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ESTIMATION OF THE OUTPUT GAP USING UOB AND DSGE MODELS -EURO AREA-

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ABSTRACT

In this paper I try to give an answer to the debate of the policy makers about the importance of the estimation of the output gap. It's known that natural output is not observed, so even the output gap is not directly observable. The right approach can be the use of Bayesian analysis, in order to create a link with past literature. The use of a priori distributions for structural parameters makes the nonlinear optimization of the algorithm more stable. That's why; I have estimated two different models by combining UOB and DSGE models. Both models use the approaches that the Phillips curve and the IS-Dynamic curve offer. The difference between them is that the first model uses a Pure Inflation Targeting rule and the second one the Taylor's rule where the output gap variable is present. The monetary authorities cannot observe the output gap and therefore cannot react. For that reason we will try to estimate by avoiding introducing into the equation the interested variable. Trying to confirm this reasoning I estimate another model, putting Taylor's rule in place of our Inflation Targeting Rule. The last equation includes the parameter of interest, and assuming a right reasoning for the first model, the estimated coefficient of the output gap should to be irrelevant. This does not happen, confirming the best model must absolutely include the output gap variable. The forward-looking retrospective component of inflation in the Phillips curve component is highly dominant over the backward-looking component. Both models give different weight to parameter δ. However, I have not found any substantial differences in estimating the parameter responsible for the formation of habits, θ. The output gap is a very important component in making decisions for the policy makers and therefore it should be included it in estimating the interest rate.

Keywords: Phillips curve, IS-Dynamic curve, Inflation

INTRODUCTION

This paper studies the estimation of a Neo-Keynesian model in the 1970-2009 economic cycle in order to identify the role played by the monetary policy and macroeconomic shocks (such as inflation, interest rate and output gap) in determining the volatility of the output gap. Researchers have tried to explain whether the output gap estimations are or not important for the policy makers (Orphanides and Van Norden in 2002). Instead, other researchers have objected to the way the estimations are obtained. Proxies have often been used to estimate the output gap, such as labor income share, GDP-detrended or HP-filtered GDP. The aim is to estimate the output gap of the euro area. In this analysis are used synthetic data for the euro area, source of which is the European Central Bank's AWM database. The use of synthetic data is not properly corrected as it is before of the advent of the Euro. However, to use a sample that includes a series that begins at the Euro's birth in 2010, it would be too restrictive because will have too few observations. The procedure to estimate the output gap is based on the combination of two existing base models: UC Model and DSGE Model that uses the Bayesian estimation methods. It starts with prior distribution of the parameters of interest, which is then combined with the likelihood obtained from the data and allows us to obtain the posterior distribution.

LITERATURE REVIEW

In this section I will briefly mention the results obtained using the analysis of the American data, by Tim Willems (2011). The analysis foresees two samples, both quarterly, one comprising the period 1954: III - 2010: II and the other 1982: I - 2010: II, data taken from the FRED database of St. Louis Fed. The observable variables are the inflation's rate, nominal interest rate and real GDP. The procedure implemented by Willems seeks first of all to exploit the approach of the general equilibrium. Once estimated the equation, the output gap is compared to one of its proxies, and more precisely with the HP filter. This last series was obtained by putting the smoothing parameter at 1.600, standard value for quarterly data. But as shown in Harvey and Jeager (1993), the HP filter can be considered as a UC model, obtained by separating the unobserved trend from the unobserved cycle. Comparing both series, we notice that both move in the same direction and have pro-cyclical behavior. Willems has shown that the basic approach of his model has better properties than those obtained with the usual estimation methods that are subject to significant revisions over time. First of all, there is no need to make the data stationary. This operation can also lead to loss of information by removing the non-cyclical component from the template. I would like to emphasize that this research try to improve the Willems model (2011) enriching it with shocks that follow the auto-regressive AR processes (1).

METHODOLOGY

The theoretical definition of the output gap and the deviation of the current output from the natural output are defined by the formula $y_t \equiv y_t^n - \tilde{y}_t$. The natural level of output is not directly observable. As in Harvey (1985), Watson (1986) and Clark (1989) a particular representation of the model can be:

$y_t^n = \rho_y y_{t-1}^n + \mu_t + \varepsilon_t^y$, with $\varepsilon_t^y \sim N(0, \sigma_y^2)$ (1)

$\mu_t = \mu_{t-1} + \varepsilon_t^\mu$, with $\varepsilon_t^\mu \sim N(0, \sigma_\mu^2)$ (2)

$\tilde{y}_t = \vartheta \tilde{y}_{t-1} + (1-\vartheta) E_t\{\tilde{y}_{t+1}\} - \frac{1}{\sigma}(R_t - E_t\{\pi_{t+1}\}) + \zeta_t$ (3)

Equation (3) represents the Euler equation for output, where θ is the formation of the habits. This parameter was introduced in the literature for the first time by Willems. While $\frac{1}{\sigma}$ is the intertemporal substitution elasticity that determines the impact of the actual (real) interest rate evaluated ex-ante on the consumption. Let $\tilde{y}_t$ be the current consumption, $\tilde{y}_{t-1}$the past consumption and $\tilde{y}_{t+1}$ the future consumption. As in Willems (2011) I assume that ζ_t follows an autoregressive process of the first order: $\zeta_t^{\tilde{y}} = \rho_{\tilde{y}} \zeta_{t-1}^{\tilde{y}} + \varepsilon_t^{\tilde{y}}$ with $\varepsilon_t^{\tilde{y}} \sim N(0, \sigma_{\tilde{y}}^2)$

The following equation represents the Phillips Neo-Keynesian curve: $\pi_t = \gamma \pi_{t-1} + (1-\gamma) E_t\{\pi_{t+1}\} + k\tilde{y}_t + \psi_t^\pi$.

In this equation γ is the coefficient of the retrospective component of inflation. The coefficient (1-γ) derives from the fact that in a monopoly market companies have less chance than one to change their prices every period. While $\tilde{y}_t$ measures the output gap whose effect on inflation is influenced by parameter k. The novelty of this model is based on the fact that we assume that the parameter ψ_t follows an autoregressive process of the first order and thus appears in the form $\psi_t^\pi = \rho_\psi \psi_{t-1}^\pi + \varepsilon_t^\pi$. It is called shock inflation.

$R_t = \delta R_{t-1} + (1-\delta)\phi_\pi \pi_t + \nu_t^R$

This equation is called the Pure Inflation Targeting Rule and can be disputed by the fact that monetary authorities cannot observe output gap and therefore cannot react. Another novelty of this study is that it is assumed that the monetary policy shock ν_t^R follows an autoregressive process of the first order: $\nu_t^R = \rho_\nu \nu_{t-1}^R + \varepsilon_t^R$, with $\varepsilon_t^R \sim N(0, \sigma_R^2)$.

DISCUSSION

In our analysis we will use synthetic data for the euro area. The data source is the AWM (area wide model) database of the European Central Bank. Our sample includes the period from the first quarter of 1970 to the last quarter of 2009, considering quarterly data. The three observed data series are output gap, short-term nominal interest rate and inflation.

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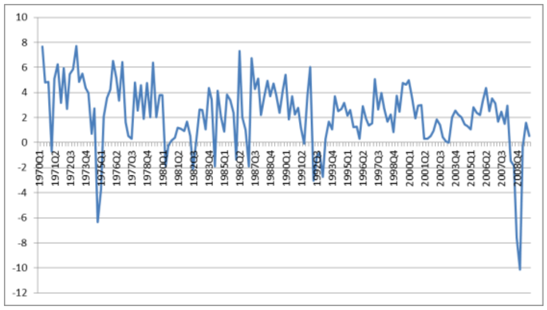
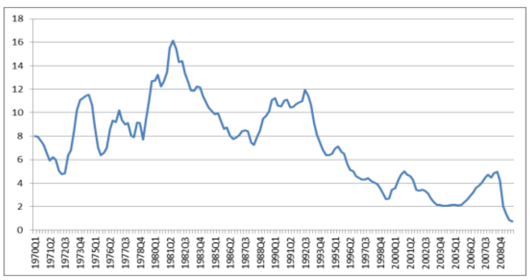
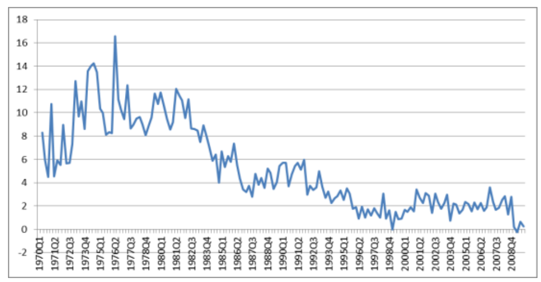
Graph 1: Output growth Series



Graph 2: Interest Rate Series



Graph 3: Inflation Series



The inflation rate is calculated from the second quarter of 1991 because we have lost the first observation as being the GDP deflator; It is calculated as 400 * [(Pt-Pt-1) / Pt-1], where Pt is the consumer price index while multiplier factor 400 is due to the fact that this rate is annualized (* 4) and then reduced to percent (* 100). Let us now analyze the priori distributions in this model. Priories are important in order to increase the knowledge that comes from the likelihood.

Table 1: A priori distributions

Parameter	*Density*	*Mean*	*Standard deviation*
γ	Beta	0.5	0.15
δ	Beta	0.5	0.15
ϑ	Beta	0.5	0.15
κ	Calibrated	0.5	-
σ	Gamma	2	1
ϕ_π	Gamma	1.5	0.2
ρ_y	Uniform*	0.5	0.288
ρ_ζ	Beta	0.8	0.1
ρ_ψ	Beta	0.5	0.15
ρ_ν	Beta	0.5	0.15
σ_π	Inverse gamma	0.01	2

σ_y	**Inverse gamma**	**0.01**	**2**
σ_R	**Inverse gamma**	**0.01**	**2**
σ_μ	**Inverse gamma**	**0.01**	**2**
σ_ζ	**Inverse gamma**	**0.01**	**2**

The prior for the variable γ follows a Beta distribution in the range [0, 1]. All values outside this range are excluded for theoretical reasons. Since the new Phillips curve has been strongly debated (Gali and Gertler (1999), Rudd and Whelan (2007)) then we set the prior's mean equal to 0.5. The prior average for interest rate smoothing (δ) has been set at 0.5 (see Smets and Wouters (2003)). Prior for the coefficient θ that expresses the importance of habits is centered at 0.5, so that it can play a substantial role for this feature. In the literature there is still no value that the researchers have agreed on regarding the Phillips curve of the New Keynesian model. Estimations for this parameter might range from very close to zero (see Cho and Moreno (2006)) at 0.77 (see Lubik and Schorfheide (2004)). I have decided to set the prior mean for k at 0.5, as the central value of the range [0, 1] and then to leave it intact. Regarding the risk factor, I have decided to fix it by 2, which is also accepted by the macro literature. The a priori average for the Taylor $\emptyset_\pi$ coefficient in inflation is equal to its standard value 1.5. The coefficient AR of the natural output level is supposed to follow a uniform variable in the range [0, 1]. I have decided to allow a substantial persistence of the shocks by setting the a priori coefficients AR ρ_ζ equal to 0.8. While for other shocks, I put a value of 0.5 as in Willems (2011). The a-priori of the standard deviations for all shocks follows a Reverse Gamma Process with an average of 0.01 and variance 2.

Convergence of interactive simulations

One of the ways to evaluate the convergence towards ergodic distribution of the two iterations is to compare the variance between and within the various Markov chains used to simulate such distribution, in order to obtain a convergence. The method I have used is MonteCarlo (MCMC) algorithm. Convergence is reached when they converge to the ergodic distribution. This method was first proposed by Gelman and Rubin (1992) and was then modified to the current version by Brooks and Gelman (1998). Usually, it's preferable to use graphical methods to evaluate the convergence. Various graphs are made between and within for the convergence of the two sets that must tend to stabilize (usually the variance between tends to decrease and the within to increase).

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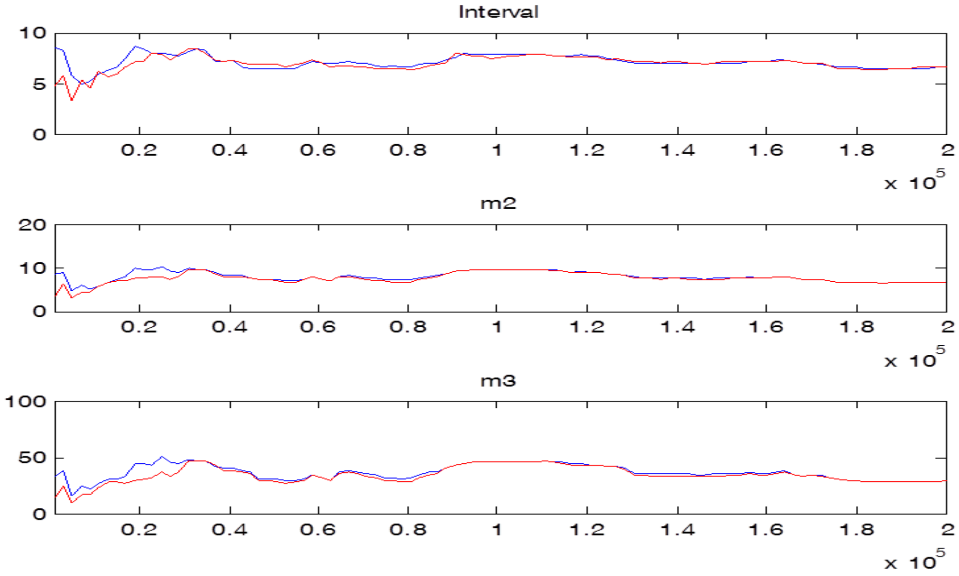
Graph 4: Model's Convergence



Blue and red lines represent specific parameters vector parameters both for variance within chains and variance between. In this case it is possible to make the comparison precisely because we have simulated two chains of 200,000 iterations for each variable. Due to the fact that the results are sensible these lines should be properly constant, although some oscillations are acceptable, and should also converge to ergodic distribution. Dynare provides us with three measures, namely three graphs: "interval" that gives us the range built around the average of the averages with a confidence level of 90%; "m2" is a measure of variance and "m3" is the third moment. If the moments detected are strongly unstable or do not converge, it means the a-priories are too few informative. It would therefore be advisable to re-evaluate the estimations with different a-priories, or alternatively use a larger number of Metropolis-Hastings simulations, for example, in the order of 400,000 instead of 200,000. Note that in this case the two lines do not deviate much from each other and except some initial oscillation tend to stabilize and converge. So we can be confident enough that the a priori choices are sufficiently informative. After passing this first rock we can then go on with the analysis and go on to analyze the posterior distributions.

Table 2: First step estimation results for the parameters

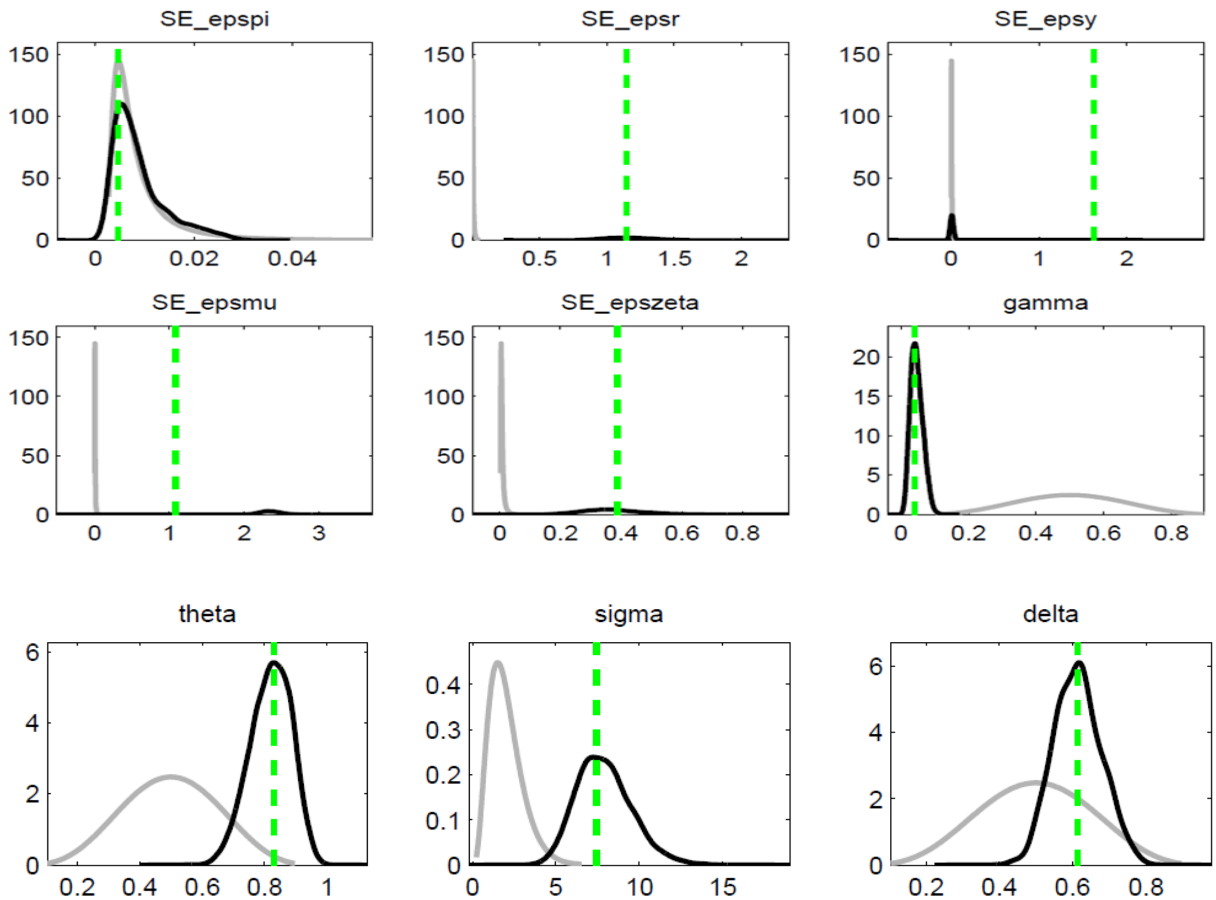
parameters	mean	mode	st.dev	t-stat
γ	0.5	0.0417	0.0185	2.2522
ϑ	0.5	0.8304	0.0696	11.9366
σ	2	7.4145	1.5044	4.9287
δ	0.5	0.6122	0.0589	10.3992
ϕ_π	1.5	1.6873	0.153	11.0303
ρ_y	0.5	0.7857	0.1374	5.7179
ρ_ζ	0.5	0.5728	0.0979	5.8486
ρ_ψ	0.5	0.5	0.1756	2.848
ρ_ν	0.5	0.7934	0.0373	21.264

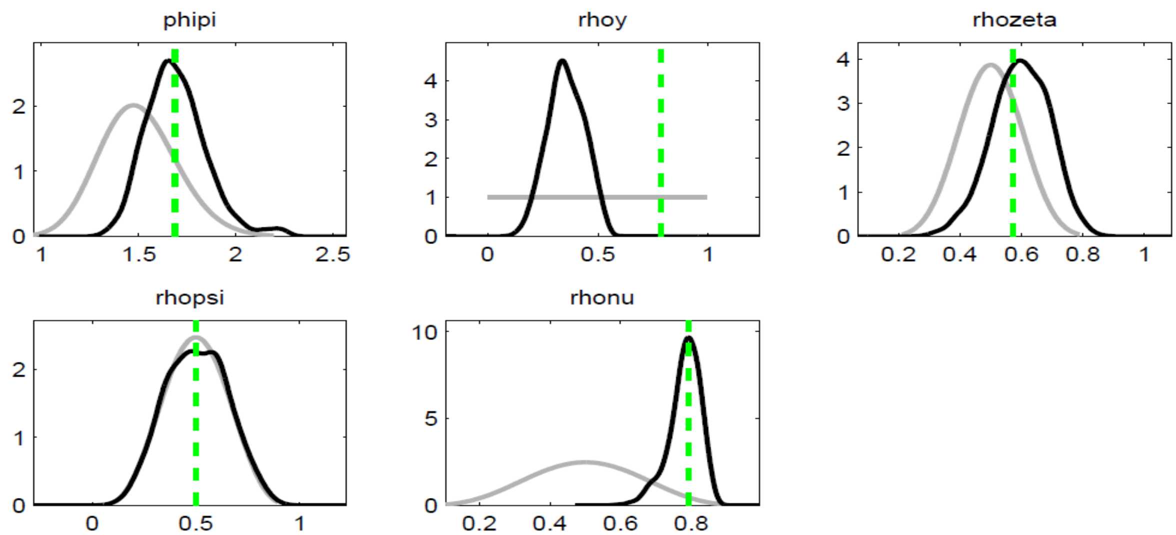
Table 3: First step estimation results for shocks

Shock	mean	mode	st.dev	t-stat
ε_π	0.01	0.0046	0.0019	2.4575
ε_R	0.01	1.1492	0.1718	6.6886
ε_y	0.01	1.621	0.3332	4.8654
ε_μ	0.01	1.0832	0.4534	2.3894
ε_ζ	0.01		0.1032	3.7595

If we compare each parameter to the values of t statistic with those of the normal standard under the null hypothesis of zero equality then what we get is always the rejection of that null hypothesis so we can conclude that all the above listed parameters are significant. In this case we need to assume normality in the posterior distribution. The value of the log-likelihood calculated by the Laplace method, assuming a normal distribution for the posterior, has a value of -899.071251.

Figure 1: Posteriori distributions





The black lines represent the posterior distributions, the gray ones are the priories while the green vertical line represents the mode of the distributions. The results show that the data are informative. Let us then analyze the results of the second step of estimation, those that give us all the posterior distribution.

Table 4: Second step estimation results for the parameters

parameters	prior mean	post. mean	conf. interval
γ	0.5	0.047	0.0198 0.0764
ϑ	0.5	0.8186	0.7218 0.9316
σ	2	7.8661	5.3707 10.3224
δ	0.5	0.6055	0.5002 0.6977
ϕ_π	1.5	1.6989	1.4509 1.9202
ρ_y	0.5	0.3548	0.2078 0.4877
ρ_ζ	0.5	0.5912	0.4423 0.7413
ρ_ψ	0.5	0.496	0.2557 0.7449
ρ_ν	0.5	0.7892	0.7275 0.8487

Table 5: Second step estimation results for the shocks

Shock	prior mean	post. mean	conf. interval

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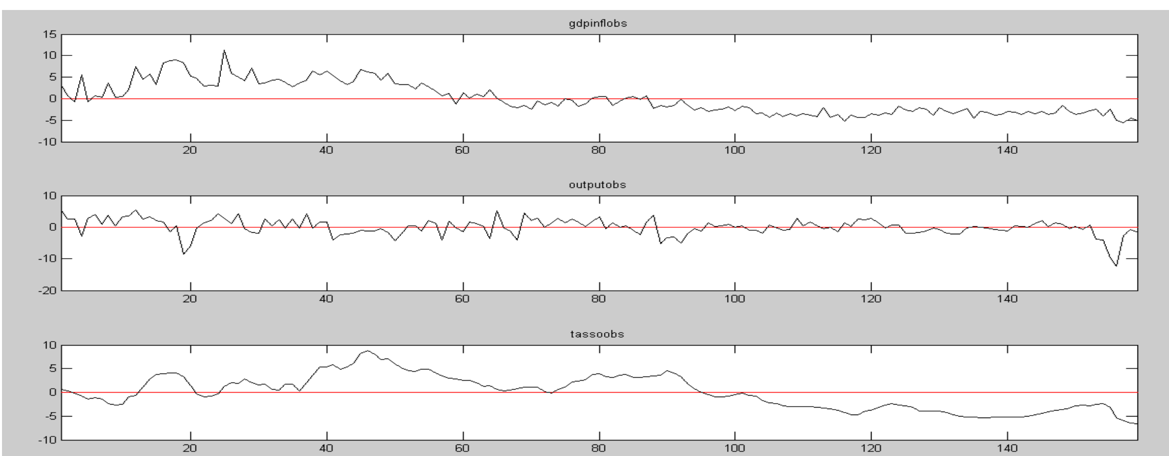
ε_π	0.01	0.0134	0.0020 0.0326
ε_R	0.01	1.1797	0.9065 1.4604
ε_y	0.01	0.0104	0.0022 0.0171
ε_μ	0.01	2.3314	2.1161 2.5539
ε_ζ	0.01	0.3702	0.2035 0.5140

The results of the second estimation step shows the average of the posteriors and the confidence interval at 90%. The retrospective component in the Phillips curve has posteriori mean of 0.0483 very small value compared to the posterior. Since this value is less than 0.5 then the forward-looking component is dominant in the model. The forward-looking component is equal to 1-γ. However, if we compare our results with those of Willems (2011) we find that our value is much smaller. Anyway, I agree with him, only that the forward-looking component is dominant. An important role is attributed to parameter θ (output gap component of 1 period), as its mean it is 0.8310. This suggests that the formation of habits is very important in explaining the data. Similar results are also found in Willems. The estimation for the coefficient of aversion to the risk σ has mean 7.7, much higher than its a priori average, in line with the results found by Willems (2011), Rabanal and Rubio Rāmirez (2005) is Lippi and Neri (2007). The value of the log-likelihood calculated using the "Modified Harmonic Mean" method (Geweke (1998)), which does not necessarily assume that the a-posterior distribution is a normal, is -891.863066 which is a slightly higher value than that calculated with The Laplace method. The following figures show, respectively, the original series of filtered and updated variable variables.

Graph 5: Inflations, Output growth e interest rate series



The output growth series can be considered stationary but around another line, which obviously is not the "smooth" series. Once we estimate the model let's know that our filtered and updated

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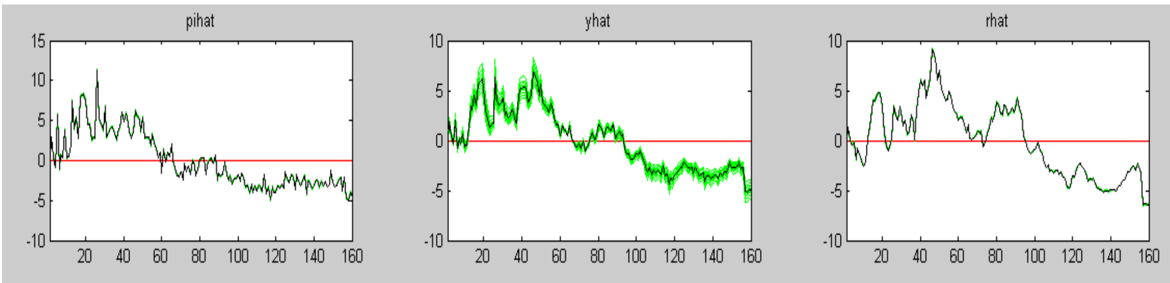
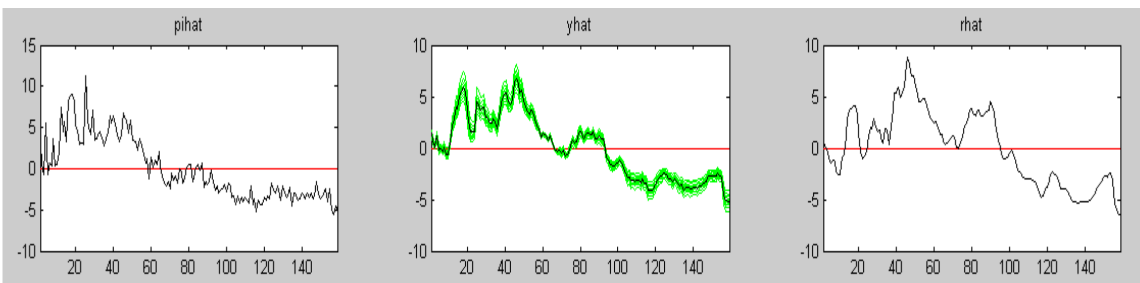
series is stationary on average around 0, so swings around the straight line indicating the chamfered series.

Graph 6: Filtered series



Graph 7: Chamfered series



There are no significant differences in the graphs corresponding to the observed inflation variables and the observed interest rate variable. The only difference we can notice and that the filtered variables are much more oscillating than the updated ones. However, we can say that during the years of the crisis the estimates are negative, also justifying the fact that interest rates are lowered by central banks.

Impuls Response Functions (IFRs)

These functions examine the response time of a variable in relation to a pulse of another variable in a dynamic system that also involves other variables. In particular, it should follow and measure the effect of an exogenous shock or innovation in one of the variables on one or more variables. The density of these functions is calculated by sampling 500 vectors of estimated parameter outputs and simulating the pulse-response function for each vector. In our case, we consider how the shocks of inflation, output gap, and interest rate affect the observed variables.

Graph 8: Inflations shocks

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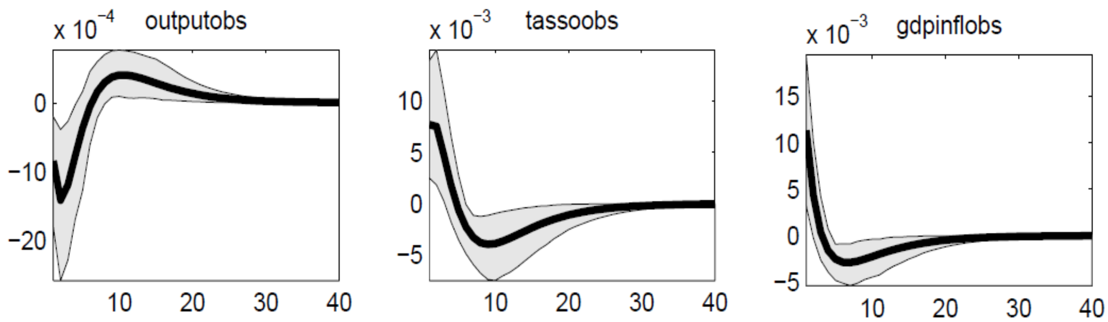
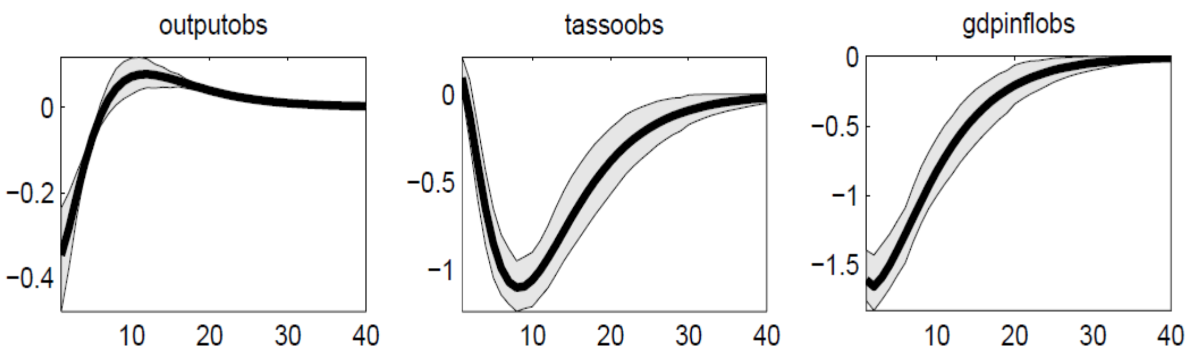


As a result, the Pure Inflation Targeting rule increases the nominal interest rate in order to open up a recession (output drops). This leads to a fall in prices and through the Phillips curve at a lower level of inflation. After this initial effect the series tend to return to stationary state, which in this case is the non-conditioned medium, ie zero for all variables since there are no constants in the model.

Graph 9: Interest rate shocks



The interest rate shock has a negative impact on the interest rate. A decline in the interest rate causes an increase of the output gap and also an increase of the inflation variable. After that, the system responds by increasing the interest rate that goes to its stationary state. Then even in this case after the initial movements the sets return to the stationary state and re-establish to zero, which is zero for the reasons mentioned earlier.

Graph 10: Output Gap shocks

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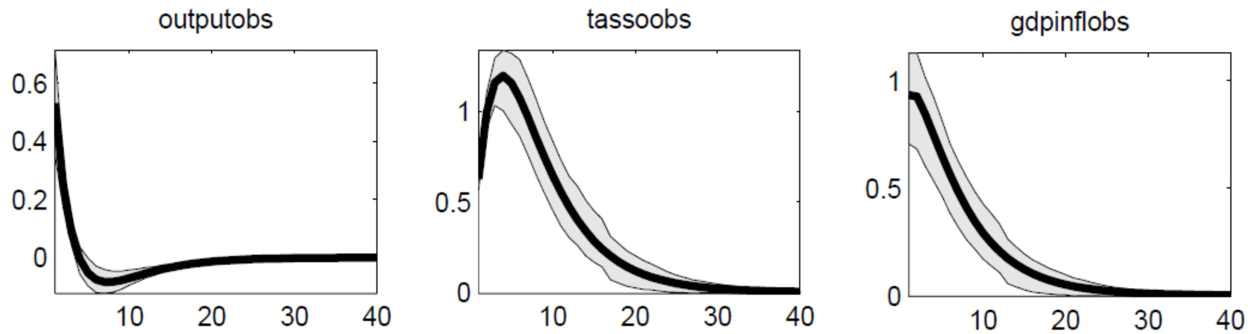

As can be seen from the chart, this shock has a negative sign, so its increment causes the output gap reduction as well as inflation through the Phillips curve. The output gap shock has a positive impact, obviously indirectly on the interest rate, but then slows down towards the steady state. I expected the variables to have difficulty returning to their stationary state since I assumed a persistence a bit stronger than the other shocks, but this is not a success.

New Model using Taylor rule

In order to estimate the data I will develop and estimate a new empirical version. The substantial difference between the previously estimated model and this will be that instead of the Pure Inflation Targeting rule we will try to use the Taylor rule.

$$R_t = \delta R_{t-1} + (1-\delta)\phi_\pi \pi_{t-1} + (1-\delta)\emptyset_y \tilde{y}_{t-1} + \nu_t^R$$

$$\nu_t^R = \rho_\nu \nu_{t-1}^R + \varepsilon_t^R$$

$$\varepsilon_t^R \sim N(0, \sigma_R^2).$$

Note that Taylor's rule is also enriched by the output gap. In spite of all, I will try to prove that this model is not suitable because the authorities can not observe the output gap and therefore can not react. Taylor's coefficient in the output gap is the additional parameter $\emptyset_y$. It is distributed as a Gamma(1.5, 0.2).

Graph 11: Model's Convergence

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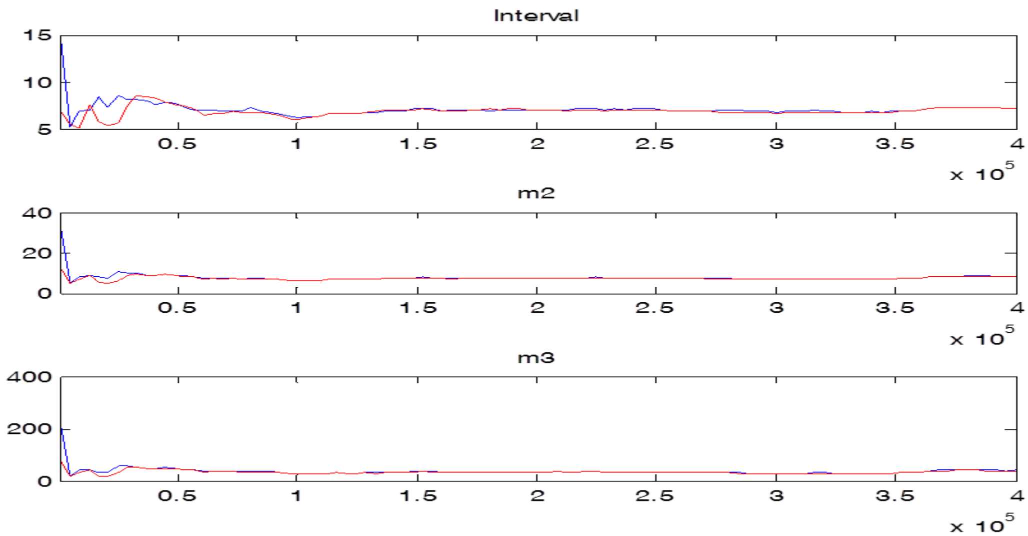

Analyzing the convergence, we can be confident enough that the priori choices are sufficiently informative. The number of iterations of the Metropolis-Hastings algorithm, which we had chosen to be 200,000, seems not to be enough as the third moment appears to have slightly different lines.

Table 6: First step estimation results for the parameters

Parameters	mean	mode	st.dev	t-stat
γ	0.5	0.0255	0.0120	2.1218
ϑ	0.5	0.8700	0.0555	15.6779
σ	2	8.6410	1.7114	5.0489
δ	0.5	0.3039	0.0845	3.5958
ϕ_π	1.5	1.4062	0.1829	7.4306
$\emptyset_y$	1.5	0.9758	0.1284	7.5986
ρ_y	0.5	0.7259	0.1446	4.9586
ρ_ζ	0.5	0.7578	0.0782	9.6960
ρ_ψ	0.5	0.5003	0.1757	2.8478
ρ_ν	0.5	0.9202	0.0118	78.1604

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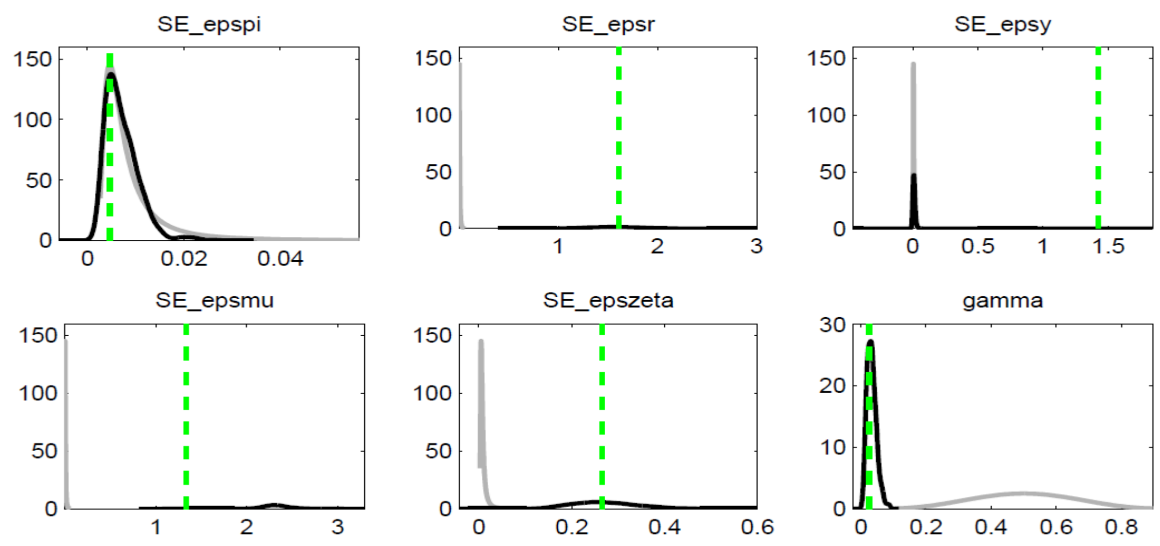
Table 7: First step estimation results for the shocks

Shock	mean	mode	st.dev	t-stat
ε_π	0.01	0.0046	0.0019	2.4523
ε_R	0.01	1.6126	0.2837	5.6840
ε_y	0.01	1.4264	0.3678	3.8785
ε_μ	0.01	1.3382	0.4596	2.9117
ε_ζ	0.01	0.2651	0.0658	4.0280

Note that all posterior standard deviations are smaller than the priories (except for the variable σ and slightly for the variableρ_ψ). Results are identical to the one obtained from the previous model. So we confirm that it is a good indication that the parameters are informative. If we compare for each parameter the values of statistic t with those of the normal standard under the null hypothesis of zero equality what we get is always the rejection of that null hypothesis. We can conclude that all of the above listed parameters are significant.

Figure 2: Posterior density



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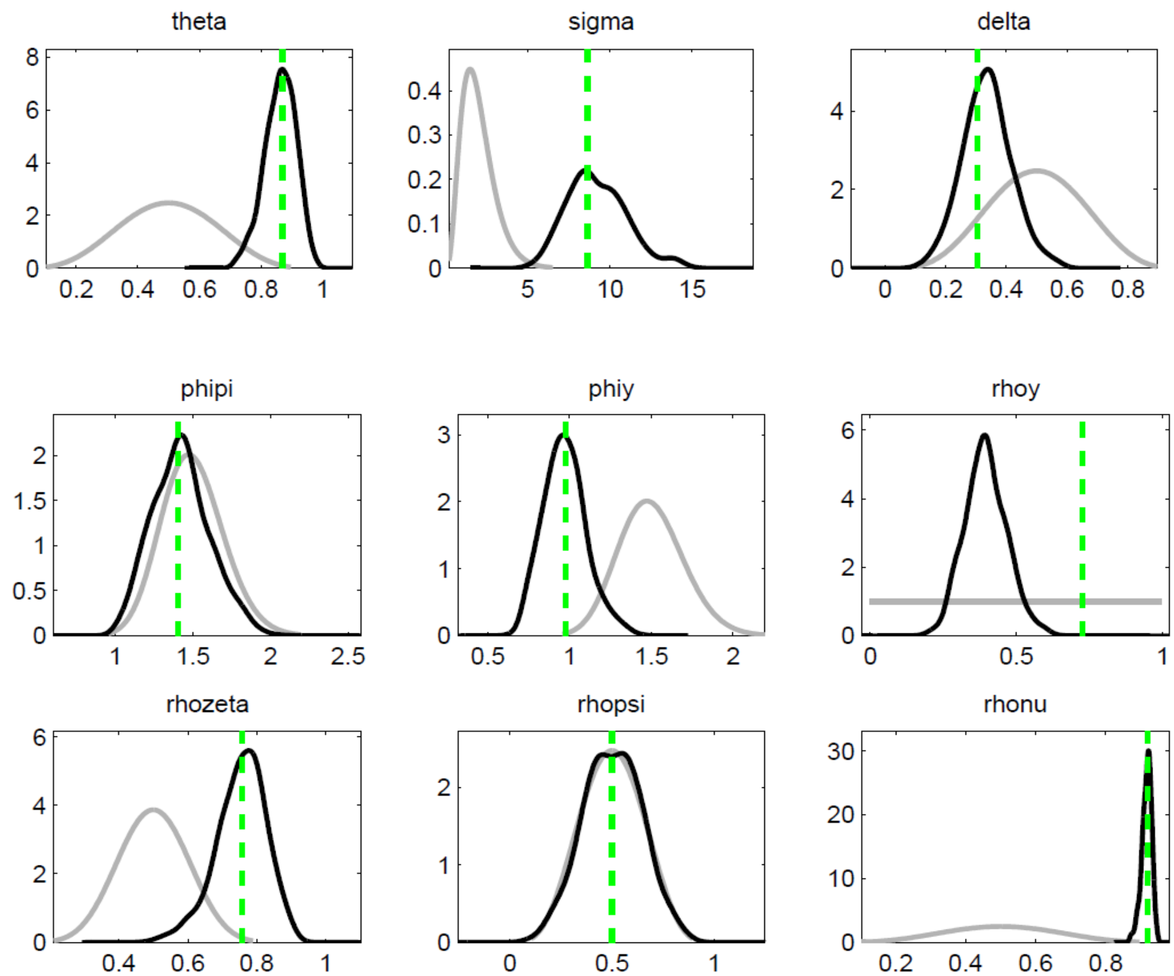

Table 8: Parameter's a-priori distributions

Parameters	prior mean	post. mean	conf. interval
γ	0.5	0.0334	0.0095 0.0535
ϑ	0.5	0.8617	0.7876 0.9468
σ	2	9.2111	6.2378 11.7586
δ	0.5	0.3350	0.1943 0.4609
ϕ_{π}	1.5	1.4231	1.1222 1.7217
$\emptyset_{y}$	1.5	0.9701	0.7332 1.1625

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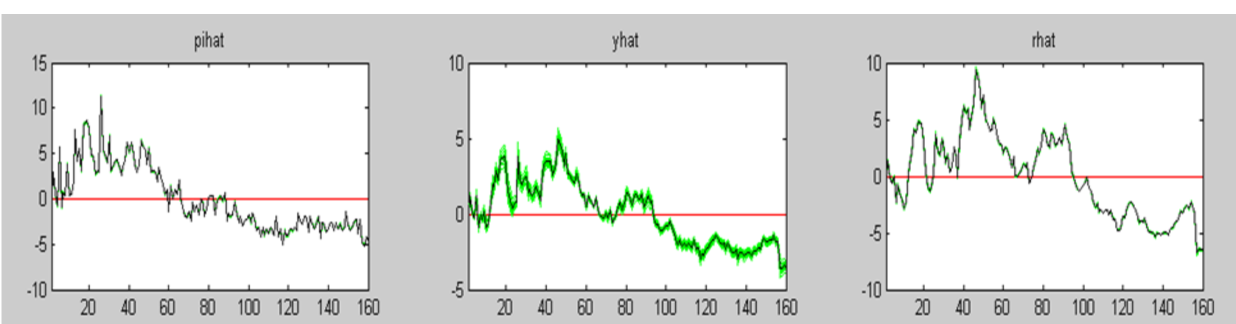
ρ_y	0.5	0.3947	0.2712 0.5010
ρ_ζ	0.5	0.7534	0.6467 0.8812
ρ_ψ	0.5	0.5014	0.2478 0.7250
ρ_ν	0.5	0.9163	0.8960 0.9413

Table 9: Shock's a-priori distributions

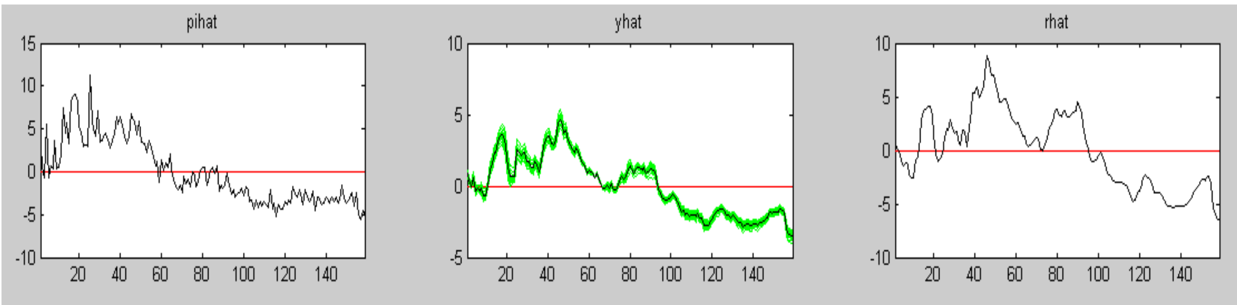
Shock	prior mean	post. mean	conf. interval
ε_π	0.01	0.0104	0.0024 0.0242
ε_R	0.01	1.5827	1.1738 2.0581
ε_y	0.01	0.0102	0.0022 0.0172
ε_μ	0.01	2.3230	2.1187 2.5466
ε_ζ	0.01	0.2694	0.1668 0.3777

This table shows the results of the second estimation step that gives us the average of the posterior and its "confidence interval" at 90%. The retrospective component in the Phillips curve has a posteriori mean of 0.0334 very small value compared to a-priori. Since this value is less than 0.5 then the forward-looking component is dominant in the model. This value is also smaller than the one obtained in the base model, which confirms the unimportant role of this parameter. While for parameter ϑ we find a high value compared to the previous, same as in Willems. The estimation for the a posteriori coefficient of aversion to the risk σ has average of 9,211, much higher than its a priori average, in line with the results found by Willems (2011), Rabanal and Rubio Ràmirez (2005) , Lippi and Blacks (2007), but also with our result. The new $\emptyset_y$ variable has a median posterior value of 0.9701 high enough to allow a significant role for that parameter.

Graph 12: Filtered Variables

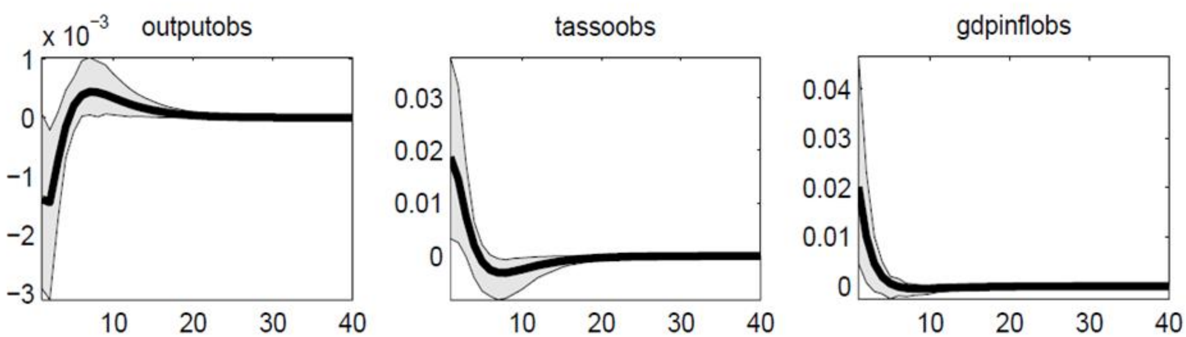


Graph 13: Variabili smusate

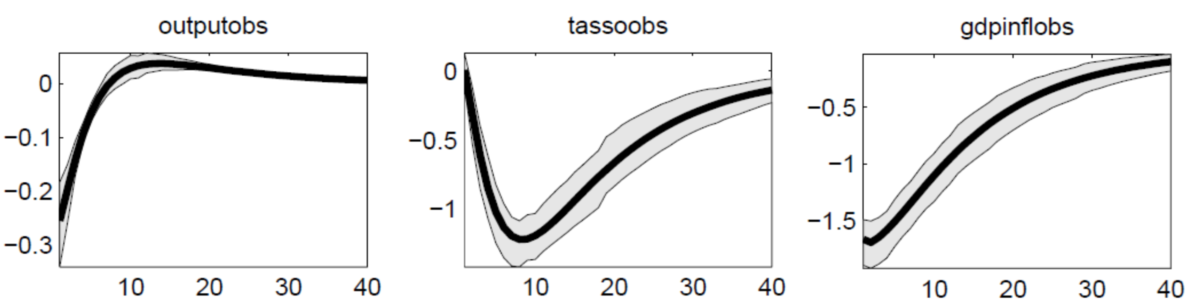


There are no significant differences in the graphs corresponding to the observed inflation variables and the observed interest rate variable.

Graph 14: Inflations shocks



Graph 15: Interest rate shocks



Graph 16: Output Gap shocks

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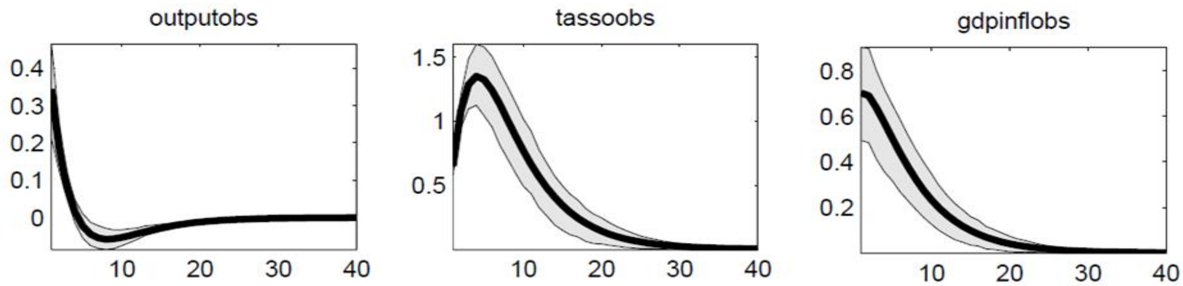

The effect of the shock to inflation cause an increase of the inflation. Taylor rule raises the nominal interest rate in order to open a recession (the output declines). This leads to a decline of the prices and through the Phillips curve at a lower level of inflation. After this initial effect the series tend to return to a stationary state. The interest rate shock has a negative impact on the interest rate. A decline in the interest rate causes an increase of the output gap and then also of the inflation. After that, the system responds by increasing the interest rate that goes to its stationary state. The shock of the output gap is likely to have the same behavior as the previous model.

Comparison between two models

Both models aim to estimate the output gap is an unobservable variable. By combining unobserved components (UCs) and DSGE (Dynamic stochastic general equilibrium models) we get consistent, robust estimations. The first model uses the Phillips curve, the Dynamic IS Curve, and a Pure Inflation Targeting rule as equations. Notice that the output gap gap is not present in the last equation. The monetary authorities can not observe the output gap and therefore can not react, that’s why it can be ommited from the equation. The equation includes the parameter of interest, and in case the reasoning made for the first model is true, I expect the estimated coefficient of the output gap to be very irrelevant. This does not happen, apparently confirming that the best model must absolutely include the output gap variable. The best way to estimate unobservable variables is to apply Bayesian analysis. Precisely because it allows us to formalize the use of a priori distributions from both previous macroeconomic studies and to create a link with past literature. In addition, the use of a priori distributions for structural parameters makes the nonlinear optimization of the algorithm more stable. We make clear the substantive differences between the two models, first considering the estimations of the a-posterior means:

Table 10: A-posteriori comparison

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parameters	prior mean	post. mean	conf. interval	prior mean	post. mean	conf. interval
γ	0.5	0.047	0.0198 0.0764	0.5	0.0334	0.0095 0.0535
ϑ	0.5	0.8186	0.7218 0.9316	0.5	0.8617	0.7876 0.9468
σ	2	7.8661	5.3707 10.3224	2	9.2111	6.2378 11.7586
δ	0.5	0.6055	0.5002 0.6977	0.5	0.3350	0.1943 0.4609
ϕ_π	1.5	1.6989	1.4509 1.9202	1.5	1.4231	1.1222 1.7217
ρ_y	0.5	0.3548	0.2078 0.4877	0.5	0.3947	0.2712 0.5010
ρ_ζ	0.5	0.5912	0.4423 0.7413	0.5	0.7534	0.6467 0.8812
ρ_ψ	0.5	0.496	0.2557 0.7449	0.5	0.5014	0.2478 0.7250
ρ_v	0.5	0.7892	0.7275 0.8487	0.5	0.9163	0.8960 0.9413
$\emptyset_y$	-	-	-	1.5	0.9701	0.7332 1.1625

The backward-looking component of the inflation γ that in the basic model has an almost irrelevant role that becomes even smaller, thus reinforcing the role of the forward-looking component. The role of the parameter responsible for the formation of habits and the risk aversion parameter becomes more important in the second model. While giving less weight to the parameters δ and ϕ_π, they still have a fairly significant role in the model. Contrary to my expectations, I found a relevant value for parameter $\emptyset_y$. This induce me to consider the output gap in Taylor's equation even though it is not observable. The value of the log-likelihood calculated using the "Modified Harmonic Mean" method of the second model is -906.658829 and is lower than the one obtained for the estimation of the first model that was -891.863066. Since we want to get the model that gives us a higher value of likelihood. The first estimated model is preferable to the second. To support this consideration is also the value of the Bayes factor. Bayes factor between 1 and 3 is no more than a simple allusion, between 3 and 20 suggests positive evidence in favor of one of the two models, between 20 and 150 suggests strong evidence against the model and more than 150 a very strong evidence. This factor is calculated as exp (ML difference between two models). In our case we get exp (10.5) = 2665128, which indicates that the second model estimated is better, but this may be due precisely because the log-likelihood drops into an areas with high density. Charts of the the original gap output series graphs, the filtered and updated ones of the two models suggest that both series of the two models move in the same direction and have cyclical behavior. They point to the same period as an economic boom or recession. The correlation between the two sets seems not to be perfect but still has a high value because the width of the second model series is greater. Substantial differences in favor of one of the models are not obvious.

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CONCLUSIONS

It's known from the existing literature that natural output is not observed, that's why even the output gap is not directly observable. The right approach to estimate it can be the use of Bayesian analysis, in order to create a link with past literature. That's why; I have estimated two different models by combining UOB and DSGE models. Both models use the approaches that the Phillips curve and the IS-Dynamic curve offer. The difference between them is that the first model uses a Pure Inflation Targeting rule and the second one the Taylor's rule where the output gap variable is present. The monetary authorities cannot observe the output gap and therefore cannot react. For that reason I will try to estimate by avoiding introducing into the equation the interested variable. Trying to confirm this reasoning I estimate another model, putting Taylor's rule in place of the Inflation Targeting Rule. The last equation includes the output gap. If I have assumed a right reasoning for the first model, the estimated coefficient of the output gap should to be irrelevant but it does not happen. That's why the best model must absolutely include the output gap variable. Another important outcome that conflicts with what was gained in Willems (2011) is the weight it gives to the forward-looking retrospective component of inflation in the Phillips curve. This component is highly dominant over the backward-looking component. The forward-looking retrospective component of inflation in the Phillips curve component is highly dominant over the backward-looking component. Both models give different weight to parameter δ. The first important model for the interest rate at time t-1 and inflation, while the second model puts more weight on inflation in deciding the interest rate at time t. However, I have not found any substantial differences in estimating the parameter responsible for the formation of habits, θ. The output gap is a very important component in making decisions for the policy makers and therefore it should be included it in estimating the interest rate.

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