On the Sources of Aggregate Fluctuations in Emerging Economies*

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Abstract

Recent research on macroeconomic fluctuations in emerging economies has resulted in two leading approaches: introducing a stochastic productivity trend, in addition to the temporary productivity shocks; or allowing for foreign interest rate shocks coupled with financial frictions. This paper compares the two approaches empirically, taking advantage of recent developments in the theory and implementation of Bayesian methods. Our model comparison exercises favor models with financial frictions over the stochastic trend model. Our results are inconclusive in terms of which of the financial frictions we consider, working capital versus endogenous spreads, is a superior choice. Finally, a model that allows for both stochastic trends and financial frictions assign a substantial role to interest rate shocks, but not to trend shocks, in generating aggregate fluctuations.

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1. Introduction

Recent research on macroeconomic fluctuations in emerging economies has resulted in two leading approaches, both of which can be seen as extensions of Mendoza's (1991) basic dynamic stochastic model. The first approach, due to Aguiar and Gopinath (2007), introduces a stochastic productivity trend, in addition to the temporary productivity shocks already present in Mendoza's model. This seemingly small addition, Aguiar and Gopinath argue, goes a very long way towards addressing well known empirical failures of the model when taken to data from emerging market economies, including the counter cyclical behavior of the trade surplus and the relative volatility of consumption and output.

A second approach, exemplified by Neumeyer and Perri (2005) and Uribe and Yue (2006), relies instead on the introduction of foreign interest rate shocks coupled with financial frictions. This approach is motivated by the observation that the cost of foreign credit appears to be countercyclical in emerging economies data. Accordingly, both Neumeyer and Perri (2005) and Uribe and Yue (2006) develop models in which country risk spreads are stochastic and interact with financial imperfections. Then they argue that those models are consistent with the empirical regularities of emerging economies.

In this paper, we compare the two approaches empirically, taking advantage of recent developments in the theory and implementation of Bayesian methods. We develop representative versions of the stochastic trend model and the random interest rates/financial frictions model; in the latter case, we distinguish between financial frictions in the form of working capital requirements and of endogenous country risk spreads. For each version we then estimate the parameters of the exogenous shocks processes, along with a few other crucial parameters. Our estimation procedure is Bayesian, which has the advantage that a natural comparison of the two models' predictive performance is given by their marginal likelihoods. We employ the Mexican dataset of Aguiar and Gopinath (2007), thus ensuring that our results can be compared with the findings of that paper.

We obtain several results of interest. The financial frictions model beats the stochastic trends model in nearly every comparison based on likelihood or marginal likelihood. We also argue that the financial frictions model has a better performance in terms of matching data moments that have received particular attention in the literature. These results are robust to various changes in assumptions.

We also estimate and analyze an encompassing model that combines both stochastic trends and financial frictions, and evaluate the relative contribution of temporary productivity shocks, trend shocks, and interest rate shocks in that setting. Our estimations indicate that, while temporary productivity shocks are responsible for the bulk of aggregate fluctuations, interest rate shocks have a sizeable role as well, generating about 12 percent of the variance of output, one fourth of the variance of consumption, one third the variance of investment, and two thirds the variance of the trade balance/output ratio. In contrast, the share of those variances due to trend shocks is nine percent or less.

Overall, our results are supportive of the view that assuming foreign interest rate shocks in conjunction with financial imperfections is a better approach than assuming stochastic trends if we are to explain fluctuations in emerging economies. In addition to the papers by Neumeyer-Perri and Uribe-Yue, this has been stressed by the literature on balance sheet effects (Cespedes, Chang and Velasco 2004) and sudden stops (Calvo 1998, Mendoza 2006). We agree with Oviedo (2005) in that, while financial frictions can enhance significantly the performance of models with stochastic interest rates, it is the introduction of interest rate shocks that may be responsible for the bulk of the improvement of the model. On the other hand, our results leave us more ambivalent than Oviedo as to whether which financial friction, working capital requirements or endogenous spreads, is superior to the other.

Our work is related to at least two other strands of the literature. One is the debate of whether fluctuations in emerging economies are dominated by domestic shocks or foreign shocks. Several years ago now, Calvo, Leiderman, and Reinhart (1993) upset the then conventional wisdom by showing that foreign interest rate shocks were a major source of fluctuations in Latin America. Our results are clearly complementary to theirs.

Finally, our paper belongs to a growing group of studies that apply developments in Bayesian methods to models and questions in open economy macroeconomics. Examples include Lubik and Schorfheide (2005), Rabanal and Tuesta (2006), and Justiniano and Preston (2006).

The rest of the paper is organized as follows. Section 2 presents the models under study. Section 3 discusses the details of our empirical approach. Section 4 presents and discusses our baseline results. Section 5 presents several robustness exercises. Section 6 concludes.

2. Competing Models

Several competing views on the sources of shocks to emerging countries can be regarded as extensions of the canonical real business cycle model of a small open economy first developed by Mendoza (1991) and discussed by Schmitt-Grohe and Uribe (2003). As stressed by Mendoza and others, the basic model has notable empirical shortcomings, which have motivated several extensions and amendments. In this paper we are concerned with the relative evaluation of two such extensions, which we describe in this section. The first one, which we will call the *stochastic trend model,* allows for permanent shocks to technology, as advocated by Aguiar and Gopinath (2007). The second one, the *financial frictions model,* allows for foreign interest rate shocks that interact with financial imperfections, as discussed by Neumeyer and Perri (2005) and Uribe and Yue (2006).

2.1. The basic small open economy model

The benchmark model of a small economy is well known. Time is discrete and indexed by $t = 0, 1, 2, ...$ There is only one final good in each period, which can be produced by a technology given by

$$Y_t = a_t F(K_t, \Gamma_t h_t)$$

where Y_t denotes output, K_t capital available in period t, h_t labor input, and F is a neoclassical production function. We use upper case letters to denote variables that trend in equilibrium, and lower case letters to denote variables that do not[1]. Also, a_t is a shock to total factor productivity, assumed to follow:

[1] The only exceptions will be the spread, S_t, and the world and domestic gross interest rates, R_t^* and R_t, to be defined later, which do not trend in equilibrium.

$$\log a_t = \rho_a \log a_{t-1} + \varepsilon_t^z \tag{2.1}$$

where $|\rho_a| < 1$, and ε_t^a is an i.i.d. shock with mean zero and variance σ_a^2. In the benchmark model, the shock ε_t^a is the only source of uncertainty. Also, and importantly for our purposes, total factor productivity is a *stationary* process.

Finally, Γ_t is a term allowing for labor augmenting productivity growth. In the benchmark model, Γ_t is assumed to follow a deterministic path:

$$\Gamma_t = \mu \Gamma_{t-1} \tag{2.2}$$

Capital accumulation is given by a conventional equation:

$$K_{t+1} = (1-\delta)K_t + I_t - \Phi\left(K_{t+1}, K_t\right) \tag{2.3}$$

where I_t denotes investment, δ the rate of depreciation, and $\Phi\left(K_{t+1}, K_t\right)$ costs of installing capital.

The economy is inhabited by a representative household with preferences of the form:

$$E \sum_{t=0}^{\infty} \beta^t U(C_t, h_t, \Gamma_{t-1}) \tag{2.4}$$

where β is a discount factor between zero and one, C_t denotes consumption, $U(.)$ a period utility function, and $E(.)$ the expectation operator. (We include Γ_{t-1} in the period utility function U to allow for balanced growth.)

The representative agent is assumed to have access to a world capital market for non-contingent debt. Her budget constraint is, therefore,

$$W_t h_t + u_t K_t + q_t D_{t+1} = C_t + I_t + D_t$$

W_t denotes the wage rate and u_t the rental rate of capital, so the first two terms in the LHS are factor receipts in period t. In addition, q_t is the price at which the household can sell a promise to a unit of goods to be delivered at $t+1$, and D_{t+1} is the number of such promises issued. The LHS describes expenditures in period t, given by consumption, investment, and debt payments.

Residents of this country face an interest rate on foreign borrowing given by the inverse of q_t, and assumed to take the form:

$$1/q_t = R^* + \kappa(\tilde{D}_{t+1}/\Gamma_t) \tag{2.5}$$

where R^* is the world interest rate, $\tilde{D}_{t+1}$ denotes the country's aggregate debt (which is equal to the household's debt D_{t+1} in equilibrium) and $\kappa(.)$ is an increasing, convex function. We assume that the interest rate faced by the household is sensitive to the debt to ensure that there is a well defined nonstochastic steady state. As shown by Schmitt Grohe and Uribe (2003), this device is one of several that can be chosen to have negligible effects on the business cycle properties of the model.

Note that we have assumed that the world interest rate is a constant. In fact, Mendoza (1991) argued that assuming it to be stochastic makes little difference for the business cycle properties of the standard model.

The standard model is completed by specifying that factor payments are given by marginal productivities:

$$\begin{aligned} u_t &= a_t F_1(K_t, \Gamma_t h_t) \\ W_t &= a_t F_2(K_t, \Gamma_t h_t)\Gamma_t \end{aligned} \tag{2.6}$$

2.2. The Stochastic Trend Model

Aguiar and Gopinath (2007) have recently emphasized that the empirical failures of the benchmark model can be remedied, by and large, by allowing labor augmenting growth to be not constant but random. Formally, the assumption (2.2) is replaced by

$$\Gamma_t = g_t \Gamma_{t-1} \tag{2.7}$$

where

$$\ln\left(g_{t+1}/\mu\right) = \rho_g \ln\left(g_t/\mu\right) + \varepsilon^g_{t+1} \tag{2.8}$$

$|\rho_g| < 1$, ε^g_t is an i.i.d. process with mean zero and variance σ^2_g, and μ represents the mean value of labor productivity growth. A positive realization of ε^g_t implies that the growth of labor productivity is temporarily above its long run mean. Such a shock, however, is incorporated in Γ_t and, hence, results in a permanent productivity improvement.

That the addition of permanent productivity shocks has the potential to eliminate the departures between the model and the data is intuitive and explained by a permanent income view of consumption. After a favorable realization of ε^g_t, productivity increases permanently. Accordingly, permanent income, and therefore consumption, can increase more than current income; this explains why consumption may be more volatile than income in emerging economies. The same reasoning implies that the representative household may want to issue debt in the world market to finance consumption in excess of current income, leading to a countercyclical current account.

2.3. Financial frictions models

Neumeyer and Perri (2005) and Uribe and Yue (2006) have argued that a superior alternative is to allow for random world interest rates that interact with financial frictions. One empirical motivation for this view is what Calvo (1998) has called "sudden stops", defined by an abrupt and exogenous halt to the flow of international credit to the economy, which forces a violent turnaround in the current account.

To develop this view, we modify the benchmark model along lines suggested by Neumeyer and Perri (2005). First, the price of the household's debt is assumed to be given by

$$1/q_t = R_t + \kappa(\tilde{D}_{t+1}/\Gamma_t) \tag{2.9}$$

instead of (2.5), where R_t is a country specific rate,

$$R_t = S_t R^*_t \tag{2.10}$$

R_t^* is the world interest rate and S_t a country specific spread. The deviations of the world interest rate from its long-run level, in turn, are assumed to follow an exogenous process

$$\ln\left(R_t^*/R^*\right) = \rho_R \ln\left(R_{t-1}^*/R^*\right) + \varepsilon_t^R \tag{2.11}$$

where $|\rho_R| < 1$ and ε_t^R is an i.i.d. innovation with mean zero and variance σ_R^2. In addition, deviations of the country spread from its long-run level are assumed to depend on expected values of the deviations in the technology process as follows

$$\log(S_t/S) = -\eta E_t \log a_{t+1} \tag{2.12}$$

Adding shocks to the world interest rate to the basic model has, in fact, been considered in the literature, with little success (see, for instance, Mendoza 1991 and Aguiar and Gopinath 2008). But random interest rates become a more compelling addition when coupled with financial frictions. So, for example, one can argue that country risk must depend inversely on expected productivity, as high productivity in the future should reduce the risk of default. Neumeyer and Perri (2005) advocated (2.12) as a shortcut to capture this idea.

An additional friction, developed by Neumeyer and Perri (2005) and Uribe and Yue (2006), is to assume that firms must finance a fraction of the wage bill in advance. Again, we follow Neumeyer and Perri's formulation, the net result of which is that equilibrium in the labor market requires

$$W_t\left[1 + \theta\left(R_{t-1} - 1\right)\right] = a_t F_2(K_t, \Gamma_t h_t)\Gamma_t \tag{2.13}$$

instead of (2.6). In words, the typical firm hires workers to the point at which the marginal product of labor (the RHS of the previous expression) equals the wage rate inclusive of financing costs (the LHS). Firms are assumed to borrow from households and forced to pay for a fraction θ of the wage bill in advance of production.

As discussed by Oviedo (2005), the working capital assumption (2.13) and the endogenous spread assumption (2.12) are two separate alternatives, in spite of Neumeyer and Perri's imposing both. Indeed, they emphasize different possibilities for improving the performance of the basic model. With the working capital assumption, a fall in the world interest rate reduces the cost of labor, which stimulates output. At the same time, it stimulates demand, as the cost of borrowing for consumption and investment falls. Hence the trade balance may in principle deteriorate at the same time as output is expanding, which can explain an acyclical or countercyclical trade balance.

With an endogenous spread, a favorable productivity shock increases output and, because the shock is persistent, reduces the interest rate applicable to the representative household's debts, thus boosting consumption and investment even beyond the boost to output. A countercyclical trade balance may then emerge, as with working capital, although it is due to a different mechanism.

Following this discussion, our empirical work below evaluates working capital and endogenous spreads both in combination or separately. The top panel of Table 1 summarizes the main dimensions considered in the empirical analysis that follows in the next two sections. The other panels describe assumptions made for robustness checks to be performed later and discussed in section 5.

3. Empirical Approach

3.1. Bayesian Analysis, in a nutshell

We adopt a Bayesian viewpoint, to a large extent because it allows for a logically coherent comparison between models that are not necessarily nested, as is the case of the stochastic trend model and the financial frictions model. To implement that viewpoint, we draw on recent theoretical and computational advances, usefully summarized by DeJong and Dave (2007), Canova (2007), Geweke (2005), and others. For completeness, this section provides a very succinct description of how we implement the Bayesian approach.

Let X denote a vector of observed data. Each one of the models reviewed in the previous section implies a probability distribution for the data, say $p_M(X|\theta^M)$, where M is an index for each model and θ^M is a vector of parameters, possibly model specific, that we want to learn about. Given a particular parameter vector, say $\bar{\theta}^M$, $p_M(.|\bar{\theta}^M)$ is a probability distribution function whose value depends on X. Having observed a realization of X, say $\bar{X}$, $p_M(\bar{X}|.)$ can be seen as a function of the parameter vector θ^M. This function is the likelihood, usually denoted by $L_M(\theta^M|\bar{X})$ to emphasize that it is function of θ^M. The likelihood functions associated with the models in the previous sections can be computed in a straightforward fashion: following Sargent (1989), we linearize each model around its nonstochastic steady state, solve the resulting linear system via standard methods, and map the solution into a state space representation from which the likelihood can be computed using the Kalman filter.

The Bayesian framework is concerned with the way our views about models and their parameters are revised in light of observed data. Prior beliefs about the parameters of each model M are given by a prior distribution, which we denote by $p_M(\theta^M)$. After observing the data $\bar{X}$, Bayes Theorem implies that posterior beliefs about θ^M, denoted by $p_M(\theta^M|\bar{X})$, must respect:

$$
\begin{aligned}
p_M(\theta^M|\bar{X}) &= \frac{p_M(\bar{X}|\theta^M)p_M(\theta^M)}{\int p_M(\bar{X}|\theta^M)p_M(\theta^M)d\theta^M} \\
&= \frac{L_M(\theta^M|\bar{X})p_M(\theta^M)}{p_M(\bar{X})}
\end{aligned}
$$

where we have defined $p_M(\bar{X})$, model *M's marginal likelihood,* as:

$$
p_M(\bar{X}) = \int L_M(\theta^M|\bar{X})p_M(\theta^M)d\theta^M
$$

If one can compute the posterior distribution $p_M(\theta^M|\bar{X})$ one can also compute, at least in principle, the posterior distribution of functions of the parameter vector θ^M. In the context of the dynamic models we are considering, such functions include impulse response functions, moments of different variables, and variance decompositions. In practice, the analytical derivation of both the posterior distribution $p_M(\theta^M|\bar{X})$ and the posterior distribution of functions of θ^M is intractable. However, recent simulation methods allow us to obtain draws from the posterior distribution $p_M(\theta^M|\bar{X})$. A histogram of the simulated draws (or a chosen function of them) then provides an approximation of $p_M(\theta^M|\bar{X})$ (or the posterior distribution of the corresponding function) with a level of accuracy that can be made arbitrarily close by increasing the number of draws.

Key for our purposes is that the marginal likelihood $p_M(\bar{X})$ is the probability of observing the data $\bar{X}$ associated with model M. So one straightforward way to compare alternative models is to compute their respective marginal likelihoods.

Given this framework, we conduct two different but complementary exercises. We estimate the stochastic trend model and the financial frictions models and compare their marginal likelihoods, which amounts to a direct comparison of the two versions in terms of their predictive power. In one of the robustness checks we also estimate the encompassing model and focus on the posterior distribution of variance decomposition of aggregate variables, including output, thus measuring the relative importance of temporary productivity shocks, trend shocks, and interest rate shocks when all of them are allowed to play a role in generating fluctuations.

3.2. Functional forms, and calibrated versus estimated parameters

We follow the standard literature on emerging market business cycles when choosing the functional forms for preferences and technology. As in Neumeyer and Perri (2005), the utility function is of the Greenwood, Hercowitz and Huffman (1988) form:

$$u(C_t, h_t, \Gamma_{t-1}) = \frac{(C_t - \tau\Gamma_{t-1}h_t^{\omega})^{1-\sigma}}{1-\sigma}$$

GHH preferences have been shown to help reproducing some emerging economies' business cycles facts by allowing the labor supply to be independent of consumption levels.

The production function is assumed to be Cobb Douglass:

$$F(K_t, X_t h_t) = K_t^{1-\alpha}(\Gamma_t h_t)^{\alpha}$$

where α is the labor's share of income.

The capital adjustment cost function is assumed to be quadratic:

$$\Phi\left(K_{t+1}, K_t\right) = \frac{\phi}{2}\left(\frac{K_{t+1}}{K_t} - \mu\right)^2$$

In turn, the function κ determining the interest rate elasticity to the country's debt has the form:

$$\kappa\left(D_{t+1}/\Gamma_t\right) = \psi\left[\exp(\frac{D_{t+1}}{\Gamma_t} - d) - 1\right]$$

For each model, we estimate some parameters and calibrate the rest. The choice of which parameters to estimate or calibrate is guided by the objectives of our investigation as well as some known facts in the existing literature.

Since a main question is the relative importance of sources of fluctuations, in each case we estimate the parameters of exogenous driving forces. Hence, the parameters of the transitory productivity process (2.1), namely the AR coefficient ρ_a and the standard deviation of the innovations σ_a, are always estimated. Where shocks to the trend are allowed, we also estimate the parameters ρ_g and σ_g of the permanent productivity process (2.8). And if the world interest rate is allowed to be stochastic, as in the financial frictions models and the encompassing model, we estimate ρ_R and σ_R in (2.11).

While the addition of the permanent productivity process is the only departure of the stochastic trend model from the benchmark model, financial frictions models introduce two other parameters: the elasticity of the spread with respect to expected productivity (η) and the working capital requirement parameter θ. Accordingly, we estimate those parameters in models that allow for financial frictions. Finally, in all cases we estimate is the parameter ϕ governing the capital adjustment function.

We calibrate the remaining parameters of each model. The calibrated parameters are given in Table 2 and take conventional values: the coefficient of relative risk aversion is set at 2, and ω and τ are set so as to imply, respectively, a labor supply elasticity of 1.6 and a third of time spent working in the long run. The labor's share of income, α, is set to be 68%. Following Aguiar and Gopinath (2008) we set the long-run levels of the foreign interest rate and debt-to-GDP ratio to 1.03 and 0.1, respectively, to pin down the steady state value of debt holdings. The quarterly depreciation rate is assumed to be 5%. Lastly, as it is common in the literature on closing small open economy models, we set the the parameter of the debt to a minimum value that guarantees the the equilibrium solution to be stationary (Schmitt-Grohe and Uribe, 2003).

3.3. Data and Implementation

For comparability, we used the Mexican data from Aguiar and Gopinath (2007) as our observed data, X. We retrieved their series for aggregate consumption (C), investment (I), output (Y), and the trade balance to output ratio (TB/Y). The data are quarterly for the period 1980:I to 2003:II.

To implement our empirical procedures requires at least two other decisions: how to deal with trends, and whether and how to include measurement error. Our choices are best explained in the context of the state space formulation of each model, which is needed to apply Kalman filtering.

As mentioned, once each model is linearized around its nonstochastic steady state, the system of equations that characterize its solution can be written in the form of a transition equation:

$$Z_t = PZ_{t-1} + Q\nu_t \tag{3.1}$$

where Z_t is a vector with the model variables, and ν_t the vector of structural shocks, and P and Q system matrices that may depend on the model parameters. Using the Kalman filter then requires specifying a measurement equation,

$$X_t = F + GZ_t + \epsilon_t \tag{3.2}$$

mapping a vector of observed data X_t to the elements in Z_t by the conformable matrices $[F, G]$, while ϵ_t are exogenous measurement errors.

Given that the data is expressed in levels, and that the solution to our models is cast in terms of log-deviations from steady states, there is a straightforward way to map a transformation of the data to the elements in the models. For illustrative purposes, consider that we have data on aggregate output in levels, Y_t. In this case, the observed data can be directly linked to its theoretical counterpart, y_t, as follows:

$$\underbrace{Y_t}_{Data} = \underbrace{y_t\ X_{t-1}}_{Model}$$

Furthermore, since the solution of the model is given in terms of log-deviations from steady state, an additional transformation is needed. It follows that if there are shocks to the trend, the measurement equation for output is

$$\underbrace{\Delta \ln (Y_t)}_{Data} = \underbrace{\ln \mu + (\widehat{y}_t - \widehat{y}_{t-1}) + \widehat{g}_{t-1}}_{Model}; \tag{3.3}$$

where Δ denotes the first difference and a hat $\widehat{}$ denotes log-deviations from steady state values (i.e. $\widehat{y}_t = \ln (y_t/y_{SS})$). Similarly, if there are no trend shocks, the measurement equation for output is

$$\underbrace{\Delta \ln (Y_t)}_{Data} = \underbrace{\ln \mu + (\widehat{y}_t - \widehat{y}_{t-1})}_{Model}; \tag{3.4}$$

Similar observations apply for the measurement equations of aggregate consumption and investment. The absence of trend in equilibrium in the trade balance share makes the mapping from the observed data to the model based data independent of which case we are considering. Moreover, because we take a linear approximation to the model-based measure of trade balance share, tby, the mapping in terms of first differences is

$$\underbrace{\Delta \left(TB/Y\right)_t}_{Data} = \underbrace{\widehat{tby}_t - \widehat{tby}_{t-1}}_{Model};$$

We choose a mapping in first differences of TB/Y, instead of levels, because typically small open economy models counterfactually deliver a quasi-random walk process in the trade balance level, inherited by the nature of the endowment process (see Garcia-Cicco, et.al., 2008).

The second issue is the treatment of the measurement errors ϵ_t. The stochastic trend model and the financial frictions models are each driven by two exogenous shocks, but we observe four separate time series. Using the four series in the estimation then leads to the well known stochastic singularity problem, unless we add at least two measurement errors. Below, we start by adding i.i.d. measurement errors to the time series of output and consumption, but further bellow we also examine the robustness of our results to estimating the model using only pairs of series and no measurement errors, and, alternatively what happens if all series are observed with error. Note that, by estimating the variance of the measurement errors, another diagnostic of the quality of each model extension is obtained by comparing their relative size.

The mechanics of our estimations follow now standard procedures. We employ the Random Walk Metropolis algorithm to generate draws from the posterior distribution $p_M(\theta^M|X)$[2]. The algorithm constructs a Gaussian approximation around the posterior mode, which we first find via a numerical optimization of $\ln L_M(\theta^M|X) + \ln p_M(\theta^M)$, and uses a scaled version of the inverse of the Hessian computed at the posterior mode, to efficiently explore the posterior distribution in the neighborhood of the mode[3]. The algorithm is used to make $150,000$ draws from the posterior distribution of each case and the initial $50,000$ draws are burned. In addition, to overcome the high serial correlation of the draws, we use every 100^{th} draw and posterior distributions are generated with the remainder 1000 draws. Convergence of the Markov chains was verified in each case by running the Geweke and Chib (1998)'s separated mean test provided with no significant convergence problems observed.

4. Results

4.1. Stochastic Trend Model

Priors. Priors for the estimated parameters were based upon earlier studies of emerging market business cycles and are described in Table 3. The upper panel of the table describes our priors for parameters that are common across all models. Our prior for ρ_a, the autoregressive coefficient of the temporary productivity shock, is given by a Beta function with

[2]See An and Schorfheide (2007) for an excellent summary of the algorithm and its implementation.

[3]The MATLAB codes that solve all the model's extensions as well as the ones that carry out the estimation are available upon request.

parameters $(356, 19)$, implying a mean of 0.95 with a standard deviation of 1.1 percent. The mean is close to the point estimate found by Aguiar and Gopinath (2004)[4], and was the same calibrated value used by Neumeyer and Perri (2005). As stated in Table 3, the interval $[0.92, 0.97]$ contains 90 percent of the mass of the prior.

Priors for σ_a were formed using a Gamma function with parameters (2.04, 0.003) delivering a mean 0f 0.5 and standard deviation of 0.37 percent. These values mimic the point estimates found by Aguiar and Gopinath (2004, 2007) and capture a prior belief that transient shocks exhibit relatively mild volatility. Lastly, the priors on ϕ were stipulated as a Gamma function with parameters (3, 2). This implies a mean value of 6 and a 90 percent interval of $[1.62, 12.59]$. That the prior is not informative reflects the fact that previous studies have found very different values for ϕ when trying to mimic the investment volatility.

The two remaining parameters common across models are the standard deviations of measurement errors. There is some debate on whether one should see such errors as truly due to measurement issues or, alternatively, as reflecting general misspecification. The debate is unresolved and provides little guidance to our views on the magnitudes of σ_Y and σ_C, so we tentatively assume Gamma distributions with mean of 2 and standard deviation of one percent for both.

The middle panel of Table 3 describes our priors for the parameters specific to the stochastic trend model, namely, those governing the process for growth (ρ_g, σ_g). We based these priors on Aguiar and Gopinath's (2004) GMM results. The prior for the autoregressive coefficient of permanent productivity shocks, ρ_g, is described using a Beta function with parameters $(285, 111)$, implying a mean of 0.72 and a standard deviation of 2.3 percent . This follows the point estimate found by Aguiar and Gopinath (2004).

The most important parameter for the hypothesis of stochastic trends as driving forces behind emerging market business cycles is the volatility of the growth shock, σ_g. We use a Gamma function with parameters $(6.8, 0.0016)$, which yields a mean of 1.09 and a standard

[4]Note that we used the working paper version of Aguiar and Gopinath's work when forming our priors, instead of the published version. This is because only in the working paper version the estimation is done using the same GHH preferences we use in our work as in the published version they use Cobb-Douglas preferences instead. While they show that the business cycles implications of using the two preferences are similar, the point estimates of the key parameters they estimate do differ substantially.

deviation of 0.42, in percentages. These values mimic the point estimates found by Aguiar and Gopinath (2004) and capture a prior belief that growth shocks' volatility is more than twice the one observed for transient shocks to technology.

Posteriors. Estimated posterior distributions for the stochastic trend model are summarized in the third column of Table 4 and prior/posterior plots are presented in Figure 1. Four main results emerge:

- The data are fairly informative in all cases, in particular with respect to the volatilities of the shocks: the estimated posteriors appear much more precise than the priors, as measured by the size of the 90% highest posterior density intervals (see Table 4).

- The data are consistent with revising our beliefs in favor of a slightly lower persistence of the temporary productivity shock; and a slightly higher one for the permanent shock.

- More significantly, the estimated posterior distribution of σ_a is clearly to the right of its prior. The posterior distribution mean of σ_a is centered at about 2.55 percent while the prior is centered at 0.53. The posterior distribution mean of σ_g is centered at 1.18 and so slightly to the right of the prior mean, but this outward shift is much smaller than the one observed for the estimated posterior distribution of σ_a. These results are clearly at odds with Aguiar and Gopinath's finding that the volatility of shocks appears to be much stronger in the permanent technology process than in the transient one. Figure 2 illustrates this by plotting the distribution of the ratio σ_a/σ_g. For illustrative purposes we present the (average) point estimate reported by Aguiar and Gopinath (2004). The plot shows that the mode of the ratio σ_a/σ_g is at least six times higher than the one reported by Aguiar and Gopinath.

- The overall assessment as to whether emerging markets' business cycles are characterized by a volatile trend is based upon the relative importance of the random walk component of the Solow residual, a nonlinear function of the ratio σ_a/σ_g and the ratio ρ_a/ρ_g. The lower panel in Figure 2 plots the prior and posterior distributions of the random walk component. Given that the posterior of the ratio ρ_a/ρ_g is left pretty much unchanged relative to the prior, while the ratio σ_a/σ_g increases significantly, we see that the random walk component is largely reduced.

It appears, therefore, that a Bayesian method that incorporates the full information in the data does not assign such a large role to trend shocks, compared with a GMM procedure that only looks at a selected subset of moments. The Bayesian procedure assigns a much higher variance to the transient technology shock, which has notable implications for key business cycle moments, as will be discussed later.

4.2. Financial Frictions Model

Priors. Priors for parameters specific to the financial frictions model, that is, those pertaining to the process of the world interest rate and to financial frictions, are given in the bottom panel of Table 3.

Our prior for ρ_R, the AR coefficient of the world interest rate process, is described a Beta function with parameters (44.3, 9.06). This prior is consistent with beliefs that the mean value is 0.83, the point estimate found by Uribe and Yue (2006), and implies a standard deviation of 5.1 percent. For σ_R we specified a prior centered at 0.72 percent, the value reported by Uribe and Yue, with a standard deviation of 0.31 percent; this is expressed by a Gamma function with parameters (5.6, 0.0013).

For η, the elasticity of the country spread to expected productivity, we use a prior with mean 1.0 and a standard deviation of 10 percent, around the value calibrated by Neumeyer and Perri (2005) for the Argentinian case. Lastly, our prior beliefs of θ, the fraction of the wage bill to be financed in advance, are centered at 1.0, the calibrated parameter used in Neumeyer and Perri (2005) for Argentina. We define, however, a fairly noninformative prior over this parameter using a Gamma function with parameters $(6.25, 0.16)$ with a standard deviation of 40 percent, given that some studies have used lower calibrated values ,as in Mendoza and Yue (2008), while others have estimated it to be significantly higher than one as in Uribe and Yue (2006).

Posteriors. The posterior distribution results are reported in the fourth column of Table

4 and prior/posterior plots are presented in Figure 3. Main results can be categorized as follows:

- Again, the data appear to be rather informative in the sense that the posterior distributions are more concentrated than the priors in most cases. The only exception is perhaps the posterior for θ, which somewhat replicates the diffuse prior used.

- Relative to the model with stochastic trends, in this case the posterior distribution for ρ_a, the autoregressive parameter of temporary productivity shocks, is centered at 0.85, a lower value relative to the prior centered at 0.95.

- Likewise, the posterior distribution of σ_a has a mean of 1.06 percent, so its location is to the right of the prior but to the left of the posterior for the stochastic trend model. This shows that the financial frictions model has less of a need for high volatility of the transitory component in order to match the data than the stochastic trend model. This may come as no surprise given that the financial frictions amplify the effects of transient technology shocks.

- The posterior mean of the distribution of the world interest rate persistence, ρ_R, is located at 0.987, well above the prior of 0.83. While the posterior mean of σ_R is located at 0.37%, nearly half the prior mean. That is, the posterior distributions of the world interest rates suggest substantial persistence and lower volatility than our priors beliefs suggested.

- The tight posterior mode for η, with its mean centered around 0.73 reveals a significant elasticity of the spread to expected movements in the country fundamentals, embedded in $E_t \ln a_{t+1}$. While this is lower than our priors beliefs centered around the value of 1.0 calibrated by Neumeyer and Perri (2005), it is still remarkable to obtain a high value given that Neumeyer and Perri's calibration was based on the observed process of the country interest rate, which we don't observe here.

- As mentioned above, the posterior for θ is only slightly more concentrated than the prior with a posterior mean virtually identical to the one in the prior distribution.

This feature, however, will be reduced when looking at the encompassing model further below.

- Last, attention should be paid to the lower values of the posterior estimates of the two measurement errors, $\{\sigma_Y, \sigma_C\}$ obtained in the estimation of the financial frictions model relative to the ones in the stochastic trend model. Indeed, the values of these two errors fall between $\{1.87, 1.93\}$ in the latter case while for the former case they fall between $\{1.65, 1.71\}$. While this is a simple diagnostic, it suggests that misspecification is likely to be more severe in a model of the business cycle driven solely by technology shocks than in one where financial frictions amplify the impact of interest rate shocks.

4.3. Model Comparison

A formal model comparison of the two models considered as benchmark is given in the top panel of Table 5. For each case, we report the values of the log-likelihood level computed at the posterior mode, $\ln L_M(\theta^M|X)$; and the values of the log-marginal data density or log-marginal likelihood, $\ln p_M(X)$.

On both counts, the financial frictions model outperforms the stochastic trend model. Indeed, the posterior odds of the financial frictions model against the stochastic trend model (the ratios of their respective marginal likelihoods) is in the order of 1 : exp(69), well above the thresholds considered as "decisive evidence" in favor of the financial frictions model (see DeJong and Dave, 2007).

For comparison purposes, the top panel of Table 5 reports the log-likelihood value for the stochastic trend model evaluated at the point GMM estimates of the parameters reported by Aguiar and Gopinath (2004) [5]. The log-likelihood value obtained using the GMM-estimated parameters is far below the levels obtained when using our Bayesian method that takes the model to be a statistical representation of the data. This gives further quantitative evidence that, within the context of the models analyzed here, a full-information method that incorporates the entire information in the data can deviate substantially from an estimation

[5] The vector of parameters $[\rho_a, \sigma_a, \rho_g, \sigma_g, \phi]$ is estimated in Aguiar and Gopinath (2004) as $[0.94, 0.41, 0.72, 1.09, 3.79]$. When computing the log-likelihood value at this vector, we use the posterior mode of the two measurement errors.

method like GMM that only looks at a selected subset of moments. And from the evidence discussed above, we know this deviation takes mainly the form of a significantly higher variance of the transient technology shock.

4.4. Selected Moments

Comparing models on the basis of their marginal log likelihoods amounts to comparing their predictive performance. To see this, rewriting the log-marginal likelihood as

$$\begin{aligned}\ln p_M(X) &= \sum_{t=1}^{T} \ln p_M\left(x_t|X^{t-1}\right) \\ &= \sum_{t=1}^{T} \ln\left[\int p_M\left(x_t|X^{t-1},\theta^M\right) p_M\left(\theta^M|X^{t-1}\right) d\theta^M\right]\end{aligned}$$

expresses that relative log marginal likelihoods are equal to relative one-step-ahead predictive performance (for a discussion, see e.g. An and Schorfheide 2008).

It could be argued that for macroeconomists, the predictive performance of each model may not be the only metric that should be used when evaluating performance. In particular, the literature on emerging market business cycle has emphasized some key moments when evaluating alternative models. For example, two moments have drawn much of the attention by researchers in the field: the countercyclicality of the trade balance and the (higher) relative volatility of consumption and investment to output. Correspondingly, we next assess the performance of the stochastic trend and financial frictions models along a selected subset of moments including these two. In doing so we are implicitly conducting a more stringent test of each model, as the estimation was not designed to match this particular set of moments.

The results of this experiment are gathered in Table 6. The first column of numbers gives the filtered sample moments of the Mexican quarterly data, in terms of standard deviations, correlations with output and the trade balance, and serial correlations. The next two columns are the corresponding moments implied by the stochastic trend model and the financial frictions model.

Consistent with the measurement equations used in previous subssection, we filter the data using simple log-differences for income, consumption and investment; and first differences for the trade balance share. Model-based moments are computed using posterior mode estimates[6]. For comparison purposes, the moments obtained in Aguiar and Gopinath (2004)'s GMM estimation are reported in the third column[7].

The results can be categorized as follows:

- In seven of the eleven moments presented in Table 6 the financial frictions model exhibits a closer match to the empirical moments than the stochastic trend model. The remaining four moments are all related to the trade-balance share. In particular, while both models deliver the countercyclical trade balance-to-GDP ratio observed in the data, the stochastic trend matches the empirical moment more closely.

- A salient failure of the stochastic trend model in matching some of the key moments lies in the high variance of the main macro aggregates exhibited, notably gY and gC. This is a direct consequence of having estimated a much higher role of the transitory shocks σ_a. This in turn leads to another qualitative dimension in which the stochastic trend model fails due to the high posterior ratio σ_a/σ_μ mentioned before (Figure 2): the model's inability to reproduce a more volatile consumption with respect to output. Similarly, Garcia-Cicco et.al. (2008) find that the relevance of growth shocks vis a vis the transitory technology shock diminishes, and thereby the relative volatility of consumption to output decreases, when more moments are added in a GMM estimation framework.

- Neither of the two models, however, replicates well the volatility of investment. This shortcoming to both models will be revaluated, however, in the robustness analysis below.

- The financial frictions model delivers a more accurate match to the volatility of output and consumption and, notably, reproduces a consumption path that is more volatile than output, as observed in the data. This is an important result obtained previously

[6] Standard errors are omitted for brevity but are available upon request.

[7] To be precise, Aguiar and Gopinath (2004) conduct the GMM estimation based upon 11 moments of which only two, the standard deviation and serial correlations of gY, are reported in Table 6. The other 9 moments used by them refer to Hodrick-Prescott filtered moments which we don't present here given that we don't use this filtering technique.

by Neumeyer and Perri (2005) for the Argentinian economy, in that, the presence of financial frictions may amplify the effects of interest rate shocks to the point of causing a response of consumption that exceeds the response in output leading to countercyclical net exports. Thus, our results extend their findings to the Mexican case and show that this particularity of emerging market business cycles can be reproduced without the need to resort to the presence of permanent shocks to trend.

- Another salient dimension along which the financial frictions model clearly outperforms the stochastic trend model is the serial correlation of the variables gY and gC. Indeed the latter model significantly underpredicts the serial correlation in both variables. It should be noted that the work by Garcia-Cicco et.al. (2008) has also presented evidence of the empirical shortcomings of a model driven by stochastic trend shocks when replicating the serial correlation of the unfiltered trade balance-to-GDP ratio.

- A comparison between the model-based moments from the estimated stochastic trend model and the ones replicated using the GMM point estimates (Table 6, columns 3 and 4) reveals some clues as to why the full-information estimation differs from the GMM results. While the GMM approach, by construction, assigns more weight to the standard deviations, the full-information method assigns weights also the correlations among the four observed variables and thus attains a better match in that dimension. Obviously, other dimensions, different than the ones presented in Table 6, will be better matched as well in a full-information approach.

5. Robustness

In this section we assess the robustness of the results presented in the previous section along four dimensions summarized in the lower panels of Table 1. First, we revisit the two models' performance with less informative priors. Second, we investigate the role played in the financial frictions model by working capital and endogenous spreads when considered separately. Third, we assess the role of measurement errors in driving the results. Fourth, we specify and assess an *encompassing* model that nests both competing models, in order to get an alternative view of the sources of fluctuations.

5.1. Less Informative Priors

When conducting Bayesian analysis, it is illustrative to inquire the extent to which results are driven by relatively tight priors. This is particularly relevant for us given that the computation of the marginal likelihood, a key measure of model performance, depends not only on the data but also on the priors.

The left half of Table 7 presents a set of alternative priors. With only a few exceptions, all priors exhibit at least twice the variance relative to the benchmark priors [8]. For the standard deviations of the shocks, all prior distributions were given by a rather diffuse prior, a Gamma function with parameters $(4, 0.005)$, with a mean of two percent and a one percent standard deviation.

The posterior results are gathered in the right half of Table 7 and are plotted in Figure 4. Overall, the new posterior means are fairly close to the previous ones. In particular, the ratio of volatilities, σ_a/σ_μ, in the stochastic trend model continues to favor a stronger role of transient productivity shocks over trend shocks. More notably, the model comparison metrics presented in Table 5 show that the results obtained earlier are robust to the new set of priors: The financial frictions model appears to have a better relative fit than the stochastic trend model as it attains a higher likelihood value. And, judging by the marginal likelihood, the financial frictions model continues to exhibit a better predictive performance.

5.2. One Financial Friction at a Time

Given the results presented thus far, one may want to investigate which of the two financial frictions, endogenous spreads or working capital requirements, is responsible for the better relative performance of the financial frictions model. To address this question, we shut down one of the two frictions at a time (see Table 1).

[8] The exceptions were the parameters ϕ and θ on which the initial priors chosen were already quite diffuse. In addition numerical instability on the convergence of the MCMC chains prevented from using more difuse priors over the parameters ρ_R and ρ_g.

We start by estimating the financial frictions model without the assumption of working capital needs by the firms, $\theta = 0$, but still allowing for the possibility of the spread to be endogenously determined and estimating the elasticty parameter η. Conversely, we shut down the assumption of an endogenous spread, $\eta = 0$, and allow for the possibility of working capital needs, estimating the parameter θ.

The results in terms of the relative model performance are reported in Table 5, while the posterior distributions and the implications for selected moments are presented in Tables 8 and 9. Three results are worth mentioning. First, judging by marginal data densities, the working capital friction appears to be the more assumption, as the model without endogenous spread achieves a higher log-marginal likelihood level than the model without working capital needs. However, while both versions of the financial frictions model attain a higher log-marginal likelihood than the stochastic trend model, neither of the two reaches a higher level than the version that combines both frictions. Second, when only one of the financial frictions is active, the parameter governing the strength of the active financial friction is increased with respect to the version with both financial frictions active. This observation is particularly severe for the model without endogenous spread where, as Table 8 shows, the mean of the posterior distribution for θ is centered at a significantly high (and implausible) value of 3.7. Third, while the model with only working capital exhibits the highest marginal likelihood, the key moments presented in Table 9 show that the mere imposition of the working capital constraint fails to generate a consumption process more volatile than output, which in turn prevents the model from generating a countercyclical trade balance-to-GDP ratio. These results are in line with Oviedo (2005) who argues that an endogenous spread is a necessary ingredient when building models that aim at replicating emerging market business cycles.

Taken together, these three results are indicative that the two financial frictions are complementary to each other and may be both necessary to build realistic building business cycles models for emerging economies.

5.3. The Role of Measurement Errors

To deal with the well known stochastic singularity problem in the full information estimation of DSGE models researchers have resorted to two alternatives: either augment the set of structural shocks up to the number of time series observed; or artificially augment the space of shocks with measurement errors. Given the horse race between competing structural shocks that we have set up, the second option was clearly more appealing and we chose to add measurement errors to the observations of output and consumption. Yet, it is nonetheless important to investigate the extent to which our results are affected by this arbitrary choice.

To do so we ran two separate robustness checks. First, we estimated the model using only pairs of observables and no measurement errors. Given that the reference variable of the business cycle is output, we chose the three pairs of observables that can be formed with output and the other variables in our dataset: $\{(gY, gC), (gY, gI), (gY, dTB/Y)\}$. Second, we estimate the model using all the four observables and adding measurement errors to all four variables. While the first check tries to explore the way in which the results are modified without the potential distortion added by any measurement errors, the second check acknowledges that probably all time series are measured with some kind of error. The results in terms of model comparison are again reported in Table 5, and Tables 8 and 9 report the parameter estimates and key moments.

The results reported in the fourth and fifth panels of Table 5 point all to the same direction. Regardless of whether the two competing models are estimated with no measurement errors, or measurement errors are added to all the observables, the marginal data densities continue to favor the financial frictions model. However, a look at the results in Table 8 shows that at least three important differences are obtained when the models are estimated with no measurement errors. (For the sake of brevity we report posterior distributions and key moments computed when the model is estimated observing $\{gY, gC\}$ and no measurement errors, but the results from the other robustness checks are qualitatively similar and are available upon request.) For the stochastic trend model, the biggest difference is that the random walk component increases as the transitory shocks' volatility falls: the ratio σ_a/σ_g is now equal to 0.82, a much lower value when compared to the 2.16 reported in the benchmark case. A second difference that arises in both models comes from the large increase in the parameter ϕ governing the capital adjustment costs. The intuition is that the estimation procedure optimally increases the size of this parameter when the measurement errors that soaked up part of the unexplained volatility in the main macro aggregates are no longer used. Third, regarding the financial frictions model, the main difference comes from the larger size of the interest rate shocks, for which the estimated standard deviation more than doubles, while the parameter governing the working capital needs shrinks to less than half.

Not surprisingly, these three differences have important implications key business cycles moments, as can be seen from Table 9. The most important change comes from the dampening of the volatility in aggregate investment experienced in both models and much closer to the empirical counterpart, which comes as a direct consequence of the increases in ϕ. Likewise, the volatility in aggregate output and consumption is more accurately reproduced in both models, although still the financial frictions model appears to hit the empirical targets more closely. It is also interesting to see that the increase in the ratio σ_a/σ_g brings the stochastic trend closer to the data by delivering a consumption volatility higher than output's, although still not as much as the required to accurately reproduce the high countercyclicality of the trade balance share. Overall, it seems that estimating the two competing models observing only pairs of series and in the absence of measurement errors not only leaves unchanged the ranking of model performance, but it also brings the two models closer to the data in terms of the specific subset of key moments that researchers have paid close attention to.

5.4. An Encompassing Model

While the literature has naturally considered stochastic trends and financial frictions separately, one can clearly specify a model in which both extensions of the benchmark model are present. A first step in this direction has already been taken by Aguiar and Gopinath (2008) where the stochastic trend model is expanded to allow for shocks to the consumption and investment Euler equations that operate through the interest rate. In this subsection we consider, as a robustness check, an *encompassing* model in which both stochastic trends and financial frictions are present. In doing so we extend the analysis undertaken by Aguiar and Gopinath (2008) in three important dimensions. First, the encompassing model includes both financial frictions embedded in the parameters η and θ. Note that while Aguiar and Gopinath (2008) did consider the possibility of an endogenous spread that reacted to fundamentals, they did not allow for the possibility of other types of financial frictions such as the need for working capital which, as documented above, appears to be a key transmission mechanism and a relevant feature in bringing theoretical models of emerging market business cycles closer to the data. Second, while Aguiar and Gopinath (2008) considered Cobb-Douglas preferences, in the encompassing model we will continue to use GHH preferences. As mentioned before, the latter set of preferences allow labor supply to be independent of consumption levels, thereby delivering the negative comovement between interest rates and output levels observed in emerging markets data both during crises *and* tranquil times. On the contrary, Cobb-Douglas preferences have shown to counterfactually deliver output and employment booms in the presence of positive interest rate shocks (Neumeyer and Perri, 2005).

Third, while Aguiar and Gopinath (2008) only allowed for the spread to be affected by transient technology shocks, in the encompassing model we also allow for permanent shocks to also affect the spread. This is natural, since the logic behind an endogenous spread is often based on the idea that default risk falls with expected productivity, regardless of whether shocks to the latter are permanent or transitory. To implement this, however, we need to modify the assumption (2.12) on country risk. So, in the encompassing model the country spread will be assumed to be given by

$$\log(S_t/S) = -\eta_1 E_t \log a_{t+1} - \eta_2 E_t \log(\mu_{t+1}/\mu)$$

One particular version of this, which we will examine, assumes that the spread is given by (2.12), except that the temporary productivity shock a_{t+1} is replaced by total factor productivity (Solow residual):

$$\log(S_t/S) = -\eta E_t \log(SR_{t+1}/SR)$$

where $SR_t = a_t g_t^a$ and $SR = \mu^\alpha$ according to the Cobb-Douglas technology specified bellow[9].

The encompassing model is the combination of one of the previous two assumptions for the spread with stochastic interest rates (2.9-2.11), the working capital requirement (2.13), and trend shocks (2.8), in addition to temporary productivity shocks (2.1) (see Table 1, bottom panel). As usual, results on the encompassing model's relative fit are reported in Table 5 (bottom panel), and the posterior distribution as well as key moments are reported in Tables 8-9 (rightmost columns) and Figure 5. In addition, and given that the encompassing model jointly considers all the three structural shocks we have considered in this work, we also include a structural variance decomposition analysis of main aggregates (output, consumption, investment, and the TB/Y ratio) in Table 10.

The most remarkable result is the small role played by trend shocks when accounting for the variance of the macroeconomic aggregates: as the results reported in Table 10 show, their share is lower than 9% in all cases. On the other hand, foreign interest rate shocks play a nontrivial role, particularly when explaining the variance in the trade balance-to-GDP ratio (69%), investment (38%), and to a lesser extent in consumption (24%). Notably, their role accounting for the variance of output (12%) falls within the estimates from previous studies: Neumeyer and Perri (2005) found that the standard deviation of Argentina's GDP in a model with financial frictions but without shocks to international rates is 3% smaller than the one in a model with interest rate shocks; and Uribe and Yue (2006) found that US interest rate shocks explain about 20% of movements in aggregate activity in a pool of emerging market economies. The large share of the variance in both output and consumption aggregates is explained by transient shocks to the technology process amplified through their effect over the spread.

A look at the estimated posterior distributions of the parameters of the encompassing model, from Table 8, helps explain the results obtained in the forecast error variance decompositions discussed above. On one hand the predominance of trend shocks is significantly reduced, as the mean of the posterior ratio for σ_a/σ_g is centered around 2.4. On the other

[9] A similar version of the encompassing model where η_1 and η_2 were separately estimated was also made. While the variance decomposition results of this version (available upon request) did not differ much from the unified version with the Solow residual, poor identification in η_2 prevented us from using this version.

hand, interest rate shocks are estimated to be highly persistent, as the posterior distribution for ρ_R is centered around 0.98; and their amplifying effect through the working capital needs is increased as the posterior estimate for θ is now centered around 1.24, a number similar to that estimated by Uribe and Yue (2006).

6. Concluding Remarks

By and large, the empirical results here favor financial frictions models relative to stochastic trends ones. One could ask, in particular, how our results can be reconciled with those of Aguiar and Gopinath (2007), who reported strong support for the stochastic trend model. The short answer, in our view, is that Aguiar and Gopinath's GMM procedure targeted only a few moments of the joint process of the aggregates observed, while our Bayesian procedure considers all moments of the process. One could, then, argue that Aguiar and Gopinath's estimates of the importance of the random walk component would be superior in terms of criterion functions that emphasize those moments targeted by their GMM procedure. But then one would also have to justify why those moments and not many others are the only ones that we may care about.

While our emphasis has been on the financial frictions/stochastic trend dichotomy, there is plenty of associated research to be done. One could, for example, compare the performance of the financial frictions model against atheoretical VARs. While the predictive performance of the latter is likely to be superior, recent work suggests that refined versions of stochastic dynamic models can be built that compete with VARs in terms of predictive power.

In terms of policy, our results lend support to the idea that attempts to ameliorate financial imperfections may result in less aggregate volatility. They are likely too to lead to increases in welfare, although this is a question about which our estimation exercises have nothing to say.

References

[1] Aguiar, M., and G. Gopinath, “Emerging Market Business Cycles: The Cycle is the Trend,” NBER WP # 10734 (2004).

[2] Aguiar, M., and G. Gopinath, “The Role of Interest Rates and Productivity Shocks in Emerging Market Fluctuations” (2008)

[3] Aguiar, M., and G. Gopinath, “Emerging Market Business Cycles: The Cycle is the Trend,” JPE 115 (2007), 69-102

[4] Calvo, G. “Capital Flows and Capital Market Crises: The Simple Analytics of Sudden Stops.” Journal of Applied Economics 1 (1998), 35-54

[5] Calvo, G., L. Leiderman, and C. Reinhart, "Capital Inflows and Real Exchange Rate Appreciation in Latin America: The Role of External Factors". IMF Staff Papers (1993) 40(1): 108–51.

[6] F. Canova, Methods for Applied Macroeconomic Research, Princeton, 2007

[7] Cespedes, L. F., R. Chang, and A. Velasco, "Balance Sheets and Exchange Rate Policy", The American Economic Review, Vol 94 No.4 (Sep. 2004)

[8] D. DeJong and C. Dave, Structural Macroeconometrics, Princeton University Press, 2007.

[9] Fernandez, A."’Tropical’ Real Business Cycles? A Bayesian Exploration". Mimeo, Rutgers University, 2007.

[10] Garcia Cicco, J., Pancrazi, R, and M. Uribe, “Real Business Cycles in Emerging Countries?”, NBER WP # 12629 (2007).

[11] Geweke, J. (2005), Contemporary Bayesian Econometrics and Statistics, Wiley.

[12] Justiniano, A. and B. Preston, (2006), “Can Structural Small Open Economy Models Account for the Influence of Foreign Disturbances?”, working paper, Federal Reserve Board and Columbia University.

[13] King, R., C. Plosser, and S. Rebelo, "Production, Growth and Business Cycles. I and II", Journal of Monetary Economics (1988) 21:195-232 and 309-42.

[14] Lubik, T. and F. Schorfheide, "A Bayesian Look at the New Open Economy Macroeconomics," in NBER Macroeconomics Annual 2005.

[15] Mendoza, E. "Real Business Cycles in a Small Open Economy," AER 81 (1991), 797-818

[16] Mendoza, E. (2006), "Endogenous sudden stops in a business cycle model with collateral constraints," NBER WP 12564.

[17] Neumeyer, A. and F. Perri, "Business Cycles in Emerging Economies: the Role of Interest Rates," JME 52 (2005), 345-80.

[18] Oviedo, M. (2005), "World Interest rates, Business Cycles, and Financial Intermediation in Small Open Economies," unpublished, Iowa State University

[19] Rabanal, P. and V. Tuesta (2006), "Euro Dollar "Euro-Dollar Real Exchange Rate Dynamics in an Estimated Two-Country Model: What is Important and What is Not," CEPR Discussion paper 5957.

[20] Sargent, T. (1989), "Two Models of Measurements and the Investment Accelerator," JPE 97, 251-87.

[21] Schmitt-Grohe, S. and M. Uribe, "Closing Small Open Economy Models", Journal International Economics 61 (2003) pp 163-185.

[22] Schmitt-Grohe, S. and M. Uribe, "Solving DSGE models using a second-order approximation to the policy function", Journal of Economic Dynamics and Control (2004), 28, 755-775.

[23] Uribe, M. and V. Yue, "Country Spreads and Emerging Countries: Who Drives Whom?", JIE 69 (2006), 6-36.

TABLES

Table 1: Cases considered(*)

CASES	Trend	Interest Rate	Spread	Working-Capital
	Dimensions considered			
Benchmark. Observables:$\{gY, gC, gI, dTB/Y\}$, Measurement Errors in $\{gY, gC\}$				
Stochastic Trend Model	$\widehat{g}_t = \rho_g \widehat{g}_{t-1} + \varepsilon_t^\mu$	$R_t^* = R^*$	$S_t = 1$	$\theta = 0$
Financial Frictions Model	$g_t = \mu$	$\widehat{R}_t^* = \rho_R \widehat{R}_{t-1}^* + \varepsilon_t^R$	$\widehat{S}_t = -\eta E_t \widehat{a}_{t+1}$	$\theta \geq 0$
Robustness 1. Less Informative Priors				
Stochastic Trend Model	$\widehat{g}_t = \rho_g \widehat{g}_{t-1} + \varepsilon_t^\mu$	$R_t^* = R^*$	$S_t = 1$	$\theta = 0$
Financial Frictions Model	$g_t = \mu$	$\widehat{R}_t^* = \rho_R \widehat{R}_{t-1}^* + \varepsilon_t^R$	$\widehat{S}_t = -\eta E_t \widehat{a}_{t+1}$	$\theta \geq 0$
Robustness 2. One Financial Friction at a time				
No Working Capital	$g_t = \mu$	$\widehat{R}_t^* = \rho_R \widehat{R}_{t-1}^* + \varepsilon_t^R$	$\widehat{S}_t = -\eta E_t \widehat{a}_{t+1}$	$\theta = 0$
No Endogenous Spread	$g_t = \mu$	$\widehat{R}_t^* = \rho_R \widehat{R}_{t-1}^* + \varepsilon_t^R$	$S_t = S$	$\theta \geq 0$
Robustness 3. Pairs of Observables,No Meas. Err. / All Observables measured with error				
Stochastic Trend Model	$\widehat{g}_t = \rho_g \widehat{g}_{t-1} + \varepsilon_t^\mu$	$R_t^* = R^*$	$S_t = 1$	$\theta = 0$
Financial Frictions Model	$g_t = \mu$	$\widehat{R}_t^* = \rho_R \widehat{R}_{t-1}^* + \varepsilon_t^R$	$\widehat{S}_t = -\eta E_t \widehat{a}_{t+1}$	$\theta \geq 0$
Robustness 4. Three Structural Shocks				
Encompassing Model	$\widehat{g}_t = \rho_g \widehat{g}_{t-1} + \varepsilon_t^\mu$	$\widehat{R}_t^* = \rho_R \widehat{R}_{t-1}^* + \varepsilon_t^R$	$\widehat{S}_t = -\eta E_t \widehat{SR}_{t+1}$	$\theta \geq 0$

(*) A hat denotes deviation from steady state. Variables without a hat denote steady state variables.

Table 2: Calibrated Parameters(*)

Variable	Description	*Value*
σ	Intertemporal Elasticity of Substitution $\left[\frac{1}{\sigma}\right]$	2.0
ω	Elasticity of Labor Supply $\left[\frac{1}{\omega-1}\right]$	1.6
α	Labor Share of Income	0.68
R^*	Gross Foreign Interest Rate	1.03
μ	Long-run Productivity Growth	1.006
τ	Labor Parameter so that $h^{ss} = 1/3$	varies
ψ	Debt Elastic Interest Rate Parameter	0.001
β	Discount Factor	varies
S	Long-run Gross Country Interesr Rate Premium	1.05
δ	Depreciation Rate of Capital	0.05
d	Debt-to-GDP Ratio (D/Y)	0.10

(*) The period is taken to be a quarter. Most values taken from Aguiar and Gopinath (2007). The discount factor in the stochastic growth model is set to be 0.98 as in Aguiar and Gopinath (2007). In the Financial Frictions Model the discount factor is set to 0.93 as in Neumeyer and Perri (2005) consistent with a gross spread of 1.054

Table 3: Prior Distributions

	Parameter	Range	Density	Mean	Std. Dev. (%)	90% Interval	
	Parameters common to both models						
ρ_a	AR Coeff. of Transient Tech. Process	$[0,1)$	Beta[356, 19]	0.95	1.12	[0.92	0.97]
σ_a	Std. Dev. of Transient Tech. Shock (%)	$\mathbb{R}^+$	Gamma[2.04, 0.003]	0.53	0.37	[0.10	1.25]
ϕ	Capital Adjustment Cost Fct. Parameter	$\mathbb{R}^+$	Gamma[3, 2]	6.0	346	[1.62	12.59]
σ_Y	Std. Dev.(%) of Meas. Error to $\Delta\ln(Y_t)$	$\mathbb{R}^+$	Gamma[4, 0.005]	2.00	1.0	[0.67	3.86]
σ_C	Std. Dev.(%) of Meas. Error to $\Delta\ln(C_t)$	$\mathbb{R}^+$	Gamma[4, 0.005]	2.00	1.0	[0.67	3.86]
	Specific to the Stochastic Trend Model						
ρ_g	AR Coeff. of Growth Process	$[0,1)$	Beta[285, 111]	0.72	2.25	[0.68	0.76]
σ_g	Std. Dev. of Growth Shock (%)	$\mathbb{R}^+$	Gamma[6.8, 0.0016]	1.09	0.42	[0.50	1.85]
	Specific to the Financial Frictions Model						
ρ_R	AR Coeff. of R^* Process	$[0,1)$	Beta[44.3, 9.06]	0.83	5.10	[0.74	0.91]
σ_R	Std. Dev. of ε^R (%)	$\mathbb{R}^+$	Gamma[5.6, 0.0013]	0.72	0.31	[0.30	1.29]
θ	Working-capital need	$\mathbb{R}^+$	Gamma[6.25, 0.16]	1.00	40.0	[0.44	1.74]
η	Elasticity of Spread to Fundamentals	$\mathbb{R}^+$	Gamma[99.2, 0.01]	1.00	10.0	[0.84	1.17]

Table 4: Posterior Distributions$^{(*)}$

Parameter	Prior	Stochastic Trend Model	Financial Frictions Model
ρ_a	0.95	0.944	0.847
	$[0.92, 0.97]$	$[0.934, 0.953]$	$[0.822, 0.869]$
σ_a	0.53	2.55	1.06
	$[0.10, 1.25]$	$[2.17, 3.09]$	$[0.91, 1.23]$
ϕ	6.0	3.747	6.73
	$[1.62, 12.59]$	$[3.045, 4.582]$	$[5.74, 7.86]$
σ_Y	2.0	1.87	1.65
	$[0.67, 3.86]$	$[1.65, 2.16]$	$[1.45, 1.89]$
σ_C	2.0	1.93	1.71
	$[0.67, 3.86]$	$[1.69, 2.21]$	$[1.51, 1.93]$
ρ_g	0.72	0.779	
	$[0.68, 0.76]$	$[0.746, 0.809]$	
σ_g	1.09	1.18	
	$[0.50, 1.85]$	$[0.93, 1.46]$	
ρ_R	0.83		0.987
	$[0.74, 0.91]$		$[0.975, 0.994]$
σ_R	0.72		0.37
	$[0.30, 1.29]$		$[0.30, 0.44]$
θ	1.0		1.01
	$[0.44, 1.74]$		$[0.56, 1.65]$
η	1.0		0.73
	$[0.84, 1.17]$		$[0.61, 0.86]$

$^{(*)}$ Results reported are posterior means and 90 percent probability intervals (in brackets)

Table 5: Model Comparisons [(*)]

CASES	Log-Likelihood	Marginal Log-Likelihood
Benchmark Cases		
Stochastic Trend Model	733.94	715.05
Financial Frictions Model	836.54	783.90
AG - GMM	41.70	n.a.
Diffuse Priors		
Stochastic Trend Model	727.10	709.96
Financial Frictions Model	849.71	826.11
One Financial Friction at a Time		
No Working Capital	835.24	780.71
No Endogenous Spread	857.51	823.73
No Measurement Errors: Estimation observing pairs of time series		
Observables: $\{gY, gC\}$		
Stochastic Trend Model	480.41	459.28
Financial Frictions Model	493.71	468.96
Observables: $\{gY, gI\}$		
Stochastic Trend Model	371.66	358.85
Financial Frictions Model	411.00	392.67
Observables: $\{gY, dNX\}$		
Stochastic Trend Model	367.20	352.68
Financial Frictions Model	502.70	478.49
Measurement Errors in all variables: Observables $\{gY, gC, gI, dNX\}$		
Stochastic Trend Model	955.78	783.86
Financial Frictions Model	951.37	926.05
Adding all 3 Structural Shocks		
Encompassing Model	840.28	783.79

[(*)] Likelihood levels are computed in the posterior mode. Results on marginal data densities are approximated by Geweke's harmonic mean estimator. Except for the cases with no measurement errors and measurement errors in all 4 variables, results are computed observing the time series for output, consumption, investment and the trade balance-to-GDP ratio, and i.i.d. measurement errors were added to the observation of output and consumption. AG-GMM stands for the log-likelihood value evaluated using the estimated parameters in Aguiar and Gopinath (2004) by GMM.

Table 6. Sample and Model-based moments

Parameter	Data	AG-GMM	Stochastic Trend Model	Financial Frictions Model
Standard Deviations (%)				
gY	1.53	1.58	4.79	2.02
gC	1.94	1.71	4.15	2.59
gI	5.66	5.52	11.94	11.02
dTB/Y	1.38	1.12	1.73	2.39
Correlation with gY				
gC	0.76	0.98	0.98	0.84
gI	0.75	0.88	0.92	0.67
dTB/Y	-0.44	-0.71	-0.46	-0.35
Correlation with dTB/Y				
gC	-0.50	-0.82	-0.60	-0.79
gI	-0.67	-0.95	-0.77	-0.91
Serial Correlation				
gY	0.27	0.27	0.08	0.28
gC	0.20	0.19	0.07	0.21

[(*)] Note: gX denotes log-differences, dX denotes first differences. Model-based moments using observables $\{gY_t, gC_t, gI_t, dTB/Y_t\}$ from the Mexican Data, 1980.1-2003.2. Moments are computed using posterior mode estimates. Standard Errors are omitted for brevity but are available upon request.

Table 7: Diffuse Priors and Posterior Distributions

	Priors					Posteriors					
						Stochastic Trend Model			Financial Frictions Model		
	Range	Density	Mean	90% Interval		Mean	90% Interval		Mean	90% Interval	
	Parameters common to both models										
ρ_z	[0,1)	Beta[5,2]	0.71	0.43	0.94	0.94	0.92	0.95	0.69	[0.62	0.74]
σ_z	R^+	Gamma[4,0.005]	2.00	0.67	3.86	3.23	2.59	3.94	1.19	[1.04	1.37]
ϕ	R^+	Gamma[3,2]	6.0	1.62	12.59	3.67	2.86	4.61	6.23	[5.18	7.44]
σ_Y	R^+	Gamma[4,0.005]	2.00	0.67	3.86	1.89	1.68	2.16	1.79	[1.58	2.02]
σ_C	R^+	Gamma[4,0.005]	2.00	0.67	3.86	1.95	1.71	2.23	1.77	[1.58	2.00]
	Specific to the Stochastic Trend Model										
ρ_g	[0,1)	Beta[146,89.5]	0.62	0.57	0.67	0.71	0.64	0.76			
σ_g	R^+	Gamma[4,0.005]	2.00	0.67	3.86	1.72	1.30	2.33			
	Specific to the Financial Frictions Model										
ρ_R	[0,1)	Beta[44.3,9.06]	0.83	0.74	0.91				0.96	[0.92	0.98]
σ_R	R^+	Gamma[4,0.005]	2.00	0.67	3.86				0.30	[0.24	0.40]
θ	R^+	Gamma[6.25,0.16]	1.00	0.44	1.74				1.00	[0.50	1.67]
η	R^+	Gamma[25,0.04]	1.00	0.70	1.36				0.64	[0.45	0.89]

Table 8: Posterior Distributions, Robustness Analysis

Parameter	Prior	No Working Capital	No Endogenous Spread	Observables: $\{gY, gC\}$		Encompassing Model
				Stochastic Trend	Financial Friction	
ρ_z	0.95	0.84	0.92	0.92	0.89	0.85
	[0.92,0.97]	[0.81,0.86]	[0.90,0.94]	[0.90,0.94]	[0.87,0.91]	[0.82,0.88]
σ_z	0.53	1.15	1.19	1.15	0.90	1.00
	[0.10,1.25]	[1.00,1.34]	[1.04,1.35]	[1.00,1.32]	[0.80,1.03]	[0.84,1.19]
ϕ	6.0	7.78	4.78	11.21	16.39	6.62
	[1.62,12.59]	[6.67,9.06]	[4.05,5.61]	[6.18,19.25]	[10.73,24.28]	[5.63,7.78]
σ_Y	2.0	1.78	1.94			1.63
	[0.67,3.86]	[1.58,2.04]	[1.72,2.21]			[1.43,1.85]
σ_C	2.0	1.82	1.85			1.69
	[0.67,3.86]	[1.61,2.08]	[1.63,2.11]			[1.50,1.94]
ρ_g	0.72			0.82		0.71
	[0.68,0.76]			[0.80,0.84]		[0.67,0.74]
σ_g	1.09			1.40		0.42
	[0.50,1.85]			[1.17,1.66]		[0.21,0.70]
ρ_R	0.83	0.98	0.96		0.90	0.98
	[0.74,0.91]	[0.97,0.99]	[0.93,0.98]		[0.85,0.94]	[0.97,0.99]
σ_R	0.72	0.40	0.21		0.78	0.36
	[0.30,1.29]	[0.34,0.47]	[0.17,0.28]		[0.60,1.05]	[0.30,0.44]
θ	1.0		3.70		0.43	1.24
	[0.44,1.74]		[2.41,5.32]		[0.19,0.79]	[0.72,1.91]
η	1.0	0.76			0.72	0.72
	[0.84,1.17]	[0.64,0.90]			[0.61,0.83]	[0.59,0.86]

Note: Results reported are posterior means and 90 percent probability intervals (in brackets)

Table 9: Sample and Model-based moments, Robustness Analysis

Parameter	Data	No Working Capital	No Endogenous Spread	Observables: $\{gY, gC\}$		Encompassing Model
				Stochastic Trend	Financial Friction	
	Standard Deviations (%)					
gY	1.53	2.08	2.03	2.85	1.64	2.06
gC	1.94	2.53	1.71	3.06	2.50	2.67
gI	5.66	10.00	6.27	5.67	6.17	11.33
dTB/Y	1.38	2.15	1.38	1.60	2.00	2.47
	Correlation with gY					
gC	0.76	0.85	0.89	0.94	0.81	0.84
gI	0.75	0.74	0.50	0.80	0.60	0.64
dTB/Y	-0.44	-0.35	0.22	-0.24	-0.31	-0.34
	Correlation with dTB/Y					
gC	-0.50	-0.79	-0.24	-0.56	-0.80	-0.78
gI	-0.67	-0.88	-0.72	-0.78	-0.94	-0.92
	Serial Correlation					
gY	0.27	0.04	0.02	0.22	0.14	0.37
gC	0.20	-0.02	0.16	0.16	0.11	0.29

Note: gX denotes log-differences, dX denotes first differences. Model-based moments using observables {gY, gC, gI, dTB/Y} from the Mexican Data, 1980.1-2003.2. Moments are computed using posterior mode estimates. Standard Errors are omitted for brevity but are available upon request.

Table 10: Forecast Error Variance Decomposition(*)

Structural Shock	gY	gC	gI	dTB/Y
ε^a	79.4	68.1	56.5	27.8
	$[65.3, 89.2]$	$[55.3, 77.7]$	$[45.9, 65.9]$	$[18.9, 37.2]$
ε^g	9.0	7.7	5.8	3.6
	$[2.1, 21.1]$	$[1.8, 17.5]$	$[1.34, 13.1]$	$[0.8, 8.4]$
ε^R	11.6	24.2	37.7	68.6
	$[6.1, 18.8]$	$[16.7, 32.4]$	$[29.2, 46.3]$	$[59.3, 77.7]$

(*) Means based on the 150,000 draws from the posterior distribution. The 90 percent interval is denoted in parenthesis. The contribution of measurement errors are not included in the analysis. The contributions are measured over an 8 time horizon period.

FIGURES

Fig.1: Stochastic Trend Model, Prior and Posterior Plots

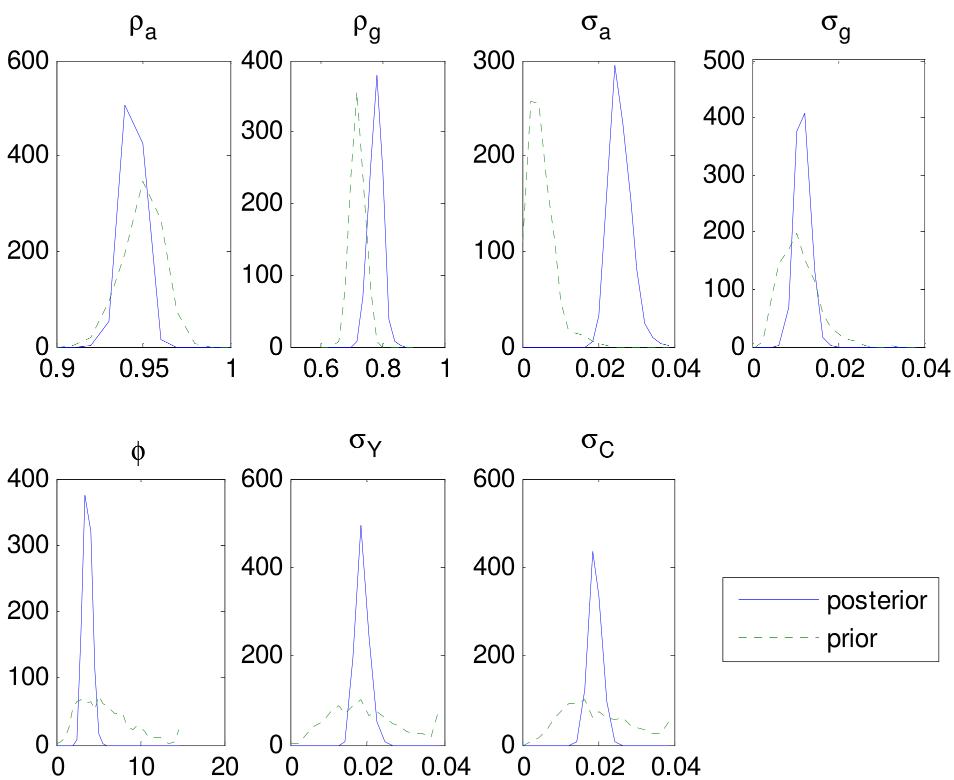


Fig.2: Volatilities Ratio and Random Walk Component in the Stochastic Trend Model

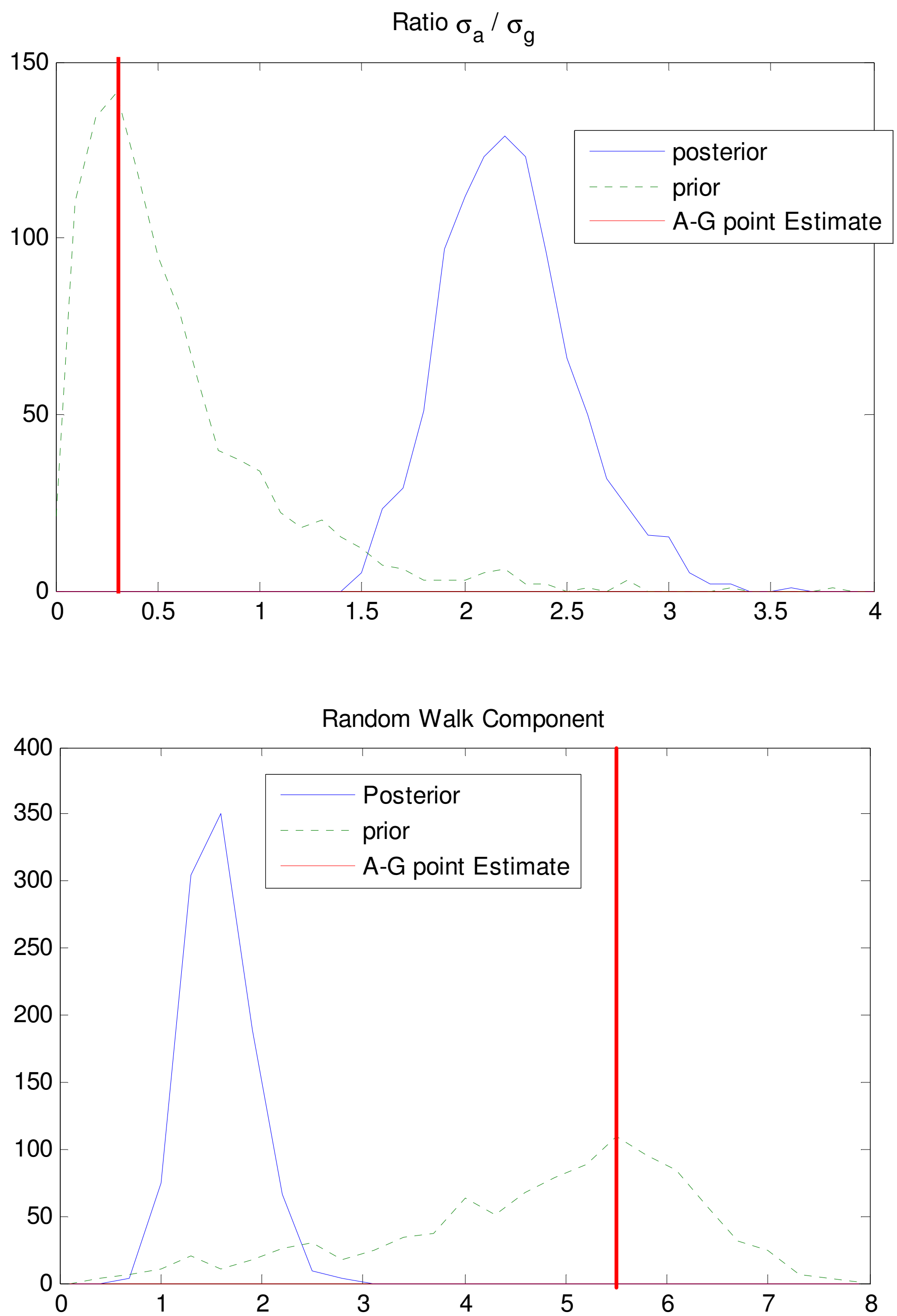


Fig.3: Financial Frictions Model, Prior and Posterior Plots

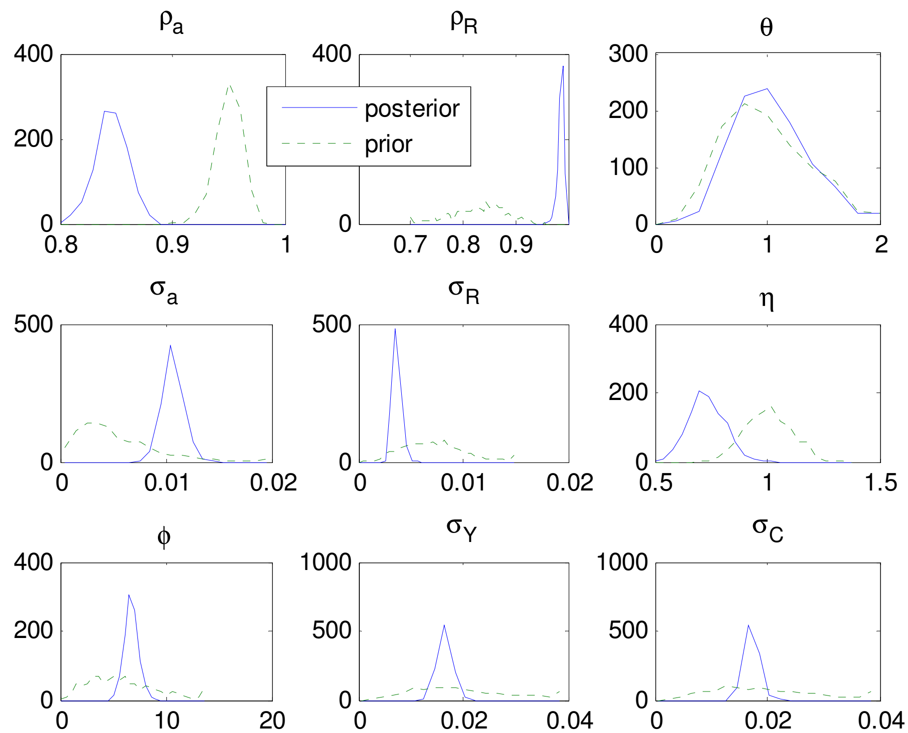
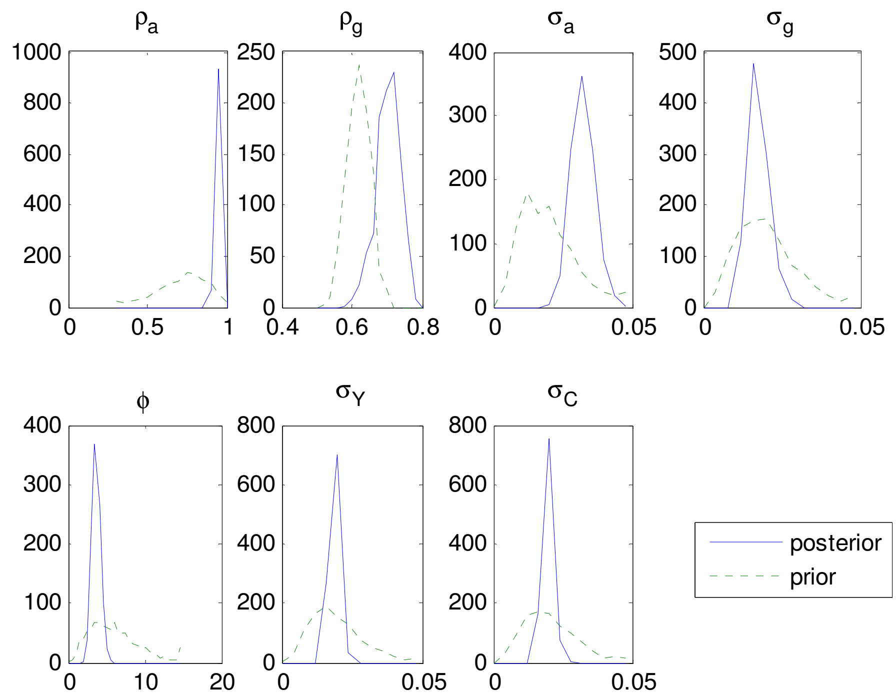


Fig.4: Diffuse Priors and Posterior Plots

Stochastic Trend Model



Financial Frictions Model

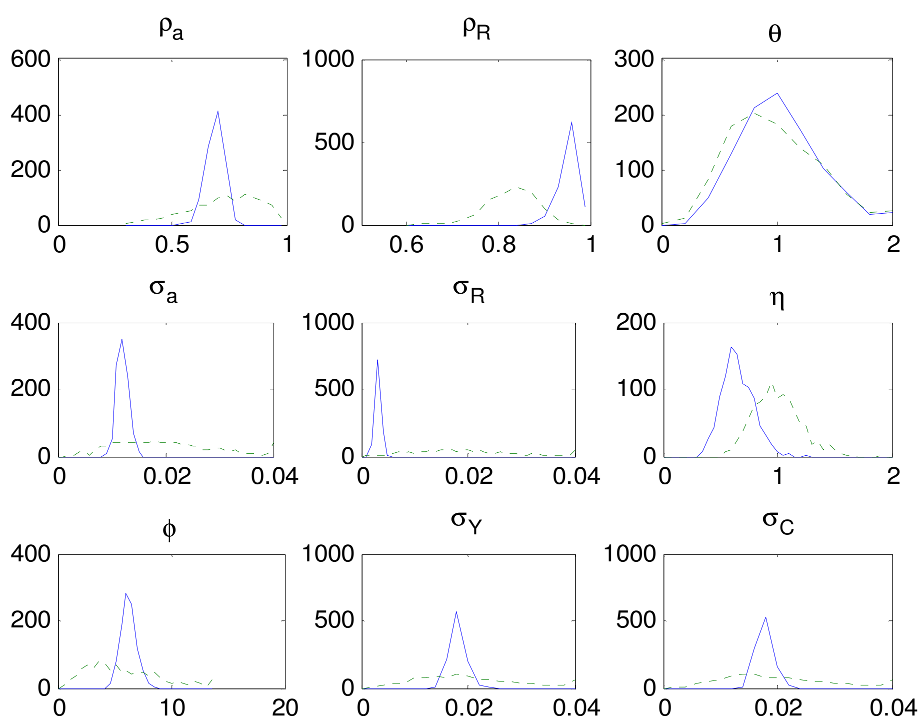


Fig.5: Encompassing Model, Priors and Posterior Plots