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. We find that the average duration of price contracts is between two and four quarters, while the average duration of wage contracts is estimated to be below two quarters. Both mechanisms of price and wage indexation are not important when autocorrelated price markup shocks are introduced in the model. These results are in stark contrast to Smets and Wouters (2003): when we use their priors, our estimated posterior distributions are similar to theirs, but the models' fit to the data is worse.

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 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.

Various approaches have estimated the structural parameters of models similar to the ones analyzed here for the euro area. 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 and Rubio-Ramírez (2004), the marginal likelihood compares models consistently, even if they are misspecified. Two additonal reasons lead us to

[1] See Fuhrer and Moore (1995) and Chari, Kehoe, and McGrattan (2000) for criticisms of its fit to U.S. data. A recent issue of the *Journal of Monetary Economics* (September 2005) discusses several issues on the estimation and fit of New Keynesian models to the data.

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 two and four quarters, while the estimated average duration of wage contracts is below two quarters. Second, both price and wage indexation are unimportant, once the models are estimated with autorregressive price markup shocks. Third, the marginal likelihood concludes that sticky wages are the most important addition to the sticky price model for explaining Euro area data. Finally, we show how some parameter estimates are affected by the choice of priors, when we use the prior distributions of Smets and Wouters (2003). In that case, we obtain similar posterior distributions to what they do, but the models' fit to the data becomes worse.

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 indexation in wages (INDW).

[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 An and Schorfheide (2006).

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):

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

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

[3] An accurate description of the different price and wage-setting assumptions can be found in Smets and Wouters (2003), Christiano, Eichenbaum and Evans (2005) and Rabanal (2007). See also the next footnote for specific functional forms.

keeping prices fixed during the period, and β is the elasticity of intertemporal substitution.[4]

Since the BSP model 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:

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

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:

$$\Delta p_t = \gamma_b \Delta p_{t-1} + \gamma_f E_t \Delta p_{t+1} + \kappa_p'(mc_t + \lambda_t) \tag{7}$$

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):

$$\Delta w_t = \beta E_t \Delta w_{t+1} + \kappa_w(mrs_t - (w_t - p_t)) \tag{8}$$

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 (8) incorporates indexation to last period's inflation rate:

$$\Delta w_t - \alpha \Delta p_{t-1} = \beta E_t \Delta w_{t+1} - \alpha\beta\Delta p_t + \kappa_w \left[mrs_t - (w_t - p_t) \right] \tag{9}$$

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. But first, let us now describe which equation we estimate for each of the versions of the model. When we estimate the BSP model, we estimate equations (1)-(6) jointly with processes for the shocks. When estimating the INDP model, we estimate the same equations as in the BSP model, but we replace equation (4) by equation (7). When estimating the EHL model we estimate the same equations as in the BSP model, but we replace equation (5) by equation (8). Finally, when estimating the EHL model we estimate the same equations as in the EHL model but we replace equation (5) by equation (9).

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.

[5] See Fagan, Henry, and Mestre (2001) for details.

Hence, we explain the behavior of price inflation, real wages, interest rates, and output at a quarterly frequency from 1980:01 to 2003:04, to be consistent with the sample period used by Smets and Wouters (2003). The real variables are linearly detrended, while nominal variables are treated as deviations from their unconditional mean.[6] Let $\psi = (\sigma, \theta_p, \theta_w, \beta, \phi, \alpha, \gamma_y, \gamma_\pi, \rho_r, \delta, \bar{\lambda}, \gamma, \rho_a, \rho_g, \rho_\lambda, \sigma_a, \sigma_z, \sigma_g, \sigma_\lambda)'$ 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 $d_t = (\Delta p_t, w_t - p_t, r_t, y_t)'$.

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 0.8 and a prior standard deviation of 2. 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. These values are in line with the survey evidence in Fabiani et al. (2006).

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), preference shifter (ρ_g), and price markup (ρ_λ) shocks 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 is twofold: First, we do not have strong

[6] We also estimated the models when the real variables are HP filtered. The results are very similar.

[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.

prior information about the standard deviations of the innovations for each model. 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, 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] Of course, this is a very strong simplication. Another possibility would be to follow Lubik and Schorfheide (2004) and model indeterminancy explicitly. Althoug interesting, this is totally out of the scope of the paper. We take the easier route of limiting the support of all parameters to the region where the model has a unique, stable solution. A possible justification for our results is provided by María-Dolores and Vázquez (2006). Using an indirect inference approach they do not find evidence of indeterminacy in the the Euro-area.

We imposed dogmatic priors over the parameters β, δ, ϕ, and $\bar{\varepsilon}$. 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,

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

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.

4 Findings

4.1 Posterior Moments

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.[11] The fourth column of Table 1 presents the estimates for the BSP model. The posterior mean of the average duration of price contracts is 2.06 quarters.[12] This value is smaller than the one reported by Galí, Gertler and López-Salido (2001) and Smets and Wouters (2003): the assumption of a production function that is concave in labor input is helping in achieving lower estimates of the average price duration. The estimates of the Taylor rule are as follows: The posterior mean of the coefficient on inflation is 1.38, with a posterior standard deviation of 0.07. The posterior mean of the coefficient on output is 0.13, while the interest rate smoothing posterior mean is 0.66. All parameter estimates on the Taylor rule are lower than those reported in Smets and Wouters (2003) and María-Dolores and Vázquez (2006). However, the parameter estimates we obtain are clearly in the region that ensures determinacy of the rational expectations equilibrium, and, in fact, the posterior probability that γ_π is smaller than one is zero. Hence, it is not necessary to worry about the monetary policy rule not responding enough to inflation fluctuations, and the possibilty of indeterminacy of equilibria.

The fifth column of Table 1 reports the results of the INDP model. The main result to

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

[11] 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 43.9 percent for BSP, 34.7 percent for INDP, 30.5 for EHL, and 44.8 for INDW.

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

notice is that the introduction of the price indexation coefficient barely changes the other parameter estimates, and the coefficient on price indexation has a posterior mean of 0.08. Clearly, once AR(1) price markup shocks are allowed for in the estimation, backward looking coefficients in the inflation equation become irrelevant.[13] 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 4.16 quarters. A surprising result is the low estimated average duration of wage contracts. The average duration of wage contracts is less than two quarters, 1.31. This is puzzling because our priors indicate that we expected that wage contracts have longer average durations than price contracts.[14] 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 quantitatively unimportant (0.18), while price and wage average contract durations are similar to the ones in EHL (4.01 and 1.29 quarters, respectively).

The rest of the estimated parameters are as follows. The posterior mean of the elasticity of intertemporal substitution, σ, is not different across models, and extends from 0.13 to 0.16. The parameter that manages the labor supply, γ, is model dependent. We estimate values close to 1.5 for the models with flexible wages (BSP and INDP), while they are larger than 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 AR coefficient for the price markup shock is higher in the models with flexible wages (0.97) than in the models with sticky wages (0.75). This is reflecting the fact that sticky wages increase inflation persistence, and hence it is not necessary to rely on highly autocorrelated shocks.

[13] A similar result was obtained by Galí and Rabanal (2005) using US data.

[14] As in the price setting case, there are interactions between the degree of monopolistic competition in wage setting, ϕ, and the duration of wage contracts. Using 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.

In order to be able to compare these results with our paper using U.S. data, we estimated the four models assuming that the price markup is *iid*. Table 2 presents those results. There are only significant differents for the models with flexible wages. Once the AR(1) component is removed, the price indexation coefficient increases to 0.68, and the average duration of price contracts increases from roughly two quarters, to 6 quarters in the case of the BSP model, and to almost 8 quarters, for the case of the BSP model. In addition, the standard deviation of the price markup shock increases to large values, in order to match inflation volatility. Hence, under *iid* price markup shocks, our results are not so different than the ones we reported in Rabanal and Rubio-Ramírez (2005), including the fact the backward looking component in the inflation equation is large, and that the average duration of wage contracts is smaller than that of price contracts.

4.2 Model Comparison

The last row of Table 1 reports the log marginal likelihood of all four models.[15] 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? Indeed, the log-marginal likelihood decreases once price indexation is introduced into the model: it decreases from 1486.3 to 1482.2. Hence, introducing price indexation to the model results in overparameterization, which is rejected by the marginal likelihood criterion, that averages all possible likelihood values implied by the model using the prior as a weight. This result is entirely explained by the presence of an AR coefficient in the price markup shock. In Table 2, where we have estimated the models with an *iid* price markup shock, the marginal likelihood is 1439.5 for the BSP model and 1462.2 for the INDP model. What this tells us is that among the models that have flexible wages, a model with pure forward looking behavior and autocorrelated price markup shocks performs best at explaining the data.[16]

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

[16] Del Negro and Schorfheide (2006) study the appropiate choice of priors to discriminate between models of intrinsic versus extrinsic inflation persistence.

The second question is: Does the inclusion of sticky wages improve the fit of the model? The log marginal likelihood difference between EHL and BSP is 93.4. This implies that we need a prior probability over INDP $3.66 \times 10^{40} (= \exp(93.4))$ 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, the marginal likelihood decreases significantly with respect to the model without indexation, so we conclude that the data do not favor wage indexation in addition to staggered wage setting. We would also like to remark that, with *iid* price markup shocks, the EHL and INDW models are nondistinguishable and the marginal likelihoods are virtually the same (see last row of Table 2).

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 81.47. This means that we will need a prior probability over the theoretical model 2.4097×10^{35} times larger than our prior over the BVAR in order to choose the economic model.[17]

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 second moments and dynamic features of the data. Figure 1 displays the observed autocorrelation of inflation, output, real wages, and nominal interest rates, and the

[17]We also compare it to a BVAR of order two with Minnesota priors and the results are very similar.

posterior means and two standard deviation bands of the implied autocorrelation of each model. Interestingly, none of the models seems to be able to capture inflation persistence, and the implied autocorrelograms are quite similar. All models (including INDP) imply that inflation is a purely forward looking phenomenon, and hence even with sticky wages or highly correlated price markup shocks, inflation persistence cannot be addressed. When it comes to matching output, the models with sticky wages do a better job than the models with flexible wages, which, in fact, overestimate output persistence at longer lags. As expected, models with sticky wages can match the autocorrelogram of real wages pretty well, and in the case of the EHL model, the fit is almost perfect. On the other hand, models with flexible wages overestimate the autocorrelation of real wages. Hence, it seems that the highly autocorrelated price markup shocks in the BSP and INDP models do not do their job: they imply too high output and real wage persistence, without helping in matching inflation persistence. Finally, the EHL model is also the one that better matches interest rate persistence.

Table 3 presents the standard deviation of the four observed variables, as well as the posterior standard deviation implied by the four models. In all cases, the fit to output, inflation, and nominal interest rate volatility is fairly good, but still all models slightly underestimate the volatility in the data. On the other hand, models with flexible wages imply a too large real wage volatility, of more than twice that observed in the data On the other hand, models with sticky wages bring the volatility of real wages closer to the data, although they still overestimate it by a substantial amount.

Figure 2 displays the response of output to (one standard deviation) monetary and technology shocks. In models, output increases when the interest rate declines by one estimated standard deviation. The introduction of sticky wages delivers a larger and more persistent response of output to monetary policy shocks, which increases even further under wage indexation. In response to technology shocks, the introduction of sticky wages does not increase the propagation mechanism. 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 somewhat seems to reduce the impact response of output: the lack of adjustment of real wages could explain this behavior.

Finally, Figure 3 displays the response of inflation to (one standard deviation) monetary and technology shocks. We observe two important features. First, no model is able to generate a hump-shaped response of inflation.[18] Clearly, this is a surprising feature of the model (at least for the INDP version). Normally, models with price indexation create some hump-shaped response of inflation. We believe that the lack of hump-shaped response is due to the fact that price indexation is estimated to be very small. Second, the flexible wage models generate larger inflation volatility but less inflation persistence in response to a monetary policy shock. This confirms the result of Table 1: since the flexible wage models do not have endogenous persistence, they need a highly autocorrelated price markup shock to match the inflation persistence that we observe in the data. However, in terms of volatility, the sticky wage models need more volatility in the price markup shock.

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 if 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. Related to this issue, Canova and Sala (2006) have discussed identification

[18] However, the response of inflation under the INDP model and *iid* price markup shocks does indeed deliver a hump-shaped response. See the working paper version of this paper (Rabanal and Rubio-Ramírez, 2003).

problems in estimating DSGE models, and how the Bayesian approach might help deal with them.

Table 4 reports SW's priors and the posterior estimates under those priors.[19] The posterior estimates, the role of nominal rigidities, and the ordering of the models based on the marginal likelihood change dramatically. 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. While the models are different and not directly comparable, we should note that under SW priors, the estimated degrees of nominal rigidities and indexation are much higher than what we obtained under our priors. Under flexible wages, there does not seem to be much updating from prior to posterior on the parameter of the Calvo lottery for prices. However, and unlike the results in Table 1, we find that the coefficient on price indexation increases to almost one, even though the price markup shock is estimated to follow an AR(1) with posterior mean of 0.89. In this case, the marginal likelihood criterion increases significantly, suggesting that price indexation improves the fit to the data under SW priors.

When we move to analyze models with sticky wages, we should remark that for the case of the INDW model, our parameter estimates on the Calvo lotteries, wage indexation, and Taylor rule coefficients are very similar to SW, even though our models lack their propagation mechanisms (habit formation in consumption, investment adjustment costs, and variable capital utilization). While there does not seem to be much updating from the prior to the posterior for the Calvo parameter governing wage stickiness, we find that the average duration of price contracts increases to about 10 quarters (an estimated θ_p of 0.9). At the same time, wage indexation increases to 0.84. The marginal likelihood criterion suggests that sticky wages is an important addition to only sticky prices, and that wage indexation is an important addition to the EHL mode.

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

The estimated coefficient on the Taylor rule increases to values ranging between 1.64 to 1.81, reflecting the increase on the prior mean to 1.7. SW find a similar value in their Taylor rule, even though their rule includes terms with the acceleration of price inflation, and output gap growth. This result indicates that there is not enough information in the data to estimate a Taylor rule with accuracy. We find estimated lower interest rate smoothing parameters than SW do: in our case they range between 0.53 to 0.72. We also find that under these priors output gap targeting becomes unimportant in the euro area.

Finally, under SW priors we estimate higher posterior means for the autocorrelation parameters ρ_a, ρ_λ and ρ_g, reflecting the shift of prior means from 0.5 to 0.8. Only in the case of sticky wages we find a low estimate for the technology shock AR(1) parameter, possibly reflecting that the high estimated rigidities provide an important propagation mechanism, and hence less "exogenous" persistence is need.

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 wage indexation, Taylor rule, and price markup autocorrelation parameters. On the other hand, the estimate for σ is always on the low side and similar in all cases, despite the fact that our priors and SW priors on this parameter are dramatically different. Finally, we would like to remark that under SW's tighter priors, the fit of the models to the data is worse: in all cases, the marginal likelihoods of Table 4 are lower than those in Table 1. In this paper we don't pretend to conduct a systematic investigation on the role of priors as Del Negro and Schorfheide (2006) do, but draw the attention on the implications they might have for model fit.

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 autorregressive price markup shocks and sticky wages are important to explain Euro area data, while price and wage indexation mechanisms are not. These results hold when we use the marginal likelihood as a model comparison device. The introduction of autocorrelated price markup shocks helps the model fit the data in several dimensions, but does not help explain inflation persistence. It remains to be seen if with additional autocorrelated shocks it is possible to fit, at the same time, the second moments of the data, as well as their autocorrelation. Finally, we have shown that under our less informative priors, our results are quite different to Smets and Wouters (2003), while when we use their priors most parameter estimates have similar posterior distributions to theirs, and hence favor an important role of nominal rigidities and price and wage indexation mechanisms to fit the data.

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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)	2.06 (0.22)	1.96 (0.23)	4.16 (0.57)	4.01 (0.53)
$\frac{1}{1-\theta_w}$	gamma$(3,1)+1$	4.00 (1.71)	1 (–)	1 (–)	1.31 (0.08)	1.29 (0.08)
ω	uniform$[0,1)$	0.5 (0.28)	– (–)	0.08 (0.08)	– (–)	– (–)
α	uniform$[0,1)$	0.5 (0.28)	– (–)	– (–)	– (–)	0.18 (0.10)
γ_π	normal$(1.5, 0.25)$	1.5 (0.25)	1.38 (0.07)	1.37 (0.07)	1.27 (0.09)	1.27 (0.09)
γ_y	normal$(0.125, 0.125)$	0.125 (0.125)	0.13 (0.03)	0.13 (0.04)	0.16 (0.04)	0.16 (0.03)
ρ_r	uniform$[0,1)$	0.5 (0.28)	0.66 (0.03)	0.66 (0.03)	0.75 (0.03)	0.74 (0.03)
σ	invgamma$(2.5, 1)$	0.8 (2.0)	0.13 (0.04)	0.14 (0.04)	0.15 (0.05)	0.16 (0.06)
γ	normal$(1, 0.5)$	1.5 (0.5)	1.51 (0.26)	1.56 (0.30)	2.22 (0.31)	2.04 (0.20)
ρ_a	uniform$[0,1)$	0.5 (0.28)	0.91 (0.02)	0.91 (0.02)	0.87 (0.04)	0.87 (0.03)
ρ_g	uniform$[0,1)$	0.5 (0.28)	0.89 (0.02)	0.89 (0.02)	0.87 (0.03)	0.86 (0.02)
ρ_λ	uniform$[0,1)$	0.5 (0.28)	0.97 (0.01)	0.97 (0.01)	0.75 (0.07)	0.75 (0.07)
$\sigma_a(\%)$	uniform$[0,1)$	50.0 (28.0)	0.48 (0.07)	0.47 (0.07)	0.72 (0.15)	0.79 (0.16)
$\sigma_\lambda(\%)$	uniform$[0,1)$	50.0 (28.0)	0.89 (0.10)	0.88 (0.09)	5.08 (1.77)	4.45 (1.65)
$\sigma_g(\%)$	uniform$[0,1)$	50.0 (28.0)	6.91 (1.76)	6.62 (1.56)	6.59 (1.99)	6.04 (1.74)
$\sigma_z(\%)$	uniform$[0,1)$	50.0 (28.0)	0.17 (0.02)	0.18 (0.02)	0.15 (0.01)	0.15 (0.01)
$log(\hat{L})$			1486.3	1482.2	1579.7	1571.3

Table 2: Prior and Posterior Distributions for the Parameters

(with iid price markup shocks)

	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)	5.99 (0.82)	7.78 (0.90)	4.81 (0.78)	4.94 (0.62)
$\frac{1}{1-\theta_w}$	gamma$(3,1)+1$	4.00 (1.71)	1 (–)	1 (–)	1.52 (0.14)	1.50 (0.09)
ω	uniform$[0,1)$	0.5 (0.28)	– (–)	0.68 (0.08)	– (–)	– (–)
α	uniform$[0,1)$	0.5 (0.28)	– (–)	– (–)	– (–)	0.05 (0.04)
γ_π	normal$(1.5, 0.25)$	1.5 (0.25)	1.19 (0.07)	1.11 (0.07)	1.17 (0.10)	1.17 (0.07)
γ_y	normal$(0.125, 0.125)$	0.125 (0.125)	0.15 (0.03)	0.14 (0.03)	0.20 (0.05)	0.22 (0.05)
ρ_r	uniform$[0,1)$	0.5 (0.28)	0.68 (0.03)	0.64 (0.03)	0.78 (0.03)	0.78 (0.03)
σ	invgamma$(2.5, 1)$	0.67 (0.90)	0.13 (0.03)	0.12 (0.04)	0.19 (0.08)	0.29 (0.16)
γ	normal$(1, 0.5)$	1.5 (0.5)	1.26 (0.22)	1.17 (0.20)	2.38 (0.33)	2.43 (0.21)
ρ_a	uniform$[0,1)$	0.5 (0.28)	0.94 (0.01)	0.93 (0.02)	0.94 (0.03)	0.95 (0.02)
ρ_g	uniform$[0,1)$	0.5 (0.28)	0.88 (0.03)	0.88 (0.03)	0.87 (0.02)	0.88 (0.02)
ρ_λ	-	– (–)	– (–)	– (–)	– (–)	– (–)
$\sigma_a(\%)$	uniform$[0,1)$	50.0 (28.0)	0.54 (0.11)	0.48 (0.11)	0.77 (0.18)	0.77 (0.17)
$\sigma_\lambda(\%)$	uniform$[0,1)$	50.0 (28.0)	57.0 (16.7)	70.9 (15.8)	29.8 (9.9)	30.6 (7.8)
$\sigma_g(\%)$	uniform$[0,1)$	50.0 (28.0)	6.91 (1.76)	7.42 (1.58)	5.77 (1.84)	4.83 (2.12)
$\sigma_z(\%)$	uniform$[0,1)$	50.0 (28.0)	0.16 (0.01)	0.17 (0.02)	0.15 (0.01)	0.15 (0.01)
$log(\hat{L})$			1439.5	1462.2	1548.1	1548.0

Table 3: Standard deviations in the data and in the models, in percent

	y	Δp	$w-p$	r
Data	1.72	0.71	1.42	0.91
BSP	1.42 (0.15)	0.66 (0.07)	3.62 (0.08)	0.79 (0.08)
INDP	1.46 (0.14)	0.68 (0.07)	3.68 (0.49)	0.82 (0.07)
EHL	1.47 (0.14)	0.58 (0.07)	2.29 (0.48)	0.65 (0.08)
INDW	1.42 (0.11)	0.58 (0.05)	1.98 (0.36)	0.67 (0.05)

Table 4: Prior and Posterior Distributions for the Parameters

(alternative priors)

	Prior Distribution		Posterior Distribution			
			BSP	INDP	EHL	INDW
		Mean (Std)	Mean (Std)	Mean (Std)	Mean (Std)	Mean (Std)
θ_p	beta	0.75 (0.05)	0.75 (0.04)	0.75 (0.04)	0.90 (0.01)	0.91 (0.01)
θ_w	beta	0.75 (0.05)	1 (–)	1 (–)	0.73 (0.02)	0.73 (0.02)
ω	beta	0.75 (0.15)	– (–)	0.95 (0.02)	– (–)	– (–)
α	beta	0.75 (0.15)	– (–)	– (–)	– (–)	0.84 (0.07)
γ_π	normal	1.7 (0.25)	1.81 (0.07)	1.70 (0.08)	1.64 (0.08)	1.62 (0.08)
γ_y	normal	0.125 (0.05)	0.02 (0.04)	0.04 (0.04)	0.07 (0.04)	0.08 (0.02)
ρ_r	beta	0.80 (0.10)	0.53 (0.04)	0.56 (0.05)	0.72 (0.05)	0.70 (0.06)
σ	normal	1.00 (0.37)	0.09 (0.02)	0.06 (0.02)	0.06 (0.02)	0.07 (0.02)
γ	normal	2.00 (0.75)	2.38 (0.56)	1.49 (0.37)	2.67 (0.54)	3.22 (0.49)
ρ_a	beta	0.85 (0.10)	0.95 (0.01)	0.91 (0.02)	0.62 (0.05)	0.37 (0.04)
ρ_g	beta	0.85 (0.10)	0.93 (0.01)	0.90 (0.02)	0.94 (0.02)	0.94 (0.01)
ρ_λ	beta	0.85 (0.10)	0.89 (0.02)	0.86 (0.02)	0.88 (0.03)	0.89 (0.02)
$\sigma_a(\%)$	invgamma*	40.0 (2)	3.58 (0.21)	3.75 (0.04)	11.06 (1.76)	14.43 (2.51)
$\sigma_\lambda(\%)$	invgamma*	15.0 (2)	2.27 (0.21)	2.02 (0.19)	15.72 (3.66)	10.15 (2.12)
$\sigma_g(\%)$	invgamma*	20.0 (2)	7.02 (1.27)	10.78 (3.04)	10.87 (2.55)	10.34 (2.73)
$\sigma_z(\%)$	invgamma*	10.0 (2)	0.77 (0.05)	0.87 (0.06)	0.84 (0.05)	0.84 (0.04)
$log(\hat{L})$			1286.7	1314.7	1456.4	1467.5
Note: for the Inverted Gamma Distribution, the degrees of freedom of the prior distribution are indicated.						

Figure 1: Autocorrelations in the Data and in the Models

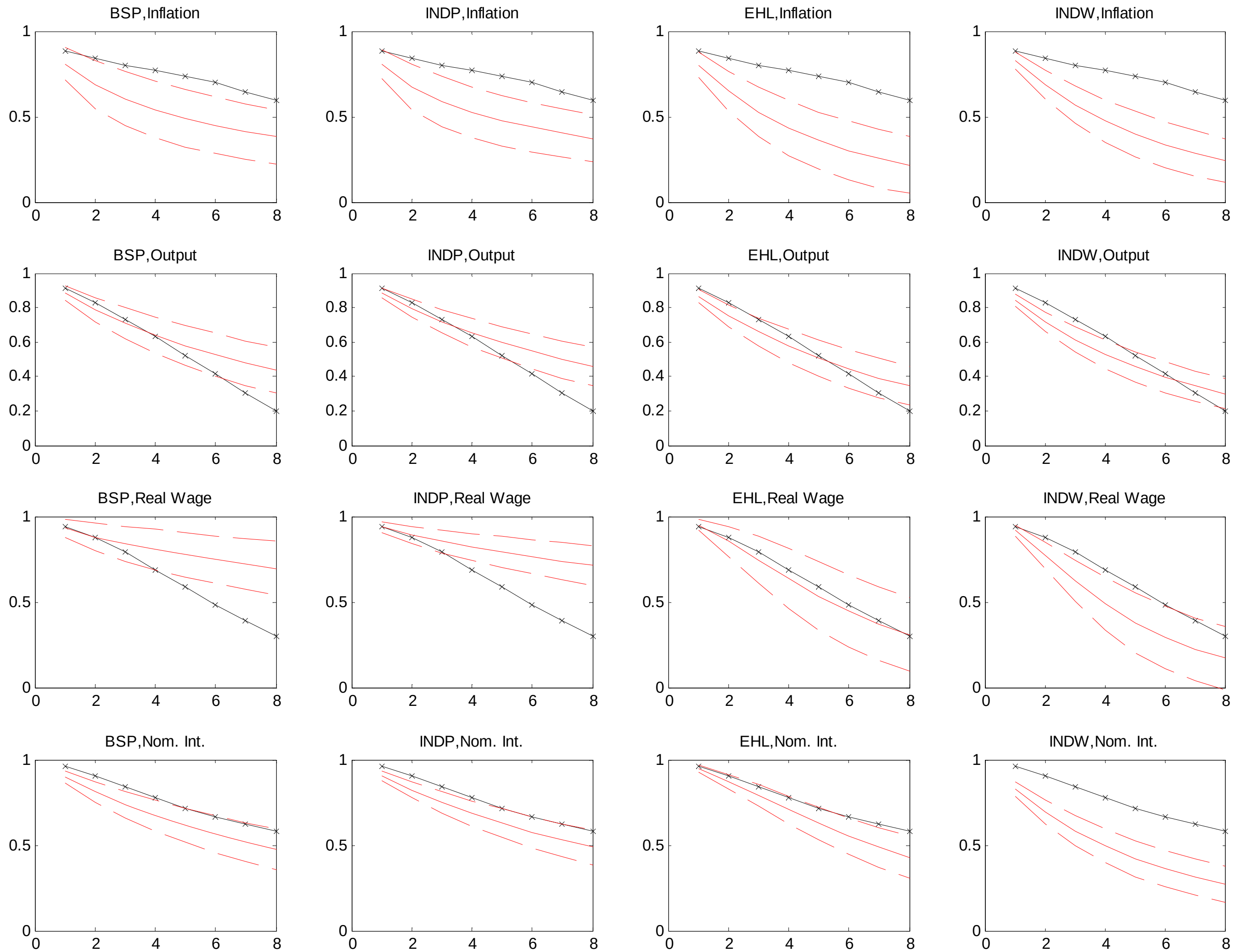

Figure 2: Impulse Response of Output

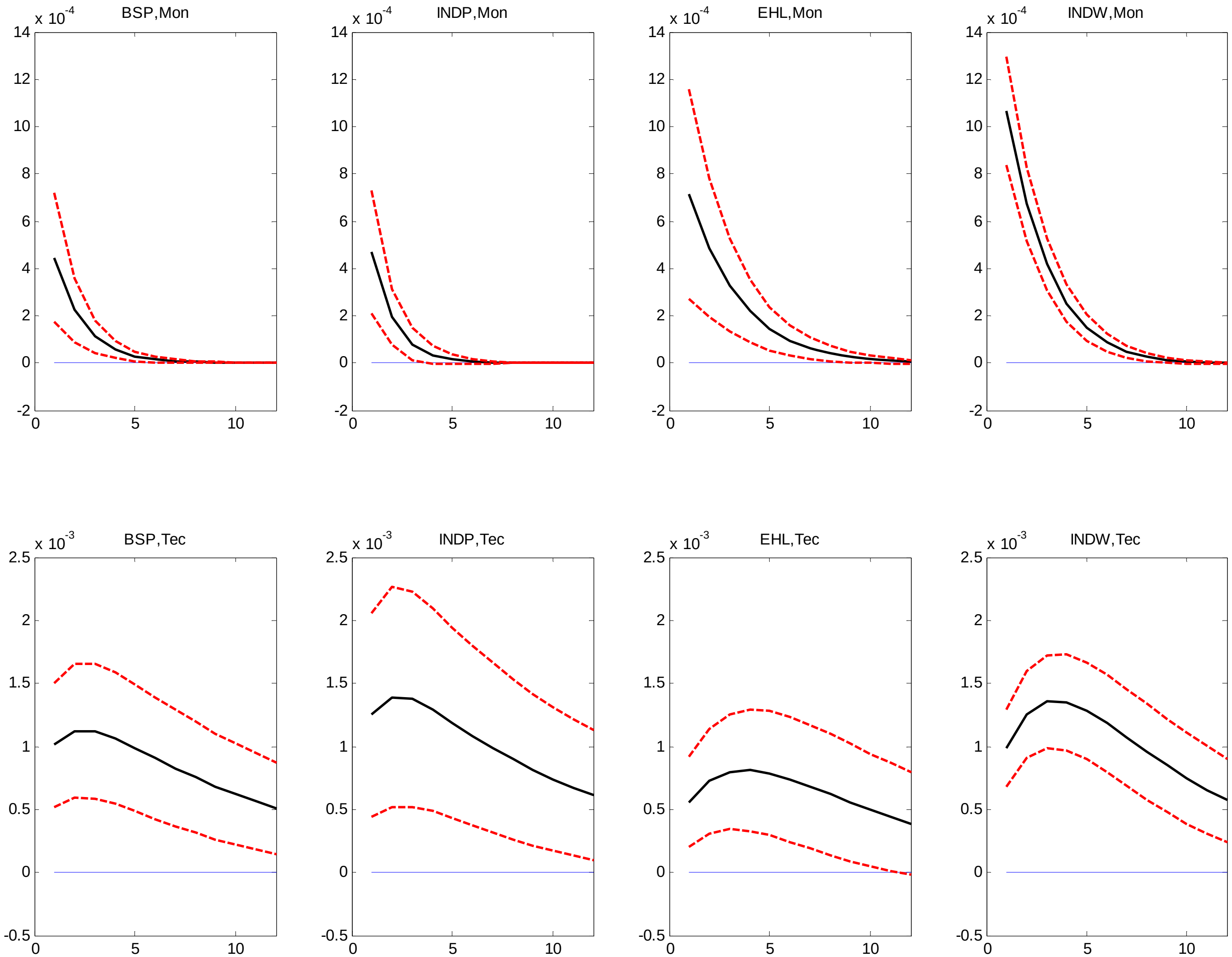

Figure 3: Impulse Response of Inflation