AN ECONOMETRIC ANALYSIS OF A CALIBRATED MACROECONOMIC MODEL FOR THE DOMINICAN REPUBLIC: A CLOSER LOOK INTO MONETARY POLICY

Paola Mariell Brens Ortega

LATIN AMERICAN AND THE CARIBBEAN ECONOMIC ASSOCIATION

July 2020

The views expressed herein are those of the authors and do not necessarily reflect the views of the Latin American and the Caribbean Economic Association. Research published in this series may include views on policy, but LACEA takes no institutional policy positions.

LACEA working papers are circulated for discussion and comment purposes. Citation of such a paper should account for its provisional character. A revised version may be available directly from the author.

© 2020 by Paola Mariell Brens Ortega. All rights reserved. Short sections of text, not to exceed two paragraphs, may be quoted without explicit permission provided that full credit, including © notice, is given to the source.
LACEA WORKING PAPER SERIES No. 0049 July 2020

An Econometric Analysis of a Calibrated Macroeconomic Model for the Dominican Republic: A Closer Look into Monetary Policy

Paola Mariell Brens Ortega
University of Nottingham
Ministry of Finance of the Dominican Republic
paolambo@gmail.com

ABSTRACT

The aim of this paper is to quantify the effects of an unanticipated monetary policy shock in key macroeconomic variables for the Dominican Republic. The modelling framework in the paper is based on Del Negro and Schorfheide (2004) DSGE-VAR procedure. The procedure allows the addition of theory to empirical models, characterized by a high degree of data fit. Given that the Dominican Republic’s key economic variables time series have a relative short span; this procedure represents a more suitable framework for monetary policy macronomic modelling as it incorporates policymaker's initial belief to the observed data. The results are aligned with macroeconomic theory and with previous empirical papers for the Dominican Republic that measure the impact of a monetary policy shock in output growth and in inflation.

JEL Classification: C32, C51, C53, C54, C61, E52.

Keywords: DSGE-VAR, Monetary Policy, New Keynesian Models.

ACKNOWLEDGEMENTS AND FINANCIAL DISCLOSURE

The findings and conclusions expressed in this paper are strictly those of the authors and do not themselves represent policy advice nor the mentioned institutions position.
1 Introduction

From a policy perspective, the quantification of how a monetary policy shock impacts output and inflation is still a relevant analysis with further room for improvement in the Econometrics literature. The importance of the subject has led to a large amount of empirical and theoretical studies; however, which modelling framework to implement in order to quantify the impact of a monetary policy shock is still an open question.

Since the 1990s, DSGE models have been the focus of macroeconomic modelling for policy analysis, given their ability to analyse policy counterfactuals, particularly in central banks. The emphasis on DSGE models comes from acknowledgement that policy analysis can only be satisfactorily carried out when the optimising behaviour of agents at the micro-economic level is taken into account. However, this does not make the DSGE models the right ones for policymakers, and central banks continue to complement their forecasting tools with a set of models for policy analysis, including simultaneous equation models (SEM) and structural VARs.

DSGE model critiques arise due to their lack of data fit as they are closely built around microeconomic foundations. However, SEM models and VARs are good for data fit, but are not safe from Lucas’s critique. SEM models are in essence a transformation from a reduced-form VAR, therefore one does not contain information that the other does not (Zellner and Palm (1974); Sims (1980); Granger and Newbold (1986)). The main difference is that SEM models typically include forward looking components that VARs do not have. Nevertheless, both modelling strategies have been implemented to explain the behaviour of an economy. These models tend to be of high dimensionality.

\footnote{See Christiano et al. (2018)}
with a large parameter vector; causing them to be data-intensive and with high chances of suffering from degrees of freedom loss resulting in poor results. Plus, the need for a large data set to guarantee the validity, makes them a non-popular choice in countries with data scarcity (i.e. Latin American Countries).

To tackle critiques from the typical modelling strategies a link with Bayesian methods have become a popular approach; as it allows for a mix of theory and data, reducing the trade-off between theory and empirics. In a Bayesian world, DSGE models use a joint probability distribution to transform a prior distribution that reflects knowledge about the parameter’s vector and thus obtain a posterior distribution that links the population moments (long run, steady-state values) with the data; making it more feasible for policy making as an improvement in the model fit is observed. In the same way, Bayesian VARs (BVARs), reduce the original VARs dimensionality and variance via a prior distribution that captures the econometrician uncertainty over the parameters vector values; this is commonly referred to in the literature as VARs with shrinking estimators. SEM models in a Bayesian framework, follows the same idea as BVARs with a semi-structural model typical.

In the Central Bank of the Dominican Republic (BCRD Spanish acronym), the Bayesian approach has been implemented in their short and medium-term modelling strategies. Since 2012, the BCRD adopted and inflation targeting scheme as their monetary policy regime. This scheme dictates its macroeconomic objectives of inflation. In their modelling strategies for the medium-term, the BCRD actively recognises inflation lags and constructs their scenario based on a theoretically valid set of instruments. The BCRD battery of models includes structural VARs, Bayesian DSGE and Bayesian SEM (B-SEM) as the basis for monetary policy analysis.
The structural VARs is a simple bivariate VAR of output and inflation following Quah and Vahey (1995) with the identification restriction being long-run prices neutrality. The B-SEM model of the BCRD is named MAMBO (Spanish acronym); a semi-structural model that characterises the transmission mechanisms of monetary policy and other macroeconomic shocks in a small and open economy context. It is one of the main models for policy analysis and projections used by the BCRD for the generation of the monetary policy report outputs and monetary policy meetings. The model is characterised by five main equations: product gap, aggregate Phillips curve, interest rate parity equation, Taylor’s rule and balance of payments. Finally, the current MAMBO considers a block of satellite equations, which will be incorporated in future versions as part of the transmission mechanism explicitly and with the appropriate interrelationships: labour market, fiscal policy, current account, credit market and interest rates market (Checo and Ramírez, 2017).

On the other hand, the Bayesian DSGE model of the BCRD was constructed to provide an analysis framework based on a rigorous theoretical component, including aspects that successfully captures the dynamics of macroeconomic variables and empirically plausible use for purposes of forecasting and policy analysis. The structure adopted in the model specification is standard in the literature of economies of small and open economy such as: Galí and Monacelli (2005), Justiniano and Preston (2006), Erceg et al. (2000) and Lubik and Schorfheide (2006). The model is characterised by relationships between macroeconomic aggregates that reflect the behaviour of the agents of the economy and the technical and institutional constraints they face. The economy is inhabited by four agents who make decisions based on the maximisation of an objective function: households, domestic producers, importers and government represented by the Central Bank. In the model,
monetary policy has real effects through the presence of a set of nominal frictions, otherwise necessary to capture the empirical persistence of macroeconomic series observed in the data and that are considered standard in the literature (Ramírez and Torres, 2015).

A modern approach that recognises the links between the models and the advantages of Bayesian methods, is to combine the theoretical strong foundations of DSGE with the empirical accurate representation observed in VARs (which is similar to the SEM accuracy). This hybrid model was introduced as a DSGE-VAR by Del Negro and Schorfheide (2004), which reported results showing that their model is competitive with a standard benchmark such as the Bayesian VAR with Minnesota Priors (Minn-VAR) in terms of forecasting and policy analysis. The basic idea of Del Negro and Schorfheide (2004) methodology is to derive from the DSGE model the steady-state conditions of the structural parameters of the economy to generate a prior assumption for the economy’s long-run values.

This is performed under a Bayesian framework, where these priors obtained from the DSGE are introduced in the prior distribution of the VARs parameters vector and is then updated with the data information to obtain a posterior distribution for the parameter vector. Basically, generating the estimation of the VAR based on a mixed sample of artificial and actual observations, with the percentage of artificial observations is controlled by a tightness parameter. This gives rise, to another advantage in Del Negro and Schorfheide (2004) methodology as the tightness parameter allows to assess the degree of misspecification in DSGE; indicating how plausible are the restrictions implied by the structural model (Del Negro et al., 2007).
Acknowledging both the lack of a DSGE-VAR style model in the BCRD and the importance of an accurate modelling framework to quantifying a monetary policy shock; this paper aims to replicate Del Negro and Schorfheide (2004) methodology for the Dominican Republic in order to quantify the impact of an unanticipated monetary policy shock in inflation and output growth. The remainder of this paper is organised as follows: Section 2 is a brief overview of monetary policy macroeconomic modelling literature and the link between DSGE and VARs. Section 3 explains the DSGE-VAR methodology; firstly, describing the DSGE model used in the analysis and then it links with the VAR. Section 4 introduces the data set used for the analysis. Section 5 presents empirical results and Section 6 concludes.

2 A Closer Look to Monetary Policy Modelling Literature

2.1 Monetary Policy Macroeconomic Modelling

Macroeconomic modelling generally has three goals: structural analysis, forecasting, and policy evaluation. In this context, long-run properties of an economy are generally resolved in the supply side of the economy; therefore, model specification and analysis tend to focus on the steady-state or long-run implications of the dynamic econometric model (Wallis, 1999). Pesaran and Smith (2011) argue that effective macroeconomic modelling entails a trade-off between theory consistency, data adequacy and policy making relevance. Pioneers models of macroeconomic modelling were categorised as either calibrated (CA) or system of equations (SEA) models; which at the same time can be considered two dimensional: how to construct the model and how to make it operational (Kim and Pagan, 1999).
The construction of the model under both approaches is linked to how the
long-run relationships are derived. CA models involve two-period maxi-
misation problems of an economy representative household and firm and then
solves for the steady-state using Euler first-order conditions and the stock-
flow constraints, typically approximating the results to log-linear relations
(Garrat et al., 2003). On the other hand, this linkage between prices and
asset returns in the economy, under SEA models are constructed via the ar-
bitrage conditions (e.g. market clears) modified for market uncertainty risks
(Garrat et al., 2003).

It should be noted that CA and SEA models typically use vector autore-
gressions (VAR) to explain the data generating process. Therefore, both ap-
proaches are comparable in their qualitative implications even though they
have different quantitative dimensions (Kydland and Prescott, 1991). Cal-
ibration was introduced by Johansen (1960) in a computable general equi-
librium (CGE) framework, by linearizing the economy general equilibrium
(GE) system around a hypothetical equilibrium; referred in recent literature
as DSGE models. In its early implementations, the construction of DSGE
from a benchmark data set required laborious modelling skills (Kim and Pa-
gan, 1999).

DSGE modelling implications also differs from SEA in the manner the model
built its expectations assumptions; SEA classically builds on the influence of
expectations formations in the contemporaneous real effect of money supply
shifts rather than its nominal effect$^2$. While DSGE expectations formation
recognises the short-term central bank’s policy instruments (i.e. interest

$^2$See Fischer (1977); Taylor (1980)
rate). Therefore, DSGE introduces to the structural equations of the economy expectations formations for the future; since these aggregate relations are built on forward-looking decisions of households and firms (Galí and Gertler, 2007).

Another difference is that SEA models construct steady-state values for output and real interest rate from smoothed trends. While even though, DSGE models introduced nominal rigidities more rigorously manner than early SEA, they modelled explicitly smoothed steady-state values for output and real interest rate in a frictionless equilibrium aligned with the underlying preferences and technology assumptions (Galí and Gertler, 2007). As modelling skills become less labour intensive, DSGE models showed intrinsic and extrinsic dynamics, plus strong and consistent micro-foundations. DSGE models, have become a popular instrument in monetary policy for forecasting and performing quantitative analysis for variables such as output and inflation. Specifically, the New Keynesian (NK) DSGE family, have become the baseline framework for many central banks.

In general, NK-DSGE models enrich the modelling framework by adding monopolistic competition, nominal rigidities and money to frictionless models such as Real Business Cycle models (RBC). NK-DSGE model was built around Friedman (1968) view, where monetary policy does not affect real variables like GDP and the real interest rate in the long-run; but in the short-run, it affects via price and wage stickiness (Christiano et al., 2018). Policymakers have found NK models attractive as they appear sensible enough and allow in the engagement of different types of policy debates, that early

---

3Dynamics arise from: inter-temporal optimisation with the resource’s constraint, stochastic driving forces, the inertia of utility functions and full information regarding agents.
models failed to answer. They have proved to forecast as well as reduced-VAR models and they are able to create counterfactual analysis given their strong theoretical background.

Nevertheless, NK-DSGE models are not safe from critiques, as a fraction of their specifications can be difficult to understand. Even though they have a clear theoretical framework, they are built around imperfect information assuming rational expectations, portraying uncertainty and non-smooth preferences over inflation and output; they restrict attention to time-dependent pricing rules which are built fixed for manipulability; lack clear labour market frictions (as unemployment) and are often built around perfect capital markets which do not consider any financial market frictions (Galí and Gertler, 2007). NK-DSGE also presents pragmatic issues that they fail to assess such as: the adequate monetary policy instrument; whether and how to make use of intermediate targets; and why central banks appear to smooth interest rate variations (Clarida et al., 1999). In the same manner, given their deep structural implications on actual time series, they fail to outperform forecasting performance of less restrictive models as VAR.

NK-DSGE critiques make conclusions to be taken with a pinch of salt, however, they still present great room for improvement and still show great performance at quantifying direction and immediate impact of a shock. In recent years, the NK-DSGE framework has been expanded to formalise explicitly weakness such as the lack of labour market frictions, time-dependent pricing rules, forecasting ability and parameters stability.4 Apart from expanding the typical framework, recent solutions for improvement are: estimating equi-

librium relationships via generalized method of moments (GMM), minimum distance estimation based on the discrepancy among VAR and DSGE model impulse response functions, Bayesian estimation and to focus on the economy long-run structure to impose restrictions while letting the short-run dynamics be unrestricted as a more flexible modelling strategy (Garrat et al., 2003).

2.2 The Relationship between DSGE and VARs

Typically, the theoretical long-run structure is specified in a model with restrictions like the DSGE and the SEA while the short-run dynamics is modelled as an unrestricted VAR, given its ability to fit the data. Nevertheless, a VAR by itself tends to not be parsimonious, as data availability tends to constraint the lag length and the inclusion of additional endogenous variables given the constraint on the degree of freedom (Del Negro and Schorfheide, 2004).

The tight relationship between DSGE and VARs arising from their qualitative implications allows for a linkage between the two modelling strategies; even though in a quantitative dimension they differ. Both approaches link data relationships in their calibrations to ensure or construct the model steady-state. Therefore, as suggested by King and Watson (1992), DSGE can be described via their implied VARs and can be compared either by their impulse response function or their forecast errors. Thus, allowing for comparison between the VAR and DSGE estimation with the goal of minimising the distance between impulse response functions (Ravenna, 2006).

Usually, the DSGE model implied restrictions are summarised by the Moving Average (MA) representation if it is linear or linearly approximated. If the MA representation is not invertible, it does not admit a VAR represen-
tation, or it may be of infinite order⁵ (Ravenna, 2006). Even if the DSGE has a VAR representation, there’s no guarantee that the structural shocks from the DSGE will be identifiable, leading to a misspecification problem. The first step for spotting misspecification issues in computing the model’s posterior probabilities; and if the prior of the VAR is very diffuse it rejects against a misspecified DSGE (Lindley’s Paradox) (An and Schorfheide, 2007).

In addition, since the VAR parameter vector is mostly larger than the DSGE model parameter vector, prior distribution specification for the VAR parameter requires careful attention but if the data favours the VAR, the DSGE structure needs to be strengthened (An and Schorfheide, 2007). One direction of the strength can be to analyse the posterior distributions of population characteristics obtained from a VAR (as a probabilistic representation of the data) that does not rigidly impose DSGE model restrictions (priors).

This strengths can be known as the DSGE-VAR approach of Del Del Negro and Schorfheide (2004), which builds on work by Ingram and Whiteman (1994). The procedure is designed to improve DSGE models forecasting and monetary policy analysis with VARs. The DSGE-VAR procedure would be discussed more thoroughly in section 3; the general idea is to shrink the VAR parameter vector towards values implied by a DSGE model. Also, this approach improves macro modelling since it provides a more flexible framework given that the DSGE restrictions may not necessarily be rigidly imposed, but the data can deviate to an extent from its structural characteristics.

⁵See Félance-Villaverde and Rubio-Ramírez (2006) for a wider discussion on invertibility issues.
2.3 Empirical Results

Following the novel of Del Negro and Schorfheide (2004) DSGE-VAR approach, in recent years there have been a few applications in the literature. Del Negro et al. (2007), extended the approach for model evaluation tool and assessed the fit of a modified Smets and Wouters (2003) DSGE model. Del Negro and Schorfheide (2009) based their analysis on an NK-DSGE model where monetary policy follows an interest rate feedback rule; their aim is assessing how deviations in monetary policy rule affect the dynamics of output and inflation in the USA economy. The authors generate three types of parameters estimations: first combining the DSGE model with a prior distribution, second generalising the shock structure and finally by computing the model based on the DSGE-VAR procedure.

Del Negro and Schorfheide (2009) results show robustness on the fact that deviating from the baseline parameters of the feedback rule is unlikely to provide substantial improvements over the estimated Volcker Greenspan policy. In addition, it appears unwanted to reduce inflation response and increase output reactions from a long-run path to deviations of output from its long-run trend. On the other hand, Menz and Baurle (2009) focus on monetary policy shocks transmission under a behavioural model, following the DSGE-VAR framework focusing on the question: do central banks need to react to nominal exchange rate fluctuations in a small open economy model for the Swiss economy. Lees et al. (2011) follow the DSGE-VAR framework to construct a model for competing with historic forecasts of the Reserve Bank of New Zealand; constructing a Bayesian VAR model with a Minnesota prior for forecast comparison. They show how the forecast obtained from this approach are competitive with the Reserve Bank of New Zealand’s judgement adjusted published forecasts.
In the same manner, Gupta and Steinbach (2013) apply the DSGE-VAR framework for the South African economy, characterising the model with an incomplete pass-through of exchange rate changes, external habit formation, partial indexation of domestic prices and wages to past inflation, and staggered price and wage setting. Similarly, the DSGE-VAR framework has been applied for other economies policy evaluation: Japan (Iiboshi (2016)), Romanian (Pop (2017)), etc. With a greater emphasis on exploiting data on survey expectations, Cole and Milani (2019) study of fit and misspecification of the NK-DSGE model using a DSGE-VAR approach with relaxations on the rational expectations hypothesis (REH); showing how modelling expectations as suggested by learning or heterogeneous expectations improve NK-DSGE model fit.

3 DSGE-VAR Modelling Framework

This section presents the modelling framework for the DSGE-VAR procedure applied to the Dominican Republic. The procedure links the prior’s distribution from a classical New Keynesian model\(^6\) with a trivariate Bayesian VAR for output growth, inflation and interest rates. For the sake of parsimony, investment, capital accumulation, the financial sector, adjustment costs and an active government are not modelled; however, this does not affect any qualitative conclusions. It is important to consider that this scenario is built for a closed economy, even though the Dominican Republic is an open economy, as this exercise seeks only to show how DSGE-VAR can aid in the correction of DSGE models’ predictions and VAR lacks theoretical foundations when evaluating monetary policy.

\(^6\)With a more detailed specification found in (Clarida et al., 1999)
3.1 The DSGE Model

The economy is formed by a unitary set of households indexed by $j \in [0, 1]$; a continuum of monopolistically competitive firms indexed by $j \in [0, 1]$; a central bank that conducts monetary policy with a nominal interest rate rule and a government that chooses spending exogenously. As in the early IS/LM Keynesian framework, in the short run the economy is affected by the central bank monetary policy decisions; differing in the fact that behavioural equations of the aggregated economy evolve explicitly around the households and firm’s optimisation problems (Clarida et al., 1999). This implies that the behaviour of the economy in time $t$, depends on the expectations of the future values of key variables (i.e. inflation) and current course of monetary policy, as nominal rigidities are present in the economy.

3.1.1 Households

Households maximise a welfare function, subject to an inter-temporal budget constraint, which reflects the availability and allocation of the resources. The representative households derive utility from real balances and consumption and disutility from labour. The utility function is log-linear with separability between consumption, real balances and labour. It is expected that a rise in consumption or real balances brings utility and a rise in labour brings disutility. Habit formation in the economy is assumed and is given by the economy level of technology, ensuring a balanced growth path. For simplicity, population growth is ignored in the household’s structure.

Households are the owners of labour and provide it to the firms, obtaining revenues from wages in return. In the same manner households have access to a domestic capital market where nominal government bonds are traded at the price of the nominal interest rate, they receive residual profits and pay
lump-sum taxes. Thus, the representative household optimisation problem is the following:

$$\max_{C_{j,t}, L_{j,t}, B_{j,t}} E_t \sum_{t=0}^{\infty} \beta^t [\frac{(c_{j,t})^{1-\alpha}}{1-\alpha} - 1 + \chi \ln \left( \frac{M_t}{P_{j,t}} \right) - L_{j,t}]$$  \hspace{1cm} (1)$$

s.t

$$C_{j,t} + B_{j,t} + M_t + T_{j,t} = W_t L_{j,t} + L_{j,t} + R_{t-1} - B_{j,t-1} - P_t + F_{j,t}$$  \hspace{1cm} (2)$$

Where $t$ index time and represent quarters in this set up, $E_t$ is the expectations operator, $\beta$ is the inter-temporal discount factor, $C$ is consumption for goods, $L$ is the number of hours worked, $\chi$ is a scale factor that represents marginal disutility with respect to labour supply (inverse of Frisch elasticity), $T$ are lump-sum taxes, $P$ is the general price level, $M$ is the economy money balances, $B$ is bonds, $W$ is real wages, $R$ is the nominal interest rate, $A$ is technology level, and $F$ are the firm’s profits. The problem of the household gives three equilibrium conditions: labour supply, Euler equation and money demand; plus, the transversality condition\(^7\) on the accumulation of assets (bonds and money) to rule out a Ponzi scheme:

$$c_{j,t}^{-\alpha} \left( \frac{1}{A_{j,t}} \right) = c_{j,t+1}^{-\alpha} \left( \frac{1}{A_{j,t+1}} \right) \beta E_t \left( \frac{R_t}{\pi_{t+1}} \right)$$  \hspace{1cm} (3)$$

$$c_{j,t}^{-\alpha} \left( \frac{1}{A_{j,t}} \right) = \frac{1}{W_{j,t}}$$  \hspace{1cm} (4)$$

\(^7\)Equation 6
\[
\chi \left( \frac{M_t}{P_t} \right)^{-1} = c_{j,t}^{-\alpha} \left( \frac{1}{A_{j,t}} \right) + c_{j,t+1}^{-\alpha} \left( \frac{1}{A_{j,t+1}} \right) \beta E_t \left( \frac{1}{\pi_{t+1}} \right) 
\]

(5)

\[
\lim_{T \to \infty} \beta^T U_{ct}(d_t) = 0
\]

(6)

Where \( d_t = [B, m] \) and \( c = \frac{C}{A} \) is the consumption level detrended by technology level. Equation 3 refers to the Euler equation for consumption which determines the household’s saving decision, in this context saving is the acquisition of bonds. Equation 4 refers to the labour supply, which states that a rise in real wages produces an increase in consumption without decreasing leisure time. This shows how households decide their level of saving, by comparing the utility rendered by consuming an additional amount today with the utility that would be reduced by consuming more in the future. Equation 5 is the money demand equation which shows that households demand for real balances depends on their inter-temporal choices of consumption.

### 3.1.2 Production Sector

A set of monopolistically competitive firms describe the economy production sector; the firms face a downward-sloping demand curve for output giving the firm’s pricing power. With a demand function derived from Dixit-Stiglitz preferences \(^8\):

\[
P_{j,t} = \left( \frac{Y_{j,t}}{Y_t} \right)^{-\frac{1}{\omega}} P_t
\]

(7)

where \( P_{j,t} \) is the profit-maximising price, \( Y_{j,t} \) is the production level, \( \omega \) is substitution elasticity between two differentiated goods. The aggregate price level \( P_t \) and aggregate demand \( Y_t \) are not controlled by the individual firms.

\(^8\)For a more detail derivation see Dixit and Stiglitz (1977).
The firms face a quadratic function for adjusting nominal prices, which introduces nominal rigidity to the economy. The adjustments costs, induced when the firm wants to change its price beyond the economy-wide inflation rate $\pi^*$, are in the form of lost output:

$$\frac{\varphi}{2} \left( \frac{P_{j,t}}{P_{j-1,t}} - \pi^* \right)^2 Y_t$$

(8)

Where the parameter $\varphi \geq 0$ governs the degree of stickiness in the economy. Production is assumed to be linear in labour $L_{j,t}$, which each firm hires from the household with technology being an exogenously given stationary unit root process:

$$Y_{j,t} = A_t L_{j,t}$$

(9)

$$\ln A_t = \ln \mu + \ln A_{t-1} + \tilde{a}_t$$

(10)

$$\tilde{a}_t = \rho_a \tilde{a}_{t-1} + \varepsilon_{a,t}$$

(11)

Where $\varepsilon_{a,t}$ represents the technology shock that affects all firms equally and adds a stochastic trend into the model. Firm $j$ chooses its labour input $L_{j,t}$ and price $P_{j,t}$ to maximise the present value of future profits:

$$E_t \sum_{i=0}^{\infty} Q_t D_{j,t}$$

(12)

subject to equations 9 and 10, where profit is given by:

$$D_{j,t} = P_{j,t} Y_{j,t} - W_t L_{j,t} - \frac{\varphi}{2} \left( \frac{P_{j,t}}{P_{j-1,t}} - \pi^* \right)^2 Y_{j,t}$$

(13)
Where \( Q \) is an intertemporal discount factor associated with firms future profit streams. This scenario considers the representative monopolistically competitive firm with a symmetric equilibrium in which firms have the same behaviour. In the same manner, in equilibrium households have access to a complete set of state-contingent claims \( E_t Q_{t+1} = E_t \beta C_{t+1}^\alpha \) the link between households and firms arising via the firm’s residual payments which direct firms to make decisions based on the household’s intertemporal rate of substitution (Del Negro and Schorfheide, 2004).

### 3.1.3 Government and Monetary Policy

The economy’s government choose spending, exogenously. It finances spending with lump-sum taxes that finance revenues shortfall and subsidies to rebate any surplus. The government’s budget constraint is the following:

\[
G_t + R_{t-1} \frac{B_{t-1}}{P_t} + M_{t-1} \frac{T_{t-1}}{P_t} \leq \frac{T_t}{P_t} + \frac{M_t}{P_t} + \frac{B_t}{P_t}
\]

where government consumption, can be defined as a fraction \( \vartheta_t \) of output \( (G_t = \vartheta_t Y_t) \), defining \( g_t \) as \( \frac{1}{1-\vartheta_t} \) and the deviation from its trend \( \tilde{g}_t \) as \( ln(\frac{g_t}{g^*}) \) following a stationary AR(1) process:

\[
\tilde{g}_t = \rho g_{t-1} + \varepsilon_{g,t}
\]

Where \( \varepsilon_{g,t} \) is the government spending shock; the government then accommodates monetary policy and endogenously adjusts primary surplus changes in the outstanding liabilities. The Central Bank affects the economy’s equilibrium via monetary policy decisions. The central bank follows a nominal interest rate rule, adjusting the nominal interest rate in response to deviations of inflation or output targets, expressed by the following equation:
\[
\frac{R_t}{R^*} = \left( \frac{R_{t-1}}{R^*} \right)^{\rho_R} \left[ \left( \frac{\pi_t}{\pi^*} \right)^{\rho_1} \left( \frac{Y_t}{Y^*_t} \right)^{\rho_2} \right]^{1-\rho_R} \rho \epsilon_{R,t} \tag{16}
\]

Where \( R^* \) is long-run nominal rate, \( \pi^* \) is the economy-wide inflation rate that sets the economy inflation target and \( Y^*_t \) is potential output, which can be defined as the technology level by normalising the steady-state hours worked to one. The parameter \( 0 < \rho_R < 1 \) determines the degree of interest rate smoothing. In addition, unexpected deviations from the policy rule can be accounted via the monetary policy shock \( \epsilon_{R,t} \).

### 3.2 Model Equilibrium

Following Del Negro and Schorfheide (2004), in equilibrium the following variables are detrended by the level of technology: output, wages, consumption and consumption marginal utility. Therefore, the model is built to have a deterministic steady-state in terms of the detrended variables; therefore, agents based their decision knowing the future values of the error term. Where the percentage deviation from its trend is defined as \( \tilde{y}_t = \ln Y_t - \ln Y^*_t \). Then the economy equilibrium equations, log-linearized, can be represented as follows:

\[
\tilde{y}_t = E_t[\tilde{y}_{t+1}] - \alpha^{-1}(\tilde{R}_t - E_t[\tilde{\pi}_{t+1}]) + (1 - \rho_g)\tilde{y}_t + \rho_a \frac{1}{\alpha} \tilde{a}_t \tag{17}
\]

\[
\tilde{\pi}_t = \frac{\mu}{r^*} E_t[\tilde{\pi}_{t+1}] + \phi (\tilde{y}_t - \tilde{y}_t) \tag{18}
\]

\[
\tilde{R}_t = \rho_R \tilde{R}_{t-1} + (1 - \rho_R) (\rho_1 \tilde{\pi}_t + \rho_2 \tilde{y}_t) + \epsilon_{R,t} \tag{19}
\]

Where \( r^* = \mu \frac{1}{\beta} \) is the long-run real interest rate and \( \phi \) parameter measures the

\[9\text{Future shocks occurrence are known at the time of computing the model's solution.}\]
overall distortion in the economy and is a function of the price adjustment costs and the demand elasticity. The equations refer to the inter-temporal consumption Euler-equation, which can be interpreted as an IS curve portraying the inverse relationship of output gap and real interest rate; a Phillips Curve that represents inflation dynamics and its relationship with output gap; and the monetary policy rule on nominal interest rate that allows for the lack of LM curve specification to achieve an equilibrium in the model\(^\text{10}\).

The following measurement equations relate deviations from steady-state and the observed data of the three key variables output growth, inflation, and interest:

\[
\Delta \ln y_t = \ln \mu + \Delta \tilde{y}_t + \tilde{a}_t \\
\Delta \ln P_t = \ln \pi^* + \tilde{\pi}_t \\
\ln R^a_t = 4 \left[ (\ln r^* + \ln \pi^*) + \tilde{R}_t \right]
\]

Where \(R^a_t\) is the annualised nominal rate. Solving the linear rational expectations system (20-22); the evolution of \(\tilde{y}_t, \tilde{\pi}_t, \tilde{R}_t, \) and \(\tilde{a}_t\) can be obtained. Whereas the DSGE model has three normally distributed and independent structural shocks with zero mean and variances \(\sigma_R, \sigma_g, \sigma_a;\) and the following deep parameters:

\[
\varepsilon_t = [\varepsilon_{R,t}, \varepsilon_{g,t}, \varepsilon_{a,t}]'
\]

\(^\text{10}\)For a detailed derivation for solving the equilibrium see Sims (2002).
\[ \theta = [\ln \mu \ \ln \pi^* \ \ln r^* \ \phi \ \alpha \ \rho_1 \ \rho_2 \ \rho_R \ \rho_a \ \rho_z \ \sigma_R \ \sigma_g \ \sigma_a]' \quad (24) \]

This shows how the DSGE model imposes tight restrictions across the underlying parameters of the moving average (MA) representation for output growth, inflation, and interest rates.

### 3.3 Construction of Prior for VAR

This section will describe the procedure for constructing the DSGE prior for the VAR resulting in the DSGE-VAR model, the methodology follows Del Negro and Schorfheide (2004). The DSGE model can be written as the following state-space representation:

\[ x_t = [\Delta \ln y_t \ \Delta \ln P_t \ \ln R^a_t]' \]

which is a less restrictive MA representation for the nx1 vector \( x_t \), where \( n \) is the number of endogenous variables. From this a VAR model with q lags of the following form is written:

\[
\begin{align*}
    x_t = & \phi_0 + \phi_1 x_{t-1} + \ldots + \phi_p x_{t-q} + u_t \\
\end{align*}
\]

(25)

Where \( u_t \) is the vector of one-step-ahead forecast errors, assumed normally distributed conditional on past information \( u \sim N(0, \Sigma_u) \). To solve VARs parsimonious issue this procedure shrinks the VAR estimates toward DSGE implied restrictions without imposing them dogmatically. The procedure uses Bayesian methods to describe the linkage between the DSGE and the VAR. Specifically, the procedure generates simulated observations from the DSGE model to augment the data later used by the VAR.
The procedure places a prior distribution on the DSGE model deep parameters vector $\theta$. Which means that a hierarchical prior consisting of a marginal distribution for $\theta$ given the simulated data and a conditional distribution for the VAR parameters given $\theta$, is constructed (Del Negro and Schorfheide, 2004). Given Bayes theorem\(^\text{11}\), the procedure constructs a joint posterior distribution for the DSGE model and VAR parameters. The procedures implicitly search for values of $\theta$ for which the distance between VAR results and VAR representations of the DSGE model result is minimal. In the following subsections the construction of the likelihood function, prior distribution and posterior distribution are explained.

### 3.3.1 The Likelihood Function

The likelihood function is constructed under the multivariate normal distribution assumption of the error term in equation 25. Defining $X$ as the $Txn$ matrix with rows $x'_t$; and $k = 1 + nq$, with $W$ be the $T\times k$ matrix with rows $w'_t = [1, x'_{t-1}, \ldots, x'_{t-q}]$, and $U$ be the $T\times n$ matrix with rows $u'_t$ and the parameter vector $\Phi = [\Phi_0, \Phi_1, \ldots, \Phi_q]$. The VAR with $q$ lags can be expressed as $X = W\Phi + U$ with likelihood function:

$$p(X|\Phi, \Sigma_u) \propto \left|\Sigma_u\right|^{-\frac{k}{2}} \exp\left(-\frac{1}{2}tr\left[\Sigma_u^{-1}(X'X - \Phi'W'X - X'W\Phi + \Phi'W'W\Phi)\right]\right)$$

(26)

conditional on observations $x_{1-q}, \ldots, x_0$. Following Del Negro and Schorfheide (2004), the VAR can be interpreted as an approximated MA representation of the underlying DSGE. Where, as $q$ gets higher, the discrepancy magnitude in the VAR diminishes. Given that the parameter vector of the DSGE is of lower dimension that the VARs, the DSGE model imposes boundaries on

\(^{11}\)The conditional distribution of a parameter $\theta$ given $Y$ is given by: $P(Y|\theta) = \frac{P(Y|\theta)P(\theta)}{P(Y)}$
the approximated vector autoregressive representation of \( x_t \) via the distribution of the priors. The prior distribution tackles the problem of too many parameters in the VAR, by reducing the dimensionality of the model.

### 3.3.2 Building the Prior Distribution

To generate the prior distribution, following Del Negro and Schorfheide (2004), actual observations are augmented with \( T^* \) artificial observations \((X^*, W^*)\) generated from the DSGE model based on \( \theta \), the augmentation of the actual observations depend on \( \lambda \) and \( T^* \) is defined as \( \lambda T \). The likelihood function for the combined sample of artificial and actual observations is obtained by pre-multiplying the likelihood function (26) with the likelihood function generated by the artificial observations:

\[
p(X^*(\theta) | \Phi, \Sigma_u) \propto |\Sigma_u|^{-\frac{T}{2}} \exp\left(-\frac{1}{2} tr \left[ \Sigma_u^{-1}(X^*X^* - \Phi'W^*X^* - X^*W^*\Phi + \Phi'W^*W^*\Phi) \right] \right)
\]

\[
p(X^*(\theta), X | \Phi, \Sigma_u) = p(X^*(\theta) | \Phi \Sigma_u) p(X | \Phi, \Sigma_u)
\]

(27)

(28)

Where the factorisation in expression (28) shows how the term \( p(X^*(\theta) | \Phi, \Sigma_u) \) can be interpreted as a prior density for the VAR parameter vector \( \Phi \) and error term covariance matrix \( \Sigma_u \). This summarises the information about the VAR parameters contained in the sample of artificial observations; if the prior is purely generated by random draws from the DSGE model, repeated simulations would lead to a stochastic variation in the prior distribution that is unwanted (Del Negro and Schorfheide, 2004). The non-standardised sample moments are replaced by scaled population moments; as a way of removing the stochastic variation from \( p(X^*(\theta) | \Phi, \Sigma_u) \):
\[
\lambda T \Gamma_{xx}^* (\theta) = X^* X^*
\]  
(29)

\[
\lambda T \Gamma_{xw}^* (\theta) = X^* W^*
\]  
(30)

\[
\lambda T \Gamma_{ww}^* (\theta) = W^* W^*
\]  
(31)

As we can obtain the population moments analytically from the DSGE model structural relationships, the Del Negro and Schorfheide (2004) procedure is efficient from a computational standpoint. Populations moments replace expression (27) with

\[
p(\Phi, \Sigma_u | \theta) \propto c^{-1} (\theta) |\Sigma_u|^\frac{\lambda T + n + 1}{2} \exp\left(\frac{1}{2} \text{tr} \left[ \lambda T \Sigma_u^{-1} (\Gamma_{xx}^* (\theta) - \Phi' \Gamma_{xx}^* (\theta) \Phi + \Phi' \Gamma_{ww}^* (\theta) \Phi) \right] \right)
\]  
(32)

With an initial improper prior \(p(\Phi, \Sigma_u) \propto |\Sigma_u|^{-(n+1)/2}\). The prior density is proper and nonsingular (i.e. has finite dimensions), for any \(\lambda T \geq k + n\) and an invertible \(\Gamma_{ww}^* (\theta)\). The normalization factor \(c(\theta)\) for the conditional prior density of the VAR parameter, can be chosen to ensure that the density integrates to one and is given by:

\[
c(\theta) = 2 \pi^\frac{n k}{2} |\lambda T \Gamma_{ww}^* (\theta)|^{-\frac{n}{2}} |\lambda T \Sigma_u^* (\theta)|^{-\frac{\lambda T - k}{2}} 2 \pi^\frac{n(\lambda T - k)}{4} \prod_{i=1}^{n} \Gamma\left[\frac{\lambda T - k + 1 - i}{2}\right]
\]  
(33)
Where the gamma function is denoted by \( \Gamma[\bullet] \). Knowing this, the following functions are defined:

\[
\Phi^*(\theta) = \Gamma_{ww}^{-1}(\theta)\Gamma_{bx}(\theta) \tag{34}
\]

\[
\Sigma_u^*(\theta) = \Gamma_{xx}(\theta) - \Gamma_{nxw}(\theta)\Gamma_{ww}^{-1}(\theta)\Gamma_{wx}(\theta) \tag{35}
\]

Conditional on \( \theta \) the prior distribution of the VAR parameters (32) is of the Inverted-Wishart (IW)– Normal (N) in which \( \Gamma_{ww}(\theta) \) is of full rank. As the number of endogenous variables \( n \) to which the model is fitted equal the number of structural shocks. The IW-N form is:

\[
\Sigma_u|\theta \sim IW(\lambda T\Sigma_u^*(\theta), \lambda T - k, n) \tag{36}
\]

\[
\Phi|\Sigma_u, \theta \sim N(\Phi^*(\theta), \Sigma_u \otimes (\lambda TT_{ww}(\theta))^{-1}) \tag{37}
\]

Overall the hierarchical structure of the prior is:

\[
p(\Phi, \Sigma_u, \theta) = p(\Phi, \Sigma_u|\theta) p(\theta) \tag{38}
\]

The coefficient matrix \( \Phi^*(\theta) \) and \( \Sigma_u^*(\theta) \) trace out a subspace of the VAR parameters space. Where \( \Phi^*(\theta) \) is the coefficient matrix that minimizes the one-step-ahead quadratic forecast error loss; with forecast error covariance matrix is given by \( \Sigma_u^*(\theta) \). The prior is designed to assign probability mass outside of the subspace traced out by \( \Phi^*(\theta) \) and \( \Sigma_u^*(\theta) \). Del Negro and Schorfheide (2004) design the covariance matrix \( \Sigma_u \otimes (\lambda TT_{ww}(\theta))^{-1} \), where \( \otimes \) is the Kronecker product, to distribute probability mass around \( \Phi^*(\theta) \) and average over \( \theta \) with respect to a prior \( p(\theta) \). The prior is designed to
moderately disperse in the directions of the VAR parameter space that is expected to be estimated roughly according to the DSGE model.

3.3.3 Posterior Distribution

To analyse the posterior distribution, Del Negro and Schorfheide (2004) procedure factorises it by the posterior density of the VAR parameters given the DSGE model parameters and the marginal posterior density of the DSGE model parameters:

\[
p (\Phi, \Sigma_u, \theta | X) = p (\Phi, \Sigma_u | X, \theta) \, p (\theta | X)
\] (39)

The maximum-likelihood estimates of $\Phi$ of and $\Sigma_u$, are $\tilde{\Phi} (\theta)$ and $\tilde{\Sigma}_u (\theta)$, respectively, based on the sum of the artificial and the observed observations:

\[
\tilde{\Phi} (\theta) = (\lambda T \Gamma^*_w (\theta) + W'W)^{-1} (T \Gamma^*_wx + W'X)
\] (40)

\[
\tilde{\Sigma}_u (\theta) = \frac{1}{(1 + \lambda) T} [ (\lambda T \Gamma^*_x (\theta) + X'X) \\
-(\lambda T \Gamma^*_w + X'W) (\lambda T \Gamma^*_ww (\theta) + W'W)^{-1} (T \Gamma^*_wx + W'X)]
\] (41)

This shows that a higher weight of the prior ($\lambda$), translate on the VARs parameters posterior conditional mean on $\theta$ closer to the restriction functions $\Phi^*$ and $\Sigma_u^*$. Since conditional on $\theta$ the DSGE model prior and the likelihood function are conjugate, the posterior distribution of $\Phi$ and $\Sigma$ is also of the Inverted Wishart–Normal form:

\[
\Sigma_u | X, \theta \sim IW((1 + \lambda) T \tilde{\Sigma}_u (\theta), (1 + \lambda) T - k, n)
\] (42)

\footnote{Greater detail found on Del Negro and Schorfheide (2004) appendix}
\[ \Phi | X, \Sigma_u, \theta \sim N \left( \tilde{\Phi} (\theta), \Sigma_u \otimes (\lambda T T^*_w(\theta))^{-1} \right) \] (43)

3.3.4 \( \lambda \) Selection

The hyper-parameter \( \lambda \) determines the effective sample size for the artificial observations, scaling the covariance matrix of the prior. If \( \lambda \) is small (large) the prior is diffuse (small variance), and the actual (artificial) observations dominate the artificial (actual) observations in the posterior (Del Negro and Schorfheide, 2004). Equation (39), shows how the posterior mean of \( \Phi \) conditional on \( \theta \) equals the OLS estimate of \( \Phi \) if \( \lambda = 0 \) and the DSGE implied restrictions are not relevant for the VAR parameter estimation. Thus, for large values of \( \lambda \), the prior concentrates along with the restriction functions \( \Phi^* (\theta) \) and \( \Sigma^*_u (\theta) \).

In the limit, Del Negro and Schorfheide (2004) procedure is equivalent to estimating a VAR subject to restrictions imposed by a DSGE model. Formally, as \( \lambda \to \infty \), conditional on \( \theta \), the posterior mean \( \tilde{\Phi} (\theta) \) approaches \( \Phi^* (\theta) \) and the variance \( \tilde{\Sigma}_u (\theta) \) goes to zero. However, this does not imply that the actual observations are not taken into account the overall posterior distribution. Analysing the marginal posterior of the DSGE parameters, \( p(\theta|X) \) obtained by combining the marginal-likelihood function:

\[ p(X|\theta) = \int p(X|\Phi, \Sigma_u) p(\Phi, \Sigma_u|\theta) d(\Phi, \Sigma_u) \] (44)

with the prior \( p(\theta)^{13} \), demonstrate the influence of the real data in the procedure. If \( T \) is fixed and \( \lambda \to \infty \), the marginal-likelihood function \( p(X|\theta) \) approaches the DSGE (quasi)-likelihood function.

\(^{13}\)Greater detail found on Del Negro and Schorfheide (2004) appendix
The function \( p^*(X|\theta) \) is obtained by replacing the unrestricted parameters \( \Phi \) and \( \Sigma_u \) in Equation (26) with the restriction functions \( \Phi^*(\theta) \) and \( \Sigma_u^*(\theta) \).

The performance of the DSGE-VAR crucially depends on the choice of \( \lambda \).

To obtain the appropriate value of the hyperparameter, via a data-driven procedure the marginal data density is maximised with respect to \( \lambda \) over some grid \( \varsigma = l_1, \ldots, l_q \):

\[
p_\lambda(X) = \int p_\lambda(X|\theta)p(\theta)\,d\theta
\]

(45)

### 3.3.5 DSGE Parameters

Del Negro and Schorfheide (2004) procedure enable posterior inference with respect to the DSGE model parameters. Although the VAR likelihood function (26) does not directly depend on the DSGE model parameters \( \theta \), the marginal distribution is updated through the sample information. The joint posterior density can be written as:

\[
p(\Phi, \Sigma_u, \theta|X) = p(\Phi, \Sigma_u|X)p(\theta|\Phi, \Sigma_u)
\]

(46)

Therefore, the information about \( \theta \) takes place indirectly via information about the VAR parameters. The procedure expects that a better fit is found when \( \lambda \) moderately deviates from the DSGE model restrictions. Defining the function:

\(^{14}\text{Greater detail found on Del Negro and Schorfheide (2004) appendix}\)
\[
q(\theta | X) = \exp \left[ -\frac{1}{2} \ln \left| \sum_u \Phi^*-1_u(\theta) \right| - \frac{1}{2} tr \left[ \sum_{u,mle}^{-1} \sum_u \Phi^*(\theta) \right] \right] 
\]
\[
- \frac{1}{2} tr \left[ \sum_{u,mle}^{-1} (\Phi^*(\theta) - \Phi_{mle}) \Gamma_{ww}^*(\theta) (\Phi^*(\theta) - \Phi_{mle}) \right] 
\]

(47)

where \(\hat{\Phi}_{mle}\) and \(\hat{\Sigma}_{u,mle}\) maximize the likelihood function (26). It can be shown, using a second-order Taylor expansion, that the logarithm of \(q(\theta | X)\) is approximately a quadratic function of the discrepancy between the VAR estimates and the restriction functions generated from the DSGE model\(^\text{15}^\text{15}\).

The intuition from following Del Negro and Schorfheide (2004) procedure is that the prior weight relative to the likelihood function is small \((\lambda \to 0)\) so that for all values of \(\theta\) the posterior distribution of the VAR parameters concentrates around \(\hat{\Phi}_{mle}\). The conditional density of \(\theta\) given \(\Phi\) and \(\Sigma_u\) projects \(\hat{\Phi}_{mle}\) onto the subspace \(\Phi^*(\theta)\). The amount of information accumulated in the marginal likelihood \(p(X|\theta)\) relative to the prior depends on the rate at which \(\lambda T\) diverges. Therefore, the more weight is placed on the simulated observations \((\lambda\) converges to zero slowly\), the more curvature and information there is in \(p(X|\theta)\)\(^\text{16}^\text{16}\) (Del Negro and Schorfheide, 2004).

### 3.3.6 Identification of Shocks

The data implementation in the procedure is not enough to map the structural shocks in the economy to the dynamic responses of the VAR variables to these shocks. Therefore, following Del Negro and Schorfheide (2004) additional restrictions are added to relate the structural shocks \(\varepsilon_t\) with the co-

\(^{15}\)See Del Negro and Schorfheide (2004) proposition 2

\(^{16}\)Greater detail found on Del Negro and Schorfheide (2004) appendix
variance matrix of the one-step-ahead forecast errors $u_t$. For this a Cholesky decomposition $\Sigma_{tr}$ of the covariance matrix $\Sigma_u$ can be constructed to show the relationship between the structural shocks and the forecast errors. In this set-up, the DSGE economic theory clearly identifies the shock, giving the unique Cholesky decomposition of $\Sigma_u$:

$$u_t = \Sigma_{tr} \Omega \varepsilon_t$$

(48)

Where $\Omega$ is an orthonormal matrix and the structural shocks are from now on standardized to have unit variance, that is $E[\varepsilon_t \varepsilon_t'] = I$ (Del Negro and Schorfheide, 2004). Basically, the method infers that forecast errors shock mappings will deviate from the mapping in the DSGE model if the implications for the covariance matrix of the residuals in the DSGE are different from the actual covariance matrix observed in the model. Equation (25) shows how in the VAR structure, the initial impact of $\varepsilon_t$ on the endogenous variables $x_t$ is given by:

$$\frac{\partial x_t}{\partial \varepsilon_t} = \Sigma_{tr} \Omega$$

(49)

As the VAR likelihood function (26) does not depend on the choice of the rotation matrix $\Omega$, there is an identification problem. To solve this, $\Omega$ usually is given from some ex-ante justification to produce ex-post impulse response functions that are in hand with the literature. Since there is no agreement on what these dimensions should be, following Del Negro and Schorfheide (2004) the DSGE model is used to identify the reduced-form VAR parameters. The DSGE model is identified; therefore, there is a unique matrix $A_0(\theta)$ for each value of $\theta$ obtained from the measurement equations (20-22), that determines the contemporaneous effect of the structural shocks on the endogenous variables. As explained in Del Negro and Schorfheide (2004),
using a QR factorisation of $A_0(\theta)$, the initial response of $x_t$ to the structural shocks can be uniquely decomposed into:

$$\left( \frac{\partial x_t}{\partial \varepsilon_t} \right)_{DSGE} = A_0(\theta) = \Sigma_{tr}^*(\theta) \Omega^*(\theta)$$

Where $\Sigma_{tr}^*(\theta)$ is lower triangular and $\Omega^*(\theta)$ is orthonormal. To identify the VAR, the triangularisation of its covariance matrix is maintained in $\Sigma_u$ and the rotation matrix $\Omega$ is replaced with $\Omega^*(\theta)$ to obtain an MA representation in terms of the structural shocks $\varepsilon_t$. This procedure is repeated for each draw of the joint posterior distribution of $\Phi, \Sigma_u$ and $\theta$.

An issue with Del Negro and Schorfheide (2004) procedure that does not affect practical implementations is that the Cholesky decomposition of $\Sigma_u^*(\theta)$ is not exactly equal to $\Sigma_{tr}^*(\theta)$ as the DSGE, VAR representation is approximated. In the same manner, since the likelihood of the reduced-form VAR does not depend on $\Omega$, the rotation matrix that is used to achieve identification is the same posteriori as it is a priori for any fixed $\theta$ (Del Negro and Schorfheide, 2004)$^{17}$. Following this, the tightness parameter would show to what extent the posterior impulse responses are forced to look like the DSGE model’s responses; larger $\lambda$ implies a more similar response.

### 3.3.7 DSGE-VAR Implementation

In Del Negro and Schorfheide (2004) DSGE-VAR procedure, the parameters are constructed with multidimensional and nonlinear probability distributions, which usually do not have a closed-form representation and must be approximated numerically. Therefore, as the initial information about the posterior is limited and the size of the parameter vector, $\theta$, is usually large; it

---

$^{17}$ Given that the distribution of $\theta$ is updated with the sample information; the rotation matrix is chosen from the data, indirectly, via learning about the DSGE model parameters.
is difficult to generate independent draws from the posterior. To resolve this issue, the procedure simulates the posterior with the Markov Chain Monte Carlo (MCMC) techniques of Metropolis-Hastings (MH) algorithm\textsuperscript{18}. By the assumption that $\lambda$ is restricted to the grid $\varsigma = l_1, \ldots, l_q$, to select a value over the grid and to generate draws from the posterior distribution of the DSGE and VAR parameters the MH steps are:

1. For each $\lambda \in \varsigma$ use the MH algorithm to generate draws from $p_\lambda(\theta \mid X) \propto p_\lambda(X \mid \theta) p(\theta)$. The steps needed to evaluate $p_\lambda(\theta \mid X)$ based on the marginal likelihood function of $\theta$ are the following, for each $\theta$:

   (a) Solve the DSGE model described in section XX. This leads to a transition equation of the form:

   $$s_t = T(\theta) s_{t-1} + R(\theta) \epsilon_t$$  \hspace{1cm} (51)

   Given this, the measurement equations (20-22) can be written in matrix form as:

   $$x_t = Z(\theta) s_t + D(\theta) + v_t$$  \hspace{1cm} (52)

   Where $s_t$ is defined such that $v_t = 0$.

   (b) From equations 51-52, the variance–covariance matrices of the shocks can be described as:

   $$E[v_t v_t'] = \Sigma_{vv}(\theta)$$  \hspace{1cm} (53)

   $$E[\epsilon_t \epsilon_t'] = \Sigma_{\epsilon\epsilon}(\theta)$$  \hspace{1cm} (54)

\textsuperscript{18}For a description see Schorfheide (2001)
\[ E[\epsilon_t v_t'] = \Sigma_{ev}(\theta) \] (55)

(c) Compute the population moments from the state-space representation (51-52).

2. Based on these draws apply Geweke (1999)\textsuperscript{19} modified harmonic mean estimator to obtain numerical approximations of the data densities \( p_\lambda(X) \).

3. Find the pre-sample size \( \hat{\lambda} \) with the highest data density.

4. Select the draws of \( \theta(s) \) that correspond to \( \hat{\lambda} \) and use standard methods to generate draws from \( p(\Phi, \Sigma_u \mid X, \theta(s)) \) for each \( \theta(s) \).

4 Introduction to the Data

To estimate the model, three macroeconomic quarterly observable variables for Dominican Republic are used: the nominal interest rate, real GDP growth and the inflation rate. The time series observations were downloaded from the Central Bank of the Dominican Republic statistics publications. The period analysed spans from 2000Q1-2018Q4, after adjustments the model estimation spans from 2001 second quarter to 2018 last quarter, which gives 71 observations for each variable. For the computation of real GDP growth and inflation, both real GDP and the CPI series are seasonally adjusted with Census-X13 method. After the seasonally adjusted series are obtained, the code converts these variables to logarithm and compute their cumulative growth rates. Following Clarida et al. (1999), for each quarter the nominal

\textsuperscript{19}Which shows that if the function has tails thinner than those of the posterior distribution, then the modified harmonic mean has a finite variance. Since the posterior distribution is asymptotically normal under certain regularity conditions, he recommends using a normal approximation of the posterior distribution with tail truncation’s.
interest rate equals the average nominal interest rate during the first month of the quarter.

Figure 1 displays the annual Real GDP growth for the Dominican Republic from 2001-2018. The average real GDP growth for this period is 5% reaching peaks growths in 2006-2007 as the economy recovered from 2003-2004 crisis. While Figure 2 and 3 displays the inflation rate and nominal interest rates for the Dominican Republic showing peaks in 2003-2004 given the financial crisis arising from the collapse of a banking institution. In the last five years, both inflation and nominal interest rates have been significantly low averaging 2.5% and 6.1%, respectively.

*Figure 1: Dominican Republic Output Growth*  
Percentage, 2001-2018

Source: Authors’ elaboration with Data from Dominican Republic Central Bank
**Figure 2: Dominican Republic Inflation Rate**
Percentage, 2001-2018

Source: Authors’ elaboration with Data from Dominican Republic Central Bank

**Figure 3: Dominican Republic Nominal Interest Rate**
Percentage, 2001-2018

Source: Authors’ elaboration with Data from Dominican Republic Central Bank
In order for the long-run relations implied in equations 17-19 to hold, the variables in the VAR should be I(0)-I(1) variables. To analyse this table 1, reports the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests statistics results for the variables in levels and first difference for nominal interest rate. The results of the tests for output growth and inflation are consistent and suggest that the variables can be considered I(0) since in levels there is evidence to reject the unit root null hypothesis. However, the nominal interest rate, showed mixed results in levels but in first-differences they reject the unit root null hypothesis and therefore the variable is stationary.

<table>
<thead>
<tr>
<th>Variable</th>
<th>ADF(0)</th>
<th>ADF(1)</th>
<th>ADF(2)</th>
<th>ADF(3)</th>
<th>ADF(4)</th>
<th>PP</th>
</tr>
</thead>
<tbody>
<tr>
<td>∆ln y</td>
<td>-5.97***</td>
<td>-5.97***</td>
<td>-5.97***</td>
<td>-4.57***</td>
<td>-4.57***</td>
<td>-6.08***</td>
</tr>
<tr>
<td>∆ln CPI</td>
<td>-4.01***</td>
<td>-4.01***</td>
<td>-4.37***</td>
<td>-4.37***</td>
<td>-4.37***</td>
<td>-3.85***</td>
</tr>
<tr>
<td>ln R</td>
<td>-2.37</td>
<td>-3.34*</td>
<td>-3.34*</td>
<td>-4.07**</td>
<td>-2.93</td>
<td>-2.91</td>
</tr>
<tr>
<td>D(ln R)</td>
<td>-6.42***</td>
<td>-6.42***</td>
<td>-3.87***</td>
<td>-4.98***</td>
<td>-4.98***</td>
<td>-6.41***</td>
</tr>
</tbody>
</table>

Source: Authors’ Elaboration

Note: Each ADF(p) statistics represents the ADF test for q lagged difference of the variable in question, the lag order is automatically selected based on AIC with a max q of 4. While the PP test is computed with a Bertlett Kernel estimation method and an automatic selection of bandwidth based on Newey-West. The ADF test is computed with an intercept and a linear trend for nominal interest rates in levels; with intercept for ∆GDP and inflation, and with nor intercept or linear trend for the nominal interest rate first difference. The table presents the t-statistics where: * denotes significance at the 10% level, ** denotes significance at the 5% level, and *** denotes significance at the 1% level.

37
Before implementing the DSGE-VAR methodology the DSGE Model structural parameters regarding long run are calibrated to match those of the Dominican Republic Central Bank DSGE Model. The household discount factor ($\beta$) is calibrated to match the historical real interest rate of the Dominican Republic. Both the degree of distortion in the economy and the risk aversion parameter are taken from the literature. The parameters associated with the government AR(1) process which measures the responsiveness of the variable to its previous period value, are estimated through OLS with quarterly data from 2000 to 2018.

<table>
<thead>
<tr>
<th>Description</th>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Long-Run Growth</td>
<td>$\ln \mu$</td>
<td>1.44</td>
</tr>
<tr>
<td>Long-Run Inflation</td>
<td>$\ln \pi^*$</td>
<td>0.98</td>
</tr>
<tr>
<td>Long-Run Real Interest Rate</td>
<td>$\ln r^*$</td>
<td>1.46</td>
</tr>
<tr>
<td>Degree of Distortion in the economy</td>
<td>$\phi$</td>
<td>0.4</td>
</tr>
<tr>
<td>Risk Aversion Parameter</td>
<td>$\alpha$</td>
<td>1.00</td>
</tr>
<tr>
<td>Inflation Parameter in Taylor Rule</td>
<td>$\rho_1$</td>
<td>1.42</td>
</tr>
<tr>
<td>Output Parameter in Taylor Rule</td>
<td>$\rho_2$</td>
<td>0.50</td>
</tr>
<tr>
<td>Responsiveness of Interest Rate</td>
<td>$\rho_R$</td>
<td>0.89</td>
</tr>
<tr>
<td>Responsiveness of Gov. Expenditure</td>
<td>$\rho_g$</td>
<td>0.94</td>
</tr>
<tr>
<td>Responsiveness of Technology</td>
<td>$\rho_a$</td>
<td>0.41</td>
</tr>
<tr>
<td>Standard Deviation of Interest Rate</td>
<td>$\sigma_R$</td>
<td>0.10</td>
</tr>
<tr>
<td>Standard Deviation of Gov. Expenditure</td>
<td>$\sigma_g$</td>
<td>0.80</td>
</tr>
<tr>
<td>Standard Deviation of Technology</td>
<td>$\sigma_a$</td>
<td>0.50</td>
</tr>
</tbody>
</table>

Source: Authors’ Elaboration
After calibrating the DSGE structural parameters, the next step before applying the DSGE-VAR methodology is to select the order of the unrestricted trivariate VAR. The VAR model selection criteria, when using the AIC selects a VAR(4), the HQ criterion selects a VAR(4), and the SC a VAR(1). For the DSGE-VAR, a VAR(4) is used, as underestimating the lag length is a critical issue (Kilian, 2001).

<table>
<thead>
<tr>
<th>Lag</th>
<th>LogL</th>
<th>LR</th>
<th>FPE</th>
<th>AIC</th>
<th>SC</th>
<th>HQ</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>334.13</td>
<td>NaN</td>
<td>2.03e-08</td>
<td>-9.20</td>
<td>-9.10</td>
<td>-9.16</td>
</tr>
<tr>
<td>1</td>
<td>448.81</td>
<td>209.06</td>
<td>1.21e-09</td>
<td>-12.02</td>
<td>-11.64*</td>
<td>-11.87</td>
</tr>
<tr>
<td>2</td>
<td>452.72</td>
<td>14.28</td>
<td>1.25e-09</td>
<td>-11.99</td>
<td>-11.33</td>
<td>-11.73</td>
</tr>
<tr>
<td>3</td>
<td>474.46</td>
<td>37.43*</td>
<td>8.77e-10*</td>
<td>-12.34*</td>
<td>-11.40</td>
<td>-11.97</td>
</tr>
<tr>
<td>4</td>
<td>482.74</td>
<td>13.58</td>
<td>9.01e-10</td>
<td>-12.33</td>
<td>-11.09</td>
<td>-11.84*</td>
</tr>
</tbody>
</table>

Source: Authors’ Elaboration
* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level
FPE: Final prediction error
AIC: Akaike Information Criterion
SC: Schwarz Information Criterion
HQ: Hannan-Quinn Information Criterion

5 Empirical Analysis

This section presents the results for the DSGE-VAR procedure applied to the Dominican Republic, with the objective of analysing the importance of choosing an adequate modelling framework when quantifying the impact of a monetary policy shock in output and inflation. The practical implementation was carried out by modifying Del Negro and Schorfheide (2004) original
code for the Dominican Republic. The considered lag length for the DSGE-VAR model was set equal to 4 as the lag length criteria previously discussed in section 4 suggested. For the MCMC method of Metropolis-Hasting, to obtain the posterior distribution, 2,500 replications where run. The posterior results along with the priors distribution are explained in the following section. Then, section 5.3, will present the impulse responses constructed to show the effects of unanticipated monetary policy decisions. Finally, section 5.4 will compare the active current BCRD policy regime with a more passive regime.

5.1 Priors and Posterior for the DSGE Parameters

The specification of the prior discussed in section 4 is completed with a distribution of the DSGE model parameters, detailed in table 4. Following Del Negro and Schorfheide (2004) the following model parameters were scaled to represent percentages: \( \ln \mu, \ln \pi^*, \ln r^*, \sigma_R, \sigma_g, \sigma_a \). The steady-state priors for growth, inflation and real interest rate are reasonably disperse and have means of 1.44%, 0.98%, and 1.46%, respectively. The quarterly steady-state values are calculated to match annual long-run values for growth rate, inflation rate, and real interest rate; 5.6%, 4% and 6% respectively.

The parameters representing the logarithm of long-run output growth and inflation rate are assumed to be normally distributed. While for the prior distribution of the density of the shock persistence parameters: \( \rho_r, \rho_g, \rho_a \) are assumed to be beta distributed to ensure stationarity. The gamma distribution is assigned for the parameters: \( \ln r^*, \phi, \alpha, \rho_1, \rho_2 \), that always take a positive value. For the standard deviations of technology, nominal interest rate and government expenditure the inverse gamma distribution.
Table 4: Prior Distribution for DSGE Model Parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Density</th>
<th>Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>\ln \mu</td>
<td>Normal</td>
<td>1.44</td>
<td>0.50</td>
</tr>
<tr>
<td>\ln \pi^*</td>
<td>Normal</td>
<td>0.98</td>
<td>0.50</td>
</tr>
<tr>
<td>\ln r^+</td>
<td>Gamma</td>
<td>1.46</td>
<td>0.50</td>
</tr>
<tr>
<td>\phi</td>
<td>Gamma</td>
<td>0.4</td>
<td>0.15</td>
</tr>
<tr>
<td>\alpha</td>
<td>Gamma</td>
<td>1.00</td>
<td>0.50</td>
</tr>
<tr>
<td>\rho_1</td>
<td>Gamma</td>
<td>1.42</td>
<td>0.25</td>
</tr>
<tr>
<td>\rho_2</td>
<td>Gamma</td>
<td>0.50</td>
<td>0.10</td>
</tr>
<tr>
<td>\rho_R</td>
<td>Beta</td>
<td>0.89</td>
<td>0.20</td>
</tr>
<tr>
<td>\rho_g</td>
<td>Beta</td>
<td>0.94</td>
<td>0.10</td>
</tr>
<tr>
<td>\rho_a</td>
<td>Beta</td>
<td>0.41</td>
<td>0.10</td>
</tr>
<tr>
<td>\sigma_R</td>
<td>Inv.Gamma</td>
<td>0.10</td>
<td>0.14</td>
</tr>
<tr>
<td>\sigma_g</td>
<td>Inv.Gamma</td>
<td>0.80</td>
<td>0.32</td>
</tr>
<tr>
<td>\sigma_a</td>
<td>Inv.Gamma</td>
<td>0.50</td>
<td>0.43</td>
</tr>
</tbody>
</table>

Source: Authors’ Elaboration

On the other hand, the posterior estimates for the DSGE model parameters are presented in table 5 for the sample period 2001Q1-2018Q4. As the chosen \( \lambda \) value, can be interpreted as the optimal mixed sample, used to estimate the VAR, \( \lambda \) aids in showing if the DSGE model is a useful source of information for the VAR estimation. As an exercise, for showing how the DSGE-VAR model is affected by the weight of \( \lambda \), table 5 shows the 90% posterior confidence intervals for \( \lambda = 0.5 \) and \( \lambda = 5 \).
Table 5: Posterior of DSGE Model Parameters: 2001Q2-2018Q4

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Prior Mean</th>
<th>( \lambda = 0.5 ) CI 90%</th>
<th>( \lambda = 5 ) CI 90%</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Lower</td>
<td>Upper</td>
<td>Lower</td>
</tr>
<tr>
<td>( \ln \mu )</td>
<td>1.44</td>
<td>0.87</td>
<td>1.71</td>
</tr>
<tr>
<td>( \ln \pi^* )</td>
<td>0.98</td>
<td>0.10</td>
<td>1.35</td>
</tr>
<tr>
<td>( \ln r^* )</td>
<td>1.46</td>
<td>0.58</td>
<td>1.14</td>
</tr>
<tr>
<td>( \phi )</td>
<td>0.4</td>
<td>0.19</td>
<td>0.62</td>
</tr>
<tr>
<td>( \alpha )</td>
<td>1.00</td>
<td>0.83</td>
<td>1.97</td>
</tr>
<tr>
<td>( \rho_1 )</td>
<td>1.42</td>
<td>1.12</td>
<td>1.85</td>
</tr>
<tr>
<td>( \rho_2 )</td>
<td>0.50</td>
<td>0.32</td>
<td>0.61</td>
</tr>
<tr>
<td>( \rho_R )</td>
<td>0.89</td>
<td>0.82</td>
<td>0.92</td>
</tr>
<tr>
<td>( \rho_g )</td>
<td>0.94</td>
<td>0.84</td>
<td>0.97</td>
</tr>
<tr>
<td>( \rho_a )</td>
<td>0.41</td>
<td>0.24</td>
<td>0.52</td>
</tr>
<tr>
<td>( \sigma_R )</td>
<td>0.10</td>
<td>0.12</td>
<td>0.23</td>
</tr>
<tr>
<td>( \sigma_g )</td>
<td>0.80</td>
<td>0.51</td>
<td>1.05</td>
</tr>
<tr>
<td>( \sigma_a )</td>
<td>0.50</td>
<td>0.33</td>
<td>0.63</td>
</tr>
</tbody>
</table>

Source: Authors’ Elaboration

5.2 Optimal \( \hat{\lambda} \)

The shape of the marginal data density function estimated in Del Negro and Schorfheide (2004) suggests that the empirical fit of the model is approximated the same for \( \lambda \) values between 0.5 and 2. A lambda value between this grid is consistent with the value that leads to the best ex-post one-step-ahead forecast performance. Following this, the hyper-parameter estimate:

\[
\hat{\lambda} = \underset{\lambda \in \varsigma}{\text{arg max}} p_\lambda(X)
\] (56)
Is applied to the Dominican Republic, between that grid of 0.5 and 2; the results generate a $\hat{\lambda}$ value of 1.5, which corresponds to doubling the observed data with simulations from the DSGE model. This value leads simulation error of the model of 2.38%.

5.3 Impulse Response

The DSGE-VAR model for the Dominican Republic could be assessed using the impulse response function (IRF). The IRF measure the reactions of the observed variables to unanticipated changes in structural shocks. The following exercise compares the IRFs generated by the structural DSGE model with the posterior IRFs, obtained after updating the initial beliefs with information from the observed data.

Following Del Del Negro and Schorfheide (2004), the following exercise illustrates the IRF response to a monetary policy shock. Specifically, it shows the response of cumulative real output growth, inflation, and interest rate with respect to an unanticipated monetary policy shock which increases the nominal interest rate in 50 basis points in the first period\(^{20}\). Moreover, the IRF is computed for the same values of the tightness parameter $\lambda$ as in Del Negro and Schorfheide (2004) and for its optimal value, . Finally, each plot presents the VAR impulse responses (dashed-and-dotted line), the corresponding 90% error bands (dotted lines), and the DSGE model impulse responses (solid lines).

\(^{20}\)The change in the nominal interest rate responds to the recent movement of the BCRD
Figure 4 shows the effects of a contractionary monetary policy shock in cumulative real output growth, inflation and the nominal interest rate. As expected, from Del Negro and Schorfheide (2004), the VAR impulse responses become closer to the DSGE as the value of $\lambda$ increases. Specifically, the distance between the posterior means of the VAR and the model’s impulse responses decreases. For all $\lambda$, the DSGE-VAR model response to inflation rate and nominal interest rate follows the structural DSGE on sign and magnitude. With the inflation response being short-lived as empirical results shown. However, the response of output differs from the structural DSGE in magnitude, while the DSGE predicts long-run money neutrality the DSGE-VAR indicates uncertainty about the long-run effects of the shock. This non-neutrality of money in the long-run for output results are aligned with impulse response based on impact identification strategies. The estimates from the DSGE-VAR are less precise that the DSGE model. The 90% confidence interval includes the mean estimates and the DSGE model IRFs are mostly included in all scenarios.

\[\text{See Del Negro and Schorfheide (2004), Garrat et al. (2003), Canova and De Nicoló (2002)}\]
Figure 4: Identified Impulse Responses for Different Lambda’s

Source: Authors’ elaboration based on results from DSGE model; based on 2001Q1-2018Q4 sample.

Figure 5 shows the effects of the contractionary monetary policy shock in cumulative real output growth, inflation and the nominal interest rate for the optimal $\lambda = 1.5$. Approximately four years after its initial impact, the nominal interest rate settles below its steady-state on 4.75 basis point. The response of inflation follows the DSGE response showing a short-lived decrease
after a year by 5.47 basis points and falling back to zero approximately in 3.5 years. On the other hand, output presents the expected negative sign and shows persistence to the monetary policy contraction. In the first two-year, output growth decreases around 17.78 basis point, settling 21.36 basis point below its base after 4 years.

*Figure 5: Identified Impulse Responses for $\hat{\lambda}$*

Source: Authors’ elaboration based on results from DSGE model; based on 2001Q1-2018Q41 sample.
5.4 Policy Regime

The BCRD have been under the chairmanship of the current governor for the time span of the study. In this period, the BCRD has maintained a proactive stance toward inflation changes raising or lowering the nominal short-term interest rate as inflation expectations were inclined to a rise or decrease in a more than proportional magnitude in order for the real interest rate to rise or decrease. Inspired by this, given the ability of the DSGE-VAR procedure to compare policy scenarios, this section will compare the active current BCRD policy regime with a more passive regime.

Under the first scenario, the response of inflation to nominal interest rate would be the current regime ($\rho_1 = 1.42$) and under the second parameter would be less active ($\rho_1 = 1$). Figure 6 shows the standard deviation of the actual data under no policy regime shift (solid line) and under the policy regime shift (dashed line). The model predicts that a decrease in the response of inflation to nominal interest rate shifts induces higher inflation levels.
Figure 6: Policy Regime Shifts Forecast

6 Conclusion

This paper quantified the effects of an unanticipated monetary policy shock in key macroeconomic variables, following Del Negro and Schorfheide (2004) DSGE-VAR procedure for the Dominican Republic. The procedure specifies the structure of the economy based on a classical NK-DSGE model for building the priors of an empirical Bayesian VAR for output growth, inflation and nominal interest rate. As the Dominican Republic key economic
variables time series has a relatively short span, this procedure allows for a more suitable framework for monetary policy macroeconomic modelling since it combines policymaker’s initial belief with the data available.

The Bayesian techniques of the models allow for a depth insight into the functioning of the economy in contrast to usual approaches. This paper is the first attempt to Monetary Policy analysis in the Dominican Republic under the DSGE-VAR procedure. The DSGE model is simplified for a closed economy, even though the Dominican Republic is an open economy, as this exercise seeks only to show how DSGE-VAR can aid in the correction of DSGE models’ predictions and VAR lacks theoretical foundations when evaluating monetary policy. The DSGE parameters were calibrated to match the data and BCRD, internal structural model.

Future improvements of this paper would lie in the hand of forecasting the future path of the key variables as monetary policy shifts. Additionally, the current DSGE model could be augmented in three ways: having the characteristic of an open economy, allowing for an active government and adding financial frictions. Also, it could be compared with several competitive models for the Dominican Republic economy to examine their empirical performance.

The approach undertaken in this paper, has been proven to be efficient as it recognizes that DSGE is a mechanism for generating priors but not to model the observed data (Sims, 2006). Nevertheless, from the review of the literature performed the same drawbacks of DSGE-VAR procedure as in Del Negro and Schorfheide (2004) seminal paper still remains. One of the drawbacks is that the structural model needs to be fully stochastically specified to employ
its rotation matrix for the VAR identification (Del Negro and Schorfheide, 2004). Another drawback is that the method does not give an indication of how useful is the information from the DSGE for the VAR since it cannot provide an exact value or interval for the hyperparameter lambda. Finally, the procedure only allows to add priors by giving more weight to the DSGE model and therefore you cannot take advantage of the forecasting strengths of Bayesian VAR. For instance, the Bayesian VAR allows to reduce the forecasting errors of traditional VAR introducing “economics-free priors” \(^{22}\).

\(^{22}\)Sims (2006) refers to this economic free priors as a prior favouring persistence, weak cross-variable connections, or smaller coefficients on more distant lags.
7 References


