

De Grauwe, Paul; Ji, Yuemei

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On the Use of Current or Forward-Looking Data in Monetary Policy: A Behavioural Macroeconomic Approach

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Poschingerstr. 5, 81679 Munich, Germany

Telephone +49 (0)89 2180-2740, Telefax +49 (0)89 2180-17845, email office@cesifo.de

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On the Use of Current or Forward-Looking Data in Monetary Policy: A Behavioural Macroeconomic Approach

Abstract

We analyse the use of current and forward-looking data in the setting of monetary policy (Taylor rule). We answer the question of whether the use of forward-looking data is to be preferred over the use of current data. We use a behavioural macroeconomic model that generates periods of tranquillity alternating with crisis periods characterized by fat tails in the distribution of output gap. We find that the answer to our question depends on the nature of the monetary policy regime. In general, in a strict inflation targeting regime the use of forward-looking data leads to a lower quality of monetary policymaking than in a dual mandate monetary policy regime. Finally, nowcasting tends to improve the quality of monetary policy especially in a strict inflation targeting regime.

Keywords: Taylor rule, behavioural macroeconomics, animal spirits, strict inflation targeting, dual mandate, nowcasting.

Paul De Grauwe
London School of Economics / UK
p.c.de-grauwe@lse.ac.uk

Yuemei Ji
University College London / UK
Yuemei.Ji@ucl.ac.uk

1. Introduction

When the central bank has to decide about what the best possible interest rate is, it bases this decision on two types of data. The first one can be called “hard data”. These relate to observations of current macroeconomic variables such as the output gap, the growth rate of GDP, inflation, etc. The second one is “soft data”. These relate to market expectations of these macroeconomic variables.

Both these data are observed imperfectly. The hard data are collected with a lag, creating noise about their true values. The soft data are usually based on surveys which may give an incomplete picture of the state of market expectations.

The quality of monetary policy-making very much depends on the quality of the data central banks rely on. During the last few years new big data and now-casting methods have been developed (see Giannone, Reichlin and Small (2008)) providing central banks with better quality and more frequent data.

In this paper we study the importance of the quality of both hard and soft data for the conduct of monetary policies. We will do this using current and forward-looking Taylor rules in the context of a behavioural macroeconomic model.

The Taylor rule has played an important role in macroeconomic analysis and in actual policymaking. When it was first proposed by Taylor(1993) it was seen more as a description of how central banks behave. Later when it was introduced in macroeconomic models (e.g. the DSGE-models) it was interpreted as a rule that could be derived from optimizing behaviour of the central bank based on a quadratic central bank loss function (see Svensson(1997, 2003))

The original Taylor rule described how the central bank sets the interest rate as a function of currently observed variables such as inflation and output gap. This was later criticized. The central bank should make decisions about the interest rate based not on currently observed values but on the forecasts (expectations) of future inflation and output gap (see Clarida, Gali, Gertler(2000), Batini, N. and Haldane, A., 1999, Svensson(1997)).

There is a large literature contrasting the different dynamics obtained from “current-looking” and forward-looking Taylor rules (for an overview of the

literature see Taylor and Williams (2010)). Notably, Rudebusch and Svensson, (1999), Levin et al. (2003), and Orphanides and Williams (2007) investigated the optimal choice in the policy rule in various models (i.e. rational expectations and learning models) and did not find a significantly large benefit from forward-looking policy rules. Levin et al. (2003) also showed that in rational expectations models rules that respond to inflation forecasts are prone to generating indeterminacy.

There is also a large amount of empirical studies investigating whether the central banks use forward-looking or current-looking rules in their policy decisions. The empirical evidence so far in this field is mixed. For example, Orphanides (2001) uses ex post data and finds that during 1987–1993, forward-looking specifications describe the Federal Reserve policy better than current-looking Taylor-type specifications. Taylor and Williams (2010) survey the recent literature and they find evidence that the current looking Taylor rule works well and are often used by central banks. Empirical studies related to the behaviour of the European Central Bank are also mixed, see for example Gorter et al (2008), Belke and Klose (2011) and Blattner and Margaritov (2010). One important issue Orphanides (2001) points out is there are information problems (i.e. real-time data availability) associated with forward-looking policy rules.

In this paper we ask the question of how the use of currently observed data of output and inflation (hard data) affects the quality of monetary policy-making as compared to the use of forward-looking soft data (market forecasts of output and inflation). The novelty of our paper is to use a behavioural macroeconomic model to analyse these questions.

The behavioural model is characterized by the assumption that agents experience cognitive limitations preventing them from having rational expectations. Instead they use simple forecasting rules (heuristics) and evaluate the forecasting performances of these rules ex-post. This evaluation leads them to switch to the rules that perform best. Thus, it can be said that agents use a trial-and-error

learning mechanism¹. This heuristic switching model produces endogenous waves of optimism and pessimism (animal spirits) that drive the business cycle in a self-fulfilling way, i.e. optimism (pessimism) leads to an increase (decline) in output, and the increase (decline) in output in turn intensifies optimism (pessimism), see De Grauwe(2012), and De Grauwe and Ji(2019). (See also Brock and Hommes (1997), Branch and McGough (2010), De Grauwe (2012), Hommes and Lustenhouwer (2019)) and many others).

We will show that the answer to the question of whether the use of forward looking data is to be preferred to the use of current data in conducting monetary policies very much depends on the monetary policy regime. We will contrast two regimes, one is the strict inflation targeting regime (SIT); the other the dual mandate regime (DM). We will show that the SIT regime produces more extreme values of animal spirits and thus more booms and busts. This then in turn increases forecasting errors and as a result tends to decrease the quality of monetary policies that rely on forward looking data. This is much less the case in a DM regime

Our analysis will also allow us to focus on the use of “nowcasting”, i.e. a technology that allows central bank to reduce the noise in the observations of current output and inflation. It will be shown that nowcasting improves the quality of monetary policy-making and that this improvement is more pronounced in the SIT- than in the DM-regime

The organization of the paper is as follows. Sections 2 to 4 describe the model and the two Taylor rules we employ in this paper. Section 5 discusses the calibration and the stability conditions of the model. Section 6 presents the basic results of the model. Section 7 compares the performance of the two Taylor rules under the two different monetary policy regimes. Section 7 provides sensitivity analysis on how different factors affect the performance of the two Taylor rules. Section 8 discusses the attractiveness of nowcasting and we conclude in section 9.

¹ There is a large literature on learning (see Evans (2001)). While some modelers adopt some weaker forms of rational expectations, namely “eductive learning”, others have developed “adaptive learning” models. The latter refer to the possibility that agents learn and update their forecasts. This updating can be done using statistical methods as in Evans and Honkapopja (2001) or in an evolutionary (trial and error) fashion.

2. The basic model structure

The basic behavioral macroeconomic model consists of an aggregate demand equation, an aggregate supply equation and a Taylor rule as described by De Grauwe (2011) and De Grauwe and Ji(2019).

The aggregate demand equation can be expressed in the following way:

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

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 two forward looking components, $\tilde{E}_t \pi_{t+1}$ and $\tilde{E}_t y_{t+1}$. The tilde above E refers to the fact that expectations are not formed rationally. How exactly these expectations are formed will be specified subsequently.

The aggregate supply equation is represented in (2). This New Keynesian Philips curve includes a forward looking component, $\tilde{E}_t \pi_{t+1}$, and a lagged inflation variable. Inflation π_t is sensitive to the output gap y_t . The parameter b_2 measures the extent to which inflation adjusts to changes in the output gap.

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

The aggregate demand and supply equations in (1) and (2) can be derived from expected utility maximization of consumers and expected profit maximization of firms (Hommes and Lustenhouwer(2019) and De Grauwe and Ji(2020)). See Appendix 1 where we provide for a microfoundation.

We will use two versions of the Taylor rule. Both versions follow the idea that interest rate policies respond to both inflation and output gap. The central bank can use two types of data to obtain information about the current output gap and inflation. These data can be “hard” or “soft”. Both hard and soft data are based on survey data and their release dates are indicated in Table 1.

Table 1. Central bank information sets at period t

Information	Survey data	Release date
Hard data (current state)	Manufacturing Purchasing Managers' Index (PMI)	Around 3 weeks into the current month
	Industrial production, Factory orders, Retail sales, Consumer spending...	30-45 days after the month ends
Soft data (expectation next 3-6 month)	Business sentiment and consumer confidence	Around 3 weeks into the current month

Sources: Banbura, Giannone, and Reichlin (2010)

In the first version of the Taylor rule the central bank, in period t, has access to 'hard data' about the current state of the economy (e.g. output gap and inflation). They then use these hard data to set the interest rate. We will call this a "current-looking Taylor rule". This behavior can be described as follows:

$$r_t = (1 - c_3)[c_1((\pi_t + \varepsilon_t) - \pi^*) + c_2(y_t + \theta_t)] + c_3 r_{t-1} + u_t \quad (3a)$$

where r_t is the interest rate in period t, π_t is the inflation rate, π^* is the target rate of inflation and y_t is the output gap. We assume that the current inflation and output gap are not observed perfectly. There is some noise that arises from the fact that at time t the current inflation and output gap are not yet observed. This noise is represented by respectively ε_t and θ_t . In Table 1, for example it is suggested that industrial production, factory orders, retail sales and consumer spending have a significant delay (more than one month after the end of the month) in its release. The central bank can increase the precision with which it observes π_t and y_t at time t by "nowcasting", i.e. by using high frequency and large data sets providing quick information about current variables like output and inflation (Giannone, Reichlin, and Small (2008)). However, even then some noise will persist. Nowcasting can then be seen as an information technology that reduces the noise ε_t and θ_t .

This current-looking Taylor rule tells us that the central bank increases (reduces) the interest rate when currently observed inflation exceeds (falls short of) the target and when the currently observed output gap is positive (negative). We assume that the central bank wants to smoothen interest rate changes (see Levin et al. (1999) and Woodford (1999, 2003)). This is shown by including a lagged interest rate. When no smoothing occurs $c_3 = 0$ we obtain the original Taylor rule. Note also that we set the natural rate of interest equal to zero.

In the second version of the Taylor rule, the central bank has access to ‘soft data’ (see Table 1). These are the surveys of business and consumer confidence, i.e. they are forecasts about output and consumption in the near future (e.g. 3-6 months). In this second version of the Taylor rule the Central bank uses this information set in setting interest rates. We can therefore call this behaviour to be *forward-looking*. This behavior is described in (3b)

$$r_t = (1 - c_3)[c_1(\tilde{E}_t\pi_{t+1} - \pi^*) + c_2\tilde{E}_ty_{t+1}] + c_3r_{t-1} + u_t \quad (3b)$$

In this formulation of the Taylor rule the central bank uses market forecasts of inflation and output gap. We do not include noise terms in the forward-looking Taylor rule. This is because market forecasts/expectation data are less subject to time delay compared to current output and inflation. With the help of big data nowadays, most central banks have good quality of data on market forecasts. According to the forward-looking Taylor rule, the central bank then raises (reduces) the interest rate when the market forecasts of inflation exceeds (is below) the target and when the forecasted output gap is positive (negative).

We have also added error terms in each of the equations (1) to (3a&b). These describe the nature of the different shocks that can hit the economy. There are demand shocks, v_t , supply shocks, η_t and interest rate shocks, u_t . It is assumed that these shocks are normally distributed with mean zero and a constant standard deviation.

3. Expectations formation and animal spirits

In this section we analyze how the forecast of output gap $\tilde{E}_t y_{t+1}$ and inflation $\tilde{E}_t \pi_{t+1}$ are formed in the model. The rational expectations hypothesis requires agents to understand the complexities of the underlying model and to know the frequency distributions of the shocks that will hit the economy. We take it that agents have cognitive limitations that prevent them from understanding and processing this kind of information. These cognitive limitations have been confirmed by laboratory experiments and survey data (see Carroll, 2003; Branch, 2004; Pfajfar, D. and B. Zakelj, (2011 & 2014); Hommes, 2011).

We assume two types of rules agents follow to forecast the output gap. A first rule is 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. A second forecasting rule is a “naïve” 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. There is ample evidence from laboratory experiments that support these assumptions that agents use simple heuristics to forecast output gap and inflation. See Pfajfar and Zakelj, (2011 & 2014), Kryvtsov and Petersen (2013) and also Assenza et al. (2014a) for a literature survey. The fundamentalist and extrapolator rules for output gap are specified as follows:

$$\tilde{E}_t^f y_{t+1} = 0 \quad (4)$$

$$\tilde{E}_t^e y_{t+1} = y_{t-1} \quad (5)$$

This kind of simple heuristic has often been used in the behavioral macroeconomics and 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), Brazier et al. (2008)). It is probably the simplest possible assumption one can make about how agents who experience cognitive limitations, use rules that embody limited knowledge to guide their behavior. They only require agents to use information they understand, and do not require them to understand the whole picture. In De Grauwe (2012) more complex rules are used, e.g. it is assumed that agents do not know the steady state

output gap with certainty and only have biased estimates of it. This is also the approach taken by Hommes and Lustenhouwer (2019).

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

$$\tilde{E}_t y_{t+1} = \alpha_{f,t} \tilde{E}_t^f y_{t+1} + \alpha_{e,t} \tilde{E}_t^e y_{t+1} \quad (6)$$

$$\alpha_{f,t} + \alpha_{e,t} = 1 \quad (7)$$

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

As indicated earlier, agents in our model are willing to learn, i.e. they continuously evaluate their forecast performance. We specify a switching mechanism of how agents adopt specific rule. As shown in Appendix 2, we follow the discrete choice theory (see Anderson, de Palma, and Thisse, (1992) and Brock & Hommes (1997)) to work out the probability of choosing a particular rule. We obtain:

$$\alpha_{f,t} = \frac{\exp(\gamma U_{f,t})}{\exp(\gamma U_{f,t}) + \exp(\gamma U_{e,t})} \quad (8)$$

$$\alpha_{e,t} = \frac{\exp(\gamma U_{e,t})}{\exp(\gamma U_{f,t}) + \exp(\gamma U_{e,t})} \quad (9)$$

where $U_{f,t}$ and $U_{e,t}$ the past forecast performance (utility) of using the fundamentalist and the naïve rules. The parameter γ measures the “intensity of choice”. It 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 .

The forecast performance affects the probability of using a particular rule. For example, as shown in Equation (8), as the past forecast performance (utility) of the fundamentalist rule improves relative to that of the naïve rule, agents are more likely to select the fundamentalist rule for their forecasts of the output gap.

Agents also have to forecast inflation. Similar heuristics rules as in the case of output forecasting are described in Appendix 3. This allows us to use the switching mechanism similar to the one specified equations (8) and (9). The procedure to solve the model is shown in Appendix 4.

The forecasts made by extrapolators and fundamentalists play an important role. In order to highlight this role we define an index of market sentiments S_t , called “animal spirits”. This index can change between -1 and +1. It reflects how optimistic or pessimistic these forecasts are. It is obtained from fraction of extrapolators ($\alpha_{e,t}$) and fundamentalists ($\alpha_{f,t}$) as follows:

$$S_t = \begin{cases} \alpha_{e,t} - \alpha_{f,t} & \text{if } y_{t-1} > 0 \\ -\alpha_{e,t} + \alpha_{f,t} & \text{if } y_{t-1} < 0 \end{cases} \quad (10)$$

where S_t is the index of animal spirits. This can change between -1 and +1. There are two possibilities:

- When $y_{t-1} > 0$, extrapolators forecast a positive output gap. The fraction of agents who make such a positive forecasts is $\alpha_{e,t}$. Fundamentalists, however, then make a pessimistic forecast since they expect the positive output gap to decline towards the equilibrium value of 0. The fraction of agents who make such a forecast is $\alpha_{f,t}$. We subtract this fraction of pessimistic forecasts from the fraction $\alpha_{e,t}$ who make a positive forecast. When these two fractions are equal to each other (both are then 0.5) market sentiments (animal spirits) are neutral, i.e. optimists and pessimists cancel out and $S_t = 0$. When the fraction of optimists $\alpha_{e,t}$ exceeds the fraction of pessimists $\alpha_{f,t}$, S_t becomes positive. As we will see, the model allows for the possibility that $\alpha_{e,t}$ moves to 1. In that case there are only optimists and $S_t = 1$.

When $y_{t-1} < 0$, extrapolators forecast a negative output gap. The fraction of agents who make such a negative forecasts is $\alpha_{e,t}$. We give this fraction a negative sign. Fundamentalists, however, then make an optimistic forecast since they expect the negative output gap to increase towards the equilibrium value of 0. The fraction of agents who make such a forecast is $\alpha_{f,t}$. We give this fraction of optimistic forecasts a positive sign. When these two fractions are equal to each other (both are then 0.5) market sentiments (animal spirits) are neutral, i.e. optimists and pessimists cancel out and $S_t = 0$. When the fraction of pessimists $\alpha_{e,t}$ exceeds the fraction of optimists $\alpha_{f,t}$ S_t becomes negative. The fraction of pessimists, $\alpha_{e,t}$, can move to 1. In that case there are only pessimists and $S_t = -1$.

4. Calibration and stability condition

As our model has strong non-linear features we use numerical methods to analyze the dynamics created by the model. In order to do so, we have to calibrate the model, i.e. to select numerical values for the parameters of the model. In Table 2 we show these numerical values with the references from the literature.

Table 2: Parameter values of the calibrated model

$a1 = 0.5$	coefficient of expected output in output equation (Smets and Wouters(2003))
$a2 = -0.2$	interest elasticity of output demand (McCallum and Nelson (1999)).
$b1 = 0.5$	coefficient of expected inflation in inflation equation (Smets and Wouters (2003))
$b2 = 0.05$	coefficient of output in inflation equation,
$\pi^*=0$	inflation target level
$c1 = 1.5$	coefficient of inflation in Taylor equation (Blattner and Margaritov(2010))
$c2 = 0.5$	coefficient of output in Taylor equation assuming a dual Mandate Central Bank (Blattner and Margaritov(2010))
$c2 = 0.1$	coefficient of output in Taylor equation assuming a strict inflation targeting Central Bank. The size of $c2$ see discussion in Belke and Klose (2011)
$c3 = 0.5$	interest smoothing parameter in Taylor equation (Blattner and Margaritov(2010))
$\gamma = 2$	intensity of choice parameter, see Kukacka, Jang and Sacht (2018)
$\sigma_v = 0.5$	standard deviation shocks output
$\sigma_\eta = 0.5$	standard deviation shocks inflation
$\sigma_u = 0.5$	standard deviation shocks Taylor
σ_ε and σ_θ	we choose low (0,0) and high value (1,0) to analyse efficiency of nowcasting
$\rho = 0.5$	memory parameter (see footnote 3)

The model is simulated over 10,000 periods. We analyze the conditions under which the model produces stable outcomes and the results are shown in Tables 2 and 3. Fixing $c3=0.5$ we allow the parameters $c1$ (inflation parameter) and $c2$ (output gap parameter) in the Taylor rule to vary.

We find in both Taylor regimes the crucial role of $c1$ in maintaining stability of the model. The parameter $c1 \geq 1$ to ensure stability in both Taylor rule regimes. This so-called Taylor principle is found in most macroeconomic models. The parameter $c2$ that expresses the central bank's preference for output stabilization also matters. General discussion on the stability condition of the behavioural models

we use can be found in De Grauwe and Ji (2020) and Hommes and Lustenhouwer(2019).

Table 2: Stability analysis, current Taylor rule ($\sigma_\varepsilon, \sigma_\theta = 0$), no noise

inflation parameter c1	output parameter c2									
	0	0,1	0,2	0,4	0,6	0,8	1	1,2	1,3	1,4
0	U	U	U	U	U	U	U	U	U	U
0,3	U	U	U	U	U	U	U	U	U	U
0,6	U	U	U	U	U	U	U	U	U	U
0,9	U	U	U	U	U	U	U	U	U	U
0,95	U	U	U	U	U	U	U	U	U	U
0,99	U	U	U	U	U	U	U	U	U	U
1	U	S	S	S	S	S	S	S	S	S
1,3	S	S	S	S	S	S	S	S	S	S
1,6	S	S	S	S	S	S	S	S	S	S
1,9	S	S	S	S	S	S	S	S	S	S
2,2	S	S	S	S	S	S	S	S	S	S
2,5	S	S	S	S	S	S	S	S	S	S

Table 3: Stability analysis, forward Taylor rule

inflation parameter c1	output parameter c2									
	0	0,1	0,2	0,4	0,6	0,8	1	1,2	1,3	1,4
0	U	U	U	U	U	U	U	U	U	U
0,2	U	U	U	U	U	U	U	U	U	U
0,4	U	U	U	U	U	U	U	U	U	U
0,6	U	U	U	U	U	U	U	U	U	U
0,8	U	U	U	U	U	U	U	U	U	U
0,9	U	U	U	U	U	U	U	U	U	U
0,99	U	U	U	U	U	U	U	U	U	U
1	U	S	S	S	S	S	S	S	S	S
1,3	U	S	S	S	S	S	S	S	S	S
1,6	U	S	S	S	S	S	S	S	S	S
1,9	U	S	S	S	S	S	S	S	S	S
2,2	U	S	S	S	S	S	S	S	S	S
2,5	U	S	S	S	S	S	S	S	S	S

In Table 2, we present the stability condition of the two Taylor rules (unstable indicated as 'u' and stable as 's'). There is a contrast here between the two Taylor rule regimes. Under the current Taylor rule regime (without noise) the model produces stable solutions for all values of $c1 \geq 1$ and $c2 \geq 0$. Under the forward-looking Taylor rule regime, a value of $c2=0$ leads to instability. Thus the forward Taylor regime produces more problems of instability and high volatility than the

current Taylor regime. Note that we have assumed that the central bank observes current variables (Current Taylor rule) and current market forecasts (Forward Taylor rule) without noise. Later we will also analyse what happens when there is noise in the observation of current variables.

The previous diagnostic stability analysis suggests that it will be useful to distinguish two types of central banks. The first one is a “Strict Inflation Targeting” central bank (SIT) whose sole objective is to stabilize inflation. This is a central bank that sets c_2 close to zero. We will assume it sets $c_2=0.1$. The second central bank can be called a “Dual Mandate” central bank (DM). This is a central bank that sets c_2 high enough to reflect its desire to stabilize the output gap. We will assume it sets $c_2=0.5$.

5. Results of the model

Before we analyze the different characteristics of the results obtained under the two monetary regimes (SIT and DM) we present some general results of the model that allow us to better understand the working of this behavioural model. We use the parameter values presented in table 1 (including setting $c_2=0.5$, thus implicitly assuming a DM central bank). We analyze the model for both the current and the forward Taylor rules.

The results obtained using the current Taylor rule (without noise) are presented in Figure 1, which shows the movements of the output gap and animal spirits in the time domain (left hand side panels). We show a sample of 300 periods (quarters) that is representative of the full simulation. The right-hand side panel shows the output gap and animal spirits in the frequency domain for the full 10,000 periods.

We observe that the model produces waves of optimism and pessimism (animal spirits) that can lead to situations where everybody becomes optimist ($S_t = 1$) or pessimist ($S_t = -1$). These waves of optimism and pessimism are generated endogenously, i.e. the i.i.d. shocks are transformed into serially correlated (persistent) movements in market sentiments.

As can be seen from the left-hand side panels, the correlation of these animal spirits and the output gap is high, reaching 0.95. Underlying this correlation is the

self-fulfilling nature of expectations (optimism and pessimism)². When agents with optimistic forecasts happen to be more numerous than those with pessimistic forecasts, this will tend to raise the output gap (see equation (3)). The latter in turn validates those who made optimistic forecasts. This then attracts more agents to become optimists. When the market is gripped by a self-fulfilling movement of optimism (or pessimism) this can lead to a situation where everybody becomes optimist (pessimist). This then also leads to an intense boom (bust) in economic activity.

This self-fulfilling nature of the dynamics also leads to different frequency distribution of output and animal spirits from the conventional macroeconomic models. These results are shown in the right-hand side panels. We find that the output gap is not normally distributed (despite the i.i.d. shocks), with excess kurtosis and fat tails. A Jarque-Bera test rejects normality of the distribution of the output gap. The origin of the non-normality of the distribution of the output gap can be found in the distribution of the animal spirits. We find that there is a concentration of observations of animal spirits around 0. This means that much of the time there is no clear-cut optimism or pessimism. We can call these “normal periods”. There is also, however, a concentration of extreme values at either -1 (extreme pessimism) and +1 (extreme optimism). These extreme values of animal spirits explain the fat tails observed in the distribution of the output gap. These fat tails episodes are usually associated with crisis situations.

When comparing these results obtained under the current Taylor rule regime with those obtained under the forward Taylor rule regime we find that they are similar. This is shown in Figure 2.

² In De Grauwe(2012) and De Grauwe and Ji(2018) empirical evidence is provided indicating that output gaps are highly correlated with empirical measures of animal spirits. It is shown that when performing causality tests on US and the Eurozone data one cannot reject the hypothesis that the output gap Granger causes the index of business confidence, and vice versa one cannot reject the hypothesis that the index of business confidence Granger causes the US and Eurozone output gap during 1999-2015. Thus there is a two-way causality between market sentiments and the output gap. This is also what we find in this model.

Figure 1. Output and animal spirits, Current Taylor

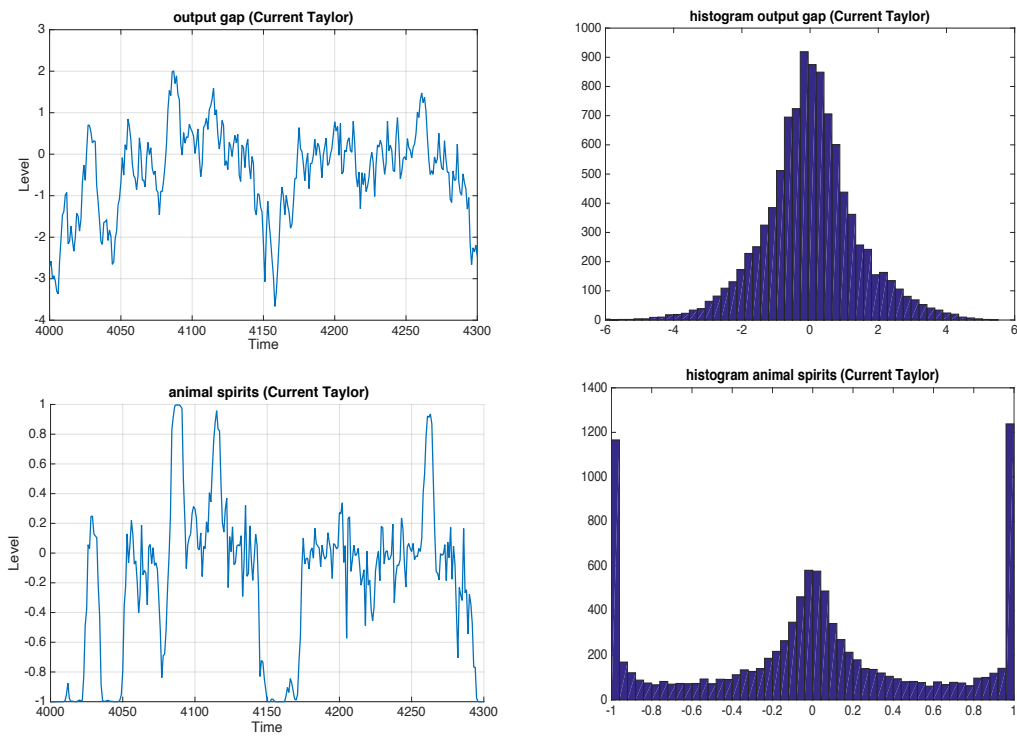
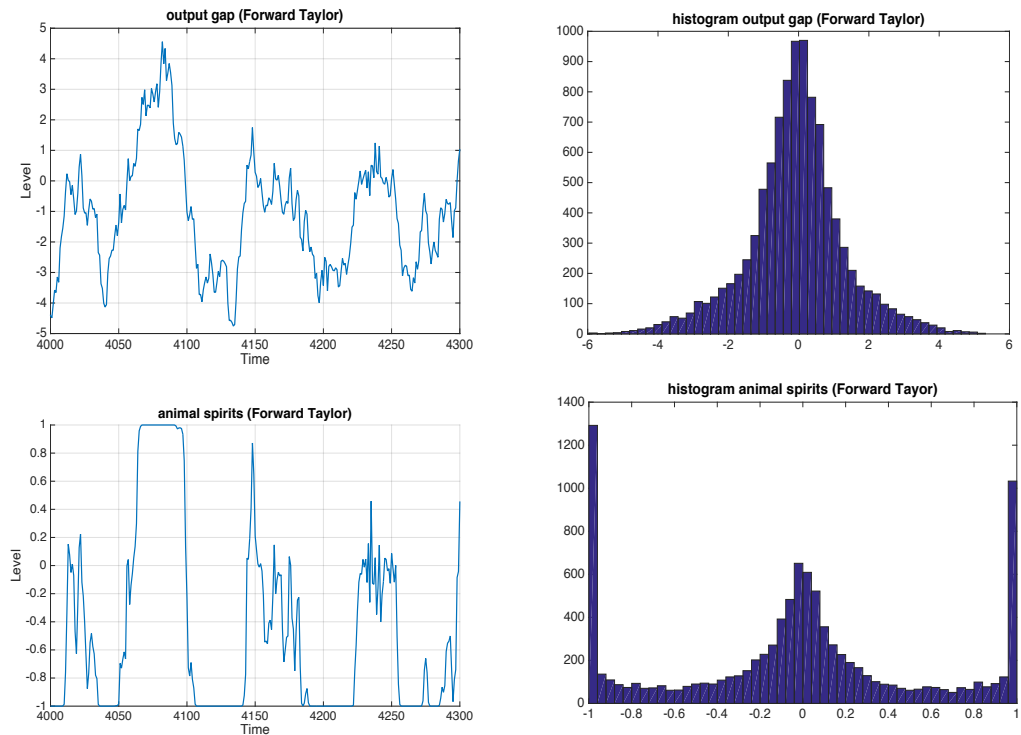


Figure 2. Output and animal spirits, Forward Taylor



6. Performance of central bank: two regimes

In this section we assume that through big data and now-casting technologies central banks have perfect knowledge about the current output gap and inflation and they also have perfect knowledge on the market forecasts of output gap and inflation. In section 7.3 we study how relaxing these assumptions affects the results. The question we ask in this section is how the information set affects the performance of the Taylor rules. Our analysis will very much depend on the regimes of central bank policy.

6.1 Strict Inflation Central Bank (SIT)

We now turn to the model in a regime of strict inflation targeting ($c_2=0.1$). We show the results in Table 4. We find that the forward looking Taylor rule (using soft data) leads to significantly more variability of the output gap and of inflation than the current Taylor rule. The standard deviations and the extreme values (minimum and maximum) of the output gap and inflation are systematically higher when the central bank takes a forward-looking attitude than when it looks at current values only.

Table 4. Output gap and inflation volatilities ($c_2=0.1$)

	std (y)	std(π)	Min(y)	Max(y)	Min (π)	Max(π)
Current Taylor	3.59	2.55	-13.2	14.8	-10.5	10.2
Forward Taylor	4.52	3.30	-18.0	19.5	-14.0	13.7

6.2 Dual Mandate Central Bank

Next we analyze the model assuming a “dual mandate” central bank, i.e. $c_2=0.5$. We analyze the model for both the current and the forward Taylor rules. In Table 5 we present indicators of variability obtained under the two Taylor rules, confirming these results. This comparison is in line with the findings from the RE models that current-looking and forward-looking policy rules produce similar results (see Taylor and Williams (2010)).

Table 5. Output gap and inflation volatilities ($c_2=0.5$, σ_4 and $\sigma_5=0$; σ_1 and $\sigma_2=0.5$)

	std (y)	std(π)	Min(y)	Max(y)	Min (π)	Max(π)
Current Taylor	1.65	1.84	-5.72	6.88	-8.22	8.23
Forward Taylor	1.80	1.98	-6.32	6.94	-7.21	6.47

How can the previous result be explained? We answer this question here. When the central bank puts too little weight on output stabilization (a small c_2) as it does in the strict inflation targeting central bank, the boom-bust dynamics is frequent and intense. This produces extreme outcomes of animal spirits and fat tails in the distribution of the output gap. This feature is present in both Taylor rules (see Figures 1 and 2). However, in the forward-looking Taylor rule this feature is exacerbated. The reason is that when booms and busts occur, i.e. when there are fat tails and extreme values of animal spirits, forecast errors made both by private agents and by the central bank become very high. As a result, a strict inflation targeting and forward-looking central bank will make many policy moves that turn out to be wrong. Put differently, the forward-looking central bank will make many policy mistakes that have to be reversed, thereby exacerbating the volatility of output gap and inflation. Thus when the forward Taylor rule is used the quality of policy-making declines, leading to greater variability of the output gap.

We checked for this interpretation by calculating the forecast errors made by agents (and by the strict inflation targeting central bank) under the current and forward Taylor rules in Figures 3 and 4. We plot the squared forecast errors of output gap (Figure 3) and inflation (Figure 4) against the animal spirits. We find that when animal spirits are close to zero (tranquil times) the forecast errors tend to be the same in the two Taylor rule regimes. As animal spirits increase (in absolute values) the forecast errors increase and more so under the forward-looking Taylor rule.

Figure 3: Squared forecast errors output gap and animal spirits

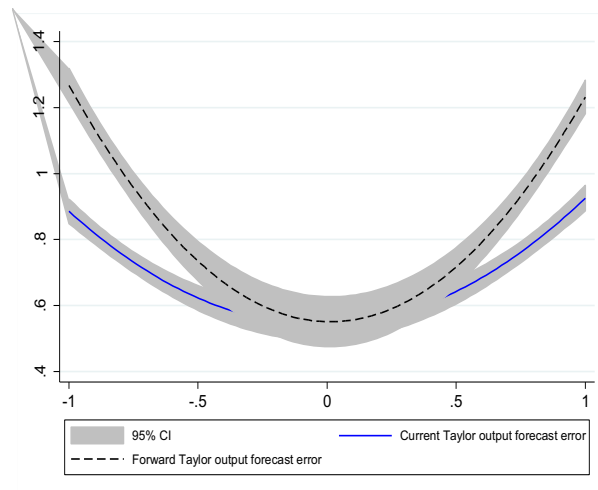
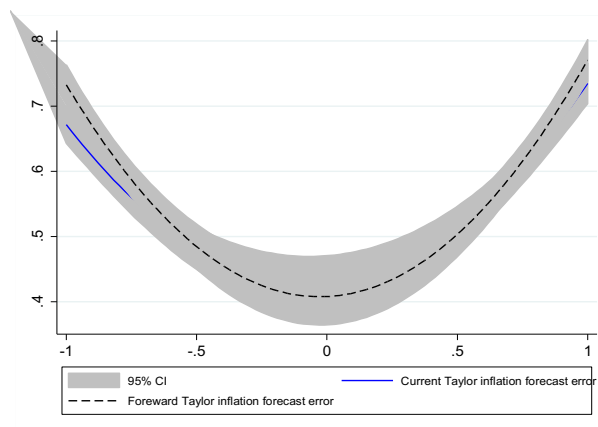


Figure 4: Squared forecast errors inflation and animal spirits



This leads to the following insight. Extreme moods of optimism and pessimism are the result of the fact that all agents tend to extrapolate what they observe today, a boom in the optimistic case or a decline in the pessimistic case. It is then better for the strict inflation central bank to use currently observed output and inflation to set the interest rate. Given the extreme volatility of these variables when animal spirits are intense, the central bank that uses market expectations will make many policy errors that have to be corrected afterwards.

From the previous analysis we conclude that in a dual mandate central bank regime the difference between current and forward-looking Taylor rules is insignificant. In contrast in a strict inflation targeting regime a forward Taylor rule produces significantly higher volatility of the output gap.

7. Performance of Taylor rules: sensitivity analysis

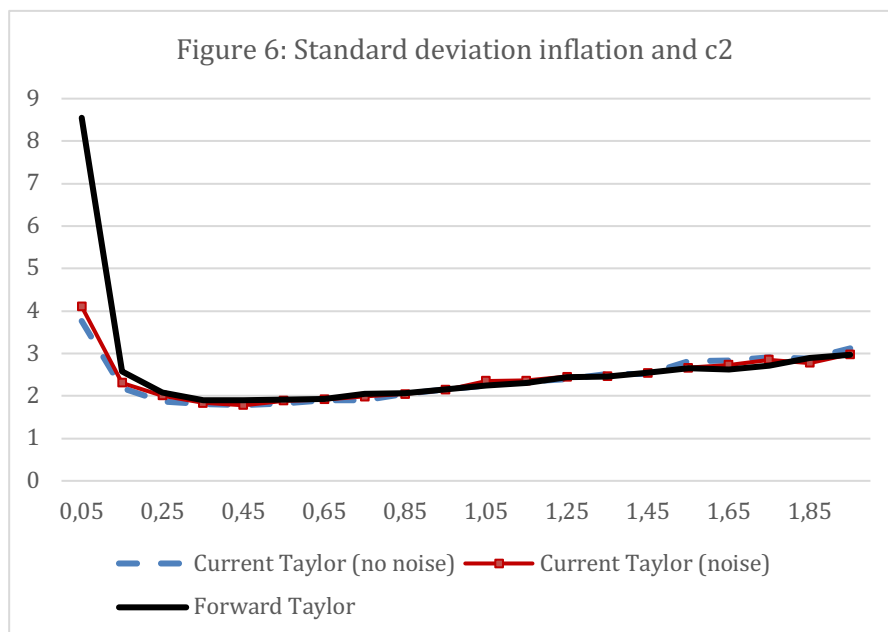
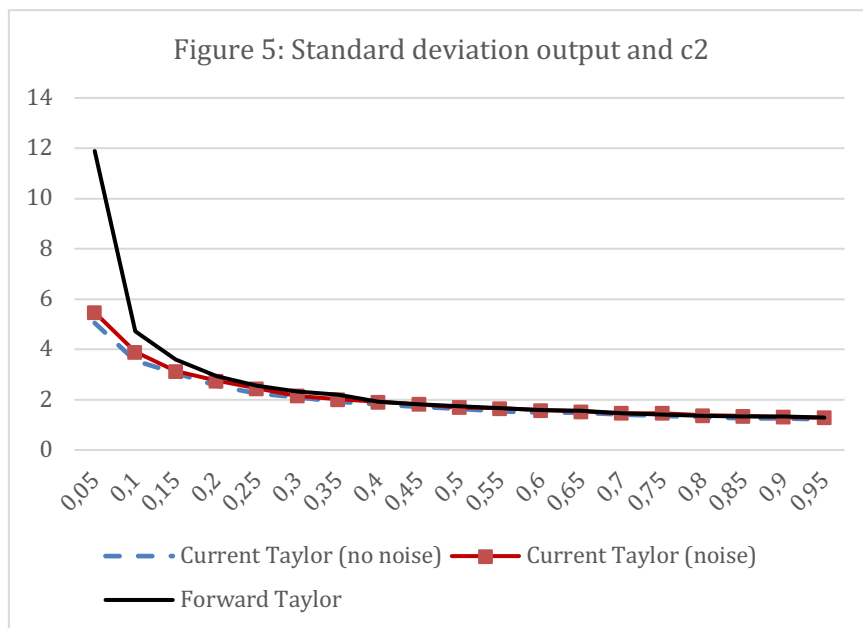
7.1 The importance of output stabilizer c_2

In order to make the previous conclusions more precise we computed the sensitivity of output volatility with respect to changes in the c_2 parameter in the Taylor rule. For the sake of completeness we repeat the exercise for inflation volatility.

We now also consider two types of current Taylor rule. In the first one, we assume as before that the central bank observes current output gap and inflation perfectly (without noise); in the second one, we assume that there is noise in the observation of these variables (we assumed a standard deviation of 1). We computed the standard deviations in output gap and inflation for different values of c_2 and we show the results in Figures 5 and 6. The parameter c_2 is shown on the horizontal axis and the standard deviations of the output gap and inflation, on the vertical axis. We find that when c_2 is large enough the differences in the performance of the different Taylor rules become very small. Only when c_2 is close to zero (strict inflation targeting) does the current Taylor rule (with and without noise) perform significantly better in keeping output and inflation volatility low than the forward Taylor rule. Thus, when central banks care about output stabilization as measured by c_2 the current and forward Taylor rules perform (almost) equally well in stabilizing output and inflation. Note that the noise in observing output and inflation has little influence on how the two current Taylor rules affect the volatility of output and inflation. We come back to this issue in the next section.

Another feature of the results of Figures 5 and 6 is the following. We observe that starting from the lowest level of c_2 increases in this parameter have the effect of reducing both the volatility of output gap and inflation. The former is not a surprise since a greater output stabilization effort from the central bank is likely to lead to less output volatility. The surprise is in the fact that this increase in output stabilization efforts by the central bank also reduces inflation volatility. This happens in the three Taylor rules (but more so in the Forward one). Where does this come from? The answer is that when c_2 is very low the model produces intense booms and busts characterized by the occurrence of fat tails. In such

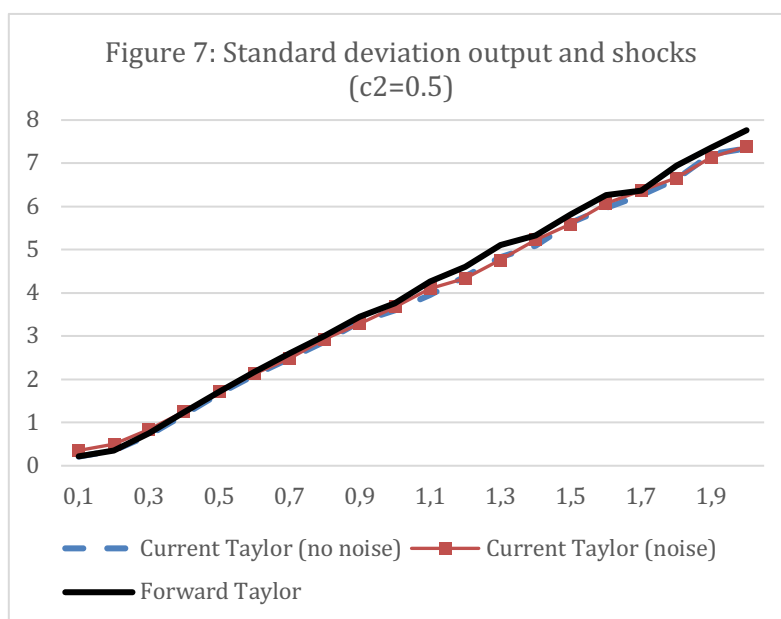
boom-bust situations both output and inflation are extremely volatile. By increasing c_2 the central bank reduces the occurrence of boom-bust scenarios and thus also the extreme volatility of both output and inflation. However, at some point when c_2 is large enough (approximately 0.5) inflation volatility starts increasing with increases of c_2 . Thus from that point on, the central bank's increased attempts at stabilizing output come at a price of more inflation volatility. This then creates the standard tradeoff between output and inflation volatility.

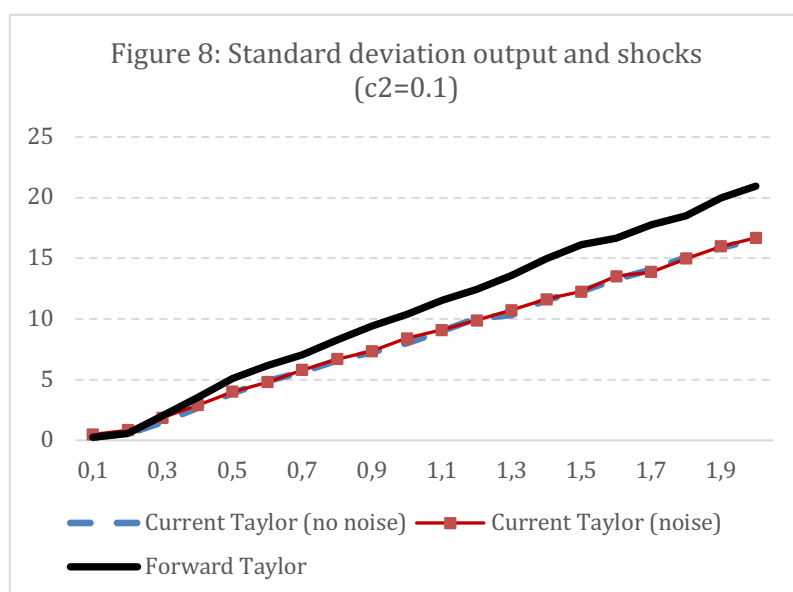


7.2 The response to exogenous shocks

In a second sensitivity exercise we simulated the model for different standard deviations of demand and supply shocks. As before, we did this for the two policy regimes, DM and SIT. We show the results in Figures 7 and 8. These figures present the standard deviations of the output gap for different values of the standard deviations of the aggregate demand and supply shocks, σ_v and σ_η in equations (1) and (2). The results have the following interpretation. In the DM-regime ($c_2=0.5$) the impact of the different Taylor rules on the volatility of output is not much affected by the size of the demand and supply shocks. This contrasts with the SIT-regime ($c_2=0.1$). In this regime we observe that as the size of the demand and supply shocks increases the forward-looking Taylor rule becomes increasingly less attractive, i.e. it leads to increases in the volatility of output in comparison with the current Taylor rules.

These, and also some of the previous results, suggest that when the central bank is giving enough emphasis to output stabilization, the nature of the data it uses to pursue its policies (soft or hard data) does not matter much. It is only when, due to a lack of sufficient output stabilization, the economy regularly gets embroiled in boom-busts dynamics that the nature of the data matters. We then find that the use of forward-looking data (soft data) in the Taylor rule leads to inferior stabilization results as compared to the use current data (hard data).





7.3 The importance of nowcasting

During the last few decades central banks have made efforts at increasing the precision with which they observe current output and inflation. The lack of precision in observing these variables comes from the fact that there is a lag between their realization and their observation. “Nowcasting” has provided for a new technology in increasing this precision. Here we ask the question how increased precision provided by nowcasting helps the central bank in reducing the volatility of output and inflation. We show the answer in Figure 9 for the two regimes, i.e. Dual-Mandate central bank and Strict Inflation Targeting central banks. On the horizontal axis we set out the noise in observing current output and inflation. This is measured by σ_ε and σ_θ . On the vertical axis we show the standard deviations of the output gap and inflation, respectively. We observe that in both regimes a decline in the noise leads to a decline in the variability of the output gap and inflation. However, this decline is more pronounced and more non-linear in the Strict Inflation Targeting central bank. Thus, nowcasting improves the quality of monetary policymaking and this improvement is the strongest in a regime where the central bank pursues a strict inflation targeting.

Although typically information about market forecasts (soft data) is obtained quicker than about current variables (hard data, see table 1) there is also noise surrounding soft data. Thus we ask the same question of how innovations in nowcasting that reduce the noise around soft data improve the quality of

monetary policymaking. The answer is given in Figure 10 which is very similar to Figure 9. The reduction of noise around the collection of market forecasts reduces the volatility of inflation and output gap and this reduction is stronger in the SIT regime than in the DM regime.

Figure 9: Standard deviation output gap and inflation with different noise in observing current variables

Dual Mandate (DM)

Strict Inflation Targeting (SIT)

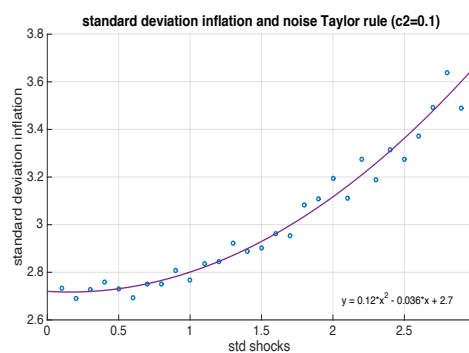
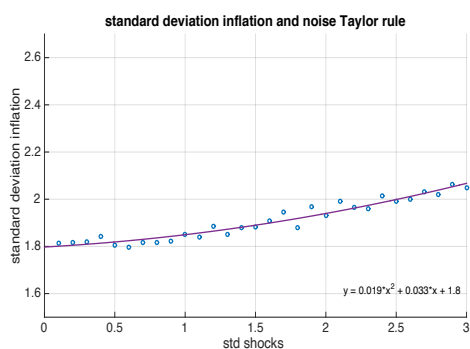
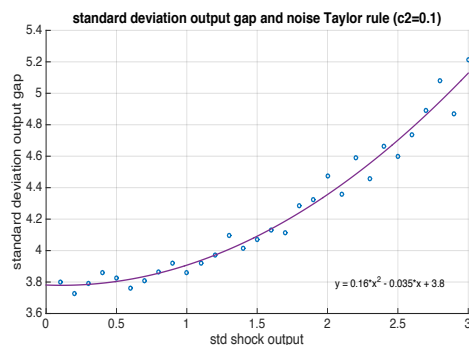
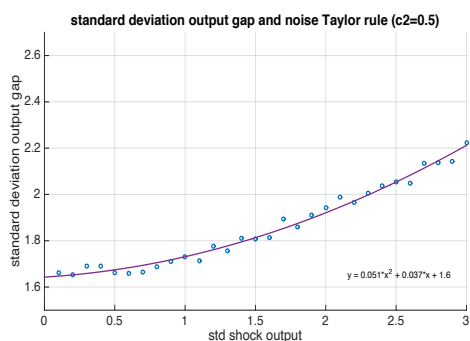
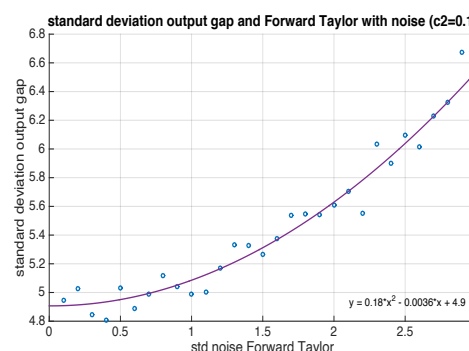
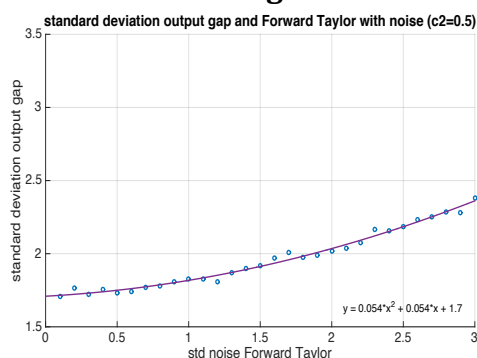
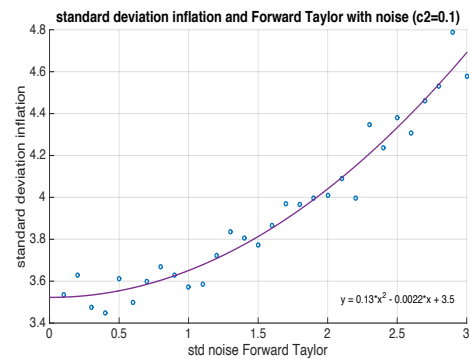
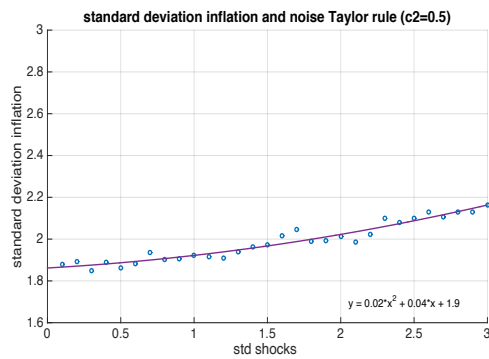


Figure 10: Standard deviation output gap and inflation with different noise in observing market forecast





8. Conclusion

Should a central bank use current or forward-looking data (hard or soft data) when setting its optimal interest rate? This question has been analyzed in great detail in the macroeconomic literature. When this question is analyzed in the context of theoretical Rational Expectations models with utility maximizing agents, the answer is generally found to be positive. However, the empirical evidence suggests that central banks do not always take a forward looking attitude. Moreover, this evidence also suggest that the benefits of using forward-looking Taylor rule are ambiguous.

We contributed to this literature by comparing Taylor rules current and forward looking data. We performed this analysis using a behavioural macroeconomic model. We have shown that in a world where agents have limited cognitive abilities and, as a result, are prevented from having rational expectations the use of forward looking data by the central bank leads to inferior outcomes in particular monetary policy regimes. We found that in “tranquil periods” when market sentiments (animal spirits) are neutral a forward-looking Taylor rule produces similar results as current-looking Taylor rule. However, when the economy is in a regime of booms and bust produced by extreme values of animal spirits (crisis periods) a central bank that bases its interest rate decisions on forecasted values of output and inflation introduces more variability in these variables. We interpreted this result as follows. Extreme moods of optimism and pessimism are the result of the fact that all agents tend to extrapolate what they observe today: a boom in the optimistic case, a decline in the pessimistic case. It is then better for the central bank to use currently observed output and inflation

to set the interest rate. Given the extreme volatility of these variables when animal spirits are extreme, the central bank that uses forward looking data will make many policy errors that have to be corrected afterwards. Thus, when the forward Taylor rule is used the quality of policy-making declines, leading to greater variability of the output gap and inflation.

We also found that the difference between the use of current and forward looking data tends to disappear when the central bank does a degree of output stabilization that reduces the occurrences of extreme values of output gap and inflation. The reason is that in such a monetary policy regime the absence of extreme booms and busts makes the forward-looking data more reliable.

In response to exogenous shock, we also found that in the SIT-regime ($c_2=0.1$), as the size of the demand and supply shocks increases the forward-looking Taylor rule becomes increasingly less attractive, i.e. it leads to increases in the volatility of output in comparison with the current Taylor rules.

Finally we showed that the use of nowcasting can significantly improve the quality of monetary policy. In fact we found that this improvement is more pronounced in the monetary policy regime based on strict inflation targeting than in the dual mandate monetary policy regime.

Appendix 1. Microfoundations of the basic behavioral model

We show that the aggregate demand and supply equations used in the main text can be micro-founded on individual utility maximization of households and profit maximization of firms.

1. Aggregate demand

Let us start by modeling the demand side of the model. This will be based on the maximization of individual's utility of consumption over an infinite horizon. The individual consumer, i , maximizes the following function over an infinite horizon:

$$E_0 \sum_{t=0}^{\infty} \beta^t U(C_t^i, N_t^i) \quad (A1)$$

where β is discount factor, U is the utility function which is assumed to have the same form every period and every agent, C_t^i is consumption of agent i in period t and N_t^i is hours worked by agent i .

The budget constraint faced by consumer i is:

$$P_t C_t^i + Q_t B_t^i \leq B_{t-1}^i + W_t N_t^i - T_t \quad (A2)$$

where B_t^i is the quantity of one period discount bond purchased by agent i in period t and maturing in $t+1$; Q_t is price of bond, P_t is the price of consumption goods, W_t is the wage rate and T_t is a lump-sum tax

First order condition for consumer's optimum (Euler equation):

$$-\frac{U_{n,t}}{U_{c,t}} = \frac{W_t}{P_t} \quad (A3)$$

$$Q_t = \beta \tilde{E}_t^i \left[\frac{U_{c,t+1}}{U_{c,t}} \frac{P_t}{P_{t+1}} \right] \quad (A4)$$

where \tilde{E}_t^i is the forecast made by agent i in period t using the behavioral heuristic explained in the main text.

Assume a CES utility function

$$U(C_t^i, N_t^i) = \frac{C_t^{i,1-\sigma}}{1-\sigma} - \frac{N_t^{i,1+\varphi}}{1+\varphi} \quad (A5)$$

First order optimality conditions can then be written as:

$$\frac{w_t}{P_t} = C_t^{i,\sigma} N_t^{i,\varphi} \quad (\text{A6})$$

$$Q_t = \beta \tilde{E}_t^i \left[\left(\frac{C_{t+1}^i}{C_t^i} \right)^{-\sigma} \frac{P_t}{P_{t+1}} \right] \quad (\text{A7})$$

Log-linearization (A6) yields the labour supply equation

$$w_t - p_t = \sigma c_t^i + \varphi n_t^i \quad (\text{A8})$$

where lower case letters are natural logarithms. We will not use this labour supply equation as I currently assume full wage flexibility.

Similarly log-linearization (A7) yields the consumption equation (Euler equation) for individual i:

$$c_t^i = \tilde{E}_t^i c_{t+1}^i - \frac{1}{\sigma} (r_t - \tilde{E}_t^i \pi_{t+1} - \rho) \quad (\text{A9})$$

where the interest rate $r_t = -\log(Q_t)$, the inflation rate $\pi_t = \log P_{t+1} - \log P_t$ and $\rho = -\log \beta$.

We follow Hommes and Lustenhouwer (2016) in assuming that the probability to follow a particular forecasting rule (heuristic) in period t is the same across agents, and independent of the heuristic they followed in the past. This follows from the fact that agents are not inherently different, but that each of them is confronted with the same choice between being following a naïve or fundamentalist forecasting rule. In addition, as in Hommes and Lustenhouwer(2016), we assume “agents know that all agents have the same probability to follow a particular heuristic in the future, and that they know that consumption decisions only differ between households in so far as their expectations are different”. In this case households’ forecasts about their individual consumption must be the same as their forecast of the consumption of any other individual. It follows that the individual’s forecast of his own consumption will coincide with the forecast of aggregate consumption:

$$\tilde{E}_t^i c_{t+1}^i = \tilde{E}_t^i c_{t+1} \quad (\text{A10})$$

where c_{t+1} is aggregate consumption.

This allows us to rewrite the Euler equation as

$$c_t^i = \tilde{E}_t^i c_{t+1} - \frac{1}{\sigma} (r_t - \tilde{E}_t^i \pi_{t+1} - \rho) \quad (\text{A11})$$

In equilibrium aggregate demand = aggregate supply of output, i.e. $c_t = y_t$

Assume that agents understand market clearing. As a result, their forecast of consumption coincides with their forecast of output. It can be written as

$$\tilde{E}_t^i c_{t+1} = \tilde{E}_t^i y_{t+1} \quad (\text{A12})$$

As a result, (A11) can be written as

$$c_t^i = \tilde{E}_t^i y_{t+1} - \frac{1}{\sigma} (r_t - \tilde{E}_t^i \pi_{t+1} - \rho) \quad (\text{A13})$$

Aggregating this expression over all agents i , and using the market clearing condition, yield

$$y_t = \tilde{E}_t y_{t+1} - \frac{1}{\sigma} (r_t - \tilde{E}_t \pi_{t+1} - \rho) \quad (\text{A14})$$

This is the aggregate demand equation used in the main text (without inertia). Thus the aggregate demand equation in our behavioral model can be micro-founded.

The aggregate demand equation used in the main text includes a lagged output gap. Such a lagged output gap can be introduced by assuming habit formation (see Fuhrer(200), Dennis(2008)). We then have a utility function of the form:

$$E_0 \sum_{t=0}^{\infty} \beta^t U(C_t^i, H_t^i, N_t^i) \quad (\text{A15})$$

where H_t^i is the habit stock of agent i .

Assuming the habit stock obeys the expression

$$H_t^i = \eta C_{t-1}^i$$

where it is assumed that external habit formation (see Dennis(2008)). This allows us to derive an aggregate demand equation of the form (see Dennis(2008))

$$y_t = \frac{1}{1+\eta} \tilde{E}_t y_{t+1} + \frac{\eta}{1+\eta} y_{t-1} - \frac{1}{\sigma} (r_t - \tilde{E}_t \pi_{t+1} - \rho) \quad (\text{A16})$$

which is the aggregate demand equation (1) used in the main text where

$$a_1 = \frac{1}{1+\eta}$$

2. Aggregate supply

There is a continuum of firms each producing a differentiated good j in monopolistically competitive markets.

The production function of firm j is specified as follows

$$Y_t^j = A_t N_t^{j,1-\alpha} \quad (\text{A17})$$

We introduce a “New-Keynesian” feature in the model which is that prices are sticky. It is customary to assume so-called Calvo pricing. It is possible to micro-found the behavioral model under the same assumptions about price rigidity as in the standard DSGE-models.

Calvo pricing assumes that each firm will reset prices in period t with probability $1 - \theta$, where θ is the fraction of firms that keep their prices fixed. Thus, θ can be considered as a measure of prices stickiness.

Each period firms that have drawn the “Calvo lottery ticket”, i.e. are allowed to change their price, will set that price, P_t^* , such that it maximizes the current value of profits generated while that price remains effective

Firms maximize expected profits with respect to P_t^*

$$\sum_{k=0}^{\infty} (\beta\theta)^k \tilde{E}_t^j \left[P_t^{j,*} Y_{t+k/t}^j - \Psi_{t+k} \left(Y_{t+k/t}^j \right) \right] \quad (\text{A18})$$

subject to the demand constraints

$$Y_{t+k/t}^j = \left(\frac{P_t^*}{P_{t+k}} \right)^{-\varepsilon} C_{t+k}^j \quad (\text{A19})$$

Where $\Psi_{t+k} \left(Y_{t+k/t}^j \right)$ is the cost function, $Y_{t+k/t}^j$ is the output of the firm that last reset its price in period t .

The first order condition of an optimum is:

$$\sum_{k=0}^{\infty} (\beta\theta)^k \tilde{E}_t^j \left[Y_{t+k/t}^j \left(P_t^{j,*} - M \psi_{t+k/t}^j \right) \right] = 0 \quad (\text{A20})$$

where $\psi_{t+k/t}^j$ is the marginal cost in $t+k$ for firm that last reset its price in t and M is mark-up, i.e.

$$M = \frac{\varepsilon}{\varepsilon-1} \quad (\text{A21})$$

Log-linearizing and solving for the price, yields

$$p_t^{j,*} = \mu + (1 - \beta\theta) \sum_{k=0}^{\infty} (\beta\theta)^k \tilde{E}_t^j \left[mc_{t+k/t}^j + p_{t+k}^j \right] \quad (\text{A22})$$

where μ is the desired mark-up, $mc_{t+k/t}$ is the (real) marginal cost. Note that $mc_{t+k/t} + p_{t+k}$ is the nominal marginal cost.

Equation (A21) says that firms resetting their price will choose a price equal to desired (equilibrium) mark-up plus expected marginal costs that will prevail as long as the price is effective (is not changed).

Using

$$\pi_t = (1 - \theta)(p_t^* - p_{t-1}) \quad (\text{A23})$$

We obtain

$$\pi_t^j = \lambda \sum_{k=0}^{\infty} \beta^k \tilde{E}_t^j [\widehat{mc}_{t+k}^j] \quad (\text{A24})$$

where $b_2 = \frac{(1-\theta)(1-\beta\theta)}{\theta} \frac{1-\alpha}{1-\alpha\varepsilon}$ and \widehat{mc}_{t+k}^j is the marginal cost expressed as a deviation from the steady state.

Thus when the deviation of marginal cost from steady state is positive a fraction of prices is adjusted upwards, leading to more inflation.

Just as in the case of the demand equation the discrete choice model of the selection of forecasting rules implies that

$$\tilde{E}_t^j [\widehat{mc}_{t+k}^j] = \tilde{E}_t^j [\widehat{mc}_{t+k}] \quad (\text{A25})$$

Finally we can rewrite

$$\pi_t^j = \beta \hat{E}_t^j [\pi_{t+1}] + \lambda \widehat{mc}_t \quad (\text{A26})$$

Aggregating over all firms j (see Hommes and Lustenhouwer(2016), we obtain

$$\pi_t = \beta \widetilde{E}_t [\pi_{t+1} + \lambda mc_t] \quad (\text{A27})$$

The last step consists in relating marginal cost to the output gap

$$\pi_t = \beta \widetilde{E}_t [\pi_{t+1}] - \lambda \hat{\mu}_t \quad (\text{A28})$$

where $\hat{\mu}_t = \mu_t - \mu = -\widehat{mc}_t$ and $\lambda = \frac{(1-\theta)(1-\beta\theta)}{\theta} \frac{1-\alpha}{1-\alpha+\alpha\varepsilon}$

In a way analogous to the assumptions on the price-setting constraints facing firms, assume that for each period only a fraction $1 - \theta_w$ of households drawn randomly from the population reoptimize their posted nominal wage. We now consider how households choose the wage for their labour when allowed to reoptimize that wage. The household will choose w_t at period t in order to maximize.

$$\tilde{E}_t^i \left\{ \sum_{k=0}^{\infty} (\beta \theta_w)^k U(C_{t+k|t}^i, N_{t+k|t}^i) \right\} \quad (\text{A29})$$

Where $C_{t+k|t}^i$ and $N_{t+k|t}^i$ respectively denote the consumption and labour supply in period $t+k$ of a household I that last reset its wage in period t . Note that the utility generated under any other wage set in the future is irrelevant from the point of view of the optimal setting of the current wage, and thus can be ignored in (A28).

Given the utility function specified in (A5), the first-order condition associated with the problem above is given by

$$\sum_{k=0}^{\infty} (\beta \theta_w)^k \tilde{E}_t^i \left\{ N_{t+k|t} U_c(C_{t+k|t}^i, N_{t+k|t}^i) \left(\frac{w_t}{p_{t+k}} - M_w \text{MRS}_{t+k|t} \right) \right\} = 0 \quad (\text{A30})$$

$\text{MRS}_{t+k|t}^i = - \frac{U_n(C_{t+k|t}^i, N_{t+k|t}^i)}{U_c(C_{t+k|t}^i, N_{t+k|t}^i)}$ denote the marginal rate of substitution between consumption and labour in period $t+k$ for the household resetting the wage in period t and $M_w = \frac{\varepsilon_w}{1 - \varepsilon_w}$. Note that ε_w measures the elasticity of substitution among labour varieties.

Log-linearizing (A30) around the steady state (zero inflation) yields the following approximate wage setting rule

$$w_t^* = \mu^w + (1 - \beta \theta_w) \sum_{k=0}^{\infty} (\beta \theta_w)^k \tilde{E}_t^i \{ mrs_{t+k|t} + p_{t+k} \} \quad (\text{A31})$$

Where μ^w is household markup. $mrs_{t+k|t}$ is the (log) marginal rate of substitution in period $t+k$ for a household that reset its wage in period t .

$$\text{Using } \pi_t^w = (1 - \theta_w)(w_t - w_{t-1})$$

We obtain:

$$\pi_t^w = \beta \tilde{E}_t^i \{ \pi_{t+1}^w \} - \lambda_w \hat{\mu}_t^w \quad (\text{A32})$$

Where $\lambda_w = \frac{(1 - \theta_w)(1 - \beta \theta_w)}{\theta_w(1 + \varepsilon_w \varphi)}$ and $\hat{\mu}_t^w = \mu_t^w - \mu^w$

Just as in the demand equation and price setting equations, the discrete choice model of the selection of forecasting rules (concerning wages inflation) implies that it is feasible to aggregate over all households i , hence:

$$\pi_t^w = \beta \tilde{E}_t \{\pi_{t+1}^w\} - \lambda_w \hat{\mu}_t^w \quad (\text{A33})$$

To obtain the Philips curve used in our model, we follow Gali (2008):

Define real wage $\omega_t = w_t - p_t$, real natural wage $\omega_t^n = w_t^n - p_t^n$, and real wage gap $\tilde{\omega}_t = \omega_t - \omega_t^n$,

$$\begin{aligned} \hat{\mu}_t^w &= \tilde{\omega}_t - \left(\sigma + \frac{\varphi}{1-\alpha}\right) y_t \\ \hat{\mu}_t &= -\tilde{\omega}_t - \frac{\alpha}{1-\alpha} y_t \end{aligned}$$

Referring to Equation (A26), the New Keynesian Philips curve is

$$\begin{aligned} \pi_t &= \beta \tilde{E}_t [\pi_{t+1}] - \lambda \hat{\mu}_t \\ &= \beta \tilde{E}_t [\pi_{t+1}] + \lambda \left(\tilde{\omega}_t + \frac{\alpha}{1-\alpha} y_t \right) \\ &= \beta \tilde{E}_t [\pi_{t+1}] + \lambda \left(\hat{\mu}_t^w + \left(\sigma + \frac{\varphi}{1-\alpha}\right) y_t + \frac{\alpha}{1-\alpha} y_t \right) \\ &= \beta \tilde{E}_t [\pi_{t+1}] + \lambda \left(\frac{\sigma(1-\alpha) + \varphi + \alpha}{1-\alpha} \right) y_t + \lambda \hat{\mu}_t^w \\ &= \beta \tilde{E}_t [\pi_{t+1}] + b_2 y_t + \lambda \hat{\mu}_t^w \end{aligned}$$

where $b_2 = \frac{(1-\theta)(1-\beta\theta)}{\theta} \frac{\sigma(1-\alpha) + \varphi + \alpha}{1-\alpha + \alpha\varepsilon}$

To obtain an aggregate supply equation with a lagged inflation, as we have in the main text an indexation scheme has to be introduced. In such an indexation scheme the prices that in the context of the Calvo rule cannot be optimized in period t are indexed to inflation in period $t-1$. This is done in Smets and Wouters(2003). It is shown there that with indexation the aggregate supply curve is of the form:

$$\pi_t = \frac{\beta}{1 + \beta \Lambda} \tilde{E}_t [\pi_{t+1}] + \frac{\xi}{1 + \beta \Lambda} \pi_{t-1} + b_2 y_t + \lambda \hat{\mu}_t^w$$

where Λ expresses the degree of indexation. When $\Lambda=0$ there is no indexation and we obtain an aggregate supply curve without lagged inflation. When $\Lambda=1$ there is full indexation and we obtain the aggregate supply curve used in the main

text. In that case the coefficients on the forward looking and lagged inflation add up to 1. This leads to equation (2) in the main text.

APPENDIX 2: Selecting the forecasting rules in output forecasting

We define the forecast performance (utility) of a using particular rule as follows³.

$$U_{f,t} = - \sum_{k=0}^{\infty} \omega_k [y_{t-k-1} - \tilde{E}_{f,t-k-2} y_{t-k-1}]^2 \quad (10)$$

$$U_{e,t} = - \sum_{k=0}^{\infty} \omega_k [y_{t-k-1} - \tilde{E}_{e,t-k-2} y_{t-k-1}]^2 \quad (11)$$

where $U_{f,t}$ and $U_{e,t}$ are the utilities of the fundamentalist and naïve rules, respectively. These are defined as the negative of 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 to errors made recently. The degree of forgetting turns out to play a major role in our model. This was analyzed in De Grauwe(2012).

Agents evaluate these utilities in each period. We apply discrete choice theory (see Anderson, de Palma, and Thisse, (1992) and Brock & Hommes(1997)) in specifying the procedure agents follow in this evaluation process. If agents were purely rational they would just compare $U_{f,t}$ and $U_{e,t}$ in (10) and (11) and choose the rule that produces the highest value. Thus under pure rationality, agents would choose the fundamentalist rule if $U_{f,t} > U_{e,t}$, and vice versa. However, psychologists have stressed that when we have to choose among alternatives we are also influenced by our state of mind (see Kahneman(2002)). The latter can be influenced by many unpredictable things. One way to formalize this is that the utilities of the two alternatives have a deterministic component (these are $U_{f,t}$ and

³ (10) and (11) can be derived from the following equation:

$$U_t = \rho U_{t-1} + (1 - \rho) [y_{t-1} - \tilde{E}_{t-2} y_{t-1}]^2 \quad (10')$$

where ρ can be interpreted as a memory parameter. When $\rho = 0$ only the last period's forecast error is remembered; when $\rho = 1$ all past periods get the same weight and agents have infinite memory. We will generally assume that $0 < \rho < 1$. Using (9') we can write

$$U_{t-1} = \rho U_{t-2} + (1 - \rho) [y_{t-2} - \tilde{E}_{t-3} y_{t-2}]^2 \quad (10'')$$

Substituting (10'') into (10') and repeating such substitutions ad infinitum yields the expression (10) where

$$\omega_k = (1 - \rho) \rho^k$$

$U_{e,t}$) and a random component $\xi_{f,t}$ and $\xi_{e,t}$. The probability of choosing the fundamentalist rule is then given by

$$\alpha_{f,t} = P \left[(U_{f,t} + \xi_{f,t}) > (U_{e,t} + \xi_{e,t}) \right] \quad (12)$$

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 the naïve rule. In order to derive a more precise expression one has to specify the distribution of the random variables $\xi_{f,t}$ and $\xi_{e,t}$. It is customary in the discrete choice literature to assume that these random variables are logistically distributed. One then can obtain the probabilities specified in (8) and (9).

The parameter γ measures the “intensity of choice”. It is related to the variance of the random components. Defining $\xi_t = \xi_{f,t} - \xi_{e,t}$ we can write (see Anderson, Palma and Thisse(1992)):

$$\gamma = \frac{1}{\sqrt{\text{var}(\xi_t)}}$$

When $\text{var}(\xi_t)$ goes to infinity, γ approaches 0. In that case agents’ utility is completely overwhelmed by random events making it impossible for them to choose rationally between the two rules. As a result, they 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.

APPENDIX 3: 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 a naïve rule. (See Brazier et al. (2008) for a similar setup). We assume an institutional set-up in which the central bank announces an explicit inflation target. The fundamentalist rule then is 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 naïve 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.

$$\tilde{E}_t^f \pi_{t+1} = \pi^* \quad (13)$$

where the inflation target is π^* . The “naïve” rule is defined by

$$\tilde{E}_t^e \pi_{t+1} = \pi_{t-1} \quad (14)$$

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

$$\tilde{E}_t \pi_{t+1} = \beta_{f,t} \tilde{E}_t^f \pi_{t+1} + \beta_{e,t} \tilde{E}_t^e \pi_{t+1} \quad (15)$$

$$\beta_{f,t} + \beta_{e,t} = 1 \quad (16)$$

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, yielding equations similar to (8) and (9).

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

Appendix 4 Solving the model

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

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

i.e.

$$\mathbf{AZ}_t = \mathbf{B}\tilde{\mathbf{E}}_t \mathbf{Z}_{t+1} + \mathbf{CZ}_{t-1} + \mathbf{b}r_{t-1} + \mathbf{v}_t \quad (17)$$

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

$$\mathbf{Z}_t = \mathbf{A}^{-1}[\mathbf{B}\tilde{\mathbf{E}}_t \mathbf{Z}_{t+1} + \mathbf{CZ}_{t-1} + \mathbf{b}r_{t-1} + \mathbf{v}_t] \quad (18)$$

The solution exists if the matrix \mathbf{A} is non-singular, i.e. $(1-a_2c_2)-a_2b_2c_1 \neq 0$. The system (18) describes the solutions for y_t and π_t given the forecasts of y_t and π_t discussed in equations (6) and (15). The solution for r_t is found by substituting y_t and π_t obtained from (18) into (3).

In Table 1 the parameters used in the calibration exercise are presented. The values of the parameters are based on what we found in the literature. We indicate the sources from which these numerical values were obtained. The model was calibrated in such a way that the time units can be considered to be quarters. 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%. These shocks produce standard deviations of the output gap and inflation that mimic the standard deviations found in the empirical data using quarterly observations for the US and the Eurozone. The way we did this is described in more detail in De Grauwe and Ji(2020). Finally, it should be mentioned that the parameter values in Table 1 ensure local stability of the steady state.

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