DSGE Models and Central Banks

Camilo E. Tovar

Bank for International Settlements

Abstract

Over the past 15 years there has been remarkable progress in the specification and estimation of dynamic stochastic general equilibrium (DSGE) models. Central banks in developed and emerging market economies have become increasingly interested in their usefulness for policy analysis and forecasting. This paper reviews some issues and challenges surrounding the use of these models at central banks. It recognises that they offer coherent frameworks for structuring policy discussions. Nonetheless, they are not ready to accomplish all that is being asked of them. First, they still need to incorporate relevant transmission mechanisms or sectors of the economy; second, issues remain on how to empirically validate them; and finally, challenges remain on how to effectively communicate their features and implications to policy makers and to the public. Overall, at their current stage DSGE models have important limitations. How much of a problem this is will depend on their specific use at central banks.

1 Introduction

Over the past 15 years there has been remarkable progress in the specification and estimation of dynamic stochastic general equilibrium (DSGE) models.[1] As a result central banks have become increasingly interested in their usefulness for policy analysis. Today many central banks, both in developed and emerging market economies (EMEs) have developed their own models and, currently, many others are beginning or are planning to do so.[2] Notwithstanding these rapid advances and the growing interest, the use of DSGE models still remain in the periphery of the formal policy decision making process in most central banks.[3] In fact, it remains to be seen whether these models will be adopted in the core process of forecasting and policy analysis frameworks, or whether they will only be employed as a supplementary tool outside the core framework.

DSGE models are powerful tools that provide a coherent framework for policy discussion and analysis. In principle, they can help to identify sources of fluctuations, answer questions about structural changes, forecast and predict the effect of policy changes, and perform counterfactual experiments. They also allow to establish a link between structural features of the economy and reduced-form parameters, something that was not always possible with large-scale macroeconomic models. However, as any new tool, DSGE models need to prove their ability to fit the data and confirm their usefulness as policy tools. In fact, it was only recently, following the work of Christiano et al (2005), that evidence was put together showing that an optimization-based model with nominal and real rigidities could account successfully for the effects of a monetary policy shock. Furthermore, it was only until the work of Smets and Wouters (2003) that it was shown that a New Keynesian model could track and forecast time series as well as, if not better than, a vector autoregression estimated with Bayesian techniques (BVAR).

Given the apparent benefits of having a fully integrated framework for policy analysis and the progress made in the literature in estimating these models it is natural to ask: why are DSGE models not yet part of the core decision making framework? There are several possible explanations for this. In part, this has to do with the newness of the technology in terms of its modelling aspects and the technical and computing tools required to solve them. The complex nature of DSGE models

---

[1] See Gali and Gertler (2007), Goodfriend (2007), and Mankiw (2006) for a historical overview of how macroeconomists reached what is now considered a new consensus or "new neoclassical synthesis". See also Woodford (2003), Clarida, Gali and Gertler (1999) and Goodfriend and King (1997) for a more in depth discussion of the main components of this synthesis. Finally, see Obstfeld and Rogoff (1995 and 2002) for early contributions to this framework in open economies.

[2] Some central banks that have developed DSGE models are the Bank of Canada (ToTEM), Bank of England (BEQM), Central Bank of Chile (MAS), Central Reserve Bank of Peru (MEGA-D), European Central Bank (NAWM), Norges Bank (NEMO), Sveriges Riksbank (RAMSES) or the US Federal Reserve (SIGMA). Also, multilateral institutions like the IMF have developed their own DSGE models for policy analysis (ie GEM, GFM, or GIMF). For a list of articles describing these models see Castillo et al (2009), Laxton (2008), Pesenti (2008), Adolfson et al (2007 a,b,c), Christoffel et al (2007), Kumhof and Laxton (2007), Medina and Soto (2007a), Brubakk et al (2006), Erceg et al (2006) and Harrison et al (2005).

[3] Some exceptions are the Bank of Canada, Bank of England, Central Bank of Chile, Norges Bank and Sveriges Riksbank.

may have also limited their acceptance among policy makers, as notation can get very messy, thus creating a natural barrier for the communication of the results to policy makers, not to mention to the public.[4] Furthermore, understanding the workings of these models requires well trained macroeconomists with a modelling culture and strong statistical and programming skills. This also implies that central banks may need to invest additional resources to develop such models, something that might not always be considered a priority or simply resources might be scarce.

From a more technical point of view there are important concerns related to the degree of misspecification of current DSGE models. Of course, such concerns are not necessarily exclusive to them. Nonetheless, as new models are brought into the policy process, it is necessary to carefully examine the practical merits of the advances made. This includes evaluating how they deal with major critiques, including those made to the old macroeconomic models of the 1970s (eg lack of appropriate microfoundations, incapacity to reproduce business cycle features of the data or incredible identifying assumptions).[5] Well-known economists have argued that DSGE models are too stylized to be truly able to describe, in a useful manner, the dynamics of the data. Sims (2006), for instance, considers DSGE models to be only story-telling devices and not hard scientific theories. He argues that there is no aggregate capital or no aggregate consumption good, and that the real economy has a rich array of financial markets, which have not been included so far in a wide and successful manner into these models. As such, he considers that although the models help to think about how the economy works, "it does not make sense to require these models to match in fine detail the dynamic behavior of the accounting constructs and proxy variables that make up our data". Others have also warned about the "principle of fit"(ie models that fit well should be used for policy analysis, and models that do not fit well should not be used).[6] For instance, Kocherlakota (2007) shows that a model that fits the available data perfectly may provide worse answers to policy questions than an alternate, imperfectly fitting model.[7] This is particularly true if incorrect priors, when using Bayesian estimation techniques, are employed for the dynamics of shock processes. An implication of his analysis is that calibration of behavioural parameters may be a more successful approach.

However, DSGE models are and will be taken to the data, but doing so may be quite challenging. Even with the current sophisticated econometric and statistical methods available, certain constraining preconditions may be necessary. For

---

[4]A priori there is no reason for DSGEs to be more complex than older ones. However, the methods for solving and estimating are not the standard ones found in the older literature. A good example of this is the econometric methods employed. For instance, Bayesian techniques are not yet standard components of econometric courses in PhD programmes in economics.

[5]See Faust (2008) for a critical view of DSGE models from the perspective of the major criticisms made to large scale macroeconomic models during the 1970s.

[6]Notice that this resembles to some extent Sims' (1980) arguments that large scale models may fit the data well, but that they may provide misleading answers due to the non-credible identification restrictions.

[7]The result follows from a policy question concerning the labour response to a change in the tax rate. In two models considered (one perfectly fitting the data and one with worse fit) the answer depends on the elasticity of labour supply. The estimate of this parameter in turn depends on a non-testable assumption about how stochastic shocks to the labour-supply curve covary with tax rates.

instance, data transformations, such as detrending and the elimination of outliers, together with the selection of appropriately stable periods or the elimination of structural breaks, are common prerequisites to take these models to the data (Canova 2007 and DeJong and Dave 2007).[8] Furthermore, estimates may be biased by model misspecification and parameter identification may not always be easy to achieve. In fact, although parameter identification is known to be a prerequisite for the estimation of parameters in any empirical study, it has rarely been studied in the context of DSGE models. Overall, the combination of such difficulties may cast doubts on the practical use of available DSGE models, which may also be more significant in EMEs given the frequent underlying problems related to data, rapid structural change and frequent policy shifts.[9]

While the views highlighted in the previous paragraphs may sound pessimistic, it must be recognised that a lot of progress has been made with DSGE models. Even at their current stage of development, these models have already proven to be useful for central banks. In fact, a number of these institutions across the world have employed these models to analyse relevant policy issues. For instance, the Federal Reserve Board's SIGMA model has been used to analyse the impact of a wide variety of shocks, such as those arising from monetary policy, increased government spending, rising home consumption demand, falling currency risk premia, changes in foreign demand, permanent productivity growth, reductions in labour and capital tax rates or in assessing the quantitative effects of fiscal shocks on the trade balance (Erceg et al 2006 and 2005). Edge et al (2008) have also built a more disaggregate DSGE model to improve the understanding of the historical evolution of natural rates of output and interest in the US.[10] At the Central Bank of Chile, the MAS model has been employed to quantify the contribution of different shocks to the business cycle, to compare the effects of transitory copper-price shocks under different fiscal rules or to analyse the factors accounting for current account developments (Medina and Soto 2007a; Medina and Soto 2007b; Medina et al 2008). The Sveriges Riksbank's RAMSES model has been applied to generate alternative scenarios to future alternative paths for wages, interest rates, external developments or for the analysis of monetary policy trade-offs arising under optimal monetary policy in an estimated DSGE model (Adolfson et al 2008a, 2007a, 2007b). Finally, some central banks have already begun to employ these models for forecasting, with very promising results (see Adolfson et al 2007a).

Nonetheless, and despite the progress made in the theoretical and empirical use of these models, it remains an open issue how should DSGE models be employed for policy analysis and forecasting at central banks.[11] There are different views.

---

[8]Of course, any empirical analysis requires a careful handling of the data. However, the methods available (at least those employed so far) are not well suited to handle some of these issues in a natural integrated manner. In fact, there is a need of establishing a careful correspondence between what is being characterised by the model and what is being measured by the data. As a result current econometric estimations of DSGE models are highly sensitive to the data fed into the model and the transformations made to it.

[9]After presenting a DSGE model at an EME central bank a high level ranking officer said that taking a DSGE model to the data was "like driving a Ferrari on a bumpy road".

[10]This disaggregate model aims at complementing the analyses performed with the large scale macroeconometric model (FRB/US) currently employed by the Federal Reserve Board.

[11]This discussion is embedded in a broader one of what dimensions of reality do DSGE models

The most common is to consider seriously the full implications of the model (plus add sufficient number of shocks) and fit the data (ie the Smets and Wouters 2003, 2007). Interestingly, this view acknowledges that it is possible to begin from the premise that all models are false. Therefore the challenge is to choose the best possible model among a collection of those available. That is what the Bayesian approach attempts to do. For instance, alternative models can be compared with the use of posterior odds ratios (eg Fernández-Villaverde and Rubio-Ramírez 2005). An alternative view, which is possibly less dogmatic, recognizes that as of today, unrestricted multivariate models such as vector-autoregressive models (VARs) still do better than DSGEs when they are applied to real data (ie data that has not been processed by removing the trend, either by filtering or by regression). Under this view, the DSGE model is useful as a mechanism for generating a prior which aids the estimation of a BVAR (Del Negro and Schorfheide 2004). A subtle difference is that this approach does not generate a model of the data. A final view, is to proceed with calibration methods. Although the current trend is to estimate these models, a number of central banks have opted for calibrating their models. Noteworthy examples are the Bank of Canada's ToTEM model or the DSGE models currently being developed by the Board of Governors.

It is still early to determine which approach will work better in terms of forecasting and policy analysis. For sure, more work needs to be done in three main areas. The first is the structure of DSGE models. Indeed, despite the progress made so far, DSGEs have yet to incorporate successfully relevant economic transmission mechanisms and/or sectors of the economy. The second area is the empirical validation and use of these models: how should they be taken to the data? And finally, for a successful implementation of DSGEs for policy analysis it is necessary to ask how to communicate effectively the features and implications of the model to policy makers and the public. Without attempting to be an exhaustive review of the literature, this article highlights, in a non-technical manner, some of these issues and challenges arising from these three questions.

The paper is structured as follows: after this introduction, Section 2 presents a brief description of the main features of the benchmark DSGE model and discusses some current modelling weaknesses. Section 3 reviews how these models are

---

mimic. For instance, Geweke (2007) argues that the widespread interpretation is that DSGE models provide a predictive distribution for an observable sequence of quantities and/or prices. Such interpretation, called by him, *"strong econometric interpretation"* is the basis for the conventional use of likelihood-based econometric methods. However, for him it is widely accepted that DSGE models fare badly under such interpretation. An alternative common interpretation is that DSGE models should only mimic the world along a carefully specified set of dimensions (eg a few sample moments as in the real business cycle literature). However this *"weak econometric interpretation"* has equally strong assumptions. As a result, DSGE models under such interpretation do not perform well, either. Finally, he argues that the correct interpretation is to accept that DSGE models only explain certain dimensions of the data. Therefore, rather than explaining *sample* moments, DSGE models have implications for specified *population* moments of the observable data. Under such interpretation DSGE models provide the prior distribution for the dimensions that the model claims to explain. This is what Geweke calls the *"minimal econometric interpretation"*. Under such interpretation, DSGE models provide the prior distribution of the population moments that the model intends to describe, which can then be compared with the posterior distribution predicted by an auxiliary econometric model.

validated empirically. In particular, after highlighting some important data considerations that arise in estimating these models, the discussion focuses on the strengths and weaknesses of current estimation methods and on the manner in which the literature has addressed misspecification and identification issues. Section 4 presents a discussion about the use of these models for policy evaluation and forecasting, which is followed by a brief discussion of whether DSGE models are truly structural or not, that is, whether they address the "Lucas critique" or not. Section 5 then shifts its attention to the challenges that may arise in communicating the results of these models, highlights some principles that may help in showing its advantages for policy making and discusses the role of judgement. A final section concludes.

2   Modelling Challenges

Most DSGE models available in the literature have a basic structure that incorporates elements of the New Keynesian paradigm and the real business cycle approach.[12] The benchmark DSGE model is an open or closed economy, fully microfounded model with real and nominal rigidities (see, for instance, Christiano et al 2005 and Smets and Wouters 2003).[13] In this model, households consume, decide how much to invest and are monopolistic suppliers of differentiated types of labour, which allows them to set wages. In turn, firms hire labour, rent capital and are monopolistic suppliers of differentiated goods, which allows them to set prices. Both households and firms face a large number of nominal frictions (eg sticky wages and prices or partial indexation of wages and prices) limiting, in each respective case, their ability to reset prices or wages. On the real side, capital is accumulated in an endogenous manner and there are real rigidities arising from adjustment costs to investment, variable capital utilisation or fixed costs. Households preferences display habit persistence in consumption, and the utility function is separable in terms of consumption, leisure and real money balances. Fiscal policy is usually restricted to a Ricardian setting, while monetary policy is conducted through an interest rate feedback rule, in which the interest rate is set in response to deviations from an inflation target and some measure of economic activity (eg output gap). Furthermore, some degree of interest rate smoothing is often assumed. This basic model is enriched with a stochastic structure associated with different types of shocks, such as supply side shocks (productivity and labour supply), demand side shocks

---

[12] As highlighted by Gali and Gertler (2007) the new keynesian paradigm that emerged in the 1980s was an attempt to provide microfoundations for keynesian concepts such as inefficiency of aggregate fluctuations, nominal price stickiness and the non-neutrality of money. By contrast, the real business cycle literature aimed at building quantitative macroeconomic models from explicit optimizing behaviour at the individual level. See also Mankiw (2006).

[13] Whether DSGE models are truly microfounded or not are also a matter of debate. For instance, some economists question its microfoundations because they assume away any agent coordination problems or because they rely on hyper-rational, self-interested agents. Colander et al (2008) offers a critical overview of DSGE models and suggests some alternative lines of research that incorporate heterogeneous interacting agents or that drop the agent rationality assumption. In turn, Faust (2008) offers a discussion of the practical merits of the advances of DSGE models, including a discussion of whether microfounded models should be regarded as the best guide for policy.

(preference, investment specific, government spending), cost-push or mark-up shocks (price mark-up, wage mark-up, risk premium) and monetary shocks (interest rate or on other target variables). These shocks are often assumed to follow a first-order autoregressive process.

In general, the framework is designed to capture plausible business cycle dynamics of an economy. On the monetary side, it attempts to capture some of the most important elements of the transmission mechanism (although some surprising and paradoxical results have been found).

This benchmark model, which reflects the advances made in DSGE modelling during the past decade and a half, faces some important challenges. Although I do not pretend to make an exhaustive list, it is possible to mention that more work is required in modelling financial markets, incorporating more explicitly the role of fiscal policies or in addressing modelling issues relevant for small open economies or EMEs. Of course, other specific aspects may need to be considered, in particular, improving the interaction between trade and financial openness, modelling labour markets or modelling inflation dynamics (for instance, regarding the role of expectations and pricing behaviour).[14] Next, a selected number of these issues are reviewed.

2.1   Financial Market Frictions

Possibly the main weaknesses in current DSGEs is the absence of an appropriate way of modelling financial markets. The relevance of the financial structure of the economy is well known as reflected by the repetitive waves of financial crises across the world (eg 1930s Great Depression, 1980-90s Japanese crisis, 1980s Latin American crisis, 1994 Tequila crisis, 1997 Asian crises, or the most recent financial turmoil triggered by the US subprime mortgage market, among others). Therefore, by excluding a formal modelling of financial markets or financial frictions, the current benchmark DSGE model fails to explain important regularities of the business cycle (thus putting too much weight on, say, monetary policy or productivity shocks). It also excludes any possible analysis of other key policy issues of concern for central banks, such as financial vulnerabilities, illiquidity or the financial systems' procyclicality.[15] In fact, the weak modelling of financial markets in these models also limit

---

[14]Issues related to the modelling of labour markets or inflation dynamics are not discussed here. For an up to date discussion of how to model labour markets in DSGE models see the special issue of the Journal of Monetary Economics vol 55, July 2008 (eg Christoffel and Kuester 2008; Krause et al 2008 or Christiano et al 2007b). Issues related to inflation dynamics are not discussed either. However, readers should be aware that there is an important strand of literature arguing that rational expectations sticky-price models fail to provide a useful empirical description of the inflation process. See, for instance, the published papers by the ECB Inflation Persistence Network (http://www.ecb.eu/home/html/researcher_ipn.en.html) and the literature for state-dependent pricing (in contrast to time-dependent pricing such as the Calvo price-setting behavior) where firms are free to adjust whenever they would like (see Gertler and Leahy 2008 or Dotsey et al 1999).

[15]The procyclicality of financial systems can be explained by information assymetries between borrowers and lenders, as highlighted in the financial accelerator literature. Nonetheless, the innapropriate responses by financial markets to changes in risk over time and the manner in which agents measure it can be another important source of procyclicality (see Borio 2006, Borio and

their use for stress testing in financial stability exercises.[16]

The financial accelerator has been the most common approach to incorporate financial frictions into a DSGE framework (Bernanke, Gertler and Gilchrist 1999 and Cespedes et al 2004). Such framework has been employed to capture firms' balance sheet effects on investment by relying on a one-period stochastic optimal debt contract with costly-state verification. The key aspect is that such setting allows to endogenously determine a external finance premium above the risk-free interest rate. This approach has also been applied to capture balance sheet effects in the banking sector (eg Choi and Cook 2004). In terms of its empirical relevance, recent research has found that for the Euro Area and for the US the financial accelerator plays a relevant role in amplifying shocks that move prices and output in the same direction (eg monetary policy shocks) as well as in explaining the business cycle (Christiano et al 2007a). However, a key weakness of the financial accelerator is that it only addresses one aspect of many possible financial frictions.

Portfolio choice in sticky-price models is another area that has not yet been successfully incorporated into mainstream DSGE models, but is increasingly relevant with financial openness. In open economy DSGE models, international financial linkages have traditionally only been captured in terms of net asset positions and the current account.[17] Therefore, the difficulty of modeling the optimal portfolio choice has also meant that modelling gross portfolio positions has not been entirely satisfactory. Only recently has the literature made significant progress towards incorporating the portfolio choice problem in a modern macroeconomic DSGE framework. For instance, Engel and Matsumoto (2005) have modelled the portfolio choice problem in a standard DSGE model with sticky-prices and complete markets, and more recently, Devereux and Sutherland (2006), proposed a solution method to embed the portfolio choice problem in a modern macroeconomic model with multiple assets and incomplete markets.[18] In principle, it appears that their framework should allow dealing with certain issues, such as the size and composition of a country's portfolio, return differentials, dynamics of capital flows and its implications for monetary and fiscal policies (see Devereux and Sutherland 2007). In general, although appealing, due to its "simplicity", it remains to be seen whether the solution method proposed by these authors will truly perform satisfactorily for policy analysis and become part of the benchmark DSGE framework.

Incorporating the term structure of interest rates is another challenging area for DSGEs. In the current DSGE benchmark model the link between expected interest rates and output is determined by the forward looking IS curve, which expresses output as a function of the ex-ante real interest rate. By solving such an equation

---

Lowe 2002, Borio et al 2001).

[16]I am only aware of an attempt of integrating a DSGE model and banking stress testing exercises (Jokivuolle et al 2007). However, this is not done in an integrated manner. That is, the DSGE model is employed to generate coherent macroeconomic scenarios that are then employed for the banking stress testing exercises.

[17]Lane and Milesi-Ferretti (2007, 2001) show that gross portfolio holdings have grown rapidly, particularly in the last decade.

[18]Devereux and Sutherland (2006) argue that the body of empirical evidence on the failure of risk-sharing across countries cast doubt on the hypothesis that international financial markets are complete.

in a forward manner, it is the expected path of the short-term real interest rate that determines the extent of inter-temporal substitution and hence future output. In this setting, the long-term interest rate only matters to the extent that it embeds expectations of future short-term interest rates. As a result, shifts in the term premium of interest rates play no role in determining output.

Rudebusch et al (2007) use a standard DSGE framework to study the relationship between the term premium and the economy. However, as they highlight, in practice, the DSGE asset pricing framework has computational and practical limitations that keeps the model from being useful for practical purposes. Such limitations can be grouped into two categories. One is associated with theoretical uncertainties, and the second with computational problems.[19] As for the former the main issue is that there is no consensus on how to model asset prices, and therefore there is a lack of consensus on how to analyse the "term-premium". A well-known example of this is the "equity-premium" puzzle (ie the excess average rate of return differential between stocks and bonds). As for the latter, the problem is that log-linearisation around a steady state is not applicable to asset pricing, because, by construction, it eliminates all risk premiums in the model (ie the term premium is zero in a first-order approximation, and constant in the case of a second-order approximation, therefore higher-order approximations are required).

2.1.1   Collateral Constraints

Another way of incorporating financial frictions is through collateral constraints. Although little work has been done in this area, progress has been made by Iacovello (2005) who analyses the interactions between housing prices, economic activity (consumption) and monetary policy. In particular, the main component of the model is the introduction of household and firm collateral constraints for borrowing, thus limiting both consumption and investment, and therefore affecting real activity. Therefore, by introducing such collateral constraints into the DSGE model, asset price fluctuations amplify the business cycle. Iacovello and Neri (2008) have estimated a DSGE model with household collateral constraints for the US, which allows them to address questions regarding the dynamics of residential investment and housing prices or the extent of spillovers from the housing market to the rest of the economy. They find that demand and supply shocks drive the volatility of housing investment and housing prices, and that collateral effects magnify non-housing consumption. Gerali et al (2008) have also extended the framework and introduced monopolistic financial intermediaries, in a spirit similar to Christiano et al (2007a) who introduce perfectly competitive financial intermediaries. With no doubt, this line of research relying on collateral constraints seems to offer a promising avenue to improve the manner in which financial and credit frictions are incorporated into the models.

2.1.2   Currency Risk Premia

Currency risk premia is a particularly important area in which DSGE models have faced important challenges. In small open economies models the basic limitation is

---

[19]Computationally speaking the problem has to do with the lack of closed-form solutions.

that a solution is required to the problem caused by the fact that agents are able to borrow at a fixed interest rate. This would allow them to finance consumption streams indefinitely unless such behaviour is ruled out (see Schmidt-Grohé and Uribe 2003). The most common approach has been to attach a reduced-form risk premium to foreign debt, which is usually modelled as an increasing function of the level of borrowing. In this manner agents are forced to limit foreign borrowing to finance consumption. In DSGE models, an exogenous shock to the risk-premia is often added with the aim of capturing the high volatility observed in the data, a problem that can be particularly severe in EMEs where sovereign risk can be highly volatile, as seen during past financial crises. Of course, by DSGE standards, the great weakness of this approach is that it lacks microfoundations. Recently, it has been shown that including the expected change of the exchange rate into the risk premia, which induces a negative correlation between these two variables, is able to improve the empirical fit of estimated DSGE models (Adolfson et al 2008b). The key aspect of this modelling variation is that it generates persistent and humped-shaped real exchange rate responses, which are often difficult to obtain.

Modelling currency risk premia is also relevant for developed economies because in linearised solutions the uncovered interest rate parity (UIP) holds. And it is known from the "forward premium bias puzzle" that UIP fails empirically. Indeed, rather than finding that forward rates are equivalent to expected future short rates as implied by UIP, the literature has found that there is a negative correlation among these rates. The failure of UIP in DSGE models is therefore likely to generate flawed predictions about the exchange rate behavior, even if the proposed solutions mentioned above are implemented. Of course, the extent to which this is a problem will also depend on the use given to these models.

2.2 Improving the Analysis of Fiscal Policies: Abandoning Ricardian Equivalence

Benchmark DSGE models have paid little attention to the role of fiscal policy, therefore minimising any possible interaction of fiscal policies with monetary policy. This has been partly because of the assumption of Ricardian equivalence. As a result, the distribution of taxes across time become irrelevant and aggregate financial wealth does not matter for the behaviour of agents or for the dynamics of the economy because bonds do not represent net real wealth for households.

Incorporating more meaningfully the role of fiscal policies requires abandoning frameworks with the Ricardian equivalence. But how can this be achieved? Two possibilities are available. The first is to move to an overlapping generations (OLG) framework,[20] and the second (which has been the most common way of handling the problem) is to rely on an infinite-horizon model with a type of liquidity constrained agents (eg "rule of thumb agents").[21] Although both types of models are capable

---

[20]For a treatment of DSGE models in OLG frameworks see Ganelli (2005) and Bénassy (2007).

[21]In the basic setting, agents are unable to smooth consumption over time due to exogenous forces. Furthermore, agents cannot access the market to borrow or lend. In this respect, it is worth clarifying that this approach is not equivalent to modelling endogenously a collateral constraint. For applications of such approach at central banks see Erceg et al (2005), Forni et al (2009) or

of capturing the short-run effects of fiscal policy, only OLG structures appear to be able to generate medium and long-term crowding-out effects of fiscal policy.[22] Indeed, Kumhof and Laxton (2007) have developed a very comprehensive model for the analysis of fiscal policies, which incorporates four non-Ricardian features.[23] In their analysis of the effects of a permanent increase in the US fiscal deficits and debt, they find medium and long-term effects that differ significantly from those of a liquidity constrained agents. Furthermore, they find deficits to have a significant effect on the current account.

2.3   DSGE Modelling in EMEs

Modelling and capturing the dynamics of EMEs is no easy task. This is partly related to idiosyncratic structural features exhibited by these economies, as well as due to the historical vulnerabilities to external factors and resulting periods of high macroeconomic instability. Under such circumstances an important question to ask is: what features of the benchmark DSGE model need to be modified as to capture relevant features characterising EMEs? For instance, one of them is introducing features of "dollarisation".[24] In partially dollarised economies a foreign currency (dollar or euro) takes over the basic functions of the domestic currency. Such situation may lead to three possible outcomes (Castillo et al 2006): i) transaction dollarisation or currency substitution, in which the foreign currency becomes the main medium of exchange; ii) price dollarisation, in which all prices are indexed to changes in the exchange rate and, finally, iii) financial dollarisation. Financial dollarisation may arise both as a result of a dollarisation of assets, ie dollars become the preferred denomination for savings, or as result of liability dollarisation, in which debts are denominated in foreign currency, while revenues are denominated in domestic currency, thus creating a currency mismatch. In Latin America, some studies have analysed the role of different types of dollarisation in DSGE frameworks (see Castillo et al 2006 or Tovar 2006). For instance, Castillo et al (2006) show that by explicitly modelling dollarisation the DSGE model improves its fit to the data.[25] In particular, currency substitution reduces the output response to interest rates, im-

---

Medina and Soto (2007a). In this last paper, the rule of thumb agents are relevant for analysing the Chilean structural fiscal rule.

[22]Results by Forni et al (2009) confirm this. They use a DSGE model featuring a fraction of non-Ricardian agents to estimate the effects of fiscal policy in the euro area, finding mild Keynesian effects of fiscal policy. That is, innovations in fiscal policy variables have small and short-lived expansionary effects on private consumption. More generally, they find that fiscal policy variables contribute little to the cyclical variability of the main macro variables.

[23]First, OLG agents with finite economic lifetimes. Second, a stylized form of life-cycle income pattern in which the average agent exhibits declining labour productivity throughout his lifetime. Third, liquidity constrained agents who do not have access to financial markets to smooth consumption, so that they have to vary their consumption one-for-one with their after-tax income. Finally, distortionary labour and consumption taxes.

[24]The modelling of sovereign risk premia is also an area of interest to EMEs. In this respect the discussion parallels that of financial market frictions and currency risk premia.

[25]Currency substitution can be modelled in the benchmark model by including both domestic and foreign currency as composites of aggregate consumption. Price dollarisation can be modelled by exogenously assuming that a subset of firms that produce home goods set their prices in a foreign currency.

proving the fit of consumption volatility. Also price dollarisation adds an additional Phillips curve that generates endogenous persistence and increases the sensitivity of inflation to exchange rate movements. Furthermore, by introducing different types of dollarisation the weight of the central bank response to deviations of the CPI and the exchange rate from the target increases. Finally, the volatility of observed fluctuations in time series and of the model's shocks is typically high relatively to that of developed economies.

Due to dollarisation, the exchange rate is also likely to play a much larger role in EMEs than in developed economies. For instance, in EMEs currency devaluations are frequently said to have contractionary effects on output due to financial dollarisation. This effect contrasts with standard theoretical modelling in advance economies where currency devaluations are thought to have expansionary effects, say, due to the expenditure-switching effect. As a result, in modelling EMEs, mechanisms need to be included allowing currency devaluations to have a potential contractionary role (see Tovar 2006, 2005). Equally important is that exchange rate regimes are likely to play an important role. In general, very few DSGE applications have taken into account the role of "de facto" exchange rate regimes. Certainly, fully endogenising the choice of exchange rate regimes may be a daunting task. Notwithstanding, it is possible to capture shifts in the exchange regime in a DSGE by making appropriate adjustment to the models. An option is to introduce a time-varying weight on the exchange rate component of an augmented interest rate rule.[26]

3   Taking Models to the Data

The attractiveness of taking DSGE models to the data is that they are derived from first principles. That is, they describe the general equilibrium allocations and prices of the economy in which all the agents dynamically maximise their objectives (utility, profits, etc) subject to budget or resource constraints. Therefore the parameters describe the preferences of agents, the production function and other structural features of the economy. These "deep" parameters (ie parameters that do not vary with policy) are the main goal of estimation. By doing so, it is in principle possible to avoid the "Lucas critique", according to which only models in which the parameters do not vary with policy interventions are suited to evaluate the impact of policy change (Lucas 1976).

Therefore, there has been a growing body of literature aiming to ensure that DSGE models provide an accurate description of the data. The problem is that if modelling is a complex task, more so is the estimation of DSGE models. From an empirical point of view, a complication is that none of the models actually represent the data generating process (DGP) of the time-series of interest and, in general, they

---

[26]However, such a solution leads into another controversial and unresolved matter: whether the exchange rate should enter the monetary policy rule, even in countries that have adopted inflation targeting regimes. Of course, the extent of how relevant is the exchange rate for monetary policy will be a function of the degree of exchange rate pass-through. In this respect, although, the literature has offered alternatives for the modelling of exchange rate pass-through, a more complicated exercise is allowing for time-varying degrees of exchange rate pass-through (see Laxton and Pesenti 2003).

are not specifically designed for that purpose (see Geweke 2007). They were designed to gain insight about specific economic relationships, rather than to describe the actual economy.[27]   Notwithstanding, for these models to be of practical use for policy they need to describe observed features of the economy. In fact, desirable or not, research on DSGE models appears to have been driven by what Kocherlakota (2007) calls the "principle of fit" (ie models that fit well should be used for policy analysis, and models that do not fit well should not be used). So, what are the key elements that need to be taken into account as to be able to take DSGE models to the data? In what follows, different aspects related to the data, estimation methods, model specification, parameter identification and policy simulation of DSGE models are discussed. However, before discussing them, the reader should be warned that many of the issues raised are not necessarily exclusive of DSGE models. Nonetheless, the discussion is focused on the manner in which the DSGE literature has addressed or failed to consider certain issues.

3.1   Data Sets

Econometricians often fail to be able to observe the theoretical concepts modelled (eg the output gap). So, a first question is: how to match the theoretical concepts in DSGE models with those of the observed data? This is not trivial (and certainly the problem is not exclusive to these models). In the DSGE literature, the theoretical concepts have been captured not against specific data figures (say GDP levels or inflation), but against filtered data (eg by using the Hodrick-Prescott filter). Filtering decomposes the data into a cyclical component and a trend component. The cyclical component is what is frequently fed into the model. By doing so, the analysis focuses on the business cycle frequencies, mainly because it is considered that DSGE models are better suited to explain short-run rather than long-run cycles. However, filtering has important implications (see discussion in DeJong and Dave 2007 and Del Negro and Schorfheide 2003). One is that, forecasting stays out of the reach of DSGE models, given that the goal is to forecast actual, rather than filtered data. The second is that the dynamics obtained do not match those required by policy makers, weakening the usefulness of DSGE models as policy tools. Alternatives often used are the linear detrending and demeaning of variables, as well, as transforming variables so that they are stationary around a balanced growth path. In this last case, the problem is that the trend is often assumed to follow an exogenous stochastic process, which is imposed by the researcher.

The lack of appropriate data to feed these models has also led researches to explicitly recognise the role of measurement errors or to incorporate into the estimation information contained in different data series.[28]   Augmenting the number

---

[27]An aspect to keep in mind is that new DSGE models should not exclude a priori responses that could be theoretically grounded simply because they depart from the responses of other available models at central banks (eg a large scale macroeconomic model). In fact, in conversations with some central banks I learned that DSGE models have allowed to improve their existing large scale semi-structural macroeconomic models.

[28]Here measurement errors are considered from a different perspective to that of just solving the stochastic singularity problem, which arises when there are fewer theoretical shocks than endogenous observable time series (see section 3.3.2).

of data series employed in the estimation of DSGE models seems to be relevant, mainly because researchers have maintained the assumption that all relevant information for the estimation is adequately summarized by a small number of data series. Relying on such small data sets appears to be at odds with the fact that central banks and financial market participants monitor and analyze large number of data series. Furthermore, research has shown that information contained in large data sets is relevant for the evolution of macroeconomic time series (Bernanke and Boivin 2003). Relying on few data series to estimate DSGE models may lead to biased estimates and distorted inference. For instance, Boivin and Giannoni (2006) have proposed a factor type analysis to exploit the information from a potentially large panel of data series in a systematic way. Therefore, rather than assuming that theoretical concepts are matched by a single data series, these are instead treated as unobserved common factors for which data are just imperfect indicators. Their approach allows the extraction of a latent measure of the theoretical concept and a series-specific component (or measurement error). It also allows exploitation of the information from indicators that are not directly and unambiguously linked to a specific concept of the data.

Another aspect that is frequently highlighted or encountered in practice is that DSGE models are estimated under the presumption that there is a steady-state for the economy. This implies that ratios of certain variables need to be constant. Of course, the data does not always support this assumption (Fukač and Pagan 2006). For instance, this can be particularly problematic in EMEs, where the changing and highly volatile environment frequently results in highly volatile data series, often contaminated by a significant number of structural breaks. As a result, large samples of good data (without large structural breaks or episodes of high volatility) necessary to feed these stylised models are often not available, thus making it impossible to perform tests on structural breaks or parameter stability and, therefore complicating the applicability of these models for policy analysis. In this respect, one might wonder whether under currently available time series the parameter estimation performed using historical evidence (and generated under different regimes) is truly informative for certain policy analysis, or even more for forecasting.

The overall difficulties of DSGE modelling and estimation in EMEs are well illustrated if one thinks of applying these models to Latin American economies. For instance, the shifts observed across the region in the degree of trade and financial openness, monetary policy frameworks and exchange rate regimes during the last fifteen to twenty years are not easily captured within current available frameworks and, therefore, not easily controlled for when taking the models to the data (Tovar 2006). Furthermore, the structural changes experienced by these economies have also resulted in trending behaviours in some variables that are difficult to explain with the models (eg the steady decline from high inflation levels). In addition, Latin America, as well as other developing regions of the world, has been exposed to severe external shocks, that triggered sharp business cycles. Such events create at least two kind of problems. On the one hand, the effects of large but low probability events are difficult to capture theoretically as well as empirically. On the other hand, such events may be highly non-linear and standard solution methods, in particular log-

linearisations, may fail to recognize these features, thus leading to inadequate policy recommendations.

3.2 Estimation Methods

Two main methods for evaluating DSGE models have been proposed: calibration and econometric estimation. Calibration methods were very popular a few years ago, but their popularity has declined.[29] This partly reflects improvements in computational power and the development of new econometric methods, which have made more accessible and appealing econometric estimation. In fact, today most central banks aim at developing and estimating DSGE models. Because of this trend, the focus of this section will be on the issues and challenges arising in the econometric estimation of the models.[30]

In the literature there are different econometric techniques available for estimating DSGE models. Examples of these include estimation of equilibrium relationships with generalized method of moments (GMM), minimum distance estimation based on the discrepancy between VAR and DSGE impulse response functions, maximum likelihood and Bayesian methods (see Canova (2007), DeJong and Dave (2007), An and Shorfheide (2007), Ruge-Murcia (2007) and Favero (2001) for detailed reviews of the different approaches). An important difference that arises among these different approaches has to do with the amount of information that each method is able to handle. For instance, GMM methods only use part of the information implied by the model, while (full-information) likelihood methods exploit all the implications of the DSGE model. It is for this reason that the most important strand of the literature has focused on estimation methods built around the implied likelihood function derived from the DSGE model. Typically, this has also entailed using the Kalman filter[31] and the (log) likelihood function. A now common approach is to augment the log-likelihood with priors and perform Bayesian estimation.

As of today, due to the computational burden often associated with the likelihood evaluation for the solution of the non-linear expectational equations implied by DSGE models, the empirical literature has concentrated its attention on the estimation of first-order linearised DSGE models.[32] Although first-order approximations have major weaknesses, as they may eliminate the role of second moments in the optimality conditions, they are until now the main tool employed for evaluating

---

[29]However, calibration should be considered a fundamental building block in the construction and estimation of models, for instance, to learn about the properties of the models.

[30]See Bierens (2007) for a recent presentation on calibration methods. See also Murchison and Rennison (2006) for a discussion on why the Bank of Canada opted for calibrating their model. In particular, they highlight that as their model grew, the number of parameters also increased, reducing the confidence that optimization routines were converging on a global minimum. The Central Bank of Colombia´s Patacon model is another example of a central bank that has opted for calibration.

[31]In non-linear DSGE models a sequential Monte Carlo filtering can be employed. See Fernández-Villaverde and Rubio-Ramírez (2006).

[32]Fernández-Villaverde et al (2006) consider this situation to be unsatisfactory as they prove that second-order approximation errors in the solution of the model have first-order effects on the likelihood function. In other words, the likelihood implied by the linearised model diverges from the likelihood implied by the exact model.

empirically DSGE models.[33] In general, little is known about the implications of different approximation methods, but for sure they are likely to have non-trivial implications for the dynamics (Canova 2007).

Maximum likelihood (ML) has a number of weaknesses (see discussion in Canova 2007). One is the stochastic singularity problem, which we discuss below. The second is that one must assume that the model correctly represents the process generating the data up to a number of parameters. Since joint estimation of all the relationships implied by the model is performed, ML estimates are unlikely to be consistent if the model has some degree of misspecification. That is, this method is very sensitive to model misspecification (see discussion below). Equally important, there is an issue of parameter identification as DSGE models, in particular small scale models, often lead to likelihood functions that have large flat sections or very rocky appearance (see discussion below). Furthermore, it has been argued that pure ML estimation of DSGE models suffers from the "dilemma of absurd parameter estimates" (An and Schorfheide 2007). That is, estimates of structural parameters generated with ML methods are often at odds with additional information that economists might have.

Because of the weaknesses associated with pure ML methods, it has been argued that a better way of estimating these models is by augmenting the likelihood with priors about parameter distributions. This allows construction of posterior distributions from which to draw inferences about the parameters. Bayesian methods are considered to be able to handle the weaknesses of pure maximum likelihood methods for several reasons. First, the prior reweighs the likelihood, so that if the likelihood reaches a peak at a point that is at odds with the prior then the marginal density of the DSGE model will be low. That is, an appropriate prior can add curvature to a flat likelihood function or "iron out bumps". Equally important, posterior inference does not depend on the model being the correct data generating process. And most importantly, Bayesian methods are able to incorporate the policy makers' views about what has been learned in the past about the economy or as a device for incorporating micro-level information for the estimation of parameters (eg labour supply elasticities or mark-ups). In this respect, Del Negro and Shorfheide (2008) argue that prior distributions either reflect subjective opinions or summarise information derived from data not included in the estimation sample. This last case is equivalent to simplifying the likelihood function for a larger set of observations that would be too complicated to model directly. In other words, if the prior is constructed using pre-sample data this would be equivalent to assuming that the structure of the economy changed prior to the beginning of the estimation sample.

Despite its attractiveness, Bayesian estimation has weaknesses. First, priors can distort the results if the likelihood function imposes little information. In other words, the selection of certain priors may produce outcomes that look good from a theoretical perspective, even if the data is mute about the parameter value. As a result, "absurd parameter estimates" may by itself be an indication of specification

---

[33]First-order approximations fail to be appropriate for evaluating welfare across policies that do not affect the steady state of the model, eg when analysing asset pricing (see discussion in 2.1), or when risk considerations are relevant. See Schmidtt-Grohé and Uribe (2004) and Kim et al (2008) for a discussion on second-order approximations. See also An and Shorfheide (2007).

problems with the model. In fact, Kocherlakota (2007) warns about the role of priors when introduced not as auxiliary information, but just for the sake of achieving identification. In particular, he shows that if the prior does not reflect auxiliary information (ie information that really contain information about what economists know about a parameter), the resulting estimates can be severely biased, even if the model fits the data exactly. It is also for this reason that Fukač and Pagan (2006) suggest comparing pure ML estimates with Bayesian estimates, something that is almost never done in practice. An exception is Iskrev (2008), who has looked into this issue using the model developed by Smets and Wouters (2003). He finds that alternative prior specifications have significant effects on parameter estimates. In particular, he finds that the policy coefficients in a Taylor rule do differ between the ML and the Bayesian estimates. Second, the effects of priors can affect posterior odds ratios and therefore model comparison. Sims (2003) argues that when applied to model comparison, posterior odds tend to emerge as implausibly decisive. In particular, posterior odds are directly proportional to prior odds and sensitive to the degree of dispersion of the prior even when the likelihood is concentrated relative to the prior.

It is for these reasons that the literature on DSGE models has started to explore more formal ways of constructing priors. For instance, Del Negro and Schorfheide (2008) provide a framework for constructing prior distributions for different classes of parameters in DSGE models, such as those determining the steady-state, the endogenous propagation of shocks or the law of motion of exogenous disturbances. When implementing their methodology, these authors find that a medium-scale DSGE model is unable to discriminate among theories that differ in the quantitative importance of real rigidities (posteriors mirror the priors) and find that priors for the exogenous parameters may inadvertently favour different model specifications over others. In essence, these problems highlight the need for a careful assessment of parameter identification in DSGE models (see discussion in section 3.4).

A second important criticism of Bayesian estimation, of a more technical nature, is that posterior estimates of the structural parameters rely on computationally intensive simulation methods (eg Metropolis-Hasting algorithm). The problem with this, is that replication of Bayesian results may not be straightforward. For instance, Fukač and Pagan (2006) report that they were unable to replicate the posterior mode of a "well-known" paper in the literature even after a million simulations, thus concluding that it is unclear whether published studies are in fact a good representation of the "true" posteriors.

3.3 Misspecification Issues

DSGE models are by their nature crude approximations of the data generating process (DGP) or law of motion of the economy. Therefore, the goal of estimating a DSGE model is to minimize the distance between the true DGP and the time series generated by the model (see discussion in Fernández-Villaverde and Rubio-Ramírez 2004). Several factors may explain why a model fails to resemble closely the DGP. One possibility is that the model imposes cross-equation restrictions that are at odds with the data (say, because there are misspecified structural relationships, wrongly

specified exogenous process or omitted non-linearities). Another is related to the fact that the model may predict certain combinations of endogenous variables to be deterministic. Therefore, if the exact linear definition established by the model does not hold in the data, then any attempt to estimate the model would fail.

3.3.1 Invalid Cross-Equation Restrictions

One important source of misspecification is the cross-equation restrictions on the time series representation imposed by the DSGE model. This simply highlights that when taking a model to the data it is necessary to have in mind that there is a trade-off between the theoretical coherence and empirical fit. In other words, even though the DSGE model may match the data in many important dimensions, its simplified structure also implies that it is likely to fail in many others. Of course, unrealistic restrictions are likely to manifest themselves in poor out-of-sample fit, in particular, when compared with VARs that have been estimated with well-designed shrinkage methods.

Although invalid cross-coefficient restrictions may appear to be a major obstacle for using DSGE models for policy analysis, the literature has proposed approaches for dealing with it. One approach which appears to be quite promising for policy analysis and forecasting is to employ information contained in a DSGE model in a less direct manner. In their DSGE-VAR framework, Del Negro and Schorfheide (2007, 2004) show that a relatively simply DSGE model employed as a prior in a VAR is able to improve the forecasting performance of the VAR relative to an unrestricted VAR or a Bayesian VAR. What makes this approach appealing for forecasting and policy analysis is that it relies on the DSGE to set priors, rather than using the DSGE for forecasting in a direct manner. However, the DSGE-VAR framework can still be improved as prior information on other dimensions related to the dynamics of the data may be necessary (Sims 2008 a, 2008b and Sims 2006).

Using a different perspective, Juselius and Franchi (2007) have proposed a manner of evaluating whether the implications of a model are robust to misspecification by employing an alternative statistical model that nests the DSGE model implications.[34] More precisely, the method evaluates the assumptions of a model with the statistical properties of the data by translating the assumptions underlying a DSGE model into a set of testable assumptions on a cointegrated VAR model. These authors find, using Ireland's (2004) DSGE model, that most of the assumptions underlying its model (eg that the trend is excludable from the long-run relations, that hours worked are stationary, that output consumption and capital are trend stationary and that productivity shocks are the main driving forces of the model) were not just testable but also rejected. More importantly, they also find evidence of parameter non-constancy, an issue to which we will return later, as it may indicate that these models are not truly addressing the "Lucas critique".

3.3.2 Stochastic Singularity

The stochastic singularity problem which affects any likelihood based estimation method arises because DSGE solutions may determine identities among variables or

---

[34]See also the overview by Hoover et al (2008).

combinations of them.[35] Therefore, if such identities are not satisfied in the data, any attempt to fit the model will fail. As a result, the literature has dealt with this problem in at least two manners, by: i) incorporating structural shocks or ii) adding measurement errors.

Structural Shocks   The stochastic singularity problem can be addressed by incorporating additional structural disturbances until the number of shocks equal the number of endogenous series employed in the estimation, as suggested by Smets and Wouters (2003). In the literature these shocks are often assumed to follow a first-order autoregressive process or a random walk. This procedure has its appeal only if the structural shocks have an appropriate economic interpretation. From a practical point of view, it also has some weaknesses. A basic one is that the postulated shocks can, by themselves, be a source of misspecification. Another problem is that introducing additional shocks increases identification problems, as more parameters need to be estimated or calibrated. Finally, as highlighted by Kocherlakota (2007), simply adding shocks to models to fit the data better should not increase the confidence in the model's predictions. For sure, shocks need a structural interpretation. However, some shocks often used in the literature are frequently questioned on the basis of their interpretation. For instance, mark-up shocks are frequently criticised on the basis that they can stand up for changes in taxes, the degree of competition or relative prices in flexible price sectors (eg food and energy) among others. A similar argument seems to apply to the investment specific shock on the investment adjustment cost term, which is often said to capture "investment specific technology shocks". However, this broad interpretation also seems to suggest that it captures unmodelled relevant features that may affect investment (eg due to the lack of modelling a financial sector in the model).

Measurement Errors   This is the procedure originally proposed by Sargent (1989) and more recently emphasised in the DSGE literature by Ireland (2004). In Ireland (2004) measurement errors are introduced as a way of capturing the movements and co-movements in the data that a DSGE model because of its simplified structure cannot explain (ie misspecification). Measurement errors allow the extraction of information from a larger set of variables to estimate the parameters of the model. Furthermore, it is also useful if the actual variables employed in the estimation do not match their model counterparts (Canova 2007 and Boivin and Giannoni 2006). Measurement errors also allow simple checks of the quality of the model by comparing the size of the measurement errors with those of the structural shocks (significant differences would suggest misspecification) or by performing variance decompositions.

However, measurement errors are not grounded on economic theory, implying that some of the dynamics of the model may be driven by forces that are completely exogenous to the model and which have no clear economic interpretation. As such, many consider that they defeat the purpose of having a fully structural model and

---

[35]If one attempts to predict a vector time series, say, y_t by a function of past y_s, then the resulting forecast error covariance matrix is non-singular. Therefore, any model that generates a rank-deficient covariance matrix for y_t will be at odds with the data, as it will be singular.

that it implies "giving up the idea that the model is a good representation of the data" (Canova 2007). Furthermore, in Ireland (2004) they are introduced with an autocorrelated structure. This is arbitrary, and just as in the case of structural shocks, it implies adding more parameters to estimate.

3.4 Identification

A basic condition for any methodology to deliver sensible estimates and meaningful inferences for policy analysis is to ensure the identification of parameters. The parameters of a model are identified if no two parameterizations of that model generate the same probability distribution. Alternatively, one can say that for identification to occur a researcher must be able to draw inference about the parameters of a theoretical model from an observed sample. However and despite its importance, identification is an aspect that has rarely been addressed in the empirical DSGE literature, mainly due to computational issues.[36]

One of the few studies to address the issue of identification in the context of DSGE models is Canova and Sala (2006). They argue that there are several reasons why identification might not be achieved. The first is due to what they call *observational equivalence*. This occurs if the population objective function does not have a unique maximum, so that the mapping between structural parameters and reduced form statistics is not unique. The implication is that different models, with potential different interpretations, may be indistinguishable from the point of view of the objective function. The second is related to *under-identification* problems, which occurs if the objective function is constant for all values of that parameter in a selected range. In practice this may occur if a parameter disappears, say for instance, due to the log-linearisation of the model or if two parameters enter the objective function in a proportional manner, a phenomenon known as *partial identification*. The third occurs if the objective function is flat or lacks curvature (*weak identification*). In such case different values of the parameters around a neighbourhood may lead to the same value of the objective function. Finally, the fourth is associated with the *limited information identification* problem. That is, a parameter may be identified if all the information is employed, but remains unidentified or under-identified if only partial information is employed. This type of identification problems may arise, for instance, if certain shocks are missing from the model or when matching impulse responses, because only certain responses are employed.

A relevant issue is to distinguish whether identification problems are associated with the objective function used for estimation or whether they are intrinsic to the model (Canova and Sala 2006). In the first case, identification could be solved by using an appropriate objective function. In the second case, it would require reparameterising the model. Most studies on DSGE models rely on the likelihood function, implying that having a well-behaved likelihood is a necessary but not

---

[36]In principle, a necessary and sufficient condition for local identification is for the information matrix of the log-likelihood implied by the model to be of full rank. However, the analytical mapping of the parameter space to the log-likelihood function is usually not available for DSGE models. In fact, in most cases the likelihood function has no analytical solution, thus implying that the information matrix has to be solved for numerically. But numerical differentiation is highly inacurate for non-linear functions such as those found in DSGE models. See Iskrev (2008).

sufficient condition for proper estimation. This, of course, also has implications for Bayesian estimation, in particular, because the posterior distribution is proportional to the prior. Therefore, if these two distributions differ it would imply that the data carries relevant information. In practice this would mean that carrying a sensitivity analysis by using more diffuse priors (ie greater variance) could help detect potential identification problems. As a result an improper use of Bayesian methods, by specifying tight priors, would hide identification problems.

Another important source of identification problems may arise when employing small sample sizes. In fact, as discussed in the previous study, they can introduce significant bias in parameter estimates, thus inducing economic dynamics that differ significantly from those of the true DGP.

Iskrev (2008) illustrates some of the problems that may arise with parameter identification in DSGE models. In particular, this author has studied parameter identification in the benchmark model; ie Smets and Wouters (2003). He shows that although all deep parameters are locally identifiable, identification is weak mainly because of the structure of the model. The implication then is that more informative data does not solve the identification issue. From a practical point of view, he finds that the model has difficulties distinguishing between the elasticity of intertemporal substitution, habit persistence and the autocorrelation coefficient of the preference shock. Similar identification problems are also found regarding the parameters affecting labour supply and the response coefficients in the monetary policy rule.

Overall, identification is a major issue in social sciences that needs to be dealt with in any empirical analysis, and DSGE models are no exception. As such, possibly the best way of dealing with it is to understand what features of the model could lead to the identification problem.

4   Policy Evaluation and Forecasting with DSGE Models

Statistical evaluation of DSGE models are often not enough for economic purposes. The reason is that this would not tell us much about why the model may fail to fit the data. When maximum likelihood estimates are performed, it is possible to make an economic evaluation by computing important unconditional moments, such as cross-correlations among variables, which can then be compared with those of the data. In addition, to learn about the dynamics of the model it is possible to obtain impulse response functions and variance and historical decompositions. Of course, evaluating forecasting performance is also possible. In Bayesian frameworks most of the previous analysis are also possible, but additional tools also become available (see An and Schorfheide 2007), such as posterior predictive checks, posterior odds comparison or comparisons with VARs, as in Del Negro and Schorfheide (2004) or Rabanal and Rubio-Ramírez (2005).

Given the battery of tools available for evaluating models, it is unavoidable to ask how good are these models forecasting. Some light in this respect is offered by a central bank that is leading in terms of DSGE modeling, the Sveriges Riks-

bank. Adolfson et al (2007a) look at the forecast performance of BVARs and DSGE models vis-à-vis the Riksbank's official forecast. They show that it is possible to construct a DSGE model that makes inflation forecasts as good as those obtained with the more complicated judgmental procedure typically used at the Riksbank. In particular, they report that the DSGE model is able to generate a smaller forecast error for the consumer price index 7-8 quarters ahead than the official Riksbank forecast. Nonetheless, the reliability of the DSGE model's inflation forecast is somewhat poorer compared to the BVAR one. As for the GDP growth forecast, the model compares relatively well relative to the BVAR, the Riksbank's assessments and an autoregressive model. Finally, their results are less satisfactory for interest rate forecasts. In particular, the DSGE model is found to underperform in forecasting the forward interest rate in the short-run vis-a-vis other forecasting methods, possibly reflecting the difficulties in modeling risk premia. Evidence on forecasting reported by other central banks at different seminars and conferences also indicate that DSGE models forecasts can perform well. For instance, Christoffel et al (2007) show that unconditional forecasts of the New Area Wide Model (NAWM) compare favourably in relation to a BVAR and a random walk, in particular, for real GDP and GDP inflation over horizons that extend beyond a year. They also show that such forecasts, once conditioned on a larger set of variables, improve the model performance over certain horizons.

4.1 Are DSGE Parameter Estimates Truly Structural?

A common argument made in favour of DSGE models is that the micro-foundation of the model and the separation of the deep structural parameters (ie parameters for preferences, technology, or those describing the law of motion of aggregate shocks) from expectational parameters (which are dependent on policy regimes) guarantees that the model is robust for policy analysis. In other words, DSGE models are not subject to the "Lucas critique" and therefore can be used to quantitatively evaluate policy (see Woodford 2003).

However, concerns about the possibility of time varying parameters are a main interest both in academic and policy circles. In fact, extraordinary changes associated with policy interventions, which can be particularly notorious in emerging markets (eg shifts in exchange rate and monetary policy regimes, reforms, financial crises) but which also affect advanced economies, have led many to ask whether the parameters estimated in DSGE models are truly structural. For this reason, it is commonly argued that the selection of appropriate stable sample periods or the elimination of structural breaks is necessary before the model is taken to the data. Indeed, a common approach found in the literature is the estimation of DSGE models for different sub-samples. For instance, this approach is frequently employed when studying changes in monetary policy in the US and assessing the Federal Reserve's response before and after Volcker's appointment in 1979. In other countries such an approach has also been applied; however, in doing so, a common problem is that these analyses end up relying on few observations, thus raising further questions on the validity of results. Also there is another, more serious, problem with such an approach, as it implies that agents are unable to forecast the change in policy.

In general, dealing with structural breaks is a major challenge that has not yet been fully addressed in the literature, and which poses major identification issues. Some recent work in this area has been done by Fernández-Villaverde and Rubio-Ramírez (2007). In particular, they ask how stable over time are the so called "structural parameters" of DSGE models? For them there are at least three ways to think about parameter drift in estimated DSGE models. The first is a purely econometric one. In this case parameter drift is convenient as it helps fit the data. The second has to do with the characteristics of the environment in which agents understand and act upon. That is, the deep parameters of the model (eg capital shares in the production function) vary over time. And finally, parameter drift might be the only way to allow a misspecified model to fit the data. This may occur, for instance, if the data is fitted with an infinitely lived agent model when the data was actually generated by an overlapping generations (OLG) model. Of course, one could add that time varying parameters in DSGE models have also been treated as exogenous shocks (eg a technology shock) and therefore are invariant to policy changes.

Relying in quite sophisticated methods (ie applying a non-linear solution method for the model and relying on a Markov structure of the state-space representation to evaluate the likelihood function) Fernández-Villaverde and Rubio-Ramírez (2007), evaluate i) the role of time varying parameters in the Taylor rule of a model applied to the US. In this respect, their results confirm that monetary policy in the US has become much more aggressive since 1979 (ie the weight on inflation has increased) and that the inflation target was relaxed in the 1970s but not enough to account for the high inflation; ii) the extent of price and wage rigidities as captured by the Calvo adjustment probabilities, finding that the indexation parameters are mirrors of inflation. Of course, this leads them to conclude that there is strong evidence of the changing nature of nominal rigidities in the economy as well as of misspecification along the dimension of price and wage fundamentals. Such misspecification may be the result of: a) omitted variables in the model; b) that pricing is a state-dependent phenomena rather than a time-dependent (ie Calvo or Taylor pricing); and c) that price rigidities might be an endogenous phenomena.

Overall, the evidence just discussed indicates that there are large variations of parameter over time so caution has to be placed when considering the result of DSGE models that do not consider this.

5   Communicating DSGE Results

Policy decisions depend on different factors and views about how the economy works. To make decisions, policy makers often rely (and should rely) on different models. The problem is that current existing models employed at central banks do not always allow to frame a discussion and understand why certain dynamics are taking place. For instance, VARs are often used at central banks. A weakness of them is that if someone dislikes some of its predicted dynamics it may be difficult to discuss and agree why. Such problem arises because VARs impose very little restrictions, making it difficult to provide a story for some of its predictions. In this respect, DSGEs may be a superior alternative to the extent that they offer a very precise and coherent

framework of where restrictions come from. From a policy perspective, this means that if you do not like the results, it is possible to identify what is behind them and explain them. Overall, given their structure, DSGE models appear to be in principle useful tools for framing policy discussions.[37]

Although DSGE modelers at central banks often claim that DSGEs are good story-telling devices, there is an important caveat. How to communicate DSGE results? One common complaint about DSGEs from a policy maker's perspective is that such models need to make their results *comprehensible*, *sensible*, *flexible* and, above all, *reliable*. As for *comprehensibility*, the problem is related to the number of parameters that need to be tracked. In DSGEs, there is a type of "curse of dimensionality" problem, because the bigger the scale of the model the larger the number of parameters to be estimated. The implications are many. In terms of communication it easily complicates determining the drivers of particular results. Furthermore, it may complicate the mapping between the theoretical model's results and real world phenomena.

As regards to *sensibility*, the challenge is to convince policymakers that the model actually fits the data. The efforts made in the literature to prove a model's fit to the data have already been discussed. However, in terms of communication it is not always enough to interpret the coefficients and report counterfactual exercises say, for instance, with impulse response functions. In fact, the dynamics of different series may be difficult to interpret not only in terms of the direction but also in terms of its absolute and relative magnitudes. Sensibility also implies being able to qualify the extent to which certain phenomena of the real world is explained by what is left outside the model.

The third relevant issue is that of *flexibility*, in the sense that models need to be able to adapt and meet the policy makers' changing preferences and incorporate elements of their opinions and attitudes (Fukač and Pagan 2006). In general, policymakers are likely to have different views about how the economy works, and decisions will depend on their judgment. In considering judgment one has to take into account some important elements. For instance, as discussed in Faust (2005) policy decisions may depend on i) the manner in which an issue is framed; ii) when presented at brute force (eg an $X\%$ chance of recession), judgment is affected by the story that comes with it; and iii) experts may not reliably take into account their successes and failures when assessing current judgments. In this respect, it seems that DSGE models are likely to help frame policy decisions and provide a more neutral story from which to discuss, thus creating a more "disciplined judgement".

The final point is that of *reliability*. This of course involves many of the issues already discussed at length in this paper, such as identification issues and misspecification. Only time and experience will help make DSGEs prediction more reliable. In this respect, there are some basic steps that can be made to ground the model and help build credibility on it. The first is to report DSGE results side-by-side with those of other "more traditional" analysis available at central banks (eg against VARs results). The second is to provide examples of how the model predicts the

---

[37]Certainly, by adding few restrictions VARs may have an advantage in forecasting when compared with DSGE models. As a result, it may not be surprising that the former will generally outperform the latter when forecasting.

behaviour of the economy in past episodes. This can easily be done with historical decompositions (eg see Adolfson et al 2007a). This, of course offers transparency about the models strengths and weaknesses. The final step is to communicate the structure of the model within the central bank. This increases the transparency of the model and allows better feedbacks about its strengths and weaknesses.

DSGE models are not likely to outperform other traditional models available at central banks, at least for now. Therefore, there is also a question about what to do if it is known that certain aspects of the DSGE model do not fit the data. Should the DSGE model be discarded? Alvarez–Lois et al (2008) discuss this issue by explaining how the Bank of England Quarterly model (BEQM) is employed. They argue that the BEQM was built with a "core" theoretical component (ie a DSGE model) and some "non-core" theoretical equations that include additional variables and dynamics not modeled formally (or not microfounded) in the core DSGE model. These two platforms are then combined for projections and for the direct application of judgment.[38] The reason for relying on a core/non-core approach is because policy makers may feel uncomfortable in relying too much on unobserved factors (ie shocks or measurement errors) as they have to provide policy watchers with a plausible story that can be related to observed developments. By comparing the core model with the non-core they are then able to tell a story about how much weight to put on a purist, textbook explanation, and how much to put on other factors that, while ad-hoc, may exhibit plausible correlations. In a sense, this approach resembles to a large extent Del Negro and Schorfheide's (2004) DSGE-VAR approach. Of course, such core/non-core approach raises the issue of the extent to which it is desirable to leave room for judgment within the model.

Applying judgement is more an art than a science and in policy making it is sometimes unavoidable. Adolfson et al (2007a) conclude that incorporating judgments into formal models is desirable. In this manner, forecasts could reflect both judgments and historical regularities of the data. Of course, the question is how to formally do it? This is a relatively unexplored area. Reichlin (2008), for instance, has proposed to do so by treating as noisy the observations of possibly more informed forecasts and using the Kalman filter to extract the signal. In contrast, Sims (2008a) considers that judgement can be treated in a more natural way with Bayesian inferential methods by combining judgemental information (which can be naturally characterised as beliefs) with information emerging from observed data.

Overall, DSGE models offer a lot of potential for policy making and, in its purist form, offer a coherent framework to discuss policy issues. But this strength is only potential. In that sense, it appears that we should avoid asking too much from the models. If they are not fully ready for "prime time", it might be better to just employ them in what is known to be their greatest strength, helping develop economic intuition, rather that just forcing them to explain empirical regularities.

---

[38]Reichlin (2008) argues that judgement and story-telling come into forecast at central banks for several reasons: i) to take into account rare unexpected events; ii) to incorporate short term forecasts and the path on the endogenous variables; and iii) to discuss informed/educated scenarios on exogenous variables.

6 Conclusions

DSGE models are powerful tools that provide a coherent framework for policy discussion and analysis. In principle, they can help to identify sources of fluctuations, answer questions about structural changes, forecast and predict the effect of policy changes, and perform counterfactual experiments. Such features and the rapid advances in the academic literature has attracted the attention of central banks across the world, some of which have already developed and employ these models for policy analysis and forecasting. This paper reviewed some of the issues and challenges surrounding their use for policy analysis. Despite the rapid progress made in recent years, at their current stage of development, these models are not fully ready to accomplish all what is being asked from them. They still fail to have a sufficiently articulated description of the economy, which may be forcing them to downplay or ignore important interactions in the economy. Nonetheless, this should not stop central banks from using DSGE models to gain insight into the workings of an economy.

Looking forward, DSGE models will face important challenges. The first is that more realism is likely to create more complex models, making them more difficult to understand, handle, analyse and communicate. Thus, seems undesirable to create new large and intractable DSGE models. Second, these models are unlikely to outperform other traditional models available at central banks, at least for now. That is, they will have to live side-by-side with other policy models and tools. How much weight they will receive in forecasting and in formal policy decisions will depend on their ability to fit the data.

Overall, without being an exhaustive review of the literature, this paper has aimed at highlighting some of the achievements and limitations of DSGE models, while putting into perspective some of the practical merits and difficulties that may arise in employing them for policy making at central banks.

References

Adolfson, M, S Laséen, J Lindé and L Svensson (2008a). "Monetary Policy Trade-offs in an Estimated Open-Economy DSGE Model", NBER Working Paper 14510. National Bureau of Economic Research, Cambridge, Mass.

Adolfson, M, S Laséen, J Lindé and M Villani (2008b). "Evaluating an Estimated New Keynesian Small Open Economy Model", *Journal of Economic Dynamics and Control*, vol 32, Issue 8, August, pp 2690–2721.

Adolfson, M, M Andersson, J Lindé, M Villani and A Vredin (2007a). "Modern Forecasting Models in Action: Improving Macroeconomic Analyses at Central Banks", *International Journal of Central Banking*, vol 3, no 4, December, pp 111–144.

Adolfson, M, S Laséen, J Lindé and M Villani (2007b). "RAMSES – a New General Equilibrium Model for Monetary Policy Analysis", *Economic Review* 2, Sveriges Riksbank.

Aldolfson, M, S Laséen, J Lindé and M Villani (2007c). "Bayesian Estimation of an Open Economy DSGE Model with Incomplete Pass-through", *Journal of International Economics*, vol 72, no 2, pp 481–511.

Alvarez-Lois, P, R Harrison, L Piscitelli and A Scott (2008). "On the Application and Use of DSGE Models", *Journal of Economics Dynamics and Control*, vol 32, Issue 8, August, pp 2428–2452.

An, S, and F Schorfheide (2007). "Bayesian Analysis of DSGE Models", *Econometric Reviews*, 26:2, 113–172.

Benássy, J (2007). *Money, Interest and Policy: Dynamic General Equilibrium in a Non–Ricardian World*. MIT Press.

Bernanke, B, M Gertler and S Gilchrist (1999). "The Financial Accelerator in a Quantitative Business Cycle Framework" in J Taylor and M Woodford (eds) *Handbook of Macroeconomics*. Volume 1C, North Holland.

Bernanke, B and J Boivin (2003). "Monetary Policy in a Data Rich Environment", *Journal of Monetary Economics*, vol 50, no 3, April, pp 525–546.

Bierens, H (2007). "Econometric Analysis of Linearized Singular Dynamic Stochastic General Equilibrium Models", *Journal of Econometrics* vol 136, Issue 2, February, pp 595–627.

Boivin, J and M Giannoni (2006). "DSGE Models in a Data-rich Environment", NBER Technical Working Paper no 332. National Bureau of Economic Research, Cambridge, Mass.

Borio, C (2006). "Monetary and Prudential Policies at a Crossroads? New Challenges in the New Century", BIS Working Paper no 216, September.

Borio, C, and P Lowe (2002). "Asset Prices, Financial and Monetary Stability: Exploring the Nexus", BIS Working Paper, no 114, July.

Borio, C, C Furfine and P Lowe (2001). "Procyclicality of the Financial System and Financial Stability: Issues and Policy Options", BIS Papers no 1, March.

Brubakk, L, T Anders, J Maih, K Olsen and M Østnor (2006). "Finding NEMO: Documentation of the Norwegian Economy Model", Staff Memo no 2006–6.

Canova, F (2007). *Methods for Applied Macroeconomic Research*. Princeton University Press.

Canova, F, and L Sala (2006). "Back to Square one: Identification Issues in DSGE Models", Working Paper Series no 583, European Central Bank, January.

Castillo, P, C Montoro and V Tuesta (2009). "MEGA-D: Modelo de equilibrio general agregado con dolarización parcial para la economía peruana", Documento de Trabajo 2009–003. Central Reserve Bank of Peru.

Castillo, P, C Montoro and V Tuesta (2006). "An Estimated Stochastic General Equilibrium Model with Partial Dollarization: a Bayesian Approach", Central Bank of Chile Working Papers, no 381, December.

Céspedes, L, R Chang and A Velasco (2004). "Balance Sheets and Exchange Rate Policy", *American Economic Review*, vol 94, no 4, September, pp 1183–1193.

Choi, W, and D Cook. (2004). "Liability Dollarization and the Bank Balance Sheet Channel", *Journal of International Economics*, vol 64, no 2, December, pp 247–275.

Chrisitiano, L, R Motto and M Rostagno (2007a). "Financial Factors in Business Cycles", Mimeo, European Central Bank.

Christiano, L, M Trabant, K Walentin (2007b). "Introducing Financial Frictions and Unemployment into a Small Open Economy Model", Sveriges Riksbank Working Paper Series 214, November.

Christiano, L, M Eichenbaum and C Evans (2005). "Nominal Rigidities and the Dynamic Effects to a Shock of Monetary Policy", *Journal of Political Economy*, vol 113, no 1, pp 1–45.

Christoffel, K, G Coenen and A Warne (2007). "Conditional versus Unconditional Forecasting with the New Area-Wide Model of the Euro Area", papers presented at the Central Bank Workshop on Macroeconomic Modelling 2007, Norges Bank.

Christoffel, K, and K Kuester (2008). "Resuscitating the Wage Channel in Models with Unemployment Fluctuations", *Journal of Monetary Economics*, vol 55, July, pp. 865–887.

Clarida, R, J Gali and M Gertler (1999). "The Science of Monetary Policy: A New Keynesian Perspective", *Journal of Economic Literaure*, vol 37, pp 1661–1707.

Colander, D, P Howwit, A Kirman, A Leijonhufvud and P Mehrling (2008). "Beyond DSGE Models: toward an Empirically Based Macroeconomics", *American Economic Review: Papers and Proceedings*, vol 98, no 2, pp 236–240.

DeJong, D, and C Dave (2007). *Structural Macroeconometrics*, Princeton University Press.

Del Negro, M, and F Schorfheide (2008). "Forming priors or DSGE Models (and how it Affects the Assessment of Nominal Rigidities)", *Journal of Monetary Economics*, vol 55, pp 1191–1208.

Del Negro, M, and F Schorfheide (2007). "Monetary Policy Analysis with Potentially Misspecified Models", NBER Working Paper 13099. National Bureau of Economic Research, Cambridge, Mass.

Del Negro, M, and F Schorfheide (2004). "Priors from Equilibrium Models for VARs", *International Economic Review*, vol 45, pp 643–673.

Del Negro, M, and F Schorfheide (2003). "Take your Model Bowling: Forecasting with General Equilibrium Models", *Economic Review*, Federal Reserve Bank of Atlanta, Fourth Quarter.

Devereux M, and Sutherland (2007). "Monetary Policy and Portfolio Choice in an Open Economy Macro Model", *Journal of the European Economic Association*, vol 5, no 2–3, pp 491–499.

Devereux M, and Sutherland (2006). "Solving for Country Portfolios in Open Economy Macro Models", Working Paper, University of British Columbia.

Dotsey, M, R King, and A Wolman (1999). "State Dependent Pricing and the General Equilibrium Dynamics of Output", *Quarterly journal of Economics*, vol 114, no 2, May, pp 655–690.

Edge, Rochelle, M Kiley and JP Laforte (2008). "Natural Rate Measures in an Estimated DSGE Model of the US Economy", *Journal of Economic Dynamics and Control*, vol 32, Issue 8, August, pp 2512–2535.

Engel, C, and A Matsumoto (2005). "Portfolio Choice in a Monetary Open-Economy DSGE Model", IMF Working Paper WP/05/165.

Erceg, C, L Guerrieri and C Gust (2006). "SIGMA: a New Open Economy Model for policy Analysis", *International Journal of Central Banking*, vol 2, no 1, December, pp 111–144.

Erceg, C, L Guerreri and C Gust (2005). "Expansionary Fiscal Shocks and the US Trade Deficit", *International Finance*, vol 8, no 3, pp 363–397.

Faust, J (2008). "DSGE Models in a Second Best World of Policy Analysis", mimeo. available at http://e105.org/faust

Faust, J (2005). "Is Applied Monetary Policy Analysis Hard?", Mimeo Federal Reserve Board.

Favero, C (2001). *Applied Macroeconometrics*, Oxford University press.

Fernández-Villaverde, J, and J Rubio-Ramírez (2007). "How Structural Are Structural Parameters", NBER Working Paper 13166. National Bureau of Economic Research, Cambridge,Mass.

Fernández-Villaverde, J, and J Rubio-Ramírez (2006). "Estimating Macroeconomic Models: a Likelihood Approach", NBER Technical Working Paper 321. National Bureau of Economic Research, Cambridge,Mass.

Fernández-Villaverde, J, and J Rubio-Ramírez (2005). "Comparing new Keynesian models of the business cycle: A Bayesian approach", vol 52, pp 1151–1166.

Fernández-Villaverde, J, and J Rubio-Ramírez (2004). "Comparing Dynamic Equilibrium Models to Data: a Bayesian Approach", *Journal of Econometrics*, vol 123, pp 153–187.

Fernández-Villaverde, J, J Rubio-Ramírez and M Santos (2006). "Convergence Properties of the Likelihood of Computed Dynamic Models", *Econometrica*, vol 74, Issue 1 pp 93–119.

Fernández-Villaverde, J, J Rubio-Ramírez, T Sargent and M Watson (2007). "A, B, C (and D's) for Understanding VARs", *American Economic Review*, vol 97, no 3, pp 1021–1026.

Forni, L, L Monteforte and L Sessa (2009). "The General Equilibrium Effects of Fiscal Policy: Estimates for the Euro Area", *Journal of Public Economics*, vol 93, Issues 3–4, April, pp 559–585.

Fukač, M, and A Pagan (2006). "Issues in Adopting DSGE Models for Use in the Policy Process", Working paper Series 6/2006, Czech National Bank, November.

Gali, J and M Gertler (2007). "Macroeconomic Modeling for Monetary Policy Evaluation", *Journal of Economic Perspectives*, vol 21, no 4, Fall, 25–46.

Ganelli, G (2005). "The New Open Economy Macroeconomics of Government Debt", *Journal of International Economics*, vol 65, no 1, pp 167–184.

Gerali, A, N Stefano, L Sessa and F Signoretti (2008). "Credit and Banking in a DSGE model", mimeo, Banca de Italia.

Gertler, M, and J Leahy (2008). "A Philips Curve with an Ss Foundation", *Journal of Political Economy*, vol 116, no 3, pp 533–572.

Geweke, J (2007). "Models, Computational Experiments and Reality", University of Iowa, mimeo.

Goodfriend, M (2007). "How the World Achieved Consensus on Monetary Policy", *Journal of Economic Perspectives*, vol 21, no 4, Fall, 47–68.

Goodfriend, M and R King (1997). "The New Neoclassical Synthesis and the Role of Monetary Policy", NBER Macroeconomics Annual 1997.

Harrison, R, K Nikolov, M Quinn, G Ramsay, A Scott and R Thomas (2005). Bank of England Quarterly Model. Bank of England.

Hoover, K, S Johansen and K Juselius (2008). "Allowing the Data to Speak Freely: the Macroeconometrics of the Cointegrated Vector Autoregression", *American Economic Review: Papers and Proceedings*, vol 98, no 2, pp 236–240.

Iacovello, M (2005). "House Prices, Borrowing Constraints and Monetary Policy in the Business Cycle", *American Economic Review*, vol 95, pp 739–764.

Iacovello, M, and S Neri (2008). "Housing Market Spillovers: Evidence from an Estimated DSGE Model", Banca de Italia.

Ireland, P N, (2004). "Taking Models to the Data", *Journal of Economic Dynamics and Control*, vol 28, Issue 6, March, pp 1205–1226.

Iskrev, N (2008). "How much do We Learn from Estimating DSGE Models – a Case Study of Indentification Issues in a New Keynesian Business Cycle Model", University of Michigan, mimeo.

Jokivuolle, E, J Kilponen, T Kuusi (2007). "GDP at Risk in a DSGE Model: an Application to Banking Sector Stress Testing", Bank of Finland Research Discussion Papers, no 26.

Juselius, K, and M Franchi (2007). "Taking a DSGE Model to the Data Meaningfully", *Economics: The Open-Access, Open-Assessment E-Journal*, Vol. 1, 2007–4. http://www.economics-ejournal.org/economics/journalarticles/2007-4.

Kim, J, S Kim, E Schaumburg and C Sims (2008). "Calculating and Using Second-order Accurate Solutions of Discrete Time Dynamic Equilibrium Models", *Journal of Economic Dynamics and Control*, no 32, pp 3397–3414.

Krause, M, D López-Salido and T Lubik (2008). "Inflation Dynamics with Search Frictions: a Structural Econometric Analysis", *Journal of Monetary Economics*, vol 55, July, pp. 892–916.

Kocherlakota, N (2007). "Model Fit and Model Selection", Federal Reserve Bank of St. Louis Review, July/August.

Kumhof, M, and D Laxton (2007). "A Party without a Hangover? On the Effects of US Government Deficits", IMF Working Paper 07/202, August.

Lancaster, T (2004). *An Introduction to Modern Bayesian Econometrics*. Blackwell publishing.

Lane, P, and G Milesi-Ferretti (2007). "The External Wealth of Nations Mark II: Revised and Extended Estimates of Foreign Assets and Liabilities, 1970–2004", *Journal of International Economics*, vol 73, no 2, November, pp 223–250.

Lane, P, and G Milesi-Ferretti (2001). "The External Wealth of Nations: Measures of Foreign Assets and Liabilities for Industrial and Developing Countries", *Journal of International Economics*, vol 55, pp 263–94.

Laxton, D (2008). "Getting to Know the Global Economy Model and Its philosophy", IMF Staff Papers, vol 55, no 2, pp 213–242.

Laxton, D, and P Pesenti (2003). "Monetary Policy Rules for Small Open, Emerging Economies", *Journal of Monetary Economics*, vol 50, no 5, pp 1109–1146.

Lucas, R (1976). "Econometric policy evaluation: a critique", in K. Brunner and A Meltzer, *The Phillips Curve and Labor Markets*, North Holland.

Mankiw, G (2006). "The Macroeconomist as Scientist and Engineer", *Journal of Economic Perspectives*, vol 20, no 4, Fall, pp 29–46.

Medina, J and C Soto (2007a). "Copper Price, Fiscal Policy and Business Cycle in Chile", Central Bank of Chile Working Papers no 458, December.

Medina, J and C Soto (2007b). "The Chilean Business Cycle through the Lens of a Stochastic General Equilibrium Model", Central Bank of Chile Working Papers, no 457, December.

Medina, J, A Munro and Soto (2008). "What Drives the Current Account in Commodity Exporting Countries? The Cases of Chile and New Zealand", BIS Working Paper no 247, March.

Murchison, S, and A Rennison (2006). "ToTEM: The Bank of Canada's New Quarterly Projection Model", Bank of Canada Technical Report, no 97.

Obstfeld, M, and K Rogoff (1995). "Exchange Rate Dynamics Redux", *Journal of Political Economy*, vol 103, pp. 624–660.

Obstfeld, M, and K Rogoff (2002). "New Directions for Stochastic Open Economy Models", *Journal of International Economics*, vol 50, no 1, pp 117–153.

Pesenti P (2008). "The Global Economy Model: Theoretical Framework", *IMF Staff Papers*, vol 55, no 2, pp. 243–284.

Rabanal, P and J Rubio-Ramírez (2005). "Comparing New Keynesian Models of the Business Cycle: A Bayesian Approach", *Journal of Monetary Economics*, vol 52, pp 1151–1166.

Reichlin, L (2008). "Discussion: Taking DSGE Models to the Policy Environment by Alvarez-lois, Harrison, Piscitelli and Scott", *Journal of Economics Dynamics and Control*, vol 32, Issue 8, August, pp 2453–2459.

Rudebusch, G, B Sacks and E Swanson (2007). "Macroeconomic Implications of Changes in the Term Premium", *Federal Reserve Bank of St. Louis Review*, July/August.

Ruge-Mucia, F (2007). "Methods to Estimate Dynamic Stochastic General Equilibrium Models", *Journal of Economic Dynamics and Control*, vol 31, August, pp 2599–2636.

Sargent, T (1989). "Two Models of Measurement and the Investment Accelerator", *The Journal of Political Economy*, vol 97, no 2, April, pp. 251–287.

Schmidtt-Grohé, S, and M Uribe (2004). "Solving Dynamic General Equilibrium Models Using a Second-Order Approximation to the Policy Function", *Journal of Economic Dynamics and Control*, vol 28, pp 755–775.

Schmidtt-Grohé, S, and M Uribe (2003). "Closing Small Open Economy Models", *Journal of International Economics*, vol 61, pp 163–185.

Schorfheide, F (2005). "Bayesian Methods in Macroeconomics", in S Durlauf and L Blume, *The New Palgrave Dictionary of Economics*, Palgrave Macmillan, forthcoming.

Sims, C (2008a). "Improving Monetary Policy Models", *Journal of Economics Dynamics and Control*, vol 32, Issue 8, August, pp 2460–2475.

Sims, C (2008b). "Making Macro Models Behave Reasonably", Mimeo. Available at: http://sims.princeton.edu/yftp/ReasonableModels/MakingReasonable.pdf

Sims, C (2006). "Comment on Del Negro, Schorfheide, Smets and Wouters". Available at: http://sims.princeton.edu/yftp/DSSW806/DSseattleComment.pdf

Sims, C (2003). "Comments on Smets and Wouters", Available at http://sims.princeton.edu/yftp/Ottawa/SWcommentSlides.pdf

Sims, C (1980). "Macroeconomics and Reality", *Econometrica*, vol 48, no 1, January, pp 1–48.

Smets, F and R Wouters (2007). "Shocks and Frictions in US Business Cycles: a Bayesian DSGE Approach", *American Economic Review*, vol 97, no 3, pp. 586–606.

Smets, F and R Wouters (2003). "An Estimated Stochastic Dynamic General Equilibrium Model of the Euro Area", *Journal of the European Economic Association*, vol 1, no 5, pp 1123–1175.

Tovar, C (2006). "An analysis of devaluations and output dynamics in Latin America using an estimated DSGE model", BIS Working Paper, forthcoming.

Tovar, C (2005). "The mechanics of devaluations and the output response in a DSGE model: how relevant is the balance sheet effect?" BIS Working Paper, no 192. November.

Woodford, M (2003). "*Interest and prices*." Princeton University Press.

Please note:

You are most sincerely encouraged to participate in the open assessment of this article. You can do so by either rating the article on a scale from 1 (bad) to 5 (excellent) or by posting your comments.

Please go to:

www.economics-ejournal.org/economics/journalarticles/2009-16

The Editor