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Monetary Policy in an Uncertain World: Probability Models and the Design of Robust Monetary Rules

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MONETARY POLICY IN AN UNCERTAIN WORLD: PROBABILITY MODELS AND THE DESIGN OF ROBUST MONETARY RULES*

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1. Introduction

> *Uncertainty is not just an important feature of the monetary policy landscape; it is the defining characteristic of that landscape.* **Alan Greenspan**[1]

This paper addresses the role of macroeconomic models for real world policy-making. Perhaps this is not the ideal time to make a case for the use of formal models for this purpose as current versions of models on offer were not designed to analyze to even take into account the complete break-down of credit markets. However I will argue that whilst we should certainly be reassessing our models, something I will return to later in the paper, it is important not to throw out the baby with the bath-water. Once normal service is resumed in the world economy I am optimistic that the use of rigorous models in the formulation of monetary and fiscal policy will continue to be an essential component of the policy procedures followed by central banks and finance ministries in both developed and emerging economies.

To be sure the current crisis has highlighted the centrality of uncertainty and robustness for both policymakers and modellers. Inevitably economists differ in their theoretical frameworks and this is the most fundamental source of uncertainty. However I would suggest there has been a remarkable convergence in the profession towards a common methodology based on firm micro-foundations and systems estimation. This is reviewed in the next section. But even if we can agree on a modelling framework and we believe the data is sufficiently

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[1] Federal Reserve Bank of Kansas (2003), Opening Remarks.

reliable for the estimation of our model there is another source of uncertainty with which to contend - that from changes in behavioural relationships. If the model is micro-founded these changes must originate from the parameters and functional forms defining consumer tastes and technology. A tractable way of dealing with these is to assume exogenous stochastic shocks shift preferences and change productivity. A robust monetary policy will then set out to maximize some expected welfare criterion averaged over the distributions of these shocks.

But there is far more to robust policy then dealing with exogenous uncertainty. Policymakers must also incorporate robustness with respect to model uncertainty that takes into account the possibility that their modelling framework is wrong and within each framework they must allow for the fact that they estimate parameter *distributions* and not just their mode. With parameter distribution we have in effect a distribution of models. In the words of Sims (2007) models now become *probability models*. Armed with a series of probability models across different modelling frameworks the policymaker can now incorporate risk assessment and robust rules into the conduct of policy.

The paper is organized as follows. Section 2 provides a brief survey of the evolution of macroeconomic modelling strategies over the past thirty or so years. Section 3 discusses different approaches to robustness. Section 4 discusses the concept of probability model before going onto our application of this idea in section 5. Section 6 is devoted to Dynamic Stochastic General Equilibrium (DSGE) models of emerging economies and Section 7 concludes with suggestions for future directions for research.

2. Towards A Common Modeling Methodology

The past forty years or so has seen a remarkable transformation in macro-models used by central banks, policymakers and forecasting bodies. In the 1960s-70s econometric models were based on equation-by-equation estimation of reduced form behavioural equations without explicit expectations. Large models were then constructed using these behavioural relationships as building blocks alongside identities defining aggregate demand, trade balances and the government budget constraint. The introduction of first adaptive and then rational expectations led to what proved to be a fatal blow for this generation of models - the Lucas

Critique (Lucas (1972)). In the context of forward-looking agents with rational expectation this critique showed that apparently stable empirical backward-looking relationship between, for example, consumption, post-tax income and real consumption was not independent of the policy rule in place. The implication of this finding is that these models were at best suitable for forecasting on the basis of a continuation of existing policy and were unfit for the purpose of examining the consequences of different policies. Looking back from the vantage point of today, these apparently structural models were no better that VARs for forecasting and ranking policies.

Early models certainly lacked coherence in that different behavioural relationships involving the same optimizing agent such as the firm often led an independent existence. The seminal paper Kydland and Prescott (1982) produced the first small coherent dynamic general equilibrium macro model built from solid micro-foundations with expected utility optimizing forward-looking agents. This first 'Real Business Cycle' (RBC) model was stochastic and therefore of Dynamic Stochastic General Equilibrium (DSGE) form, with only one exogenous shock to technology. Despite this simple structure, the model was remarkably successful at reproducing the volatilities of some observed variables.

Although there were many dimensions along which the RBC model failed on its own terms (notably in reproducing observed output persistence and the volatility of hours), the move to the latest incarnation of New Keynesian (NK) DSGE models was driven, at least within academia, by the need to replicate the monetary transmission mechanism from monetary shocks to short-run fluctuations revealed by numerous VAR studies. Central banks of course seized upon this development of an intellectually sound model that the same time gave them a raison d'etre. The main features of the NK DSGE models are first a real RBC core with an outer shell consisting of nominal rigidities and other frictions. These are increasingly estimated by systems estimation using Bayesian-Maximum Likelihood Estimation. DYNARE developed by Michel Juillard and his collaborators has proved a very popular software package for carrying out the estimation procedure. NK DSGE models are widely used especially by central banks and are generally seen to constitute an "impressive achievement" Blanchard (2008). But there are acknowledged shortcomings. The first is fundamental and common to

RBC and NK models alike problems with rationality and Expected Utility Maximization (EUM). The second is that DSGE models examine fluctuations about an exogenous balanced growth path and there is no role for endogenous growth. The third consists of a number of empirical concerns and finally there is another fundamental problem with any micro-founded macro-model that of heterogeneity and aggregation. We consider these in turn.

The assumption of rationality in general and that of rational expectations in particular has naturally generated a lively debate in economics and the social sciences. The assumption of perfect rationality has come under scrutiny since the 1950s when Herbert A. Simon claimed that agents are not realistically so rational so as to aspire to pay-off maximization. Instead he proposed 'bounded rationality' as a more realistic alternative to the assumption of rationality, incorporating players' inductive reasoning processes. This is the route that the Agent-Based Computational Economics (ACE) models take (see, for example, LeBaron and Tesfatsion (2008). Certainly, experimental studies of decision-making show human behaviour to be regularly inconsistent and contradictory to the assumption of perfect rationality. That said, experiments using people and ACE models suggest agents can *learn* to be rational so that rationality may well be a reasonable empirical postulate to describe behaviour near a long-run steady state. This view is supported by *statistical learning* in theoretical macro-models which converges to rational expectations equilibria (see Evans and Honkapohja (2001)).

Models can only be beaten by alternative models. A model of irrationality has to pin down why one decision is preferred to another and here we observe that analytically tractable theories of the inconsistency and irrationality in human behaviour simply have not yet been developed. Hence our best analytical models are based on the rationality assumption as we unfortunately have nothing superior on offer. However we can be more positive than that at least when it comes to competitive behaviour. Darwinian selection helps rational (that is, profit-maximizing) firms (profit-maximizing) to succeed in competition.

Perhaps the most convincing argument for adopting the rationality argument is provided by Myerson (1999). If we first appreciate that the aim of social sciences is not only to predict human behaviour in the abstract but also, crucially, to analyze social institutions and assess proposals for their reform. As such, it is useful to evaluate these institutions under the assumption of perfect rationality, which in turn intimates that the agents in the institution are always seeking to maximize their payoff. In this way, we can solve for flaws as either defects in the institutional structure (and thereby institutional reform is the required solution) or as flaws in the rationality of the agents (which begs for improved education and/or provision of information for individuals). Accordingly this has become a logical and useful assumption for economists in order to see with more clarity when social problems must be solved by institutional reform. This argument can be refined to illustrate why this individual perfection assumption should be one of intelligent rational maximization, as in the models of non-cooperative game theory. Thus an argument for reform of social institutions (rather than for re-education of individuals) is most persuasive when it is based on a model which assumes that individuals intelligently understand their environment and rationally act to maximize their own welfare.[2]

Even if we accept utility maximization, there still is an issue of whether it should be *expected* utility maximization (EUM). An alternative supported by experiments is *Prospect Theory* which takes into account that people behave as if extremely improbable events are impossible and extremely probable events are certain (see Shiller (1999)). Prospect theory can explain phenomena such as the equity premium puzzle. However it is extremely difficult in incorporate into general equilibrium modelling; in the words of Shiller "EUM can be a workhorse for some sensible research".

Turning to our second limitation - the lack of a role for endogenous growth. As Lucas (1987) pointed out the welfare gains from eliminating business cycle fluctuations in the standard RBC model are very small and are dwarfed by the gains from increased growth. It is true that adding New Keynesian frictions significantly increases the gains from stabilization policy, but they still remain small compared with those from increased growth. Surprisingly there has been little work on introducing long-run growth into DSGE models; Wang and Wen (2008) is

[2] I am grateful to Mustapha Doukoure for this summary of the Myerson argument.

a rare example of such an attempt. This is clearly an important priority for future work.

Our third limitation centres on the empirical dimension. Although Bayesian Maximum Likelihood estimation is a giant step forward from the calibration methods of earlier RBC models there are concerns associated with identification, ability to match VARS, too many shocks required, too little attention to priors and the parametric assumptions surrounding technology and consumer preferences. Identification issues are a very active area of research (see, Canova and Sala (2006)), Iskrev (2008), Ratto (2008), for example, research that is feeding into toolboxes available in DYNARE. The critique by Chari *et al*. (2008) focuses mainly on ill-conceived shocks in a standard NK model that are not structural or consistent with micro-econometric evidence. Many of the other issues are discussed in an excellent recent review, Fernandez-Villaverde (2009).

Not all these empirical concerns can be addressed by better econometrics. Although asset prices make an appearance in the standard DSGE model they still do a terrible job at matching them with data. Our models cannot account for a range of financial observations ranging from the equity premium (Mehra and Prescott (1985)) to the slope of the yield (Campbell (2003)). As Smith (2008) points out these are first-order conflicts between data and theory about levels and not the second-order considerations about covariances considered up to now. One response is compromise theoretical rigor for statistical fit by combining DSGE and VAR (or rather global VAR or GVAR) structures as Pesaran and Smith (2006). Another response is to improve the models by exploring different utility functions (or 'exotic preferences') as in Barro (2007).

Finally we turn to what is perhaps the most important issue in micro-founded macroeconomics -that of heterogeneous agents and aggregation. The first generation of DSGE models, the RBC models stayed within the representative agent paradigm. The current wave of New Keynesian models have made only the slightest deviation from this framework by assuming consumers have access to complete markets. Then if though they may differ in their initial tastes, are subject to staggered wage contracts and are subject to idiosyncratic shocks they still face a common budget constraint and the economy in aggregate does not depend on the distribution of individual qualities. By contrast a recent literature is developing macroeconomics from the study of average consumption, output and inputs involving the interaction of these representative households and firms, to the study of the entire distribution of these variables. A recent insightful survey of these developments is provided by Heathcote *et al*. (2009).

Aggregation certainly matters! For example in a standard RBC model but with indivisible labour, An et al. (2008) show that a representative agent model can only explain the data if one assume an implausible household utility function. However progress in embracing heterogeneity has been confined to simple RBC models and still faces technical problems in solving for a rational expectations equilibrium. ACE models (again see LeBaron and Tesfatsion (2008)) certainly tackle aggregation head-on and dispense with the latter problem by ditching rational expectations. But should central banks go down this path for their models? To quote LeBaron and Tesfatsion they (ACE models) "raise some practical complications for the applied econometrician... computational methods such a method of moments might be too computationally costly to undertake ... Researchers at central banks might never decide to fit giant ACE macro models to data." Aggregation remains a difficult problem in macroeconomics. Economics cannot copy the success of statistical physics in tackling this problem because unlike atoms and molecules in physics, economic agents are conscious and calculating!

3. In Praise of Robustness

> *... the ECB has no intention of being the prisoner of a single system ... We highly praise robustness. There is no substitute for a comprehensive analysis of the risks to price stability.*
> **Jean-Claude Trichet**[3.]

All these modelling alternatives highlight the need for robustness in policy design. Here the literature is sharply divided between two schools: the first has been developed by Hansen and Sargent (2003), Hansen and Sargent (2007) (henceforth HS) and assumes *unstructured uncertainty* using a minimax robustness criterion to design

[3] Trichet (2005)

monetary rules. It has three key ingredients that distinguishes it from alternatives. First, it conducts 'local analysis' in the sense that it assumes that the true model is known only up to some local neighborhood of models that surround the 'approximating' or 'core' model. Second, it uses a minimax criterion without priors in model space. Third, the type of uncertainty is both unstructured and additive being reflected in additive shock processes that are 'chosen' by malevolent nature to feed back on state variables and so has to maximize the loss function the policy-maker is trying to minimize.

There are a number of question marks against the HS approach to robustness. First it pursues *optimal* policy, not optimized *simple* rules. As Levine and Pearlman (2008) show if one designs simple operational rules that mimic the fully optimal but complex rule then they take the form of highly unconventional Taylor Rules which must respond to Nature's malign interventions. They would be very hard to sell to policymakers.

HS robust control may be appropriate if little information is available on the underlying uncertainty facing the policymaker. But is this really the case with respect to the effect of particular monetary rules on the macro-economy? Central banks devote considerable resources to this end in their assessment of the forecasting properties of the approximating model, those of rival models and estimates of parameter uncertainty gleaned from various estimation methods. To then fail to fully utilize the fruits of this exercise seems both incongruous and a counsel of despair. The Bayesian approach using probability models by contrast fully utilizes the modelling efforts of the policymaker and further exploits all the information available including priors. This we now turn to.

4. Probability Models

> *...when reasonably large groups of people, like central banks and policy boards, need to talk about uncertainty and relate large amounts of data to the current state of their uncertainty, the language of probability is the only clear means of communication.* **Christopher Sims**[4]

[4] Sims (2007).

A probability model is a form of scenario exercise, but it is far more than that. It offers an estimated *joint distribution* over the uncertain values of the model parameters and, as I indicate in the next section the concept can be extended to a distribution over rival models as well. As Sims (2007) points out, "this is a uniquely Bayesian notion". Why should policy models be probability models? Basically the reason is that they provide a rigorous method of assessing and responding to the uncertainty involved in the use of a particular model, or set of models.

The first attempt at constructing a probability model in the sense proposed by Sims was the DSGE model of Smets and Wouters (2003) (followed by Smets and Wouters (2007)) estimated by Bayesian-Maximum-Likelihood methods resulting in a posterior joint estimate of the model parameters. The first use of such a model for the design of robust monetary rules was Batini *et al*. (2006) (followed by Levine *et al*. (2008)) discussed in the next section). DSGE models have since been adopted by central banks around world, including a number in emerging economies, the FRB and its regional branches and the IMF.

The use of a probability model for practical monetary policy-making has been particularly developed by the Riksbank. Their model has a large number of frictions and exogenous shocks (see Adolfson *et al*. (2007)). The Riksbank pursues an inflation target and publishes fan charts based on the joint distribution of parameter values of their model. Figure 1 shows the main fan charts from a recent Riksbank Monetary Policy Report. In effect these charts set out the "rule" mapping current information into policy actions. Alternative projections conditional on a looser or tighter monetary stance (different rules) and on possible external disturbances supplement these central forecasts. Although inflation targeting is now very common, only a small number follow the Riksbank in publishing forecasts of their policy rates. In doing so, the announcement of both instruments and outcomes is equivalent to a commitment to a Taylor-type rule, but arguably is more understandable and more likely to build up credibility. The next section describes how a series of probability models can be use to design a robust rule in the form of an explicit Taylor-type rule that could then be used to produced fan charts such as in Figure 1.

5. A Robust Bayesian Procedure and Some Results

> *... the conduct of monetary policy ... has come to involve, at its core, crucial elements of risk management. This conceptual framework emphasizes understanding as much as possible the many sources of risk and uncertainty that policy makers faces, quantifying those risks when possible, and assessing the costs associated with each of the risks. In essence, the risk management approach to monetary policy making is an application of Bayesian decision-making.* **Alan Greenspan**[5]

Following Levine *et al*. (2008), we first show how robust policy considerations may be embedded within a very general Bayesian probabilistic decision framework. Consider uncertainty of two forms: exogenous stochastic white noise shocks ('states of nature') and model uncertainty (which decomposes into model structure and parameter uncertainty where parameters include those capturing the persistence the covariances of the exogenous shocks). Let Ξ, Θ and Υ represent, respectively, the states of nature, the parameter set and the actions that a policymaker may take. Whenever policy $\upsilon \in \Upsilon$ (e.g., an inflation targeting rule) is implemented for state of nature $\xi \in \Xi$, a given model $m_i, i \in 1, M$, taken from M discrete candidates and a given set of parameters $\theta_i \in \Theta_i$, a loss is incurred: $\mathcal{L}_i : \Xi \times \Theta_i \times \Upsilon \to \mathbb{R}$. Evaluating this over all possible states of nature yields an expected loss

$$\Omega_i(\theta_i, \upsilon) = E\left[\mathcal{L}_i\left(\upsilon, \theta_{i,}\xi\right)\right] = \int_{\Xi} \mathcal{L}_i\,(\upsilon, \theta_i, \xi) f\left(\theta_{i,}\xi\right) d\xi \qquad (1)$$

where the expectation is taken with respect to the distribution of ξ , $f\ (\theta_i, \xi\ )$. In particular, for a central value $\overline{\theta}_i$ of θ_i this expected loss is denoted by $\Omega_i\left(\overline{\theta}_i, \upsilon\right)$.

For a given model $m_i, i\ \in [1, M\ ]$ and a set of observed data $y\ \in Y$, there may be a posterior distribution for θ_i given by $p_i(\theta_i\ |y, m_i\ )$, so that there is a posterior risk for this model and the given policy which is given by

$$\Omega_i(\upsilon) = \int_{\Theta_i} \Omega(\theta_i, \upsilon) p_i(\theta_i | y, m_i)\, d\theta_i \qquad (2)$$

5 Greenspan (2004).

This provides a measure of robustness of the policy for a given model, given the distribution of parameters for that model. Calculation of (1) is numerically facilitated in discrete space by Markov Chain Monte Carlo (MCMC) methods that allow the sampling of a given distribution (e.g. the model's posterior density) by simulating an appropriately constructed Markov chain. Thus the integral in (2) is approximated by a sum.

Now assume in addition that there is model uncertainty, with posterior odds given by prob (m_i is the correct model $|y) = \lambda_i,\ 1 \leq i \leq M$. The Bayesian policymaker seeks υ to be robust to this as well, so that the posterior risk in this case is given by

$$\overline{\Omega}(\upsilon) = \sum_{i=1}^{M} \lambda_i \Omega_i(\upsilon) \tag{3}$$

which incorporates *both* inter-model uncertainty or Model Averaging (BMA) of Brock et *al* (2003, 2007) *and* intra-model uncertainty. Note that the rival models approach (which we do not utilize in this paper, since we have a posterior distribution that we can use) arises as the special case $\lambda_i = \frac{1}{M}, \forall_i$ and is usually computed for the central values $\overline{\theta}_i$ of each model m_i only:

$$\overline{\Omega}^{Rival}(\upsilon) = \frac{1}{M} \sum_{i=1}^{M} \Omega\left(\overline{\theta}_i, \upsilon\right) \tag{4}$$

Thus the generation of the MCMC draws permits us to capture uncertainty in a structured manner: for a given model the policymaker knows not only the central location of, say, wage indexation, but also its dispersion from the MCMC draws of the posterior density. A Bayesian policymaker would exploit this information, and will further acknowledge the many candidate models that may characterize the economy (the BMA standpoint).

The policymaker would typically also choose an optimal (simple) rule υ^{opt} for each of the cases $\Omega_i(\overline{\theta}_i, \upsilon), \Omega_i(\upsilon)$ and $\overline{\Omega}(\upsilon)$, so that in the last case we end up with the *Robust Bayesian Rule*. The differences $\Omega_i(\upsilon) - \Omega_i(\overline{\theta}_i, \upsilon)$ and $\overline{\Omega}(\upsilon) - \Omega(\overline{\theta}_i, \upsilon)$ compare the welfare loss outcome under robust policy with that when the true model turns out to be m_i with parameter central values $\overline{\theta}_i$. We take these as measures of the *cost of robustness*.

Equation (3) represents the statement of Bayesian uncertainty and is formally standard, e.g., Leamer (1978), Koop (2003). The nature and seriousness of (3) lies in its implementation. We make some points on our own implementation. First, and most bluntly, we take the Bayesian statement seriously. By contrast, in much of the literature, uncertainty forms - data, exogenous elements, model, and parameter - are considered separately. Second, the policymaker's welfare criterion is assumed to be a quadratic approximation of the representative agent's utility function (using the "large distortions" approximation); invariably past studies have used ad-hoc welfare measures independent of the preferences of the agent's optimization environment. This, however, negates the agenda of building micro-founded models in the first place. The final point relates to an environment of bi-lateral decision makers in forward-looking settings. Although the policymaker may insure against structured uncertainty, there is no guarantee the private sector gaze into the same deluxe crystal ball. If they do, then the robust Bayesian rule defines the common environment. If not, then the CB and private sector may have different perceptions of the state of the world and the former must contemplate robust rules integrated over mis-perceptions of model type $\{m = m_i, m^e = m_j\} M_{j \neq i}$ where $m^e = m_j$ denotes that the private sector believes in model j. That defines the *model-inconsistent robust Bayesian rule*.

The model posterior probabilities referred to in this analysis are constructed as follows. Let $p_i\ (\theta|m_i)$ represent the *prior* distribution of the parameter vector $\theta \in \Theta$ for some model $m_i\ \in M$ and let $\mathcal{L}\ (y|\theta, m_i)$ denote the likelihood function for the observed data $y\ \in Y$ conditional on the model and the parameter vector. The joint posterior distribution of θ for model m_i combines the likelihood function with the prior distribution:

$$p_i(\theta|y,m_i)\ \alpha\ L(y|\theta,m_i)p_i(\theta|m_i) \tag{5}$$

Bayesian inference also allows a framework for comparing alternative and potentially mis-specified models based on their marginal likelihood. For a given model $m_i \in M$ and common dataset, the latter is obtained by integrating out vector θ,

$$L(y|m_i) = \int_\Theta L(y|\theta, m_i)p(\theta|m_i)d\theta \tag{6}$$

where $p_i(\theta|m_i)$ is the prior density for model m_i, and $L(y|m_i)$ is the data density for model m_i given parameter vector θ. To compare models (say,m_i and m_j) we calculate the posterior odds ratio which is the ratio of their posterior model probabilities (or Bayes Factor when the prior odds ratio, $\frac{p(m_i)}{p(m_j)}$, is set to unity):

$$PO_{i,j} = \frac{p(m_i|y)}{p(m_j|y)} = \frac{p(y|m_i)p(m_i)}{p(y|m_j)p(m_j)} \tag{7}$$

$$BF_{i,j} = \frac{p(y|m_i)}{p(y|m_j)} \tag{8}$$

Components (7) and (8) are important as they provide a framework for comparing alternative and potentially mis-specified models based on their marginal likelihood. Such comparisons are important in the assessment of rival models.

Based on this framework Levine *et al.* (2008) propose a general methodology and application for designing robust simple monetary rules. The first step is the estimation of a number *n* of rival DSGE models. In this particular study we considered variants of the seminal Smets and Wouters (2003) model of the Euro area distinguished by the existence or otherwise of price and wage indexing. This admittedly only considered robustness is over a narrow range of modelling alternatives, but the methodology can be applied to a greater diversity of model. Using Bayesian-Maximum Likelihood estimation resulted in estimated model probabilities, $p(m_i|y)$ in (7) and parameter joint distributions $p_i\ (\theta|y, m_i)$ for each model in (5). These represent our 'quantified risks' stressed in the Greenspan quote.

The purpose of the exercise is to design robust interest rate inflation targeting rules that respond to expected future price and current wage inflation about the steady state. They are of the form

$$i_t = \rho i_{t-1} + \theta_\pi E_t \pi_{t+j} + \theta_{\Delta\omega} \Delta\omega_t ; \rho \in [0,1] \tag{9}$$

where i_t is the nominal interest rate set at the beginning of period t, π_t is current price inflation over the interval $[t - 1, t]$, $E_t\pi_{t+j}$ denotes expectations at time t of inflation over the interval $[t + j - 1, t + j\,]$ and Δw_t is the corresponding current wage inflation rate. The lagged term represents a smoothing effect and if $\rho = 1$ we have an integral rule in which the change in the interest rate responds to price and wage inflation. All variables are proportional deviations about their steady states. This form of interest rate rule is then designed to incorporate *increasing degrees of robustness*:

- *Model-variant and parameter robustness* by maximizing expected welfare with respect to parameters ρ, $\theta_\pi$and $\theta_{\Delta\omega}$ across the rival models and across estimated parameter distributions within each model.

- First assume *model-consistent expectations* : private sector and central bank believe in the same model and parameter combination

- Then allow for *model-inconsistent expectations* where the private sector and central bank can have different perceptions of the true model and parameter combination.

Thus under Bayesian decision-making, the central bank has no single model of the economy to communicate to the private sector (or to which it itself necessarily subscribes) and no ex-ante knowledge of the realized state of the economy. Likewise, with an a*ctive* private sector. Both consider many scenarios in their decision-making and in the case of model-inconsistent expectations they do so without coordination.

Three results stand out in this study. First there is general support for the proposition that robustness in the face of model uncertainty calls for a more *cautious* policy; that is a lower responses to current or expected inflation captured by the parameter θ_π or to current inflation reflected in $\theta_{\Delta\omega}$ and more *gradualism* (high ρ). This result in fact goes back to Brainard (1967), but it should be pointed out that it contrasts with the robust policy rules that arise from the Hansen-Sargent minimax approach that see robust policy as being faster and more aggressive.

Second, forward-looking inflation targeting rules perform badly in the sense they raise the welfare costs of fluctuations compared with optimal simple rules that only respond to current inflation. The source of this result is the well-known problem of indeterminacy - forward-looking rules certainly pin down expectations of future inflation, but fail to uniquely anchor the current price level resulting in an infinite number of equilibrium paths that will return the economy to its steady-state (see, for example, Levin *et al.* (2003), Woodford (2003), chapter 4 and Batini *et al.* (2006).

Third, current inflation targeting rule perform well in the sense they lower the welfare costs of fluctuations across all model parameter combinations and model variants but the current wage inflation rule is best of all. Robust design not even essential for such a rule. The best wage inflation rule found by minimizing the expected welfare loss with respect to the parameters ρ and $\theta_{\Delta\omega}$ for one central parameter combination (the modes of the joint distribution) and model performs very well across all parameter combinations and models. The best wage inflation rule is one where the change in interest rate responds to wage inflation- this of course implies that the current interest rate should respond to the nominal wage *level*.

The attractive stabilization properties of the wage inflation rule have also been reported by Levin *et al*. (2006), but only for what we call model variant robust rules. The results owes a lot to the particular way in which inflation costs are modelled (as in Woodford (2003) as originating from the dispersion of labor demand across firms setting staggered wages and prices. The robustness exercise is perhaps too limited in that one should consider alternative labor market models with associated alternative models of the costs of inflation. This I suggest is just one future area for research, taking us to the final section of the paper.

6. DSGE Models and Emerging Economies

> *...capital inflows are raising the tensions of the "impossible trinity"*. **IMF (2008)**.

While there is a substantial body of literature devoted to understanding business cycle dynamics in developed economies, research focusing on emerging economies is relatively sparser. Data limitations have often been identified as a cause, but the real challenge is to provide sensible explanations for the markedly distinct observed fluctuations in these economies. Indeed, some stylized facts may be pointed out: output growth tends to be subject to larger swings in developing countries, private consumption, relative to income, is substantially more volatile, terms of trade and output are strongly positively correlated, while real interest rates and net exports are countercyclical (see Agenor *et al*. (2000) and Neumeyer and Perri (2005), for example). Emerging market economies are also vulnerable to sudden and sharp reversals of capital inflows, the "sudden stops" highlighted in Calvo (1998). Understanding these differences and carefully modeling the transmission mechanism of internal and external shocks is crucial to the design of stabilization programs and the conduct of economic policies.

Thus, in Batini *et al*. (2009a) we develop a two-bloc model of an emerging open economy interacting with the rest of the world. Alongside standard features of small open economies (SOE) such as a combination of producer and local currency pricing for exporters and oil imports, our model incorporates financial frictions in the form of a financial accelerator, where capital financing is partly or totally in foreign currency, as in Gertler *et al*. (2003) and Gilchrist (2003). This intensifies the exposure of a SOE to internal and external shocks in a manner consistent with the stylized facts listed above. In addition, we allow for liability dollarization and liquidity-constrained households, which further amplify the effects of financial stress. We then focus on monetary policy analysis, calibrating the model using data for India and the US economy. The Indian economy is small in relation to the world economy and we therefore treat it as a small open economy.

Many emerging economies conduct their monetary and fiscal policy according to the 'three pillars macroeconomic policy framework': a combination of a freely floating exchange rate, an explicit target for inflation over the medium run, and a mechanism that ensures a stable government debt-GDP ratio around a specified long run, but may allow for counter-cyclical adjustments of the fiscal deficit over the business cycle. By contrast, the currency monetary policy stance of the Indian Reserve Bank intervenes in the foreign exchange market to prevent what it regards as excessive volatility of the exchange rate. On the fiscal side, Central Government has a rigid fiscal deficit target of 3% of GDP irrespective of whether the economy is in boom or recession (Shah (2008)). Thus, our framework allow us to contrast these implied policy prescriptions for interest rate rules.

There is now a growing literature that compares alternative monetary policy regimes in their ability to stabilize emerging economies when faced with shocks and financial frictions. Some papers close to ours include Gertler *et al*. (2003), Cespedes et al. (2004), Cook (2004), Devereux *et al*. (2006) and Curdia (2008). All these papers confirm the result in this paper that flexible exchange rate regimes outperform a peg. Only Curdia (2008) compares these regimes with the optimal policy, but only in deterministic exercise in which optimal policy is designed following a sudden stop. By contrast our rules are optimal or, the case of simple rules optimized within the category or rule in anticipation of a range of future stochastic shocks. An important feature of our work is the introduction of a zero lower bound into the construction of policy rules.

Finally future modelling developments will include the introduction of a large informal sector into our DSGE model and an attempt to estimate the model by Bayesian-MaximumLikelihood methods using the calibration here as priors. In doing so we will confront the data limitations associated especially with the informal and partly hidden economy by adopting a consistent partial information assumption for the econometrician and private sector alike, as in Levine *et al*. (2009).

7. The 'Road Ahead'?

All models are wrong, but some are useful. **Box (1979)**.

The paper has attempted an overview of the 'journey so far' for macroeconomic modelling. Where do my remarks leave the 'road ahead' ? To organize my conclusions it is useful to view a macro-model as being constructed in two stages: first a model of the aggregate economy given a particular model of how expectations are formed by economic agents; and second, the model of expectations formation. We consider these two stages in turn

- **Better Models given Expectations Formation**

There are a number of areas where DSGE models need developing, especially for emerging economies. Until recently as with their RBC antecedents the New Keynesian forms still omitted involuntary unemployment. We are now seeing labour markets models with unemployment (see for example Blanchard and Gali (2007) and Thomas (2008) but practically nothing with the informal economy (see Batini et al. (2009b). Another major lacuna in the NK models has been the absence of a banking sector. The monetary transmission mechanism existed simply through one nominal interest on a riskless bond, 'set' by the central bank. The seminal work on financial frictions by Bernanke et al. (1999) introduced a risk premium paid by firms with an implicit intermediary financial institution. But it is only very recently that a comprehensive banking sector has appeared - see Goodfriend and McCallum (2007) as a representative example of this development. In general to move toward more heterogeneous models rather than attempting to model the full distribution of agents it makes sense to first work on more disaggregated models by introducing formal and informal sector, credit-constrained non-Ricardian (poor) household alongside Ricardian (well-off) households, entrepreneurs and workers etc.

- **Models of Expectations Formation**

Staying broadly within the rational expectations paradigm a number of refinements are on offer that assume that agents are not able to perfectly observe states that define the economy. The 'Rational Inattention' literature (Sims (2005), Luo and Young (2009), Luo (2006)) fits into this agenda. The basic idea is that agents can process information subject to a constraint that places an upper bound on the information flow. Borrowing from information theory (which in turn borrows from statistical physics) the idea is formalized by an upper bound on the decrease in entropy that ensues as agents proceed from a prior to a posterior of a signal. Levine *et al*. (2007) propose a general framework for introducing information limitations at the point agents form expectations. A more drastic deviation from rational expectations is provided by the statistical rational learning literature already mentioned. This introduces a specific form of bounded rationality in which utility-maximizing agents make forecasts in each period based on standard econometric techniques such as least squares. In many cases this converges to a rational expectations equilibrium. All these refinements contrast with the drastic alternative offered by the very recent 'Animal Spirits' approach (Akerlof and Shiller (2009), DeGrauwe (2009)). The latter paper is particularly apposite as it proposes a radical alternative to a standard New Keynesian model with rational expectations. Some agents are optimists and some are pessimists and use ad hoc simple rules to forecast future output. There are shifts from optimism to pessimism are driven by a form of adaptive expectations which drive endogenous cycles and inertia without inertial mechanisms such as habit and indexing. This framework provides an interesting challenge to the existing paradigm which needs to show that, with the refinements set out here, it can too explain the same stylized facts without recourse to these inertial mechanisms.

By treating DSGE models estimated by Bayesian-Maximum-Likelihood methods I have argued that they can be considered as probability models in the sense described by Sims (2007) and be used for risk-assessment and policy design. This is true for any one model, but with a range of models on offer it is possible also to design interest rate rules that are simple and robust across the rival models and across the distribution of parameter estimates for each of these rivals as in Levine *et al*. (2008). After making models better in the sense described in the first part of this section, a possible road ahead is to consider rival models as being distinguished by the model of expectations. This would avoid becoming 'a prisoner of a single system' at least with respect to expectations formation where, as we have seen, there is relatively less consensus on the appropriate modelling strategy.

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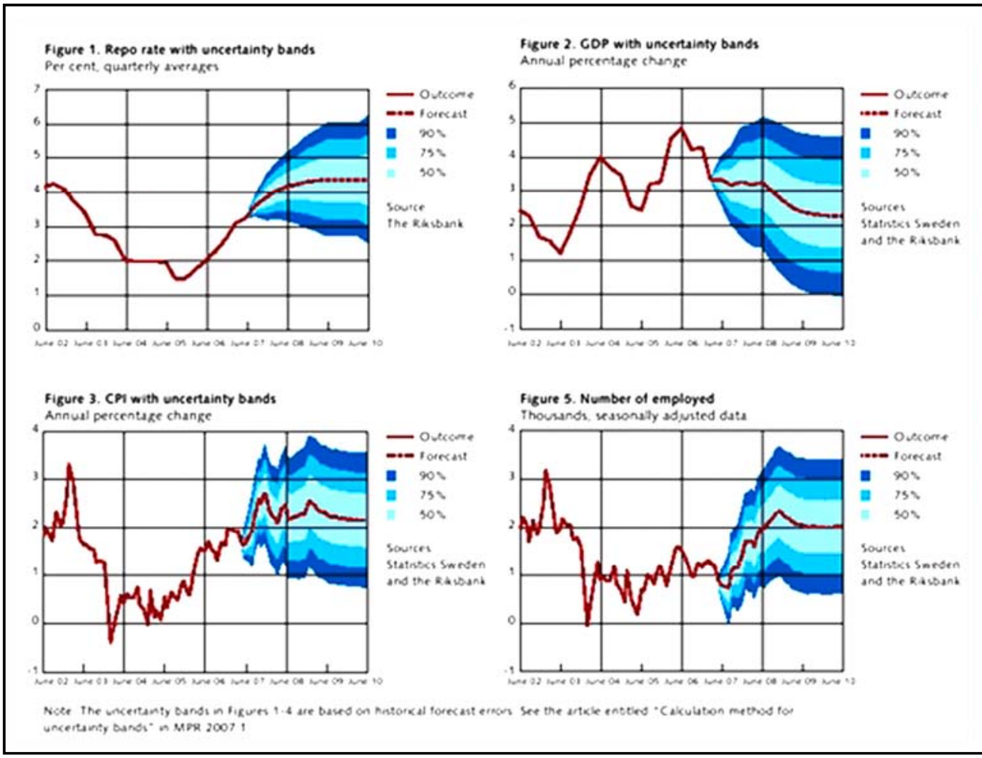

Figure 1: Main fan charts from the Riksbank's Monetary Policy Report 2007:1