A Naive Approach to Estimating Monetary Policy Rules

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1 Introduction

After John Taylor's seminal contribution, the estimation of the monetary policy rule followed by central banks has been explored extensively in the literature. Recently this interest has somewhat subsided, possibly due to economies entering the zero lower bound regime where the Taylor type rule for monetary policy is idle. However, it is likely that interest in this question will revive now that economies seem to be slowly exiting the zero bound.

As has been shown, estimating the interest rate rule that central banks follow is not a trivial task. A naive approach of regressing the interest rate on inflation and/or the output gap is hindered by obvious endogeneity issues. Even more sophisticated approaches that attempt to deal with this issue can be controversial. For example, an important contribution is due to Clarida et al. (1998) who computed the coefficients of the monetary policy rule and found that there was a regime change of monetary policy in 1979 (separating the pre- and post-Volcker era). Even this approach has been criticised as not adequately dealing with endogeneity. Sims and Zha (2006), for example, try to perform a similar estimation while including more structural elements in their exercise and find that the evidence points to a relatively stable monetary policy over the same period. Cochrane (2011) goes further and claims that the results based on direct estimations of a Taylor-like equation will always deliver some value which will be a function of not only the true policy parameter but other parameters of the structural model. Hence, abstracting from the structural model means losing the ability to recover the real parameter. This result poses the question whether there are other methods to extract the actual policy parameter(s).

An obvious solution is to use the standard DSGE models and examine whether we can learn something from them. However, once models have been calibrated there is a clear (albeit not trivial) way to compare them by comparing their likelihood, but a problem arises when models are estimated, as it becomes less straightforward to pick the most plausible model and hence the corresponding estimated parameter. While maintaining this consideration in mind, a case can be made that if a series of models are estimated and produce similar values for the same parameter[1], then this is an indication about the actual value of that parameter. In this paper my goal is to uncover the values of the parameters of the monetary policy rule equation.

My strategy it to examine some well-known theoretical models, while introducing similar monetary policy rule specifications across each of them. I first check the validity of each model by a practical approach. Namely, I simulate data based on some monetary policy rule specification and then examine whether an estimation of the model recovers the relevant parameters. I then proceed to estimating a set of parameters based on real US data using the same models. As long as multiple models produce similar values for the estimates, I regard this as an indication about the true value of the corresponding parameters.

My estimations include variations, whose goal is to illuminate a series of aspects. Thus, I vary the set of estimated parameters and I vary the prior specifications that I use in the estimations. This exercise provides hints with regard to our power to identify the values of parameters and subsequently with regard to what these values are. Lastly, I also vary the time period in the real data for which I perform the main estimations, in order to assess the existence of a structural break in the conduct of monetary policy, as has been claimed in the literature.

Furthermore, performing these simple estimations is not only a way of learning something about the monetary policy rule. It could also teach us something about the models themselves. For example, if a specific model seems to consistently "disagree" compared to other models, then this could also give us a hint about the quality of the model itself.

Even though I perform a large number of estimations, my prior choices still have a limited range and I have by no means exhausted the possible options for priors. As will also be explained later, I have used some very simple specifications. This also illustrates how this method can very quickly become impractical as the different choices of priors and their combinations can lead to an exponential increase in the number of estimations. Still, the exercises that I perform lead to some notable conclusions and can help with intuition building with regard to the use of New-Keynesian models.

[1] Of course, technically it is not the case that parameters in different models can be the "same". So, what is meant is that the parameter has the same structural interpretation. So, for example, the coefficient multiplying the inflation rate in the interest rate policy rule equation is in this sense considered the same across models.

I proceed by explaining in section 2 the Macroeconomic Model Database resources that I have used. In section 3 I present the models that I have used for the exercises. In section 4 I explain the reasoning behind my approach. In section 5 I describe the estimations that I perform. In section 6 I comment on my results. Section 7 concludes and, finally, the appendix contain all the graphs which show my results.

2 MMB Resources

In this investigation I make extensive use of the resources provided by the Macroeconomic Model Database (MMB). The MMB is an archive of macroeconomic models coupled with Matlab applications that enable model comparison. The models are written in ".mod" files and implemented through the Dynare software.

In particular, the MMB offers the capability of comparing different macroeconomic models in a common framework. This mainly entails the comparison of impulse response functions. To this end, the files have a set of variables that are harmonised across models. These variables are: the interest rate, output, output gap and inflation. Based on these variables a Taylor (1993) type monetary policy rule can be integrated in all models. Thus, all models share a set of possible parameters that characterise the monetary policy rule. The MMB offers some predefined rules based on the literature, but the user can also choose a rule based on custom values for the parameters multiplying the corresponding variables and their leads and lags. In particular, the monetary policy rule equation of the MMB is linear and takes the following form:

$$(\text{interest})_t = \rho \cdot (\text{interest})_{t-1} + \alpha \cdot (\text{inflation})_t + \beta \cdot (\text{output gap})_t + \gamma \cdot (\text{output})_t + \epsilon_t$$

Above I do not include lags or leads but the software offers the capability to add any lag of the variables on the right hand side or any lead (leads are also expected values). In addition, given this specification a user can compute and compare the impulse response functions for the same basic model but with different implementations of the monetary policy rule. On the other hand, a user can also compare the impulse response functions of different models that use the same monetary policy rule.

In this investigation I do not use the MMB application directly, but I use the mod files included in the archive. The harmonisation of these files with respect to the monetary policy rule provides the groundwork for the exercises that I want to perform. Firstly, it is easy to simulate data based on any of these files and any monetary policy rule that I choose. Then, it takes relatively little work to enhance the files with the respective Dynare options that will perform Bayesian estimation on these DSGE models. The reason for this is twofold. Firstly, as mentioned, all models have the same four variables, namely output, inflation, output gap and interest. Thus, it is easy to use a dataset that contains these variables for the estimation of all models. Secondly, the files also have a harmonised expression for the monetary policy rule and the parameters that define it. Hence, it is straightforward to estimate these parameters which have the same name across the files.

3 Summary of models used

The models that I will use are taken from the MMB. I have chosen models of theoretical interest and avoided models that already have estimated parameters.

The models that will be used for the analysis are Rotemberg and Woodford (1997),Ireland (2004), Galí et al. (2007), Christoffel and Kuester (2008), Blanchard and Galí (2010) and Stracca (2013). For expositional purposes I shall refer to these models in the same abbreviations as the MMB uses, namely, RW97, IR04, GLSV07, CK08, BGUS10 and ST13 respectively. More details about these models can be found in the respective papers, short descriptions of the models are available in the MMB_model_description.pdf file and I also provide a short summary here.

3.1 Rotemberg and Woodford (1997)

This is a well known standard New-Keynesian model that probably needs no introduction; however, I provide a short summary for completeness.

The structural elements of the model are based on rationally optimising individuals. This makes the model safe from the well know Lucas (1976) critique of econometric policy. Incorporating optimising individuals in the model also allows the evaluation of policies with regard to welfare.

Households enjoy consumption and leisure per period and they are maximising their expected discounted utility from these variables, having an infinite horizon. The consumption that the household values is produced as an aggregate consumption good from a continuum of differentiated goods, based on an aggregator functional according to Dixit and Stiglitz (1977). All consumption in this model should be thought of as non-durable. In addition, money does not offer any liquidity services and in general money balances are not present in the model. Total aggregate demand is assumed to consist of the consumption of the household plus a quantity G_t, which changes exogenously. This could be thought of as government spending but it could be given an alternative interpretation also.

Each variety of the differentiated intermediate input is produced by firms which set their price under monopolistic competition. However, they are not able to optimise their price in every period. They are constrained by a Calvo (1983) style stickiness to only be able to reoptimise with a constant probability. Based on these assumptions it turns out that firms set prices proportional to the present discounted value of marginal costs. Moreover, the model produces a relationship that has been called the New-Keynesian Phillips Curve and it connects current inflation with expected discounted inflation plus a weighted deviation of output from some "natural level".

The authors provide a second order approximation to the loss function by which they can evaluate alternative monetary policies. Under their setup it is optimal to keep inflation always at 0, as then firms never change their price and they are practically not bound by the stickiness. However, they comment that this is not possible given a zero lower bound. In general, the authors conclude that even complete inflation stabilisation at a positive value would not be possible given a low average inflation.

3.2 Ireland (2004)

This is a New-Keynesian model that features money balances explicitly. Instead of Calvo style stickiness, prices are sticky due to adjustment costs according to Rotemberg (1982). In addition, the model features preference shocks. Here, money balances enter the utility function explicitly and not necessarily in a separable manner with respect to consumption. When utility is non-separable in terms of money balances and consumption, real balances affect the marginal rate of intertemporal substitution. Hence, money balances appear not only in the money demand equation but in the IS curve also. As optimising firms set prices on the basis of marginal costs, the forward looking Phillips curve reflects a measure of real marginal costs. These will depend on the level of wages, which are in turn linked to the optimising household's marginal rate of substitution between consumption and leisure. Thus, non-separability of the utility function implies the appearance of money balances in both the IS and the Phillips curve equations.

The author uses this setup in order to perform an estimation of the parameters. He concludes that money demand has to be taken into consideration in order to properly measure the effects that real money has on output and inflation. Finally, he also finds that money has a minimal direct effect on inflation and output.

3.3 Galí et al. (2007)

This is a New-Keynesian model that features rule-of-thumb consumers. In particular, there is a λ proportion of the population that has no access to capital markets and just consume their current labor income. Thus, these consumers exhibit an extreme hand-to-mouth behaviour, about the source of which the authors take no stance. They do mention, however, such factors as myopia of agents, lack of access to financial markets and borrowing constraints as possible factors. In addition, the model features an explicit government sector. Fiscal policy follows the following rule:

$$t_t = \phi_b b_t + \phi_g g_t$$

So taxes are a constant fraction of the level of debt, b_t, and a constant fraction of government purchases, g_t, which are assumed to follow a first order autoregressive process. There is a continuum of intermediate inputs, each of which is produced by a monopolistically competitive firm that combines capital and labour; these firms also produce a standard Calvo style price stickiness. The firms producing the final good, that is consumed by the household, operate under perfect competition and use the intermediate goods as inputs.

In this model the level of employment has a direct effect on the level of consumption due to the presence of rule-of-thumb consumers. Thus, an expansion in government purchases has the potential of increasing consumption through their effect on employment. Then the increase in consumption would boost the economy even further, which could lead to a multiplier effect similar to traditional Keynesian models. The effects described above will only realise if the response of taxes and interest rates to the increase in government purchases is sufficiently small.

The model featuring imperfectly competitive firms and rule-of-thumb consumers produces a positive comovement between consumption and government spending even for values of λ as low as 25%.

3.4 Christoffel and Kuester (2008)

This is a New-Keynesian model featuring a wage channel of inflation. In particular, each household has u_t unemployed members and accordingly $1 - u_t$ employed members. The economy has three sectors. The retail sector sells the final good to households or to the government under perfect competition. Its sole inputs are intermediate differentiated goods, which are produced by the wholesale sector. There is a continuum of wholesale firms with a unit mass of 1. Each firm hires labour in order to produce the differentiated intermediate good, which they sell under monopolistic competition, while facing Calvo style price stickiness. Finally, labour is produced by the labour good firm. Each of these firms hires a single worker. Hence, in each period there are $1 - u_t$ such firms, where u_t is the unemployment rate. These firms take as input the hours worked by the individual and depending on the level of productivity, which is the same for the sector, the amount of the labour good is produced. Productivity follows an autoregressive process of order 1.

In this model the nature of the labour market is of most interest. Each period separation occurs at a constant rate, while matches occur according to a matching function which is increasing and concave with respect to the level of unemployment. Each filled vacancy produces a surplus which is divided between the household and the labour good firm. Given the constant separation rate, the worker has a constant probability of staying employed, while the wage is rebargained each period with a given probability. This also corresponds to a Calvo style wage rigidity. When the wage is rebargained it reflects the optimal wage. The surplus is divided according to Nash bargaining, while households have constant bargaining power. Thus, the wage is also determined. An additional difference of the model compared the standard case is that workers only bargain over the level of the wage and not about the hours worked, while it is usual to assume that negotiations take place about both variables. Thus, firms can freely choose the hours worked based on the hourly wage.

The authors find that higher wages all else equal induce higher marginal costs and consequently higher inflation. Thus, they claim that the model is successful in reproducing the pronounced fluctuations of unemployment over the business cycle.

3.5 Blanchard and Galí (2010)

This is a New-Keynesian model which introduces search and matching aspects in the labor market. In particular, the model features unemployed individuals and firms that can hire out of the pool of the unemployed. At the same time employed individuals can also lose their job at a rate δ. The ratio of the number of people hired each period to the number of unemployed turns out to be a crucial economic variable. This is defined to be the labour market tightness, θ, but it can also be viewed as the job finding rate for those who are unemployed. The model features costs of hiring which are increasing in labour market tightness.

After introducing wage rigidities, employment becomes a function of current and anticipated productivity. After also introducing Calvo style nominal rigidities it turns out that the monetary authority cannot achieve both optimal unemployment and optimal inflation, but there is a tradeoff. In general it is shown that inflation reacts negatively both to the *level* of unemployment and to the *change* of unemployment. When δ and θ are both high the effect of the level of unemployment is relatively more important compared to the change of unemployment and vice versa when both δ and θ are low. These two cases are referred to as fluid and sclerotic and they are associated with the US and European labour markets respectively. In my estimations I use the calibration of the model that corresponds to the fluid labour market, i.e. for US.

The authors go on to show that optimal monetary policy will neither aim at pure inflation targeting nor at pure unemployment stabilisation, but it will try to accommodate both aspects. They also find that a simple Taylor rule performs much better than either of the extreme policies for both fluid and sclerotic labour markets. However, strict inflation targeting performs worse than the other policies especially for the sclerotic labour market case.

3.6 Stracca (2013)

This is a New-Keynesian model which features both standard money, issued by a central bank, and inside money, ie money which is created by banks. In particular, the model has a representative household, a final good producer, intermediate goods producers and a bank, while there is a central bank implementing monetary policy.

On the production side this is in general a standard New-Keynesian model with capital. So, there is a continuum of intermediate goods firms that operate under monopolistic competition and produce differentiated products, while also facing quadratic price adjustment costs according to Rotemberg (1982). These products are bought by the final good producing firm and they are combined as inputs for the production of the final good. The main point of difference of this model is that the intermediate goods firms have to finance all their costs, namely the cost of capital and labour, by debt. Thus, each period they have to borrow from the bank.

The household enjoys standard utility from consumption and leisure and wants to maximise the discounted sum of expected utility in the future. It also owns as usual the financial assets (except the loans given to firms by banks). The main differences with respect to the household stem from the fact that it can place deposits with the bank. Then it can use these deposits to purchase the consumption good. So, instead of a a more common cash in advance constraint there is a *deposit* in advance constraint, which includes both the deposits and the currency, that the household has to hold in order to buy the consumption good. In addition, the author adds a quadratic negative term in the household's utility, which reflects the disutility of the household from the changes in the level of deposits from one period to the next.

Finally, the bank can finance its loans from deposits, bonds that it issues and credit from the central bank. In addition, to the standard interest that it has to pay for these liabilities, the bank also faces an *an intermediation cost on deposits* which takes the form $\omega_t d_t / m_t$, where m_t is the amount of outside money, d_t is the amount of inside money and ω_t is an exogenous process which follows an AR(1) process and entails the banking distress shock. According to this specification, the cost of issuing more deposits is proportional to the leverage of the bank limited in terms of inside vs outside money.

The author finds that the impact of the inside money supply shock is small. On the contrary, a money demand shock is significantly larger and has a contractionary impact. In addition, simulating conditions of a banking crisis lead to a fall in consumption and investment and to a rise in outside money, ie currency. Lastly, optimal monetary policy is not considerably different to the standard case of inflation stabilisation, when the central bank also reacts to the quantity of inside money.

3.7 Choice of Models

The choice of models was motivated by both theoretical and practical considerations. Firstly, I deemed that the best way to present the results would be through the common presentation of the posteriors of all models in the same figure for each type of estimation. In order for the graphs to remain relatively clear and easy to read I restricted the number of models to six.

Secondly, it is not trivial to compute the mode, for the Bayesian estimation, correctly for any combination of model, prior distribution and dataset used. Given the large number of estimations that I am performing I used the same options for all the models. In particular, while using Dynare I used a specific option for the computation of the mode[2]. Thus, I also faced the aforementioned problem, which led me to exclude many models for which estimations frequently failed. Unfortunately, even while making this choice I was not able to ensure that estimations were always feasible.

Given the constraint described above I tried to include models that address important aspects in the business cycle. I think of RW97 as the standard New-Keynesian model, GLSV07 introduces rule-of-thumb consumers and thus has a traditional Keynesian flavour to it, CK08 and BGUS10 explicitly model a labour market and so a wage channel of inflation and, lastly, IR04 and ST13 introduce some form of money in the model.

[2] mode_compute=1, which uses a common optimisation routine.

4 The naive approach

Bayesian techniques have been used extensively in the DSGE literature. For example, Smets and Wouters (2003) and Smets and Wouters (2007) have famously estimated the structural parameters of two models that aim to capture the features of the economy in the Euro Area and the US respectively.

The approach and the methodological tools used in the context of Bayesian estimation of DSGEs have been investigated extensively beyond the general literature for Bayesian estimation. A sound methodology has been developed for the formation of priors, for example in Del Negro and Schorfheide (2008). Tests have been invented to check whether individual parameters can be identified by the estimation of a model, for example in Iskrev (2010). There are methods to compare models while also taking into account model misspecification, for example in Schorfheide (2000).

Contrary to these relatively sophisticated methods I intend to simply perform a series of estimations and compare them side by side. I will follow what I will call a "naive" approach. We know that the posterior distribution that is generated from Bayesian estimation is a combination of the information contained in the prior distribution and the information available in the data, filtered through the model. Thus, it is expected that if the prior mean is equal to the value of the parameter of the data generating process, then the posterior distribution will have the same mean as the prior. Conversely, if the prior mean is higher (lower) than the value of the parameter of the data generating process then the posterior distribution should have a mean that is lower (higher) than the mean of the prior distribution and thus closer to the value of the true parameter.

From another perspective once we know that the value of some parameter has to lie within some interval and we see that the posterior distribution does not significantly overlap with that region, then this is an indication that the model is misspecified.

As an example, we may want to find the parameter estimates for monetary policy in a model that is relatively close to the data generating process. Then, according to the naive approach, we can repeatedly perform estimations with different prior distributions until we reach a point where the posterior is centred around the same value as the prior distribution, even if the posterior variance is lower than the prior variance. Then, we can use the posterior mean that we found as our estimate of the true parameters. Of course this procedure is much less sophisticated than other methods in use and there is no theoretical guarantee that the process is valid.

Moreover, it would certainly be arbitrary to assume that a specific model is "close enough" to the data generating process. This is why I use a series of models and I perform many variations of the estimations. However, the models could plausibly all be far removed from the actual data generating process, especially when I couple them with the same monetary policy rule for the purpose of comparison. However, in this case, it is reasonable to expect that they would not all agree to the wrong answer, but probably they would produce diverging results[3]. Thus, if the posterior distributions seem to disagree between models, we can take this as an indication that models are not close enough to each other and probably to the data generating process.

In general, even if the process here provides no rigorous inference and my results are based on inspection of the posterior distributions produced by the estimations, I believe that the exercises that I perform can be quite useful for intuition building around monetary policy rules in the context of New-Keynesian models. Beyond this it is interesting to know if different New-Keynesian models provide similar results when estimated under a variety of prior specifications connected with monetary policy and, in the case that they do agree, what the results are.

In addition, apart from performing estimations based on real data, I perform a series of estimations based on calibrated data. This I see as a preliminary exercise which provides a reference point to which the main estimations can be compared. For example, if similar estimations produce completely different results when performed with data calibrated from the model being estimated compared to real data, then this is again an indication that the model may not be a good proxy for the data generating process.

5 Estimations

5.1 Types of Estimations

The main point of variation in my estimations is the different parameters that I estimate in the monetary policy rule. So, I estimate four sets of parameters that imply the following monetary policy rules.

First type:

$$(\text{interest})_t = \overset{(2,0.1)}{\alpha} \cdot (\text{inflation})_t + \overset{(0.5,0.1)}{\beta} \cdot (\text{output gap})_t + \epsilon_t \tag{1}$$

Second type:

$$(\text{interest})_t = \overset{(2,0.1)}{\alpha} \cdot (\text{inflation})_t + \epsilon_t \tag{2}$$

[3]The possibility of this being just a coincidence cannot be ruled out though, especially when the argument expressed is not formal in a statistical sense.

Third type:

$$\begin{aligned}(\text{interest})_t = \overset{(2,0.1)}{\alpha_0} \cdot (\text{inflation})_t + \overset{(0,0.1)}{\alpha_1} \cdot (\text{inflation})_{t-1} + \overset{(0,0.1)}{\alpha_2} \cdot (\text{inflation})_{t-2} \\ + \overset{(0,0.1)}{\alpha_3} \cdot (\text{inflation})_{t-3} + \overset{(0,0.1)}{\alpha_4} \cdot (\text{inflation})_{t-4} + \epsilon_t\end{aligned} \tag{3}$$

Fourth type:

$$\begin{aligned}(\text{interest})_t = \overset{(2,0.1)}{\alpha_0} \cdot (\text{inflation})_t + \overset{(0.5,0.1)}{\beta_0} \cdot (\text{output gap})_t + \overset{(0,0.1)}{\beta_1} \cdot (\text{output gap})_{t-1} \\ + \overset{(0,0.1)}{\beta_2} \cdot (\text{output gap})_{t-2} + \overset{(0,0.1)}{\beta_3} \cdot (\text{output gap})_{t-3} + \overset{(0,0.1)}{\beta_4} \cdot (\text{output gap})_{t-4} + \epsilon_t\end{aligned} \tag{4}$$

The variables denoted with greek letters are the parameters being estimated in each case. The two values shown over the parameters in parentheses are the prior mean and the prior variance respectively, that I usually apply in the various estimations[4]. The prior distribution that I use in all cases is the normal distribution.

5.2 Variations with respect to priors

5.2.1 Variation of first type of estimation

The first variation with respect to the prior distribution is performed for the first type only. In particular, I perform two series of estimations. In the first one I vary the prior mean of α in equation 1. The prior mean takes the values 1.4, 1.7, 2, 2.3 and 2.6 instead of just 2. In the second series I vary the prior mean of β in equation 1. The prior mean takes the values -0.2, 0, 0.2, 0.4, 0.6 instead of 0.5.

5.2.2 Variation of all types of estimation with respect to prior mean

This variation with respect to the prior distribution is with regard to the prior means of all types of estimations.

For the first type the prior mean of β is set to 0.7 instead of 0.5 in equation 1.

For the second type the prior mean of α is set to 4 instead of 2 in equation 2.

For the third type the prior means of α_1, α_2 and α_3 is set to 0.3 instead of 0, 0.2 instead of 0 and 0.1 instead of 0 respectively in equation 3.

For the fourth type the prior means of β_0, β_1, β_2 and β_3 are set to 0.3 instead of 0.5, 0.2 instead of 0, 0.1 instead of 0 and 0.1 instead of 0 respectively in equation 4.

[4] As is described below, I also perform estimations in which I vary these values for the prior distributions.

5.2.3 Variation of all types of estimation with respect to the prior variance

This variation with respect to the prior distribution is with regard to the prior variance of all types of estimations.

For all parameters in all types of estimations I use the same prior mean but I use double the prior standard deviation compared to the original estimations, i.e. I use 0.2 instead of 0.1.

5.3 Variations with respect to data used

5.3.1 Simulated Data: From each model separately

As I mentioned already, I provide estimations based on simulated data in order to provide a benchmark for the estimations with the real data. The first kind of simulated data that I use are produced from each model separately.

In this case I produce simulated data from each of the six models described above. I use a monetary policy rule which corresponds to equation 1. I set the values of parameters α and β to 2 and 0.5 respectively. These values correspond to the parameters that govern the response of the interest rate to inflation and the response of the interest rate the output gap respectively. In addition, each time that a model is being estimated the corresponding simulated data from the same kind of model is being used.

5.3.2 Simulated Data: From the RW97 model

Moreover, I also use data simulated with the RW97. Again, I set the values of parameters α and β to 2 and 0.5 respectively in a monetary policy rule that goes according to equation 1.

This case differs from the previous one, because now each model is not estimated with data that were generated from the same model. On the contrary, for all models in the estimations (apart form RW97 itself) the estimation is being performed based on data simulated from a foreign model.

5.3.3 Real Data

The main results of the paper refer to the estimations that are based on real data. Here, I use the same data as Smets and Wouters (2007). The data spans the period from 1947:3 to 2004:4. In SW07 itself a subsample of the data is used, namely 1966:1 to 2004:4. It is claimed that the data before this date exhibit a different behaviour. In my case, I perform the main regressions with the data from 1980:1 to 2004:4. The reason that I restrict the sample is the view, also expressed in Clarida et al.

(1998), that there was a shift in the conduct of monetary policy starting with Volcker. As mentioned earlier, I use only the variables that are harmonised across the models, namely output, inflation and the interest rate[5]. I first demean the data and then use the following observation equations in Dynare, to link the dataset with the mod files:

```
dy = output-output(-1);

pinfobs = inflationq/4;

robs = interest/4;
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As a result my observation equations are the same up to a constant as the ones used by Smets and Wouters (2007)[6].

In general, as in the simulations my goal is to estimate the parameters that are part of the monetary policy rule equation. However, real data will not be as “well-behaved” as simulated data with respect to each model. Hence, in order to improve the feasibility of the estimation, for each model used in the estimation individually, I add the standard deviation of the shocks as parameters to be estimated, so that the models have enough amplification to capture the data. The prior means that I use for the standard deviations follow the calibrations available in the MMB mod files[7]. I assigned a prior standard deviation which equal to the prior the mean divided by five in all cases. The results that I show are restricted to the parameters of the monetary policy rule.

In case that the number of shocks is at least three, the procedure above works normally. However, there are two models that have two shocks only. In this case it is impossible to perform Bayesian estimation based on a dataset with three observed variables[8]. Thus, for these models I use the variables related to output and the interest rate.

It is arguable that I should have used a time series that ends later than the one I am using. However, this is not a major issue, because the monetary policy rules that I estimate do not contain a zero lower bound. Hence, I do not want to estimate the model for periods that the zero lower bound holds and clearly there is not enough time after the zero lower bound period to perform separate estimations. Thus, the additional time for which I could have added data is quite small and the additional value of such data would not be enough to overcome the clear advantages that stem from the fact that I am using the same data as Smets and Wouters (2007), in terms of comparability of

[5]In the dataset they are named dy, pinfobs and robs respectively.

[6]I was able to insure this by combining the official SW07 code and the replicated version which is included in the MMB

[7]In few cases where these numbers were not given I assigned a prior mean of 1

[8]Otherwise the problem of stochastic singularity arises.

my results.

5.3.4 Real Data: Different subsamples

In order to assess some claims in the literature I also estimate some variations, where I vary the subsample of the data being used. Now, I only perform the first two types of estimations.

Firstly, I perform the estimations for the subsample from 1966:1 to 2004:4 instead of 1980:1 to 2004:4. This is also the period that Smets and Wouters (2007) used to perform their estimations.

Then, I perform the estimations for the subsample from 1947:3 to 1979:4 instead of 1980:1 to 2004:4. In the main estimations I use the whole sample after the claimed break in the conduct of monetary policy. In this variation I estimate the whole sample *before* the claimed break in the conduct of monetary policy. I could have also excluded the period before 1966, as Smets and Wouters (2007) claimed that the observables behaved very differently before that time period. However, the time period would be too short for the estimations to provide good results.

Finally, I perform the estimations for the full available sample form 1947:3 to 2004:4 instead of 1980:1 to 2004:4.

5.4 Overview of estimations

Table 1 contains a summary of all the estimations that are shown in the appendix. The rows describe the variations with respect to the sample that is being used for the estimations (according to 5.3), while the columns describe the variations with respect to the prior specifications for the bayesian estimations (according to 5.2). In each of the cells I list the numbers of the types of monetary policy (according to 5.1) that are being estimated at the top and the corresponding figures at the bottom. Clearly, when a cell is not occupied then there are no corresponding estimations being shown. In the files that accompany this paper the full Dynare output for the above estimations is also available. Finally, I want to point out at this point that the scaling of the y-axis is the same in all the graphs in order to facilitate comparisons.

5.5 Why not estimate more parameters?

In this paper I restrict the estimation to as few parameters as possible beyond those that govern monetary policy. In particular, I only additionally estimate the variance of the shocks in the models in order to allow them to capture the amplification in the data[9]. A reasonable criticism would be to

[9]When using the simulated data from each specific model I do not estimate these parameters, as it is not necessary.

	Baseline	Series of Prior Means (5.2.1)	Alternative Prior Means (5.2.2)	Alternative Prior Variance (5.2.3)
Simulated Data: From Each Model Separately (5.3.1)	1,2,3,4 1,2,3-4,5-6	1 7 -16		
Simulated Data: From RW97 (5.3.2)	1,2,3,4 17,18,19-20,21-22	1 29-38		1,2,3,4 23,24,25-26,27-28
Real Data: 1980 to 2004 (5.3.3)	1,2,3,4 39,40,41-42,43-44	1 57-66	1,2,3,4 45,46,47-48,49-50	1,2,3,4 51,52,53-54,55-56
Real Data: 1966 to 2004 (5.3.4)	1,2 67,68			
Real Data: 1947 to 2004 (5.3.4)	1,2 69,70			
Real Data: 1947 to 1979 (5.3.4)	1,2 71,72			

Table 1: Overview of Estimations

ask whether I should have tried to estimate more parameters, in order to allow the models to fit the data as much as possible. While I do not doubt that this could also be an interesting exercise, I did not follow this route for two main reasons.

Firstly, one of the main points of the paper, besides estimating the coefficients in the monetary policy rule, is to evaluate the performance and the behaviour of the models themselves. The models that I used are calibrated. Thus, if I went on to estimate all the parameters of the models (or even as many as possible), then I would not really be dealing with the original models, as most of the parameters would have different values. Of course, they would still be connected to the original models, but I think that the value of a parameter is a fundamental choice of the modeller. Changing these values would mean that I am introducing a new model, which depends on the estimation choices that I have made myself. Thus, evaluating these models would not be as interesting as evaluating some models which are as close as possible to the models that are known in the literature.

Secondly, the comparison of the models is done in a relatively objective way given the monetary policy specification that I choose to use in each estimation. However, if I estimated more parameters in these models, then the ability of each model to capture the data would depend on the specific choices for prior distributions that are applied to parameters that may even be model-specific. In addition, even if parameters are common across models, their importance and their role can vary. Thus, the prior distribution that I would use even for them could affect my results one way or the other. Given that the prior specifications cannot be completely objective, I think it is more valuable for this exercise to estimate as few parameters as possible beyond the ones in the monetary policy rule.

6 Results

6.1 Simulations: Data simulated from each model separately

Firstly, I comment on the results based on simulated data. The first basic result which is worth mentioning is that the estimation of the correct model seems to be providing the correct results. So, in Figure 1 the estimated model matches the model from which the data were simulated and the prior mean is equal to the parameter values used in the simulation. In all cases the true values are quite probable under the posterior distributions that arise from the estimations. This is a reassuring first step, because these are the ideal conditions for the estimation. If the correct values were not recovered at this stage, then the entire exercise of using these models for estimations based on actual data would be called into question.

However, even in this ideal case, some comments can be made. While the posterior distributions of the coefficient on the output gap seem to all be centred around the true value, the same is not true for the coefficient on inflation. In this case, there is a lot of variety with respect to the variance of the posterior distribution. For some of the models the posterior distribution seems to hardly have a smaller variance than the prior distribution, while for others the posterior variance is clearly smaller and the posterior distribution graph is clearly narrower[10]. Moreover, the posterior distributions are not centred around the true value of the parameter. This means that caution should be shown, as relatively small movements of the posterior distribution in comparison to the prior distribution can just be a product of chance instead of indications about the true values of the parameters.

When estimating different sets of parameters the results are mixed. In this case, the parameter of the response to inflation is estimated and the response to the output gap is assumed to be 0. We see in Figure 2 that this dramatically changes the result of the estimations. So omitting the estimation of one of the variables leads to dramatically different posterior distributions for at least three of the models (ST13, GLSV07 and BGUS10). For these models there is practically no overlap between the posterior distribution and the value used in the simulation. This is an unfortunate, but still expected result, which echoes Cochrane (2011) who points out that regressions would just recover a value which can be some function of more than one structural parameters of the data generating process. Similarly to this conclusion, it is natural that an estimation of the wrong specification for monetary policy would introduce bias to the remaining estimated parameters and this bias is clearly a function of other parameters in the model.

The situation is a bit better in the following estimations. Figure 3 shows an estimation where there is the same omitted estimated parameter as before but there are extra redundant estimated parameters, namely the parameters governing the response of monetary policy to the lags of inflation. Interestingly, the redundant estimated parameters seem to improve the accuracy of the posterior distributions with respect to the parameter governing the response of monetary policy to inflation. Now only one (BGUS10) out of the posterior distributions shows no overlap with the true parameter value. Furthermore, only two cases (ST13 and BGUS10) show significant non-zero estimates for the parameters on some of the lags of inflation.

[10] At this point it is worth noting that all graphs that are presented in the appendix have the same size for the y-axis regardless of the height of the posterior distribution. I made this choice in order to improve comparability across the different estimations. In addition, even if the posterior distribution is not completely shown in the figures their shape and characteristics are still clear.

Lastly, in Figure 4 both coefficients on inflation and the output gap are estimated, but other redundant parameters are also estimated, namely the coefficients on the lags of the output gap. In this case the posterior distributions for the two original parameters show good results and they always overlap with the true values of the parameters. Furthermore, the coefficients on the lags of the output gap are not significantly different from 0 with the possible exception of ST13 which shows a somewhat erratic behaviour. It is reasonable that these estimations would perform better as there are no estimated parameters missing and only parameters are added whose prior is centred at 0.

As a variant of the estimation in Figure 1, I estimate the same parameters but with different prior means (5.2.1). The results of the first series of estimations are quite positive. By varying the prior mean that I attach to the coefficient on inflation it is clear that the data seem to prefer a value around 2, which is the value used in the simulations. For example in Figure 7, the prior mean that I have used is 1.4 instead of 2. For all estimated models the posterior distribution is centred at a value larger than 1.4. Interestingly, the distance that the posterior distributions cover varies rather smoothly for different models. So, RW97 is the closest to the prior distribution and it has a posterior distribution centred close to 1.5, while IR04, which exhibits the largest movement, has a posterior distribution centred close to 2 and the other models are located somewhere in between. In Figure 8 where the prior mean is equal to 1.7 we get a very similar situation, but now the posterior distributions are all centred to the right of 1.7, as expected. Then in Figure 9 we get a picture which is very similar to the estimation shown in Figure 1, and all posterior distributions are centred around 2. This is of course expected as the estimations shown in Figure 9 are exactly the same as the ones shown in Figure 1, I repeat the estimation and show it in a separate graph for ease of comparability between the estimations[11]. Going on to the next two Figures, 10 and 11, there is an analogous situation as before. Now the posterior distributions are centred around values at least as large as 2 and lower than 2.3 and 2.6 respectively, as expected given the prior means that correspond to each graph. It is interesting to note that in Figure 11 the estimation of BGUS10 shows a posterior distribution for the coefficient on the output gap that is significantly different from 0.5 which is the true value. This would be surprising if the posterior distribution of the coefficient on inflation overlapped with the true value in the simulations, which is 2. However, this is not the case. Even though the posterior distribution in this case has been shifted away from 2.6 towards the true value of 2, it is actually

[11]Dynare uses by default a specific seed to draw the random draws for the Bayesian estimation. The reason that results shown in the two graphs are not exactly the same should be because I have repeated the estimation with a different number of draws.

centred around 2.3 and the posterior distribution does not show significant overlap with the true value. Other than this exception, the posteriors on the coefficient on the output gap do not show substantial variation when the prior means of the other parameter vary.

The results of the second series of estimations are quite similar as before. In this case I vary the prior mean of the coefficient on the output gap. In Figures 13 to 16 the posterior distributions are always centred in between the prior mean and the true value, which in this case is 0.5. This is actually true for the estimations shown in Figure 12 also. However, in this case the prior mean (i.e. -0.2) seems to be too far away removed from the true value and some of the models' estimations show erratic behaviour.

6.2 Simulations: Data simulated based on the Rotemberg and Woodford (1997) model

Next, I provide comments on the simulations that I performed based on data that were simulated using the Rotemberg and Woodford (1997) model. The monetary policy that I coupled the model with operates according to the first type of estimation (Equation 1) that I described above with a value of 2 and 0.5 for α and β respectively. In these estimations I am also estimating the variance of the shocks for each model. This I did not deem necessary when estimating the models based on the native simulations.

Firstly, I performed the same basic four types of estimations as above. Immediately there is a clear difference. In Figure 17 the correct prior specification for monetary policy is used. Clearly RW97, which is the model used in the simulation, can accommodate the simulated data[12]. Only one other model seems to be recovering the true parameters of monetary policy (ST13). In all other cases, the posterior distributions are significantly removed from the true values and in two cases (IR04 and GLSV07) the models seem to not be able to accommodate the data. Interestingly, in all cases the posterior distributions seem to be centred around values which are smaller than 2 and 0.5 for the two estimated coefficients respectively. In general, it is important to note that model misspecification seems to be a real problem if one wants to estimate the coefficients of the monetary policy rule. This of course is not surprising, but it shows that one should be extremely cautious when estimating such parameters assuming a specific model. In addition, this indicates that maybe we should not expect the models to agree in the posterior distributions that they produce when they are estimated based

[12] I say that a model cannot accommodate the data when the posterior distributions of the estimated parameters seem to be cramped at the limits that the prior distribution allows.

on the same data.

In Figure 18 the coefficient on the output gap is not estimated. Here, we see a similar picture compared to the previous figure, but RW97 is also not able to recover the true value for one of the coefficients. Now that the monetary policy rule being estimated is effectively misspecified the results of the estimations do not show a significant difference in comparison to the case where the data are simulated by the same model being estimated. The models in this estimations seem able to accommodate the data but most are unable to produce posteriors that are consistent with the true value of the coefficient on inflation. Similar comments can be made for the following results shown in Figures 19 to 22. Next, in Figures 23 to 28 I repeat the same estimations, but now the standard deviation of the coefficients being estimated is doubled. The results are similar to before in terms of their general qualitative characteristics, but also somewhat similar in terms of specific results. So, we see that the results in Figure 23 are similar to the results in Figure 17 with respect to the tendencies that the posterior distributions of each model exhibit, but the values around which the posterior distributions are centred, are still not the same. Thus, it is clear that the prior distribution with the lower variance seems to be restricting the posterior distributions relatively more. On the other hand the similar tendencies that are exhibited by the posterior distribution by inspection indicate that the estimations' results are robust to small changes in the choice of the prior variance. Finally, we see that the prior variance determines to a great extent the size of the posterior variance. However, this exercise shows that the strength of this effect is not invariant to the size of the initial prior variance. Thus, as is natural we see that when the prior variance is higher, the posterior distribution becomes significantly narrower compared to the baseline case where prior variance is low.

Next, I perform the exercise of varying the prior means as I did before, given the correct specification of monetary policy being estimated. Figures 29 to 33 and Figures 34 to 38 contain the results of this exercise with respect to the coefficient on inflation and the output gap respectively. Here, there are no smooth results as before. The posterior distributions of the different estimations do not all uniformly point to the same direction as before. Hence, this exercise does not point to any value for the coefficients.

6.3 Real Data

At this point I comment on the results of the main estimations which are performed with real data. In Figure 39 I perform the first type of estimation. Already, two estimations are not feasible (BGUS10 and ST13). The posterior distributions of the coefficient on inflation show some overlap but in general do not point towards the same value. On the contrary, the posterior distributions of the coefficient on the output gap for all models seems very similar and centred between 0.4 and 0.5. In addition, I should comment that the posterior variance seems to be very similar to the prior variance for both coefficients.

When only the coefficient on inflation is estimated (Figure 40), the posterior distributions show more agreement. Four out of the five estimations are centred between 1.8 and 2 and they show significant overlap. Only BGUS10 has a posterior distribution with significantly lower values, under 1.6.

When the lags of inflation are also estimated (Figures 41 and 42) the posterior distributions on the coefficient on inflation contemporaneously still show significant overlap. Now, BGUS10 is also much closer to the other posterior distributions. However, the posterior distributions of the coefficients on the lags of inflation are never and for no model significantly different from zero. This does not necessarily imply that the lags of inflation are not taken into account by monetary policy, but it is an indication that based on such models and the length of the time series used we are not likely to identify the number of lags that the monetary authority responds to.

Next, I estimate the coefficients on the lags of the output gap, while still estimating the coefficients on inflation and the output gap contemporaneously (Figures 43 to 44). The posteriors on inflation are centred around 1.8 to 2; the posteriors on the output gap are even more similar, all ranging between 0.4 and 0.5, apart from BGUS10 which is a bit lower. Interestingly, when looking at the posterior distributions on the lags of the output gap, in all cases the posterior distributions tend to be negative. This is significant for very few models, but the tendency is clear.

Next, I perform the same estimations again, once for each of the four types of estimations, but now I have varied the prior mean of one or more of the estimated parameters. In Figure 45 I have varied the prior mean of the coefficient on the output gap to 0.7. The posterior distributions of the coefficient on inflation are almost identical to the basic estimations shown in Figure 39. In addition, the posterior distributions of the coefficient on the output gap also show a very similar behaviour. However, here again the prior is also playing a role and even though the posteriors have in both cases a tendency to move to the left, they still cover similar distance and, thus, the estimation with the higher prior has a higher posterior. In Figure 46 only the coefficient on inflation is estimated, but now I have used a much higher prior mean than what is normal, namely I have used a value of 4. In this case, three out of the six models (IR04, BGUS10 and GLSV07) cannot accommodate the data, while the three remaining ones show normal behaviour; the posterior distributions are significantly higher than the basic estimation (Figure 40), but they show a decreasing tendency compared to the prior. In Figures 47 and 48 I estimate the coefficients on inflation and the lags of inflation. I only vary the prior means that I use on the lags of inflation, to 0.4, 0.3, 0.2 and 0.1 for each of the four lags of inflation respectively. The results are consistent with the basic estimation (Figures 41 and 42). In all cases the posterior distributions tend to move towards 0, even if in some cases the movement is not much compared to the prior. In Figures 49 and 50 the coefficients on the lags of the output gap are estimated in addition to the coefficients on inflation and the output gap contemporaneously. Here I have varied the prior means to 0.3, 0.2, 0.1 and 0.1 of the coefficients on output gap contemporaneously and on the lags up to order 3 respectively, while leaving the prior of the coefficient on the lag of inflation of order 4 unchanged. Thus, I have decreased the prior for the contemporaneous coefficient and increased for the three lags. As is natural, the resulting posteriors are more positive than the basic case (Figures 43 and 44), but one can still see a tendency for these posteriors to occupy the negative domain.

In the next variation I double the standard deviation of the prior distributions for the coefficients of monetary policy being estimated. Here the results are not that encouraging. For instance in Figure 51, some of the models behave in a similar way compared to the basic estimation (39). However there are also considerable differences. Most notably, the posterior distributions of the coefficient on the output gap are not as uniform as they were in the basic estimation; the same is true for the coefficient on inflation. Unfortunately, this part shows that the estimations are not very robust under variations of the prior variance. The same comments can be made about the following estimations where the prior variance is higher. I should point out that here also, as can be seen in Figures 53 and 54, posteriors on the coefficients on the lags of inflation are almost never significantly different from 0. In addition, Figures 55 and 56 still show the tendency of the coefficients on the lags of inflation to be negative and here we also see the unusual shape of the posterior distribution in the case of ST13, which has two peaks. This happens because the draws of the Metropolis-Hastings algorithm were too few and the two chains that are being used have not converged. This highlights the need to always check for the convergence of the MH algorithm, given that the number of necessary draws may differ across models.

Finally, I perform the series of estimations in which I estimate the same coefficients as in the first type of estimation, but I sequentially vary the size of the prior means. This, as mentioned before, seemed to work with the simulated data (Figures 7 to 11 for the coefficient on inflation and Figures 12 to 16 for the coefficient on the output gap). Unfortunately, when using real data the estimations

(Figures 57 to 61 for the coefficient on inflation and Figures 62 to 66 for the coefficient on the output gap) do not seem to clearly point towards some specific values for the two estimated coefficients. For many models the posterior distributions seem to be centred somewhere around the prior distribution without a clear preference for some values when the prior means of the distributions change.

6.4 Real Data: Different subsamples in search of a structural break

Finally, I also perform estimations in which I vary the subsample of the time series. For this exercise I only use the first two types of estimations (according to 5.1) (in the first the coefficients on inflation and the output gap are estimated while in the second only the coefficient on inflation is estimated). In all these estimations we can clearly see that the results are different compared to the main subsample of real data that has been used previously. In many cases the models cannot accommodate the data, estimations are not feasible and in general the estimations exhibit relatively volatile behaviour.

In Figures 67 to 68 I use the subsample that was also used by Smets and Wouters (2007), namely from 1966 to 2004. This is interesting because Smets and Wouters (2007) chose to not use any data before 1966[13]. Their reasoning for this is that the first years were not representative of the rest of the sample. Hence, the following period should exhibit at least some uniformity. However, within this period the structural break in the conduct of monetary policy is supposed to have happened according to large part of the literature. It is clear that the estimations produce very different results compared to the main subsample (Figures 39 and 40). This finding seems to be consistent with the view that there was a break in the conduct of monetary policy. However, this is not necessarily the only explanation for such a result. In the following four figures I perform the same estimations, but in Figures 69 and 70 I use the data from beginning to start, namely from 1947 to 2004, while in Figures 71 and 72 I use the data from 1947 to 1979, the year when the structural break is supposed to have happened. In these figures the models cannot accommodate the data and even the few cases that show reasonable posterior distributions do not show any uniformity with each other. Moreover, they seem even more erratic than the previous estimations. This means that we do not have more indications about the existence of the structural break. It is highly likely that we are seeing the fact pointed out by Smets and Wouters (2007), namely that the data in the beginning behave quite differently than the rest of the sample.

[13] Actually they used the data from 1956 to 1965 to train their sample and used the following data for their estimation. Thus, the data before 1956 they found unsuitable.

7 Conclusion

In conclusion, I should point out that only the estimations that I exhibit in the appendix constitute more than 400 individual estimations of models. At the same time, the variations with respect to priors that I have applied are not very extensive. For example, the monetary policy shock has no autocorrelation in any estimation that I performed. In addition, I did not perform estimations where the interest rate would respond to lags of itself, neither did I add any expected value, of inflation for example, in the monetary policy rule. These are just a few of the standard aspects that monetary policy could entail. Thus, it is clear that the approach that I am taking, apart from being non-rigorous, has obvious practicality concerns, as exploring more variations and also using more models would make even the inspection of the estimations practically impossible.

However, I was still able to draw some conclusions from the exercises that I performed. An important first step is that estimations based on simulated data from the same model can roughly recover the values of the parameters. This sounds trivial, but is not completely so. Certainly it is expected that a correct estimation would be able to identify the true values of the parameters. However, this should be feasible with a certain number of observations and in this case we can see that 100 quarters can provide significant information.

Furthermore, estimating New-Keynesian models based on data simulated from another New-Keynesian model led to posterior distributions that did not capture the true values of the parameters in the monetary policy rule. This is not surprising, but it also means something subtle, namely that monetary policy is coupled with the other varying aspects of the models that I used. It is possible that monetary policy is uncoupled with other aspects of a model. In this case, estimating the monetary policy of any New-Keynesian model using any other New-Keynesian model would produce the same results. Clearly, this is not the case in the exercises that I performed. This could also be proven theoretically by examining the dynamics of the models, but it is still a notable result that can be seen through the estimations.

Moreover, the estimations based on real data or even the ones based on the simulated data from another New-Keynesian model did not in general converge to a single value for the estimated coefficients of the monetary policy rule. Thus, the models are not similar enough for this purpose and if DSGE models are to be used in order to identify the values of the parameters governing monetary policy, then there has to be a preliminary step, in which the suitable DSGE models for this task will have to be chosen. Despite this, in general, negative conclusion about the effectiveness of the estimations, there is at least one positive result. The estimations which included the lags of the output gap showed that monetary policy tends to respond negatively to these lags. This is an interesting idea, even though it could be produced by some other aspect in the real economy that these models are not capturing and not directly by the response of monetary policy to the lags of the output gap.

Finally, by using different subsamples of the data I was able to see that estimations perform much differently. My goal was to evaluate the claim of a structural break in the conduct of monetary policy after the 80s. If the estimations produced exactly the same results independently of the sample used then this would be a strong argument against the existence of a break. However, the erratic results that appear for the different samples may not prove but are certainly consistent with the existence of such a break.

8 Appendix

8.1 Based on data simulated for each model separately

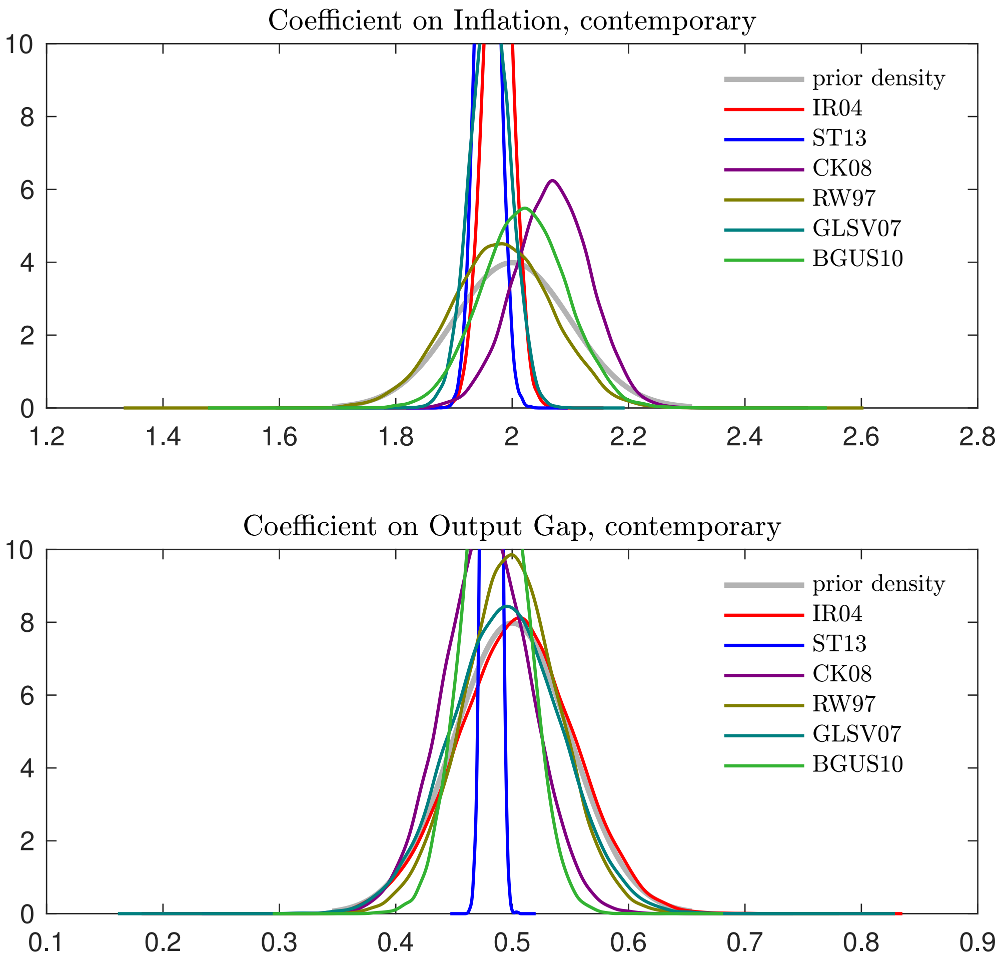


Figure 1: Prior distribution and posterior distribution for each model – In this subsection the estimations presented were produced with simulated data. I simulated 104 observations for each model. The monetary policy that I used has a response to inflation and output gap, with coefficients 2 and 0.5 respectively. For each model I used the same data for all estimations shown in this subsection, namely for all the different choices of priors that I conducted. In this figure the prior means and the estimated coefficients correspond to the true model used for the simulation.

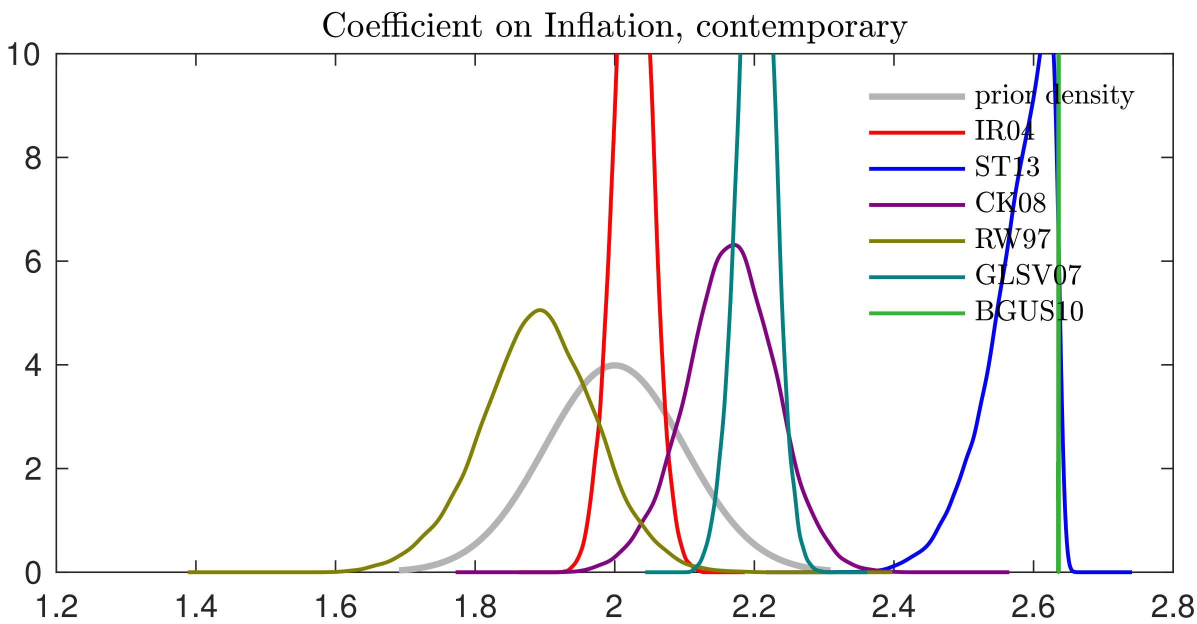


Figure 2: Prior distribution and posterior distribution for each model – In this subsection the estimations presented were produced with simulated data. In this figure I only estimate the coefficient on inflation and I use a prior mean which equals the value of the parameter in the simulation. I remind the reader that in the simulation monetary policy also responded to the output gap.

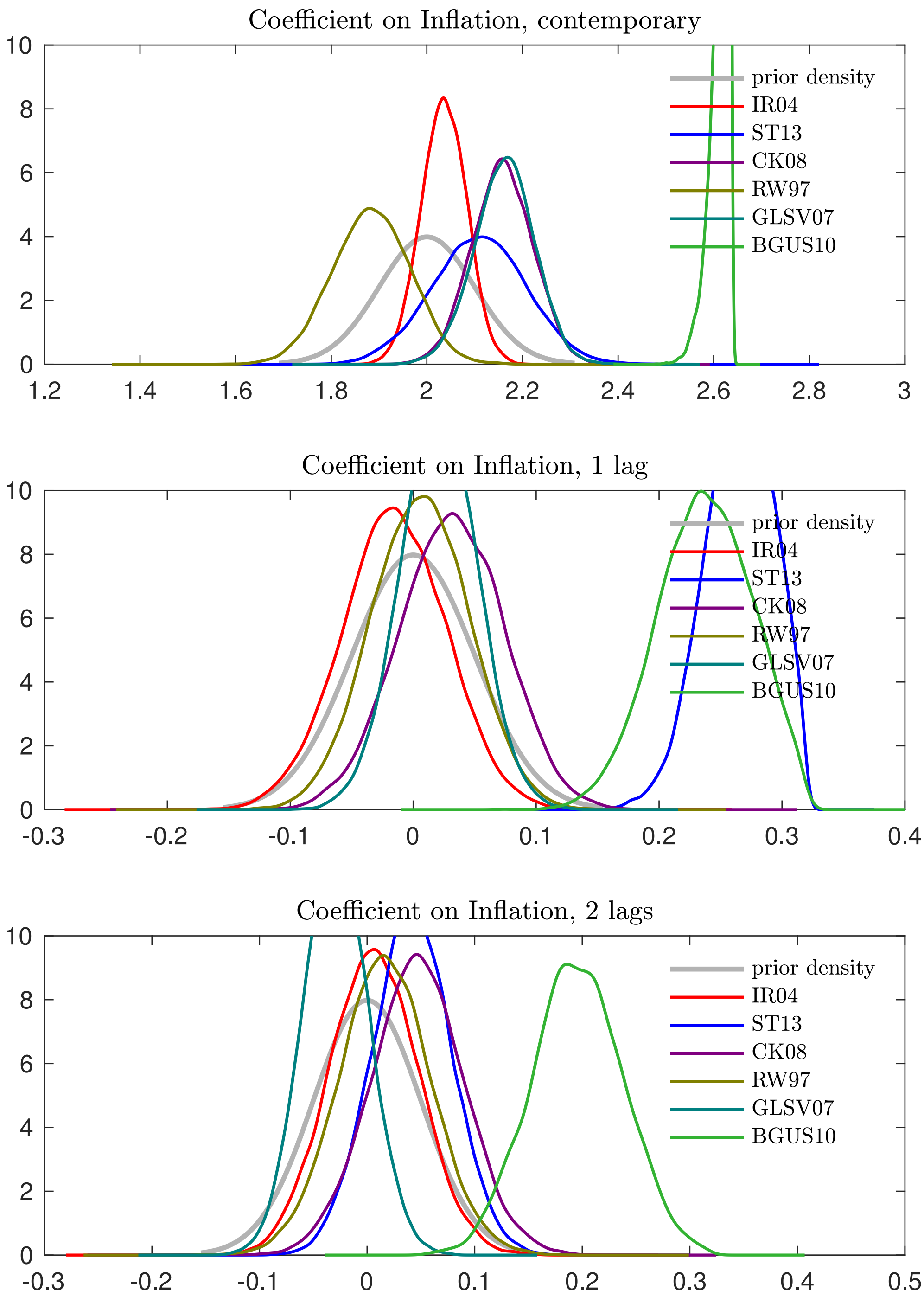


Figure 3: Prior distribution and posterior distribution for each model – In this subsection the estimations presented were produced with simulated data. In this and the following figure I estimate the coefficient on inflation and the coefficients on the lags of inflation. I use a prior mean for the response to inflation contemporaneously which equals the value of the parameter in the simulation. I remind the reader that in the simulation monetary policy did not respond to the lags of inflation, but did respond to the output gap.

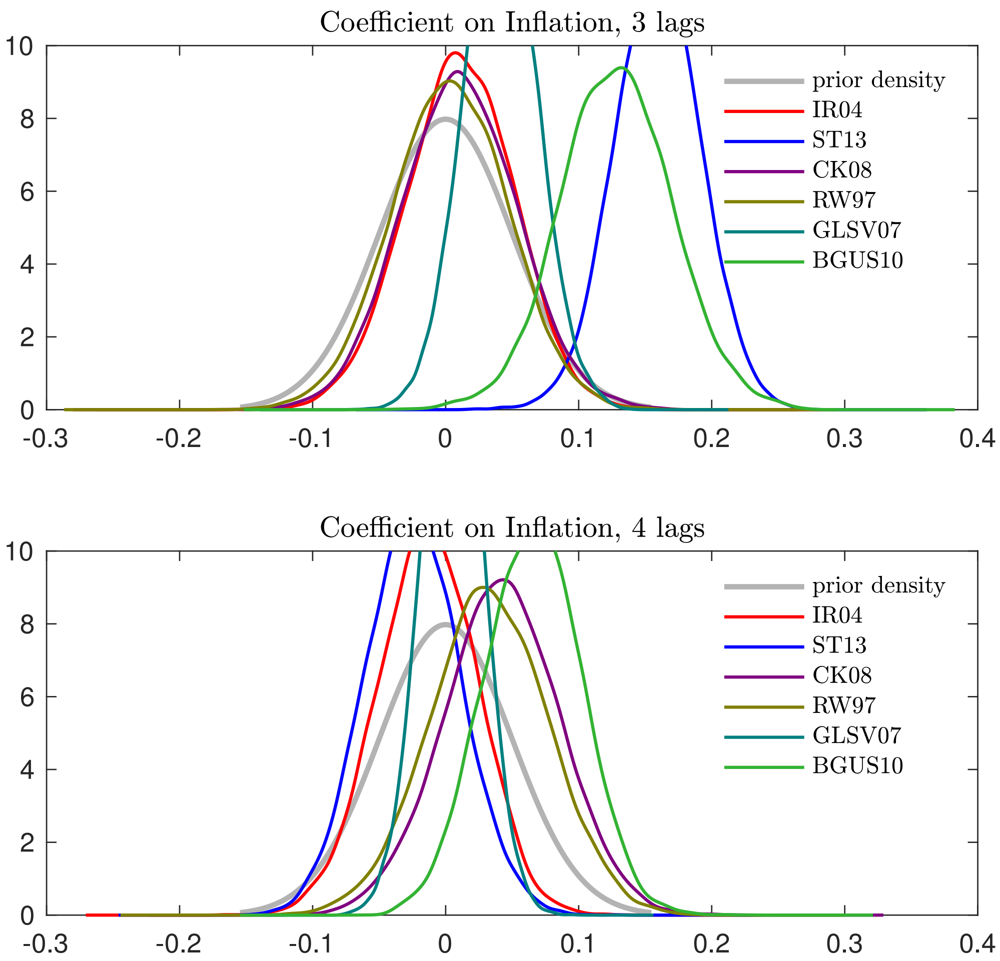


Figure 4: Prior distribution and posterior distribution for each model – In this subsection the estimations presented were produced with simulated data. In this and the previous figure I estimate the coefficient on inflation and the coefficients on the lags of inflation. I use a prior mean for the response to inflation contemporaneously which equals value of the parameter in the simulation. I remind the reader that in the simulation monetary policy did not respond to the lags of inflation, but did respond to the output gap.

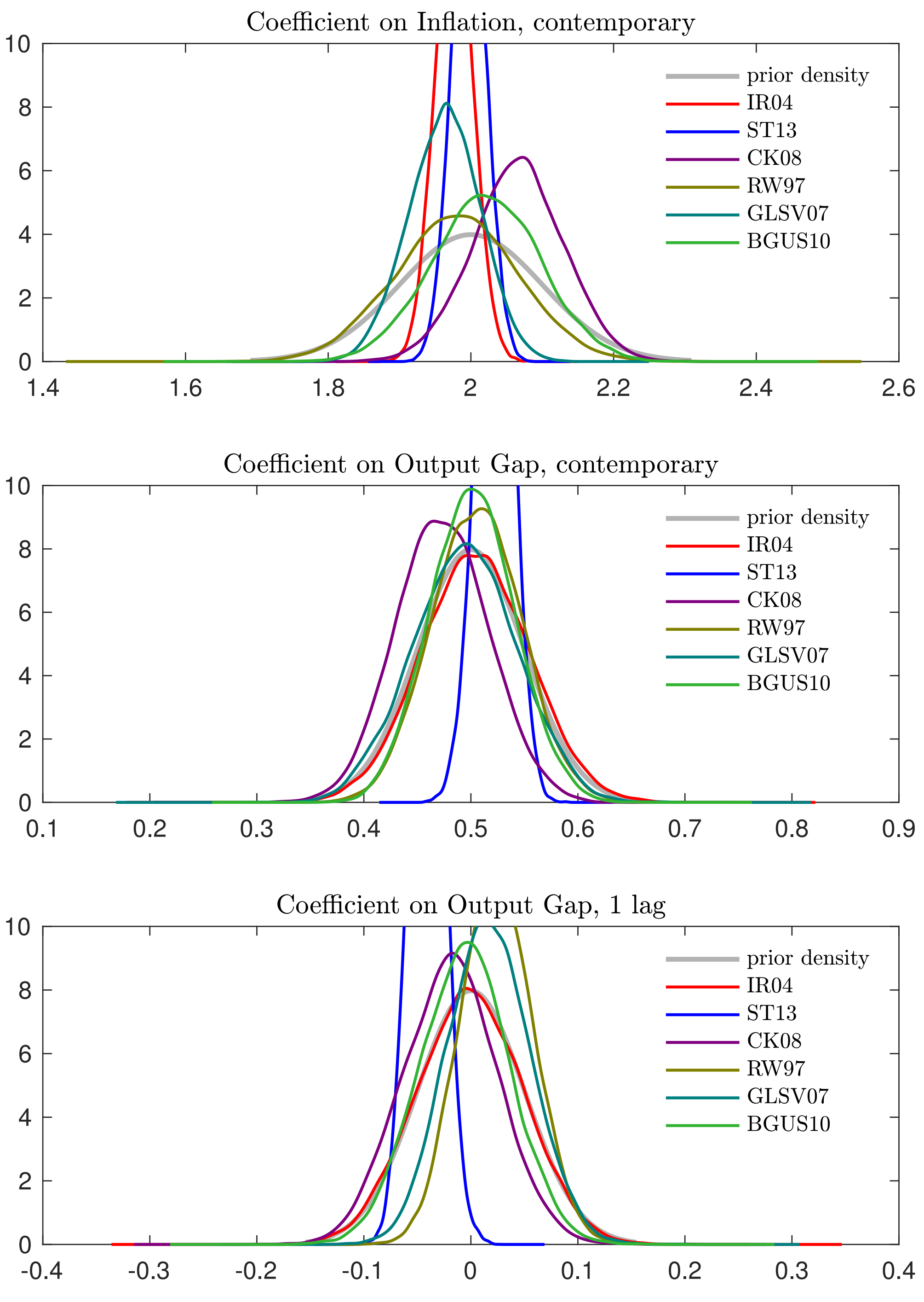


Figure 5: Prior distribution and posterior distribution for each model – In this subsection the estimations presented were produced with simulated data. In this and the following figure I estimate the coefficients on inflation, on the output gap and the lags of the output gap. I use a prior mean for the response to inflation and to the output gap contemporaneously which equal the values of the parameters in the simulation. I remind the reader that in the simulation monetary policy did not respond to the lags of the output gap.

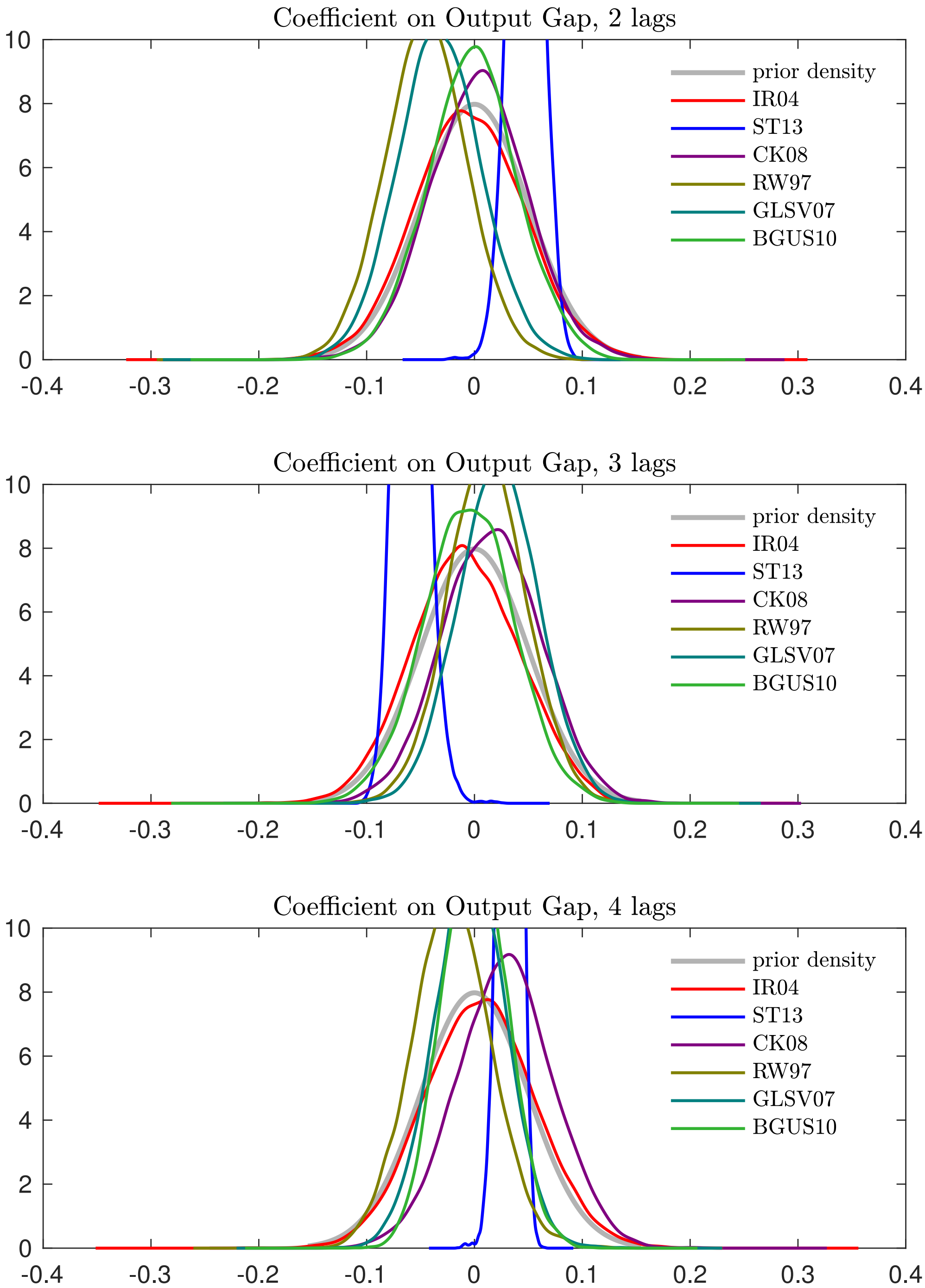


Figure 6: Prior distribution and posterior distribution for each model – In this subsection the estimations presented were produced with simulated data. In this and the previous figure I estimate the coefficients on inflation, on the output gap and the lags of the output gap. I use a prior mean for the response to inflation and to the output gap contemporaneously which equal the values of the parameters in the simulation. I remind the reader that in the simulation monetary policy did not respond to the lags of the output gap.

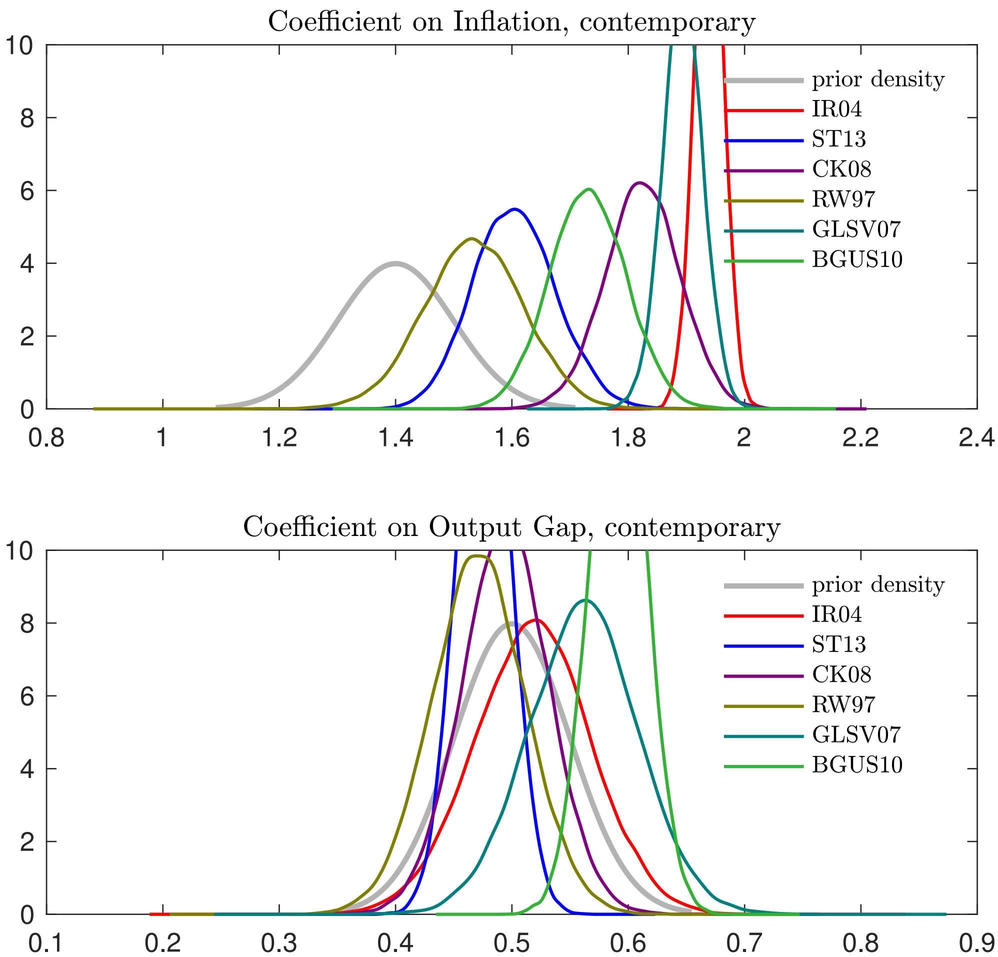


Figure 7: Prior distribution and posterior distribution for each model – In Figures 7 to 16 I perform a series of estimations which are the most clear example of the naive approach mentioned in the paper. Here I estimate those coefficients that are non zero in the simulation, the coefficient on inflation and the coefficient on the output gap. In Figures 7 to 11 I vary the prior mean of the coefficient on inflation. The prior mean then varies from 1.4 to 2.6, while 2 was the value used in the simulation.

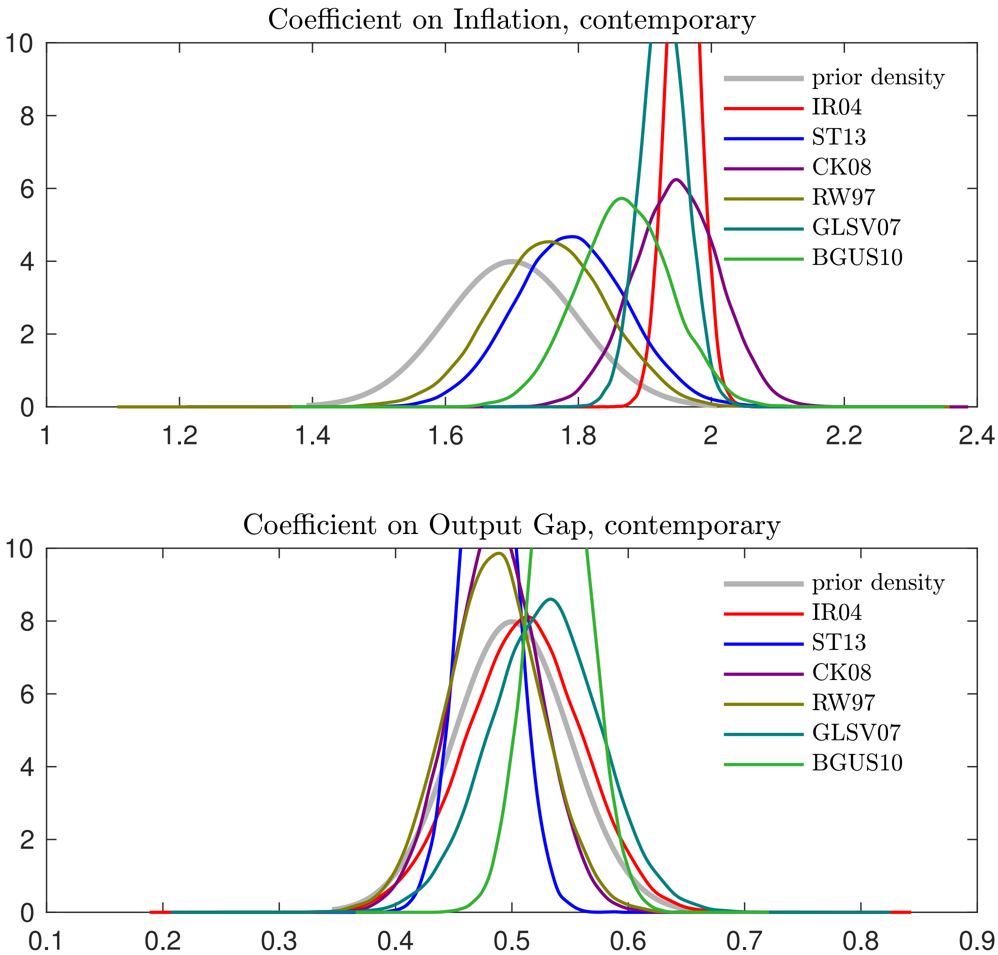


Figure 8: Prior distribution and posterior distribution for each model – In Figures 7 to 16 I perform a series of estimations which are the most clear example of the naive approach mentioned in the paper. Here I estimate those coefficients that are non zero in the simulation, the coefficient on inflation and the coefficient on the output gap. In Figures 7 to 11 I vary the prior mean of the coefficient on inflation. The prior mean then varies from 1.4 to 2.6, while 2 was the value used in the simulation.

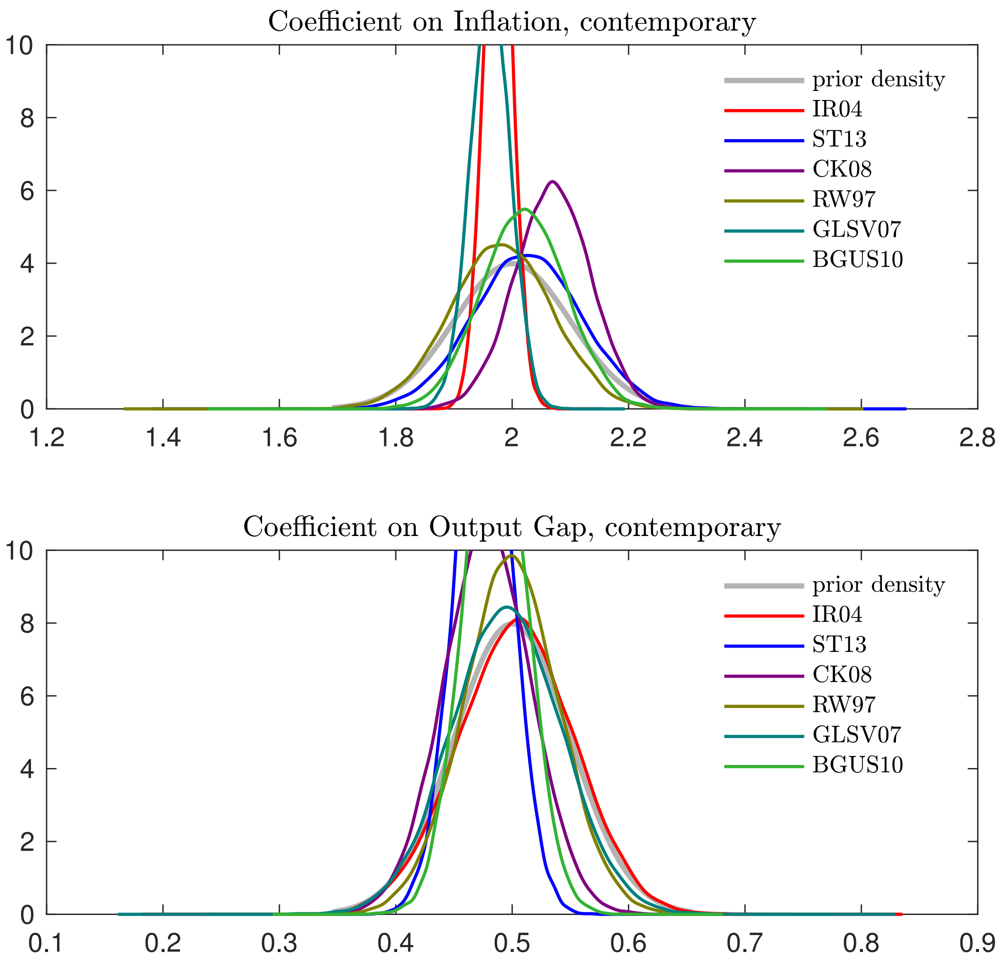
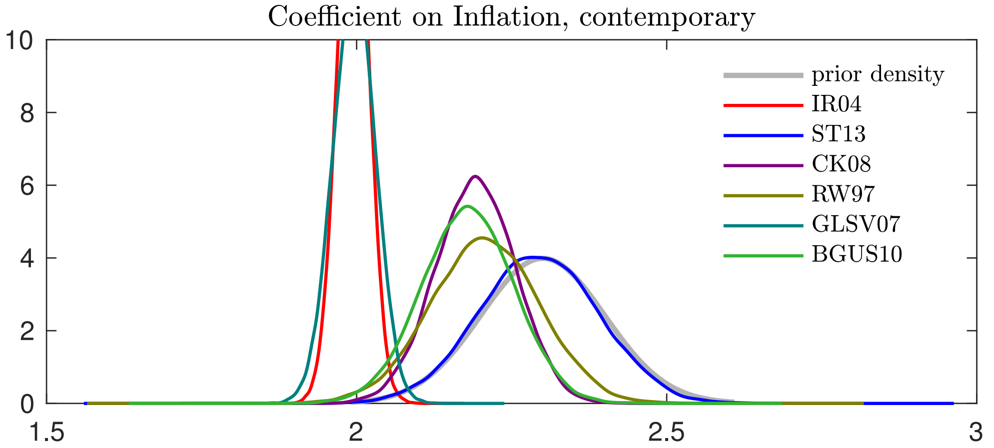


Figure 9: Prior distribution and posterior distribution for each model – In Figures 7 to 16 I perform a series of estimations which are the most clear example of the naive approach mentioned in the paper. Here I estimate those coefficients that are non zero in the simulation, the coefficient on inflation and the coefficient on the output gap. In Figures 7 to 11 I vary the prior mean of the coefficient on inflation. The prior mean then varies from 1.4 to 2.6, while 2 was the value used in the simulation.



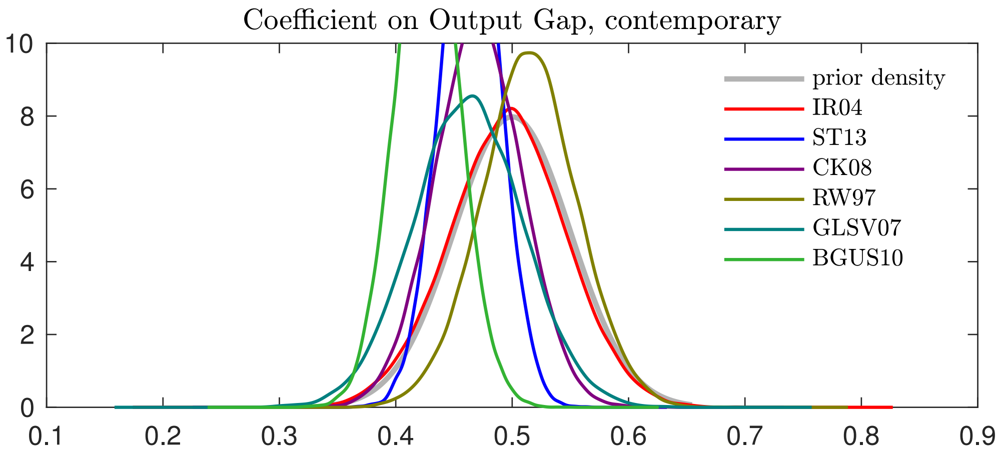


Figure 10: Prior distribution and posterior distribution for each model – In Figures 7 to 16 I perform a series of estimations which are the most clear example of the naive approach mentioned in the paper. Here I estimate those coefficients that are non zero in the simulation, the coefficient on inflation and the coefficient on the output gap. In Figures 7 to 11 I vary the prior mean of the coefficient on inflation. The prior mean then varies from 1.4 to 2.6, while 2 was the value used in the simulation.

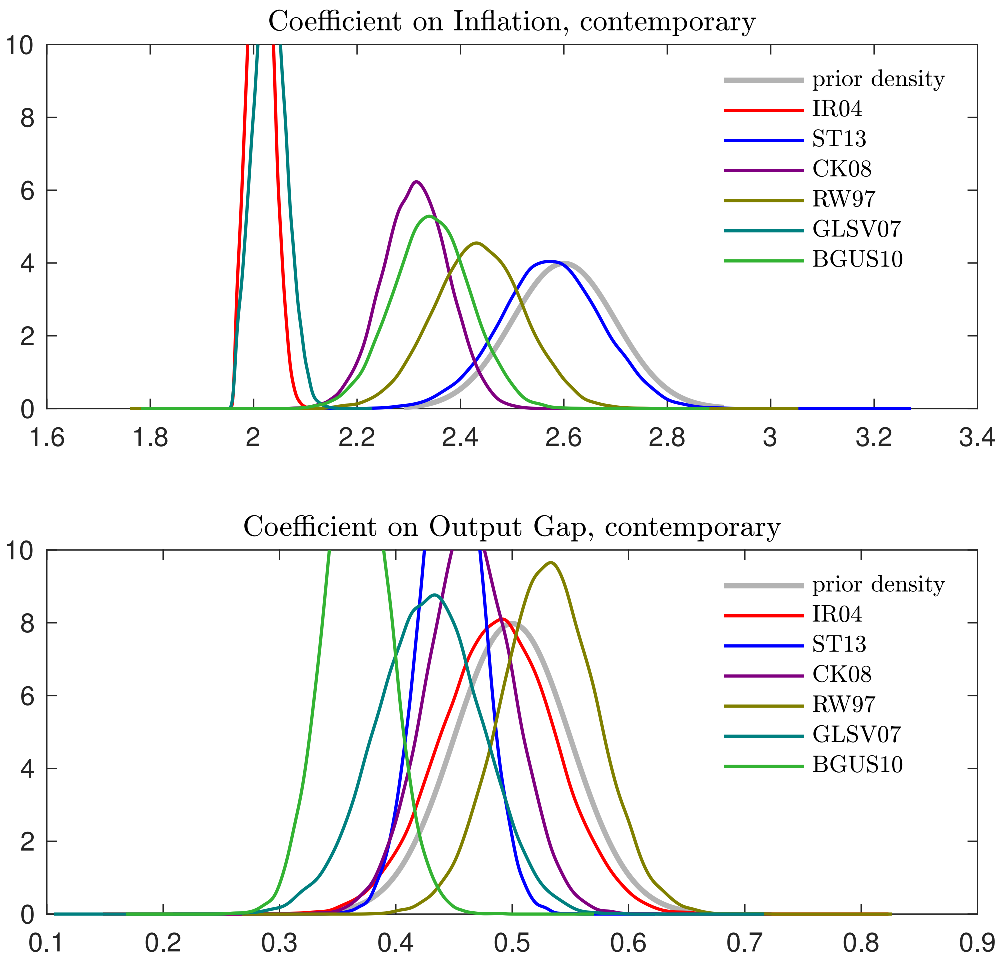


Figure 11: Prior distribution and posterior distribution for each model – In Figures 7 to 16 I perform a series of estimations which are the most clear example of the naive approach mentioned in the paper. Here I estimate those coefficients that are non zero in the simulation, the coefficient on inflation and the coefficient on the output gap. In Figures 7 to 11 I vary the prior mean of the coefficient on inflation. The prior mean then varies from 1.4 to 2.6, while 2 was the value used in the simulation.

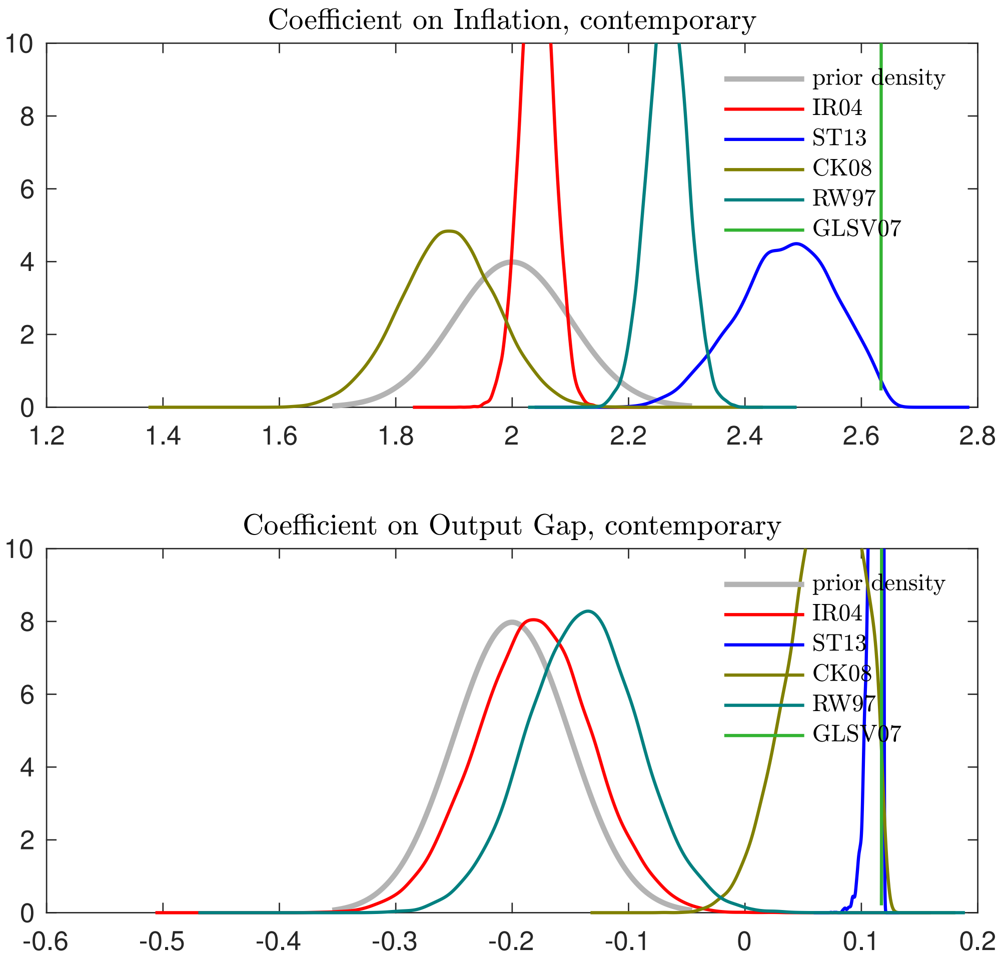


Figure 12: Prior distribution and posterior distribution for each model – In Figures 7 to 16 I perform a series of estimations which are the most clear example of the naive approach mentioned in the paper. Here I estimate those coefficients that are non zero in the simulation, the coefficient on inflation and the coefficient on the output gap. In Figures 12 to 16 I vary the prior mean of the coefficient on the output gap. The prior mean then varies from -0.2 to 0.6, while 0.5 was the value used in the simulation.

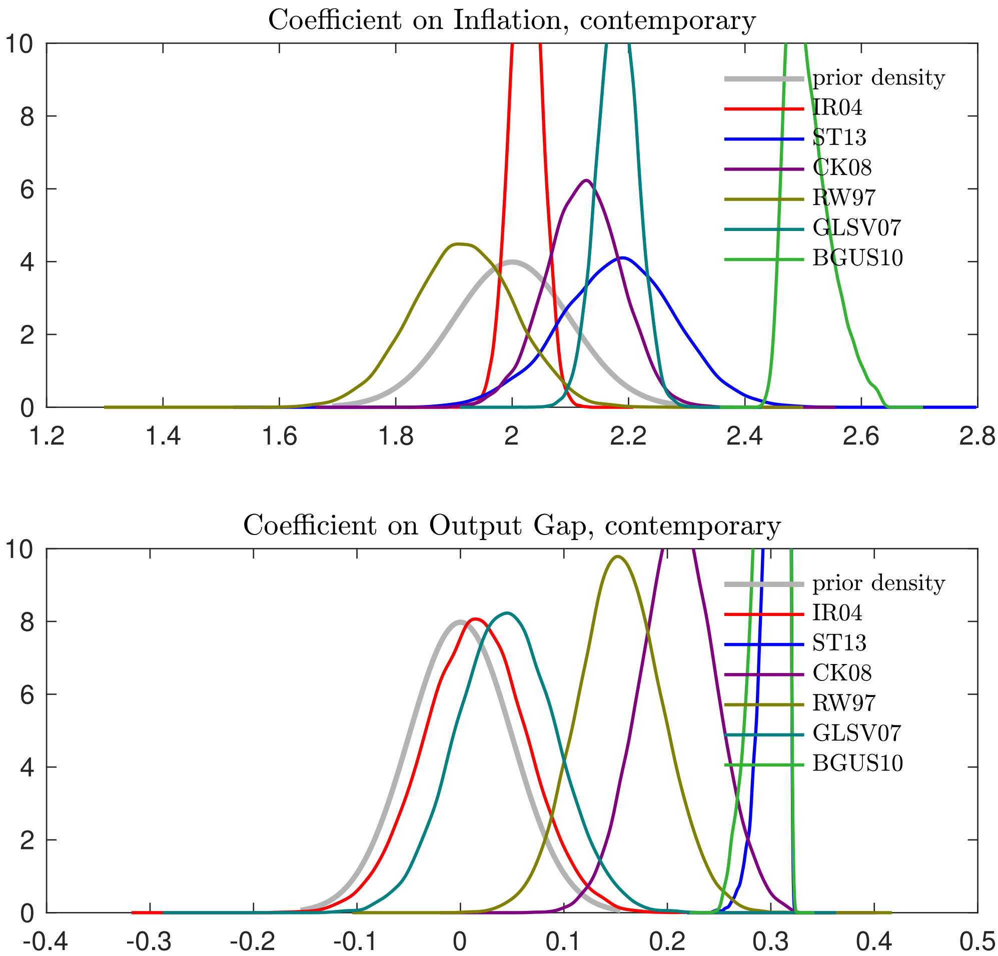


Figure 13: Prior distribution and posterior distribution for each model – In Figures 7 to 16 I perform a series of estimations which are the most clear example of the naive approach mentioned in the paper. Here I estimate those coefficients that are non zero in the simulation, the coefficient on inflation and the coefficient on the output gap. In Figures 12 to 16 I vary the prior mean of the coefficient on the output gap. The prior mean then varies from -0.2 to 0.6, while 0.5 was the value used in the simulation.

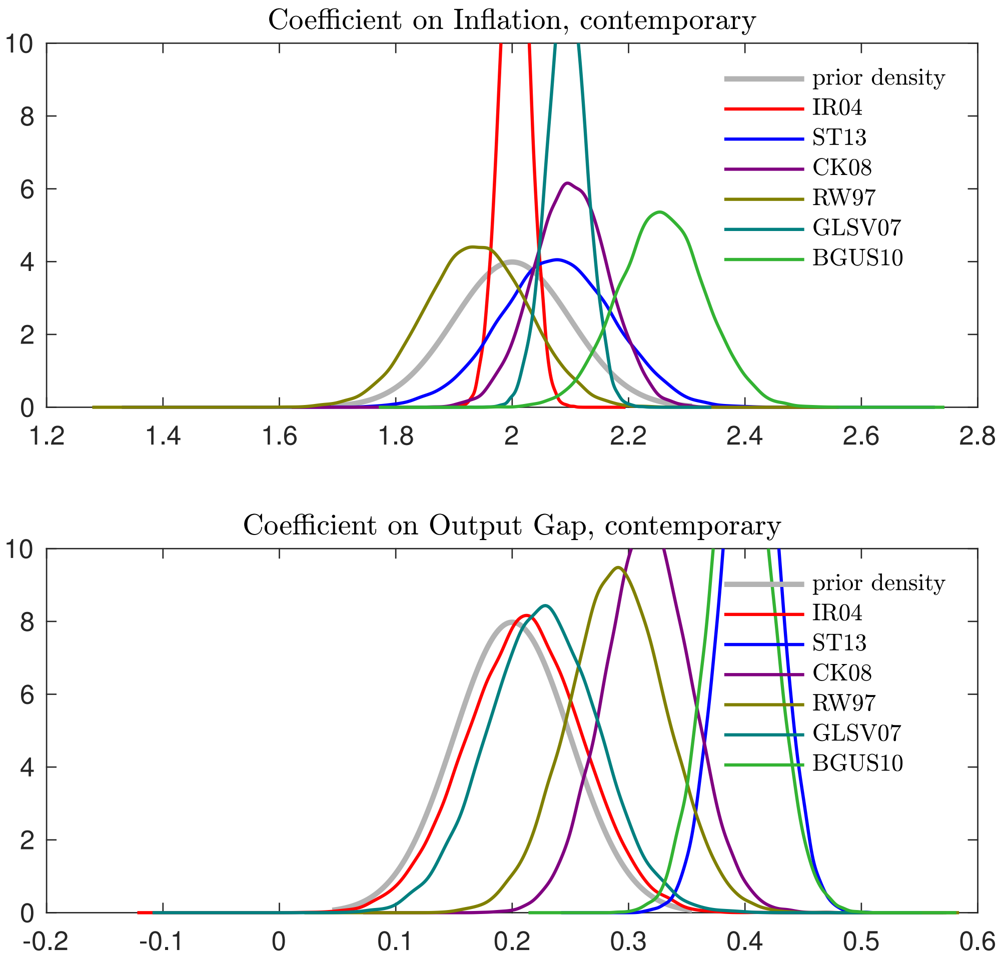


Figure 14: Prior distribution and posterior distribution for each model – In Figures 7 to 16 I perform a series of estimations which are the most clear example of the naive approach mentioned in the paper. Here I estimate those coefficients that are non zero in the simulation, the coefficient on inflation and the coefficient on the output gap. In Figures 12 to 16 I vary the prior mean of the coefficient on the output gap. The prior mean then varies from -0.2 to 0.6, while 0.5 was the value used in the simulation.

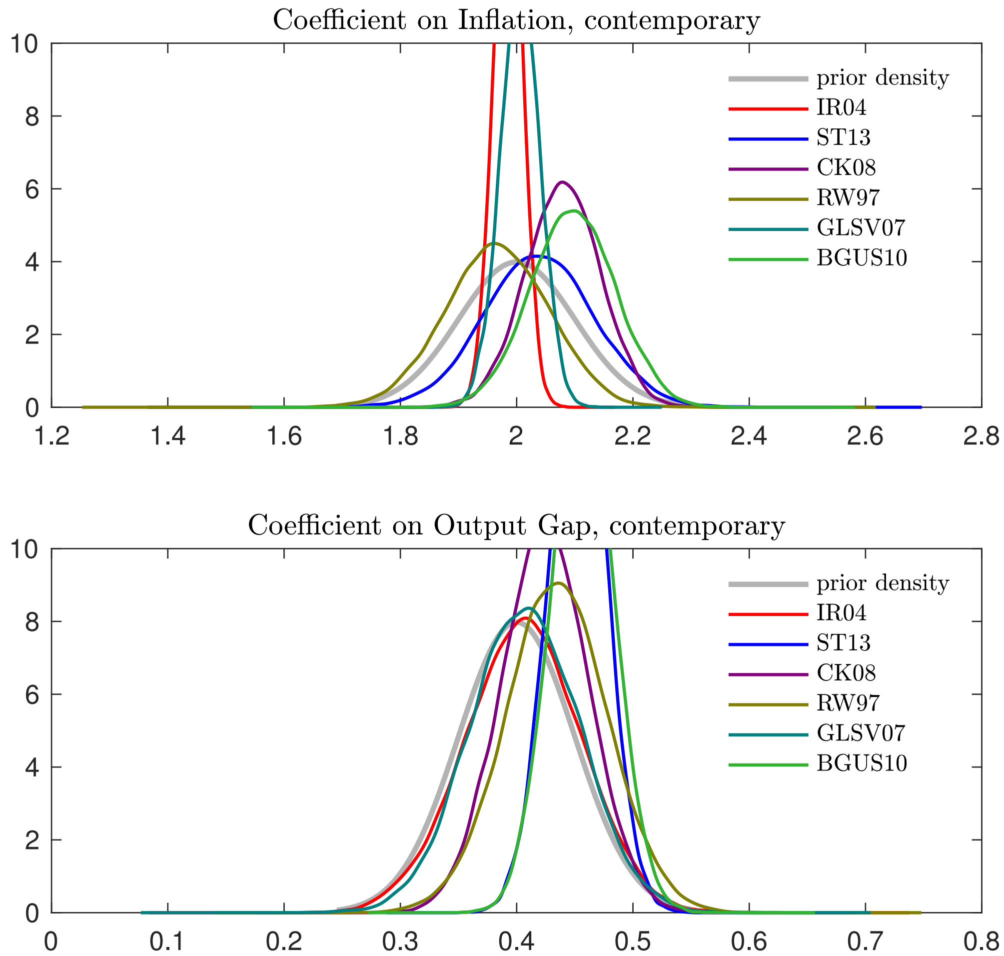


Figure 15: Prior distribution and posterior distribution for each model – In Figures 7 to 16 I perform a series of estimations which are the most clear example of the naive approach mentioned in the paper. Here I estimate those coefficients that are non zero in the simulation, the coefficient on inflation and the coefficient on the output gap. In Figures 12 to 16 I vary the prior mean of the coefficient on the output gap. The prior mean then varies from -0.2 to 0.6, while 0.5 was the value used in the simulation.

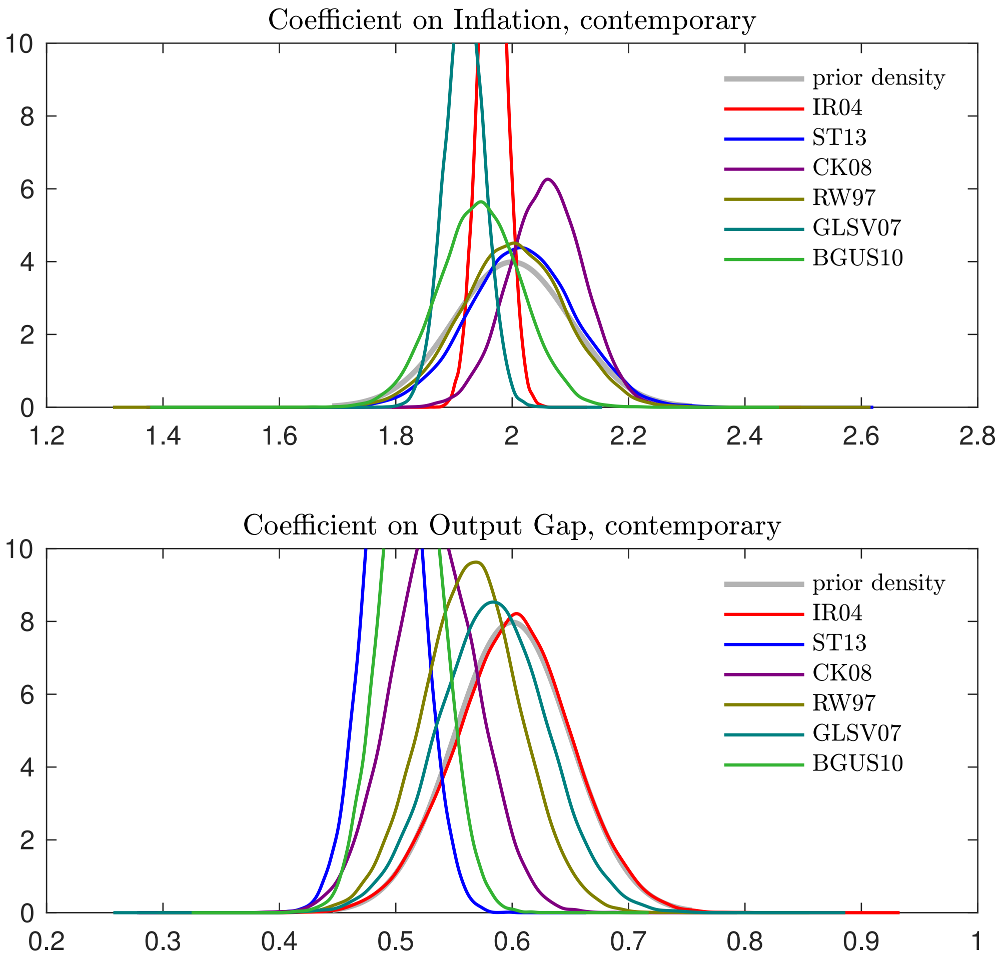


Figure 16: Prior distribution and posterior distribution for each model – In Figures 7 to 16 I perform a series of estimations which are the most clear example of the naive approach mentioned in the paper. Here I estimate those coefficients that are non zero in the simulation, the coefficient on inflation and the coefficient on the output gap. In Figures 12 to 16 I vary the prior mean of the coefficient on the output gap. The prior mean then varies from -0.2 to 0.6, while 0.5 was the value used in the simulation.

8.2 Based on data simulated from the Rotemberg, Woodford (1997) model

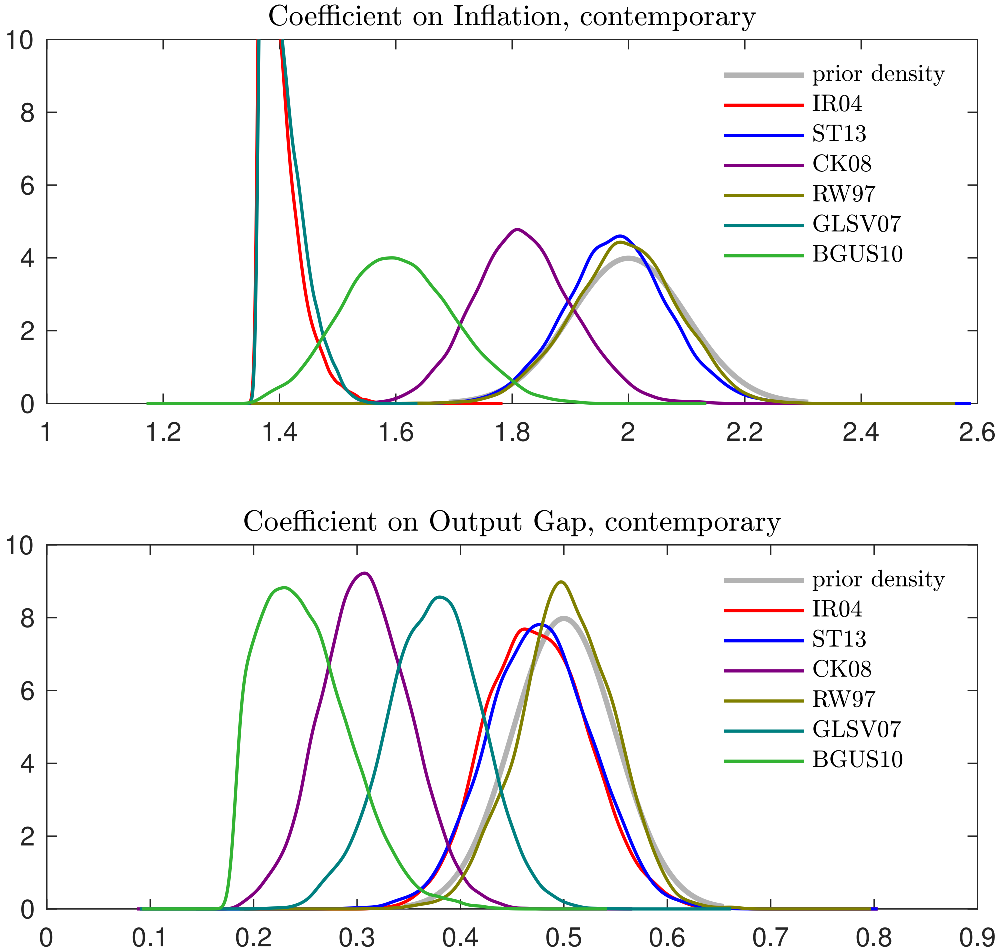


Figure 17: Prior distribution and posterior distribution for each model – In this subsection the estimations presented were produced with simulated data. I simulated 104 observations with the RW97 model. The monetary policy that I used has a response to inflation and output gap, with coefficients 2 and 0.5 respectively. For all models I used the same data for all estimations shown in this subsection, namely for all the different choices of priors that I conducted. Thus, only in the case of RW97 do the simulated data arise from the model that is being estimated. The standard errors of the model shocks are also estimated for each estimation, but they are not presented here. In this figure the prior means and the estimated coefficients correspond to the true model used for the simulation.

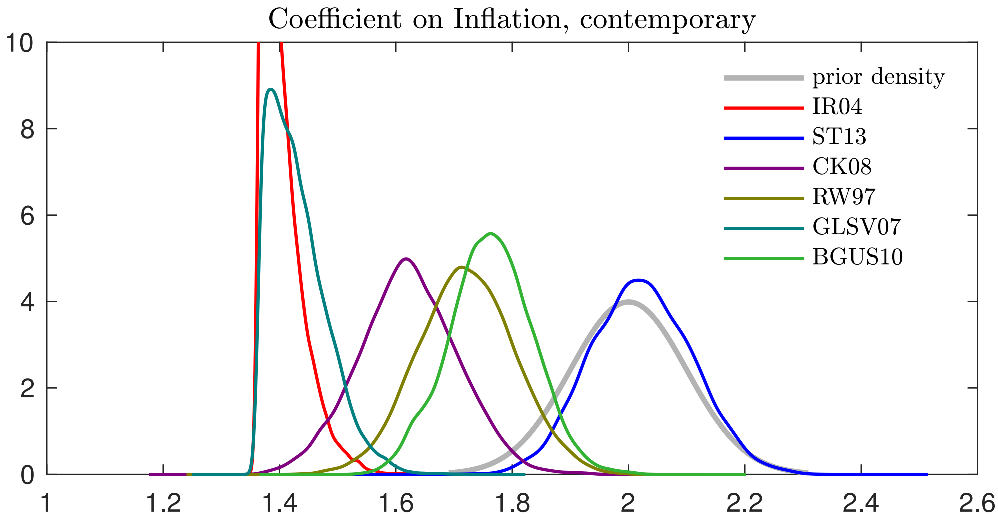


Figure 18: Prior distribution and posterior distribution for each model – In this subsection the estimations presented were produced with simulated data from the RW97 model. In this figure I only estimate the coefficient on inflation and I use a prior mean which equals the value of the parameter in the simulation. I remind the reader that in the simulation monetary policy also responded to the output gap.

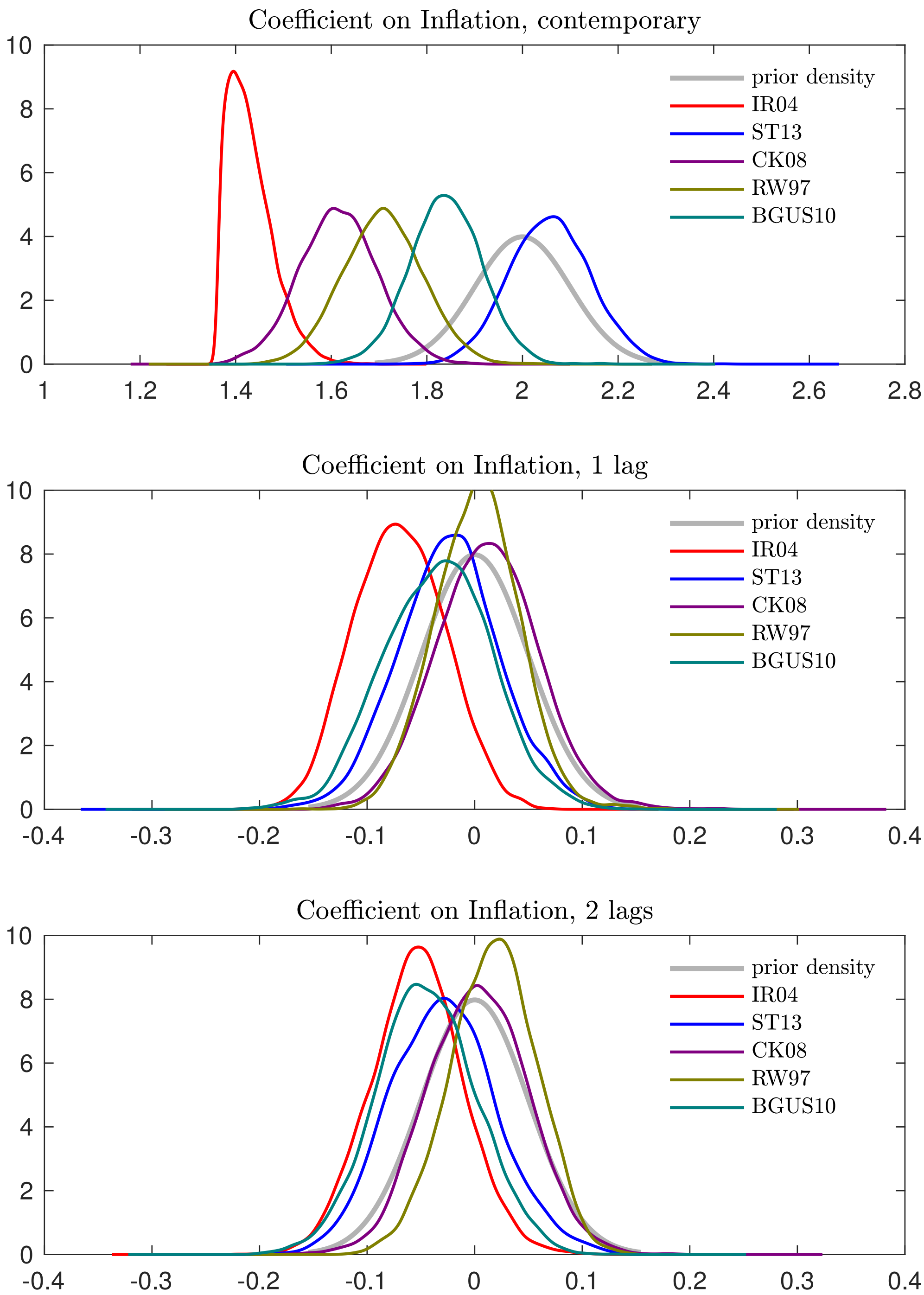


Figure 19: Prior distribution and posterior distribution for each model – In this subsection the estimations presented were produced with simulated data from the RW97 model. In this and the following figure I estimate the coefficient on inflation and the coefficients on the lags of inflation. I use a prior mean for the response to inflation contemporaneously which equals value of the parameter in the simulation. I remind the reader that in the simulation monetary policy did not respond to the lags of inflation, but did respond to the output gap.

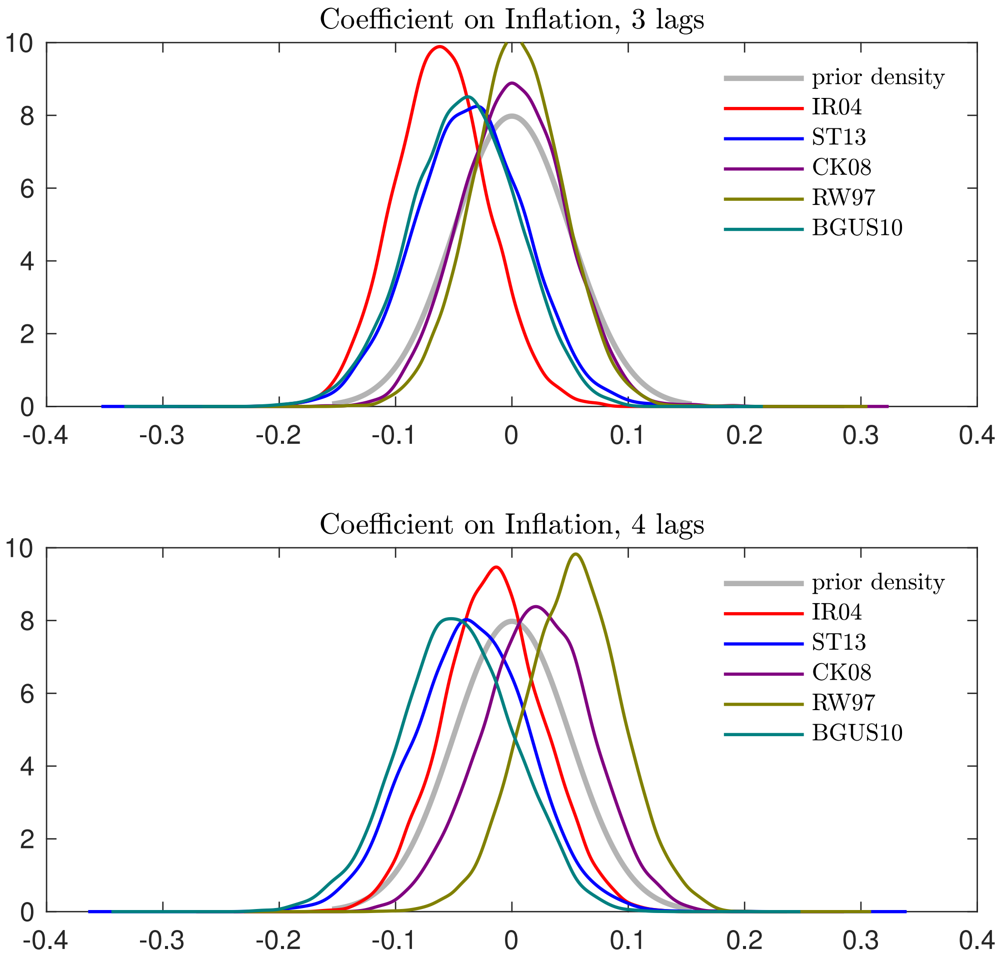


Figure 20: Prior distribution and posterior distribution for each model – In this subsection the estimations presented were produced with simulated data from the RW97 model. In this and the previous figure I estimate the coefficient on inflation and the coefficients on the lags of inflation. I use a prior mean for the response to inflation contemporaneously which equals value of the parameter in the simulation. I remind the reader that in the simulation monetary policy did not respond to the lags of inflation, but did respond to the output gap.

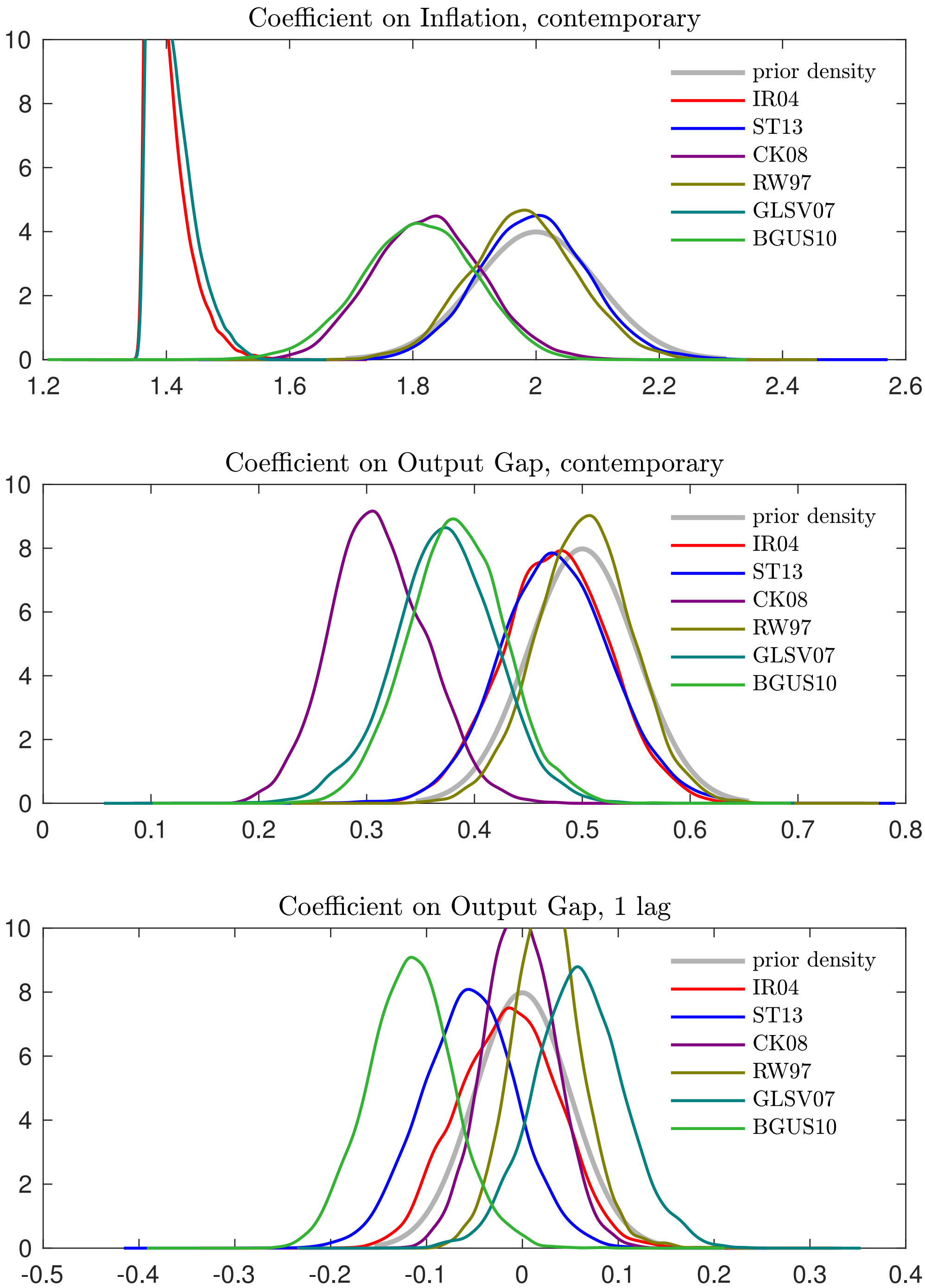


Figure 21: Prior distribution and posterior distribution for each model – In this subsection the estimations presented were produced with simulated data from the RW97 model. In this and the following figure I estimate the coefficients on inflation, on the output gap and the lags of the output gap. I use a prior mean for the response to inflation and to the output gap contemporaneously which equal the values of the parameters in the simulation. I remind the reader that in the simulation monetary policy did not respond to the lags of the output gap.

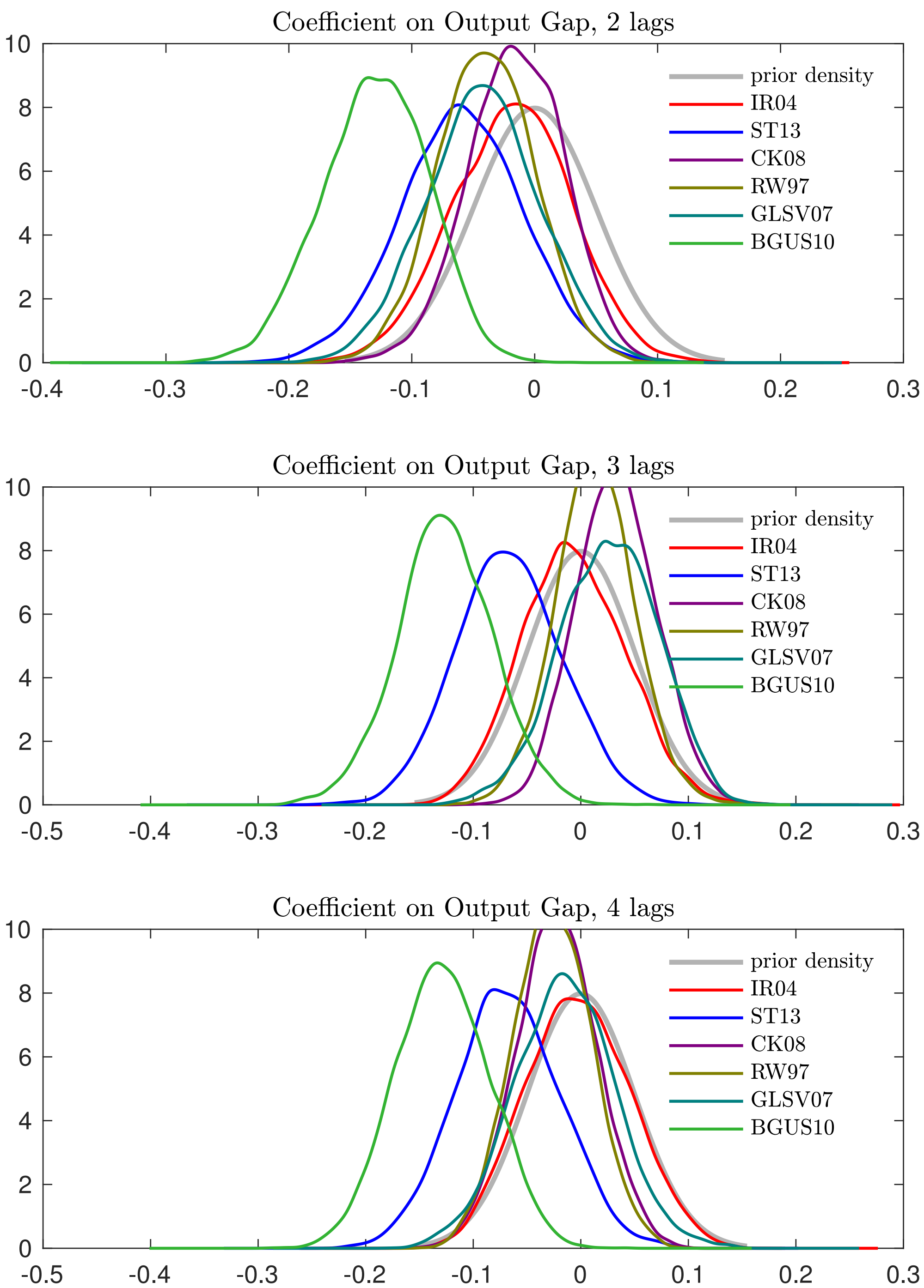


Figure 22: Prior distribution and posterior distribution for each model – In this subsection the estimations presented were produced with simulated data from the RW97 model. In this and the previous figure I estimate the coefficients on inflation, on the output gap and the lags of the output gap. I use a prior mean for the response to inflation and to the output gap contemporaneously which equal the values of the parameters in the simulation. I remind the reader that in the simulation monetary policy did not respond to the lags of the output gap.

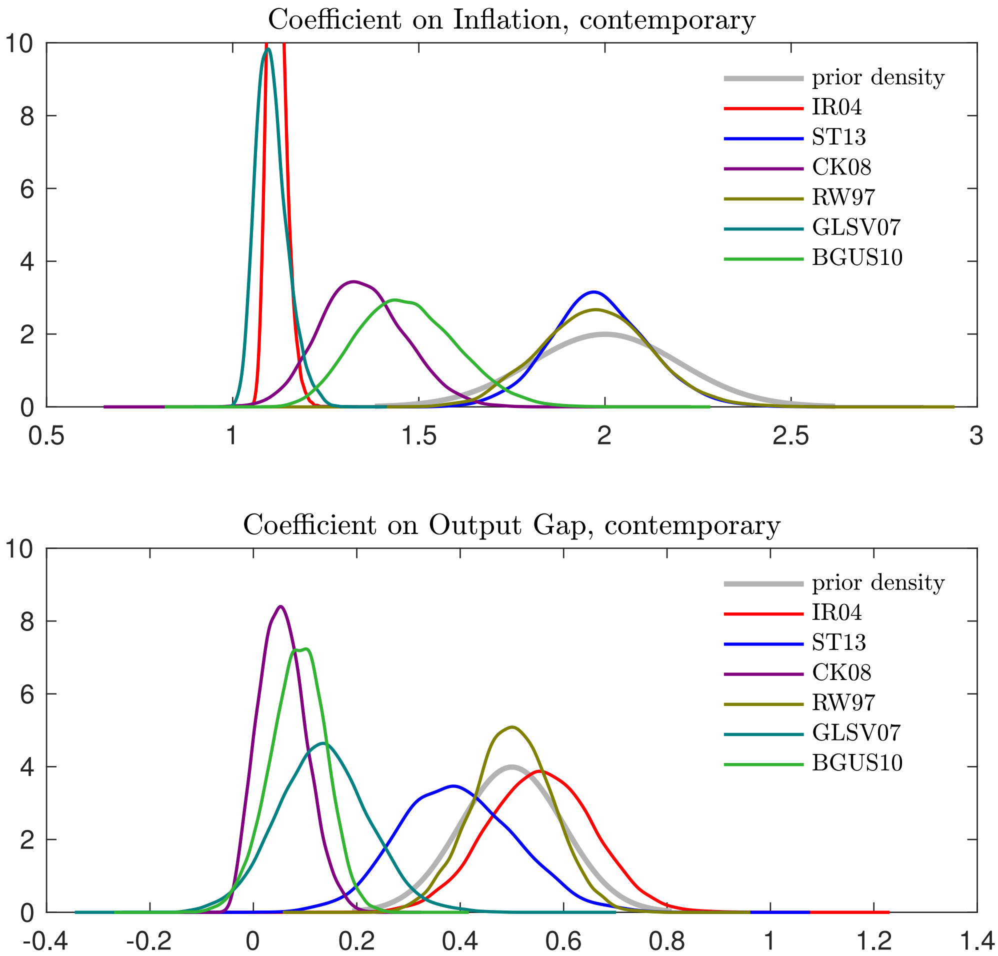


Figure 23: Prior distribution and posterior distribution for each model – In this subsection the estimations presented were produced with simulated data. I simulated 104 observations with the RW97 model. The monetary policy that I used has a response to inflation and output gap, with coefficients 2 and 0.5 respectively. For all models I used the same data for all estimations shown in this subsection, namely for all the different choices of priors that I conducted. Thus, only in the case of RW97 do the simulated data arise from the model that is being estimated. In Figures 23 to 28 the difference with the previous four estimations is that the prior variance is double as high for all estimated parameters. The standard errors of the model shocks are also estimated for each estimation, but they are not presented here. In this figure the prior means and the estimated coefficients correspond to the true model used for the simulation.

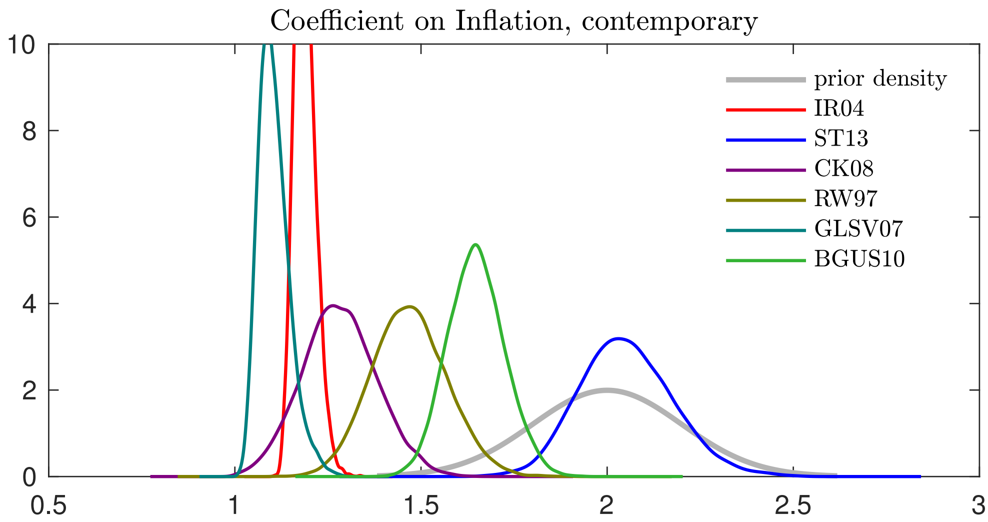


Figure 24: Prior distribution and posterior distribution for each model – In this subsection the estimations presented were produced with simulated data from the RW97 model. In this figure I only estimate the coefficient on inflation and I use a prior mean which equals the value of the parameter in the simulation, while the prior standard deviation is double compared to the basic case. I remind the reader that in the simulation monetary policy also responded to the output gap.

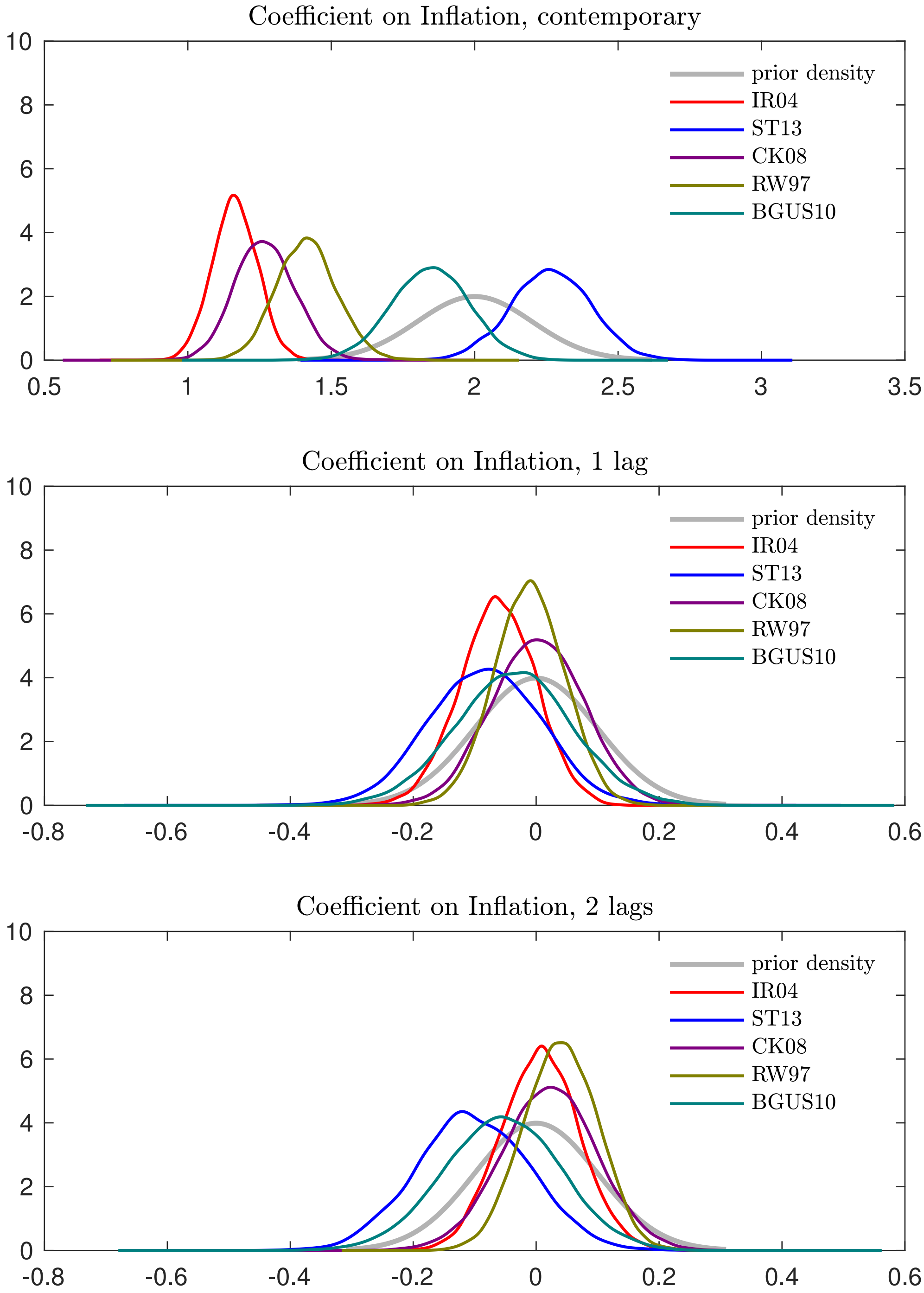


Figure 25: Prior distribution and posterior distribution for each model – In this subsection the estimations presented were produced with simulated data from the RW97 model. In this and the following figure I estimate the coefficient on inflation and the coefficients on the lags of inflation. I use a prior mean for the response to inflation contemporaneously which equals value of the parameter in the simulation, while the prior standard deviation is double compared to the basic case. I remind the reader that in the simulation monetary policy did not respond to the lags of inflation, but did respond to the output gap.

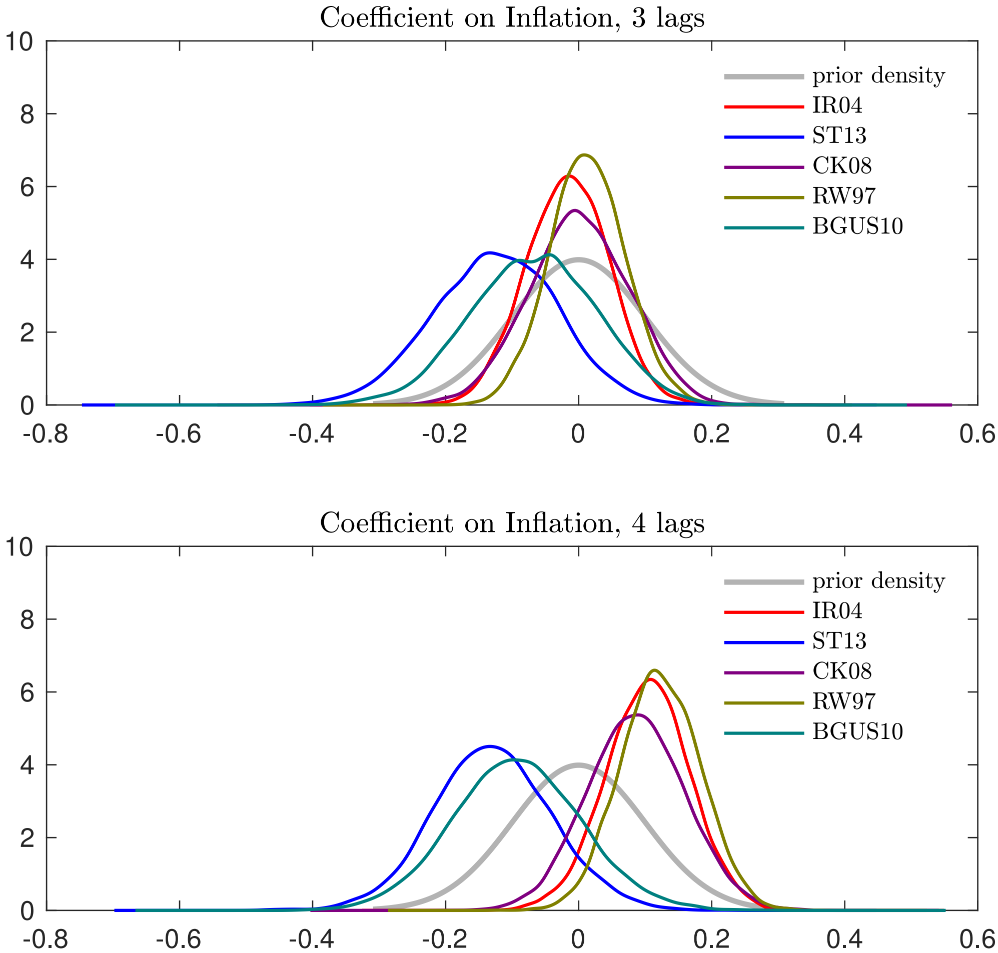


Figure 26: Prior distribution and posterior distribution for each model – In this subsection the estimations presented were produced with simulated data from the RW97 model. In this and the previous figure I estimate the coefficient on inflation and the coefficients on the lags of inflation. I use a prior mean for the response to inflation contemporaneously which equals value of the parameter in the simulation, while the prior standard deviation is double compared to the basic case. I remind the reader that in the simulation monetary policy did not respond to the lags of inflation, but did respond to the output gap.

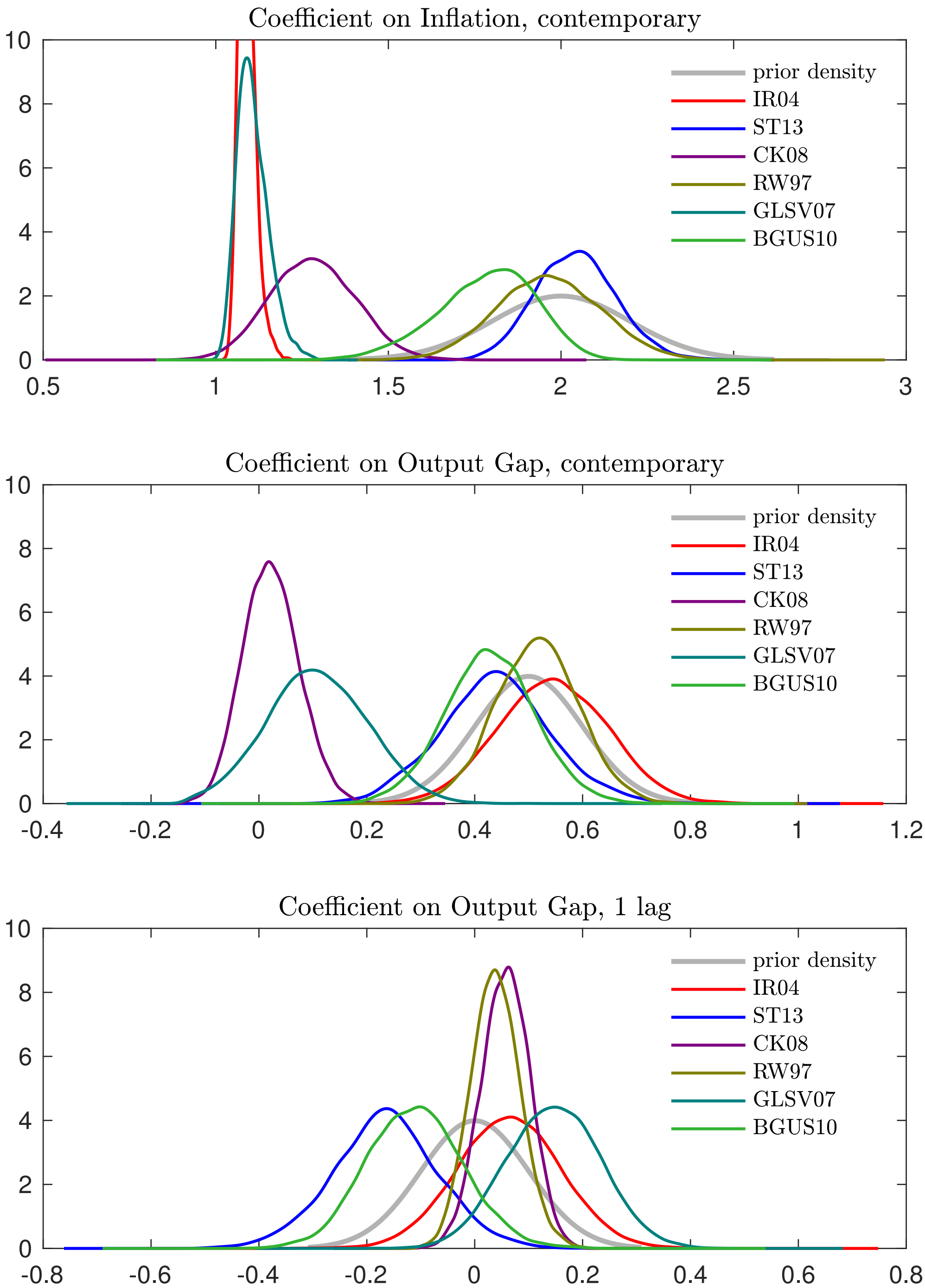


Figure 27: Prior distribution and posterior distribution for each model – In this subsection the estimations presented were produced with simulated data from the RW97 model. In this and the following figure I estimate the coefficients on inflation, on the output gap and the lags of the output gap. I use a prior mean for the response to inflation and to the output gap contemporaneously which equal the values of the parameters in the simulation, while the prior standard deviation is double compared to the basic case. I remind the reader that in the simulation monetary policy did not respond to the lags of the output gap.

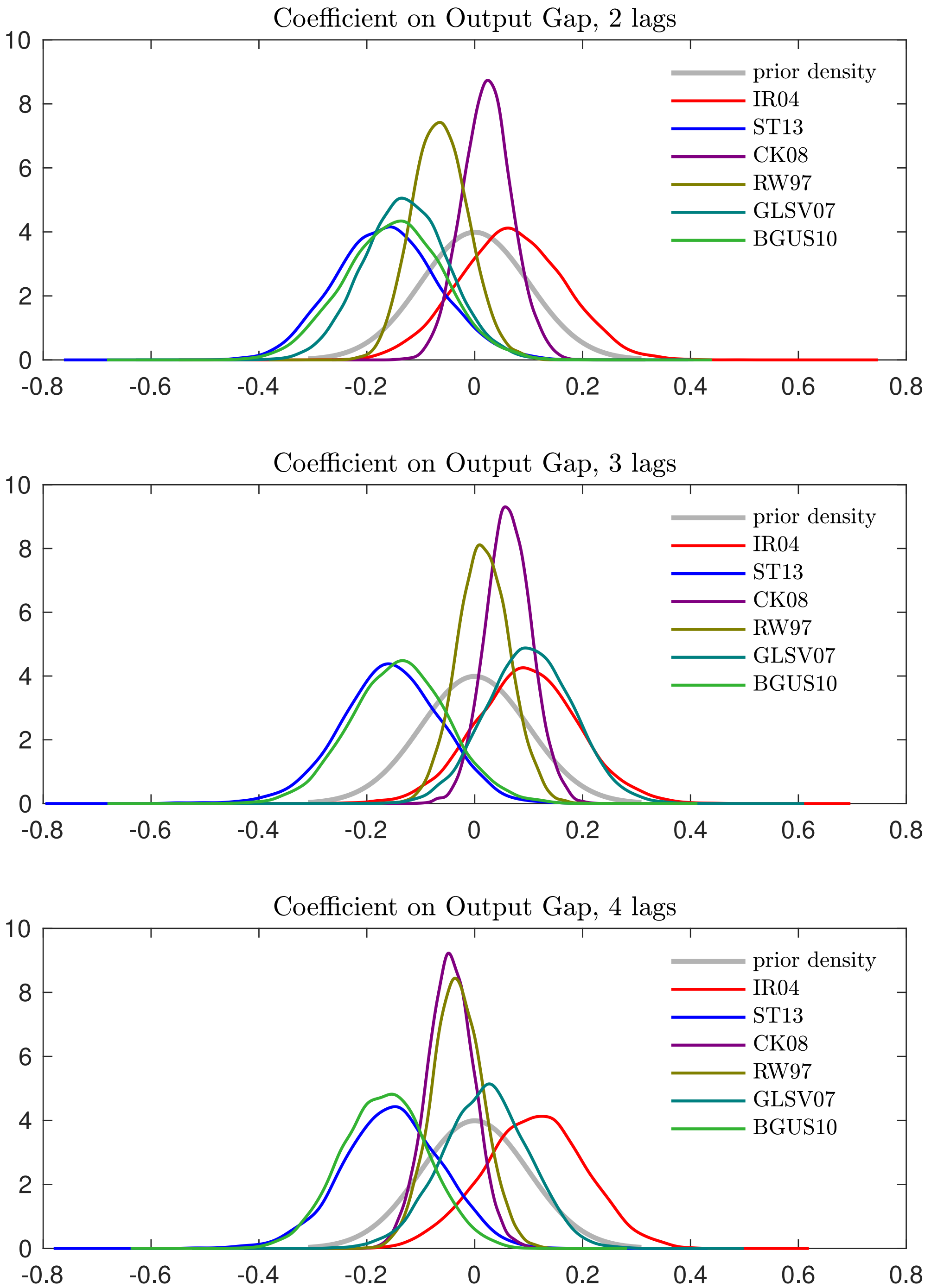


Figure 28: Prior distribution and posterior distribution for each model – In this subsection the estimations presented were produced with simulated data from the RW97 model. In this and the previous figure I estimate the coefficients on inflation, on the output gap and the lags of the output gap. I use a prior mean for the response to inflation and to the output gap contemporaneously which equal the values of the parameters in the simulation, while the prior standard deviation is double compared to the basic case. I remind the reader that in the simulation monetary policy did not respond to the lags of the output gap.

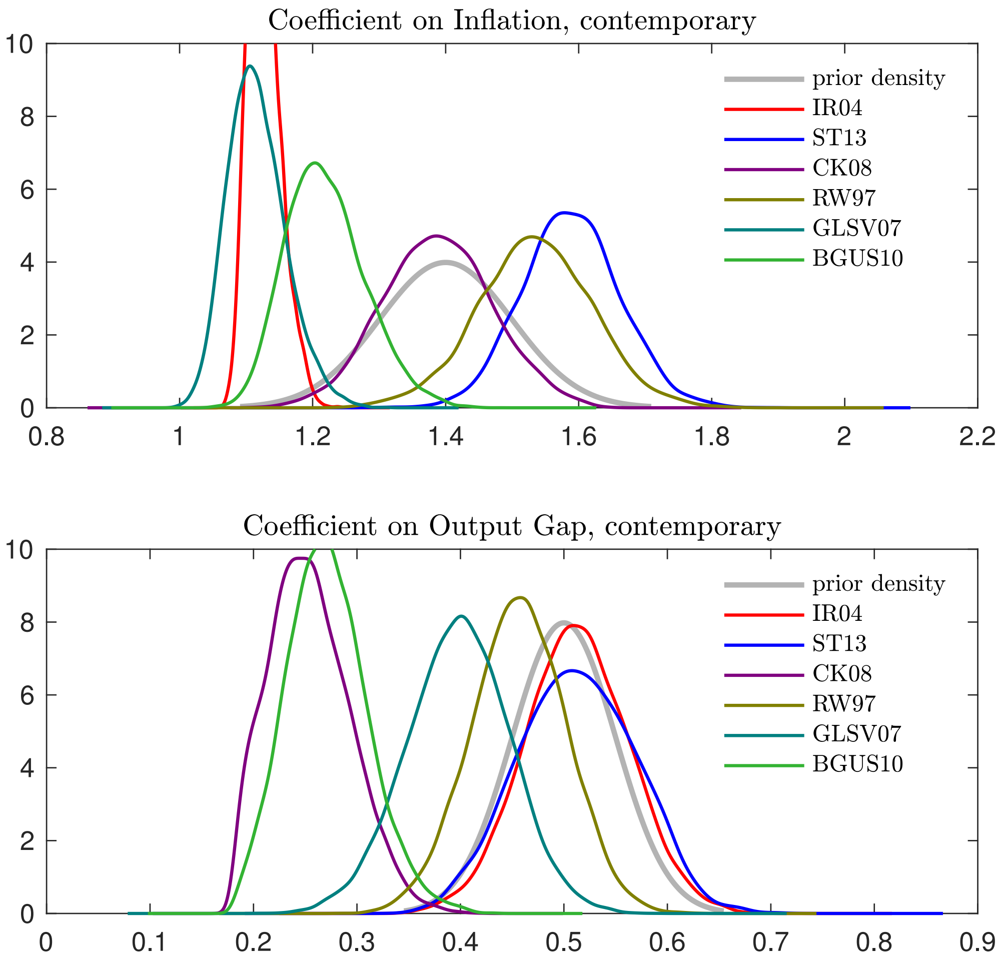


Figure 29: Prior distribution and posterior distribution for each model – In this subsection the estimations presented were produced with simulated data from the RW97 model. In Figures 29 to 38 I perform a series of estimations which are the most clear example of the naive approach mentioned in the paper. Here I estimate those coefficients that are non zero in the simulation, the coefficient on inflation and the coefficient on the output gap. However, in Figures 29 to 33 I vary the prior mean of the coefficient on inflation. The prior mean then varies from 1.4 to 2.6, while 2 was the value used in the simulation.

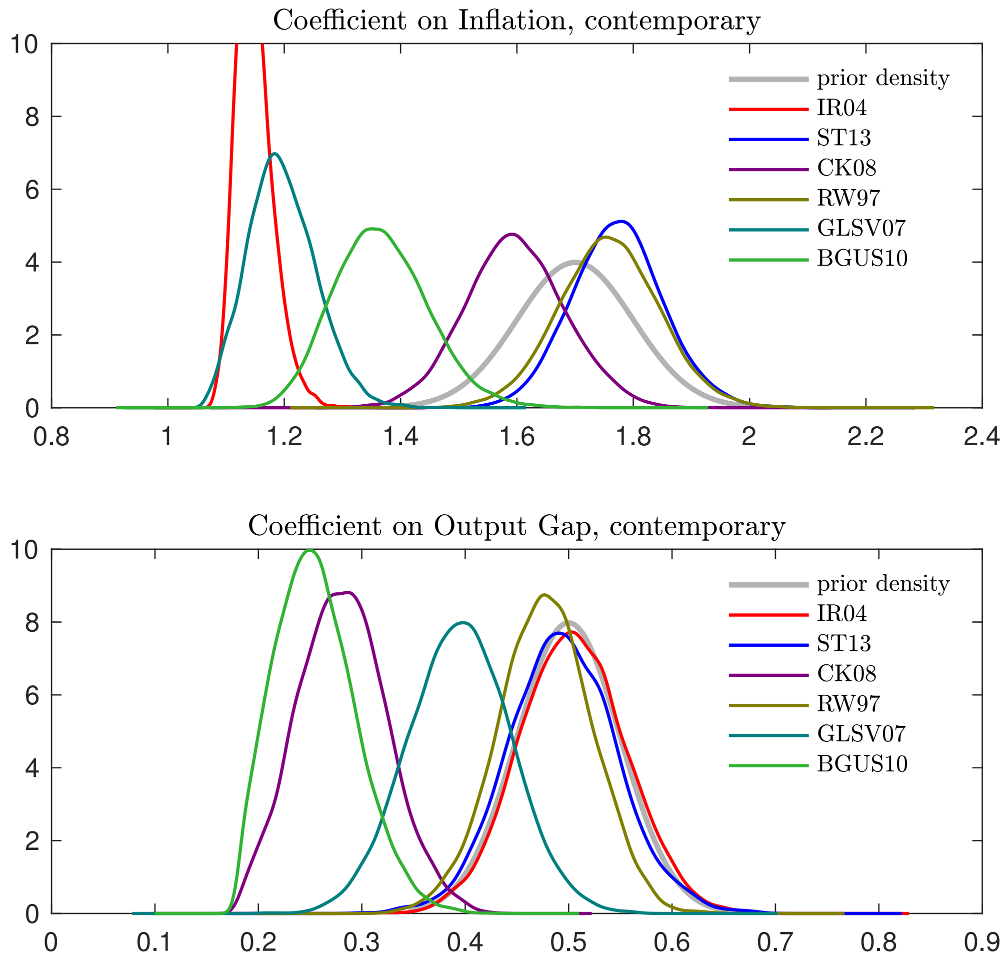


Figure 30: Prior distribution and posterior distribution for each model – In this subsection the estimations presented were produced with simulated data from the RW97 model. In Figures 29 to 38 I perform a series of estimations which are the most clear example of the naive approach mentioned in the paper. Here I estimate those coefficients that are non zero in the simulation, the coefficient on inflation and the coefficient on the output gap. However, in Figures 29 to 33 I vary the prior mean of the coefficient on inflation. The prior mean then varies from 1.4 to 2.6, while 2 was the value used in the simulation.

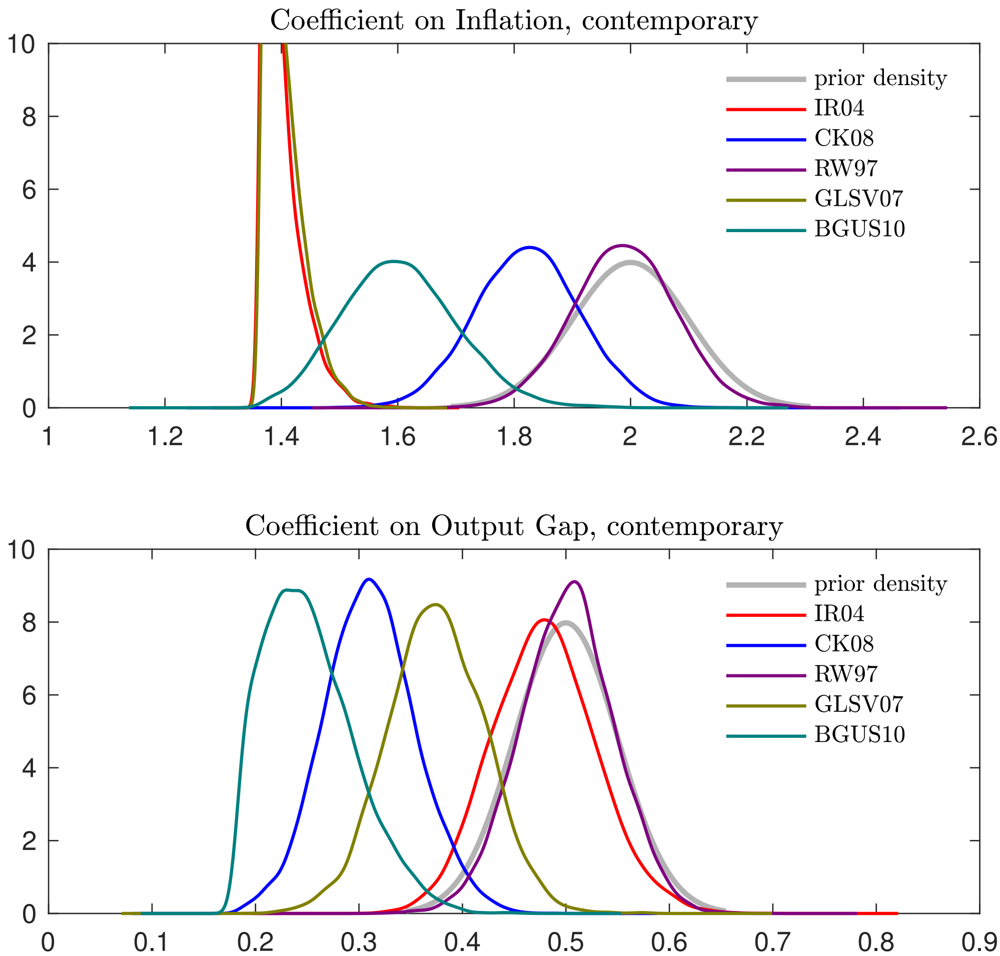


Figure 31: Prior distribution and posterior distribution for each model – In this subsection the estimations presented were produced with simulated data from the RW97 model. In Figures 29 to 38 I perform a series of estimations which are the most clear example of the naive approach mentioned in the paper. Here I estimate those coefficients that are non zero in the simulation, the coefficient on inflation and the coefficient on the output gap. However, in Figures 29 to 33 I vary the prior mean of the coefficient on inflation. The prior mean then varies from 1.4 to 2.6, while 2 was the value used in the simulation.

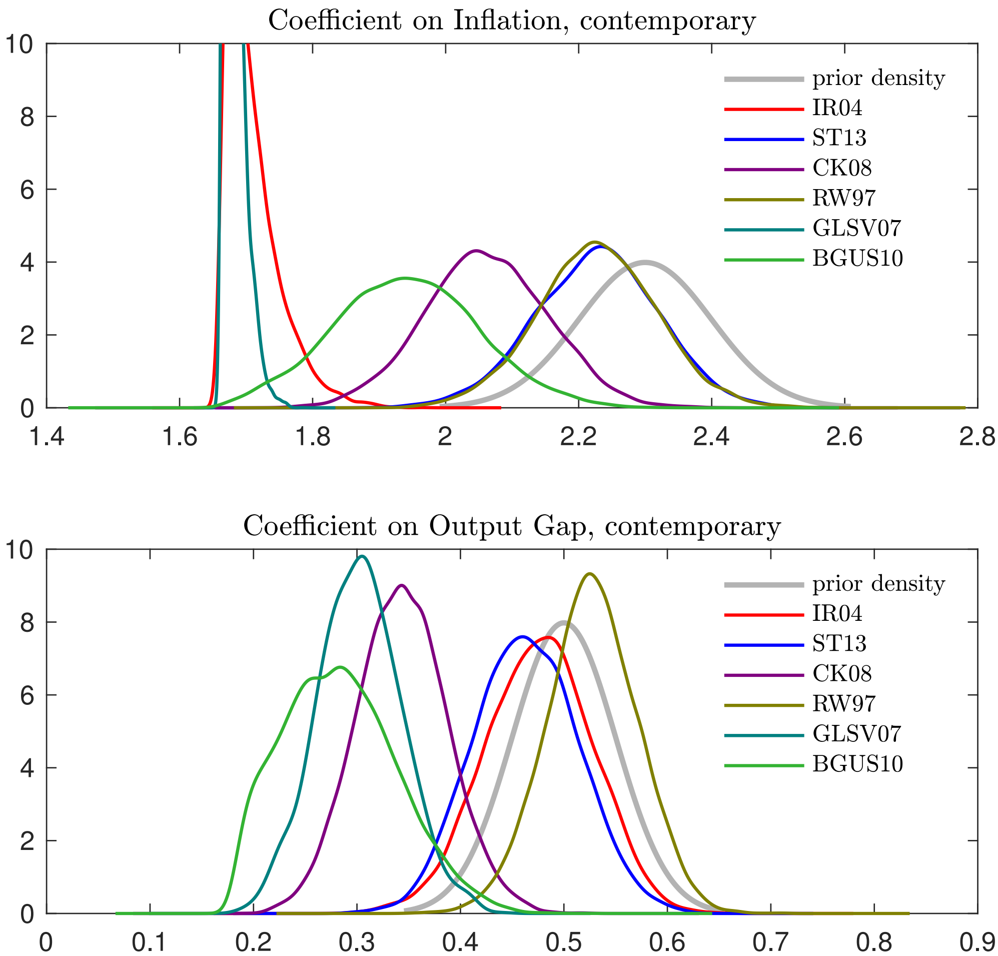


Figure 32: Prior distribution and posterior distribution for each model – In this subsection the estimations presented were produced with simulated data from the RW97 model. In Figures 29 to 38 I perform a series of estimations which are the most clear example of the naive approach mentioned in the paper. Here I estimate those coefficients that are non zero in the simulation, the coefficient on inflation and the coefficient on the output gap. However, in Figures 29 to 33 I vary the prior mean of the coefficient on inflation. The prior mean then varies from 1.4 to 2.6, while 2 was the value used in the simulation.

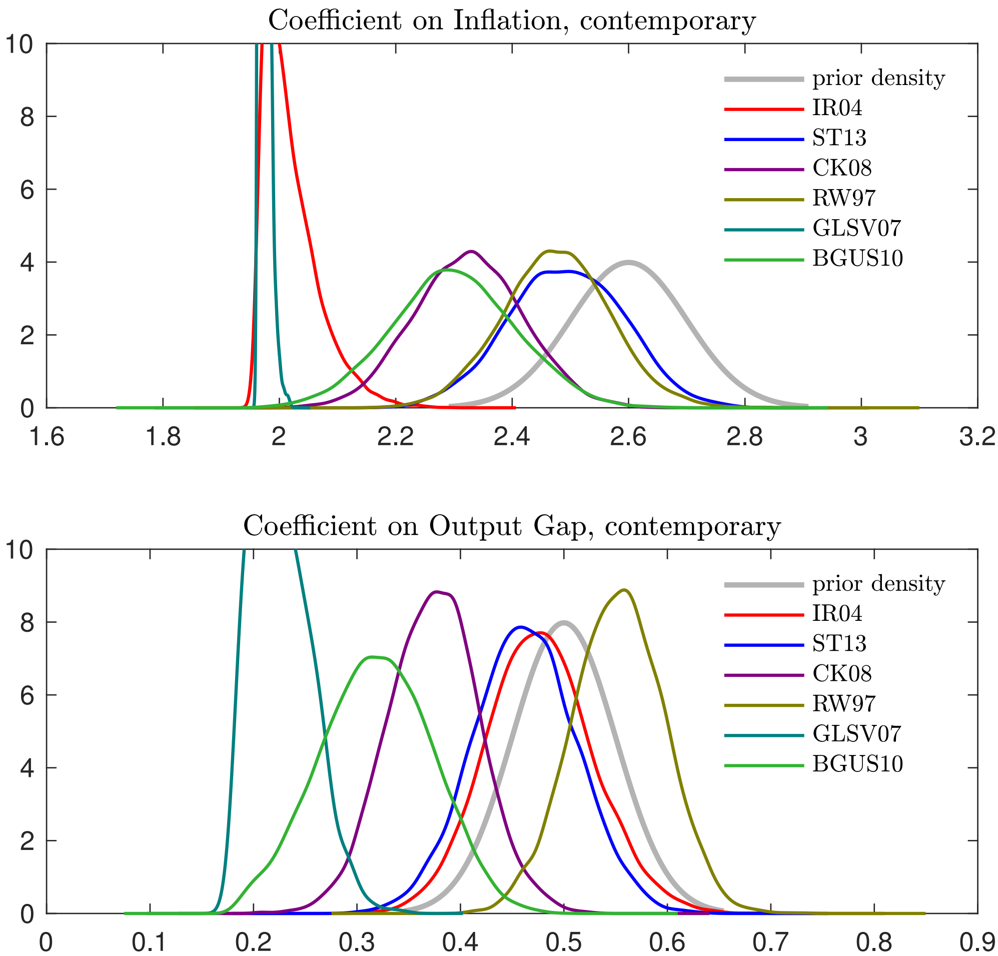


Figure 33: Prior distribution and posterior distribution for each model – In this subsection the estimations presented were produced with simulated data from the RW97 model. In Figures 29 to 38 I perform a series of estimations which are the most clear example of the naive approach mentioned in the paper. Here I estimate those coefficients that are non zero in the simulation, the coefficient on inflation and the coefficient on the output gap. However, in Figures 29 to 33 I vary the prior mean of the coefficient on inflation. The prior mean then varies from 1.4 to 2.6, while 2 was the value used in the simulation.

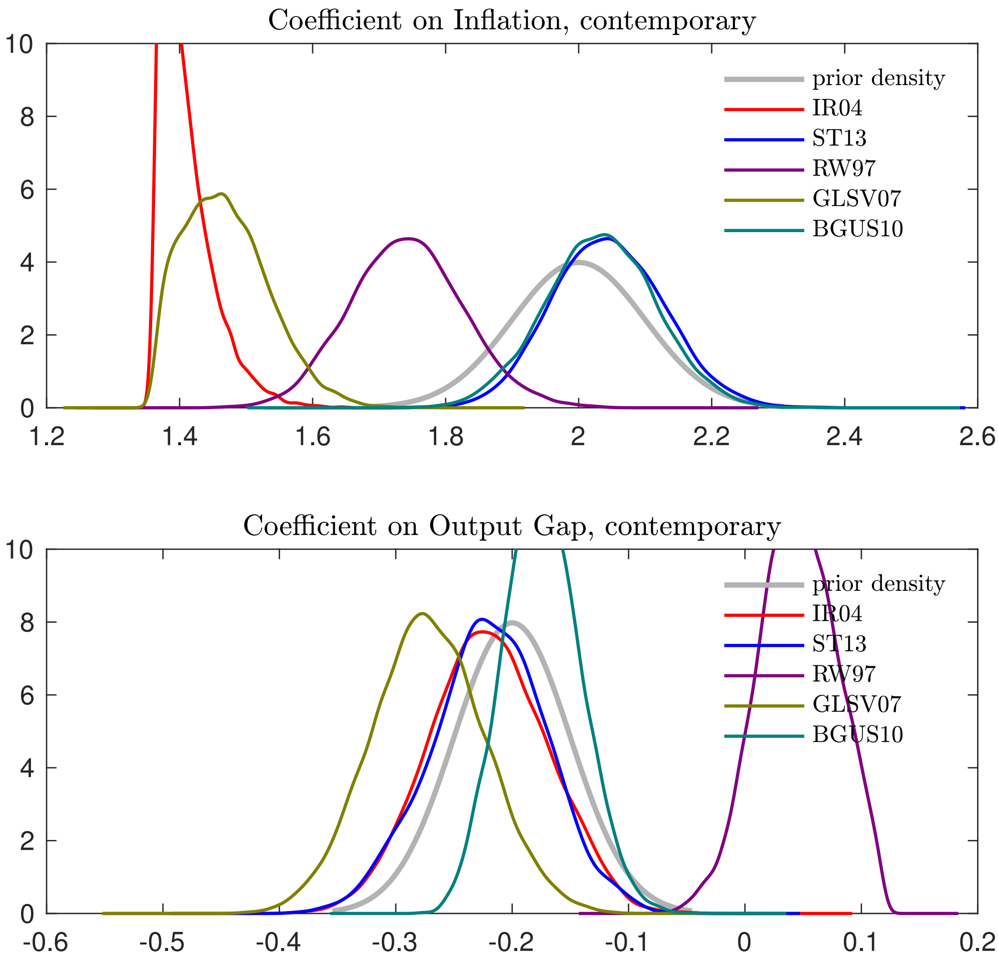


Figure 34: Prior distribution and posterior distribution for each model – In this subsection the estimations presented were produced with simulated data from the RW97 model. In Figures 29 to 38 I perform a series of estimations which are the most clear example of the naive approach mentioned in the paper. Here I estimate those coefficients that are non zero in the simulation, the coefficient on inflation and the coefficient on the output gap. However, in Figures 34 to 38 I vary the prior mean of the coefficient on the output gap. The prior mean then varies from -0.2 to 0.6, while 0.5 was the value used in the simulation.

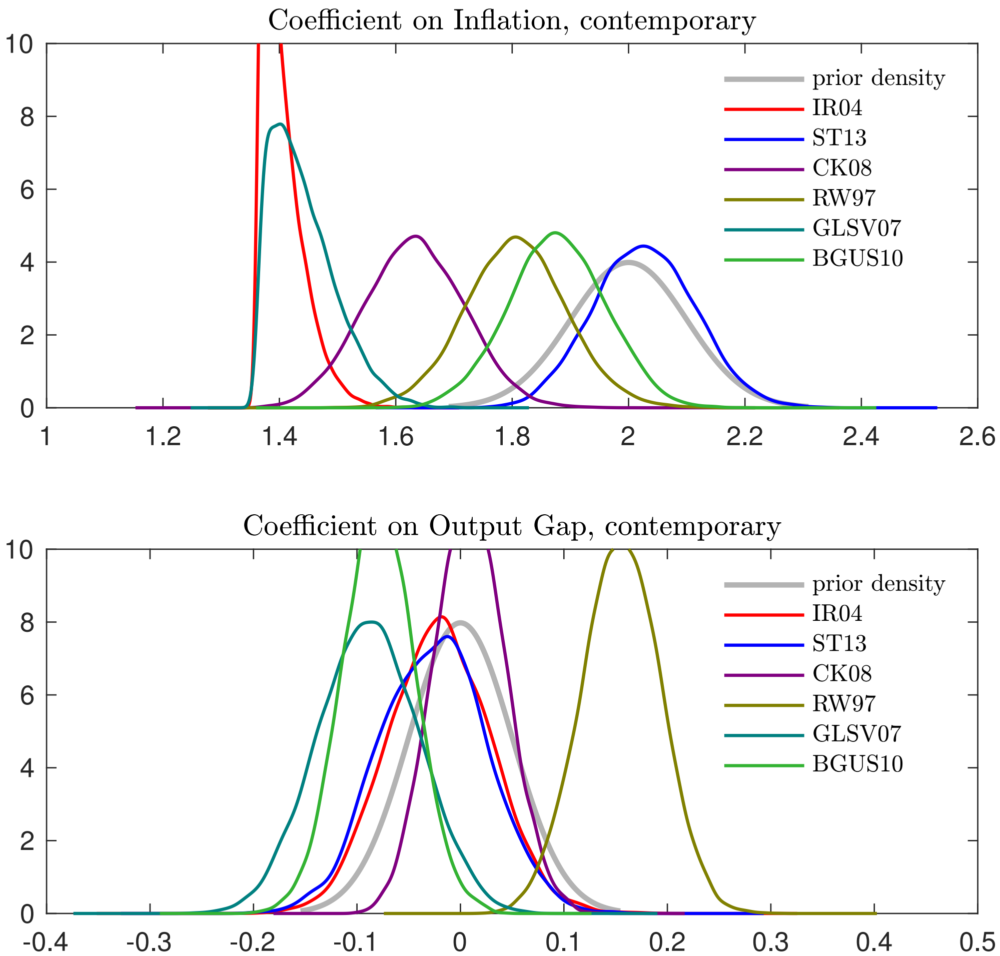


Figure 35: Prior distribution and posterior distribution for each model – In this subsection the estimations presented were produced with simulated data from the RW97 model. In Figures 29 to 38 I perform a series of estimations which are the most clear example of the naive approach mentioned in the paper. Here I estimate those coefficients that are non zero in the simulation, the coefficient on inflation and the coefficient on the output gap. However, in Figures 34 to 38 I vary the prior mean of the coefficient on the output gap. The prior mean then varies from -0.2 to 0.6, while 0.5 was the value used in the simulation.

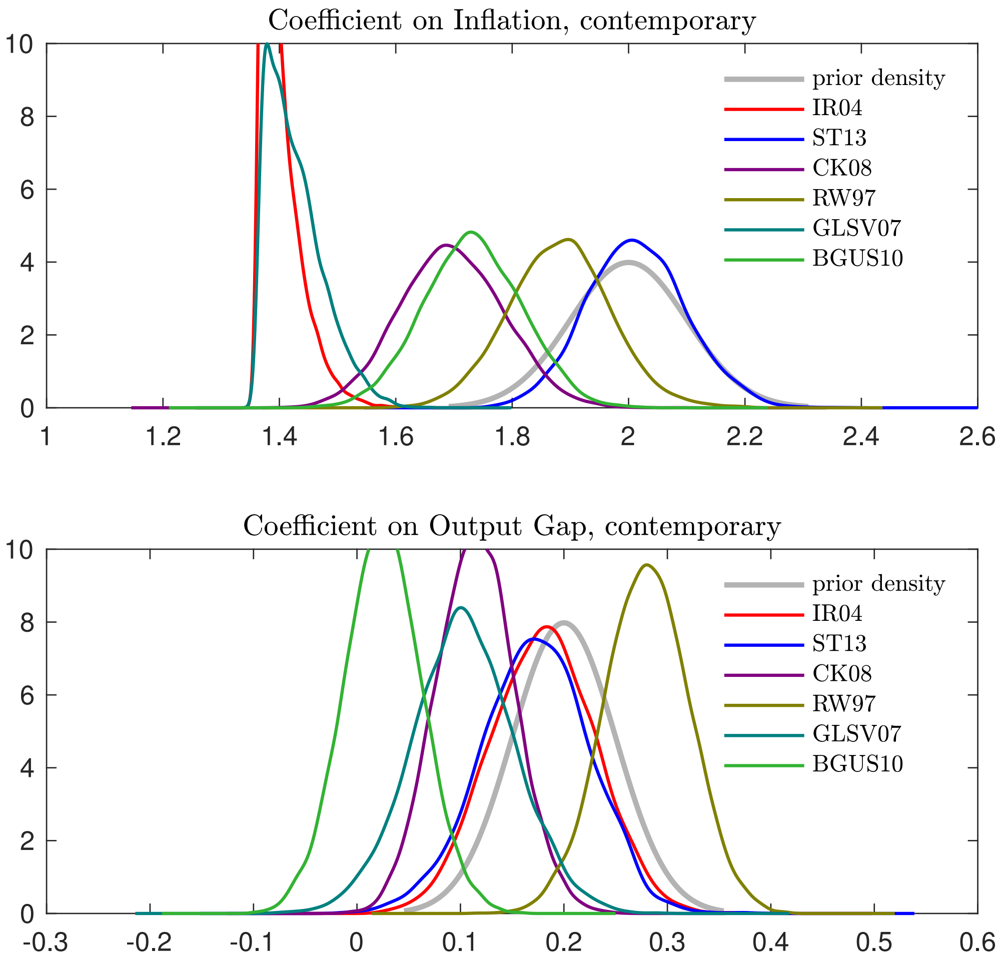


Figure 36: Prior distribution and posterior distribution for each model – In this subsection the estimations presented were produced with simulated data from the RW97 model. In Figures 29 to 38 I perform a series of estimations which are the most clear example of the naive approach mentioned in the paper. Here I estimate those coefficients that are non zero in the simulation, the coefficient on inflation and the coefficient on the output gap. However, in Figures 34 to 38 I vary the prior mean of the coefficient on the output gap. The prior mean then varies from -0.2 to 0.6, while 0.5 was the value used in the simulation.

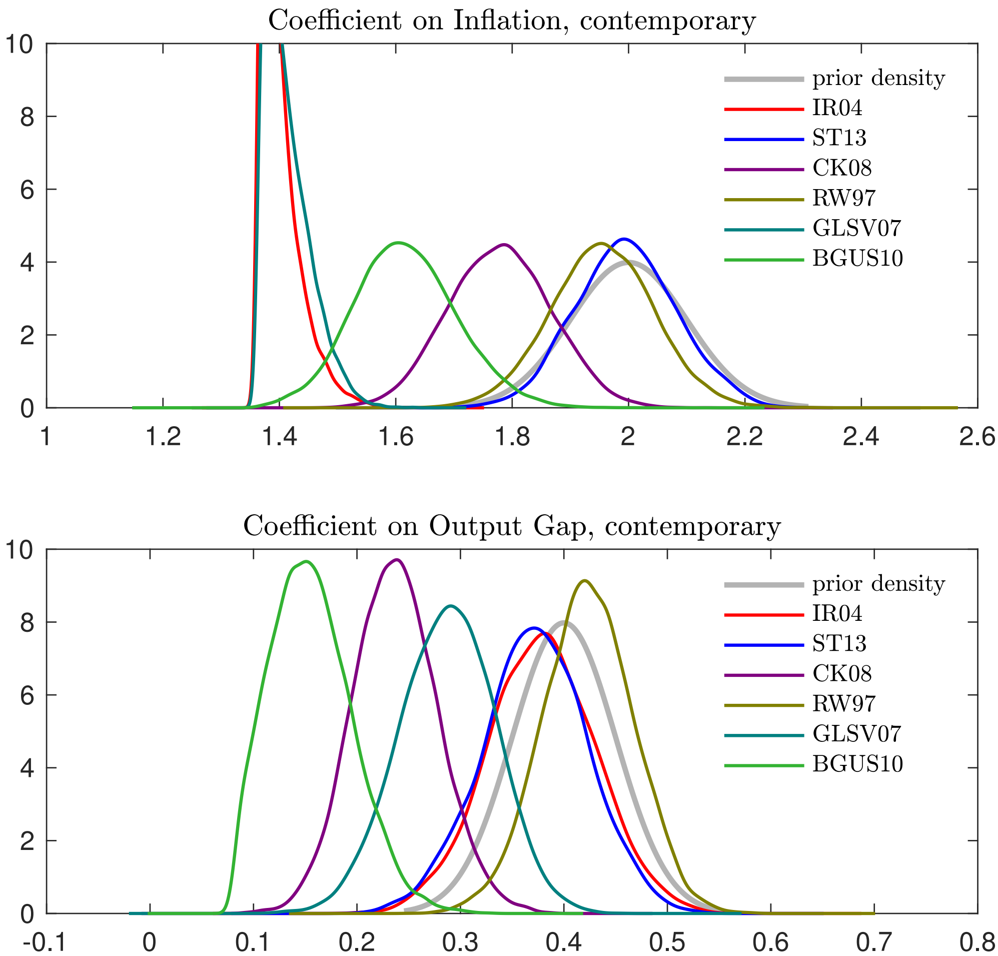


Figure 37: Prior distribution and posterior distribution for each model – In this subsection the estimations presented were produced with simulated data from the RW97 model. In Figures 29 to 38 I perform a series of estimations which are the most clear example of the naive approach mentioned in the paper. Here I estimate those coefficients that are non zero in the simulation, the coefficient on inflation and the coefficient on the output gap. However, in Figures 34 to 38 I vary the prior mean of the coefficient on the output gap. The prior mean then varies from -0.2 to 0.6, while 0.5 was the value used in the simulation.

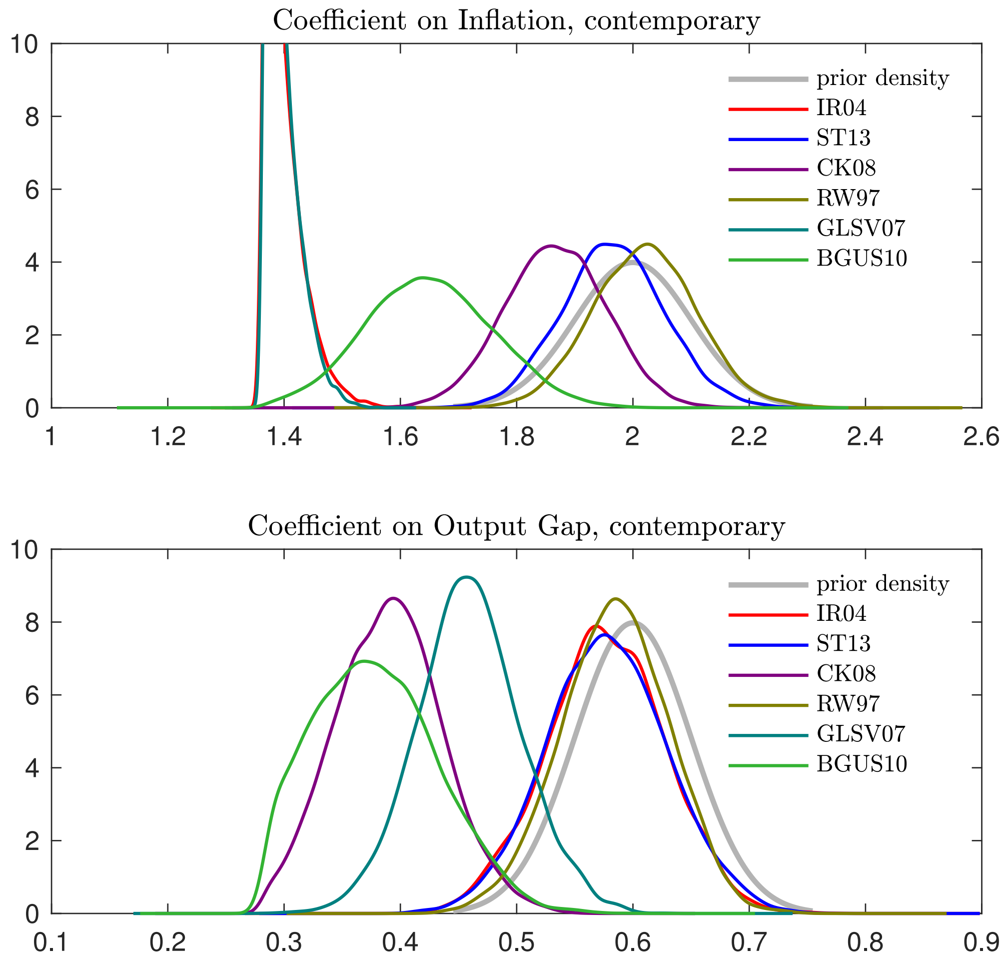


Figure 38: Prior distribution and posterior distribution for each model – In this subsection the estimations presented were produced with simulated data from the RW97 model. In Figures 29 to 38 I perform a series of estimations which are the most clear example of the naive approach mentioned in the paper. Here I estimate those coefficients that are non zero in the simulation, the coefficient on inflation and the coefficient on the output gap. However, in Figures 34 to 38 I vary the prior mean of the coefficient on the output gap. The prior mean then varies from -0.2 to 0.6, while 0.5 was the value used in the simulation.

8.3 Based on real data

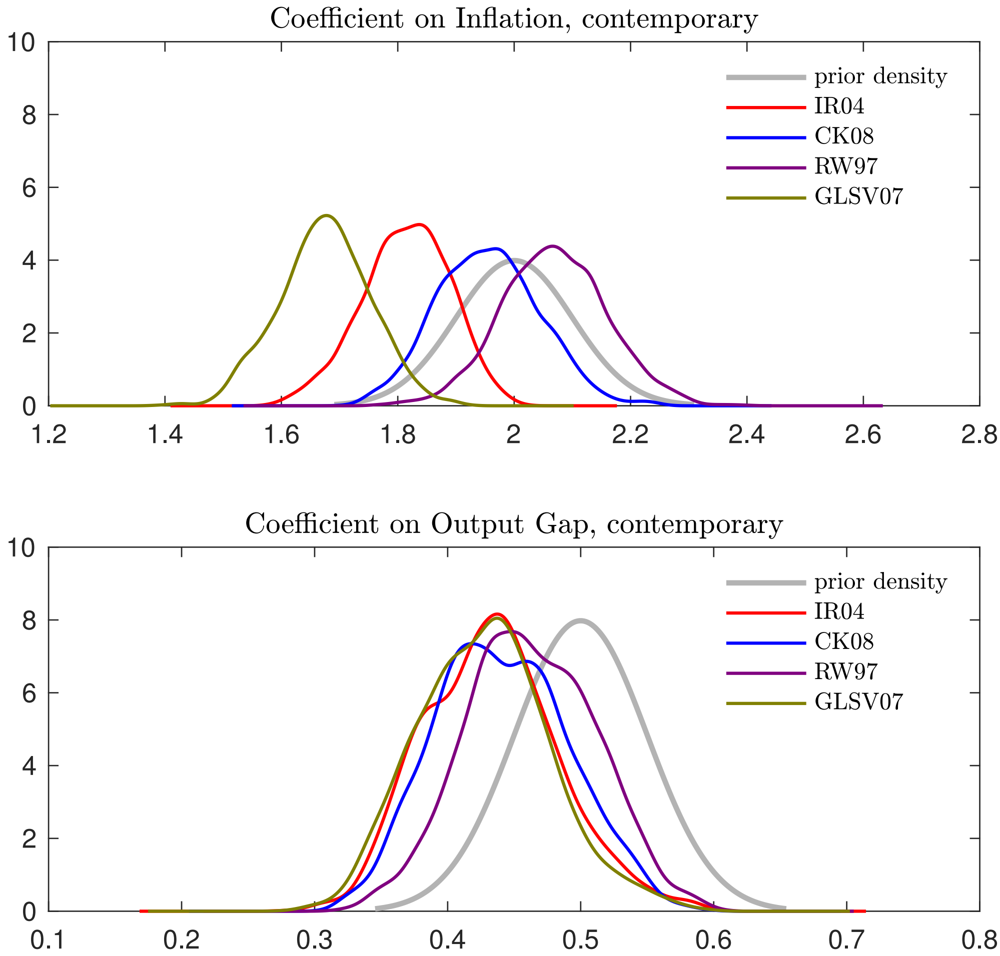


Figure 39: Prior distribution and posterior distributions – In this subsection I perform estimations based on real data. The data is the same as what is used by Smets and Wouters (2007). In Figures 39 to 44 I use the same data for all estimations, i.e. the subset of data from 1980 to 2004. In this figure I estimate the coefficients on inflation and the output gap. In all the estimations in this subsection the standard deviations of the shocks of each estimated model are also estimated.

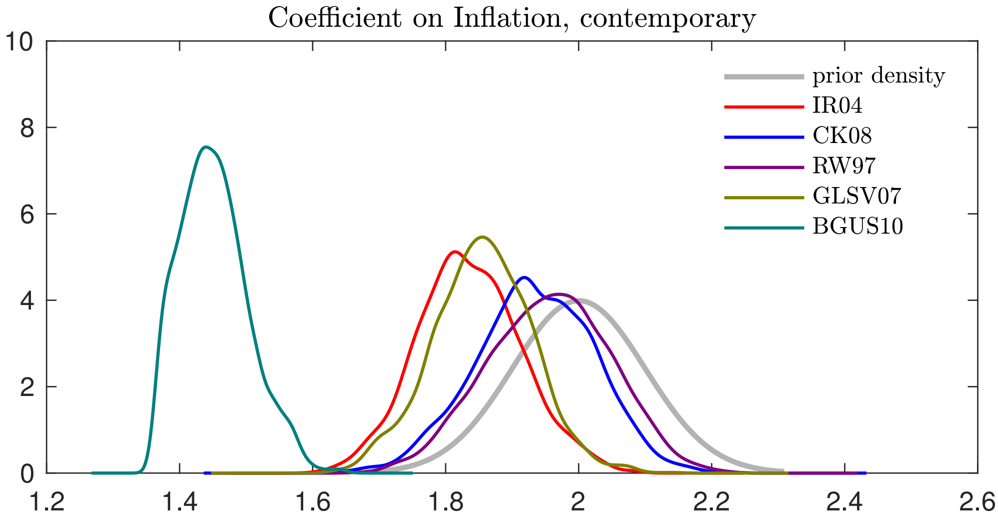


Figure 40: Prior distribution and posterior distributions – In this subsection I perform estimations based on real data. In this figure only the coefficient on inflation from the monetary policy rule is estimated.

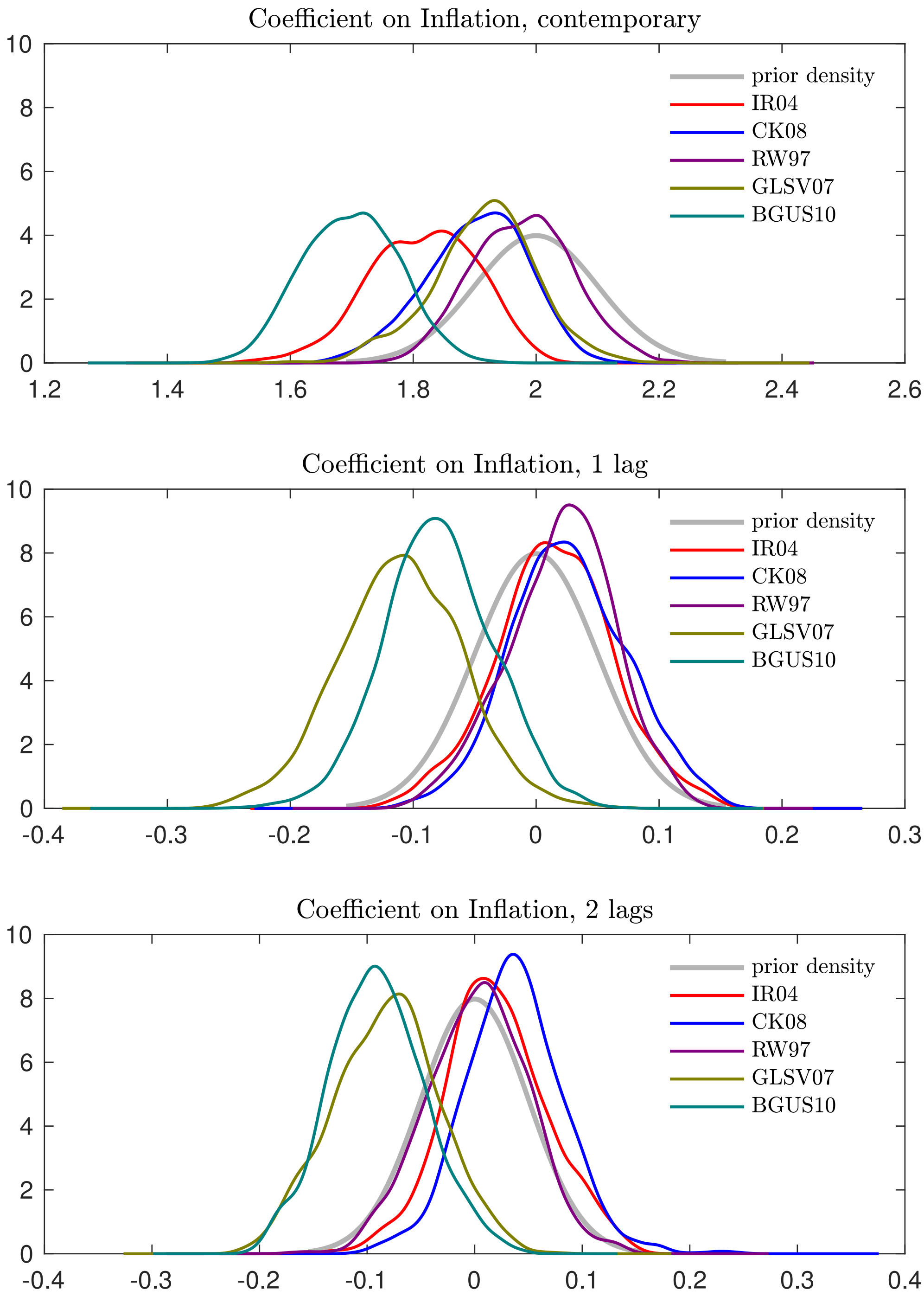


Figure 41: Prior distribution and posterior distributions – In this subsection I perform estimations based on real data. In this and the following figure the coefficient on inflation and the coefficients on the inflation lags are estimated from the monetary policy rule.

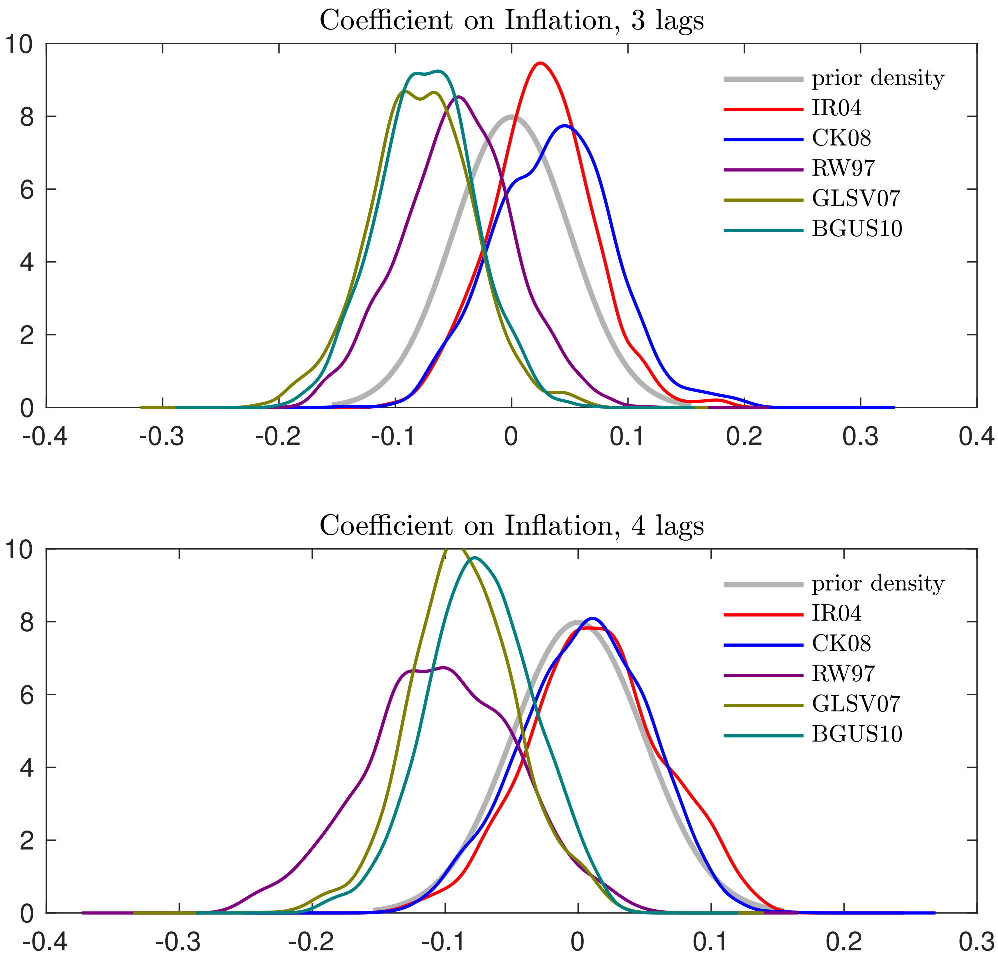


Figure 42: Prior distribution and posterior distributions – In this subsection I perform estimations based on real data. In this and the previous figure the coefficient on inflation and the coefficients on the inflation lags are estimated from the monetary policy rule.

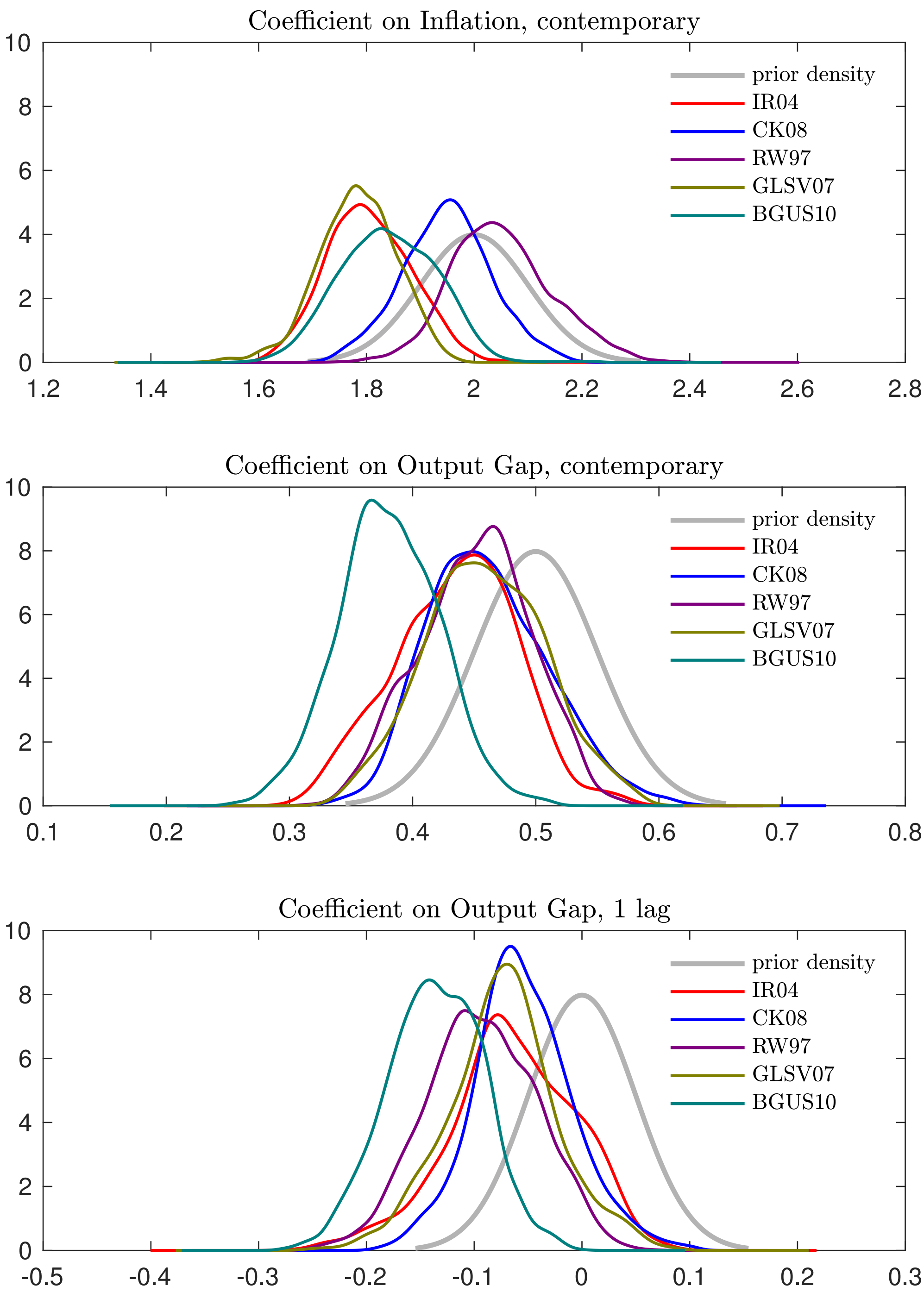


Figure 43: Prior distribution and posterior distributions – In this subsection I perform estimations based on real data. In this and the following figure the coefficient on inflation, the output gap and the coefficients on the lags of the output gap are estimated from the monetary policy rule.

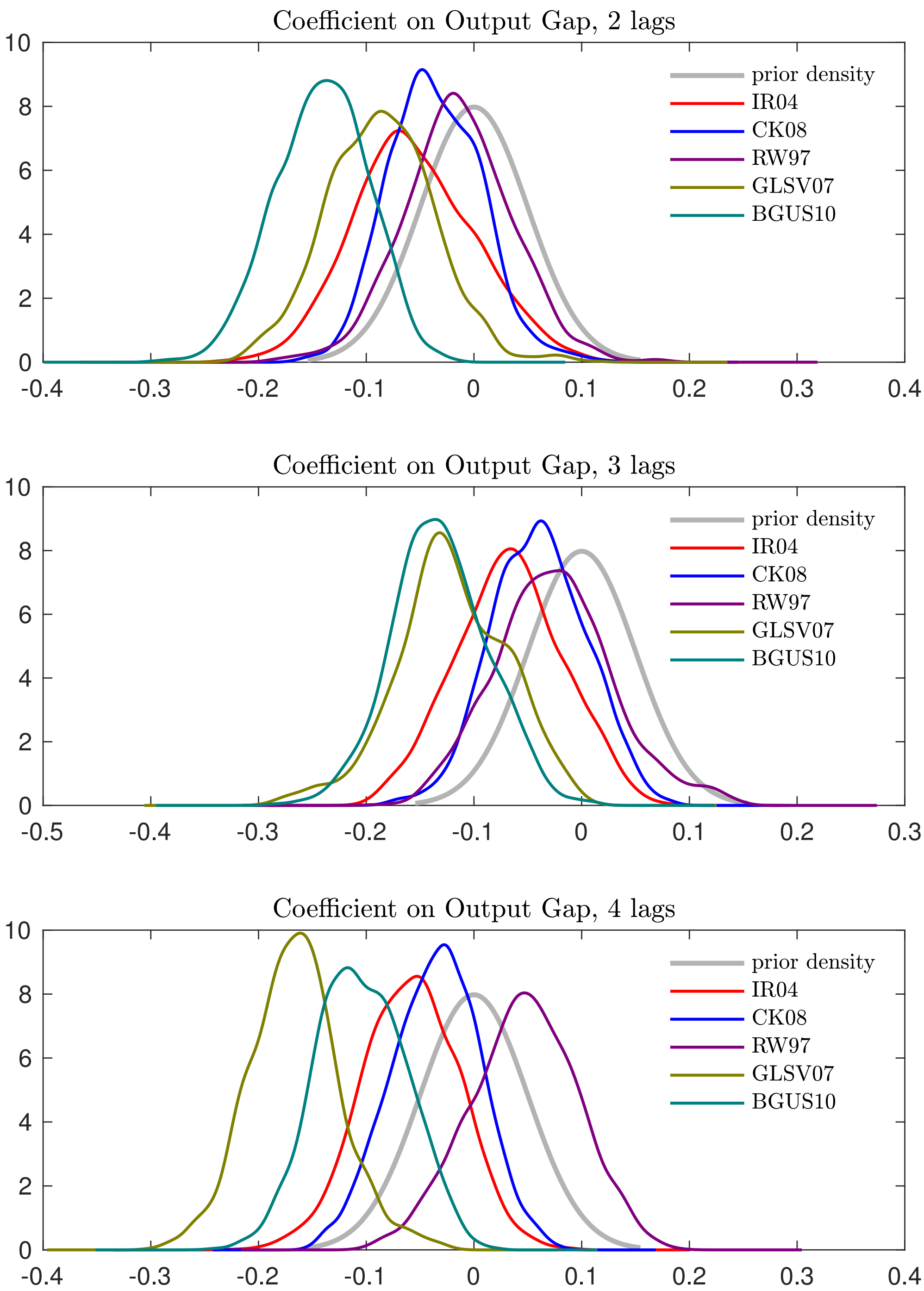


Figure 44: Prior distribution and posterior distributions – In this subsection I perform estimations based on real data. In this and the previous figure the coefficient on inflation, the output gap and the coefficients on the lags of the output gap are estimated from the monetary policy rule.

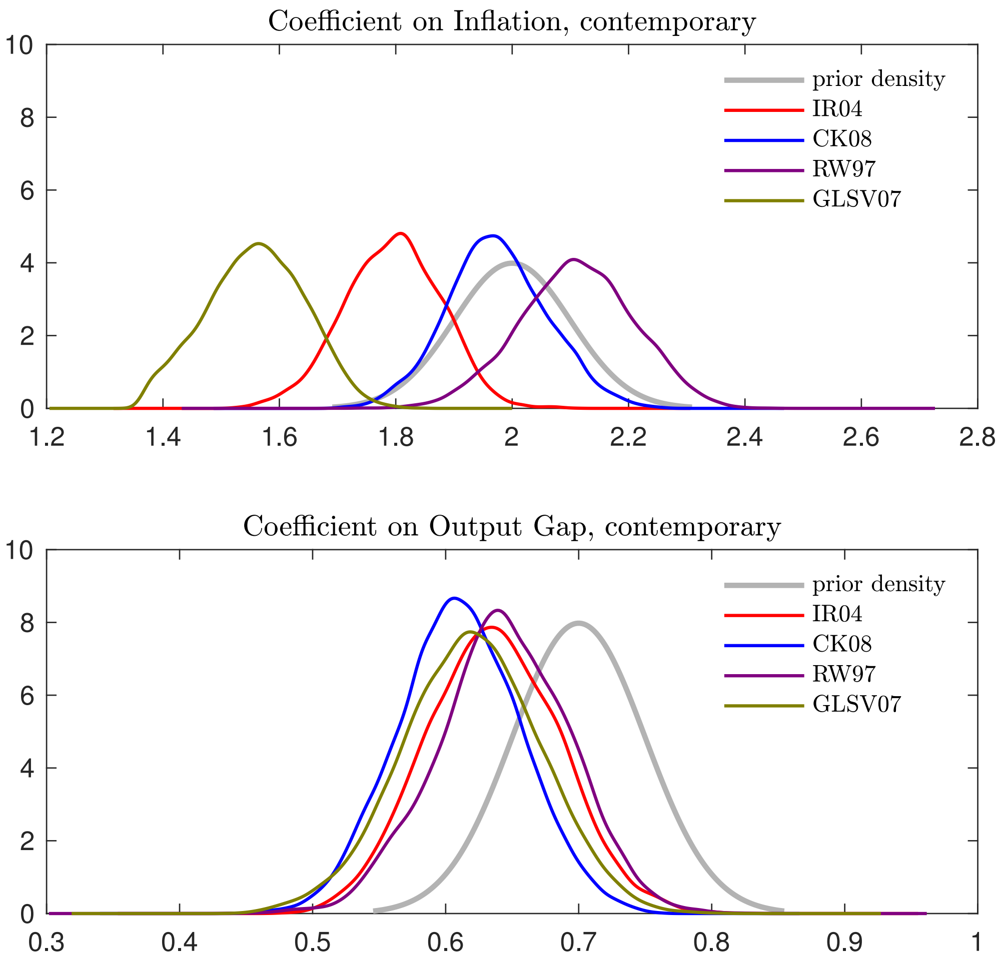


Figure 45: Prior distribution and posterior distributions – Here, I continue the estimations based on real data as before, but now in Figures 45 to 49 I have varied the prior means compared to the previous estimations. In this figure I estimate the coefficients on inflation and the output gap. The prior mean of the coefficient on the output gap is 0.7 compared to 0.5 in the basic case.

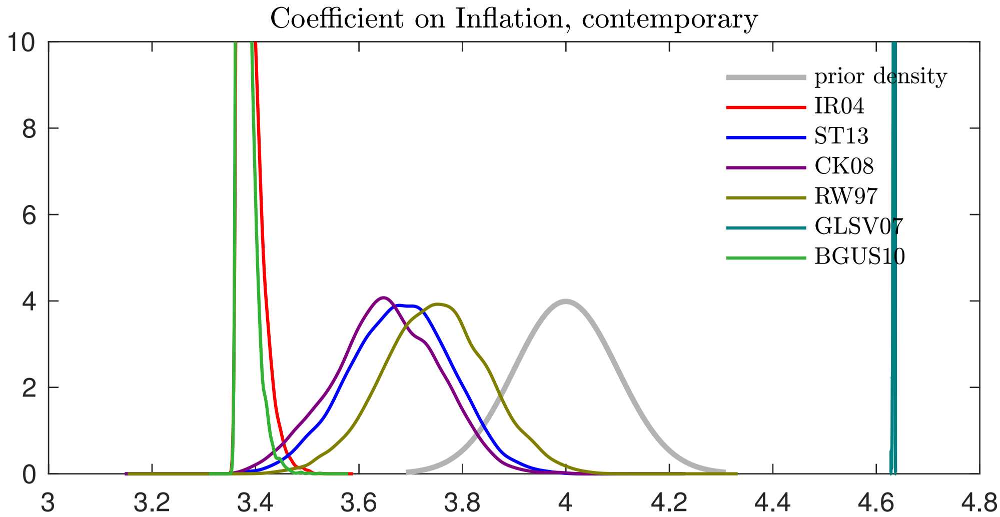


Figure 46: Prior distribution and posterior distributions – In this subsection I perform estimations based on real data with a variation with respect to the prior means compared to the basic case. In this figure only the coefficient on inflation from the monetary policy rule is estimated. The prior mean of the coefficient on inflation is 4 compared to 2 in the basic case.

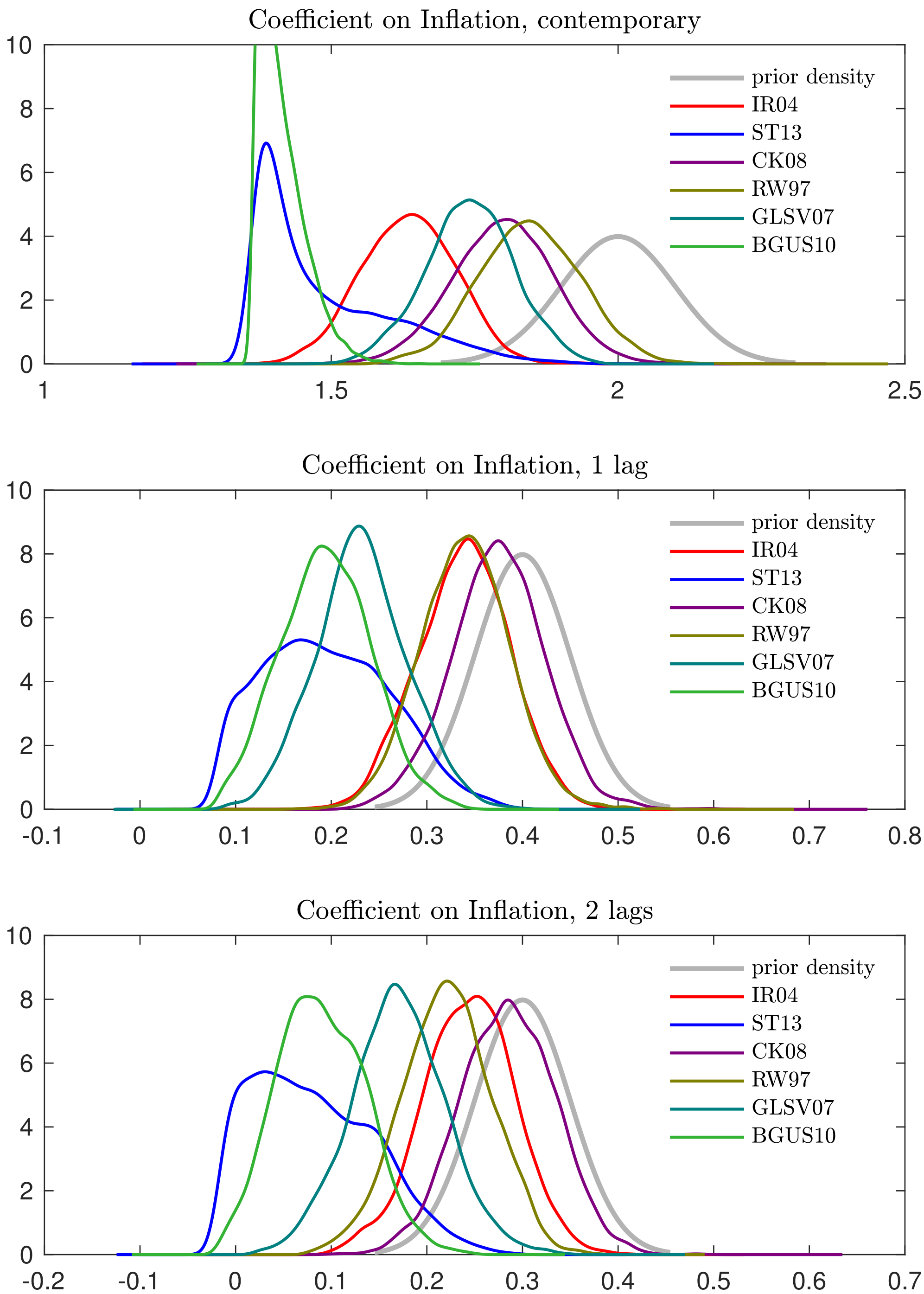


Figure 47: Prior distribution and posterior distributions – In this subsection I perform estimations based on real data with a variation with respect to the prior means compared to the basic case. In this and the following figure the coefficient on inflation and the coefficients on the inflation lags are estimated from the monetary policy rule. The prior means of the coefficients on the lags of inflation are 0.4, 0.3, 0.2 and 0.1 respectively instead of 0 for all lags in the basic case.

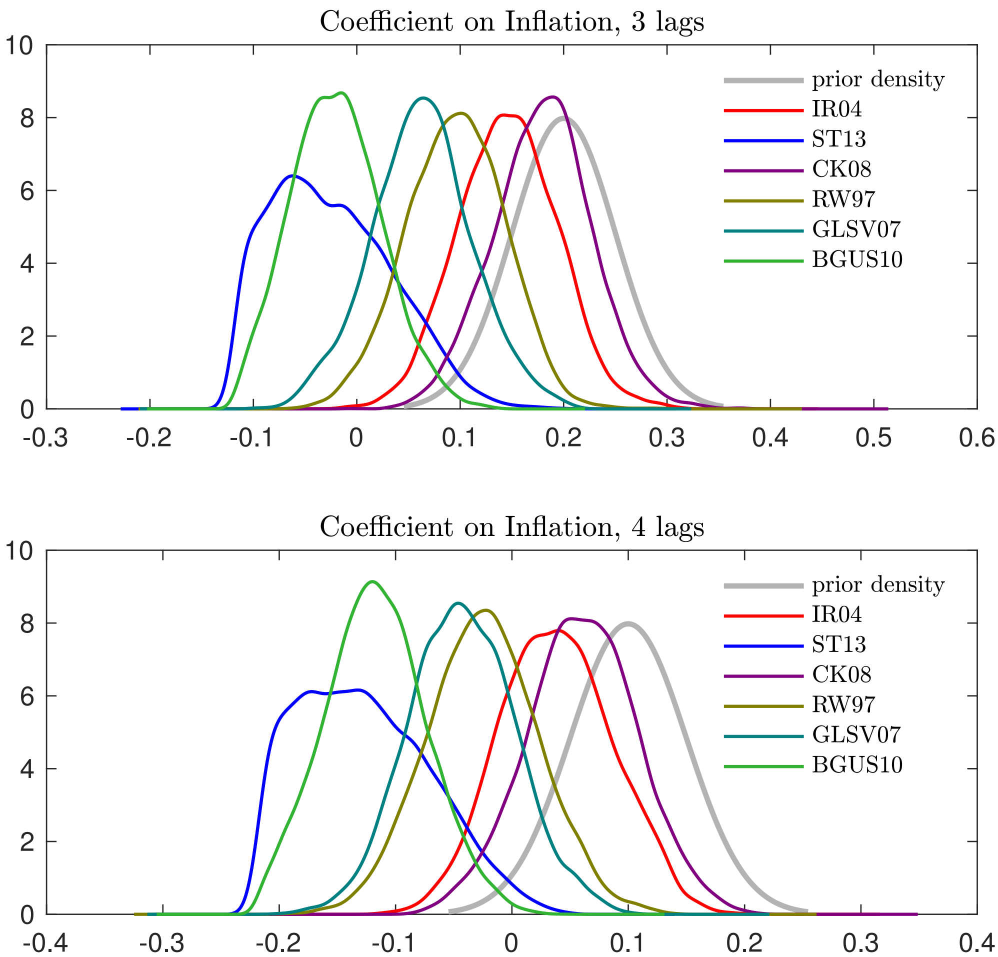


Figure 48: Prior distribution and posterior distributions – In this subsection I perform estimations based on real data with a variation with respect to the prior means compared to the basic case. In this and the previous figure the coefficient on inflation and the coefficients on the inflation lags are estimated from the monetary policy rule. The prior means of the coefficients on the lags of inflation are 0.4, 0.3, 0.2 and 0.1 respectively instead of 0 for all lags in the basic case.

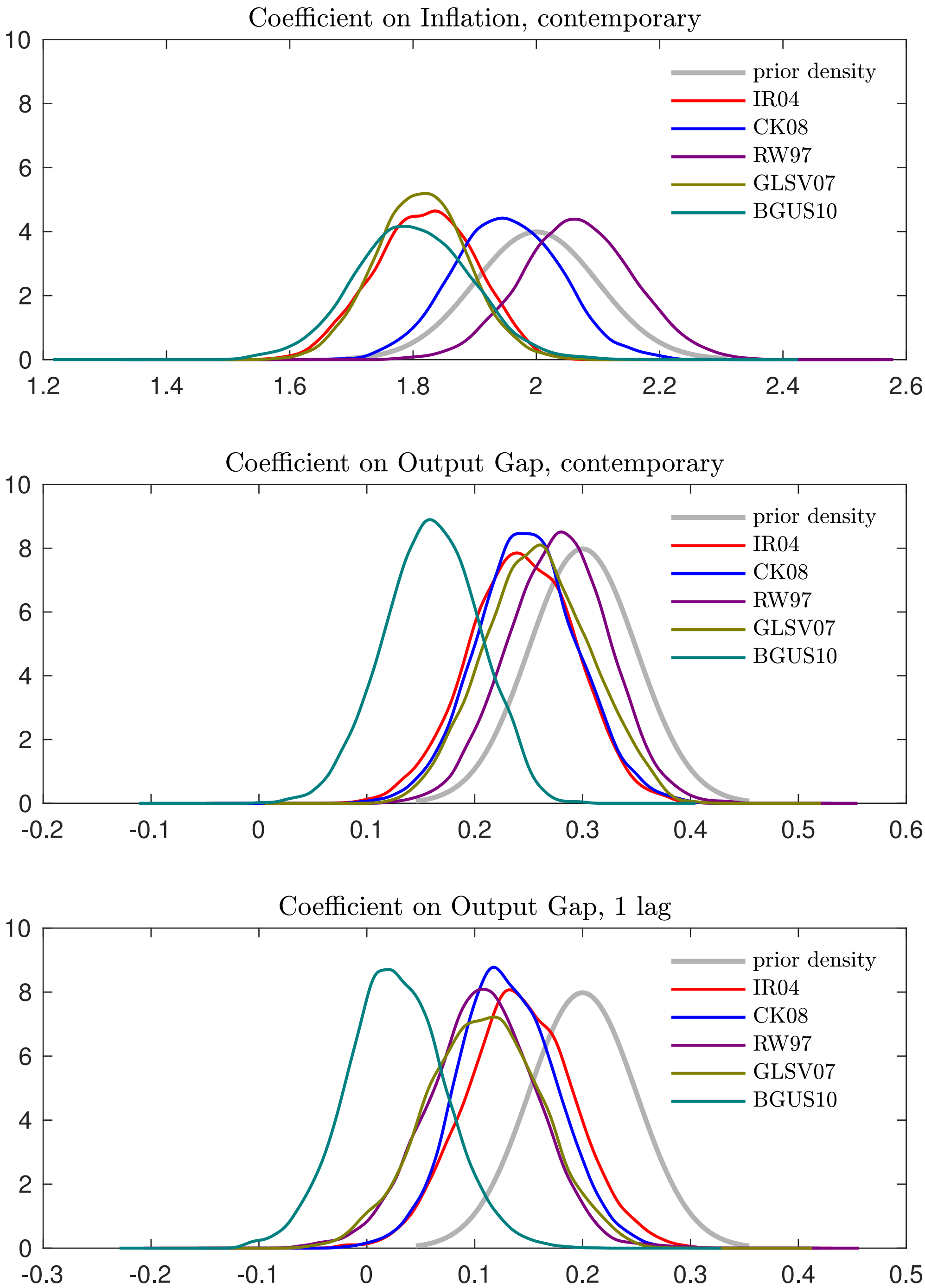


Figure 49: Prior distribution and posterior distributions – In this subsection I perform estimations based on real data with a variation with respect to the prior means compared to the basic case. In this and the following figure the coefficient on inflation, the output gap and the coefficients on the lags of the output gap are estimated from the monetary policy rule. The prior means of the coefficients on the output gap and its lags are 0.3, 0.2, 0.1, 0.1 and 0 respectively instead of 0.5 for the coefficient on the output gap contemporaneously and 0 for all the lags in the basic case.

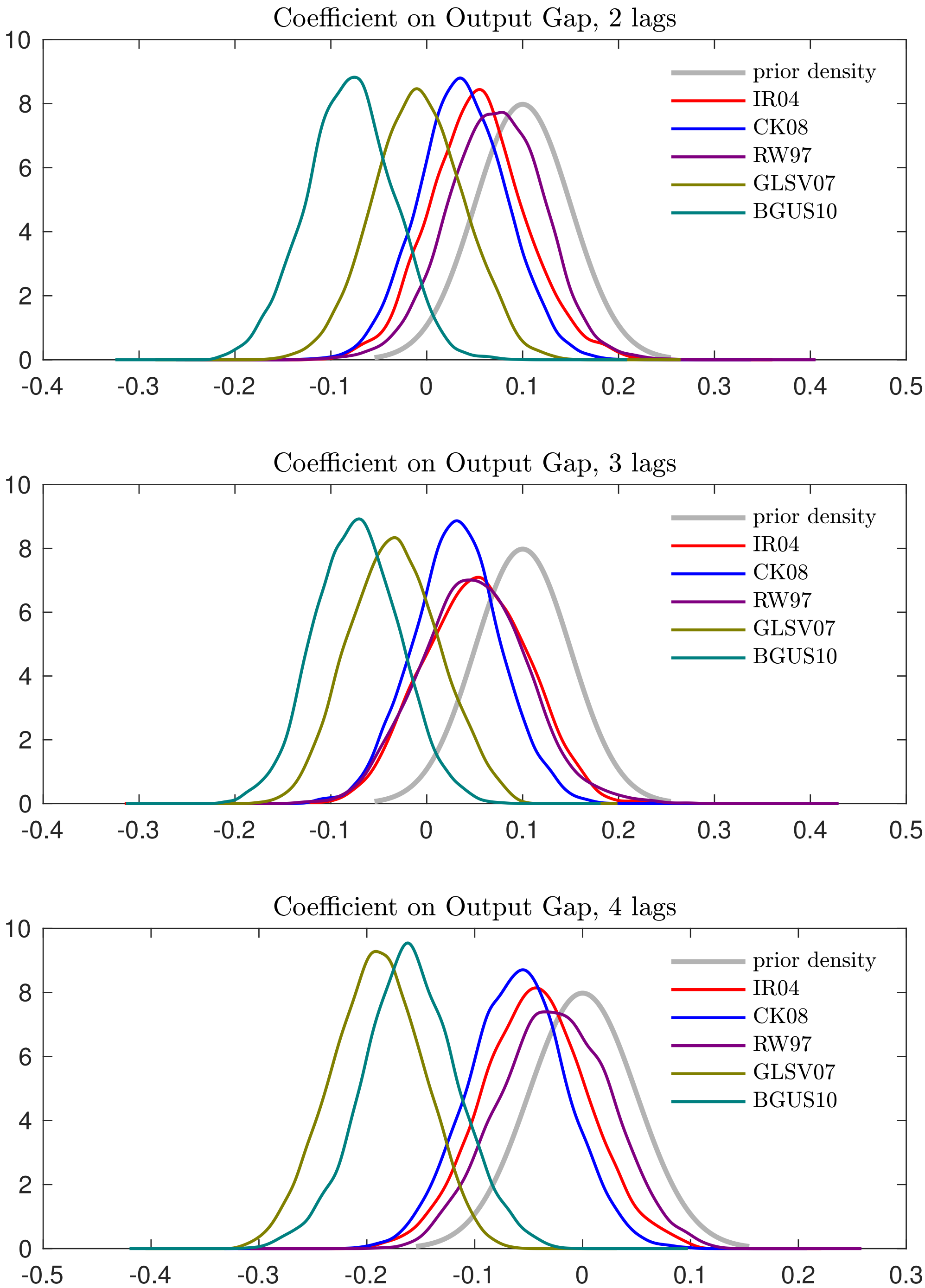


Figure 50: Prior distribution and posterior distributions – In this subsection I perform estimations based on real data with a variation with respect to the prior means compared to the basic case. In this and the previous figure the coefficient on inflation, the output gap and the coefficients on the lags of the output gap are estimated from the monetary policy rule. The prior means of the coefficients on the output gap and its lags are 0.3, 0.2, 0.1, 0.1 and 0 respectively instead of 0.5 for the coefficient on the output gap contemporaneously and 0 for all the lags in the basic case.

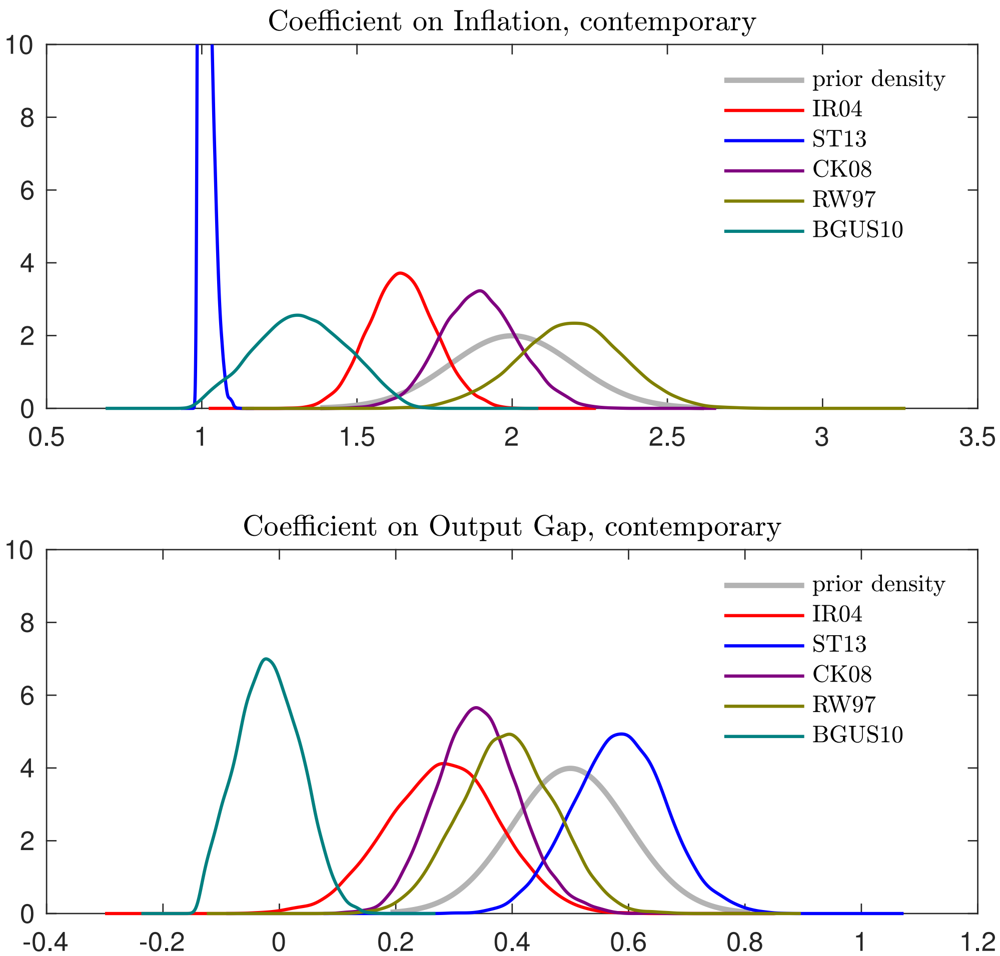


Figure 51: Prior distribution and posterior distributions – Here, I continue the estimations based on real data as before, but now in Figures 51 to 56 I have varied the prior variance compared to the previous estimations. In particular, I have used double the standard deviation compared to the baseline case. In this figure I estimate the coefficients on inflation and the output gap.

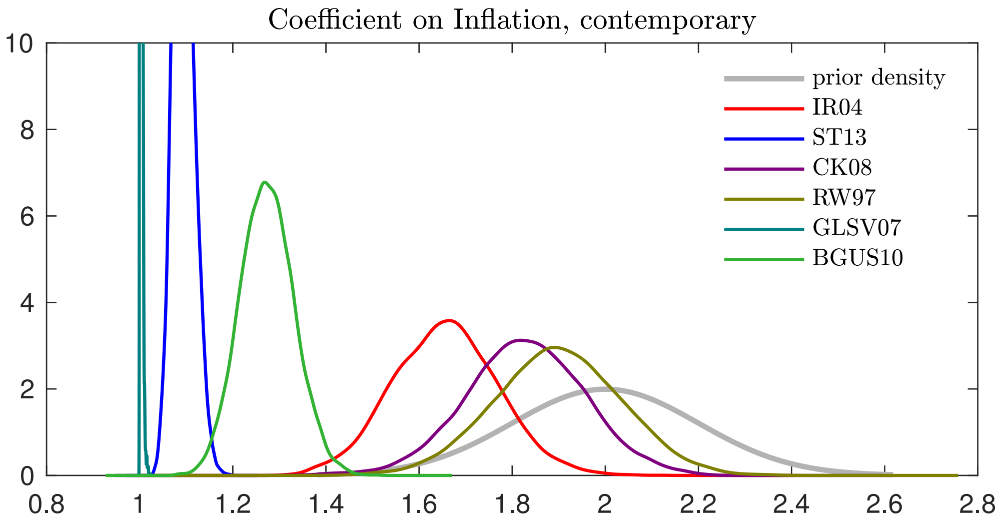


Figure 52: Prior distribution and posterior distributions – In this subsection I perform estimations based on real data. In this figure only the coefficient on inflation from the monetary policy rule is estimated, while I have used double the prior standard deviation compared to the baseline case.

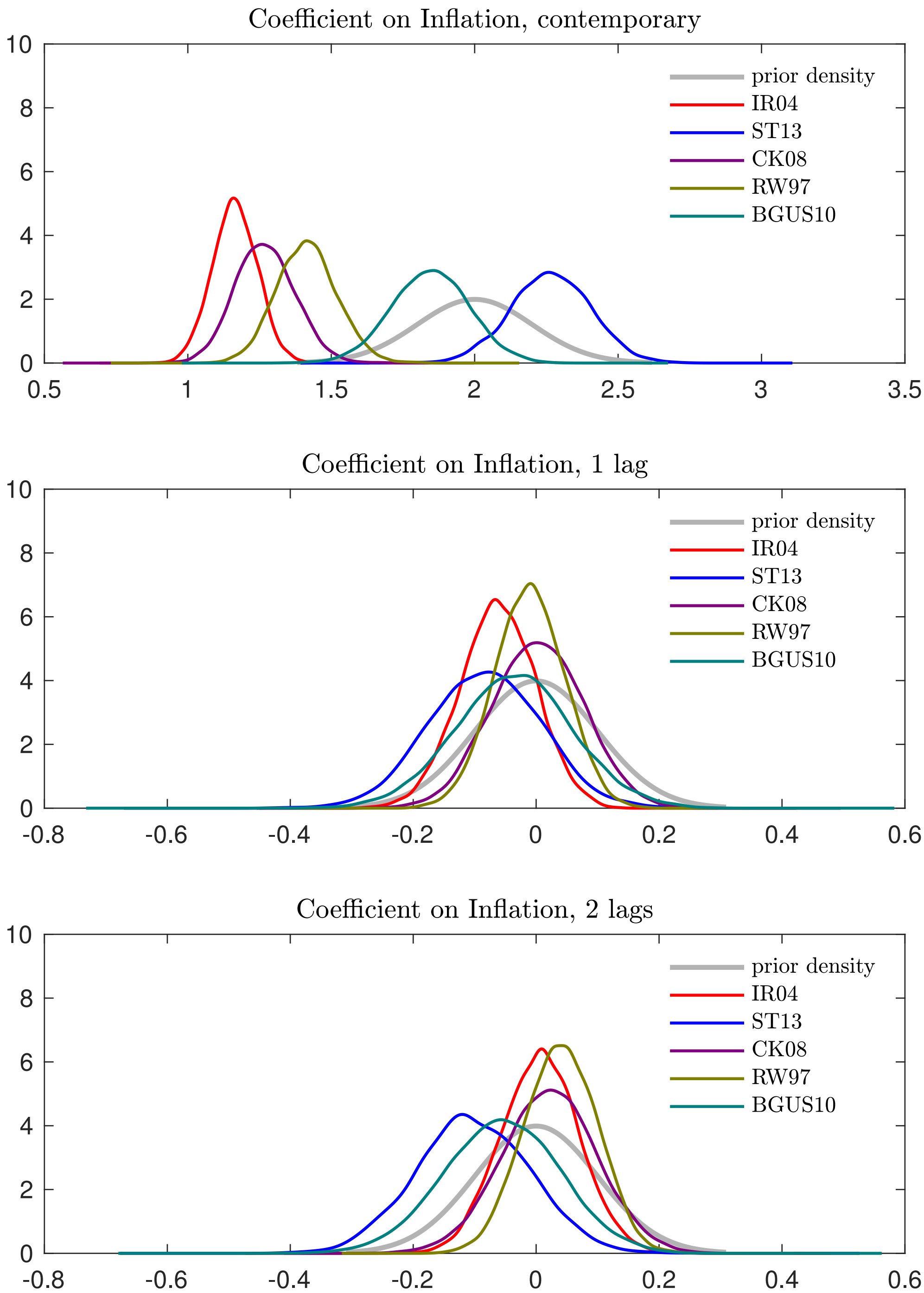


Figure 53: Prior distribution and posterior distributions – In this subsection I perform estimations based on real data. In this and the following figure the coefficient on inflation and the coefficients on the inflation lags are estimated from the monetary policy rule, while I have used double the prior standard deviation compared to the baseline case.

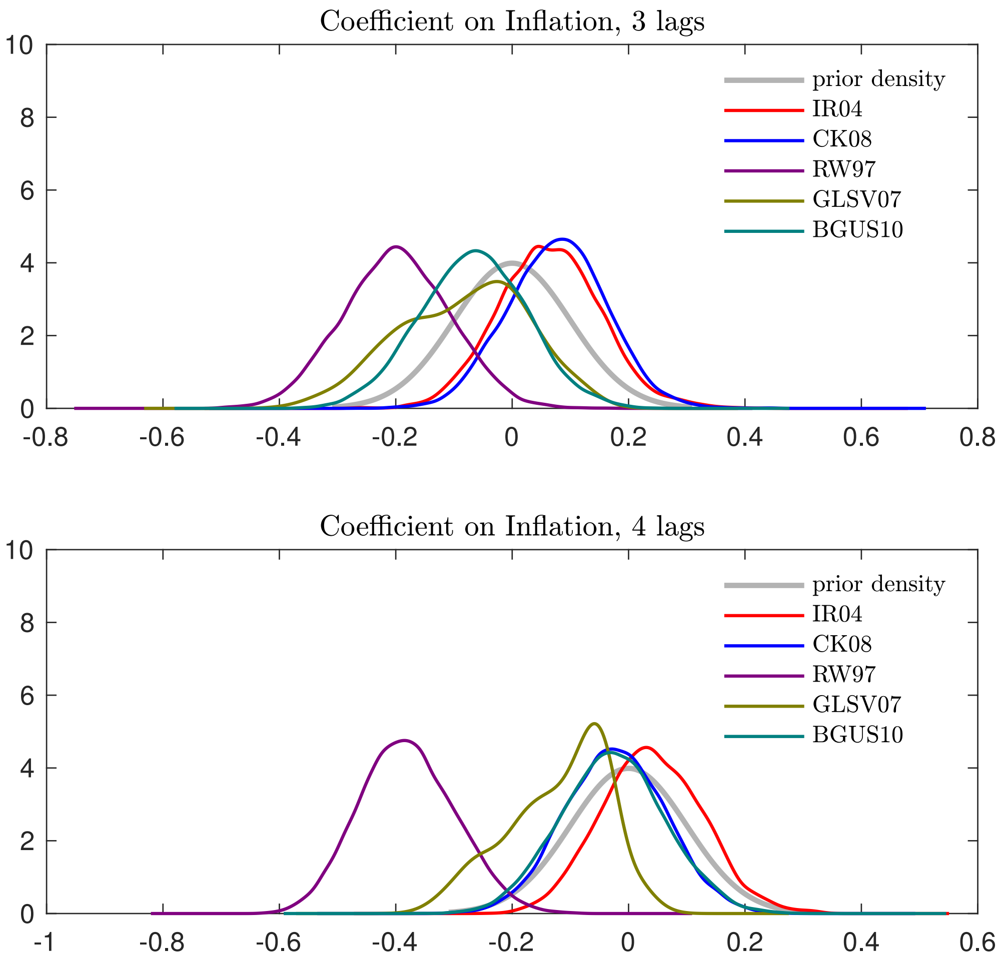


Figure 54: Prior distribution and posterior distributions – In this subsection I perform estimations based on real data. In this and the previous figure the coefficient on inflation and the coefficients on the inflation lags are estimated from the monetary policy rule, while I have used double the prior standard deviation compared to the baseline case.

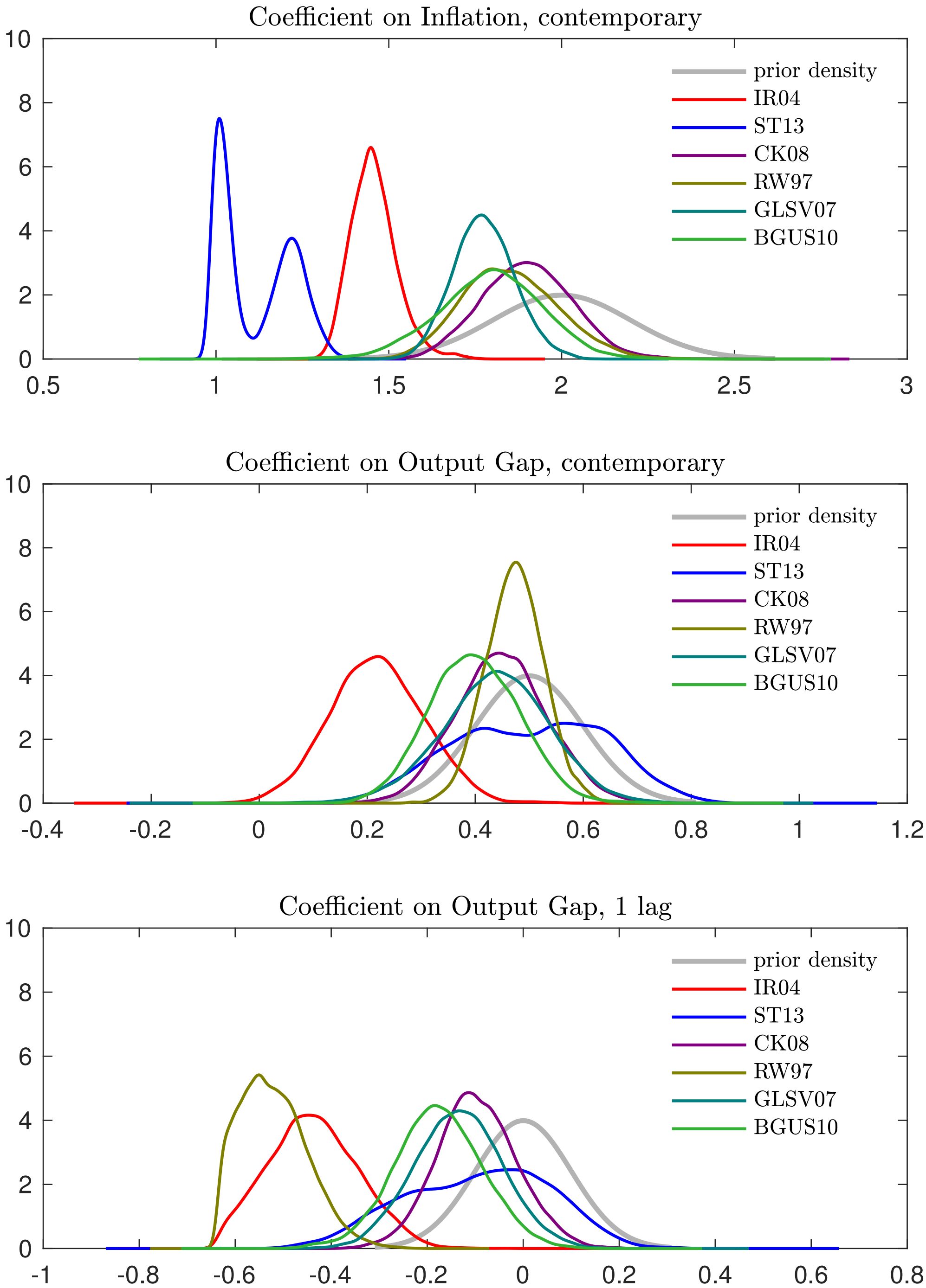


Figure 55: Prior distribution and posterior distributions – In this subsection I perform estimations based on real data. In this and the following figure the coefficient on inflation, the output gap and the coefficients on the lags of the output gap are estimated from the monetary policy rule, while I have used double the prior standard deviation compared to the baseline case.

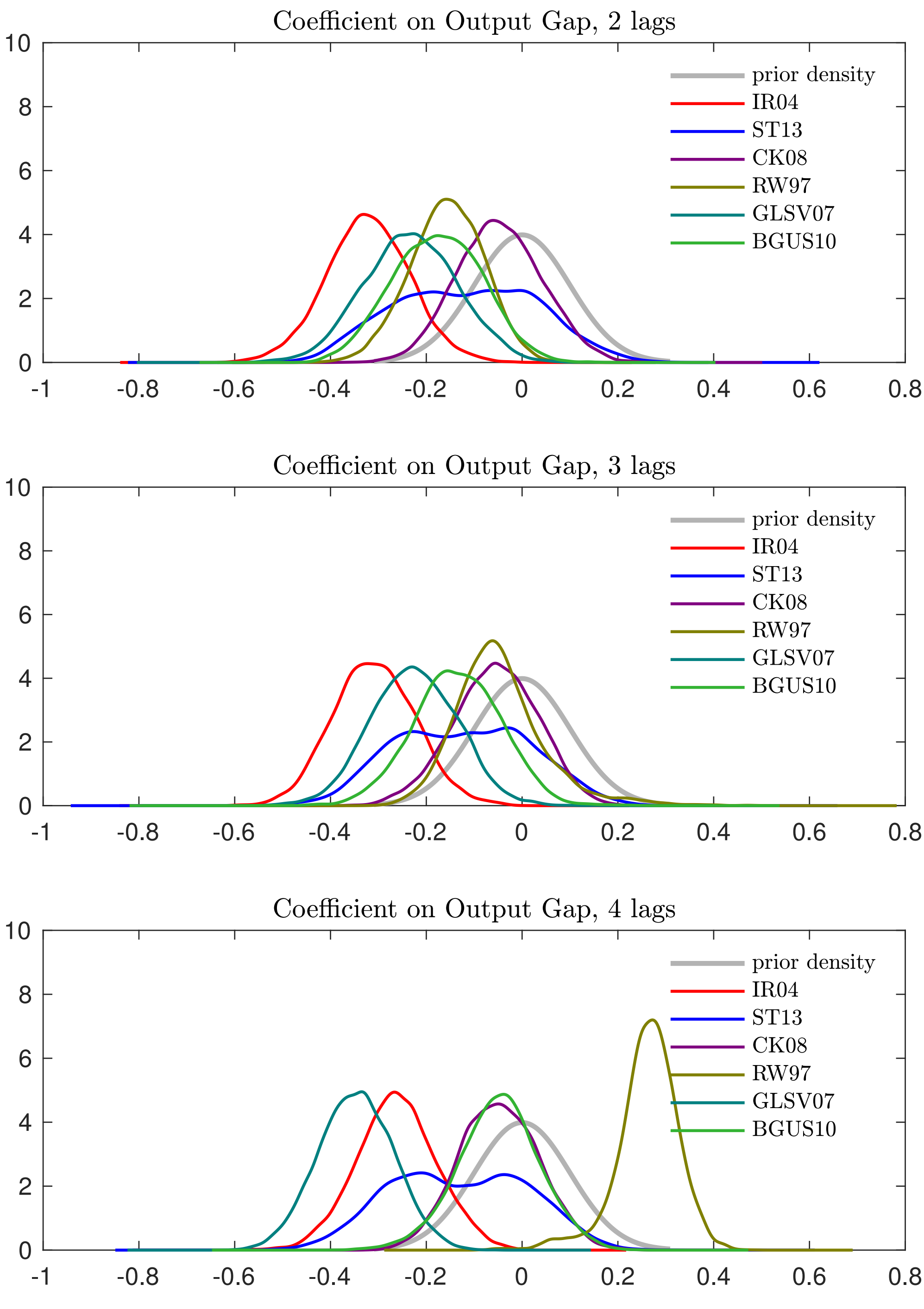


Figure 56: Prior distribution and posterior distributions – In this subsection I perform estimations based on real data. In this and the previous figure the coefficient on inflation, the output gap and the coefficients on the lags of the output gap are estimated from the monetary policy rule, while I have used double the prior standard deviation compared to the baseline case.

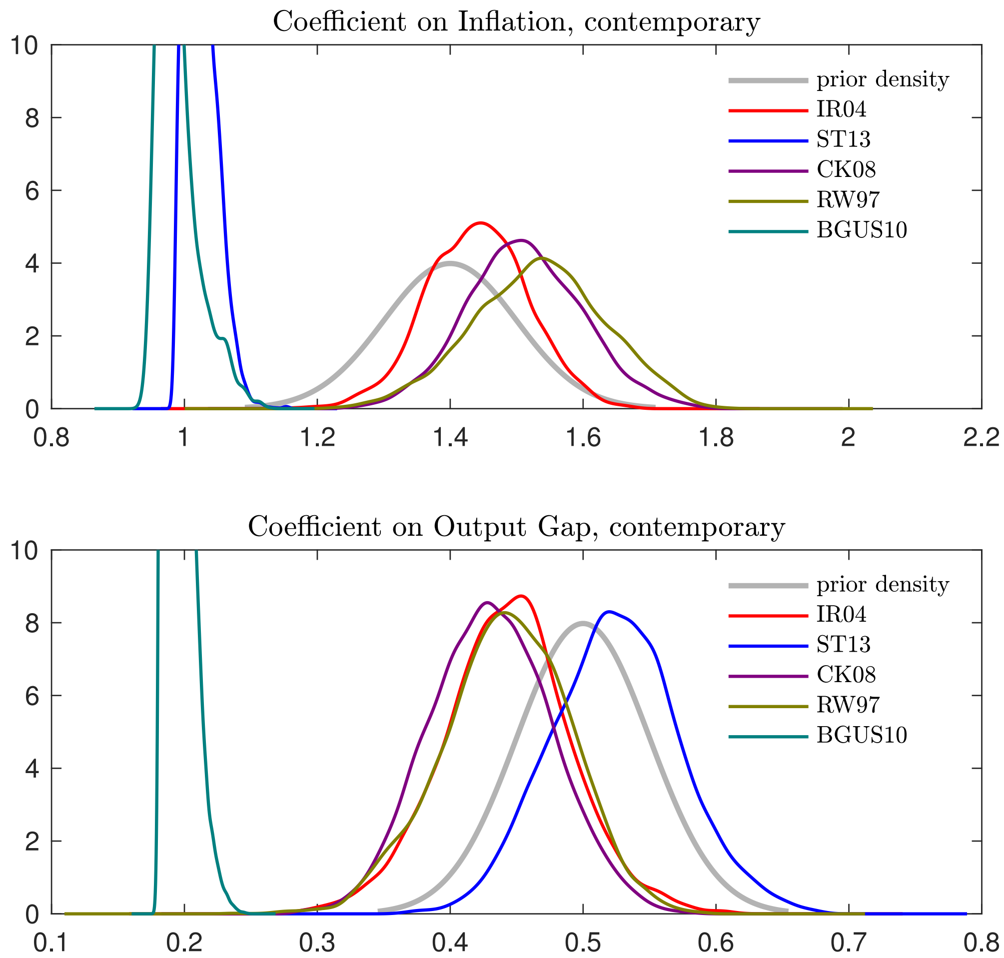


Figure 57: Prior distribution and posterior distribution for each model – In this subsection I perform estimations based on real data. In Figures 57 to 66 I perform a series of estimations which are the most clear example of the naive approach mentioned in the paper. Here I estimate the coefficient on inflation and the coefficient on the output gap. However, in Figures 57 to 61 I vary the prior mean of the coefficient on inflation. The prior mean then varies from 1.4 to 2.6.

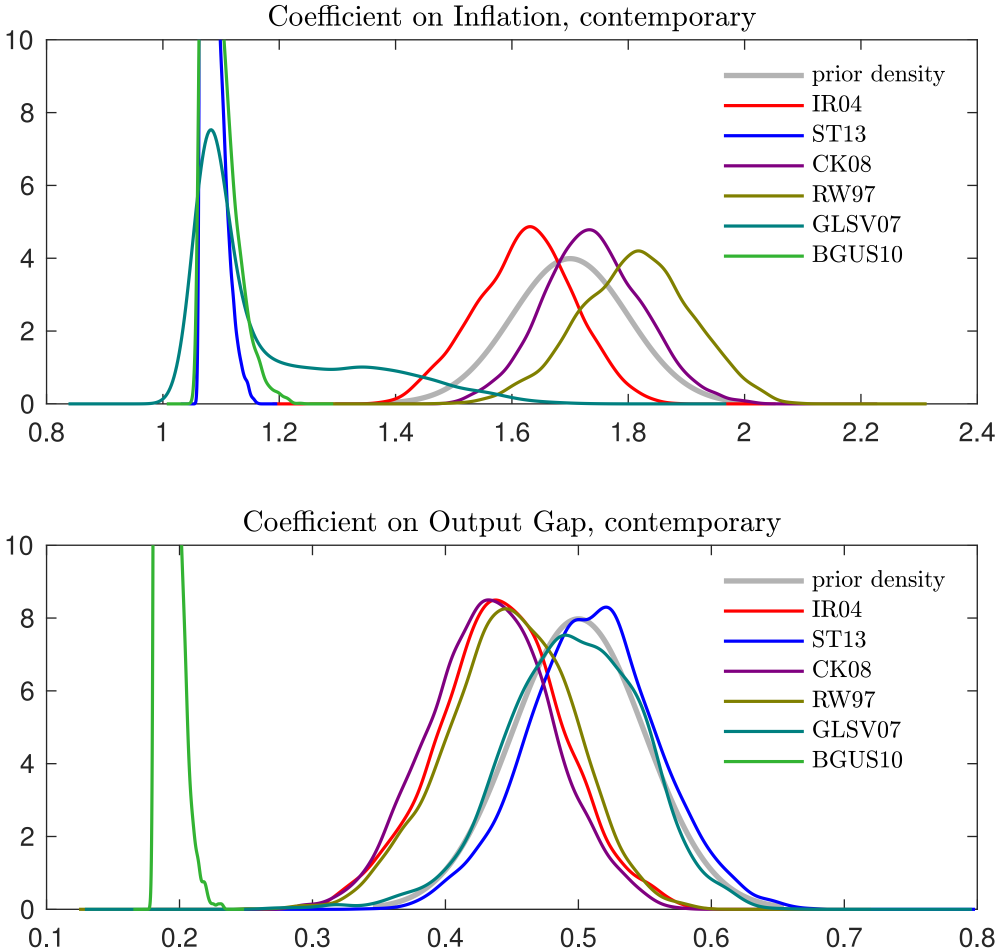


Figure 58: Prior distribution and posterior distribution for each model – In this subsection I perform estimations based on real data. In Figures 57 to 66 I perform a series of estimations which are the most clear example of the naive approach mentioned in the paper. Here I estimate the coefficient on inflation and the coefficient on the output gap. However, in Figures 57 to 61 I vary the prior mean of the coefficient on inflation. The prior mean then varies from 1.4 to 2.6.

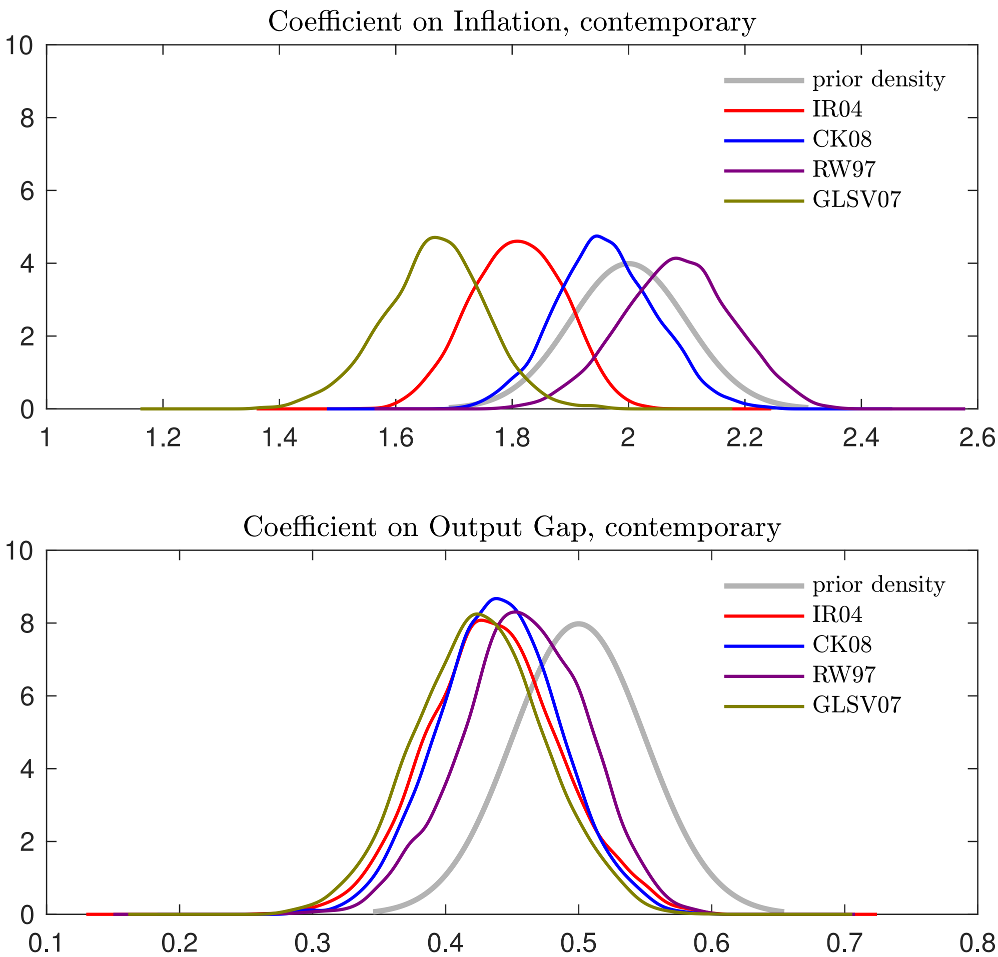


Figure 59: Prior distribution and posterior distribution for each model – In this subsection I perform estimations based on real data. In Figures 57 to 66 I perform a series of estimations which are the most clear example of the naive approach mentioned in the paper. Here I estimate the coefficient on inflation and the coefficient on the output gap. However, in Figures 57 to 61 I vary the prior mean of the coefficient on inflation. The prior mean then varies from 1.4 to 2.6.

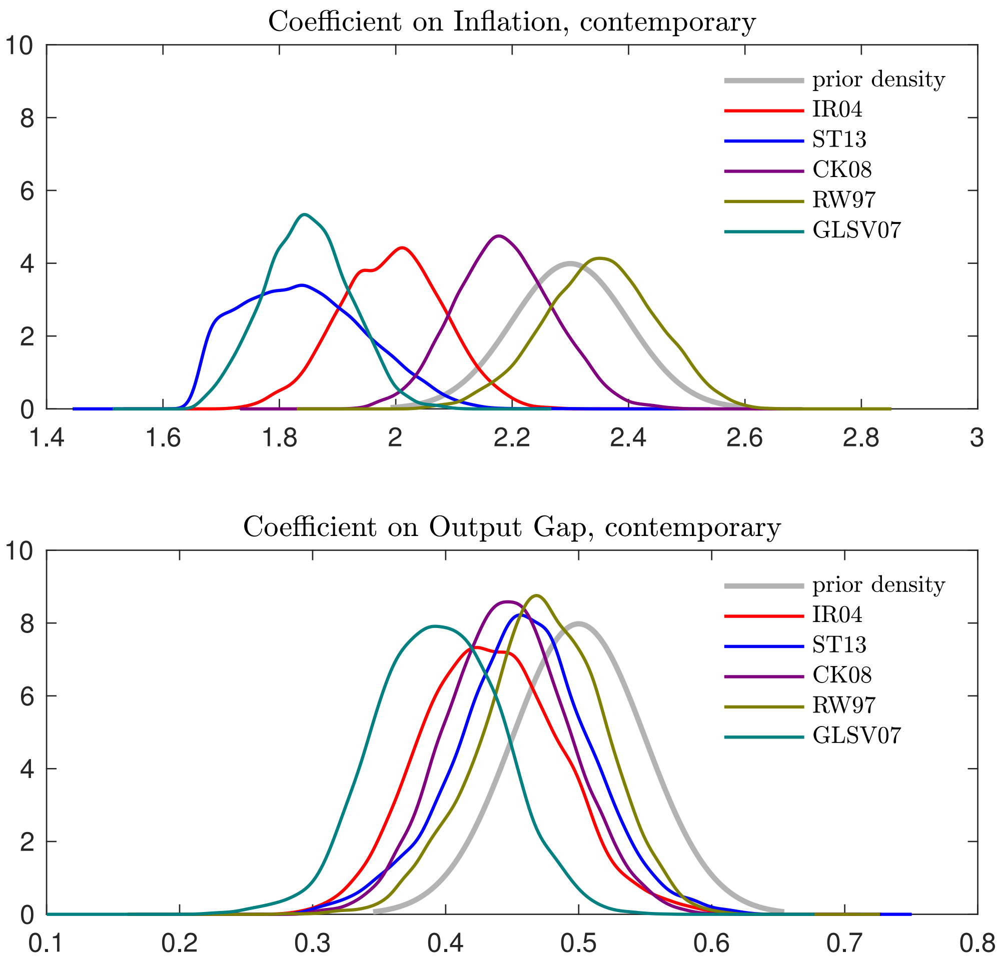


Figure 60: Prior distribution and posterior distribution for each model – In this subsection I perform estimations based on real data. In Figures 57 to 66 I perform a series of estimations which are the most clear example of the naive approach mentioned in the paper. Here I estimate the coefficient on inflation and the coefficient on the output gap. However, in Figures 57 to 61 I vary the prior mean of the coefficient on inflation. The prior mean then varies from 1.4 to 2.6.

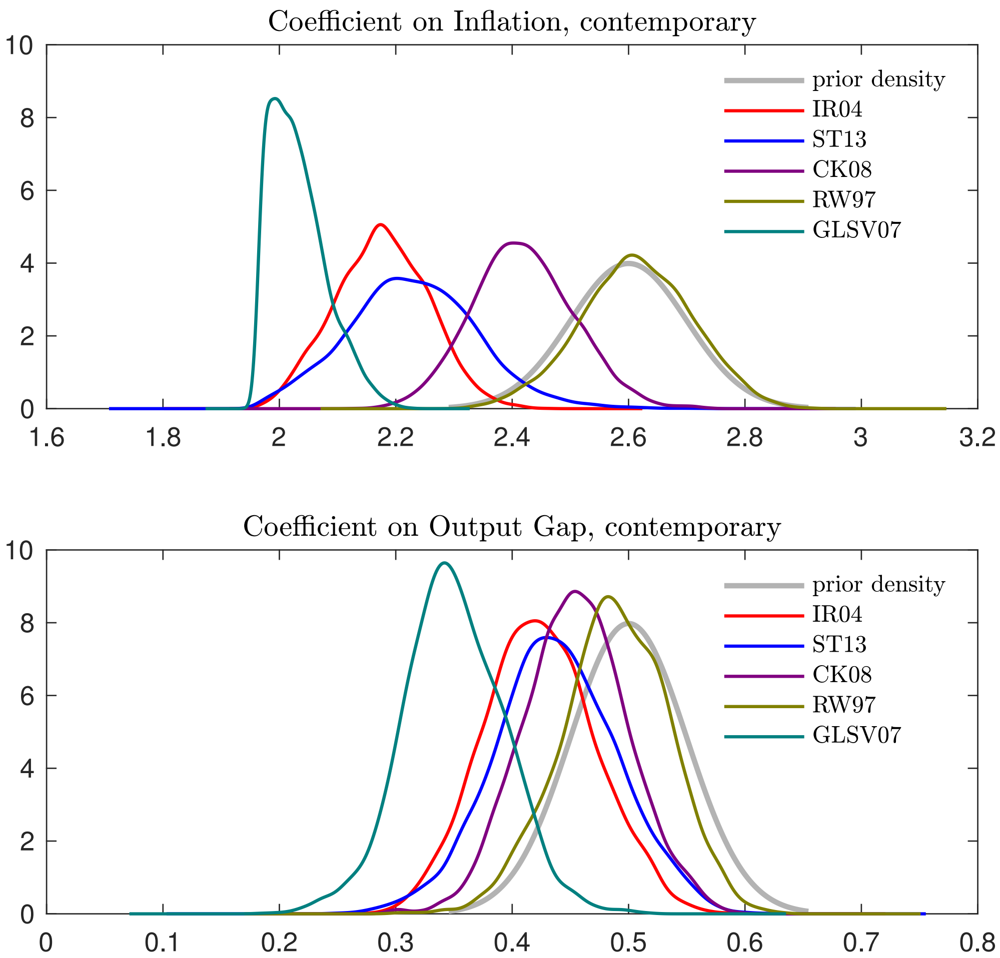


Figure 61: Prior distribution and posterior distribution for each model – In this subsection I perform estimations based on real data. In Figures 57 to 66 I perform a series of estimations which are the most clear example of the naive approach mentioned in the paper. Here I estimate the coefficient on inflation and the coefficient on the output gap. However, in Figures 57 to 61 I vary the prior mean of the coefficient on inflation. The prior mean then varies from 1.4 to 2.6.

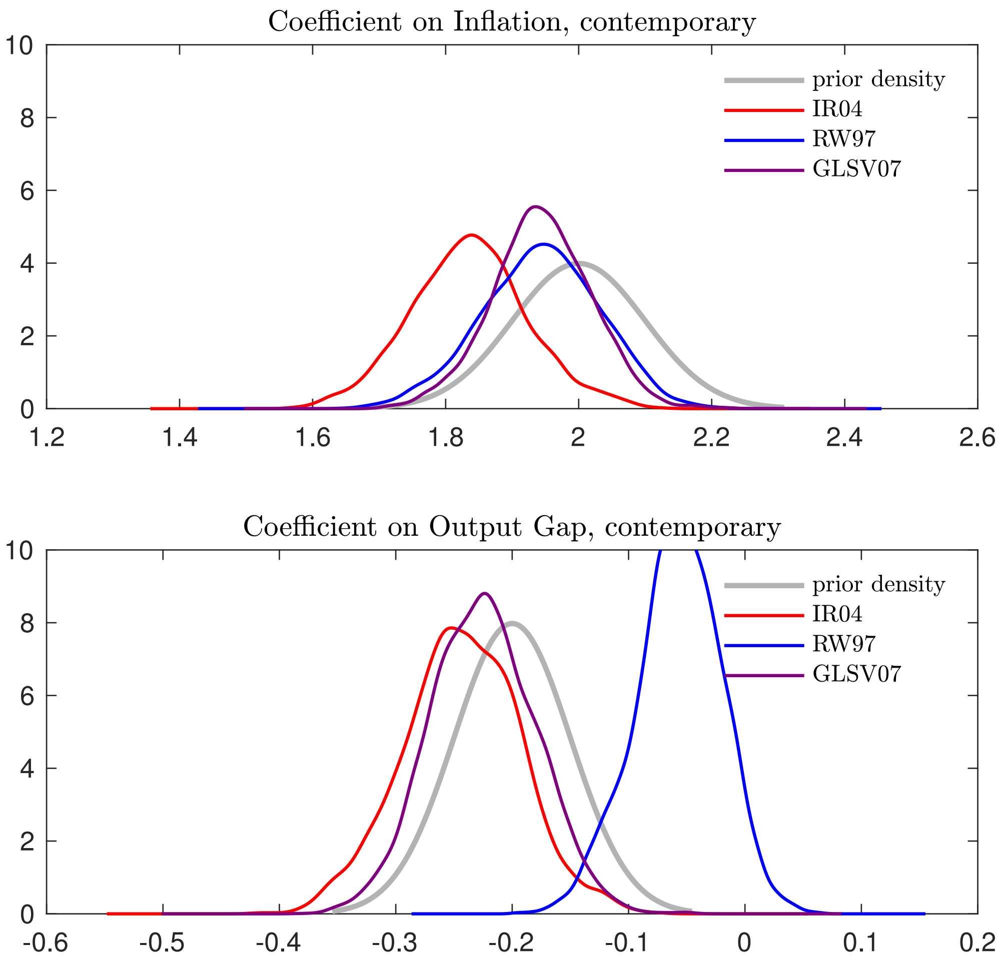


Figure 62: Prior distribution and posterior distribution for each model – In this subsection I perform estimations based on real data. In Figures 57 to 66 I perform a series of estimations which are the most clear example of the naive approach mentioned in the paper. Here I estimate the coefficient on inflation and the coefficient on the output gap. However, in Figures 62 to 66 I vary the prior mean of the coefficient on the output gap. The prior mean then varies from -0.2 to 0.6.

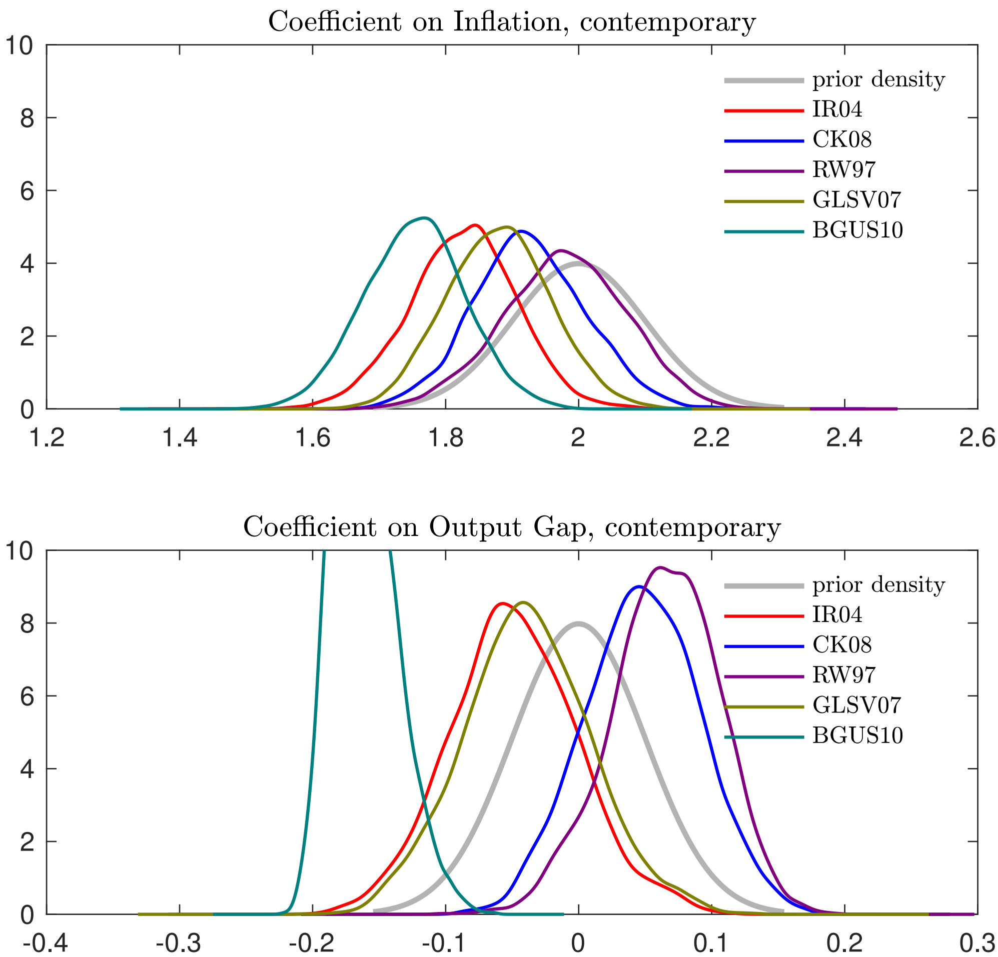


Figure 63: Prior distribution and posterior distribution for each model – In this subsection I perform estimations based on real data. In Figures 57 to 66 I perform a series of estimations which are the most clear example of the naive approach mentioned in the paper. Here I estimate the coefficient on inflation and the coefficient on the output gap. However, in Figures 62 to 66 I vary the prior mean of the coefficient on the output gap. The prior mean then varies from -0.2 to 0.6.

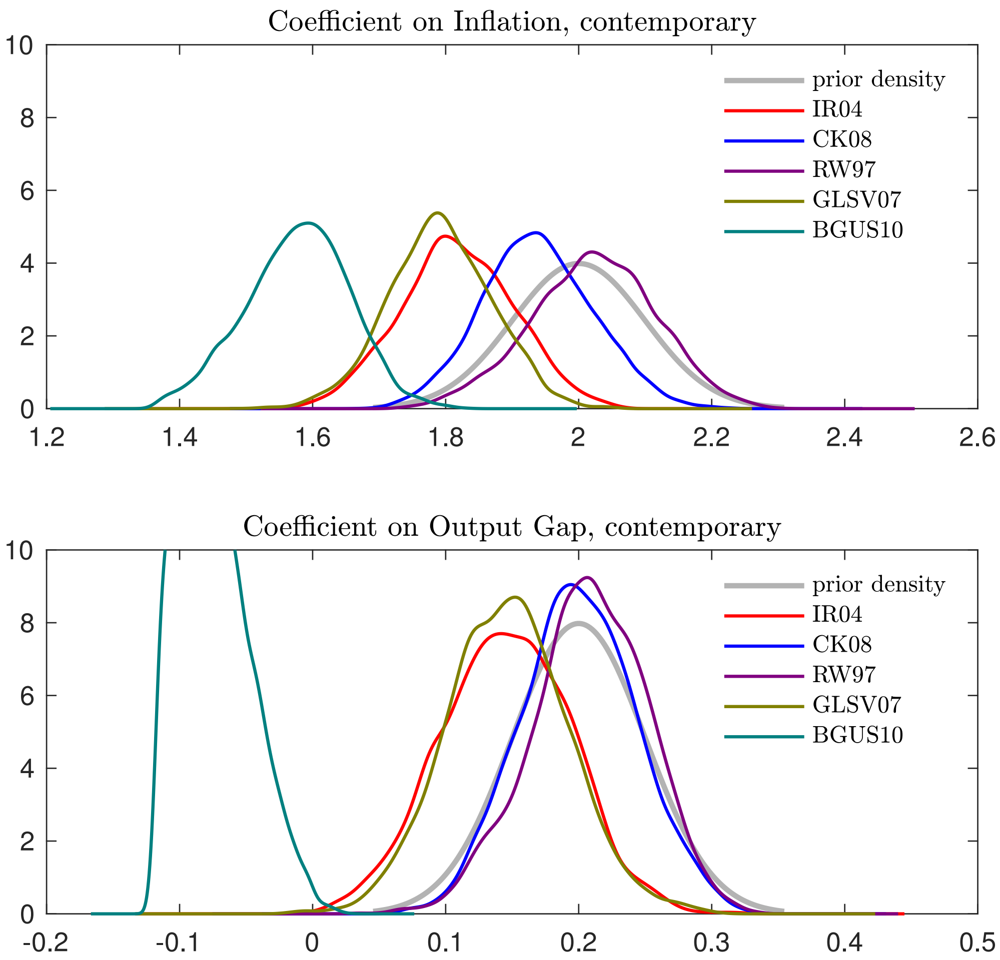


Figure 64: Prior distribution and posterior distribution for each model – In this subsection I perform estimations based on real data. In Figures 57 to 66 I perform a series of estimations which are the most clear example of the naive approach mentioned in the paper. Here I estimate the coefficient on inflation and the coefficient on the output gap. However, in Figures 62 to 66 I vary the prior mean of the coefficient on the output gap. The prior mean then varies from -0.2 to 0.6.

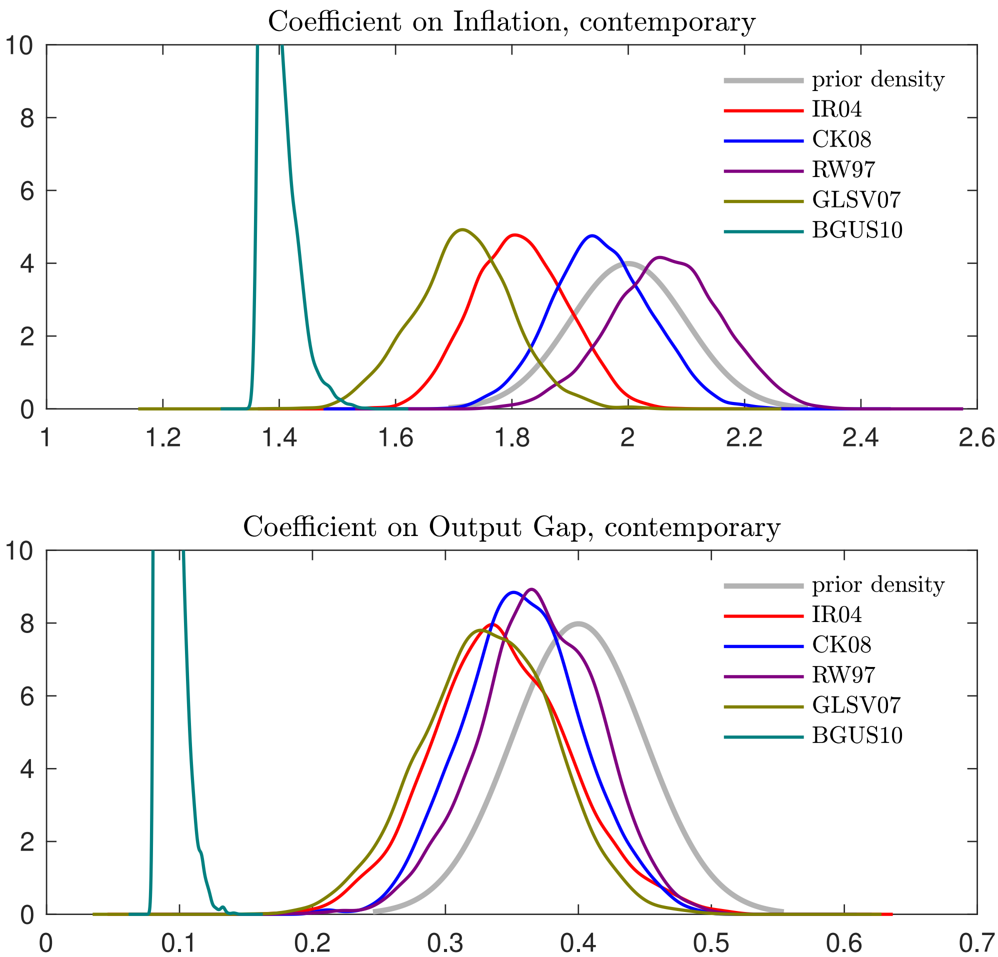


Figure 65: Prior distribution and posterior distribution for each model – In this subsection I perform estimations based on real data. In Figures 57 to 66 I perform a series of estimations which are the most clear example of the naive approach mentioned in the paper. Here I estimate the coefficient on inflation and the coefficient on the output gap. However, in Figures 62 to 66 I vary the prior mean of the coefficient on the output gap. The prior mean then varies from -0.2 to 0.6.

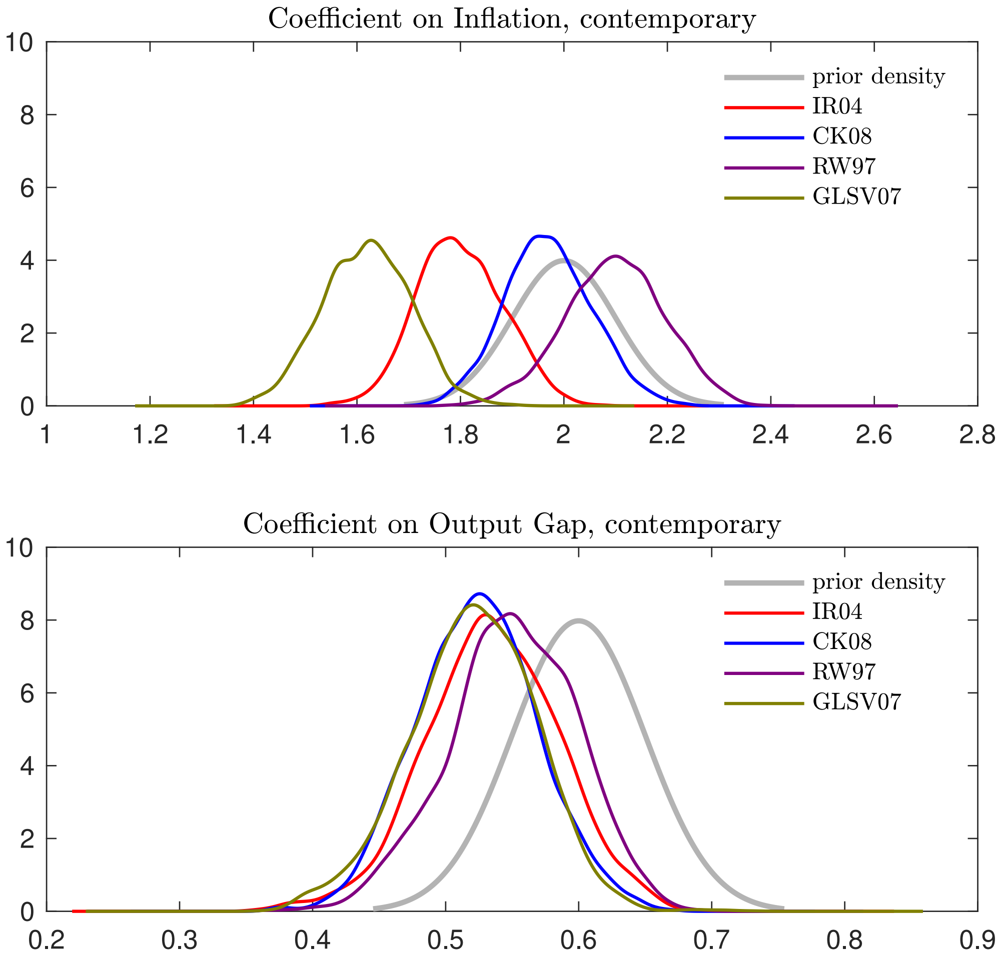


Figure 66: Prior distribution and posterior distribution for each model – In this subsection I perform estimations based on real data. In Figures 57 to 66 I perform a series of estimations which are the most clear example of the naive approach mentioned in the paper. Here I estimate the coefficient on inflation and the coefficient on the output gap. However, in Figures 62 to 66 I vary the prior mean of the coefficient on the output gap. The prior mean then varies from -0.2 to 0.6.

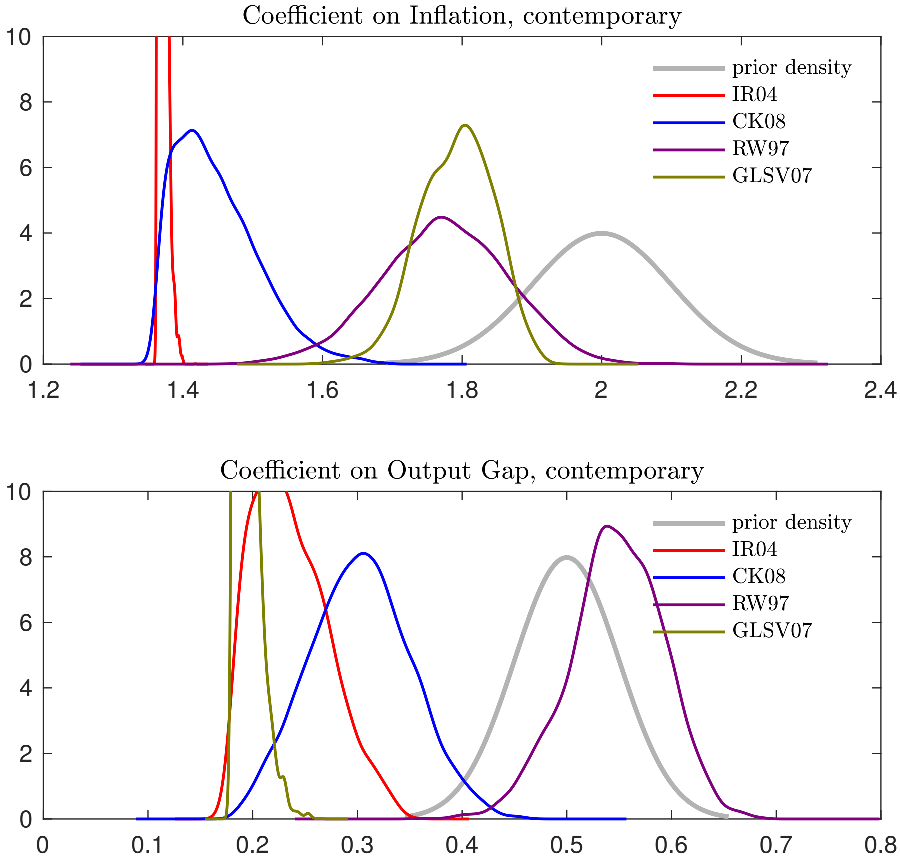


Figure 67: Prior distribution and posterior distributions – In Figures 67 to 72 I still use real data but I vary the subsample that I am using. In this and the following figure I use data from 1966 to 2004; this is also the subsample that was used by Smets and Wouters (2007). In this figure I estimate the coefficients on inflation and the output gap.

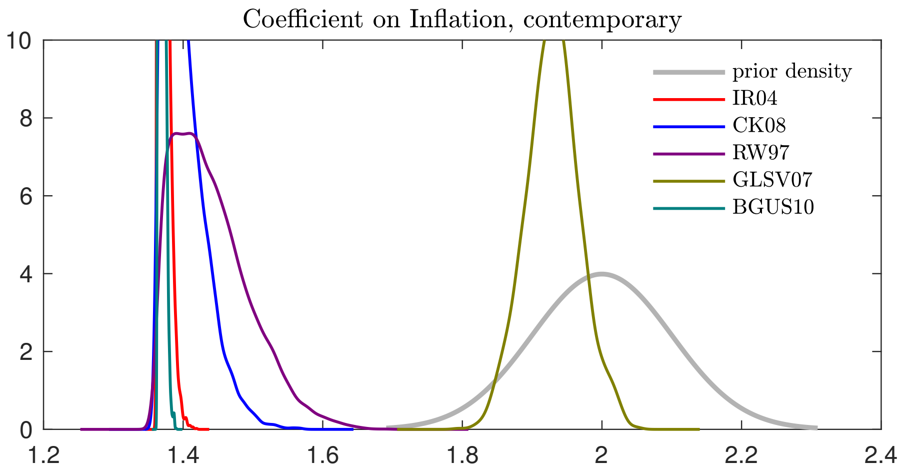


Figure 68: Prior distribution and posterior distributions – In this figure I estimate the coefficient on inflation only from the monetary policy rule

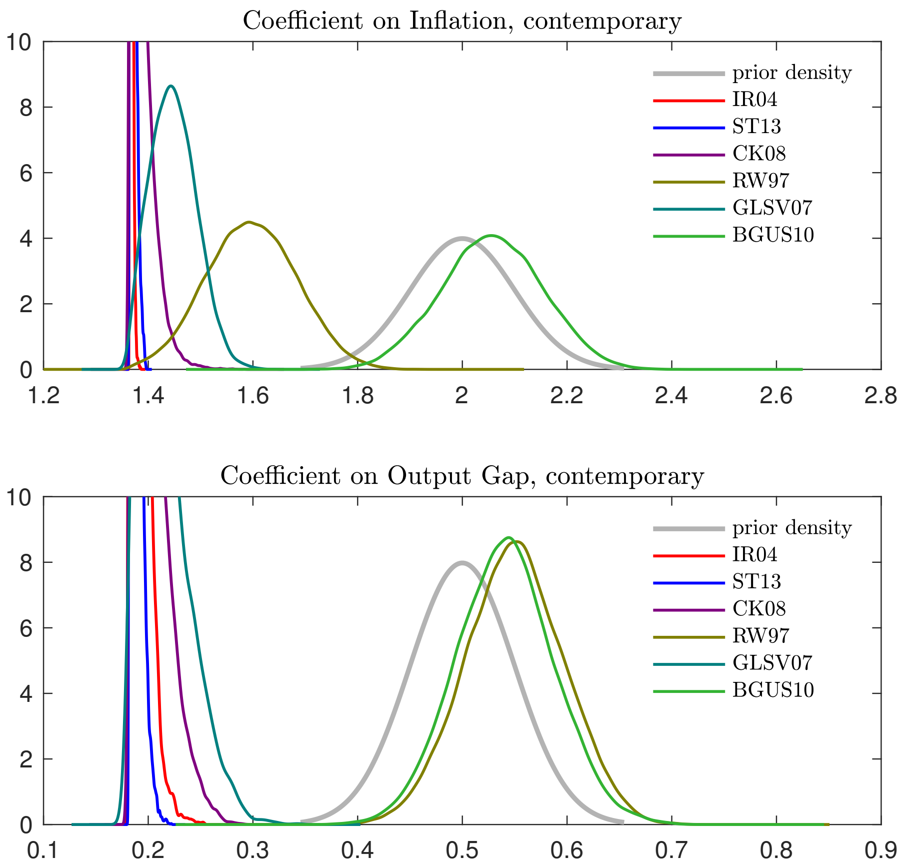


Figure 69: Prior distribution and posterior distributions – In Figures 67 to 72 I still use real data but I vary the subsample that I am using. In this and the following figure I use the entire sample from 1947 to 2004. In this figure I estimate the coefficients on inflation and the output gap.

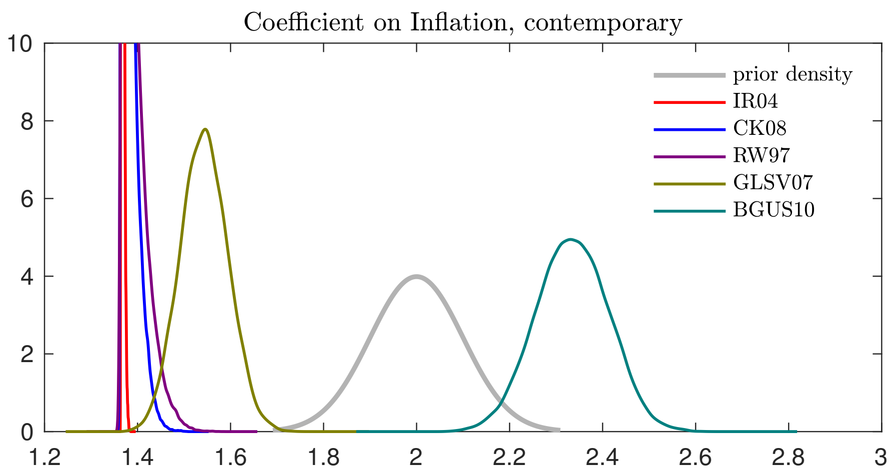
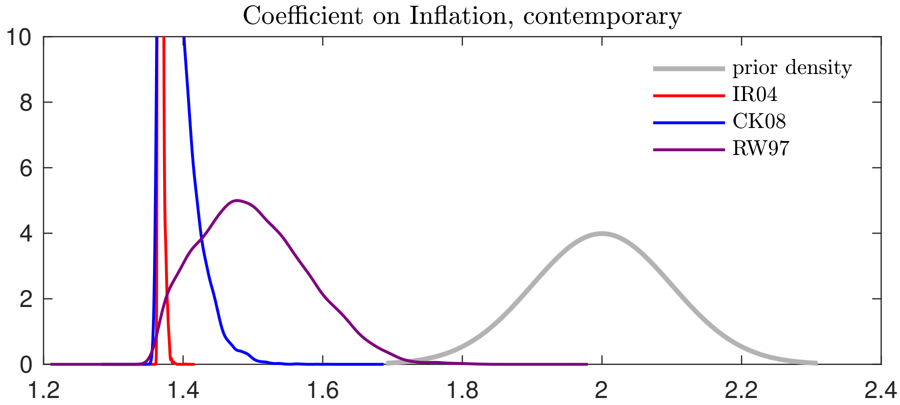


Figure 70: Prior distribution and posterior distributions – In this figure I estimate the coefficient on inflation only from the monetary policy rule



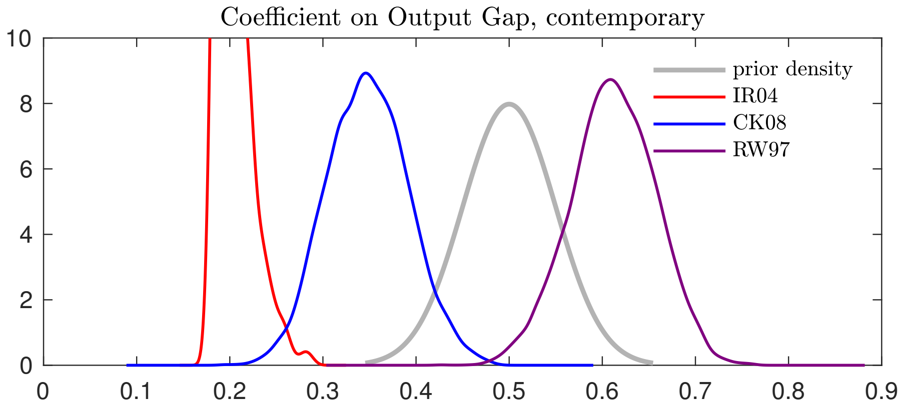


Figure 71: Prior distribution and posterior distributions – In Figures 67 to 72 I still use real data but I vary the subsample that I am using. In this and the following figure I use data from 1947 to 1979; after this date there is a claimed break in the conduct of monetary policy. In this figure I estimate the coefficients on inflation and the output gap.

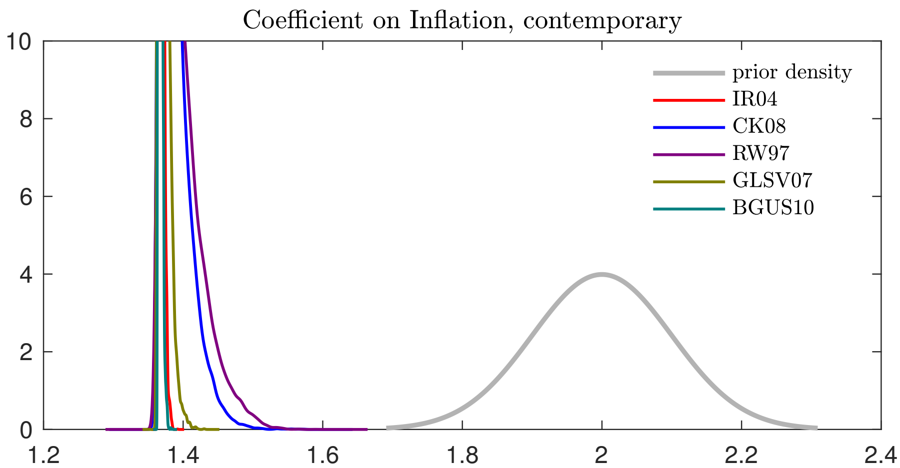


Figure 72: Prior distribution and posterior distributions – In this figure I estimate the coefficient on inflation only from the monetary policy rule.

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