Comparing New Keynesian Models in the Euro Area: A Bayesian Approach*

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Abstract

This paper estimates and compares four versions of the sticky price New Keynesian model for the Euro area using a Bayesian approach. The main results are: First, we find that the average duration of price contracts is between five and eight quarters and that price indexation is important. Second, average duration of wage contracts is estimated to be between two and three quarters, while wage indexation is unimportant. Third, the marginal likelihood indicates that sticky wages are important in the Euro area. Finally, using Smets and Wouters (2003) more informative priors, we present results that may indicate that data is not informative and, therefore, priors have a big influence on posteriors estimates.

Keywords: Nominal Rigidities, Indexation, Bayesian Econometrics, Model Comparison.

JEL Classification: C11, C15, E31, E32.

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1 Introduction

In this paper, we use a Bayesian approach to estimate and compare the sticky price model of Calvo (1983) and three extensions, using Euro area data. The baseline New Keynesian model of Calvo has become the benchmark for analyzing monetary policy, but its fit to the data has been challenged for various reasons.[1] As a result, extensions have been considered to improve its fit to the data. However, the existing literature lacks a formal comparison between competing alternatives using Euro area data. The paper fills this gap.

The first extension adds price indexation to the baseline model. As a result, both expectations of future and lagged inflation, together with real marginal costs, determine current inflation. The second extension includes staggered wage contracts to the baseline model as in Erceg, Henderson, and Levin (2000). As Galí, Gertler and López-Salido (2001) point out, in a pure forward-looking model, inflation persistence is driven by the sluggish adjustment of real marginal costs. Adding sticky nominal wages delivers sticky real wages, increasing inflation persistence, which is a main shortcoming of the baseline model. Finally, in the third extension, we add wage indexation to the sticky price-wage setup.

Although we are not aware of any formal work comparing different New Keynesian models for the Euro area, various approaches have estimated the structural parameters of models similar to the ones analyzed here. Galí, Gertler and López-Salido (2001) estimate the inflation equation of a Calvo model with price indexation using Generalized Method of Moments. Smets and Wouters (2003) estimate a dynamic general equilibrium model with nominal and real rigidities and compare its fit to the data with statistical Bayesian Vector Autoregressive (BVAR) models.

Although structural estimation is an interesting exercise itself, looking at the overall fit and comparing different alternatives is necessary to evaluate the models' performance. In this regard, the Bayesian approach is very convenient since, as shown by Fernández-Villaverde

[1] See Fuhrer and Moore (1995) and Chari, Kehoe, and McGrattan (2000) for criticisms of its fit to U.S. data.

and Rubio-Ramírez (2004), the marginal likelihood compares models consistently, even if they are misspecified.

Two additonal reasons lead us to choose the Bayesian approach. First, it takes advantage of the general equilibrium approach. As discussed in Leeper and Zha (2000), estimation of reduced-form equations suffers from identification problems. Second, Fernández-Villaverde and Rubio-Ramírez (2004) show that it outperforms maximum likelihood in small samples.[2]

The main results of this paper are as follows: First, we estimate an average duration of price contracts between six and eight quarters, while the estimated average duration of wage contracts is below three quarters. Second, price indexation is important, while wage indexation is unimportant. Third, the marginal likelihood concludes that sticky wages are the most important addition to the sticky price model for explaining the Euro area data. Finally, using Smets and Wouters (2003) more informative priors, we study whether the data contain enough information to allow the researcher to estimate all the parameters of the models analyzed here. We present results that may indicate that data is not informative and, therefore, priors have a big influence on posteriors estimates.

The remainder of the paper is organized as follows: In Section 2 we present the baseline sticky price model and the three extensions that we compare. In Section 3 we explain the data and the priors used. In Section 4 we present and discuss the results, leaving Section 5 for concluding remarks.

2 The Models

In this section we describe the four models. Our baseline model is a sticky price model where, as in Calvo (1983), intermediate good producers face restrictions in the price setting process (BSP). We extend this baseline model in three different ways. First, we allow for indexation in prices (INDP). Second, in the spirit of Erceg, Henderson, and Levin (2000), we introduce staggered wage contracts (EHL). Finally, we allow for both staggered wage contracts and

[2] For a detailed explanation on the application of the Bayesian approach to estimation and comparison of general equilibrium models, we refer the reader to Schorfheide (2003).

indexation in wages (INDW).

Since these four models are well known in the literature[3] we explain only the equations that describe the linear dynamics of each model. These equations are obtained by taking a log-linear approximation around the steady state of the first order conditions of households, firms, and the resource constraints that describe the symmetric equilibrium.

2.1 Baseline Model (BSP)

First, we have the Euler equation that relates output growth with the real rate of interest

$$y_t = E_t y_{t+1} - \sigma(r_t - E_t \Delta p_{t+1} + E_t g_{t+1} - g_t) \tag{1}$$

where y_t denotes output, r_t is the nominal interest rate, g_t is the preference shifter shock, p_t is the price level, and σ is the elasticity of intertemporal substitution.

The production function and the real marginal cost of production are:

$$y_t = a_t + (1 - \delta)n_t, \qquad mc_t = w_t - p_t + n_t - y_t \tag{2}$$

where a_t is a technology shock, n_t is the amount of hours worked, mc_t is the real marginal cost, and w_t is the nominal wage. δ is the capital share of output.

The marginal rate of substitution (mrs_t) between consumption and hours is:

$$mrs_t = \frac{1}{\sigma} y_t + \gamma n_t - g_t \tag{3}$$

where γ is the inverse elasticity of labor supply with respect to real wages.

The pricing decision of the firm under the Calvo-type restriction delivers the following forward-looking equation for price inflation (Δp_t):

$$\Delta p_t = \beta E_t \Delta p_{t+1} + \kappa_p (mc_t + \lambda_t) \tag{4}$$

[3] An accurate description of the various models can be found in Rabanal and Rubio-Ramírez (2003). See also the next footnote for specific functional forms.

where $\kappa_p = \frac{(1-\delta)(1-\theta_p \beta)(1-\theta_p)}{\theta_p(1+\delta(\bar{\varepsilon}-1))}$ and $\bar{\varepsilon} = \frac{\bar{\lambda}}{\bar{\lambda}-1}$ is the steady state value of ε, the elasticity of substitution between types of goods. λ_t is the price markup shock, θ_p is the probability of keeping prices fixed during the period, and β is the elasticity of intertemporal substitution.[4]

Since the BSP has flexible wages, the usual condition that real wages equal the marginal rate of substitution is met:

$$w_t - p_t = mrs_t \tag{5}$$

We use the following specification for the Taylor rule:

$$r_t = \rho_r r_{t-1} + (1-\rho_r)\left[\gamma_\pi \Delta p_t + \gamma_y y_t\right] + z_t \tag{6}$$

where γ_π and γ_y are the long-run responses of the monetary authority to deviations of inflation and output from their steady state values, and z_t is the monetary shock. We also include an interest rate smoothing parameter, ρ_r.

[4] To obtain equations (1)-(4), we assume that each household $j \in [0,1]$ maximizes the following utility function subject to a standard budget constraint.

$$U^j = E_0 \sum_{t=0}^{\infty} \frac{G_t (C_t^j)^{1-\frac{1}{\sigma}}}{1-\frac{1}{\sigma}} - \frac{(N_t^j)^{1+\gamma}}{1+\gamma},$$

where G_t is a preference shifter shock, C_t^j is consumption of the final good and N_t^j are hours worked. The production functions of intermediate goods (Y_t^i) for $i \in [0,1]$ and final goods (Y_t) are:

$$Y_t^i = A_t (N_t^i)^{1-\delta}, \qquad Y_t = \left[\int_0^1 (Y_t^i)^{\frac{\varepsilon_t - 1}{\varepsilon_t}} di\right]^{\frac{\varepsilon_t}{\varepsilon_t - 1}}$$

where A_t is a technology shock, and N_t^i is an aggregate index of labor input across all types of labor supplied by households.

$$N_t^i = \left[\int_0^1 (N_t^{i,j})^{\frac{\phi-1}{\phi}} dj\right]^{\frac{\phi}{\phi-1}}.$$

The aggregate price level and wage levels are:

$$P_t = \left[\int_0^1 (P_t^i)^{1-\varepsilon_t} di\right]^{\frac{1}{1-\varepsilon_t}}, \qquad W_t = \left[\int_0^1 (W_t^j)^{1-\phi} dj\right]^{\frac{1}{1-\phi}}.$$

Then, the price mark-up shock in the text is $\lambda_t = \frac{\varepsilon_t}{\varepsilon_t - 1}$.

We specify the shocks to follow the stochastic processes:

$$\begin{aligned} a_t &= \rho_a a_{t-1} + \varepsilon_t^a \\ g_t &= \rho_g g_{t-1} + \varepsilon_t^g \\ z_t &= \varepsilon_t^z \\ \lambda_t &= \varepsilon_t^\lambda \end{aligned}$$

where each innovation ε_t^i follows a $Normal\ (0, \sigma_i^2)$ distribution, for $i = a, g, z, \lambda$, and innovations are uncorrelated with each other. We now explain how the three extensions modify the basic equations (4) and (5).

2.1.1 Model with Sticky Prices and Price Indexation (INDP)

In this case, equation (4) is replaced by:

$$\Delta p_t = \gamma_b \Delta p_{t-1} + \gamma_f E_t \Delta p_{t+1} + \kappa_p'(mc_t + \lambda_t) \tag{5'}$$

where $\kappa_p' = \frac{\kappa_p}{1+\omega\beta}$, $\gamma_b = \frac{\omega}{1+\omega\beta}$, and $\gamma_f = \frac{\beta}{1+\omega\beta}$, and ω is the degree of price indexation. The wage setting equation remains the same (5).

2.1.2 Model with Sticky Prices and Wages (EHL)

In this case, both price and wage inflation behave in a forward-looking way. The price inflation equation is given by (4). Introducing the Calvo-type wage restriction delivers the following process for the nominal wage growth equation (Δw_t) that replaces (5):

$$\Delta w_t = \beta E_t \Delta w_{t+1} + \kappa_w(mrs_t - (w_t - p_t)) \tag{6'}$$

where $\kappa_w = \frac{(1-\theta_w)(1-\beta\theta_w)}{\theta_w(1+\phi\gamma)}$, θ_w is the probability of keeping wages fixed in a given period, and ϕ is the elasticity of substitution between different types of labor in the production function.

2.1.3 Model with Sticky Prices, Wages, and Wage Indexation (INDW)

This model extends EHL in that the nominal wage growth equation (6') incorporates indexation:

$$\Delta w_t - \alpha \Delta p_{t-1} = \beta E_t \Delta w_{t+1} - \alpha\beta\Delta p_t + \kappa_w(mrs_t - (w_t - p_t)) \quad (6")$$

where α is the degree of wage indexation.

3 Empirical Analysis

In this section, we report the data used in the analysis, the prior distributions, the mean posterior distributions, and the log of the marginal likelihoods of each model.

3.1 The Data

Even though member countries in the European Monetary Union have converged to a unified system of national accounts, an aggregate data set for the area is difficult to construct. The Econometric Modeling Unit at the European Central Bank has constructed a "synthetic" data set for the Euro area to overcome this problem.[5] If we use the "synthetic" data, we have to assume that monetary policy was also conducted in an aggregated way. Smets and Wouters (2003) have shown that a Taylor rule would approximate the behavior of the "synthetic" European Central Bank's conduct of policy quite well.

Hence, we explain the behavior of price inflation, real wages, interest rates, and output at a quarterly frequency from 1970:01 to 2003:04. The real variables are linearly detrended, while nominal variables are treated as deviations from their unconditional mean.[6] Let $\psi = (\sigma,\ \theta_p,\ \theta_w,\ \beta,\ \phi,\ \alpha,\ \gamma_y,\ \gamma_\pi,\ \rho_r,\ \delta,\ \bar{\lambda},\ \gamma,\ \rho_a,\ \rho_g,\ \sigma_a,\ \sigma_z,\ \sigma_g,\ \sigma_\lambda)'$ be the vector of structural parameters. We use standard solution methods for linear models with rational expectations and the Kalman filter to evaluate the likelihood of the four observable variables $d_t = (\Delta p_t, w_t - p_t, r_t, y_t)'$.

[5] See Fagan, Henry, and Mestre (2001) for details.
[6] We also estimated the models when the real variables are HP filtered. The results are very similar.

3.2 The Priors

Table 1 presents the prior distribution of the parameters. The elasticity of intertemporal substitution, σ, follows an inverse gamma distribution. Our choice implies a prior mean of 0.67 and a prior standard deviation of 0.90. The relatively large prior uncertainty reflects the wide variety of estimates for this parameter. We also pick a gamma distribution for the average duration of prices.[7] Our selection entails that the average duration of prices has a prior mean of 3 and a prior standard deviation of 1.42. This alternative reflects the facts presented in Taylor (1999) for the United States.

Regarding the Taylor rule coefficients, we select normal distributions. We set the mean of γ_π to 1.5 and that of γ_y to 0.125, which are Taylor's original guesses.[8] We also use a normal distribution for the prior of the inverse of the elasticity of the labor supply, γ, centered at 1 and with a standard deviation of 0.5. The interest rate smoothing coefficient, ρ_r, the autoregressive parameter of the technology, ρ_a, and the autoregressive parameter of preference shifter, ρ_g, have a uniform prior distribution between $[0, 1)$. Finally, we opt for a prior uniform distribution between $[0, 1)$ for the all standard deviations of the innovations of the stochastic shocks. The reason for this choice are twofold: First, we do not have strong prior information about the standard deviations of the innovations. Second, the lower the estimated σ_λ, the higher the estimated κ_p necessary to explain the observed inflation volatility. Since there is a negative relationship between κ_p and θ_p, the higher κ_p, the lower the estimated θ_p. Therefore, truncation of σ_λ can result in underestimation of θ_p. We want to preclude the underestimation of θ_p and be symmetric on the prior assumptions for all four standard deviations; therefore, we opt for high prior upper bounds on all four of them.

In the BSP model, wages are flexible and there is no price indexation. Therefore, we set θ_w, α, and ω to zero. In the INDP model, while we maintain θ_w and α equal to zero,

[7] Since we need to keep the probability of the Calvo lottery between 0 and 1, we formulate the prior in terms of the parameter $1/(1-\theta_p)-1$.

[8] Taylor (1993) used annualized federal funds rates and inflation data, while we use quarterly data for all series. Therefore, we would need to multiply our γ_y prior mean by four to make it comparable to Taylor's results.

we choose a prior uniform distribution between 0 and 1 for the price indexation parameter, ω. In the EHL model, we set the two indexation parameters, α and ω, to zero, and we establish a gamma distribution for the prior duration of wages with mean of four quarters and standard deviation of 1.71. This choice is motivated because we expect wage contracts to be fixed for a longer period of time than price contracts. The priors for the INDW model add to those of the EHL model the fact that the prior distribution for the wage indexation parameter, α, is assumed to be a uniform distribution between 0 and 1. Finally, we limit the support of all parameters to the region where the model has a unique, stable solution.[9]

We imposed dogmatic priors over the parameters β, δ, ϕ, and $\overline{\varepsilon}$. The reasons are as follows: First, since we do not consider capital, we have had trouble estimating β and δ. Second, there is an identification problem between the probability of the Calvo lottery, θ_p, and the mean of the price markup, $\overline{\varepsilon}$.[10] Therefore, it is not possible to identify θ_p and $\overline{\varepsilon}$ at the same time. Similarly, the same problem emerges between θ_w and ϕ. The values we use ($\beta = 0.99$, $\delta = 0.36$, $\phi = 6$ and $\overline{\varepsilon} = 6$) are quite conventional in the literature.[11]

4 Findings

4.1 Posterior Moments[12]

The last four columns of Table 1 present the mean and the standard deviation of the posterior distributions of the parameters for the four models.[13] The fourth column of Table 1 presents the estimates for the BSP model. The posterior mean of the average duration of price

[9] We use an appropriate normalizing constant to ensure that the prior is a proper density.

[10] The slope of the Phillips curve, κ_p, is the only one containing $\overline{\varepsilon}$ and θ_p.

[11] Another alternative would be to impose priors on the combination of parameters that we cannot identify. Although this is an interesting exercise that would emphasize the economic relation between the parameters, it would slow down the computation of the posterior, making the model intractable.

[12] In order to save space, we do not plot histograms of the posterior distributions. They are available at the following URL address http://www.econ.umn.edu/~rubio/graphs2.html

[13] We use a Metropolis Hasting algorithm to draw a chain of size 500.000 from the posterior distribution of ψ. The number of draws used here may seem larger than the number of draws used by other authors, but we find that for fewer draws, some of the parameters did not converge. The acceptance rates are 43.2 percent for BSP, 40.9 percent for INDP, 39.79 for EHL, and 34.94 for INDW.

contracts is 5.84 quarters.[14] This value is similar to the one reported by Galí, Gertler and López-Salido (2001), although somewhat smaller than the one reported by Smets and Wouters (2003). The estimates of the Taylor rule are as follows: The posterior mean of the coefficient on inflation is 1.01, while the posterior mean of the coefficient on output is 0.06, both lower than the values in Smets and Wouters (2003). The interest rate smoothing posterior mean is 0.75, also lower than reported in Smets and Wouters (2003).

The fifth column of Table 1 reports the results of the INDP model. The main differences are that the estimated coefficient on price indexation is 0.77, higher than what Rabanal (2003), Smets and Wouters (2003), and Galí, Gertler, and López-Salido (2001) obtained for the Euro area, and the estimated average duration of price contracts increases to 7.67 quarters. The estimates of the Taylor rule for the INDP model are almost identical to those obtained for the BSP model.

We present the EHL model in the sixth column of Table 1. The estimated average duration of price contracts is 5.26 quarters. A surprising result is the low estimated average duration of wage contracts. The average duration of wage contracts is less than three quarters, 2.34. This is puzzling because our priors indicate that we expected that wage contracts have longer average durations than price contracts.[15] The estimated Taylor rule is very close to the one obtained for models with flexible wages. The only difference is that this specification implies a higher interest rate smoothing parameter (more in line with the value reported by Smets and Wouters, 2003). The last column of Table 1 presents the estimates of the INDW model. The wage indexation parameter is very close to zero (0.07), while price and wage average contract durations are similar to the ones in EHL (5.25 and 2.23, respectively).

The rest of the estimated parameters are as follows. The posterior mean of the elasticity

[14] Our results depend on the particular values chosen for the discount factor, β, and the mean of the price markup, $\bar{\varepsilon}$. However, for a reasonable range of values for those parameters, the average duration of prices does not change significantly.

[15] There are interactions between the degree of monopolistic competition in wage setting, ϕ, and the duration of wage contracts. Trying other values of ϕ between 6 and 10 (i.e., markups in the 10 to 20 percent range) did not increase the average duration of wage contracts.

of intertemporal substitution, σ, extends from 0.07 to 0.11. The parameter that manages the labor supply, γ, is model dependent. This reveals the fact that when agents cope with wage rigidities they cannot supply their desired amount of labor. We estimate values close to 1 for the models with flexible wages (BSP and INDP), while they are closer to 2 for the models with wage stickiness (EHL and INDW). Finally, we find high (around 0.9) and similar correlation coefficients for the technology and preference shifter shocks.

The posterior mean for σ_λ is always very large (being 95.68 percent in the case of the INDP model). This result validates the choice of our prior distribution for σ_λ. As a comparison, all other standard deviation estimates are lower than 12 percent. The large estimates for σ_λ are related to the fact that these models are not able to match inflation persistence. Since the model is not able to generate a persistent enough inflation process, it generates inflation variability with a very volatile mark-up process.

4.2 Model Comparison

The last row of Table 1 reports the difference between the log marginal likelihood[16] of each model with respect to the log marginal likelihood of BSP. The results are as follows: The first question we need to answer is: How important is the presence of price indexation to lagged inflation to explain Euro area data? The log marginal likelihood difference between INDP and BSP is 44.51. Therefore, to choose BSP over INDP, we need a prior probability over model BSP 2.14×10^9 (= exp(44.51)) times larger than our prior probability over INDP. This evidence supports the assumption of backward-looking behavior in price setting in Europe.

The second question is: Does the inclusion of sticky wages improve the fit of the model? The log marginal likelihood difference between EHL and INDP is 74.80. This implies that we need a prior probability over INDP 3.06×10^{32} (= exp(74.80)) times larger than our prior over EHL in order to reject the fact that sticky wages improve the model. This factor is very high, so the data strongly favor EHL.

The third question is: How much does wage indexation add to EHL? In this case, we

[16] To compute the marginal likelihood, we use the harmonic mean method as described in Geweke (1998).

would only need to have a prior probability over EHL 55.70 (= exp(4.02)) times larger than our prior over INDW in order to choose EHL. This factor is much smaller than any other reported before, so we conclude that the data have trouble favoring wage indexation.

Finally, we compare the four models to a Bayesian VAR of order one with Minnesota prior (BVAR). This exercise is relevant because policymakers are interested in how theoretical models compare with an unrestricted benchmark model. We choose the BVAR because it is one of the most widely used statistical models in policy analysis. The results strongly favor the BVAR: the difference in log marginal likelihoods between the BVAR and the highest ranked theoretical model is 74.44. This means that we will need a prior probability over the theoretical model 2.13×10^{32} times larger than our prior over the BVAR in order to choose the economic model.

This result contradicts Smets and Wouters' (2003) findings. Two reasons seem to be behind this difference. First, they use a model with more shocks and, therefore, with more degrees of freedom to match the data. Second, as it will be shown in Section 4.4, Smets and Wouters' (2003) results may be driven by their choice of priors.

4.3 Autocorrelations and Impulse Responses

In this section we examine the internal propagation mechanism of each model and how well they fit some dynamic features of the data. Figure 1 displays the observed autocorrelation of inflation and output, and the posterior means and two standard deviation bands of the implied autocorrelation of each model. Since the wage indexation parameter is estimated to be small, the dynamics of INDW are indistinguishable from EHL and, hence, not reported. The first row of Figure 1 displays output autocorrelation. All three models are able to reproduce output persistence. In fact, at longer lags, the autocorrelogram of the data decays faster than in the models. The second row displays the autocorrelation of inflation. In this case the BSP and EHL models can replicate the first three autocorrelatons of the data. At longer lags these two models cannot match observed inflation persistence. On the other hand, the INDP model does the best job of matching inflation persistence. This may explain why backward-looking behavior in price setting seems to be so important.

Figure 2 displays the response of output to (one standard deviation) monetary and technology shocks. In all three models, output declines when monetary policy tightens. However, the introduction of sticky wages delivers a much larger and persistent response of output to monetary policy shocks. In response to technology shocks, the introduction of sticky wages also has very important consequences. While the BSP and INDP models display a positive, hump-shaped response of output to a technology shock, typical of sticky-price models, the introduction of sticky wages delivers a negative response of output to technology shocks. The lack of adjustment of real wages in response to the technology shock explains this behavior.

Finally, Figure 3 displays the response of inflation to (one standard deviation) monetary and technology shocks. We observe two important features. First, only the INDP model is able to generate a hump-shaped response of inflation. Second, the EHL model is able to generate larger inflation volatilty in response to these two shocks. This confirms the result of Table 1: Since they do not have endogenous persistence, flexible wage models need a the price mark-up shock with larger volatility to match the inflation persistence that we observe in the data.

4.4 Robustness: A Comparison with Smets and Wouters (2003)

Smets and Wouters (2003, SW henceforth) estimate a model similar to ours, but one that allows for capital accumulation and looks at a larger set of variables. The objective of this exercise is twofold. On the one hand, we want to examine how our point estimates (posterior means) depend on the choice of the prior distribution, and on the other hand, we study whatever the data contain enough information to allow the researcher to estimate all the parameters.

The priors used in SW are more informative (lower standard deviation) than ours. Hence, if, when using SW's priors, some posterior moments look more like the prior moments, we may conclude that the data do not provide enough information to estimate those particular parameters accurately, and the point estimates may be highly conditional on the priors.

Table 2 reports SW's priors and the point posterior estimates under those priors.[17] SW's prior means on price and wage contract duration are similar to ours, while priors on price and wage indexation have higher mean and lower standard deviation. Posterior estimates of price and wage durations are independent of the prior used, while the posterior estimates of the wage indexation parameter is higher under SW's priors. Therefore, we conclude that the data do not provide enough information on wage indexation.

SW priors on the Taylor rule are also different. Their prior mean on the elasticity of the nominal interest rate to inflation, γ_π, is 1.7, while ours is 1.5. At the same time, although the mean of their prior on γ_y is 0.125, like ours, their standard deviation is lower. These priors affect the posterior mean of γ_π and γ_y, since both are estimated to be higher in SW. Again, this result indicates that there is not enough information in the data to estimate a Taylor rule with accuracy. Finally, SW's prior means on the autocorrelation parameters ρ_a and ρ_g are also lower than ours. These priors lower the posterior point estimates of both parameters.

It is very important to point out that in the Bayesian environment there are no "correct" priors. Priors are chosen by the researcher based on her prior befief. Therefore, the purpose of this section is not to critize SW's priors, but to emphasize that the data may not have enough information about the indexation, Taylor rule, and autocorrelation parameters.

5 Concluding Remarks

In this paper, we have used a Bayesian approach to estimate and compare the baseline sticky price model of Calvo (1983) and three extensions, using Euro area data. Our main results are that price indexation and sticky wages are important to explain Euro area data, while

[17] We should note that the prior distributions and moments on θ_p and θ_w are written in terms of θ_p and θ_w, while the posterior moments are written in terms of durations ($\frac{1}{1-\theta_p}$ and $\frac{1}{1-\theta_w}$).

wage indexation is not. These results also hold when we use the marginal likelihood as a model comparison device. Finally, we analyze the dynamics of each of the models, finding that sticky wages deliver an empirically relevant negative response of output to technology shocks.

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Table 1: Prior and Posterior Distributions for the Parameters

	Prior Distribution		Posterior Distribution			
			BSP	INDP	EHL	INDW
		Mean (Std)	Mean (Std)	Mean (Std)	Mean (Std)	Mean (Std)
$\frac{1}{1-\theta_p}$	gamma$(2,1)+1$	3.00 (1.42)	5.84 (0.21)	7.67 (0.27)	5.26 (0.46)	5.25 (0.53)
$\frac{1}{1-\theta_w}$	gamma$(3,1)+1$	4.00 (1.71)	1 (–)	1 (–)	2.34 (0.62)	2.23 (0.33)
ω	uniform$[0,1)$	0.5 (0.28)	– (–)	0.77 (0.08)	– (–)	– (–)
α	uniform$[0,1)$	0.5 (0.28)	– (–)	– (–)	– (–)	0.07 (0.08)
γ_π	normal$(1.5, 0.25)$	1.5 (0.25)	1.01 (0.02)	1.02 (0.02)	1.12 (0.09)	1.17 (0.12)
γ_y	normal$(0.125, 0.125)$	0.125 (0.125)	0.06 (0.03)	0.07 (0.02)	0.02 (0.12)	0.05 (0.01)
ρ_r	uniform$[0,1)$	0.5 (0.28)	0.75 (0.02)	0.74 (0.02)	0.91 (0.01)	0.91 (0.01)
σ	invgamma$(2.5,1)$	0.67 (0.90)	0.11 (0.03)	0.11 (0.02)	0.07 (0.02)	0.07 (0.03)
γ	normal$(1, 0.5)$	1.5 (0.5)	1.04 (0.20)	1.16 (0.20)	2.36 (0.62)	2.59 (0.47)
ρ_a	uniform$[0,1)$	0.5 (0.28)	0.94 (0.01)	0.93 (0.01)	0.92 (0.04)	0.92 (0.03)
ρ_g	uniform$[0,1)$	0.5 (0.28)	0.93 (0.02)	0.93 (0.02)	0.92 (0.03)	0.91 (0.03)
$\sigma_a(\%)$	uniform$[0,1)$	50.0 (28.0)	0.56 (0.13)	0.49 (0.09)	2.39 (1.23)	2.32 (0.90)
$\sigma_z(\%)$	uniform$[0,1)$	50.0 (28.0)	0.22 (0.02)	0.23 (0.02)	0.18 (0.01)	0.18 (0.01)
$\sigma_\lambda(\%)$	uniform$[0,1)$	50.0 (28.0)	75.90 (3.73)	95.68 (2.80)	35.86 (2.04)	35.43 (6.88)
$\sigma_g(\%)$	uniform$[0,1)$	50.0 (28.0)	6.3 (1.5)	6.48 (1.13)	9.89 (1.36)	11.37 (3.24)
$log(\hat{L})$			–	44.51	119.31	123.33

Table 2: Prior and Posterior Distributions for the Parameters

	Prior Distribution		Posterior Distribution			
			BSP	INDP	EHL	INDW
		Mean (Std)	Mean (Std)	Mean (Std)	Mean (Std)	Mean (Std)
θ_p	beta$(55.5, 18.5)$	0.75 (0.05)	6.05 (0.37)	7.87 (0.37)	6.35 (0.22)	5.13 (0.35)
θ_w	beta$(55.5, 18.5)$	0.75 (0.05)	1 (–)	1 (–)	3.99 (0.17)	2.78 (0.27)
ω	beta$(5.5, 1.84)$	0.75 (0.15)	– (–)	0.58 (0.05)	– (–)	– (–)
α	beta$(5.5, 1.84)$	0.75 (0.15)	– (–)	– (–)	– (–)	0.26 (0.07)
γ_π	normal$(1.7, 0.25)$	1.7 (0.25)	1.89 (0.11)	1.79 (0.11)	1.68 (0.10)	1.69 (0.12)
γ_y	normal$(0.125, 0.01)$	0.125 (0.01)	0.11 (0.01)	0.11 (0.01)	0.12 (0.01)	0.12 (0.02)
ρ_r	beta$(13, 3)$	0.80 (0.10)	0.63 (0.04)	0.57 (0.05)	0.92 (0.02)	0.91 (0.01)
σ	invgamma$(2, 1.25)$	0.67 (0.90)	0.06 (0.01)	0.06 (0.01)	0.06 (0.01)	0.07 (0.03)
γ	normal$(2, 0.25)$	2.00 (0.25)	0.95 (0.19)	1.22 (0.28)	2.49 (0.33)	2.59 (0.47)
ρ_a	beta$(10, 1.76)$	0.85 (0.10)	0.91 (0.02)	0.92 (0.02)	0.72 (0.04)	0.69 (0.04)
ρ_g	beta$(10, 1.76)$	0.85 (0.10)	0.86 (0.02)	0.87 (0.02)	0.91 (0.03)	0.89 (0.02)
$\sigma_a(\%)$	invgamma$(6, 0.5)$	40.0 (–)	2.39 (0.23)	2.46 (0.02)	12.43 (1.99)	9.59 (1.81)
$\sigma_z(\%)$	invgamma$(21, 0.5)$	10.0 (–)	1.47 (0.12)	1.49 (0.13)	1.36 (0.11)	1.36 (0.11)
$\sigma_\lambda(\%)$	invgamma$(15, 0.5)$	15.0 (–)	83.72 (9.77)	97.74 (6.76)	56.16 (2.28)	31.13 (3.58)
$\sigma_g(\%)$	invgamma$(14.4, 0.5)$	20.0 (–)	11.20 (1.82)	10.85 (1.48)	12.47 (1.74)	11.04 (1.89)

Figure 1: Autocorrelation Functions

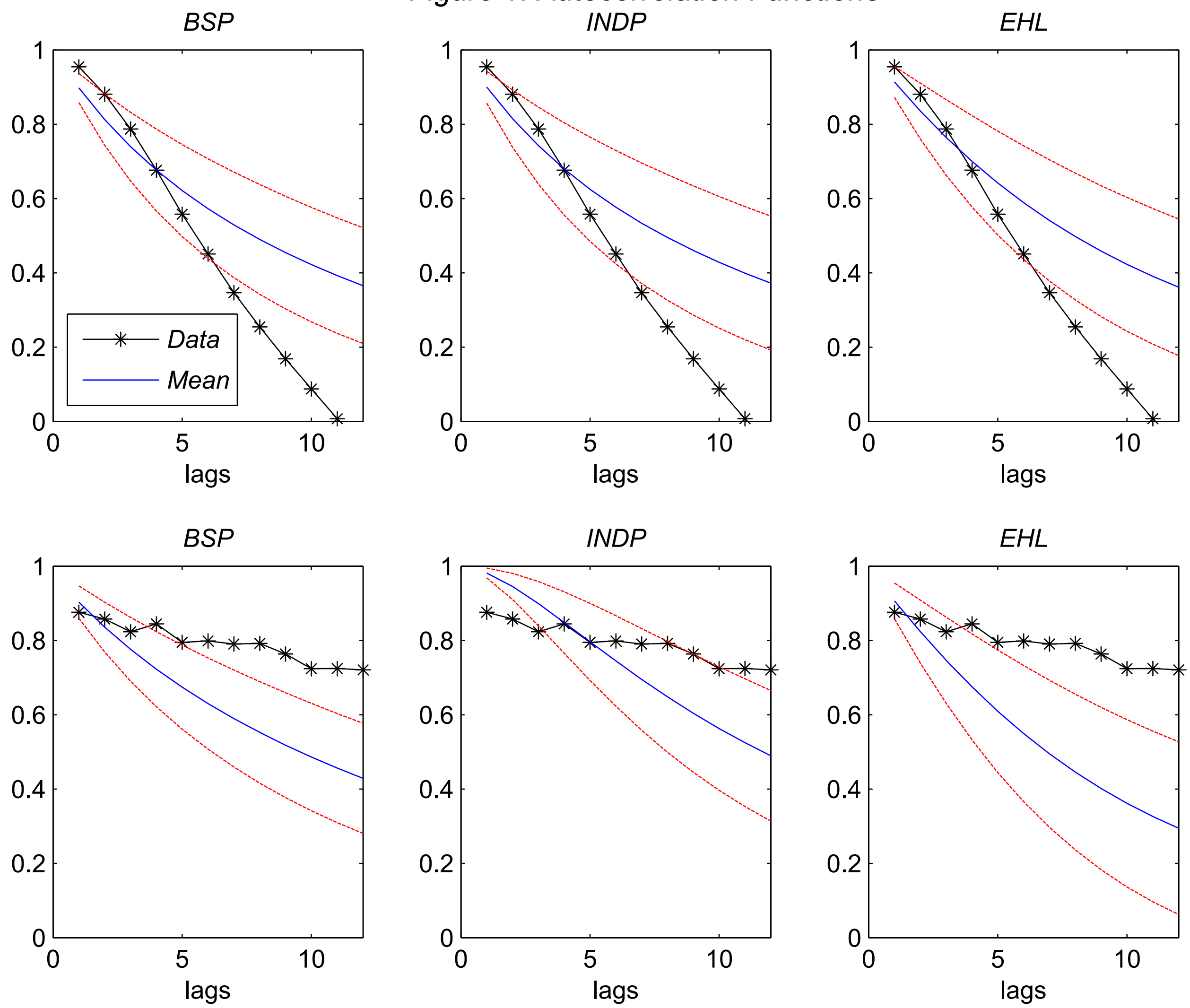

Figure 2: Impulse Response Functions for Output

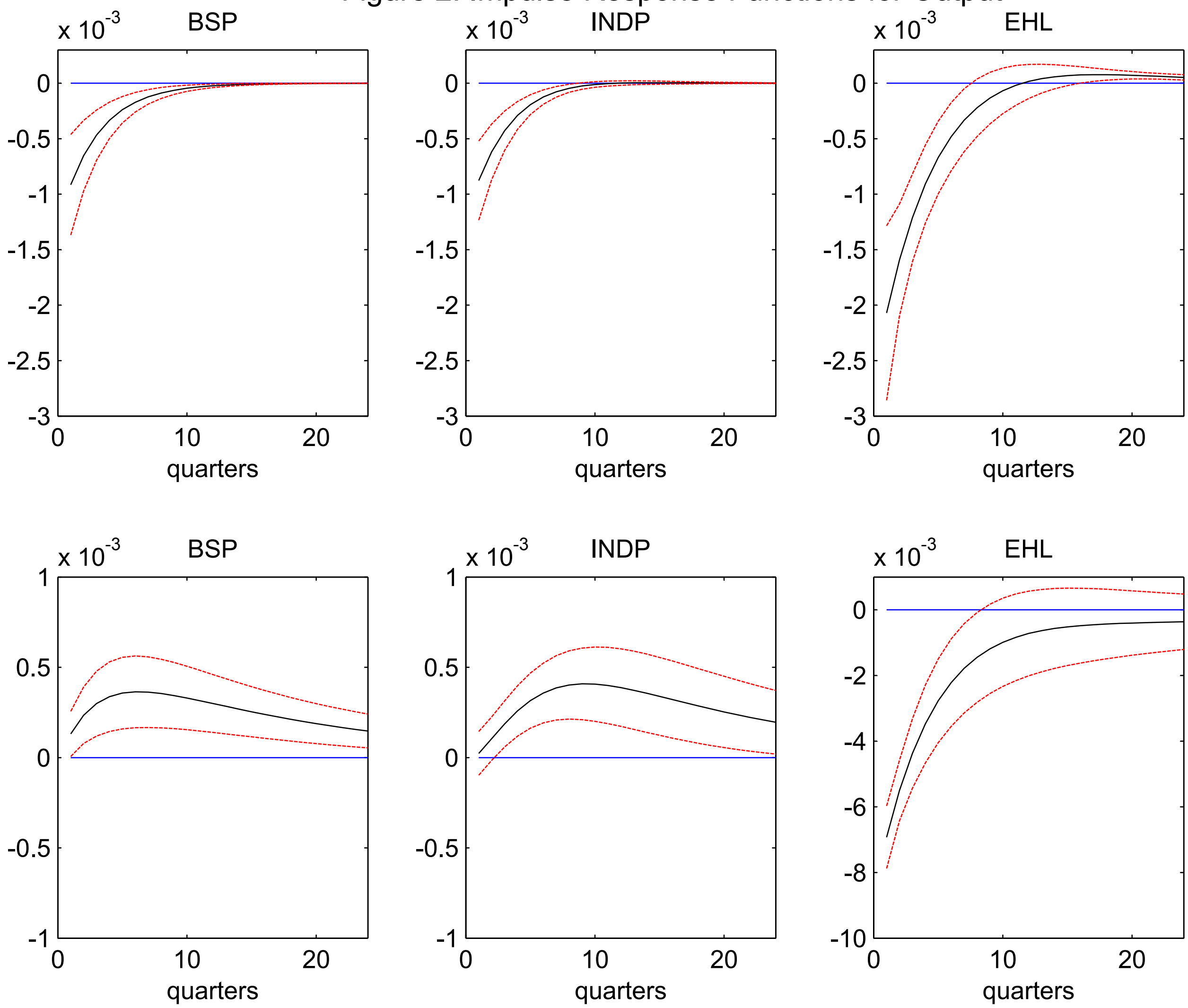

Figure 3: Impulse Response Functions for Inflation