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Abstract

Serial correlation in macroeconomics is pervasive. Macroeconomic modellers find it impossible to model this feature without relying on serially correlated shocks. Using a behavioral macroeconomic model, I show that serial correlation in inflation and output can easily be explained in the context that agents do not have rational expectation. This important feature is missing in the standard New Keynesian rational expectations models. The rational expectation models need serially correlated *exogenous* shocks to account for the high serial correlation in inflation and output while the behavioral model produces serial correlation in these variables *endogenously*. I also show that inertia in the beliefs about the future is a strong force in producing the serial correlation in inflation and output.

JEL-Codes: E000.

Keywords: behavioral macroeconomics, serial correlation, inflation, output gap, inertia in belief, endogenous business cycle.

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1. Introduction

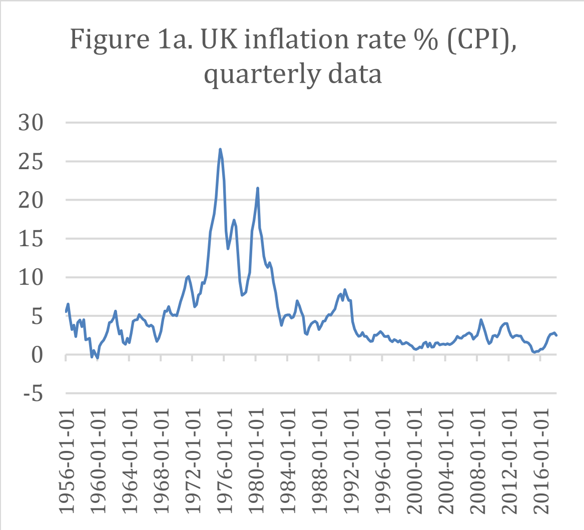
It is well-known that there is a lot of inertia in the economic system. This manisfests itself in strong serial correlation in important macroeconomic variables such as inflation and output. The origin of this inertia is still poorly understood. In New Keynesian macroeconomic models the emphasis in the explanation of inertia has been put on rigidities in wages and prices and on habit formation by consumers. But as will be shown in this paper, such rigidities in aggregate demand and supply equations are typically insufficient to explain the pervasiveness of serial correlation in macroeconomic variables.

In this paper I use a behavioral macroeconomic model (see also De Grauwe(2012)) and I show that the serial correlation in inflation and output can easily be explained in the context of such a model. I will also contrast the results of this model with those obtained from standard New Keynesian Rational Expectations macroeconomic models. I will make clear that while the standard New Keynesian RE-model needs serially correlated *exogenous* shocks to account for the high serial correlation in inflation and output, the behavioral model produces serial correlation in these variables *endogenously*. The inertia in beliefs about the future will be shown to play a crucial role in producing this endogenous serial correlation.

The rest of the paper is organized as follows. Section 2 provides the empirical evidence for the existence of serial correlation in inflation and output gap. Section 3 then studies the New-Keynesian RE model and analyzes how this model accounts for the observed serial correlation in these macroeconomic variables. Section 4 presents the behavioral macroeconomic model and shows how this model is capable do generating seriel correlation without having to rely on exogenous serially correlated shocks. It is argued that this provides for a more staisfactory macroeconomic theory relying on a realistic assumption on non rational expectation. The paper concludes in Section 5.

2. Serial correlation: empirical evidence

Serial correlation in macroeconomics is pervasive. To echo this, I show evidence by focusing on inflation and the output gap in the UK and the US in the post war period. In Figure 1a and 1b, I show the inflation rates (quarterly data) since 1956 (UK) and 1960 (US). In Figure 2a and 2b, I present the autocorrelation functions, computed from these data. I observe that autocorrelation is very high. The first order autocorrelation coefficient is typically higher than 0.95 and it takes a long time (20-30 quarters) for autocorrelation to disappear. Thus it appears that there is a lot of inertia in the inflation data. It should be noted that these are two countries that are considered to be quite flexible yet the persistence in inflation remains significantly high. See more empirical analyses related to this issue in O'Reilly and Whelan (2005), Gadea and Mayoral (2005) and Pivetta and Reis (2007).



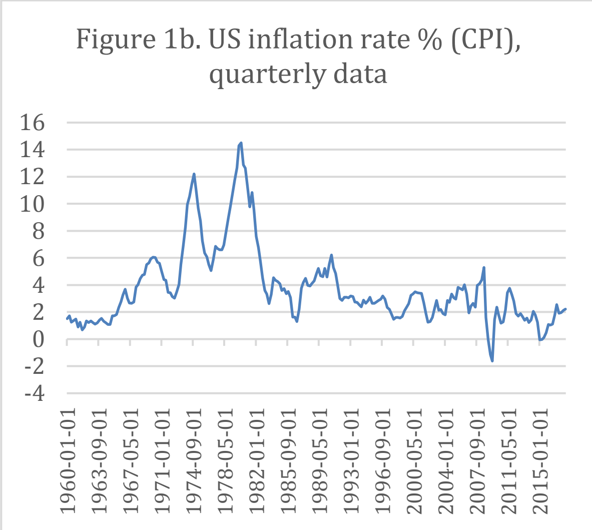


Figure 2a.

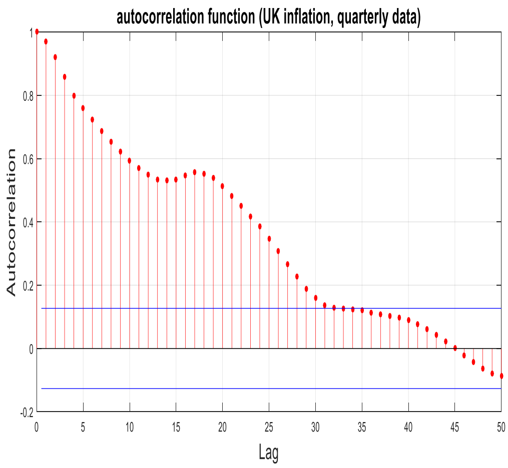
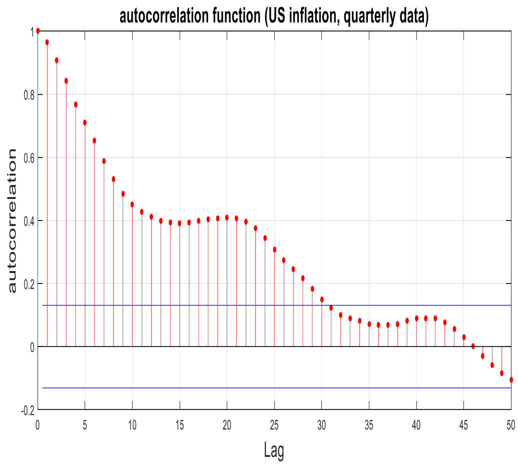
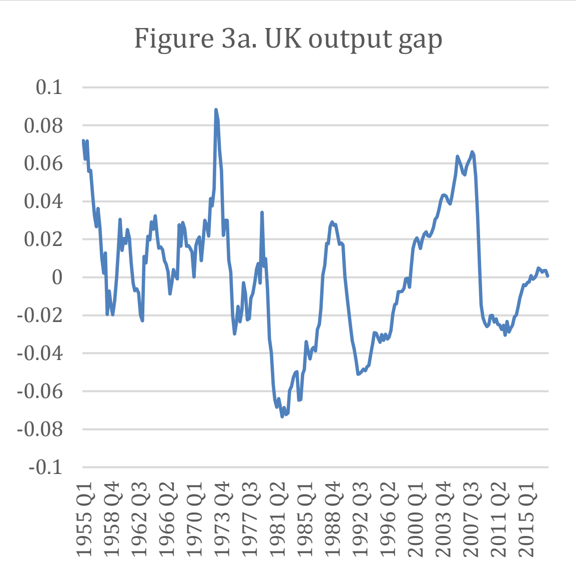


Figure 2b.



A similar feature is found in the output gap data. I first show the output gap data for the UK and US in Figures 3a and 3b. I computed the output gap using the HP filter (for more details about the way I construct this see appendix and a literature reference). In Figure 4a and 4b, I present the autocorrelation functions associated with these data. Again we find very high autocorrelation in the output gap, i.e. first order autocorrelation coefficients exceeding 0.95 and long lags (20-25). See similar conclusion on US output gap using another method in Basistha and Nelson (2007).

The question I want to analyze in the following sections is: how do existing macroeconomic models explain the existence of high serial correlation in inflation and the output gap? We will see that rational expectation and behavioural models give very different explanations.



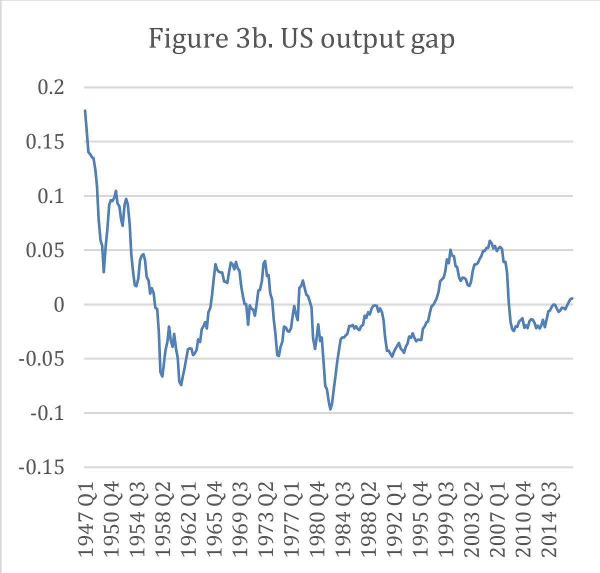


Figure. 4a

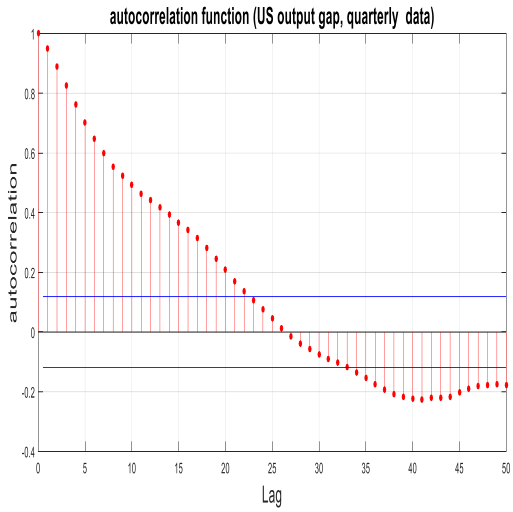
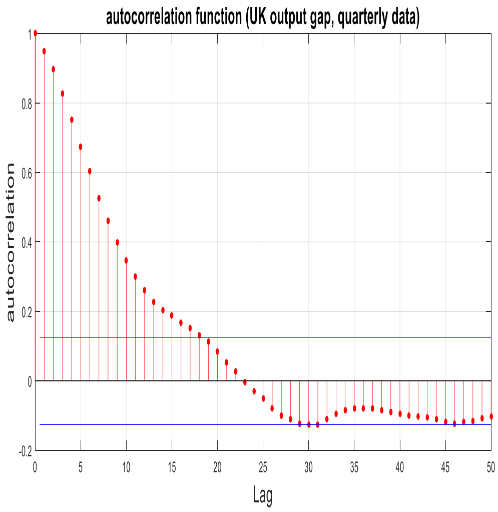


Figure. 4b



3. Serial correlation in New Keynesian Rational Expectations models

The analysis on the serial correlation is based on a simplified reduced form three-equation model similar to Gali (2008). The model I use consists of an aggregate demand equation, an aggregate supply equation (New Keynesian Philips curve) and a Taylor rule as follows in equations (1), (2) and (3). Like the conventional rational expectation models, these equations can be derived from utility maximization of individual consumers and profit maximization of individual firms. I will use the same equations in the behavioural model in section 4.

$$y_t = a_1 \widetilde{\mathrm{E}}_t y_{t+1} + (1 - a_1) y_{t-1} + a_2 \left(r_t - \widetilde{\mathrm{E}}_t \pi_{t+1} \right) + \varepsilon_t \qquad (1)$$

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

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

where y_t is the output gap in period t, r_t is the nominal interest rate, π_t is the rate of inflation. I follow the procedure introduced in New Keynesian DSGE-models of adding a lagged output, lagged inflation and lagged interest rate in the model. This can be justified by invoking inertia in decision-making. It takes time for agents to adjust to new signals because there is habit formation or because of institutional constraints. For example, contracts cannot be renegotiated instantaneously. In addition, the central bank is assumed to smooth the interest rate. This smoothing behavior is represented by the lagged interest rate r_{t-1} in equation (3).

Agents are assumed to make forecast of future output gap and inflation. In this section I assume that these forecasts are based on the rational expectation hypothesis. In the next section I will introduce a behavioural assumption. I calibrate the model. The parameter values are shown in Table 1. In order to obtain a stable solution, c1 (the inflation parameter in the Taylor rule) must exceed 1. This is also sometimes called the "Taylor principle",(see Woodford(2003), chapter 4, or Gali(2008)).

Table 1: Parameter values of the calibrated model

a1 = 0.5	coefficient of expected output in output equation; =1, without structural inertia.
a2 = -0.2	interest elasticity of output demand
b1 = 0.5	coefficient of expected inflation in inflation equation; =1, without structural inertia.
b2 = 0.05	coefficient of output in inflation equation
$\pi^*=0$	inflation target level for the CB
c1 = 1.5	coefficient of inflation in Taylor equation
c2 = 0.5	coefficient of output in Taylor equation
c3 = 0.5	interest smoothing parameter in Taylor equation; =0, without structural inertia.
σ_ε = 0.5	standard deviation shocks output
σ_η = 0.5	standard deviation shocks inflation
σ_u = 0.5	standard deviation shocks Taylor

Finally, I 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, u_t. I will generally assume that these shocks are normally distributed with mean zero and a constant standard deviation of 0.5.

The way I proceed is as follows I first strip the model from all inertias (i.e. I eliminate the lags in the demand and supply equations). This makes the model in fact a real business cycle model.

Then, I add the lags allowing us to determine the importance of the inertia in the system in producing serial correlation. I call this structural inertia. I will show that this is typically insufficient to mimic real life serial correlation in inflation and output gap. I discuss how the New-Keynesian RE-model solves this problem.

Figure 4 shows the autocorrelation function of inflation obtained by simulating the model assuming white noise error terms and absence of structural inertia. I did the same for the output gap and the results are shown in Figure 5. Not surprisingly, this model does not produce serial correlation in inflation and output gap. The reason is that without inertia in demand and supply and without serial correlation in the error terms this is a model that predicts prices and output to adjust instantaneously

Figure 4.

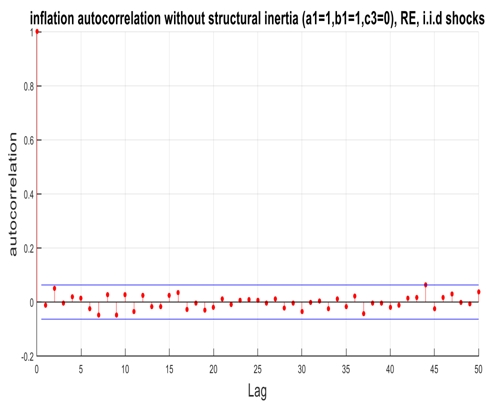
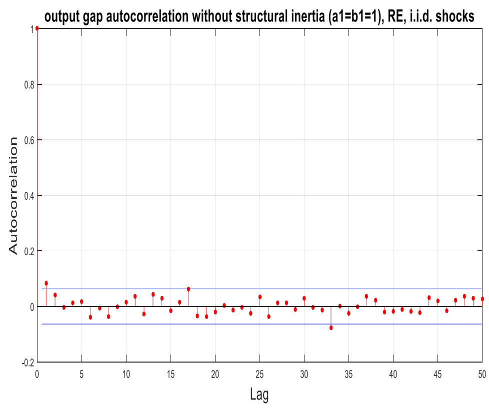


Figure 5.



In order to obtain serial correlation, one has to introduce inertia/rigidities in the aggregate demand and supply. Maintaining the assumption of white noise error terms, I obtained the autocorrelation functions as shown in Figures 6 and 7.

Figure 6

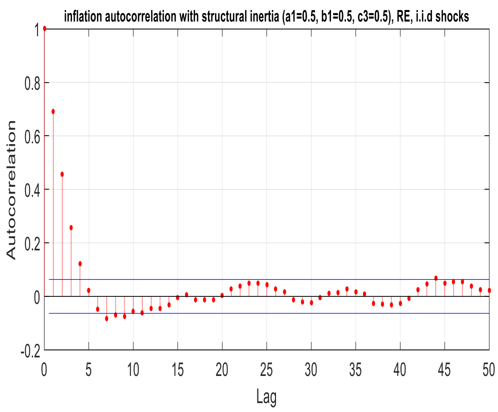
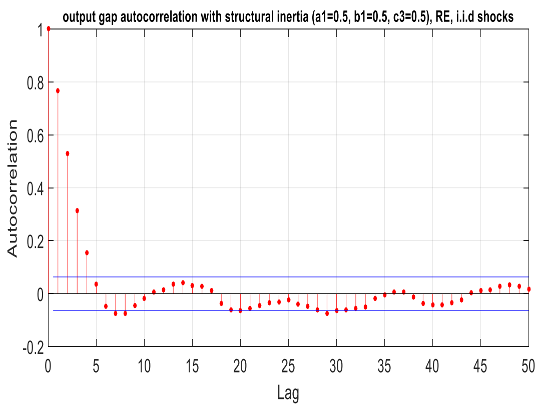


Figure 7



We observe from these figures that adding rigidities (structural inertia) creates some serial correlation in inflation and output gap, but clearly insufficiently to mimic empirically the observed serial correlation shown in Figures 2 and 4. The first order serial correlation coefficients are around 0.7 and the lagged autocorrelation coefficients vanish quickly (after about 5 quarters).

In order to solve this problem of insufficient serial correlation produced by the standard New Keynesian model, practitioners have relied heavily on introducing serial correlation in the error term. I did the same here and asked the question how much serial correlation in the error terms is necessary to mimic real life serial correlation in inflation and output gap? I show the results of this exercise in Figures 8 and 9. Using first order serially correlated error terms of 0.9 (which is the typical level assumed in this literature), I am able to produce the serial correlations in inflation and output gap that resemble those obtained in reality. Thus I conclude that New Keynesian RE-models need exogenously generated serially correlated error terms to mimic a strong empirical regularity.

This conclusion is supported by a large DSGE literature. DSGE macroeconomists estimated the New-Keynesian RE-models by introducing a large number of error terms with strong serial correlation (see Chari and et al. (2009) for some major criticisms). These models (see for example Smets and Wouters (2008)) include a long list of exogenous shocks from total factor productivity, investment-specific technology, and monetary policy to wage markups, price markups, exogenous spending and risk premia that are highly serially correlated. This feature in the DSGE literature shows that macroeconomists are unable to explain the inertia in the business cycle movements endogenously. The inertia in the demand and supply equations are insufficient to generate serial correlation in output gap and inflation that comes close to what one observes in reality. Most of the action comes from the error terms. Put differently, in these models the serial correlations in inflation and output gap are explained outside the macroeconomic model, by imposing serial correlation in the exogenous shocks hitting the economy. Some of the assumptions on the serial correlation are very implausible and therefore this is certainly not very satisfactory. One would hope that a macroeconomic theory is capable of explaining such a pervasive phenomenon as serial correlation from within the theory. That is what I try to do in the next section.

Figure. 8

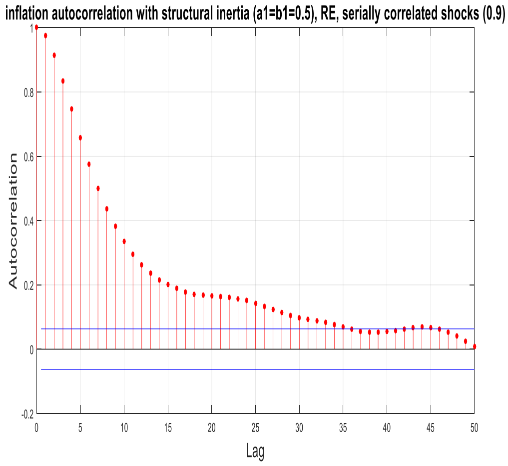
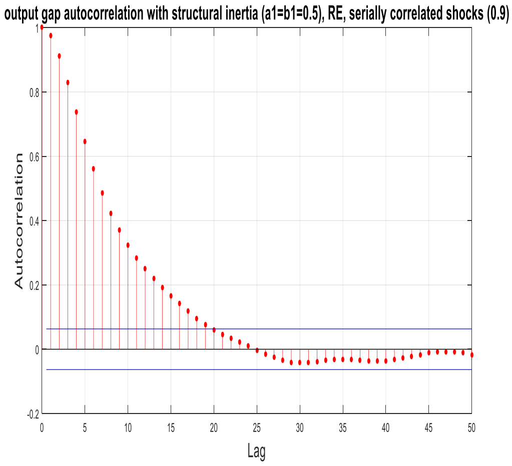


Figure. 9



4. Serial correlation in a Behavioural macroeconomic model.

In this section I use a behavioural macroeconomic model (De Grauwe (2012), De Grauwe and Ji (2018)) to analyse the sources of serial correlation[1]. I contrast the results with the New Keynesian model. The model has the same three equations set up (i.e. an aggregate demand, aggregate supply equations and Taylor rule) as shown in equations. (1)–(3). The model differs from the New Keynesian RE model in the expectation formation. I assume 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 mechanism. This is also called "adaptive learning".

This adaptive learning 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 term intensifies optimism (pessimism), see De Grauwe(2012), and De Grauwe and Ji(2016).

An important feature of this dynamics of optimism and pessimism is that the movements of the output gap are characterized by periods of tranquility alternating in an unpredictable way with periods of intense movements of booms and busts. More technically, the dynamics of optimism and pessimism leads to a non-normal distribution of the output gap with excess kurtosis and fat tails. This is a model that does not need large outside shocks to generate large movements in output.

[1] There is now a quickly expanding literature on "agent-based models" and "behavioral macreconomic models" See e.g. Tesfatsion, L. (2001), Colander, et al. (2008), Farmer and Foley(2009), Gatti, et al.(2011), Westerhoff(2012), De Grauwe(2012), Hommes and Lustenhouwer(2016)). For a recent survey see Dilaver, Jump and Levine (2018)).

Note that this behavioural model can be micro-founded (i.e. it can be derived from utility maximization of the individual consumer and profit maximization of the firm). For more details see Hommes and Lustenhouwer(2016). This study discusses the stability condition of the Taylor rule in which the output and inflation stabilizer parameters c1 and c2 should be sufficiently large. I apply the same parameters to the behavioural model as the ones in the Table 1, which satisfy the stability condition.

I will use this model to show that serial correlation in output gap and inflation can be generated endogenously, without having to resort to serial correlation in the error terms. First I present the expectation formation process in this model (section 4.1). In section 4.2 I present the capacity of this model to produce serial correlation compared to the rational expectation models. In section 4.3, I analyse the sources of serial correlation in this model.

4.1 Expectation formation in the behavioural model

Agents are assumed to use simple rules (heuristics) to forecast the future output gap and inflation. The way I proceed is as follows. I first concentrate on the output gap and assume two types of forecasting rules. 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 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 of forecasting output gap are specified as follows:

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

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

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

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

where $\alpha_{f,t}$ and $\alpha_{e,t}$ are the probabilities that agents use a fundamentalist or an extrapolative rule , respectively. Also, $\alpha_{f,t} + \alpha_{e,t} = 1$. I will define the way we obtain $\alpha_{f,t}$ and $\alpha_{e,t}$ in the next section.

This kind of simple heuristic has often been used in the behavioural economics 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)). 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.

Thus the specification of the heuristics in (4) and (5) should not be interpreted as a realistic representation of how agents forecast. Rather is it a parsimonious representation of a world where agents do not know the “Truth” (i.e. the underlying model). The use of simple rules does not mean that the agents are irrational and that they do not want to learn from their errors. 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(2016).

Likewise, 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). 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 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.

$$\widetilde{\mathrm{E}}_t^{tar}\pi_{t+1} = 0 \tag{7}$$

assuming the inflation target is π^* =0. The “extrapolators” are defined by

$$\widetilde{\mathrm{E}}_t^{ext}\pi_{t+1} = \pi_{t-1} \tag{8}$$

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

$$\widetilde{\mathrm{E}}_t\pi_{t+1} = \beta_{tar,t}\widetilde{\mathrm{E}}_t^{tar}\pi_{t+1} + \beta_{ext,t}\widetilde{\mathrm{E}}_t^{ext}\pi_{t+1} = \beta_{ext,t}\pi_{t-1} \tag{9}$$

where $\beta_{tar,t}$ and $\beta_{ext,t}$ are the probabilities that agents use a fundamentalist and an extrapolative rule, respectively. Also $\beta_{tar,t} + \beta_{ext,t} = 1$. I will define the way we obtain $\beta_{tar,t}$ and $\beta_{ext,t}$ in the next section.

One important feature of this model is agents do not stick to one particular forecasting rule. As indicated earlier, agents in this model are willing to learn, i.e. they continuously evaluate their forecast performance. This willingness to learn and to change one’s behavior (i.e. forecasting rule) is a very fundamental definition of rational behavior. Thus the agents in the model are rational in the sense that they learn from their mistakes. The concept of “bounded rationality” is often used to characterize this behavior. There are two steps to define such behaviour. The first step in the analysis then consists in defining a criterion of success. This will be the forecast performance (utility) of a particular rule. Define the utility of using the fundamentalist and extrapolative rules as follows:

$$U_{f,t} = \rho U_{f,t-1} - (1-\rho)\left[y_{t-1} - E_{t-2}^{f} y_{t-1}\right]^2 \quad (10)$$

$$U_{e,t} = \rho U_{e,t-1} - (1-\rho)\left[y_{t-1} - E_{t-2}^{e} y_{t-1}\right]^2 \quad (11)$$

where $U_{f,t}$ and $U_{e,t}$ are the utilities of the fundamentalist and extrapolating rules, respectively. These are defined as the negative of the mean squared forecasting errors (MSFEs) of the forecasting rules. Agents look at the MSFEs at period t as well as the error prior to period t. Parameter ρ introduces geometrically declining weights on past forecast errors, and measures the degree of forgetfulness of agents. The degree of forgetfulness turns out to play a major role in this model. This was analyzed in De Grauwe(2012). Here, we assume ρ=0.5 that is used often in this literature.

The second step consists in evaluating these utilities and adapting to the rule that has produced a better utility. I 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 an individual has to choose among alternatives he is also influenced by his state of mind (see Kahneman(2002)). 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 $U_{f,t}$ and $U_{e,t}$ in (10) and (11)) and a random component $\varepsilon_{f,t}$ and $\varepsilon_{e,t}$ The probability of choosing the fundamentalist rule is then given by

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

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 an extrapolative rule. In order to derive a more precise expression one has to specify the distribution of the random variables $\varepsilon_{f,t}$ and $\varepsilon_{e,t}$. It is customary in the discrete choice literature to assume that these random variables are logistically distributed (see Anderson, Palma, and Thisse(1992), p.35). One then obtains the following expressions for the probability of choosing the extrapolative rule:

$$\alpha_{e,t} = \frac{exp(\gamma U_{e,t})}{exp(\gamma U_{f,t}) + exp(\gamma U_{e,t})} = 1 - \alpha_{f,t} \quad (13)$$

Equation (13) says that as the past forecast performance (utility) of the extrapolative rule improves relative to that of the fundamentalist rule, agents are more likely to select the extrapolative rule for their forecasts of the output gap. The parameter γ measures the "intensity of choice". It is related to the variance of the random components. Defining $\varepsilon_t = \varepsilon_{f,t} - \varepsilon_{e,t}$ we can write (see Anderson, Palma and Thisse(1992)): $\gamma = \frac{1}{\sqrt{var(\varepsilon_t)}}$.[2]

This 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.

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. 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. One then obtains the following expressions for the probability of choosing the extrapolative rule:

$$\beta_{ext,t} = \frac{exp(\gamma U_{ext,t})}{exp(\gamma U_{tar,t}) + exp(\gamma U_{ext,t})} = 1 - \beta_{f,t} \quad (14)$$

where $U_{tar,t}$ and $U_{ext,t}$ are the forecast performances (utilities) associated with the use of the fundamentalist and extrapolative rules in equation (15) and (16). These are defined in the same way as in (10) and (11), i.e. they are the negatives of the weighted averages of past squared forecast errors of using fundamentalist (inflation targeting) and extrapolative rules, respectively.

$$U_{tar,t} = \rho U_{tar,t-1} - (1-\rho)[y_{t-1} - E_{t-2}^{tar} y_{t-1}]^2 \quad (15)$$

---

[2] When var(ε_t) goes to infinity, 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. We set γ=2 in our simulation.

$$U_{ext,t} = \rho U_{ext,t-1} - (1-\rho)[\pi_{t-1} - E_{t-2}^{ext}\pi_{t-1}]^2 \tag{16}$$

The model is solved by substituting the expectations formations routine described in this section into the thee-equations model (equations. (1)-(3)). For more detail see De Grauwe(2012).

4.2. **Serial correlation in the Behavioural macro model**

In this section I use the behavioural macroeconomic model described in the previous sections to present the serial correlation results. I will contrast these with the New Keynesian RE-model.

I proceed in a similar way as in the section 3. I first simulate the model using the same calibration as in Table 1, assuming no rigidities (no structural inertia). I also assumed i.i.d. white noise error terms. I then simulate the model assuming structural inertia maintaining the assumption of white noise error terms. The results are shown in Figures 10 and 11. Strikingly, the behavioural model is capable of mimicking serial correlation in the inflation and output gap that comes very close to the observed data. This is the case even when I assume no structural inertia. Comparing these results to the Figures 4-9 in section 3 using the rational expectation models, I find that the behavioural model succeeds in producing serial correlations in output gap and inflation *endogenously*, without the need to rely on structural inertias or high autocorrelations in the error terms.

Figure. 10

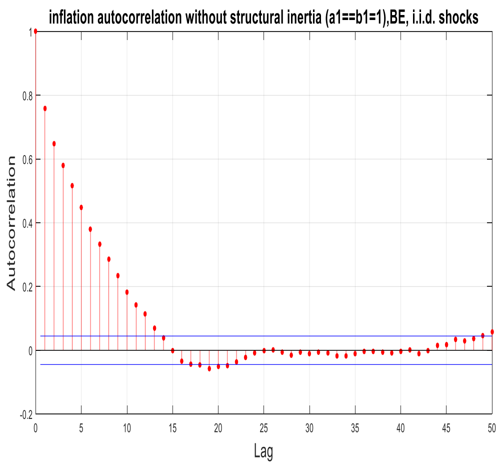


Figure. 11

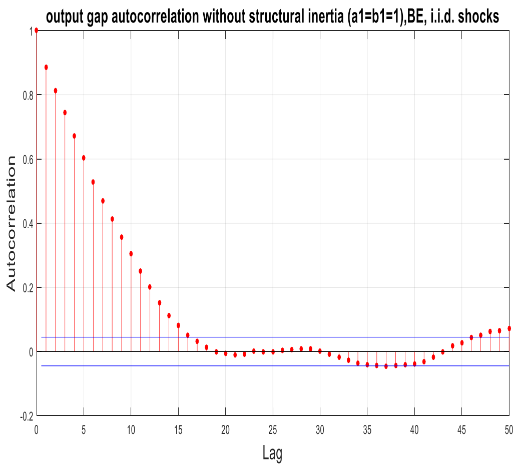


Figure. 12

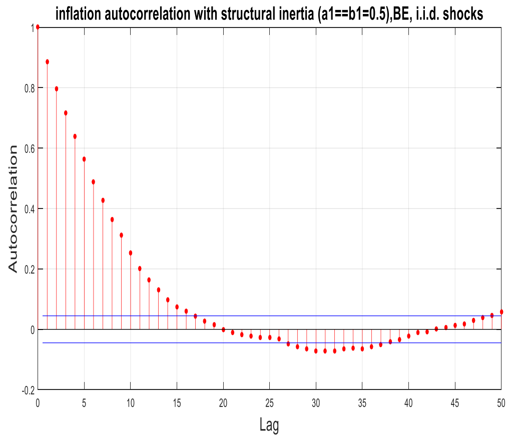
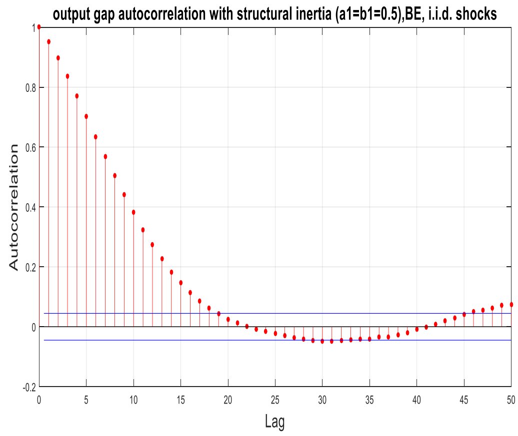


Figure. 13



4.3 The source for autocorrelation and long lags

What is the source of serial correlations and long lags in output gap and inflation we have seen in the behavioural model? This has a lot to do with the forecasting assumption I use. It is useful to turn to equations (6) and (9) which describe the forecasts made by agents. I rewrite them here:

$$\widetilde{\mathrm{E}}_{\mathrm{t}} y_{t+1} = \alpha_{e,t} y_{t-1}$$

$$\widetilde{\mathrm{E}}_{t} \pi_{t+1} = \beta_{ext,t} \pi_{t-1}$$

We can see that the market forecasts are determined by the fraction of agents ($\alpha_{e,t}$ and $\beta_{ext,t}$) who extrapolate the past observations of output and inflation. This introduces serial correlation in the model, the extent to which will depend on the size of these fractions. As we have seen these fractions are determined by the performance (utility) of these rules. If extrapolation leads to good forecasting, performance will be high and the degree of serial correlation will also be high in the system. In addition, these forecasting rules are self-fulfilling: for example, a strong performance of a positive forecasting of the output gap, leads to a boost in output reinforcing the performance of the rule. As a result, the self-fulfilling nature of these rules creates even stronger serial correlation in these fractions. See also Hommes and Zhu (2014) which explore this issue under a New Keynesian Philips supply curve setting.

I show this in figures 14 to 17. Figures 14 and 15 present the simulated values of the probabilities (or fractions) of agents using the extrapolative rule in forecasting output gap and inflation (i.e. $\alpha_{e,t}$ and $\beta_{ext,t}$). There are two features of the results. First, the probabilities (or fractions) of using the extrapolative rule are different from zero. In fact, during most of the periods in the sample, the probabilities (or fractions) of agents using the extrapolative rules are higher than 0.5, sometimes close to 1. The mean probability of using the extrapolative rule in the output gap forecasting is 0.75 and the mean probability in inflation forecasting is 0.66. Second, these probabilities are not constant. They are time dependent indicating that agents switch rules depending on how well these perform.

Figures 16-17 present the autocorrelation functions of these fractions. It is striking to find that the autocorrelation pattern in these fractions is high. This corroborates what I said earlier: the self-fulfilling nature of these forecasting rules. Take for example the forecasts of the output gap. These forecasts, when they extrapolate the boom observed in the previous period reinforce the boom thereby creating a sustained upward movement in the output gap. The opposite happens when a recession observed in the previous period is extrapolated into the future. This dynamics creates strong serial correlation in the output gap. A similar extrapolation dynamics is responsible for serial correlation in inflation.

These results also imply that the expectations formation in this behavioural models is a stronger force producing serial correlation than the inertia in the structural equations. As a result I do not need to import exogenous serially correlated shocks. This contrasts with mainstream DSGE-models where the only source of endogenous serial correlation comes from inertia in the structural equations, but as argued before, is insufficient to generate the serial correlation in inflation and output gap observed in reality..

There is an important strand in the DSGE literature which stresses the importance of learning to produce macroeconomic inertia (see e.g. Milani (2007)). This model produces important insights, however, its limitation is that it still relies on strong serial correlation in the exogenous demand and supply shocks to generate the results.

Figure. 14

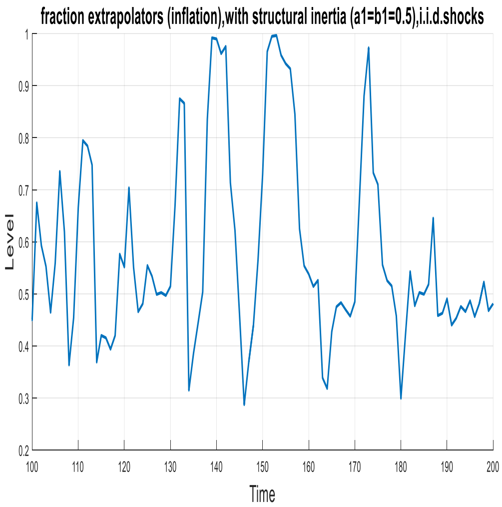


Figure. 15

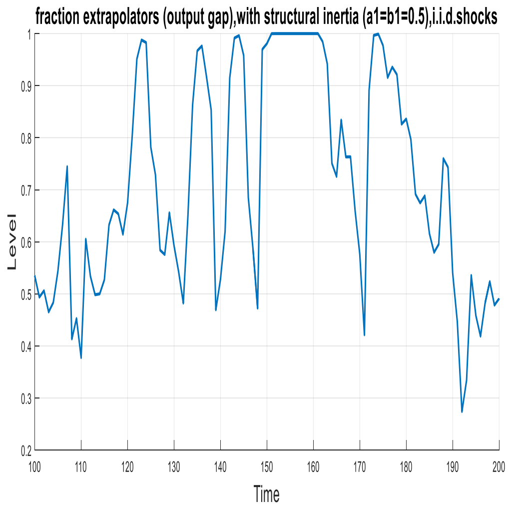


Figure. 16

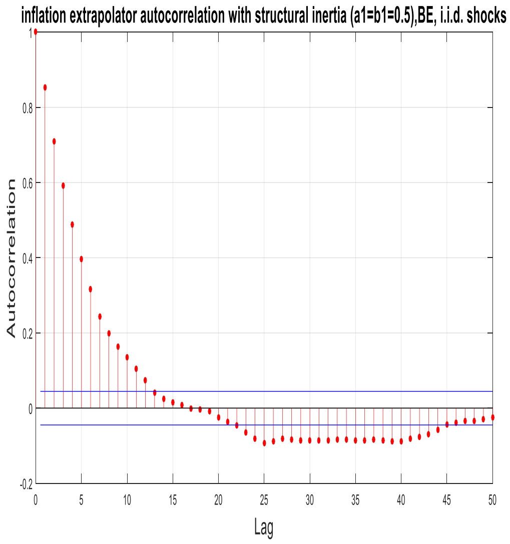
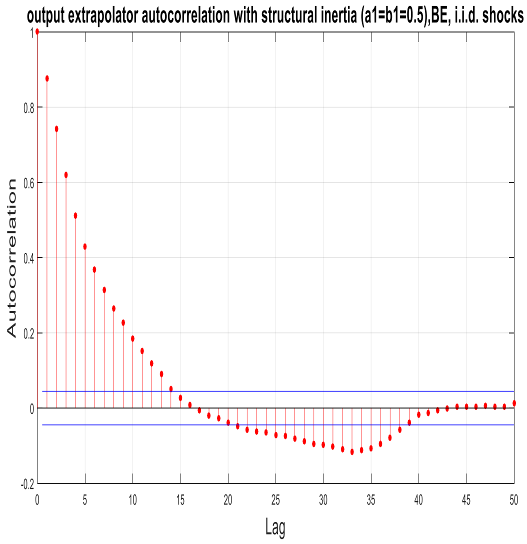


Figure. 17



The intuition behind my results can be formulated as follows. There is a varying fraction of agents who extrapolate (positive or negative) developments in output gap and inflation. They do this because this simple heuristic turns out to be performing well. It can be said that these agents have some beliefs about the future based on past experience. Agents do not change their beliefs every period, however. As with most beliefs, there is inertia. Beliefs change as a result of an accumulation of evidence that other beliefs do better. This is the mechanism underlying the switching behaviour in this model. Agents evaluate how well their forecasts (beliefs) have been doing in the past. This is a relatively slow process as is made clear by the autocorrelation functions of the fractions of extrapolators (Figures 16 and 17).

The inertia in the beliefs about the future is a strong force in producing serial correlation. It is stronger than the inertia in the demand and supply equations. It is the fundamental factor behind the pervasive serial correlation in inflation and output gap. As a result, in the behavioural model there is no need to invoke serial correlation of the exogenous shocks to explain the pervasive nature of the serial correlation in output gap and inflation. I obtain an endogenous explanation.

5. Conclusion

We observe a lot of serial correlation in important macroeconomic variables such as inflation and output gap. New Keynesian RE-macroeconomic models emphasize rigidities in wages and prices and habit formation by consumers in the explantion of serial correlation in these macroeconomic variables. I have shown in this paper that rigidities in aggregate demand and supply equations are insufficient to explain the pervasiveness of serial correlation in inflation and output gap. As a result, practioners of these mainstream models have been forced to "import" serial correlation by assuming serially correlated shocks. I do not dispute that shocks can be serially correlated, but assumptions that these shocks (e.g. total factor productivity, wage markups, price markups and exogenous spending) are highly correlated are very often implausible. A theory that relies too much on exogenous shocks to explain the serial correlation in key variables such as inflation and output gap is not a very satsifactory theory. A macroeconomic theory should be able to explain one of the most pervasive empirical regularities endogenously. This is what I have attempted to achieve in this paper.

I used a behavioral macroeconomic model (see also in De Grauwe(2012)) and I showed that the serial correlation in inflation and output can easily be explained in the context of such a model. This explanation relies on the heuristics agents use in making forecasts. Some of these heuristics is based on extrapolating past observations of inflation and output gap. Agents use such easy heuristics because of cognitive limitations and because these simple heuristics generally perform well in forecasting. In addition, as these forecasting rules have a strong self-fulfilling nature they introduce strong serial correlation in inflation and output gap.

The way I interpreted these results is as follows. Agents develop some beliefs about the future based on past experience. These agents do not change their beliefs every period, however. As with most beliefs, there is inertia. Beliefs change only as a result of an accumulation of evidence that other beliefs do better. This is the mechanism underlying the switching behaviour in the behavioural macroeconomic model. Agents evaluate how well their forecasts (beliefs) have been doing in the past. This is a relatively slow process.

The inertia in the beliefs about the future is a strong force in producing serial correlation. As I have shown, it is stronger than the inertia in the demand and supply equations, stressed in New Keynesian RE-models. It is the fundamental factor behind the pervasive serial correlation in inflation and output gap. As a result, in the behavioural macroeconomic model there is no need to invoke serial correlation of the exogenous shocks to explain the pervasive nature of the serial correlation in output gap and inflation. Inertia in inflation and output can be explained endogenously.

Appendix.

Using the GDP quarterly data from the Federal Reserve Bank of St. Louis, I compute the potential output and this also allows me to compute the output gap in Figures 3a and 3b. There are two measures of potential output in the literature: one relies on statistical filters such as the Hodrick-Prescott (HP) filter, the other on the estimation of the economy-wide production function. Vetlov and et al. (2011) has pointed out that the latter estimation of the potential output works is similar to results of the HP filtered output (see also Justiniano and Primiceri (2008) and Sala et al. (2010)). Therefore, I use the conventional HP filter to compute potential output and output gap. Here, I set λ=150000 which allows me to get a rather smooth potential output curve. This exercise is based on the assumption that the potential production capacity (in the long term sense) should be determined by technology, capital and working population which are relatively stable and therefore can generate a smooth potential output curve such as the one in Figures A1 and A2. This is also in line with Gali (2003) who defines output gap as 'the deviation of output from its equilibrium level in the absence of nominal rigidities'.

Figure A1

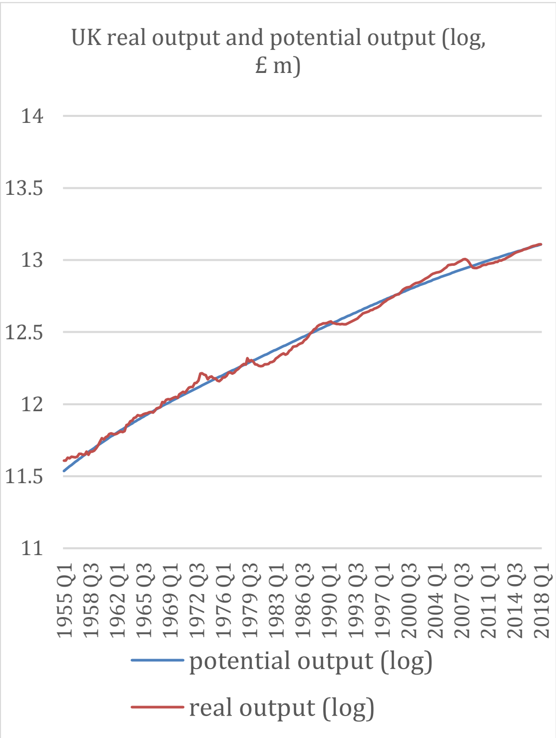
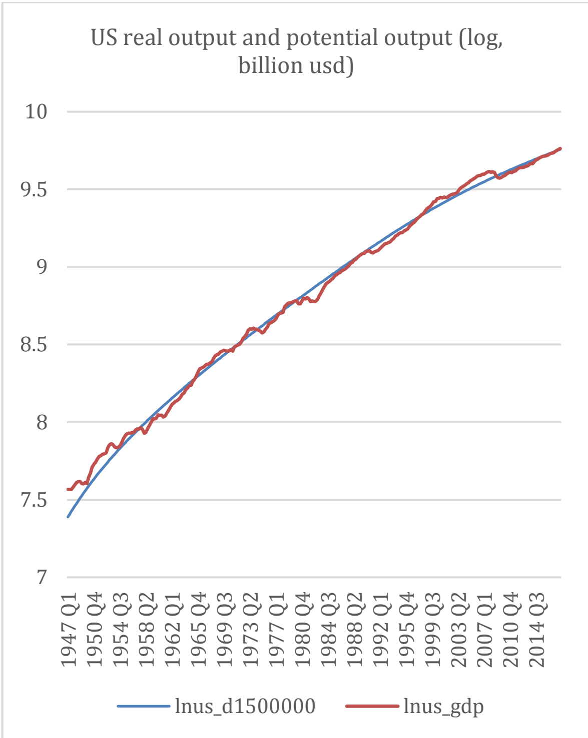


Figure A2



I am aware that if we use a much smaller λ (like the one in the real business cycle literature e.g. =1600), the potential output estimates in the UK and the US would appear more cyclical than the ones in Figure A1 and A2. The problem is that estimates using a smaller λ risk underestimating serial correlation in output gap. Using a very large λ=150000 actually helps to mitigate such problems by removing as much of the cyclical component as possible. The serial correlation in output gap I obtain in this exercise is similar nature as the serial correlation in inflation: the first order serial correlation is very high and with long lags of around 25.

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