic random (white noise) shocks of the model. These white noise shocks are transformed into "animal spirits" in an endogenous way.

[10] Critics of the heuristic model presented here may argue that the comparison between the rational and the behavioral model is unfair for the rational model. Indeed, the heuristic model generates inertia because the evaluation and selection process of the different heuristics is backward looking. This is the reason why the behavioral 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 behavioral 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 by contrasting rational expectations models with learning models.

[11] It should be noted that in each of these models fluctuations can also arise as the outcome of a boundedly rational learning process. Another attempt to produce endogenous fluctuations is to be found in Kurz (1994) and Kurz and Motolese (2011).

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

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

1.14 Conclusion

In mainstream new Keynesian rational expectations models, large disturbances in output and prices only occur if there are large exogenous shocks in demand and supply or in the policy environment. Without these exogenous shocks rational and superbly informed agents peacefully optimize. They may have to wait a little to do this because of wage and price rigidities but in the end they satisfy their desired plans. Only tornado-like external shocks can disturb this peaceful environment.

The model presented in this chapter is very different. It is capable of generating large movements in output (booms and busts) without having to rely on large exogenous shocks. We assumed throughout this chapter that the exogenous disturbances are normally distributed. Yet the behavioral model is capable of generating a statistical distribution of output movements that is not normally distributed and that has fat tails. These are large movements in output that occur with a higher probability than the normal distribution predicts.

The underlying mechanism that produces these movements are the waves of optimism and pessimism ("animal spirits") generated endogenously and that have a self-fulfilling property. We found that periods of tranquility during which the animal spirits remain quiet are followed (unpredictably) by periods when the animal spirits take over, i.e., large movements of optimism or pessimism lead the economy to a period of boom and bust.

Thus our behavioral model produces a theory of the business cycle that is very different from the standard new Keynesian rational expectations (DSGE) model.

In the latter model the booms and busts in output are always the result of large exogenous shocks. In the DSGE world, the financial crisis that started in August 2007 and the intense recession that followed it were produced by a sudden exogenous shock in 2007 that, as a tornado, created havoc in the financial markets and in the macroeconomy. In fact, it is now standard practice for DSGE modelers to simulate the consequences of the financial crisis on the economy by introducing an exogenous increase in risk aversion (and thus the risk premium).[12] In contrast, the behavioral model developed in this chapter is capable of producing endogenous booms and busts. This model leads to the view that the bust of 2007–8 was the result of a boom generated by excessive optimism prior to that date.

Throughout this chapter we assumed small and normally distributed shocks to highlight the potential of the model to generate large and nonnormally distributed movements in output. In the real world, large exogenous shocks do occur. As a result, the movements in output and prices will always be a mix of internally generated dynamics and outside disturbances. In the next chapter we therefore analyze how external shocks are transmitted in the behavioral model.

[12] Interestingly, this is also the view of major bankers when they were questioned during hearings in the U.S. Congress in January 2010. These bankers used metaphors such as "a perfect storm" and "a tornado" to describe the causes of the financial crisis.

Appendix 1: Parameter Values of the Calibrated Model

Behavioral 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
```

Appendix 2: Matlab Code for the Behavioral Model

```
%% Parameters of the model
mm=1;           %switching parameter gamma in Brock Hommes
pstar=0;        %the central bank's inflation target
eprational=0;   %if all agents have rational forecast of inflation this
                    parameter is 1
epextrapol=0;   %if all agents use inflation extrapolation this parameter is 1
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
A=[1 -b2;-a2*c1 1-a2*c2];
B=[b1 0;-a2 a1];
C=[1-b1 0;0 1-a1];
T=2000;
TI=250;
K=50;           %length of period to compute divergence
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 in mean squares errors
rhoout=0.0;     %rho in shocks output
rhoinf=0.0;     %rho in shocks inflation
rhotayl=0.0;    %rho in shocks Taylor
rhoBH=0.0;
epfs=pstar;     %forecast inflation targeters
p=zeros(T,1);
y=zeros(T,1);
plagt=zeros(T,1);
ylagt=zeros(T,1);
r=zeros(T,1);
epf=zeros(T,1);
epc=zeros(T,1);
ep=zeros(T,1);
ey=zeros(T,1);
CRp=zeros(T,1);
FRp=zeros(T,1);
```

```
alfapt=zeros(T,1);
eyfunt=zeros(T,1);
CRy=zeros(T,1);
FRy=zeros(T,1);
alfayt=zeros(T,1);
anspirits=zeros(T,1);
epsilont=zeros(T,1);
etat=zeros(T,1);
ut=zeros(T,1);
%%%%%%%%%%%
% behavioral model %
%%%%%%%%%%%
  alfap=0.5;
  alfay=0.5;
  K1=K+1;
for t=2:T
  epsilont(t)=rhoout*epsilont(t-1) + sigma1*randn;
                    %shocks in output equation (demand shock)
  etat(t)= rhoinf*etat(t-1) + sigma2*randn;
                    %shocks in inflation equation (supply shock)
  ut(t)=rhotayl*ut(t-1) + sigma3*randn;
                    %shocks in Taylor rule (interest rate shock)
  epsilon=epsilont(t);
  eta=etat(t);
  u=ut(t);
  shocks=[eta;a2*u+epsilon];
  epcs=p(t-1);
  if eprational=1;
    epcs=pstar;
  end
  eps=alfap*epcs+(1-alfap)*epfs;
  if epextrapol=1;
    eps=p(t-1);
  end
  eychar=y(t-1);
  eyfun=0+randn/2;
  eyfunt(t)=eyfun;
  eys=alfay*eychar+(1-alfay)*eyfun;
  forecast=[eps;eys];
  plag=p(t-1);
  ylag=y(t-1);
```

```
    rlag=r(t-1);
    lag=[plag;ylag];
    smooth=[0;a2*c3];
    D=B*forecast + C*lag + smooth*rlag + shocks;
    X=A  D;
    p(t)= X(1,1);
    y(t)= X(2,1);
    r(t)= c1*p(t)+c2*y(t)+c3*r(t-1)+u;
    if square=1;
       r(t)= c1*(p(t))^2+c2*y(t)+c3*r(t-1)+u;
    end
    plagt(t)=p(t-1);
    ylagt(t)=y(t-1);
    CRp(t)=rho*CRp(t-1) - (1-rho)*(epcs-p(t))^2;
    FRp(t)=rho*FRp(t-1) - (1-rho)*(epfs-p(t))^2;
    CRy(t)=rho*CRy(t-1) - (1-rho)*(eychar-y(t))^2;
    FRy(t)=rho*FRy(t-1) - (1-rho)*(eyfun-y(t))^2;
    alfap=rhoBH*alfapt(t-1) + (1-rhoBH)
                *exp(mm*CRp(t))/(exp(mm * CRp(t)) + exp(mm * FRp(t)));
    alfay=rhoBH*alfayt(t-1) + (1-rhoBH)
                *exp(mm*CRy(t))/(exp(mm * CRy(t)) + exp(mm * FRy(t)));
    alfapt(t)=alfap;
    alfayt(t)=alfay;
    if eychar>0;
       anspirits(t)=alfay;
    end
    if eychar<0;
          anspirits(t)=1-alfay;
    end
end
autocory=corrcoef(y,ylagt);
autocorp=corrcoef(p,plagt);
coroutputanimal=corr(y,anspirits);
%% mean, median, max, min, standard deviation, kurtosis
Kurt=kurtosis(y);
%% Jarque-Bera test
[ jb,pvalue, jbstat]=jbtest(y,0.05);
```

Appendix 3: Some Thoughts on Methodology in Mainstream Macroeconomics

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 structure of the model. The real business cycle (RBC) theory introduced the idea that macroeconomic models should be "micro-founded," i.e., should be based on dynamic utility maximization (Kydland and Prescott 1982). While RBC model had no place for price rigidities and other inertia (which is why it is sometimes called the new classical model), the new Keynesian school systematically introduced rigidities of different 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 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; Christiano et al. 2001; Smets and Wouters 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, for example, 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 continually 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 macroeconomic 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, for example, 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.

Plausibility and Empirical Validity of Rational Expectations

The new Keynesian DSGE models embody the two central tenets of modern macroeconomics. The first one is that a macroeconomic model should be based ("microfounded") 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 with 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 to make empirical predictions that are not rejected by the data. If it fails to do so, even 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 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 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 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 and Lovallo 1999; 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 problems 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 is 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 Solow 2005; Colander et al. 2008).[13]

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.

---

[13] 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, for example, De Long et al. 1990).

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 to the question of the empirical validity of the rational macromodels in general and the DSGE models in particular.

In this chapter we have discussed the failure of the DSGE models to predict a dynamics that comes close to the dynamics of the observed output movements, except when the step is taken to assume that the unexplained dynamics in the error terms is in fact an exogenous force driving an otherwise correct model. This problem of standard DSGE models has also been noted by Chari et al. (2009), who conclude that most of the dynamics produced by the standard DSGE model (e.g., Smets and Wouters 2003) comes from the autoregressive error terms, i.e., from outside the model.

The correct conclusion from such an empirical failure should be to question the underlying assumptions of the model. But surprisingly, this has not been done by DSGE modelers, who have kept their faith in the existence of rational and fully informed agents.

The issue then is how much is left over from the paradigm of the fully informed rational agent in the existing DSGE models? 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 statistical tricks to improve the fit of the model.

Top-Down versus Bottom-Up Models

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).)

The previous discussion leads to the following interesting and surprising insight. 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.