Forecasting the Spanish Economy Combining Structural and Reduced-Form Models

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Abstract

The post-crisis environment has posed important challenges to standard forecasting models. Linear approximations became poorer since the Great Recession put into question the small deviation around the trend assumption. In this paper, we compare the pseudo real-time forecasting accuracy of a structural DSGE model (Smets and Wouters, 2007) estimated for Spain with that of several reduced-form time series models and their combinations (hybrid DSGE models such as DSGE–VAR and Augmented-(B)VAR). Our empirical findings suggest that: (i) the out-of-sample forecasting performance of the structural model is capable of competing with all considered alternatives; (ii) reduced-form VARs benefit with the imposition of economic priors from more complex New Keynesian DSGE models; and (iii) structural models contain useful information to expand the (B)VAR variable space.

Keywords: Bayesian VAR, DSGE models, real time data, forecast comparison

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Introduction

Forecasting macroeconomic variables has become paramount for both practitioners and policymakers since the prediction of key macroeconomic time series is the cornerstone of economic policy decisions in governments and central banks. Under such a setting, structural methods based on economic theory such as Dynamic Stochastic General Equilibrium (DSGE) models were not considered as useful tools for forecasting analysis in macroecomics until very recently. In fact, their forecasting performance was tipically underscored by their inability to track and predict co-movements of aggregate time series over the business cycle.

As pointed out by Diebold (1998), macroeconomics forecasting follows two different approaches: structural and non-structural forecasting methods. Non-structural macroeconomic forecasting methods attempt to exploit the reduced-form correlations between macroeconomic variables, while structural macroeconomic forecasting is grounded on economic theory. The related literature acknowledges that the advantages of VARs and Bayesian VARs made them extremely appealing to macroeconomists: they are easy to estimate, generate out-of-sample forecasts, and are very flexible[1]. However, they contain no (unrestricted VARs) or little (Structural VARs) economic theory. The alternative approach to purely statistical methods is structural forecasting, using a theory-based approach. The structural macroeconomic forecasting was built upon dynamic stochastic general equilibrium (DSGE) modelling developments [2].

Very recently, Del Negro and Schorfheide (2013) suggest that DSGE model forecast should become the benchmark for forecasting horse races. However, when comparing its real-time forecasting accuracy with that of several reduced form time series models, it has been demonstrated that none of them are efficient and there is no single best forecasting method (Gürkaynak et al., 2013). In fact, simple AR models are most accurate at short horizons and DSGE models are most accurate at long horizons when forecasting output growth, while results reversed for inflation. A few recent exceptions, such as Cai et al. (2018) based on the NY Fed DSGE model, have empirically shown that close variants of DSGE models including additional variables as observables perfom relatively well compared to that of both the Blue Chip and SPF surveys in terms of output growth forecasting accuracy.

In this paper, we aim at testing the forecasting accuracy of hybrid models, combining structural and non-structural forecasting methods with particular interest in the Spanish economy. We follow the seminal DSGE modelling approach of Smets and Wouters (2007) (SW henceforth) and build upon the lines of Del Negro and Schorfheide (2004) DSGE–VAR method, and by expanding the variable space where the reduced-form models operate with artificial series from a structural model (Augmented–(B)VAR–DSGE) we follow Fernández-de-Córdoba and Torres (2011). It is worthy to mention that, in empirical arena, our model shares many features with other DSGE models developed at policy-making institutions around the

[1]See for instance Sims (1980), Litterman (1986a) and Litterman (1986b).

[2]DSGE models have a strong theoretical background as they are firmly grounded on modern micro-foundations. A broad class of macroeconomic models that spans the standard neoclassical growth model (see King and Rebelo, 1999) as well as New Keynesian monetary models with real and nominal frictions that are based on the work of Christiano et al. (2005) and Smets and Wouters (2003) is emcopassed under the term *DSGE model*.

world. Some examples are the Federal Reserve Board (Erceg et al., 2006), the European Central Bank (Warne et al., 2008), the Bank of Canada (Murchison and Rennison, 2006), the Bank of England (Harrison et al., 2005), the Bank of Finland (Kilponen and Ripatti, 2006; Kortelainen, 2002) and the Bank of Sweden (Adolfson et al., 2007).

Turning into the Spanish economy, our approach is of particular interest since the crisis and post-crisis environment posed important challenges to standard forecasting models at least for three reasons: (i) linear approximations became poorer since the Great Recession put into question the small deviation around the trend assumption; (ii) the persistence of the recession and the very gradual recovery could square better with a medium-term phenomenon perspective than with the standard business cycle one; (iii) policy-driven structural changes (i.e., financial regulation, structural reforms, etc) along with ongoing processes such as the zero lower bound (ZLB), deleveraging, or fiscal consolidation can be naturally understood as different regimes.

Some DSGE models developed recently for the Spanish economy are those used at the Bank of Spain (Andrés et al., 2006; Andrés et al., 2010; Andrés et al., 2017), and at the Spanish Ministry of Economics and Finance, MEDEA (Burriel et al., 2010), the REMS model (Boscá et al., 2007;Boscá et al., 2010; Boscá et al., 2018; or Goméz-González and Rees, 2018). As such, our modelling approach is comparable to its peers and can borrow from many years of experience of DGSE modeling of the Spanish economy.

The main contributions of the paper are twofold. First, this paper places in a forecasting competition the structural approaches we have already referred to, using a large-scale DSGE model for the Spanish economy in the New Keynesian tradition (and DSGE, DSGE–VAR and Augmented–(B)VAR–DSGE methods) with the standard non-structural VAR and BVAR methods. The New-Keynesian, SW model with sticky prices and wages was chosen for several reasons. The scale of DSGE models has consistently grown over time and those New Keynesian features that have been incorporated, have improved our understanding of key macroeconomics variables. Simpler RBC canonical models have proven to track relatively well macroeconomic variables for the Spanish economy at long horizons, but we would like to make a forecasting assessment within a more complex DSGE model using alternative techniques. Second, while large-scale, New-Keynesian DSGE models have proven to perform relatively well for forecasting purposes for the euro area, this is the first attempt - to the best of our knowledge - to use such class of models to expand the variable space where the reduced-form models operate with artificial series from the structural model (Augmented VAR-DSGE) for the Spanish economy.

Our approach to model evaluation is based on an out-of-sample exercise conducted for the Spanish economy, focusing on forecasting four crucial macroeconomic variables: output, consumption, investment, and inflation. The forecast accuracy is assessed based on recursive sample starting in Q3:1995 and ending in Q3:2018, for a total of ninety-three periods. The evaluation sample starts at Q3:2007, meaning that every single model is re-estimated forty-four times. The following twelve quarters are estimated to assess forecasting accuracy, which is measured by the root mean square error (RMSE) of the forecast.

Our empirical findings suggest that the out-of-sample performance of the DSGE–VAR model competes well with all alternatives considered. In short, we document that: (i) the DSGE model based on SW performs realtively well in spite of a difficult evaluation sample to deal with; (ii) reduced-form VARs benefit from the imposition of an economic prior when the structural model underlying priors assessment has a fair degree of complexity; and (iii) structural models contain useful information to enlarge the (B)VAR variables space and thus improves, although to a slight extent, its forecasting properties. In particular, they benefit from incorporating either the risk premium or total factor productivity shock as observable conditional on the imposition of a non-economic prior[3].

The structure of this paper is organized as follows. The DSGE is presented in Section 1 along with the data description. Reduced form models such as (B)VARs are introduced in Section 2, whilst in Section 3 we describe DSGE-VAR and Augmented-(B)VAR-DSGE models. We analyse the forecasting performance of estimated models in Section 4, and a final section concludes.

1 The Smets-Wouters model

In this section, we initially describe the main features of the linearized SW DSGE model. For the sake of brevity, this section acts as broad-level overview of the above-mentioned model taken to the Spanish economy. The section then continues by providing further details on data construction and documenting estimation results. The dataset employed is homogenous across all alternative structural and non-structural models.

1.1 Model Formulation

We draw extensively from SW, therefore we rigorously stick to their notation. The model formulation is coherent with a balance growth path driven by a deterministic labor-augmenting technological progress in the steady-state. Beyond this, the model embeds many nominal and real frictions shaping representative household and firm optimal decisions.

1.1.1 Households Optimal Choices

Consider an infinite horizon representative consumer with a non-separable utility function defined over consumption goods (with external habits) and leisure so that saving choices are directly affected from labor decisions. Labor supplied is differentiated by a working union which exerts some monopolistic power over wages turning into an explicit equation suitable for the introduction of sticky nominal wages in the fashion of Calvo (1983). Additionally, households also rent capital services to firms and base their capital accumulation decision according to the investment adjustment costs they face. Consumption dynamics is disciplined by the following Euler equation

[3]Yet out-of-sample forecasting accuracy is not significant by itself. Further research on equal predictive accuracy tests is still to be done.

$$c_t = c_1 c_{t-1} + (1 - c_1)E_t c_{t+1} + c_2(l_t - E_t L_{t+1}) - c_3(r_t - E_t \pi_{t+1} + \varepsilon_t^b) \tag{1}$$

where $c_1 = (\lambda/\gamma)/(1 + \lambda/\gamma)$, $c_2 = c_1/(\sigma_c\lambda/\gamma)[(\sigma_c - 1)(W_*^h L_*/C_*)]$, and $c_3 = c_1/(\sigma_c\lambda/\gamma)(1 - \lambda/\gamma)$. Equation (1) implies that current consumption, c_t, depends on a weighted average of previous and future expected consumption, the expected hours worked growth, $(l_t - E_t L_{t+1})$, and the ex-ante real interest rate plus the risk premium shock, ε_t^b. The latter introduces an exogenous stochastic disturbance within the optimal saving decision. The risk premium shock measures the wedge between the interest rate controlled by the central bank and the assets remuneration accruing to households. It is assumed to follow an usual autoregressive process: $\varepsilon_t^b = \rho_b \varepsilon_{t-1}^b + \eta_t^b$. Parameter λ gives the extent of consumption habit persistence (i.e., $\lambda = 0$ stands for no habit) and σ_c regulates the elasticity between current and future consumption (when labor is fixed). Finally, γ indicates the steady-state growth rate of the economy.

Investment dynamics is dictated by the investment Euler equation

$$i_t = i_1 i_{t-1} + (1 - i_t)E_t i_{t+1} + i_2 q_t + \varepsilon_t^i \tag{2}$$

where $i_1 = 1/(1 + \beta\gamma^{1-\sigma_c})$, $i_2 = i_1\gamma^2\varphi$, φ is the steady-state elasticity of the investment adjustment cost function, and β is the traditional households discount factor. Also in this case current investment, i_t, is a function of past and expected future investment choices other than the usual Tobin's Q (q_t), and the investment technology shock whose exogenous process also follows the usual autoregressive form: $\varepsilon_t^I = \rho_I \varepsilon_{t-1}^I + \eta_t^I$.

Finally, the arbitrage equation for the value of capital boils down to

$$q_t = q_1 E_t q_{t+1} + (1 - q_1)E_t r_{t+1}^k - (r_t - E_t \pi_{t+1} + \varepsilon_t^b) \tag{3}$$

where $q_1 = \beta\gamma^{-\sigma_c}(1 - \gamma)$. Equation (3) states that the current value of capital is determined by its future expected value and the ex-ante real interest rate, including the risk premium shock.

1.1.2 Goods Market

The problem of the representative firm is to find optimal values for the utilization of labor and capital services given the following production function of the Cobb-Douglass form

$$y_t = \phi_p(\alpha k_t^s + (1 - \alpha)l_t + \varepsilon_t^a) \tag{4}$$

where inputs, capital services (k_t^s) and hours worked (l_t), and TFP dynamics $(\varepsilon_t^a = \rho_a \varepsilon_{t-1}^a + \eta_t^a)$ are standard. In this regard, α is the capital share of income and ϕ_p is one plus the share of fixed production costs.

Given the presence of utilization costs, the capital services used in current production, k_t^s , are a function of the stock of capital installed in the last quarter and the degree of capital utilization, z_t, that is

$$k_t^s = k_{t-1} + z_t. \tag{5}$$

Then, by household optimization choice it turns out that

$$z_t = z_1 r_t^k \tag{6}$$

so that the rate of capital utilization is proportional to the capital remuneration. Moreover, $z_1 = (1-\psi)/\psi$, where ψ is a positive function of the elasticity of capital utilization adjustment cost function.

The law of motion of installed capital

$$k_t = k_1 k_{t-1} + (1-k_1) i_t + k_2 \varepsilon_t^I \tag{7}$$

does not only depend on the flow of investment but also by the investment specific technology shock. Parameters $k_1 = (1-\delta)/\gamma$ and $k_2 = (1-k_1)(1+\beta\gamma^{(1-\sigma_c)+2}\varphi)$ are convolutions of structural parameters.

Since the goods market is monopolistically competitive, firms cost minimization introduces a wedge between the labor marginal product and cost, defined as price mark-up:

$$\mu_t^p = \alpha(k_t^s - l_t) + \varepsilon_t^a - w_t \tag{8}$$

which crucially depends on the factors ratio and TFP dynamics.

Similarly to Smets and Wouters (2003), prices are sticky and their adjustment for the fraction of non-optimizing firms is only allowed by means of a partial indexation to inflation mechanism. Inflation dynamics is summarized by means of the New-Keynesian Phillips curve:

$$\pi_t = \pi_1 \pi_{t-1} + \pi_2 E_t \pi_{t+1} - \pi_3 \mu_t^p + \varepsilon_t^p \tag{9}$$

in this regard, $\pi_1 = \iota_p/(1+\beta\gamma^{1-\sigma_c}\iota_p)$, $\pi_2 = \pi_1\beta\gamma^{1-\sigma_c}/\iota_p$, and $\pi_3 = \pi_2/\beta\gamma^{1-\sigma_c}[(1-\beta\gamma^{1-\sigma_c}\xi_p)(1-\xi_p)/\xi_p((\phi_p-1)\varepsilon_p+1)]$. ι_p is the degree of price indexation to past inflation, ξ_p is the degree of price stickiness, $(\phi_p - 1)$ is the steady-state goods market mark-up, and ε^p is the Kimball goods market aggregator. Inflation is a positive function of both past and future expected inflation, the price mark-up shock, ε_t^p, and depends negatively on the current price mark-up instead. The price mark-up shock is characterized as an ARMA(1,1): $\varepsilon_t^p = \rho_p \varepsilon_{t-1}^p + \eta_t^p + \mu_p \eta_{t-1}^p$.

Finally, firms optimal factors choice implies that the rental rate of capital is an inverse function of the capital to labor ratio but is increasing in the real wage

$$r_t^k = -(k_t - l_t) + w_t. \tag{10}$$

1.1.3 Labor Market

Given its monopolistically competitive set up, the functioning of the labor market resembles the one of the goods market. In particular, the wage mark-up equals the difference between the real wage and the marginal rate of substitution between consumption and hours worked

$$\mu_t^w = w_t - \left(\sigma_l l_t + \frac{1}{1 - \lambda/\gamma} (c_t - \lambda/\gamma c_{t-1}) \right) \tag{11}$$

where σ_l is the elasticity of labor supply with respect to the real wage.

As before, given the presence of wage stickiness and a partial indexation mechanism of wages to inflation, also real wages adjustment to the optimal wage mark-up is sluggish:

$$w_t = w_1 w_{t-1} + (1 - w_1)(E_t w_{t+1} + E_t \pi_{t+1}) - w_2 \pi_t + w_3 \pi_{t-1} - w_4 \mu_t^w + \varepsilon_t^w \tag{12}$$

with $w_1 = 1/(1 + \beta\gamma^{1-\sigma_c})$, $w_2 = (1 + \beta\gamma^{1-\sigma_c}\iota_w)w_1$, $w_3 = \iota_w w_1$, and $w_4 = w_1[(1 - \beta\gamma^{1-\sigma_c}\xi_w)(1 - \xi_w)/(\xi_w((\phi_w - 1)\varepsilon_w + 1))]$. In analogy with the goods market, ι_w, ξ_w, $(\phi_w - 1)$ and ε^w are the degree of wage indexation, the probability of optimizing the real wage, the labor market steady-state mark-up and the Kimball labor market aggregator, respectively. Current real wage, w_t, is a function of past and future expected real wages, expected, current and past inflation, the wage mark-up and a wage mark-up disturbance, ε_t^w. The latter also follows an an ARMA(1,1) process: $\varepsilon_t^w = \rho_w \varepsilon_{t-1}^w + \eta_t^w + \mu_w \eta_{t-1}^w$.

1.1.4 Equilibrium

Households are Ricardian and public expenditure evolves exogenously: $\varepsilon_t^g = \rho_g \varepsilon_{t-1}^g + \eta_t^g + \rho_{ga} \eta_t^a$. The correlation with the TFP shock, ρ_{ga}, serves estimation purposes as public spending exogenous process also accounts for net exports, which may be affected by internal productivity developments.

Markets clear so that the aggregate resource constraint reads

$$y_t = c_y c_t + i_y i_t + z_y z_t + \varepsilon_t^g \tag{13}$$

where c_y is the steady-state ratio between consumption and output, i_y is defined analogously and equals $(\gamma - 1 + \delta)k_y$ (where k_y is the capital stock to output ratio), and $z_y = R_*^k k_y$, where R_*^k is the steady-state rental rate of capital.

Finally, a monetary rule is needed to close the model and this is a non-trivial issue for a Euro-Area (EA henceforth) country member. In principle the European Central Bank sets its monetary policy according to the EA fundamentals. This would probably call for a more articulate modeling choice of the external sector which however abstracts from our research interest. In this regard, we can take action in two ways, either we assume that Spain has a domestic monetary authority or we assume the Taylor rule is completely exogenous from Spanish fundamentals and it is tuned according to EA inflation and GDP dynamics. Since for the implementation of the latter approach we would need to include EA inflation and GDP as additional observables, we stick to the canonical SW formulation and therefore opt for the following empirical monetary policy rule:

$$r_t = \rho r_{t-1} + (1-\rho)\{r_\pi \pi_t + r_y(y_t - y_t^p)\} + r_{\Delta y}[(y_t - y_t^p) - (y_{t-1} - y_{t-1}^p)] + \varepsilon_t^r \qquad (14)$$

The central bank gradually adjusts the policy rate in response to inflation, output gap and output gap growth. The extent of its reaction to the target variables is up to r_π, r_y and $r_{\Delta y}$, respectively. In this regard ρ describes the degree of interest rate smoothing. Finally, it is assumed that the monetary policy shock follows the stochastic process: $\varepsilon_t^r = \rho_r \varepsilon_{t-1}^r + \eta_t^r$.

1.2 Solving the DSGE model

The model has fourteen endogenous variables: $y_t, c_t, i_t, q_t, k_t^s, k_t, z_t, r_t^k, \mu_t^p, \pi_t, \mu_t^w, w_t, l_t,$ and r_t. Their dynamics is described from equation (1) to (14). Finally, the dynamics of the system is led by seven exogenous disturbances: $\varepsilon_t^a, \varepsilon_t^b, \varepsilon_t^i, \varepsilon_t^g, \varepsilon_t^p, \varepsilon_t^w, \varepsilon_t^r$, whose error terms are all Normal and identically, independently distributed.

1.3 Data, calibration and estimation

1.3.1 The data

The observables in the model are equivalent to those employed in SW: Gross Domestic product (GDP_t), consumption ($CONS_t$), investment (INV_t), wage (WAG_t), inflation (P_t), nominal interest rate ($INT.RATE_t$), and hours worked ($HOURS_t$).

Data for GDP, private consumption, investment, hours worked and compensation per hour worked are all taken from the quarterly national accounts, as compiled by the Spanish national statistical institute (INE) and transmitted to Eurostat. Investment refers to total gross fixed capital formation (i.e. all non-financial productive assets and all sectors). Consumption, investment and compensation are deflated using the GDP deflator. GDP, consumption, investment and hours worked are all defined in per capita terms by dividing by population, also sourced from the quarterly national accounts. All series are seasonally and working day adjusted. Inflation refers to the first difference of the log of the GDP deflator. The interest rate is the Spanish interbank overnight offered rate, sourced from DataStream. Consumption, investment, GDP, wages and hours are expressed in 100 times log. The interest rate and inflation rate are expressed on a quarterly basis. The sample time span is from Q3:1995 to Q3:2018.

The SW DSGE model considers seven observables and seven structural shocks, therefore there is no need of adding any measurement error. The corresponding set of measurement equations in the model is:

$$Y_t = \begin{bmatrix} dlGDP_t \\ dlCONS_t \\ dlINV_t \\ dlWAG_t \\ dlP_t \\ INT.RATE_t \\ lHOURSt_t \end{bmatrix} = \begin{bmatrix} \bar{\gamma} \\ \bar{\gamma} \\ \bar{\gamma} \\ \bar{\gamma} \\ \bar{\pi} \\ \bar{r} \\ \bar{l} \end{bmatrix} + \begin{bmatrix} y_t - y_{t-1} \\ c_t - c_{t-1} \\ i_t - i_{t-1} \\ w_t - w_{t-1} \\ \pi_t \\ r_t \\ l_t \end{bmatrix} \tag{15}$$

where l and dl represents 100 times log and log difference, respectively; $\bar{\gamma} = 100(\gamma - 1)$ is the balanced growth path growth rate of GDP, consumption, investment and wage; $\bar{\pi} = 100(\Pi_* - 1)$ is the quarterly steady-state inflation rate and $\bar{r} = 100(\beta^-1\gamma^{\sigma_c}\Pi_* - 1)$ is the steady state nominal interest rate.

From now onwards, for sake of simplicity, we will refer to $dlGDP_t$,$dlCONS_t$,$dlINV_t$ and dlP_t as ΔY_t, ΔC_t, ΔI_t, and π_t, respectively.

1.3.2 Calibration

Most of the parameters in SW are estimated, only five are calibrated. They are the Kimball labor and goods market aggregators ($\varepsilon^w = \varepsilon^p = 10$), the steady-state exogenous share of spending ($g_y = 0.18$), the capital depreciation rate ($\delta = 0.025$) and the steady-state gross wage mark-up ($\phi = 1.5$). In addition, due to lack of identification issues arising during the model recursive estimation, we also have to calibrate two more parameters. They are the MA coefficient of the price mark-up shock ($\mu^p = 0.68$) and the share of fixed costs in production ($\Phi = 1.5$) whose calibration is in line with the model estimation considering the whole sample and are pretty similar to estimates in SW.

1.3.3 Estimation

The rest of the parameters are estimated using Bayesian methods.[4] Priors elicitation is the same as in SW with just a few case specific changes. Since prices and wages can be assumed to be stickier in Spain

[4] Until now Bayesian inference is carried out by means of the Metropolis-Hastings algorithm with two chains of 100000 draws each with a burnin rate of 20%.

than in the US, the corresponding parameters (ξ_p and ξ_w) are centered on a higher mean with a stricter standard deviation. As a consequence also price and wage indexation parameters (ι_p and ι_w) priors have the same mean. To reflect differences in the policy mandates of the ECB and the FED, the mean of r_π is increased, along with a slightly smaller standard deviation, while the Taylor rule parameters fixing the nominal interest rate reaction to changes in the output gap have a lower mean. In this regard, due to identification issues, the standard deviation of r_y must have been shrunk up to 0.01. This is not surprising since Spanish GDP dynamics can hardly track the way the European Central bank conducts monetary policy.

Concerning the shock processes, both TFP and public expenditure shock persistence is set with a higher mean and tighter standard deviation, whilst the standard deviation of ρ_{ga} is slightly coarser. Finally, we shrink the standard deviation of the persistence of both public expenditure and wage mark-up shocks.

Table 1 summarizes priors elicitation and posterior estimates of all estimated parameters considering the whole sample available.

TABLE 1A – Structural parameters estimates (prior and posterior distributions).

	Prior Distribution			Posterior Distribution			
	Distr.	Mean	St. Dev.	Mode	Mean	5%	95%
φ	Normal	4.00	1.50	5.48	6.05	4.23	7.87
σ_c	Normal	1.50	0.37	1.08	1.12	0.90	1.33
h	Beta	0.70	0.10	0.51	0.50	0.38	0.61
ξ_w	Beta	0.75	0.10	0.91	0.90	0.87	0.93
σ_l	Normal	2.00	0.05	2.04	1.95	0.89	2.99
ξ_p	Beta	0.75	0.05	0.92	0.92	0.89	0.95
ι_w	Beta	0.75	0.15	0.68	0.61	0.34	0.69
ι_p	Beta	0.75	0.15	0.98	0.95	0.90	1.00
ψ	Beta	0.50	0.15	0.52	0.56	0.37	0.76
r_π	Normal	1.70	0.20	1.63	1.63	1.47	1.80
ρ	Beta	0.75	0.10	0.93	0.93	0.90	0.95
r_y	Normal	0.10	0.01	0.06	0.06	0.05	0.08
$r_{\Delta y}$	Normal	0.06	0.05	0.09	0.09	0.06	0.13
$\bar{\pi}$	Gamma	0.63	0.10	0.56	0.59	0.45	0.73
$100(\beta^{-1}-1)$	Gamma	0.25	0.10	0.14	0.17	0.07	0.27
$\bar{l}$	Normal	0.00	2.00	1.86	1.84	-0.08	3.89
$\bar{\gamma}$	Normal	0.40	0.10	0.22	0.22	0.15	0.28
α	Normal	0.30	0.05	0.19	0.20	0.15	0.24

Note: The posterior distributions are obtained using the Metropolis-Hastings algorithm.

Despite a prior mean of 0.40 and a sample mean of 0.36, the trend growth rate is estimated to be just 0.22. This could reflect the difficulties the model encountered trying to deal with the financial crises occurred in our sample. The estimated inflation growth rate is slightly lower than the sample mean and quite aligned to the prior mean, whilst the nominal interest rate is roughly 6% on annual basis.

Similar to SW, the data appear to be very informative on the stochastic processes for the exogenous shocks. In particular TFP and public expenditure turn out to be very persistent in spite of a very low value of ρ_{ga}.

Finally, coming back to the structural parameters, overall their posterior mean is not too far away from the prior one, the only exception concerns wage and price indexation parameters which are lower (0.61) and higher (0.95), respectively. Then, also in this case the estimated mean of investment adjustment cost

Table 1b – Shocks processes estimates (prior and posterior distributions).

	Prior Distribution			Posterior Distribution			
	Distr.	Mean	St. Dev.	Mode	Mean	5%	95%
σ_a	Inv.Gamma	0.10	2.00	0.67	0.67	0.58	0.76
σ_b	Inv.Gamma	0.10	2.00	0.12	0.11	0.05	0.15
σ_g	Inv Gamma	0.10	2.00	0.55	0.57	0.50	0.65
σ_I	Inv.Gamma	0.10	2.00	0.46	0.45	0.30	0.60
σ_r	Inv Gamma	0.10	2.00	0.15	0.16	0.13	0.19
σ_p	Inv.Gamma	0.10	2.00	0.24	0.25	0.22	0.29
σ_w	Inv.Gamma	0.10	2.00	0.68	0.66	0.55	0.77
ρ_a	Beta	0.85	0.10	0.95	0.94	0.91	0.97
ρ_b	Beta	0.50	0.20	0.85	0.87	0.78	0.98
ρ_g	Beta	0.85	0.10	0.95	0.95	0.92	0.98
ρ_I	Beta	0.50	0.20	0.56	0.61	0.41	0.83
ρ_r	Beta	0.50	0.20	0.24	0.26	0.10	0.42
ρ_p	Beta	0.50	0.20	0.09	0.12	0.01	0.21
ρ_w	Beta	0.50	0.20	0.43	0.42	0.26	0.58
μ_w	Beta	0.50	0.20	0.75	0.66	0.44	0.82
ρ_{ga}	Beta	0.50	0.20	0.20	0.21	0.04	0.37

Note: The posterior distributions are obtained using the Metropolis-Hastings algorithm.

is a way higher than its prior mean (6.05) and the capital share of income is quite lower (0.20) instead.

2 Reduced-Form Models

In this section, we briefly describe the procedure followed for recursively estimating non-structural models: reduced-form VAR and Bayesian VAR. We follow an agnostic approach and no identification strategy is imposed. Both models are estimated using the same data as in the left hand-side of equation (15).

The VAR is a standard Vector Auto-regression with lag order equal to four including all the 7 observables of interest. The model (as it is for each of the models here) is estimated recursively. This implies the coefficients vary for each evaluation sample.

The Bayesian VAR is also standard and considers the same observables and lag order as above. We impose a Normal-Wishart prior (so as univariate VAR). The hyperparameters calibration is the following. The autoregressive coefficient is set to 0.8, the overall tightness hyperparameter (λ_1) equals 0.1 and the lag decay hyperparameter (Λ_3) equals two [5].

3 DSGE Hybrid Models

In this section, we define two different types of DSGE hybrid models. They refer to those models combining elements, or information, from structural and reduced–form models. In this regard, our approach is twofold. First, based on the seminal work of Del Negro and Schorfheide (2004), the DSGE model is used as an economic prior for estimating a non–structural model (i.e., VARs). Such class of models is labeled by the related literature as DSGE-VAR. The second type of DSGE hybrid model is based on the methodology proposed by Fernández-de-Córdoba and Torres (2011), where the VAR information set is broadened to include those series retrieved from the DSGE model as additional observables. We refer to this class of

[5] Bayesian VAR estimates are largely unchanged by exploiting different sets of non-economic priors.

models as Augmented-(B)VAR-DSGE.

3.1 DSGE–VAR

The DSGE–VAR model estimation, based on Del Negro and Schorfheide (2004), implicitly restricts the DSGE model parameters space so that it is possible to draw posterior inferences about them. Ideally, the larger is the distance between the OLS estimates of the unrestricted VAR parameters and those of the VAR representation of the DSGE model, the less informative would become the DSGE–VAR parameters estimates (i.e., the DSGE model performs poorly at explaining the actual data). In this regard, the extent to which the DSGE model performs in terms of forecasting accuracy highly relies on the hyperparameter Λ, whose bounds are such that $\Lambda \in [0, +\infty)$. The smaller is Λ, the worse the DSGE model fits the data. The lesson extracted from such approach is that the estimated DSGE model may be useful to generate artificial data, and then combine both artificial and observed data under a VAR modeling framework. As previously mentioned, the ratio between the two data sources is Λ.

For the sake of clarity, let us consider ϕ and Σ_u as the VAR parameters and θ the DSGE model parameters. The DSGE–VAR posterior can be factorized in the posterior density of the VAR parameters given the DSGE model parameters and the marginal posterior density of the DSGE model parameters [6].

$$p(\phi, \Sigma_u, \theta|Y) = p(\phi, \Sigma_u|Y, \theta)p(\theta|Y)$$

without any loss of generality, this boils down to:

$$p(\phi, \Sigma_u, \theta|Y) = p(\phi, \Sigma_u|Y)p(\theta|\phi, \Sigma_u)$$

giving the extent to which the DSGE–VAR estimation allows to draw posterior inferences about the DSGE model parameters. In principle, and according to the posterior simulator implemented by the original approach of Del Negro and Schorfheide (2004), an optimal λ can be chosen to maximize the log of the marginal data density. However, given: (i) data constraints which only allows for recursive out–of–sample forecasting exercise; and (ii) identification issues, the DSGE–VAR forecasting performance evaluation is undertaken over a grid of values for Λ. Then, according to the forecast performance on GDP, Consumption and Investment (which are our main object of interest) the most appropriate DSGE prior weight is selected.

Finally, for benchmarking purposes, a brief comparison to Del Negro et al. (2007) is due since it is the most closely related approach. They also extend their methodology to a cointegrating framework (i.e., DSGE–VECM model) for the Euro Area by means of the estimation of the SW DSGE model to investigate its in-sample fitting and forecasting performances. Yet it is worthwhile to highlight the fact

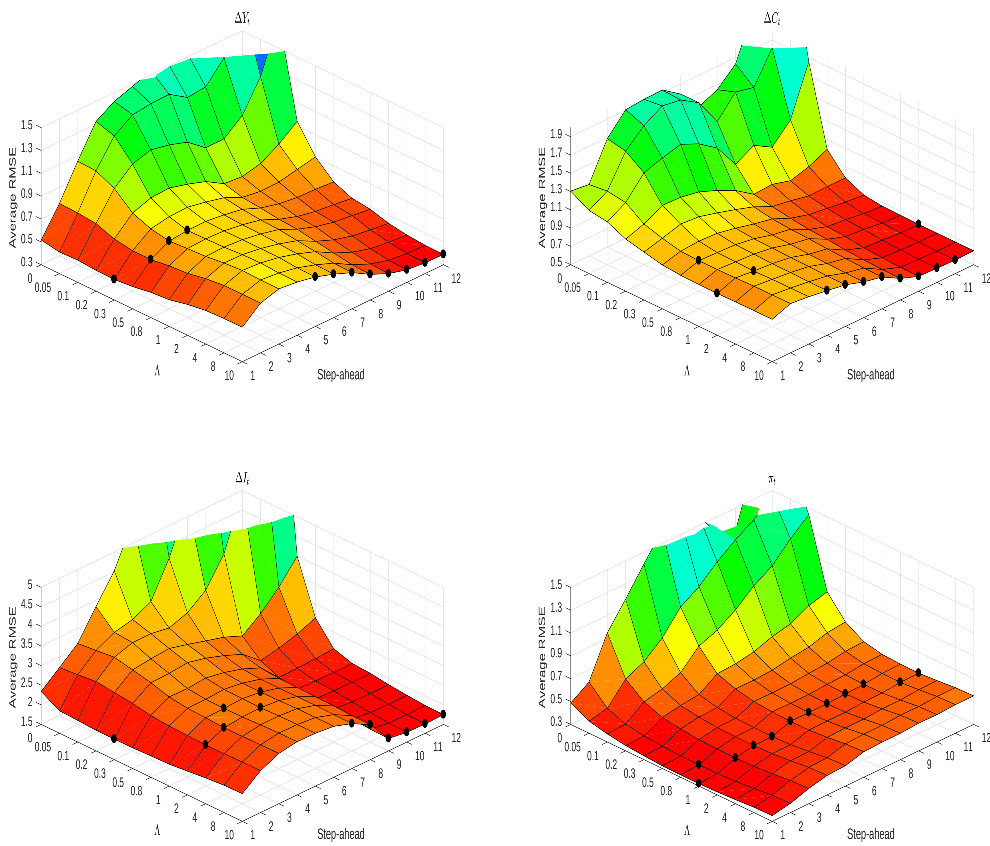
[6] Thus, in a sense, this procedure is equivalent to estimating a Bayesian VAR whose priors are assessed by means of a DSGE model estimated on the same data. In this sense it is possible to refer to Λ as the prior weight.

that the cointegrating restrictions imposed are essentially rejected by the data, inducing a worse forecasting performance of the model (although they seem to help for impulse responses identification). As far the main interest of this paper is forecasting the Spanish business cycle, the canonical DSGE–VAR formulation is considered.

3.1.1 Model Selection

Figure 1 below summarizes the DSGE–VAR average root mean square errors (RMSE), over 12–steps ahead for different values of Λ. The grid points for the DSGE prior weights range from 0 to 10. Black dots identify the best forecasting performance for each step ahead across different DSGE prior weights.

FIGURE 1. Forecasting accuracy for different DSGE prior weights. Average Root Mean Square Error.



Note: The figure reports the results relative to the forecasting accuracy over the evaluation sample (Q32007-Q32018) using point forecasts at different horizons (quarters) and different DSGE prior weights (Λ). The variables we forecast are GDP growth (ΔY_t), consumption growth (ΔC_t), Investment growth (ΔI_t) and inflation (π_t).

At first sight, it is far from unclear that VAR forecasts (i.e., when $\Lambda = 0$) follow an explosive path. In this regard, the DSGE prior mitigates this issue along all forecasting horizons. In particular, the smallest average RMSEs at shorter forecasting horizons are clustered across relatively small values of Λ. As the forecasting horizon increases, higher values of Λ provide lower forecast errors. This not surprising since, as previously mentioned, the VAR forecast errors are following an explosive path and they benefit from a higher DSGE prior weight in the long run. However, the first–step ahead forecast reflects the model ability to approximate the log-data density and relatively small values of Λ produce the more accurate forecasts. This result suggests that the economic prior is generally accepted, but with limitations. Overall, the average RMSEs of the model are quite flat beyond $\Lambda = 0.3$. For simulation purposes, such value has been therefore considered as prior weight for our benchmark model comparison.

3.2 Augmented–(B)VAR–DSGE

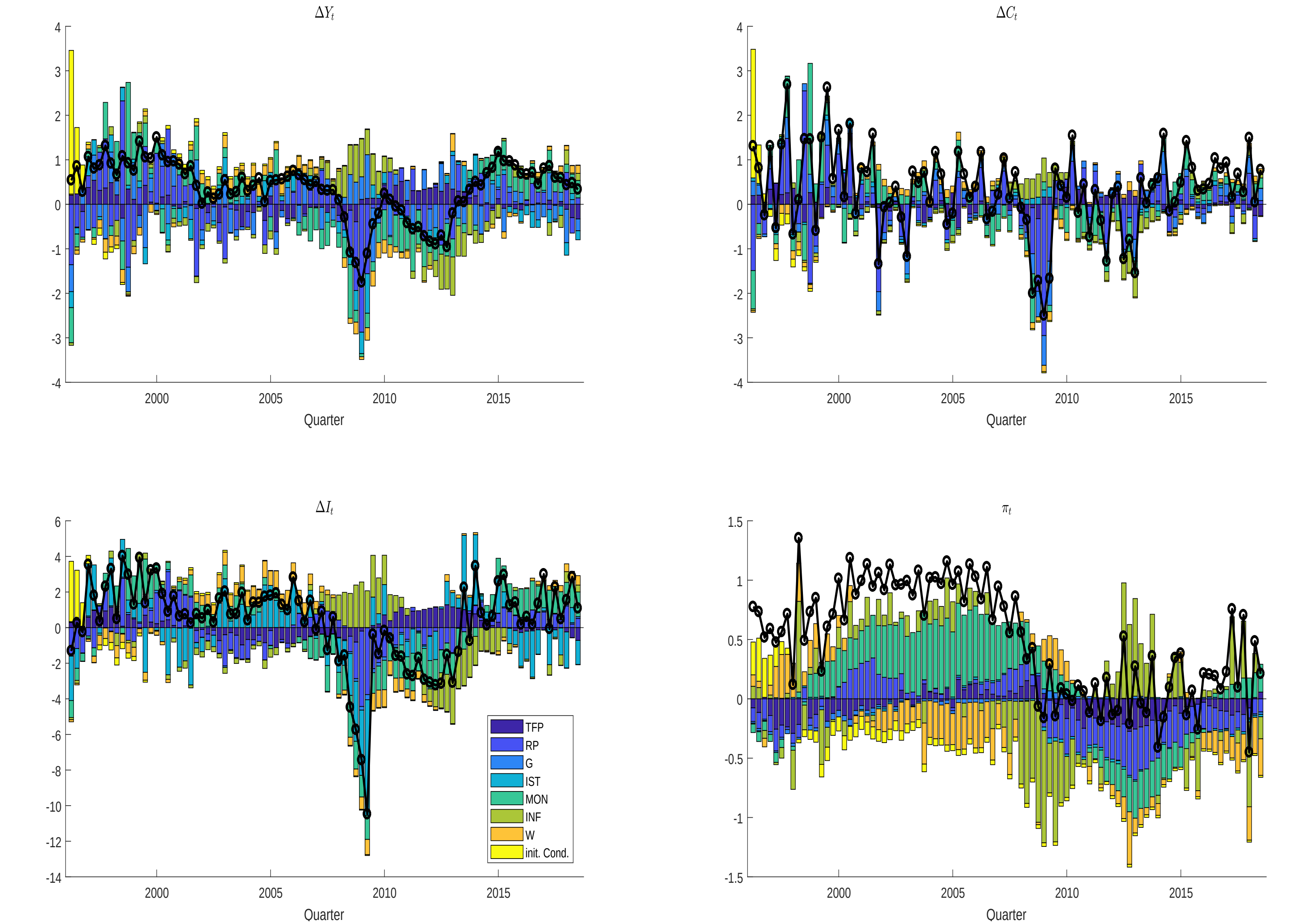
The Augmented–(B)VAR–DSGE estimation procedure is inspired by the work of Fernández-de-Córdoba and Torres (2011). The key idea behind is that an unrestricted (B)VAR contains only limited information on business cycle determinants in contrast with the rich structural dynamics disciplined by DSGE models. Thus, a natural step to enrich the (B)VAR information content is to include unobserved variables produced by the DSGE model. However, our modeling approach differs from that of Fernández-de-Córdoba and Torres (2011) at least along three key dimensions. First, the underlying DSGE model under consideration in this paper in order to augment the (B)VAR variables dimension is far richer than the simple Real Business Cycle (RBC) model they use. Second, our framework allows us to choose from many different unobserved variables exploiting the features of the underlying structural model. Third, the way artificial data is extracted from the DSGE model is different, since it exploits more deeply the advantages of confronting the structural model to the data. A set of different structural shocks and all their possible combinations are explored to enlarge the (B)VAR estimation space. All structural shocks (as in SW) are considered as unobserved variables: the total factor productivity (TFP) shock, the risk premium (RP) shock, the public expenditure (G) shock, the investment specific technology (IST) shock, the monetary policy shock (MON) shock, the inflation (INF) shock and the wage mark-up (W) shock.

The (smoothed) shocks are extracted from the DSGE model in a recursive procedure, so that the extracted series vary in each vintage of the Augmented–(B)VAR estimation. All priors are homogeneous with those of the BVAR.

3.2.1 DSGE Historical Decomposition and Augmented-(B)VAR Model Selection

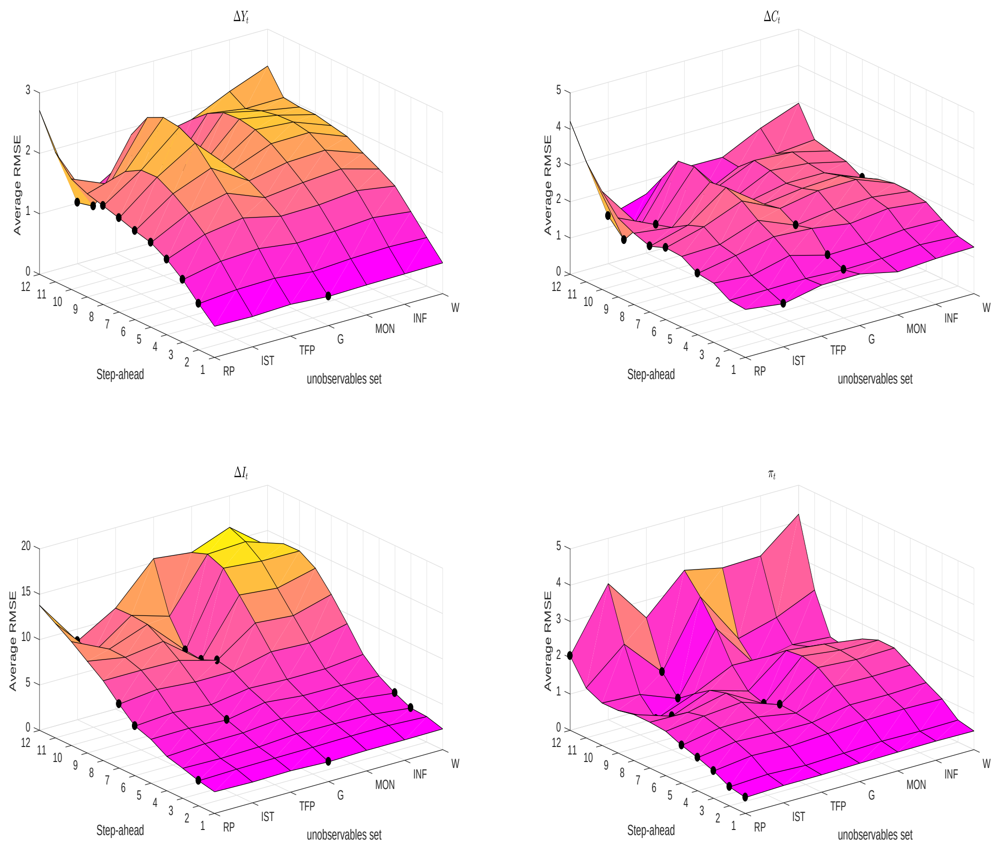
In Figure 2, we plot the historical decomposition of shocks for GDP, consumption, investment and inflation. As shown, the risk premium shock contribution is clearly the most relevant business cycle driver for all of the observables except investment, which is unsurprisingly dominated by investment shocks. The public expenditure shock (which also proxies net export dynamics) is also a crucial business cycle determinant. Inflation dynamics are obviously dominated by the monetary policy and inflation shocks, even if the public expenditure shock plays an important role also in this case. However, given the historical decomposition results, we expect both the risk premium and public expenditure shocks to convey the most valuable information when enlarging the VAR variable space.

Figure 2. Shocks Contribution to Each Variable Historical Decomposition (%).



Note: Shocks historical decomposition components for output growth (ΔY_t), consumption (ΔC_t), investment (ΔI_t) and inflation (π_t) retrieved from the Bayesian estimation of SW DSGE model for Spain.

Figure 3. Average RMSEs for different Augmented-VAR models.

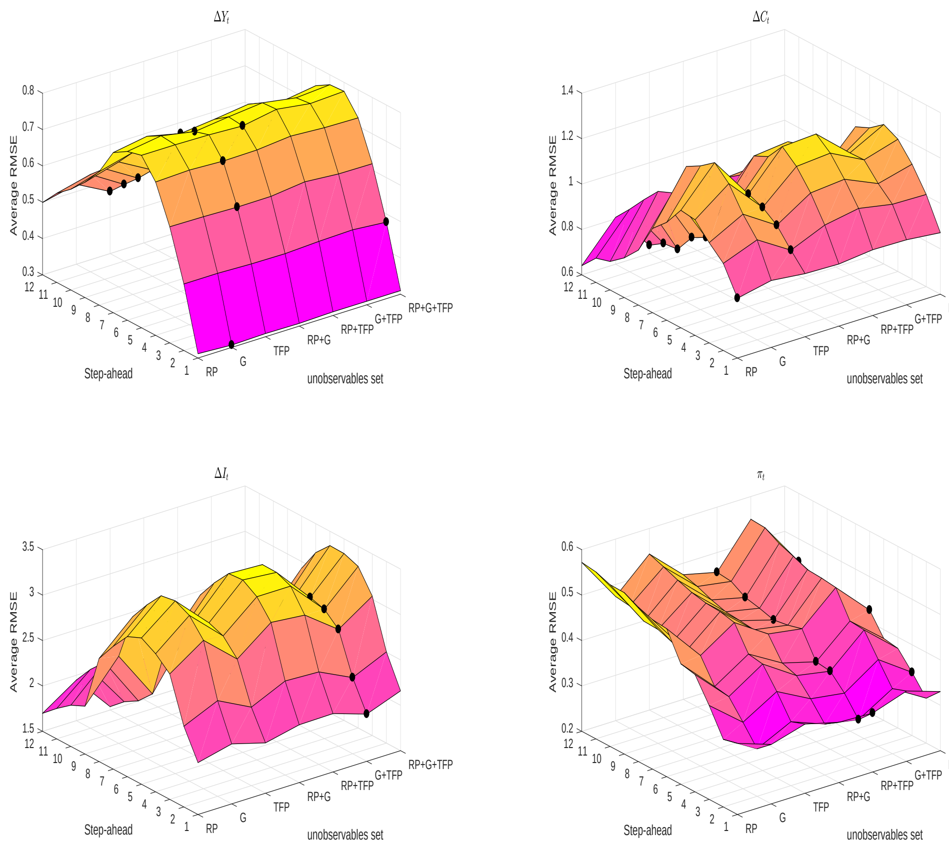


Note: Average Root Mean Square Errors (RMSE) of output growth (ΔY_t), consumption (ΔC_t), investment (ΔI_t) and inflation (π_t) for several Augmented-VARs.

In Figure 3, we report the forecasting performance of seven different Augmented-VARs. Black dots identify the most accurate model, in terms of forecasting performance, for each step ahead. Every single Augmented-VAR model differs depending on the unobserved variable considered. As expected, Augmented-VARs forecast errors are clearly explosive. In line with the historical decomposition, the simulation suggests that the risk premium shock is containing the most relevant information for all variables and particularly for GDP. Somehow surprisingly, IST shocks does not help improve forecasting investment dynamics. The public expenditure shock does help improve forecasting investment, as well as conveying valuable information for consumption. Lastly, TFP shocks do not seem to play any particularly paramount role.

Turning into the Augmented-BVAR model, the curse of dimensionality is easily overcome. We follow the same procedure and try to augment the BVAR model with some combinations of unobserved variables extracted from the DSGE model. The initial set of shocks is reduced to three such that the Augmented-BVAR yields the most accurate forecasting performance. Alternatively, the variable space is also augmented

Figure 4. Average RMSEs for different Augmented-BVAR models.



Note: Average Root Mean Square Errors (RMSE) of output growth (ΔY_t), consumption (ΔC_t), investment (ΔI_t) and inflation (π_t) for several Augmented-BVARs. In this case, since the

with all potential combinations of those three shocks: the total factor productivity, risk premium, and public expenditure shock.

Unlike previous results, the average RMSEs for the Augmented-BVARs reported in Figure 4 show dramatic differences. Albeit the curse of dimensionality is no longer an issue, the most relevant information is still conveyed by a single shock– TFP. This result is validated for all of the real variables, even though investment forecasts further benefit from the inclusion of public expenditure along with TFP. Concerning inflation, the best forecasting properties are reached either by including the government spending shock and TFP, or by adding the risk premium shock too.

To sum up, the out–of–sample exercise suggests that the Augmented-VAR model exhibiting better forecasting performance is mainly reached by including the risk premium shock (in line with Cai et al., 2018). For the Augmented-BVAR instead, only the TFP shock is to be considered. Given the time span of the Spanish data sample, it is not surprising that the risk premium shock behaves as the main business cycle driver. It proxies disruptions in a financial sector which is not explicitly modeled. Such disruptions are partly responsible for those structural breaks witnessed by the data in the aftermath of the Lehman's collapse. However, the risk premium shock does not generate a desirable positive co–movement of real variables which is usually empirically observed. By contrast the TFP shock does. Thus, by imposing a statistical prior to the Augmented-VAR, the model is able to address stationarity issues and therefore the information content of the risk premium shock is to some extent less valuable whilst the TFP shock becomes much more appealing.

4 Forecast evaluation

This section analyses the out-of-sample performance of the competing models over the four key macroeconomic variables for the Spanish economy.

As already mentioned, the time span of our sample is from Q3:1995 to Q3:2018, for a total of ninety-three quarterly observations, and the evaluation sample starts at Q3:2007, implying that each model is recursively estimated forty-four times.

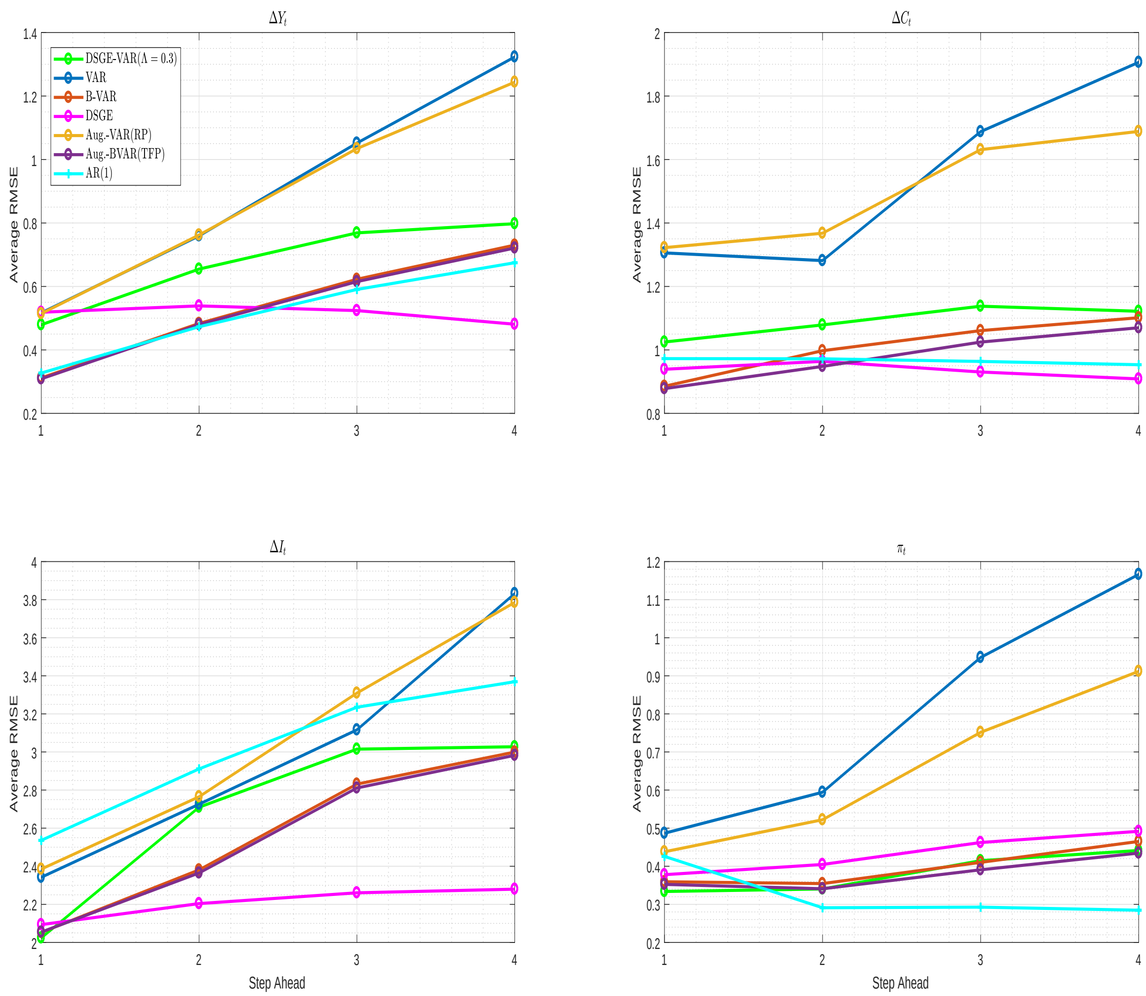
We compute average root mean square errors over 12 steps ahead for GDP, consumption, investment and inflation for seven different models. They are VAR, BVAR, DSGE, DSGE–VAR, Augmented–VAR–DSGE with the risk premium shock shock as additional observable (AVAR henceforth), Augmented–BVAR–DSGE with TFP as additional observable (ABVAR henceforth) and a naive AR(1). All the VAR and akin to models have a lag order of four. In Figure 5 we plot the first four steps-ahead average root mean squared errors (ARMSE) for our variables of interest.

The first thing to notice is that the naive benchmark performs relatively well in the short run, especially for GDP and Consumption (for the former it is the best alternative at step ahead 2) and inflation for which it outperforms all the competitors from step ahead 2 onwards. By contrast, it systematically fails to predict investment although the forecasting performance of all the alternatives is relatively worse as compared to GDP, consumption and inflation. Second, BVAR and ABVAR are very competitive along all the dimensions as expected. Third, the DSGE-VAR model performs relatively well. By contrast, Fernández-de-Córdoba and Torres (2011) report very large ARMSEs for this model.[7] In this sense, having a more structured DSGE as economic prior for the VAR seems to be of great help, especially if we consider that, differently from them, our evaluation sample is less suitable to forecast evaluation exercises as it embeds different financial crises.

Table 2 summarizes the ARMSEs percent gain with respect to an AR(1). A positive number stands for a gain, vice versa such gain is negative when there is a loss in relative prediction accuracy.

[7] Our DSGE-VAR model is labeled as VAR-DSGE in Fernández-de-Córdoba and Torres (2011) in spite of the conventional wisdom. In order to avoid confusion, we stick to the usual literature labeling of our hybrid model, that is DSGE-VAR.

FIGURE 5. Real-time forecasting accuracy, Average Root Mean Squared Errors (RMSE).



Note: The top and bottom panels compare the average RMSEs for the SW DSGE models, DSGE–VAR ($\Lambda = 4$), DSGE, A(B)VAR, and reduced form models, (B)VAR and AR(1), for one through four quarters ahead for output growth (ΔY_t), consumption (ΔC_t), investment (ΔI_t) and inflation (π_t). The forecasts included in these calculations are from Q32007 to Q32018. Section 4 provides the details of the forecast comparison exercise.

Table 2 – Forecast Evaluation Along Different Horizons, ARMSE

	Steps Ahead											
	1	2	3	4	5	6	7	8	9	10	11	12
						GDP (ΔY_t)						
VAR	-0.58	-0.61	-0.78	-0.96	-1.01	-1.13	-1.29	-1.46	-1.60	-1.82	-2.52	-4.02
BVAR	0.05	-0.02	-0.05	-0.08	-0.10	-0.11	-0.11	-0.09	-0.04	0.03	0.08	0.14
DSGE	-0.59	-0.14	**0.11**	**0.29**	**0.34**	**0.34**	**0.34**	**0.35**	**0.38**	**0.41**	**0.39**	**0.37**
DSGE-VAR	-0.46	-0.38	-0.30	-0.18	-0.14	-0.11	-0.09	-0.08	-0.07	-0.08	-0.15	-0.22
AVAR	-0.57	-0.61	-0.75	-0.84	-0.98	-1.11	-1.31	-1.66	-1.89	-1.09	-2.65	-3.71
ABVAR	**0.06**	**-0.01**	-0.04	-0.07	-0.10	-0.10	-0.09	-0.06	0	0.07	0.13	0.18
						CONSUMPTION (ΔC_t)						
VAR	-0.34	-0.32	-0.75	-1.00	-1.04	-1.17	-1.11	-1.04	-1.29	-1.58	-2.31	-3.98
BVAR	0.09	-0.03	-0.10	-0.16	-0.18	-0.15	-0.12	-0.09	-0.08	0.04	0.05	0.10
DSGE	0.03	0.01	**0.03**	**0.05**	**0.05**	**0.04**	**0.04**	**0.07**	**0.14**	**0.13**	**0.12**	0.09
DSGE-VAR	-0.05	-0.11	-0.18	-0.18	-0.13	-0.13	-0.11	-0.11	-0.13	-0.09	-0.10	-0.10
AVAR	-0.36	-0.41	-0.69	-0.77	-1.06	-1.22	-1.14	-1.58	-2.03	-2.81	-3.69	-4.96
ABVAR	**0.10**	**0.02**	-0.06	-0.12	-0.16	-0.14	-0.13	-0.06	-0.07	0.03	0.04	**0.10**
						INVESTMENT (ΔI_t)						
VAR	0.08	0.06	0.04	-0.14	-0.31	-0.56	-1.10	-1.66	-2.93	-2.90	-2.69	-2.20
BVAR	0.19	0.18	0.12	0.11	0.11	0.14	0.19	0.24	0.29	0.41	0.52	0.63
DSGE	0.17	**0.24**	**0.30**	**0.32**	**0.39**	**0.39**	**0.43**	**0.46**	**0.51**	**0.61**	**0.66**	**0.72**
DSGE-VAR	**0.20**	0.07	0.07	0.10	0.11	0.16	0.21	0.25	0.21	0.28	0.34	0.42
AVAR	0.06	0.05	-0.02	-0.12	-0.40	-0.54	-0.99	-1.52	-2.60	-2.54	-2.40	-2.01
ABVAR	0.19	0.19	0.13	0.11	0.12	0.16	0.22	0.27	0.31	0.45	0.55	0.66
						INFLATION (π_t)						
VAR	-0.14	-1.04	-2.24	-3.10	-4.38	-4.86	-5.19	-4.99	-4.23	-4.05	-6.05	-10.91
BVAR	0.16	-0.22	-0.40	-0.63	-0.80	-0.91	-1.01	-1.04	-1.14	-1.16	-1.22	-1.23
DSGE	0.11	-0.39	-0.58	-0.73	-0.88	-0.89	-0.95	-0.95	-0.98	**-0.96**	**-1.00**	**-0.98**
DSGE-VAR	**0.22**	**-0.17**	-0.42	-0.55	-0.73	-0.94	-1.01	-1.06	-1.21	-1.29	-1.47	-1.54
AVAR	-0.03	-0.79	-1.57	-2.20	-3.01	-3.43	-3.76	-3.80	-3.53	-3.54	-4.32	-6.91
ABVAR	0.17	-0.17	**-0.34**	**-0.53**	**-0.69**	**-0.78**	**-0.88**	**-0.90**	**-0.97**	-1.02	-1.06	-1.10

Note: Table entries in boldface indicate the lowest ARMSE as compared to an AR(1) with drift. A positive sign indicates a gain to an AR(1), a negative sign a loss.

The ABVAR gives the best forecasts on impact for GDP and consumption growth. For investment growth the DSGE-VAR is the most accurate. The DSGE–VAR also provides the best inflation forecast on impact and is also relatively better in the second step ahead, then the ABVAR prevails over all the other forecast horizons even if it is constantly beaten by the AR(1). In this regard, the relatively poor performance of all models probably reflects a fundamental change in the way inflation is behaving in Spain since the crisis, which is not captured by any of the other variables in the model. In the second step ahead the ABVAR also dominates for both GDP and consumption, whilst investment is better predicted by the DSGE from step ahead 2 onwards. The DSGE also dominates at almost all longer forecast horizons for GDP. Overall the DSGE–VAR always provides relatively accurate forecasts for all of the variables at every forecasting horizon, even if at longer horizons is always beaten by the DSGE. Coming to the VAR, its forecast errors progressively explode and the imposition of the economic prior from the DSGE model works well in this sense[8]. In this regard, adding the risk premium shock to the observables set is of little help when it does not get things worse at longer horizons.

Finally, it is instructive giving the extent of the improvement in terms of forecasting performance brought in by the introduction of additional observables in the (B)VAR to give raise to the Augmented-(B)VAR model. In Figure 6 are displayed the Augmented-(B)VAR average root mean square error gains with respect to the (B)VAR along several steps ahead[9].

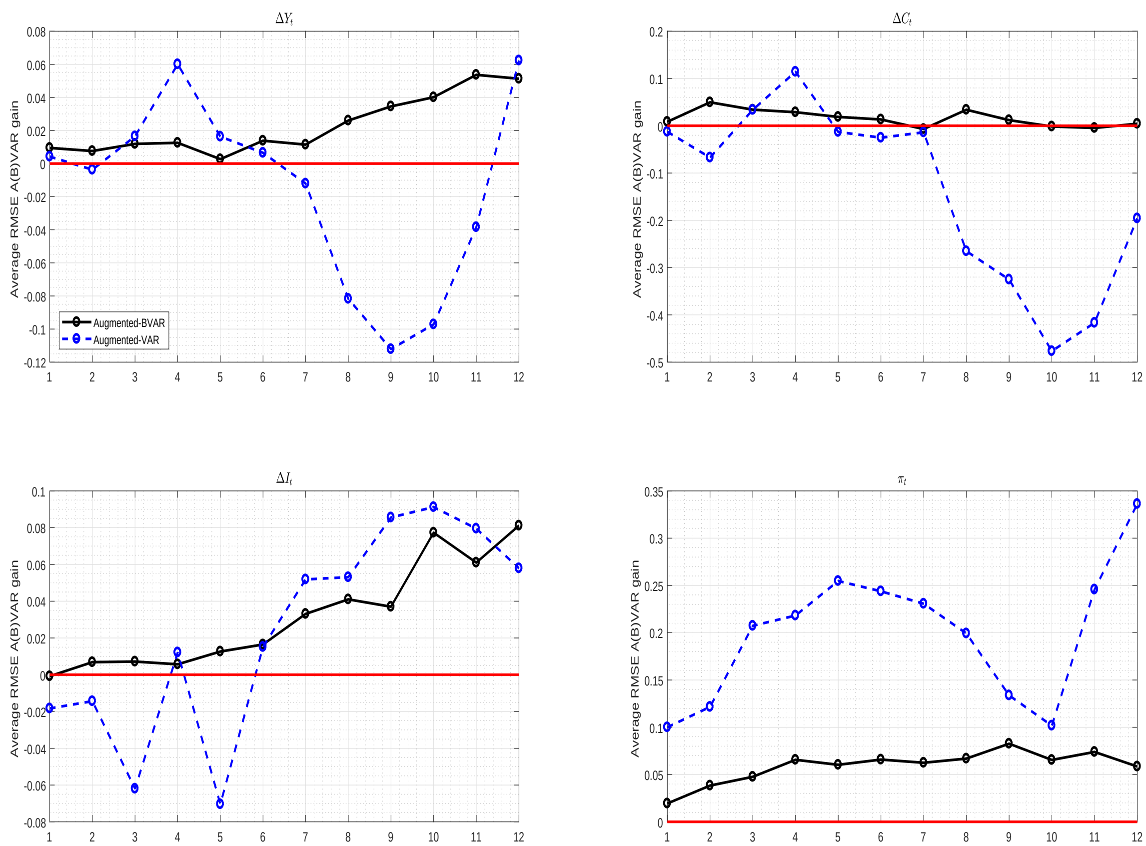
Considering Bayesian models (black continuous lines), the ARMSEs reduction averages around 2.3%, 1.6%, 3.15% and 5.89% for GDP, consumption, investment growth and inflation, respectively. It has always a positive sign and increases with the forecasting horizons for GDP, investment and inflation. By contrast, it is quite steady for consumption. Such gains are not very large (apart from inflation), but witness a constant improvement driven by the information extracted from the structural model which goes beyond the imposition of a statistical prior on the VAR. The picture is a bit more mixed for the OLS VAR (blue dashed lines), here the gain is not steady and becomes negative for GDP and consumption growth at longer forecast horizons[10]. The picture is essentially reversed for investment, whilst the gain for inflation is always strong and positive but still volatile. For GDP and consumption the Augmented-VAR losses average 1.49% and 13%, respectively. By contrast the average improvement for investment is 2.34% and for inflation 19.9%.

[8]This also helps explain why the best DSGE–VAR forecasts never beat the DSGE ones at longer forecasting horizons.

[9]The gains depicted in Figure 6 must be intended as the percentage ARMSE gains of the A(B)VAR with respect to the (B)VAR for each step ahead. This is different from the ratio of each model percentage gain to an AR(1) as it is reported in Table 2.

[10]The oscillatory pattern followed by the gains testifies the presence of some explosive complex roots in the Augmented-VAR model.

Figure 6. Average Root Mean Squared Errors (RMSE) Augmented-(B)VAR gains.



Note: The top and bottom panels compare the average RMSEs gains for the Augmented-(B)VAR with respect to the (B)VAR, for one through twelve quarters ahead for output growth (ΔY_t), consumption (ΔC_t), investment (ΔI_t) and inflation (π_t). The forecasts included in these calculations are from Q32007 to Q32018.

5 Concluding Remarks

The Spanish economy post-crisis environment posed important challenges to standard forecasting models. Linear approximations became poorer since the Great Recession put into question the small deviation around the trend assumption. To address this issue, in this paper we compare the pseudo real-time forecasting accuracy for monitoring the Spanish business cycle of the combination of the SW DSGE model and its closest variants (DSGE–VAR, Augmented–(B)VAR–DSGE) with that of several reduced-form time series models. We first demonstrate that the pseudo real-time out-of-sample forecasting performance of the structural model is capable of competing with all considered alternatives. Our second finding is that reduced-form VARs benefit with the imposition of economic priors from more complex New Keynesian DSGE models. Third, we show that structural models contain useful information to expand the (B)VAR variable space. In particular, they benefit from incorporating either the risk premium or total factor productivity shock, conditional on the imposition of a non-economic prior, as additional observable.

In closing, the focus of this paper is combining structural and non-structural forecasting methods to better fit the Spanish economy. However, out-of-sample forecasting accuracy is not significant by itself. Further research on equal predictive accuracy tests is still to be done. Besides, results may be data-driven (ie., whole sample against post-Great Recession) and testing on improvements by conditioning on either the Consensus Forecasts estimates or those from nowcasting models is with no doubt still to be explored.

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