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Abstract

In recent years DSGE (dynamic stochastic general equilibrium) models have come to play an increasing role in central banks, as an aid in the formulation of monetary policy (and increasingly after the global crisis, for maintaining financial stability). DSGE models, compared to other widely prevalent econometric models (such as VAR, or large-scale econometric models) are less a-theoretic and with secure micro-foundations based on the optimizing behavior of rational economic agents. Apart from being "structural", the models bring out the key role of expectations and (being of a general equilibrium nature) can help the policy maker by explicitly projecting the macro-economic scenarios in response to various contemplated policy outcomes. Additionally the models in spite of being strongly tied to theory, can be "taken to the data" in a meaningful way. A major feature of these models is that their theoretical underpinnings lie in what has now come to be called as the New Consensus Macro-economics (NCM) . Using the prototype real business cycle model as an illustration, this paper brings out the econometric structure underpinning such models. Estimation and inferential issues are discussed at length with a special emphasis on the role of Bayesian maximum likelihood methods. A detailed analytical critique is also presented together with some promising leads for future research.

Keywords: real business cycle; log-linearization; stochastic singularity; Bayesian maximum likelihood; complexity theory; agent-based modeling; robustness

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I. INTRODUCTION

Right from the 1970s policymakers have displayed an interest in formal models of the macro-economy with a view to using them for forecasting and policy purposes. Central banks, in particular, have felt the need to take recourse to such models as an aid in the formulation of monetary policy (and in recent years for maintaining financial stability). Typically an array of models is used to throw light on different aspects of policy, while judgment continues to play an important role in the actual policy decisions. The models used in the 1970s were basically large Simultaneous Equation Models (SEMs) , which were later followed by multiple time-series models, which in turn gradually gave way to VARs and Structural VARs in the 1990s. In the last decade or so an increasing number of central banks are actively engaged in the construction of DSGE (Dynamic Stochastic General Equilibrium) models internally by their staff with the involvement of outside academic experts (e.g. the Bank of England, the Federal Reserve Board, the European Central Bank, the IMF, Sveriges Riksbank etc.). Most of these banks are in the developed world, but it will not be long before EME central banks follow suit (Tovar (2008)).

Proponents of DSGE models attribute their recent popularity to several factors. Firstly unlike some of the widely prevalent econometric models (such as VAR, or large-scale econometric models) the DSGE models are less a-theoretic and with secure micro-foundations based on the optimizing behavior of rational economic agents. This is supposed to makes the model structural, and hence less subject to the Lucas critique.[i]. Several other advantages are also claimed on behalf of the models viz that they bring out the key role of expectations and (being of a general equilibrium nature) can help the policy maker by explicitly highlighting the macro-economic scenarios in response to various contemplated policy outcomes. Additionally, as we discuss later, the models in spite of being strongly tied to theory, can be "taken to the data" (to use a phrase which has become standard in this literature) in a meaningful way. A major feature of these models is that their theoretical underpinnings lie in what has now come to be called as the *New Consensus Macro-economics* (NCM) which established itself in the 1980s as the *weltanschauung* of the bulk of the macroeconomics profession. The NCM essentially represents a hybrid between two dominant schools of recent economic thought viz. the new classical school (Lucas (1972), Sargent (1979) etc.) and the neo-Keynesian view (Mankiw (1989), Taylor(1980) etc) -- grafting Keynesian sticky prices and wages on to an optimization model under rational expectations and with *complete* markets.

2. Real Business Cycle (RBC) Model

While DSGE models in practice can be fairly elaborate, for expository purposes, following the usual practice we take up the real business cycle (RBC) model (Hansen (1985), King et al (1988), Ireland (2004) etc.) in which a representative agent (who is a consumer, labourer, supplier of capital and producer , all rolled into one[ii]) has a linear utility function defined over consumption C_t^* and hours worked H_t^* for each period t=0,1,2… (The rationale for the asterisks is clarified later). He is supposed to maximize the expected utility function over his entire lifetime (assumed infinite).[iii]

$$Max\ \ E_0\,\{\textstyle\sum_{t=0}^{\infty}\beta^t\,[ln(C_t^*)-\gamma H_t^*]\} \qquad (1)$$

where E_t is the expectations operator denoting expectations about future values formed at time t, and the discount factor $\beta\ satisfies\ 0<\beta<1$ and the disutility factor $\gamma\ >0$

Output Y_t^* is produced with capital K_t^* and labour H_t^* via a Cobb-Douglas production function

$$Y_t^*=A_t^*\ \ (K_t^*\,)^{\theta}(\eta^t H_t^*\,)^{1-\theta} \qquad (2)$$

Here $\eta>1$ is a measure of the technical progress (of the Harrodian variety) and $0<\theta<1$.The technology shock A_t^* follows the first-order AR process :

$$ln(A_t^*)=(1-\rho)ln(A)+\rho\ ln(A_{t-1}^*)+\epsilon_t \qquad (3)$$

where $A>0\ ,\quad -1<\rho<1\quad and\ \epsilon_t\sim N(0,\sigma^2)$ and serially uncorrelated.

In addition we have the definitional identities which close the system viz.

$$Y_t^*=C_t^*+I_t^* \qquad (4)$$

where I_t^* is investment (additions to capital stock K_t^*)

$$K_{t+1}^*=(1-\delta)K_t^*+I_t^* \qquad (5)$$

with the depreciation rate δ in (0,1).

The Euler conditions for the maximization problem (1) subject to the side conditions (2) to (5) include the intra-temporal condition

$$C_t^*=\left[\frac{1-\theta}{\gamma}\right]A_t^*\,\eta^t\left[\frac{K_t^*}{\eta^t H_t^*}\right]^{\theta}\quad,\quad (t=0,\ 1\ldots) \qquad (6)$$

(which simply equates the marginal rate of substitution between consumption and leisure to the marginal product of labour) and additionally an inter-temporal optimizing condition

$$(C_t^*)^{-1} = \beta E_t \left[(C_{t+1}^*)^{-1} \left\{ \theta \left({Y_{t+1}^*}/{K_{t+1}^*} \right) + (1-\delta) \right\} \right] \quad (t = 0,1 \ldots) \tag{7}$$

(this is a formal statement of the intuitive fact that the inter-temporal rate of substitution between current consumption and expected future consumption equals the marginal product of capital). In some versions of the model a competitive market real interest rate is also appended:

$$R_t^* = 1 + \theta A_t^* \left(\frac{K_t^*}{\eta^t H_t^*} \right)^{\theta - 1} - \delta \tag{8}$$

Equations (1) to (7) or (8) constitute the DSGE formulation of the RBC model. Of course, as we have already stated earlier and which we now reiterate for emphasis, this model is highly simplified and only being used for expository purposes. DSGE models used for policy purposes such as Smets and Wouters (2003, 2004), Harrison et al (2005), Sborodone et al (2010) are considerably more elaborate and we will make a brief reference to some of these later. Among the elaborations which are most common is the introduction of a separate labour supply function, different types of firms, staggered pricing and stick wages, a monetary policy function and so on. Nevertheless the basic model used here can illustrate the essential issues which are central to DSGE modeling (while also bringing out their limitations) in an easily comprehensible manner.

3. DSGE Models : Identification Issues

Proceeding further, we log-linearize the above system around its steady state. Consider the following six detrended variables ;

$$y_t^* = \frac{Y_t^*}{\eta^t}; \quad c_t^* = \frac{C_t^*}{\eta^t}; \quad i_t^* = \frac{I_t^*}{\eta^t}; \quad k_t^* = \frac{K_t^*}{\eta^t}; \quad h_t^* = H_t^*; a_t^* = A_t^*; \; r_t^* = R_t^* \tag{9}$$

The stationary values of the above variables constitute the steady-state of the system and we denote these as $y^*, c^*, i^*, k^*, h^*, r^* and\ a^*$. Defining deviations around this steady state by $\widetilde{y}_t, \widetilde{c}_t, \widetilde{\imath}_t, \widetilde{k}_t, \widetilde{h}_t, \tilde{r}_t and\ \widetilde{a}_t$ (where $\widetilde{y}_t = ln(y_t^*/y^*)$ and the other deviations are similarly defined), we can log linearize the system (2) to (7) around the steady state using a first order Taylor series approximation. The log-linearization amounts to writing the system (2) –(8) above , with the variables in percentage deviation terms from the steady state We now have the system

$$\widetilde{y}_t = \widetilde{a}_t + \theta \widetilde{k}_t + (1-\theta)\widetilde{h}_t \tag{10}$$

$$\widetilde{a}_t = \rho \tilde{a}_{t-1} + \epsilon_t \tag{11}$$

$$\left\{\frac{\eta}{\beta} - 1 + \delta\right\}\tilde{y}_t = \left[\left(\frac{\eta}{\beta} - 1 + \delta\right) - \theta(\eta - 1 + \delta)\tilde{c}_t + \theta(\eta - 1 + \delta)\tilde{\iota}_t\right] \tag{12}$$

$$\eta\tilde{k}_{t+1} = (1 - \delta)\tilde{k}_t + (\eta - 1 + \delta)\tilde{\iota}_t \tag{13}$$

$$\tilde{c}_t + \tilde{h}_t = \tilde{y}_t \tag{14}$$

$$(\eta/\beta)E_t(\tilde{c}_{t+1}) = (\eta/\beta)(\tilde{c}_t) + \left(\frac{\eta}{\beta} + 1 - \delta\right)E_t(\tilde{y}_{t+1}) - \left(\frac{\eta}{\beta} + 1 - \delta\right)\left(\tilde{k}_{t+1}\right) \tag{15}$$

$$\tilde{r}_t = \ln(\theta) + \tilde{a}_t + (\theta - 1)\,\tilde{k}_t - (\theta - 1)\tilde{h}_t \tag{16}$$

Because of the expectations operator figuring in the system (equation (15)), special techniques have to be invoked in order to solve the system. These are discussed in Blanchard and Kahn (1980), Sims (2002), Uhlig (1995) etc. where necessary conditions for the existence and uniqueness of the solution are also presented. Blanchard and Kahn introduce a distinction between those variables which are predetermined at time t (which includes both exogenous and some endogenous variables) which are termed state variables, and those endogenous variables not so predetermined which are termed forward looking or "jump" variables. The two sets of variables are denoted by the column vector s_t and f_t respectively. Using this dichotomy the linear system (10) –(16) is put in the state-space format (see Harvey (1989), Canova (2007) etc.) and then solved using the Kalman filter. These methods can under most conditions "solve" the model in that the vector of current jump variables can be expressed as deterministic functions of the current state variables only, while the state variables are expressed in terms of their past values and shocks to the system. Thus

$$f_t = \Gamma s_t \tag{17}$$

$$s_t = \mathrm{A}s_{t-1} + \mathrm{B}\epsilon_t \tag{18}$$

where ϵ_t is the shock from (11) and A, B and Γ are matrices of appropriate dimensions.

Since in the model discussed above the key variables depending on the intra-temporal and inter-temporal optimization conditions are $\widetilde{c_t}\,, \widetilde{\iota_t}$ *and* $\widetilde{h_t}$, we let

$$f_t = \begin{bmatrix} \widetilde{c_t} \\ \widetilde{\iota_t} \\ \widetilde{h_t} \end{bmatrix} \quad and\ s_t = \begin{bmatrix} \widetilde{y_t} \\ \widetilde{k_t} \\ \widetilde{r_t} \\ \tilde{a}_t \end{bmatrix}$$

With this definition, the RBC model (log-linearized version) can be put in the following state-space format

$$\begin{bmatrix} f_t \\ s_t \end{bmatrix} = \begin{bmatrix} 0 & \Gamma\mathrm{A} \\ 0 & A \end{bmatrix}\begin{bmatrix} f_{t-1} \\ s_{t-1} \end{bmatrix} + \begin{bmatrix} \Gamma\mathrm{B} \\ \mathrm{B} \end{bmatrix}\epsilon_t \tag{19}$$

We stack the vectors $\begin{bmatrix} f_t \\ s_t \end{bmatrix}$ into a single vector say X_t and rewrite (19) as

$$X_t = \mathrm{H}X_{t-1} + \mathrm{K}\epsilon_t \tag{20}$$

It is tempting to proceed to a direct estimation of the parameters of the model (20). However this fails because most DSGE models suffer from what is called as "the stochastic singularity" problem (see Canova and Sala (2009)). This is essentially an identification problem arising from the number of shocks in the system being typically less than the observable variables. In the RBC model there is only one shock ϵ_t, whereas the observable variables are three viz. $\widetilde{c_t}, \widetilde{\iota_t}$ *and* $\widetilde{h_t}$. Several methods have been suggested to overcome this problem of which the three most in use seem to be

1. Time varying parameters
2. Adding measurement errors to the model
3. Core Non-core distinction

The interesting thing to note is that all three methods yield very similar state-space formats for the model.

Time-Varying Parameters

This method (usually associated with Smets and Wouters (2003, 2004)) introduces time variation in some of the parameters by subjecting them to stochastic shocks. In practice the number of parameters subject to the shock must be sufficient to overcome the deficit in the number of shocks. Of course as to which parameters are to be treated as fixed and which subjected to shocks is to be decided by the analyst based on previous studies or dialogue with policy-makers. In effect this procedure implies that some of the parameters are being treated as "state variables". Let the vector of these parameters be denoted as q_t. and the associated shocks by η_t then we have the additional "state equation(s)"

$$q_t = Q_1 q_{t-1} + Q_2 \eta_t \tag{21}$$

The introduction of (21) means that (17) has now to be modified to

$$f_t = \Gamma_1 \mathrm{s_t} + \Gamma_2 \mathrm{q_t} \tag{22}$$

While (18) is correspondingly modified to

$$s_t = \mathrm{A}_1 s_{t-1} + \mathrm{A}_2 q_{t-1} + \mathrm{B}_1 \epsilon_t + B_2 \eta_t \tag{23}$$

The state space format now is

$$\begin{bmatrix} f_t \\ s_t \\ q_t \end{bmatrix} = \begin{bmatrix} 0 & \Gamma_1 A_1 & \Gamma_2 Q_1 + \Gamma_1 A_2 \\ 0 & A_1 & A_2 \\ 0 & 0 & Q_1 \end{bmatrix} \begin{bmatrix} f_{t-1} \\ s_{t-1} \\ q_{t-1} \end{bmatrix} + \begin{bmatrix} \Gamma_1 B_1 & \Gamma_1 B_2 + \Gamma_2 Q_2 \\ B_1 & B_2 \\ 0 & Q_2 \end{bmatrix} \begin{bmatrix} \epsilon_t \\ \eta_t \end{bmatrix} \tag{24}$$

Adding Measurement Errors

This method (see Ireland (2004) for a full discussion) overcomes the stochastic singularity problem by introducing "measurement errors" in each of the observation equations in (17). These errors are presumed to follow a VAR model but are assumed to follow an autoregressive structure (i.e. they are not orthogonal). Thus the structure (17) is modified to

$$f_t = \Gamma s_t + u_t \tag{25}$$

The measure error process u_t follows an AR(1) process i.e.

$$u_t = M_1 u_{t-1} + e_t \tag{26}$$

The measurement errors e_t are assumed uncorrelated with ϵ_t in (20). Additionally they are assumed to have zero mean and variance covariance matrix $V = E(ee')$

The state space representation of the model is now

$$\begin{bmatrix} f_t \\ s_t \\ u_t \end{bmatrix} = \begin{bmatrix} 0 & \Gamma \mathrm{A} & \mathrm{M}_1 \\ 0 & \mathrm{A} & 0 \\ 0 & 0 & M_1 \end{bmatrix} \begin{bmatrix} f_{t-1} \\ s_{t-1} \\ u_{t-1} \end{bmatrix} + \begin{bmatrix} \Gamma \mathrm{B} & I \\ \mathrm{B} & 0 \\ 0 & I \end{bmatrix} \begin{bmatrix} \epsilon_t \\ e_t \end{bmatrix} \tag{27}$$

Since each observation equation has an attached shock, the stochastic singularity problem is overcome , as the number of shocks now is equal to or exceeds the number of observable variables. In the RBC model, for example, the number of shocks is now four while the number of observable variables is three. The difficulty with this method, however lies in the fact that the "measurement errors" admit no easy economic rationale and thus appear *ad hoc.*

Core Non-core Distinction :

From the point of view of policy applications, the approach taken by the Bank of England in developing its version of a DSGE model presents several attractive features. This model developed fully in Harrison et al (2005) and referred to as the Bank of England Quarterly Model (BEQM) distinguishes three aspects of the model viz. (i) the core model (CM) (ii) the data adjusted model (DAM) and (iii) the operational model (OM). Often, the latter two stages are referred to as the "non-core component" of the model.

The CM is a tight theoretical model solidly grounded in economic theory but does incorporate many of the institutional features and policy constraints. This corresponds to the RBC model (17) to (19) developed above. (Needless to say the BEQM core model is considerably more elaborate, though still strongly based on economic theory). We have denoted variables in the core model by an asterisk. The core model, of itself cannot be taken to the data directly, since many of the variables are not directly observable.

The DAM serves three purposes : (i) it relates the core variables to their observable counterparts (ii) it includes features such as credit market imperfections, informal sector, housing prices, agricultural sector etc. which could make the core model too complex to be tractable and (iii) it includes some relations and stylized facts for which the theoretical underpinnings are unclear (e.g. impact of monetary policy on the yield curve, factors determining the foreign exchange rate premium etc.).

The OM is the model used for actual policy purposes and incorporates extraneous information useful for policy but not amenable to formal modeling such as policymakers' judgments, consumer confidence, business surveys etc. (see Pagan (2005)). Such aspects can be modeled either by introducing specific variables (if the extraneous information can be put on a scale e.g. consumer and business confidence) or if this cannot be done (as, for example, with policymakers' or analysts' judgments) then by introducing Bayesian priors on some of the parameters in the model.

We follow the convention of denoting non-core variables without an asterisk.

We now turn to the non-core aspects of the model. Following Alvarez-Lois et al (2008), we can link the jump core variables f_t to their data counterparts using "error-correcting" equations as follows:

$$\Delta C_t = \Delta C_t^* + (1-\varphi^c)(C_{t-1}^* - C_{t-1}) + \psi^c Z_t + u_t^c \tag{28}$$

$$\Delta I_t = \Delta I_t^* + (1-\varphi^I)(I_{t-1}^* - I_{t-1}) + \psi^I Z_t + u_t^I \tag{29}$$

$$\Delta H_t = \Delta H_t^* + (1-\varphi^H)(H_{t-1}^* - H_{t-1}) + \psi^H Z_t + u_t^H \tag{30}$$

where the $\varphi's$ and $\psi's$ are parameters to be estimated, and the u's are the error terms (Gaussian white noise). The vector Z can be viewed as comprising those variables in the OM (like "business confidence" etc.) which can be put on a quantitative scale. Given the solution vector for the core DSGE model (C_t^*, I_t^*, H_t^*) the parameters $\varphi's$ and $\psi's$ can be estimated via (20) to (22) by matching the core variables with data on (C_t, I_t, H_t, Z_t). We also need to match the variables in the state vector s_t with their empirical counterparts. While empirical counterparts of $\tilde{y}_t$ and $\tilde{r}_t$ are directly observable those for $\tilde{k}_t$ and $\tilde{a}_t$ can be derived respectively from the "perpetual inventory consistency" condition (see e.g Christensen and Jorgenson (1969) , Boskin et al (1989) etc.) and from the method of "Solow residuals" (see e.g. Basu et al (2001), Larsen et al (2002) etc.). The auxiliary variables Z are modeled as unrestricted VARs in the following format

$$Z_t \quad = \Theta \mathrm{Z}_{\mathrm{t-1}} + \Lambda \mathrm{F}_{\mathrm{t-1}} + \Omega \upsilon_{\mathrm{t}} \tag{31}$$

Where F_t is the vector of observable variables, Θ, Λ and Ω are matrices of appropriate dimensions and υ_t is the error term. Combining (20)-(24), we can write the observable variable vector F_t as

$$F_t = \mathrm{M}F_{t-1} + \mathrm{N}X_t + \mathrm{N}^*X_{t-1} + PZ_t + W\xi_t$$
(25)

Consolidating equations (20), (24) and (25) yield the following state space format:

$$\begin{bmatrix} X_t \\ F_t \\ Z_t \end{bmatrix} = \begin{bmatrix} H & 0 & 0 \\ (NH + \mathrm{N}^*) & (M + P\Lambda) & P\Theta \\ 0 & \Lambda & \Theta \end{bmatrix} \begin{bmatrix} X_{t-1} \\ F_{t-1} \\ Z_{t-1} \end{bmatrix} + \begin{bmatrix} \mathrm{K} & 0 & 0 \\ \mathrm{NK} & W & P\Omega \\ 0 & 0 & \Omega \end{bmatrix} \begin{bmatrix} \epsilon_t \\ \xi_t \\ \upsilon_t \end{bmatrix} \qquad (32)$$

4. DSGE Models : Estimation

We have now discussed three approaches to overcoming the "stochastic singularity" problem. Each approach leads to an estimable and identified (exactly identified or over-identified) state space format viz. equation (24) (for the Time-Varying Parameters approach), equation (27) (for the Measurement Errors approach) and equation (32) (for the Core/Non-core approach). We now turn to the issue of estimating the parameters of the models. Basically, four estimation approaches are deployed in this context viz.

(i) Maximum likelihood
(ii) Generalized Method of Moments
(iii) Simulated Method of Moments
(iv) Indirect Inference Method

In view of the highly technical nature of this aspect, we will only have a heuristic discussion intended to broadly capture the essential flavor of these methods.

Maximum Likelihood Method

To introduce the method, let us begin with the model in (17) and (18). Here in view of there being three observable variables and one shock, the model cannot be estimated unless we use one observable variable only in the estimation process. Suppose therefore that (for the sake of specificity) that we use the first observable variable in f_t in our estimation. Our observation vector can then be written as

$x_t = hf_t$ where h=(1,0,0) and is referred to as the *selection vector*. The equation (17) is now rewritten as

$$x_t = hf_t = h\Gamma s_t = \mathrm{H}s_t \qquad (33)$$

Denote the past history of the observable variables x_t by $\mathcal{F}_{t-1}$, and the vector of parameters to be estimated by θ. Let $\bar{s}_{(t+1|t)}$ denote the forecast of s_{t+1} made at time t on the basis of $\mathcal{F}_t$. Further let $\bar{P}_{\{t+1|t\}}$ denote the MSE (mean square error) of this forecast. These forecasts and their MSE are constructed and recursively updated using the Kalman filter algorithm as discussed in Hamilton (1994). Thus under the assumption of ϵ_t in (18) being normally distributed the conditional density of x_t is given by

$$f(\langle x_t|\mathcal{F}_{t-1},\theta\rangle) = \mathrm{N}\{\mathrm{H}\bar{s}_{(t|t-1)}, \mathrm{H}\bar{P}_{(t|t-1)}\mathrm{H}'\} \tag{34}$$

from which the log-likelihood follows

$$L\big((x_1 \dots x_T|\theta)\big) = -\left(\frac{T}{2}\right) ln(2\pi) - \frac{1}{2}\, ln\big[\mathrm{H}\bar{P}_{(t|t-1)}\mathrm{H}'\big]$$
$$-\tfrac{1}{2}\textstyle\sum_{t=1}^{T}\big(x_t - \mathrm{H}\bar{s}_{(t|t-1)}\big)'\big[\mathrm{H}\bar{P}_{(t|t-1)}\mathrm{H}'\big]^{-1}\big(x_t - \mathrm{H}\bar{s}_{(t|t-1)}\big) \tag{35}$$

where T is the sample size. The parameter θ is chosen to maximize (35).

While the logic of this procedure is straightforward, (and the maximum likelihood estimators are additionally consistent and asymptotically normal), the direct application of the method rarely succeeds in practice. Optimization in the parameter space can often fail to converge if the number of parameters is large. Even in the simple RBC model underpinning equations (17) – (18), there are seven parameters viz. β, γ, η, θ, ρ, δ, and σ. The optimization hyper-surface can often be flat (and hence non-informative) about certain parameters which can mean that the maximization algorithm can oscillate without convergence indefinitely (see Canova and Sala (2009)).

For the model (27) with measurement errors added to the basic RBC, the vector x_t can now include all the observable variables (i.e. the selection vector h=(1,1,1)) and is slightly modified to

$$x_t = \mathrm{H}s_t + u_t \tag{36}$$

Correspondingly the log-likelihood is also slightly modified with the addition of a term in the variance-covariance matrix V.

$$L\big((x_1 \dots x_T|\theta)\big) = -\left(\frac{T}{2}\right) ln(2\pi) - \frac{1}{2}\, ln\big[\mathrm{H}\bar{P}_{(t|t-1)}\mathrm{H}' + V\big]$$
$$-\tfrac{1}{2}\textstyle\sum_{t=1}^{T}\big(x_t - \mathrm{H}\bar{s}_{(t|t-1)}\big)'\big[\mathrm{H}\bar{P}_{(t|t-1)}\mathrm{H}' + V\big]^{-1}\big(x_t - \mathrm{H}\bar{s}_{(t|t-1)}\big)$$

…..(37)

The parameters involved now jump to twenty-three –the seven parameters of the basic RBC, the nine elements of the matrix M_1 [iv](since we have three observable variables in x_t), and the six distinct elements of V (three each describing the variances and the covariances).

Since a pure maximum likelihood strategy can lead to computational difficulties, a *mixed estimation* strategy is often resorted to (see De Jong et al (2000), Schorfheide(2000), Ruge-Murcia (2007) etc.). Here it is assumed that the analyst has certain prior information about a subset θ_e of the parameter vector θ, based on economic theory, previous micro-studies, or on certain stylized empirical regularities in the data. The prior information can assume several forms but for analytical convenience, it is presumed that this information can be summarized as probability density functions referred to simply as *priors*. The set of remaining parameters about which we have no particular information can be termed as θ_s , and these are assigned “non-informative” or “diffuse” priors which are essentially flat or near flat distributions. The posterior distribution is related to the prior distributions via the following

$$P\big((\theta|x_1 \dots x_T)\big) \propto L\big((x_1 \dots x_T|\theta)\big)P(\theta_e) \tag{38}$$

The posterior distribution is analytically intractable in most cases and has to be tackled by numerical Monte Carlo simulation. Three alternative methods are available viz. (i) importance sampling (Geweke (1989, 1997), Richard and Zhang (2007) etc.) (ii) Gibbs sampling (Lange (1999), Tierney (1994) etc.) and (iii) Metropolis –Hastings algorithm (Hastings (1970), Gelfand and Smith (1990), Chib and Greenberg (1995) etc.). While we do not discuss these methods here, we can say that starting with a set of prior densities these methods enable us to derive a posterior density for the parameters from which the first few moments of interest to the analyst can be obtained.

The Bayesian maximum likelihood estimation method has been proving itself to be extremely popular in applications. It overcomes the identification problem, can handle large data sets, can incorporate judgments and beliefs in the prior distribution, and the posterior probabilities can be updated as and when data is revised or new shocks are observed.

Generalized Method of Moments

In practice the researcher is interested in various moments of the observed data. Let m denote the (px1) vector of the unconditional moments of interest. For the model to be identified we need $p \geq q$, where q is the number of parameters in the model. Suppose it is possible to express these moments as analytical expressions of the parameters θ. The GMM (generalized method of moments) method can be usefully deployed in this context (see Ruge-Murcia (2007), Alvarez-Lois et al (2008) etc.).[v] Define the quantity

$$G^{(1)}(\theta) = \frac{1}{T}\sum_{t=1}^{T} m_t' - E[m(\theta)] \tag{39}$$

where as before t is the sample size and m_t' are the observations on the variables of interest. (Thus if our moments of interest are $(\tilde{\iota}_t\ ), Cov(\tilde{c}_t, \tilde{h}_t)\ and\ var(\widetilde{h_t})$, then $m_t' = [\tilde{\iota}_t^2 \quad \tilde{c}_t\tilde{h}_t \quad \tilde{h}_t^2]'$). The GMM estimator is that vector θ which minimizes the expression

$$S = G^{(1)}(\theta)' W G^{(1)}(\theta) \tag{40}$$

where W is the (pxp) weighting matrix

$$W = \lim_{T\to\infty} Var\left\{\frac{1}{\sqrt{T}}\sum_{t=1}^{T} m_t'\right\}^{-1} \tag{41}$$

W is computed using the Newey-West (1987) estimator with the Bartlett (1950) kernel. Since $m(\theta)$ is expressible as an explicit function of θ, the minimization problem (40) can be solved (in principle) analytically. The asymptotic distribution of the resultant GMM estimator of θ has been shown by Hansen (1982) to be normal.

Simulated Method of Moments

In practice, the moments of interest can rarely be expressed as analytical expressions of the parameter vector θ. We then can fall back on the SMM (simulated method of moments) estimator. Defining m_t' as before, we introduce an additional vector $m_t'(\theta\ \ )$ which is generated artificially using the solution of the postulated DSGE model based on a specific parameter vector θ . The sample size in this artificially generated series is taken as a multiple τ of the actual sample size T. Typical values of τ could be 5, 10 or 20. The quantity (40) now needs to be redefined as

$$G^{(2)}(\theta) = \frac{1}{T}\sum_{t=1}^{T} m_t' - \frac{1}{(\tau T)}\sum_{j=1}^{\tau T} m_j'(\theta) \tag{42}$$

This minimization problem can be solved by Monte Carlo methods (see Hansen (1982), Duffie and Singleton (1993) etc.). Once again the resultant SMM estimator of θ is asymptotically normal, and the SMM estimator can be shown to rapidly converge to the GMM estimator as τ increases.

Indirect Inference Method

This procedure has been introduced into the literature by Smith (1993). In this method a metric is defined over two sets of VAR estimates for the parameter vector θ. The first set of VAR estimates come from an unrestricted VAR involving actual data on the observed variables and are denoted by θ^*. Next as in the case of the SMM method above an artificial data series is generated by using a specific value of θ. As in the SMM method above, the sample size of this artificial series is taken to be τT (a multiple of the original sample size T). We now estimate a *new* parameter vector based on a VAR run on this *artificially generated* series. This estimated parameter vector is denoted as $\eta(\theta)$, to explicitly note its dependence on the fixed parameter vector θ. We now generate various artificial series, each corresponding to a different value of θ, and generate new parameter vectors η by running VARs on these artificial series. The value of θ ultimately chosen is the one that minimizes the following weighted metric

$$G^{(3)}(\theta) = [\ \theta^* - \eta(\theta)]'V[\theta^* - \eta(\theta)] \tag{43}$$

The weighting matrix V is usually taken to be the variance covariance matrix of the parameter vector θ^* (from the VAR executed on the actual data). Under certain regularity conditions, Smith (1993) demonstrates the asymptotic normality of his suggested estimate.

5. DSGE Models in Practice

The RBC model discussed so far, was purely for illustrative purposes but has the advantage of highlighting the main issues arising in DSGE models in a concise and comprehensible manner. Needless to say DSGE models used for policy are considerably more elaborate. To capture the flavor of such models, we sketch below the outline of a few models actually used in policy and which have by now become fairly well established.

DSGE Models at the ECB(European Central Bank)

Currently the ECB uses two DSGE models for policy purposes viz. the New Area Wide Model (NAWM) and the model based on Christiano, Motto and Rostagno (2003, 2007) which is usually refereed to (for obvious reasons) as the CMR model. The two models are designed to address two distinct set of issues falling within the ECB mandate (see Smets et al (2010)). The NAWM is specifically intended for providing comprehensive forecasts of some key macroeconomic variables conditioned on domestic monetary and fiscal policies as also external developments in major trading partners. The CMR model is intended to serve the ECB as a useful guidepost for its monetary and financial sector policies.

The two models share a common "core" block. This block consists of four distinct sets of economic agents viz. households, firms, monetary authority and the government. Households consume final goods and supply labour with a utility function very similar to (1) but including habit persistence in consumption. Additionally households can hold bonds (domestic and international) to enable consumption smoothing. Four types of firms are distinguished viz. (i) producers of final goods for consumption and investment, (ii) domestic intermediate firms producing for the domestic market exclusively, (iii) domestic intermediate firms producing for the foreign market and (iv) foreign firms producing for the domestic market. There is imperfect competition in the international goods markets with Calvo pricing (see Calvo (1983)). The monetary authority is concerned with monetary policy setting and financial policy, whereas the government sector is concerned with budgetary allocations, spending and fiscal policy. To capture the persistence of shocks evident in the real world, the model features several real and nominal frictions e.g. wage and price stickiness, Calvo pricing with partial indexation of prices and wages that cannot be re-negotiated in that period, shocks to the “mark-ups”, costs of adjustment to the utilization rate of capital, and habit formation in consumption.

In the NAWM model, this core block is grafted onto an international bloc. This introduces additional considerations into the model such as trade flows, the exchange rate, international borrowing, capital inflows and additional transmission channels such as the uncovered interest rate parity, terms of trade and the exchange rate pass-through.. (see Christoffel et al (2008)) for an extended discussion of the NAWM).

The CMR model extends the core model by including the monetary and financial dimensions of the economy. There is a rudimentary banking system and several different types of assets (differentiated by degree of liquidity, length of maturity and risk of default) in the financial bloc. Financial frictions are introduced as well as asymmetric information in credit markets (see Christiano et al (2007)) which allows the “financial accelerator” to come into play.

The structural parameters are estimated in both models by the Bayesian maximum likelihood method discussed above.

The Bank of England DSGE Model

The Bank of England Quarterly Model (BEQM) has been in use at the Bank of England for the last decade or so, and has undergone several modifications over the years. The main structure however remains fairly close to the model expounded in Harrison et al (2005). We discuss below a slightly modified version of the original model (see Harrison and Oomen (2010)). The model is a small open economy model with five basic sectors viz. households, firms, monetary authority, the government and the rest of the world. Households decide on their purchases of domestic and imported goods, and on the level of their savings (and its distribution between holdings of money balances and net foreign assets), based on their income from supplying labour and their accumulated past savings. Firms combine labour and capital to produce goods for the domestic and export markets. The monetary policy authority and the government operate via pre-determined policy rules. In addition, the model features as in the ECB model, several real and financial frictions (see above).

In terms of methodology, the BEQM introduces three notable innovations. (i) Firstly, it distinguishes between the “core” and “non-core” aspects of the model, which have already been discussed above. (ii) Secondly, the estimation of the model is done in two stages. In the first stage the “core” model (which, as seen above, exhibits stochastic singularity) is calibrated to the data and the model and data spectra of the observable variables are compared (as in Watson (1993)). The spectral comparison can aid in the identification of structural shocks. In the second stage the identified structural shocks are appended to the non-core model and the resulting parameters estimated by the Bayesian maximum likelihood method (see above). (iii) As the number of parameters is large, they are split into two groups viz. those parameters which are important in determining the steady state of the model (Group A parameters) with little influence over its dynamic properties and those parameters which have little or no influence on the steady state but strogly influence the dynamics of the model (Group B parameters). In the BEQM model under discussion there are 27 Group A parameters and 22 Group B parameters. The Group A parameters are fixed at the estimation and evaluation stages of the model, as these parameters are more important in matching the first moments of the data rather than tracking the dynamics of the model. The parameter values in Group A are thus based in most cases on the means of the relevant observable variables, or on previous studies (e.g. productivity parameters and depreciation for example) or judgment and beliefs (e.g. the discount rate, or aversion to labour). Group B parameters are then estimated using the Bayesian maximum likelihood method.

DSGE Modelling at the FRB

The FRB uses a variety of models designed to address different objectives. Of the models in current use four seem to be particularly important : (i) FRB/US (ii) FRB/EDO (Estimated Dynamic Optimization) (iii) FRB/Global and (iv) SIGMA. Of these the first two are closed economy models focused on domestic issues, while the latter two are open economy models dealing with domestic and global policy issues. The FRB/US and FRB/Global are large-scale econometric models (intellectual successors to the FRB-MIT-Penn models of the 1970s) and the EDO and SIGMA models are DSGE models proper. Both latter models share a common basic structure but the SIGMA model involves several additional dimensions. In its current version, the full-fledged SIGMA model has seven country blocs (U.S., Euro Area, Japan, Canada, Mexico, Developing Asia and the rest-of –the world) and about 1500 equations. In views of its large dimensions, the parameters are calibrated rather than estimated. A detailed description of SIGMA is available in Erceg et al (2006) and here we discuss the simpler EDO model, which is a closed economy model and whose parameters are estimated rather than calibrated (see Gali et al (2012)). The model has two production sectors viz. a fast growing goods sector (consumer durables and non-residential investment) and a slow growing goods sector.[vi](consumer non-durables and residential investment). Correspondingly, expenditure is differentiated along five categories viz. private expenditure on durable consumer goods, on non-durable consumer goods, on residential capital, and on non-residential capital, and finally public expenditure. The model also features both nominal and real rigidities. The nominal rigidities include price and wage stickiness[vii] , whereas the real rigidities comprise habit persistence in consumption and adjustment costs to investment, to movements of factors of production across sectors and to varying the utilization rate of capital.

The model is estimated over the period 1966Q1 to 2007 Q4. with twelve observed variables (GDP, durable consumption expenditure, non-durable sector (NDS) consumption expenditure, residential investment, non-residential investment, hours worked in the non-farm business (NFB) sector, real consumption per hour in the NFB sector, GDP deflator, NDS deflator, Non-residential investment goods deflator, yield on 10-year government paper, and federal funds rate). All other variables are treated as non-observables and estimated using the Kalman filter (see our discussion in Sections 3 and 4). The model is identified by imposing exogenous shocks (fourteen in all) including two technology shocks (a sector-neutral shock to TFP (total factor productivity) and a sector –specific TFP shock), two mark-up shocks in the two production sectors considered, three shocks to consumer preference (for the three goods viz. durables, non durables, and housing services), a shock to the relative preference of households for work versus leisure, three capital efficiency shocks (to the production of consumer durables, residential investment and non-residential investment), a demand shock to the exogenous public expenditure component, a monetary policy shock (to the federal funds rate) and finally a shock to the 10-year term premium. As the number of exogenous shocks exceeds the number of observable variables, the model is in fact over-identified. The estimation method is Bayesian full maximum likeleihhod. There are 21 structural parameters in the model all of which are assigned Bayesian priors. There are twenty additional parameters (ten each for the standard deviations of the innovations and persistence effects of the exogenous shocks). The estimation is fully described in Gali et al (2012) and closely follows the methods suggested in Smets and Wouters (2003, 2004). The forecasting comparisons in Del Negro et al (2013) indicate that the EDO model's forecasting performance matches that of the other major model used by the FRB viz. the FRB/US model.

DSGE Models in EMEs

DSGE modeling in EMEs presents several challenges. Firstly, consumer behavior, market structure and the financial system show considerable variation from the experience in developed countries. Secondly, the presence of a large agrarian sector and vast segments of *financially excluded* population imply that unless these factors are explicitly allowed for, DSGE models will fail to capture vital aspects of the ground level reality. Thirdly in most EMEs volatile international capital flows introduce an inherent dimension of macroeconomic instability, which equilibrium-based DSGE models may not adequately capture. Fourthly, as Tovar (2008) points out due to the phenomenon of *dollarization,* the exchange rate is likely to play a much more important role in EMEs than in developed countries. Finally the data base in many EMEs continues to be problematic. Long time series at sufficiently high frequency on important macroeconomic aggregates such as savings, investment, GDP and balance of payments are simply not available, measurement errors abound, data availability is subject to long lags, data revisions and structural breaks etc. are all too frequent. Nevertheless, even within these constraints heroic attempts are often made to construct DSGE models for EMEs (see Levin and Pearlman (2011) for a DSGE model for India).

There is one danger which one cannot resist mentioning at this point. All too often EME policymakers "outsource" the construction of models. Models are then developed in consultancy organizations or institutions abroad, calibrated to parameters typically available in the developed country context and with a few cosmetic adaptations, marketed (often at exorbitant costs to EMEs). This can lead to serious misspecification issues.

6. DSGE Models : Advantages Claimed

The above discussion would make it clear that the construction of DSGE models can be an onerous task, involving considerable technical expertise on a wide front and other resources. The natural question that then poses itself : Is whether the involved investment in the model construction yields commensurate returns ? Opinion is sharply divided on this. DSGE proponents claim at least four major advantages for their model.

(i) Firstly, it is claimed that these models are solidly grounded in economic theory with secure micro-foundations.
(ii) Related to the above, it is maintained that the parameters in the model are structural, and hence invariant to policy shocks. This by-passes the Lucas Critique and enables policy simulations aimed at judging the impacts of policy changes on key macroeconomic variables. This it is felt is a major advantage over more data-based traditional models such as VAR or simultaneous equation models.
(iii) DSGE models seem to record a forecasting performance at least comparable to other models (the Bayesian VAR is usually chosen as the benchmark in such comparisons).
(iv) In spite of their elaborate structure, the results of simulations under alternative policy scenarios can be communicated to policymakers in an easily understood manner.

But in recent years and especially after the global financial crisis, DSGE models have come in for sharp criticism for their inability to bring out the emerging financial imbalances in the build-up to the crisis. Foe ease of discussion, I group the criticism under two headings – the econometric critiques and the more fundamental theoretical/ analytical critique. We then note some of the important policy implications of these critiques.

7. DSGE Models : Econometric Critique

One of the major advantages claimed for DSGE models is that their forecasting performance (both in-sample and out-of-sample) seems uniformly good and hence they are eminently suited for policy purposes. This “principle of fit” has been challenged by Kocherlakota (2007)[viii], who constructs two models for an artificial economy – one which gives a perfect fit and the other with an inferior fit. Yet the inferior fitting model delivers a more accurate answer to the policy question posed by the author viz. the response of output to a tax cut. This happens because the better fitting model, imposes an identifying restriction which is non-testable but false. Even though the example constructed is more in the nature of a ”thought experiment” it brings out a crucial and much neglected dimension of parameter estimation viz. that parameter estimates depend on *the data as well as the identification restrictions imposed*. The fit of the model is silent about the validity of the latter, and hence a better fitting model might be based on inappropriate identification restrictions -- the model then fails to deliver accurate policy assessments or conditional forecasts.[ix]

The “principle of fit” has other deleterious consequences. In the drive to improve the fit, ad hoc features are often introduced. Del Negro and Schorfheide (2004) provide an interesting example of this. In many DSGE models, price stickiness is often introduced via Calvo pricing (i.e. only a fraction of firms are able to re-optimize their nominal prices). The high observed persistence in inflation rates in real-world data may not be fully explained by this assumption. DSGE modelers therefore routinely follow the stratagem of adding the assumption that non-optimizing firms are able to index their prices to past inflation rates. While this assumption usually delivers the trick of inflating the fit, it is doubtful whether the indexation assumption is based on sound micro-foundations, and hence the parameters may not be structural, and hence invariant to policy shocks.

But even apart from such ad hoc mechanisms and shocks, there remains the general question of whether, in fact, the parameters of a properly micro-founded DSGE model are truly structural. Chari et al (2007, 2008) show that this may not hold in general. Their 2007 article deals with accounting for observed movements in important macroeconomic aggregates via business cycle model augmented with several *reduced form* shocks. One particular shock the so-called *labour wedge*, is shown to explain a substantial portion of the observed movements in employment. In Chari et al (2008), two structural New Keynesian growth models are built and a *structural shock* appended to the labour supply in each, which we term simply as the *wage mark-up shock* . In the first model, the wage mark-up shock is a consequence of fluctuating government policy towards labour unions and in the second, the same shock is a reflection of consumers’ changing preference for leisure . It is then shown that the two structural models are both consistent with the same reduced form *labour wedge*. But the two structural models have widely different policy implications and hence even so-called structural shocks may not always lead to unambiguous policy recommendations.

A more technical econometric criticism comes from what Buiter (2009) dubs as the “linearize and trivialize” strategy of DSGE models. In our discussion above (see Section ---) the important role of log-linearization in the build-up of DSGE models has been clearly brought out. But linearization while undoubtedly simplifying the technicalities and the estimation problem in particular, introduces a number of not so innocuous trivialization. One such relates to the scale of the shock. Large shocks have in reality more than proportionate effects on the dynamics of a system than smaller shocks. Similarly there is a critical threshold for shocks to have any effect and very large shocks can alter the very structure of a model. By not providing for these effects, as Buiter (op. cit) notes, important real-world phenomena are *ex-definitione* ruled out such as funding illiquidity, mark-to-market accounting, margin requirements, collateral calls, non-linear accelerators and the myriad other phenomena that are now widely held responsible, to varying degrees, for the recent crisis.

8. DSGE Models : Theoretical Critique

The rallying point for most of the analytical criticism on DSGE models is its strong affinity to the NCM (new consensus macro-economics). In particular five features of the NCM (all of which figure in some form or the other in most DSGE models) have come under heavy weather from critics especially after the global financial crisis (see Colander et al (2009), Akerlof and Shiller (2009), Kirman (2011) etc). These five aspects are (i) rational expectations (ii) structure of markets (iii) representative agent (iv) ergodic uncertainty and (v) transversality condition (of the associated dynamic programming problem).[x] We discuss each of these aspects in turn.

Rational Expectations Hypothesis (REH)

As our discussion above should have made clear, the REH plays a central role in most DSGE models. More than in any other profession, economists have shown a remarkable tenacity in clinging to theories even when they continuously fly in the face of facts. Nothing illustrates this better than the case of the rational expectations paradigm. Evidence lined up against the REH comes from behavioural scientists (Kahneman and Tversky (1979), Kunreuther (1978) etc.), psychologists (e.g.Gleitman (1996)) as well as from economists (Akerlof and Shiller (2009), Akerlof et al (2000) etc.). Actual behavior of economic agents rarely mimics the REH, with agents failing to discover "rational expectations equilibria" in repeated experiments. To quote some very prominent early evidence, Kahneman & Tversky (1979), Tversky and Kahneman (1974) and Kahneman & Riepe (Journal of Portfolio Management 1998) demonstrated the "irrationality" of individual decision making in laboratory experiments**.** Their main findings were that (i) Individuals exaggerate the importance of vivid over pallid evidence (TV montage over reports in newspapers/scientific journals) (ii) There is exaggeration of probabilities of recent events over those occurring earlier (iii) Individuals' errors are systematic rather than random (they are reluctant to give up pre-conceived notions, more favourably disposed towards accepting evidence confirming initial beliefs than contra-evidence etc.) and (iv) Individuals react sluggishly to new information, preferring very often to rely on heuristic decision rules in such cases. More recent evidence from financial markets point to the robustness of these earlier claims (see Lo et al (2005), Coates and Herbert (2008) etc.). Rather than exhibiting rational behavior individuals seem to function within a "bounded rationality" framework. A more realistic assessment of inflation expectations formation will have to contend with the limits on individuals' cognitive and computational abilities as well as their inability to separate their perceptions of their local environment from the overall macro environment (see Sims (2003), Caballero (2010) etc.). Thus essentially individuals have an "order-of-magnitude less knowledge than our core macroeconomic models currently assume" (see Caballero (2010), p. 91).

Attempts to incorporate insights from psychology and behavioural finance into macroeconomics are still in the making. Lo (2007), in an important contribution, proposes the AMH (Adaptive Markets Hypothesis), where individuals display "bounded rationality" in the light of information gained from experience. In this view, "Financial markets should be viewed within an evolutionary framework, where markets, policy instruments, institutions and investors interact dynamically in Darwinian (evolutionary) fashion. … Behaviour evolves through natural selection … through a process of trial and error, rather than through "optimizing" behavior." (see Allington et al (2011), p. 13).

Structure of Markets :

The NCM makes three key assumptions relative to market organization, on which several of its conclusions rest. In DSGE models, these conclusions get rarely spelt out explicitly, but are often assumed as a "matter of fact" or as a "sufficiently good approximation to the real world". The first is that markets are *complete*, the second refers to the stability of general equilibrium and the third refers to efficiency of financial markets.

Complete markets imply that there are markets for every good to cover the space of all possible states of nature (see Flood (1991)). Futures and options markets are viewed in this framework as efficient allocators of risk between hedgers and speculators (or as Flood (op. cit) p. 54, refers to it --the distribution of fat and lean meat between Jack Sprat and his wife in the nursery rhyme). In the complete markets system, intertemporal budget constraints are always satisfied and real world phenomena like illiquidity, willful default, insolvency and "market freezes" are ruled out *a priori*.

While the question of existence of a general equilibrium for markets had been satisfactorily resolved by Arrow and Debreu (1954), the actual process by which this equilibrium is attained remains an open issue. After the DSM (Debreu (1974), Mantel (1974) and Sonnenschein (1972)) result[xi] demonstrated that the Walrasian *tatonnement* process may not always lead to a general equilibrium, the search for an appropriate set of restrictions which will guarantee such convergence was intensified. While convergence has in fact been mathematically established (Smale's (1976) Global Newton method, Saari and Simon (1978), Flaschel (1991) etc.) , the implied restrictions on preferences and information are generally recognized as excessive and unrealistic (Hildenbrand (1994), Kirman (2006) etc.).

The hypothesis of efficient financial markets posits that current market prices of financial assets embody rationally all the known information about prospective returns from the asset and future uncertainty is of the "*white noise*" kind. In such a framework, "*noise traders*" (speculators) may succeed in pushing the markets temporarily away from equilibrium, but with markets clearing continuously, "*rational traders*" will bring the system back to equilibrium, by taking countervailing positions, and imposing heavy losses on those speculators who bet against the fundamentals. Equilibrium asset prices will therefore be altered only when there are "*shocks*" to the fundamentals, and while supply shocks are inevitable, the severity of demand shocks can be tempered by policy aimed at giving more access to information about fundamentals to market participants, and avoiding " *policy surprises*" or attempts to control asset prices. The inappropriateness of the EMH(efficient markets hypothesis) as a description of actual trading strategies of forex and equity traders has always been strongly suspected. Behavioural theories of human decision making (see Kahneman & Tversky (1984), Rabin & Thaler (2001) etc.) argue that in the face of complex uncertain situations, individuals do not proceed via maximizing expected utility but using *cognitive heuristics*. Such heuristics is an aid to reducing a complex task to a manageable proportion but often introduces systematic biases. The bulk of the econometric evidence on financial markets is also *contra* the EMH. (see the survey by Yalçın (2010) and the several references therein).

In the wake of the current crisis, economists are increasingly turning to the so-called *saltwater* view, which is essentially a resurrection of the 1930s Keynesian description of financial markets as being "*casinos*" guided by "*herd instincts*" (see the popular views of highly regarded economists such as Buiter (2009), De Long (2009), Krugman (2009) etc.). In the Keynesian view, investors in financial assets are not interested in a long-term perspective, but rather in speculating on short-run price behaviour. Far from basing their expectations on prospective behaviour of the underlying fundamentals, such investors are more likely to base their opinions on market sentiments (i.e. the opinion of members of peer groups and/or market leaders). This lends a dangerous edge of volatility to financial markets as any "news" affecting market sentiment strongly (in either direction) is likely to produce mood swings in market sentiment, even if the "news" in question is unlikely to alter long-term fundamentals. A more formal criticism comes from the DSM theorem noted above.

Representative Agent :

As we have seen above, the DSGE approach proceeds by developing in detail an optimization model at the micro-level and then simply "blowing it up" to the macro-level. This is done in the belief that macro-economics must solidly rest on micro-foundations. But the relationship between the micro and macro-aspects of an economy is not straightforward. Firstly, as emphasized by Stoker (2008), Chiappori and Ekeland (2009) etc., aggregating micro relationships to derive macro processes is valid only under very restrictive assumptions. Further, Howitt (2006) has highlighted the fallacy of composition inherent in such a procedure. Actually, as Colander et al (2009) correctly point out a realistic development of the microfoundations of macroeconomics has to take account of the interactions of economic agents, which in turn will be contingent on agents being heterogenous in terms of information sets, motives, capabilities etc. (see Chamley (2002), Aoki and Yoshikawa (2007), Kirman (2011) etc.). The obsession with representative agent models have made economists ignore vital areas of research like network theory (Allen and Babus (2008), Boesch et al (2006) etc.), which could lead to macro-models of greater interest to policymakers[xii]and more importantly lead to policies with greater potential for enhancing general welfare.

Transversality Condition :

A rather innocuous looking assumption in the NCM, has shown up as a major limitation in the post-crisis review of macro-economics. This, of course, is the "transversality condition" (Blanchard & Fisher (1989) Appendix 2A), which postulates in mathematical terms that in a dynamic programming problem the infinitely distant future *shadow price*s are orthogonal to the current criterion function. Transplanted into the capital asset pricing model of efficient financial markets, it is taken to imply that the expected prices in the distant future have no effect on current asset prices. This results from two related confusions -- firstly between the "shadow prices" from a mathematical optimization problem and the market prices of a decentralized economy and secondly between the purely mathematical transversality condition and long-term expectations in asset markets. From this it is but a small step to the conclusion that in the inter-temporal optimization of the representative individual, all debts are paid in full, thus effectively leaving no space for money, finance and liquidity to enter the model in a meaningful way.

Non-ergodic Uncertainty

One of the central features of Keynes' *General Theory* was the view of uncertainty in Knightian terms (*non-ergodic uncertainty*). In sharp contrast, the REH, by its very nature is tied to the assumption that the future is ergodic and hence *predictable* (perhaps within known error bounds). Given the inevitability of unanticipated changes in the real world, the REH if it claims any pretension to realism, requires a mechanism whereby individuals can quickly acquire complete knowledge of the altered probability generating mechanisms (see Frydman and Goldberg (2008), Allington et al (2011) etc.). The global crisis brought out the fatal flaw in such a narrow view. As is now well-known, the elaborate models used by credit rating agencies to rate / monitor complex products like CDOs predicated on complicated multidimensional probability distributions and copulas, were simply inappropriate to foresee the illiquidity in U.S. money markets that arose from investor herd behavior in the face of the non-ergodic uncertainty intrinsic in new complex financial innovations[xiii].

There is also a deeper explanation to this phenomenon. Walrasian general equilibrium theory as expounded in the standard Arrow-Debreu (1954) model mathematically shows that all uncertainty can be eliminated if there are enough contingent claims (which in the world of today are equated with derivative instruments). Hence the strong belief that the introduction of derivatives enhances social welfare by contributing to financial stability. Such reasoning conveniently overlooks that the Arrow-Debreu result applies only to ergodic uncertainty. In the non-ergodic real world, derivatives more often than not, can turn out to be (in Warren Buffet's popular phrase) " weapons of mass destruction".

The foundations of a more realistic macroeconomics need to be based on a theory of decision making under non-ergodic uncertainty. Such a theory, in a rudimentary form was proposed by Hurwicz (1950) and has more recently been formalized by Gilboa and Schmeidler (1989) under the rubric of "max-min expected utility". A promising line of thinking emanating from such considerations is "agent-based modeling" (see Mantegna and Stanley (2000), Rosser (1999), Gilbert (2007) etc.). In the context of financial crises, these theories would tend to focus on the complex institutional structure of financial markets and decision rules circumscribing the behavior of market participants. From an operational point of view, this line of thinking prompts regulators to pay close attention to networks and nodal interactions within the financial sector and the build-up of systemic risk (see Kirman (2011), Fafchamps and Gubert (2007) etc.).However, it must be remembered that while some of these approaches to non-ergodic uncertainty appear promising, they have not yet been incorporated into a systematic theoretical macro-economic framework.

9. Conclusion : Beyond DSGE Models

While the DSGE models superficially do give an impression of being "scientific", a closer look casts strong doubts on the validity of such a claim, rather the theories are scientific but vacuous. Real world phenomena of crucial significance to policymakers are side-stepped including incomplete markets, bargaining power, strategic interactions and coordination problems between agents, on-line learning etc. The DSGE modelers would possibly plead that they recognize the importance of these problems but they are analytically intractable. Economic policy is "hard" in the sense of being difficult to solve *formally* (see Rust (1997) for a definition of "hard" in this context). Faust (2005) has introduced two approaches in this context (i) Type A approach in which a simplified version of the problem is solved formally and (ii) Type B approach in which the problem is not simplified but non-formal solutions are admitted.

The DSGE approach seems a typical Type A approach based on the implicit assumption that successively elaborating the simple prototype model and solving it formally will ultimately converge to the ideal solution[xiv]. A more pragmatic approach would be the Type-B approach where all (or at least most) of the interesting real world features are retained but solution methods are less than fully formal. In other words, models to be of relevance to the real world must essentially rest on two pillars : (i) the micro behavior of individuals and (ii) the structure of their mutual interactions (see Colander et al (2009), Faust and Leeper (2015) etc.).

Two such approaches are emerging in the literature. The first is the econophysics literature which shifts the focus away from individual equilibria to systems equilibria and wherein evolving micro-dynamic interactions are consistent with macro equilibrium. Micro-foundations are abandoned in favour of *dimensional* analysis and the use of traditional topological methods are replaced by the methods of statistical physics (see Farmer et al (1988), Aoki and Yoshikawa (2006) and Colander (2006)).

A second, and perhaps more promising approach is the ACE (agent-based computational economics) put forth by Epstein and Axtell (1996), Tesfatsion and Judd (2006), LeBaron and Tesfatsion (2008). ACE modeling allows for a variegated taxonomy of agents including a spectrum of cognitive features ranging from passive cognition to the most sophisticated cognitive abilities. A second important aspect of ACE modeling is that it examines the evolution of macro dynamics as the number of interacting agents increases and as their interactions become more complex. The method relies heavily on experimental designs to make inferences about the behavior of different agents. The interactions are determined by the agents' internal structures, information sets, beliefs and cognitive abilities. Agent behavior is not restrained by artificial external boundary conditions such as homogeneity, stability or transversality. Using the so-called Zipf distribution, Axtell (2001) reports a model with millions of interacting agents (see also Adamic (2011))

Nevertheless, neither of the above two approaches really validate the data in a manner that our profession is accustomed to. This deficiency is important and will possibly not be long in getting satisfactorily resolved. Meanwhile should we persist with the DSGE approach in spite of its problematic foundations? Solow (2010) in his testimony before the U.S. House of Representatives Committee on Science and Technology severely indicts the DSGE business " The point I am making is that the DSGE models have nothing useful to say about anti-recession policy because they have built into its essentially implausible assumptions the "conclusion" that there is nothing for macroeconomic policy to do. ….There are other traditions with better ways to do macroeconomics..". Similarly talking about the Bank of England's disillusionment with DSGE models in the aftermath of the global crisis, Buiter (2009) refers to "the chaotic re-education" at the institution.

This "re-education" could usefully incorporate three fundamental considerations viz. (i) lesser reliance on pre-selected formal models and greater scope for exploratory data analysis (ii) robustness across model specifications in policy choices and (iii) ethical responsibility of economic researchers.

Exploratory Data Analysis

One approach which is less formal (than DSGE models) and which gives greater scope for exploratory data analysis is the CVAR (co-integrated VAR) approach developed by Johansen (1996) and elaborated in Juselius (2006) and Hoover et al (2008) . It is shown in Juselius and Franchi (2007) that the assumptions underlying a DSGE model can be translated into testable hypotheses in a CVAR framework. A second approach by Del Negro and Schorfheide (2004) (DSGE-BVAR) seems even more promising. Here the estimated parameters from a DSGE model are used as priors in an associated Bayesian VAR. A hyper-parameter λ controls the tightness with which the priors are imposed. These priors are fed into the likelihood function of the VAR to obtain the posterior distribution of the parameters. The shape of the posterior distribution for λ can help us adjudge the suitability of the tested parameters of the underlying DSGE (from the point of view of goodness-of-fit as well as model complexity). While neither of the above two approaches can claim to be perfect, they have the merit of going beyond the narrow DSGE view and allowing greater room for the data to speak.

Robustness

The issue of robustness across model specifications is a largely neglected issue in the literature. In the real world policymakers are uncertain about the model(s) that they use. This uncertainty has several dimensions viz. parameter uncertainty, uncertainty about the persistence of shocks, uncertainty about the data quality etc. In such a situation what is required is a method to study the sources of model errors. The *Model Error Modeling* literature from control theory can be useful here (see Ljung (1999)). Introducing robustness considerations in economics has been studied from a different viewpoint in McCallum (1988) Hansen and Sargent (2001), Onatski and Stock (2002) etc. These ideas however have not yet filtered down to real-world policy making.

Ethical Responsibility

Finally, the recent global crisis has brought to the fore the ethical responsibility of the economics profession. As the financial wizards went into top gear with their innovations in the build-up to the crisis, the regulators failed to get adequate and timely warning about the potential for systemic damage latent in these developments, from macroeconomists in general. Are we to believe that the leading lights of our profession were simply ignorant about the dangers posed by an over-leveraged, over-securitized and skewedly-incentivized financial sector, or as is more likely they simply looked the other way ? Either view does not redound to the profession's credit. Perhaps economists should take their ethical responsibilities far more seriously than they do now and issue timely warnings to policymakers and the general public of developments which (in their opinion) are fraught with serious consequences for society at large. In this respect they should perhaps emulate the ethical standards set up in other imperfect sciences such as medicine, jurisprudence and (now increasingly) meteorology.

Solow's (1997) characterization of academic economists as "the overeducated in search of the unknowable" is apt in the current context. Economists would be more usefully employed if instead of pursuing the Holy Grail of the true but unknown and formally perfect model, they set up a more modest agenda of studying the knowable. The lines of thinking noted briefly in the previous paragraphs (viz. the, ACE, CVAR and DSGE-BVAR models) represent precisely this line of thinking. One could not agree more with Colander ((2000), p. 131) when he sets up an agenda for those he terms the New Millenium economists as " .. search for patterns in data, try to find temporary models that fit the patterns, and study the changing nature of those patterns as institutions change".

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[i] The Lucas critique basically states that reduced form parameters may not be invariant to policy changes. Hence reduced form models have limited use for policy. Structural parameters, on the contrary are invariant to policy changes.

[ii] This assumption is not as restrictive as it appears at first sight. The model can be easily extended to introduced separately consumers, producers of intermediate and final goods, capitalists etc. at the cost of complicating the technical aspects but not changing the main narrative.

[iii] The following exposition closely follows Ireland's (2004) model.

[iv] These elements govern the persistence of the VAR residuals.

[v] The GMM is by now a well established technique in the econometrics literature (see e.g. Hall (2005), Newey (1985), Newey and West (1987) etc.).

[vi] This aspect may appear puzzling to many readers. The distinction seems to have been introduced to take account of the fact that over the period for which the model was initially estimated (1984-2007) the average real growth rate for the slow growing sectors was about 3.5% while that for the fast growing sectors was 6.5% --the nominal growth rates showing, however, more uniformity (ranging between 6.25% to 7.5%).

[vii] Firms and households face convex adjustment costs in setting their prices and wage demands respectively. These adjustment costs are assumed to depend both on lagged inflation as well as steady state inflation.

[viii] This point seems to have been made earlier by Sims (1980) and as a matter of fact was a recurrent theme in the identification debates of the 1950s (see Marschak (1950), Hurwicz (1950) etc.) – a point noted by Kocherlakota (op. cit.).

[ix] This point is further elaborated in Kocherlakota (2007) (footnote number 3) and Ohanian's (2007) comments on Kocherlakota (op. cit.).

[x] These features have been discussed in detail in one of my earlier arti

[xi] The DSM theorem may be simply explained as follows. The foundations of neoclassical economics rest on the assumption that individual demand functions satisfy Wald's (1936) WARP (weak axiom of revealed preference) (implying individual demand curves are downward sloping). The DSM theorem asserts that whereas the WARP is sufficient to ensure the existence and *local uniqueness* (of a market equilibrium), global uniqueness and stability are not ensured by WARP (or by even stronger restrictions on individual demand functions).

[xii] Charles Goodhart once famously remarked , talking about DSGE models "It excludes everything I am interested in " (quoted in Buiter (2009)).

[xiii] We recognize, of course, that securitization was one among several factors leading up to the crisis, the others being global imbalances, loose fed policy (under Greenspan), home price bubble, excessive leveraging, and lax regulation etc. Nevertheless, securitization will continue to be a key element in any narrative of the crisis.

[xiv] Mathematically speaking if the Kolmogorov complexity of the problem is polynomially bounded, this approach will succeed (see Garey and Johnson (1983)).