DSGE models for policy analysis at central banks: an overview of issues and challenges

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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 both 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 such models 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 are likely to perform well in some dimensions but not in others. Thus, if they are to be used as policy tools, room must be left for judgement.

JEL classification: B4, C5, E0, E32, E37, E50, E52, E58, F37, F41, F47.

1. INTRODUCTION

Over the past 15 years there has been remarkable progress in the specification and estimation of dynamic stochastic general equilibrium (DSGE) models. 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. Furthermore, many other central banks are beginning or are planning to do so.[1] Notwithstanding these rapid advances and the growing interest, the use of DSGE models still remains in

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[1] Some of the 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, 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). See references for a list of articles describing the framework of these models.

the periphery of the formal policy decision making process in most central banks.[2] 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.

Why are DSGE models not yet part of the core decision making framework? In part, it has to do with the newness of the technology. 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. 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 Smets and Wouters (2003), that some evidence was put together showing 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). However, even with the current sophisticated methods, taking the models to the data may be quite challenging as certain preconditions may be necessary. For 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)). Furthermore, models may suffer from misspecification and parameter identification is not always easy to achieve. Such preconditions and 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 or to rapid structural and frequent policy changes.[3]

The complex nature of DSGE models may have also limited their acceptance among policy makers.[4] Their complexity implies that notation can get very messy, creating a natural barrier for the communication of the results to policy makers, not to mention to the public. In general, understanding the workings of these models requires well trained macroeconomists with a modeling culture and strong statistical and programming skills. This of course implies that resources are needed, and these are often scarce at public institutions, in particular in EMEs.

From a more technical point of view there are also important concerns related to the degree of misspecification of current DSGE models. 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 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).[5] Indeed, Kocherlakota (2007) shows that a model that fits the available data perfectly

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2 Some exceptions are the Bank of England, Central Bank of Chile, Norges Bank and Sveriges Riksbank.

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

4 A priori there is no reason why the new models are more complex than older ones. However, the methods for solving and estimating them are not the standard ones found in the older literature. A good example of this is the econometric methods employed, Bayesian techniques are not yet a standard part of econometric course in Economic PhD programmes.

5 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.

may provide worse answers to policy questions than an alternative, imperfectly fitting model.[6] 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 behavioral parameters may be a more successful approach.

While the views highlighted in the previous paragraphs may sound a bit pessimistic, a lot of progress has been made with DSGE models, and even at their current stage of development they can be useful. The important question to answer therefore is: given their current state of development, how should DSGE models be employed for policy analysis and forecasting at central banks?

There are different views on these issues. For instance, the most common view 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)). 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. This 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-autoregreesive 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 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, although less common, is to proceed with calibration methods. In this respect, important progress has also been made. However, calibrated models are not widely known or employed at central banks, and therefore they will not be discussed it in detail here (see for example Bierens (2007)).

It is still early to determine which approach will work better in terms of forecasting and policy analysis. 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 not yet incorporated successfully relevant economic transmission mechanisms and/or sectors of the economy (eg the modeling of financial and labour markets). The second area is the empirical validation and use of these models: how should these models 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 the challenges arising from these three questions.

2. Modeling challenges

Most DSGE models available in the literature have a basic structure. The benchmark DSGE model is an (open or closed economy) fully micro-founded model with real and nominal rigidities (see for instance Christiano, Eichenbaum and Evans (2005) and Smets and Wouters (2003)). In particular, firms and households are monopolistic suppliers of differentiated goods and labor, respectively. These agents face nominal frictions so that they are unable, in each respective case, 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. Households

[6] 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.

preferences display habit persistence in consumption, and the utility function is separable in terms of consumption, leisure and real money balances. Fiscal policy is restricted to balancing the budget in all periods, while monetary policy is conducted through an interest rate feedback rule, in which the interest rate is a function of the rate of expected inflation 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 technology, preference, cost-push or markup, monetary and government spending shocks, which 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 modeling during the past decade and a half, faces some important challenges. Although we do not pretend to make an exhaustive list it is possible to mention that more work is required in modeling financial markets, incorporating more explicitly the role of fiscal policies, improving the interaction between trade and financial openness, modeling labour markets and in modeling inflation dynamics (for instance, regarding the role of expectations and pricing).[7] Of course, more specific aspects may also need to be considered, in particular, when modeling small open economies. 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 modeling 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, Japanese crisis of the 1980s-90s, 1980s Latin American crisis, the 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 modeling 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 to explain the business cycle) and excludes any possible analysis of key policy issues of direct concern for central banks, such as financial vulnerabilities, illiquidity or the financial systems´ procyclicality.[8]

The financial accelerator has been among the most common approach to incorporate financial frictions into a DSGE framework (Bernanke, Gertler and Gilchrist (1999) and Cespedes, Chang and Velasco (2004)). The financial accelerator has been employed to capture firms´ balance sheet the effects on investment by relying on a one-period stochastic optimal debt contract with costly-state verification. The key aspect is that such setting endogenously determines a risk premium above the risk-free interest rate. This approach has also been applied to capture balance sheet weaknesses in the banking sector (eg Choi and Cook (2004)). However, its main weakness is that it only addresses one aspect of many possible financial frictions. More recently, Iacovello (2005) has extended the interactions between housing prices, economic activity (consumption) and monetary policy. In particular, he introduces household and firm

7 These aspects are not fully discussed in this paper. However, it is worth mentioning 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.

8 The procyclicality of financial systems can be explained by information assymetries between borrowers and lenders, as highlighted in the financial accelerator literature (see discussion below). 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 Lowe (2002), Borio et al (2001)).

collateral constraints limiting both consumption and investment. This work offers a promising avenue to improve the manner in which financial and credit frictions are incorporated into the models.

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.[9] Therefore, the difficulty of modeling the optimal portfolio choice has also meant that modeling 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 modeled 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.[10] 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 DSGE. 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 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 associated with theoretical uncertainties and the second with computational problems.[11] On 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-know 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).

2.2 Currency risk premia

Currency risk premia is another relevant area in which DSGE models have faced important challenges. In small open economies models the basic limitation is that a solution is required

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

[10] 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.

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

to the problem caused by the fact that agents are able to borrow at a fixed interest rate, which allows them to finance consumption streams indefinitely. Several solutions have been posed to rule-out such behavior (See Schmidt-Grohé and Uribe (2003)). However, in practical terms the most common approach has been to attach a risk premium to foreign debt, which is usually an increasing function of the level of borrowing and forces agents 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. This problem can be particularly severe in EMEs, where sovereign risk can be highly volatile, as reflected during the financial crises experienced in the recent past. Of course, the great weakness of this approach is that it lacks microfoundations.

The problem 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 rate 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.

2.3 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 which limits the analysis to balanced-budget policies. As a result, the distribution of taxes across time become irrelevant and aggregate financial wealth does not matter for the behavior 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. The question is how to break the Ricardian equivalence? Two possibilities are available. The first is to move to an overlapping generations (OLG) framework[12] 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").[13] Although both types of models are capable 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. Indeed, Kumhof and Laxton (2007) have developed a very comprehensive model for the analysis of fiscal policies, which incorporates four non-Ricardian features.[14] 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.

2.4 DSGE modeling in EMEs

Modeling and capturing the dynamics of EMEs is no easy task. This is partly related to structural features exhibited by these economies as well as due to the historical vulnerabilities to ex-

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

[13] 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 modeling endogenously a collateral constrain.

[14] First, OLG agents with finite economic lifetimes. Second, a stylized form of life-cycle income pattern in which the average agent exhibits declining labor 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 labor and consumption taxes.

ternal factors and resulting periods of high macroeconomic instability. In general, 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, long enough and "clean" time series to be fed into a DSGE model may be unavailable, 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 modeling 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 behaviors 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 nonlinear and standard solution methods, in particular log-linearisations, may fail to recognize these features, thus leading to inadequate policy recommendations.

Under such circumstances an important question to ask is what features of the benchmark DSGE model need to be modified as to capture these (and possibly other) features characterising EMEs? Without making an exhaustive list, it is possible to highlight one aspect, mainly that many EMEs, including some in Latin America or in Eastern Europe, are often characterised by a high degree of "dollarisation".[15] Partial dollarisation is a common phenomenon in economies that experienced high inflation even after several years of achieving low and stable inflation. The implication is that a foreign currency (dollar or Euro) takes over the basic functions of the domestic currency. This 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 dollarization in DSGE frameworks (see Castillo et al (2006)). By explicitly modeling dollarisation the DSGE model improves its fit to the data.[16] In particular, currency substitution reduces the output response to interest rates, improving 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.

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[15] The modelling of sovereign risk premia is of central interest to EMEs. In this respect notice that the discussion is parallel to that of financial market frictions and currency risk premia.

[16] 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.

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 due to financial dollarisation. This effect contrasts with standard theoretical modeling in advance economies where currency devaluations are thought to have expansionary effects, say, due to the expenditure-switching effect. As a result, when modeling EMEs mechanisms need to be included that allow devaluations to have a potential contractionary role (eg see Tovar (2006, 2005)). Equally important is that exchange rate regimes are likely to play an important role. In general, very few papers take 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 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. However, such a solution leads us into another controversial and unresolved matter in many EMEs: 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 modeling of exchange rate pass-through, a more complicated exercise is allowing for time-varying degrees of exchange rate pass-through.

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 possible to avoid the "Lucas critique", according to which only models in which the parameters do not vary with policy changes are suited to evaluate the impact of policy changes.

As argued in the introduction, 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). Therefore, there has been a growing body of literature aiming at ensuring that DSGE models provide an accurate description of the data. The problem is that if modeling is a complex task, more so is the estimation of DSGE models. From an empirical point of view, a basic issue is that none of the models actually represent the data generating process (DGP) of the time-series of interest and, in general, they are not specifically designed for that purpose. They were designed to gain insight about specific economic relationships rather than to describe the actual economy. Notwithstanding this, for these models to be of practical use for policy they need to describe observed features of the economy. So what are then key elements that need to be taken into account as to be able to take DSGE models to the data? In what follows, we discuss issues related to the data, estimation methods, model specification, parameter identification and policy simulation.

3.1 Data sets

It is well known that econometricians often fail to be able to observe the theoretical concepts modeled (eg the output gap). So a first question is how to match the theoretical concepts with those of the observed data? This is not trivial. In many cases the lack of an appropriate match has led researches to explicitly recognise the role of measurement errors or to incorporate into the estimation information contained in different data series.[17]

Augmenting the number of data series employed in the estimation of DSGE models seems to be another relevant issue, 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, they 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 important issue in matching the data to theoretical concepts is that until recently most DSGE models have been measured 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 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 Del Negro and Schorfheide (2003)). One is that by filtering data, forecasting stays out of the reach of DSGE models since the interest is on forecasts of actual data rather than of filtered data. The second is that such dynamics do not match that required by policy makers, weakening the usefulness of DSGE models as policy tools. Alternatives often used are the linear detrending and demeaning the variables, as well, as transforming variables so that they are stationary around a balanced growth path.

One final comment is that DSGE models are guided by the idea that there is a steady state of the economy, and this implies that ratios of certain variables are constant, and the data do not always support this assumption (Fukač and Pagan (2006)).

We have already mentioned some challenges arising in estimating DSGE models in EMEs. One of them is related to the availability of data. Although we will not discuss this again, it is important to keep in mind that large samples of good data (without large structural breaks, or episodes of high volatility) are necessary to feed these stylised models. Unfortunately, such conditions are often not met in EMEs.

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.[18] This partly reflects improvements in computational power and the development

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

[18] 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.

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. However, readers are referred to Canova (2007), Ruge-Murcia (2007) and An and Schorfheide (2007) for technical details.

In the literature there are different econometric techniques available for estimating DSGE models. Examples of these include parameter calibration, 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), Ruge-Murcia (2003) 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 are considered to employ only 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[19] 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.[20] 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 empirically DSGE models.[21] 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

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19 In non-linear DSGE models a sequential Monte Carlo filtering can be employed. See Fernandez-Villaverde, Rubio-Ramírez (2006).

20 Fernandez-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.

21 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 above), or when risk considerations are relevant. See Schmidtt-Grohé and Uribe (2004) for a discussion on second-order approximations. See also An and Shofheide (2007).

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 economist's views about what has been learned in the past about the economy.

Despite its attractiveness, Bayesian estimation has important weaknesses. On the one hand, 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. For this reason, Fukač and Pagan (2006) suggest comparing pure ML estimates with Bayesian estimates, something that is almost never done in practice. In that respect, "absurd parameter estimates" may be by itself an indication of specification problems with the model. Kocherlakota (2007) also 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. The effects of priors can also affect posterior odds 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.

A second important criticism of Bayesian estimation 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 and cross-coefficient restrictions that are at odds with the data (say, because there are misspecified structural relationships, because of wrongly specified exogenous process or due to omitted nonlinearities). 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-coefficient restrictions

One important source of misspecification is the questionable 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 to dealing with it. An 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 still needs to be improved as prior information on other dimensions related to the dynamics of the data may be necessary (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. More precisely, it 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 combinations of them.[22] 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 often follow a first order autoregressive process or a random walk behavior. 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 by themselves the can 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.

[22] 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.

Measurement errors This is the procedure originally proposed by Sargent (1989) and more recently emphasised in 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. 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 some argue that it implies “giving up the idea that the model is a good representation of the data” (Canova (2007)). Furthermore, in Ireland, they are introduced with an autocorrelated structure. This is completely 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 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.

Canova and Sala (2006) study identification in the context of DSGE models.[23] 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 neighborhood 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 re-parameterising the model. Most studies on DSGE models rely on the likelihood function, implying that having a well-behaved likelihood is a necessary but not sufficient condition for proper estimation. This of course has also implications for

[23] Identification is an issue that has been discussed to a large extent in the VAR literature.

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 introduce significant bias in parameter estimates, which can induce economic behaviors that differ significantly from those of the true DGP.

Overall, identification is a major issue in social sciences that needs to be dealt with in any empirical analysis. As such, possibly the best way of dealing with it is to understand what features of the economic or econometric model could lead to the identification problem.

3.5 Are DSGE parameter estimates truly structural?

A common argument made in favor 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.

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 market (eg shifts in exchange rate and monetary policy regimes, reforms, financial crises) but which also affect advanced economies (eg technology change), have lead many to ask whether the parameters estimated in DSGE models are truly structural. This has led some to argue 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 DSGE models for different sub-samples. For instance, this approach is well known 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 Fernandez-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 drifting in estimated DSGE models. The first is a purely econometric one. In this case parameter drifting is convenient as it helps fit the data. The second has to do with the characteristic 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 drifting might be the only manner 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) Fernandez-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 fundamental. 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 that caution has to be placed when considering the result of DSGE models that do not take this into account carefully.

3.6 Policy simulation and evaluation

Statistical evaluation of DSGE models are often not enough for economic purposes. The reason is that this would not tell us much of why the model may fail to fit the data. When maximum likelihood estimates are performed, it is possible to compute 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, variance decompositions 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 Shorheide (2007)), such as posterior predictive checks, posterior odds comparison or comparisons with VARs, as in Del Negro and Schorfheide (2004)).

Given the battery of tools available for evaluating models, we now have to ask whether the models can be employed for policy analysis. Some light in this respect is offered by a central bank that is leading in terms of DSGE modeling, the Sveriges Riksbank. Adolfson et al (2007) look at the forecast performance of BVARs and DSGE models vis-á-vis the Riksbank´s official more subjective forecast. They show that it is possible to construct DSGE models that make as good inflation forecast as the much more complicated judgmental procedure typically used at central banks. In particular, they report that the DSGE model is able to generate smaller forecast error for CPI 7-8 quarters ahead than both BVAR forecast and the official Riksbank forecasts. However, the results are less satisfactory for interest rate forecasts. In particular, the DSGE model is found to overestimate the future interest rates, possibly reflecting the difficulties in modeling risk premia.

4. Communicating DSGE Results

Policy decisions depend on different factors and views about how the economy works. To make decisions, policy makers rely on different models. For instance, they can use VARs. The problem with such an approach is that if you do not like the results it is difficult to discuss and agree why. For instance, VARs impose very little restrictions compared with DSGE models, which means that the former will generally outperform the later when forecasting. The key difference between VARs and DSGEs is that the later offers a very precise and coherent framework, in which it is clear where restrictions come from. Furthermore, from a policy perspective, if you do not like the results it is possible to identify what is behind them and explain them. In principle, given their structure, DSGE models are considered to be useful tools in framing the discussion.

However, 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.

In terms of sensibility, the challenge is to convince that the model actually fits the data. The efforts made in the literature to prove a model´s fit to the data has 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. Sensitivity 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 to 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 the problem and provide a more neutral story from which to discuss.

The final point is that of reliability. This of course involves many of the issues discussed at length in this paper such as identification issues and misspecification, which I will not discuss again. Only time and experience will help make DSGE 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 by providing examples of how the model predicted the behaviour of the economy in past episodes. This can easily be done with historical decompositions (See Adolfson et al (2007)). 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? Certainly not. Alvarez–Lois et al (2005) discuss this issue with a view on the Bank of England Quarterly model (BEQM). 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 in the core DSGE model. These two platforms are then combined for projections and for the direct application of judgment. The reason for relying on a core/non-core approach is that they consider that policy makers feel uncomfortable in relying too much on unobserved factors (ie shocks or measurement errors) mainly because they have to explain to policy watchers that they have 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 short-run factors that, while ad-hoc, may exhibit plausible correlations. In this sense, this approach resembles to a large extent Del Negro and Schorfheide´s (2004) DSGE-VAR approach. Whether it is desirable to leave room for judgment in the model is debatable, and may sound appealing, but leaving room for it is at the end of the day arbitrary and a potential source of errors or of misleading policy advice. Notwithstanding, it appears that at central banks this is welcomed. Indeed, Adolfson et al (2007) conclude that it would be beneficial to incorporate judgments into formal models, so that forecasts could reflect both judgments and historical regularities of the 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 ready to forecast, 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.

5. Conclusions

Central banks are increasingly devoting resources to DSGE models. This has stimulated a growing interest in their usefulness for policy analysis and forecasting. In this paper some of the issues and challenges surrounding the use of these models for policy analysis has been reviewed. It has been recognised that DSGE models offer coherent frameworks for policy analysis, furthermore, they offer a potential value added in terms of forecasting. Nonetheless,at their current stage of development, these models are not fully ready to accomplish all that is being asked from them. They still fail to have a sufficiently articulated description of the economy to be reliable tools. Important weaknesses are the lack of an appropriate modeling of the financial and labour markets among other elements, which may be forcing the current models to downplay or ignore important interactions in the economy (say for instance, the interaction of financial liberalisation, the globalisation of the real side of the economy and inflation). However, this is not just a DSGE model problem but a general weakness of the profession. Therefore, If one is willing to accept that this should not stop us from using DSGE models to gain insight into the working of an economy, then one must be willing to accept that they are likely to perform well in some dimensions but not in others. Overall, an important conclusion for central banks is that if DSGE models are to be used as policy tools, room must still be left for judgment.

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