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, and also evaluates a model that encompasses the two approaches, taking advantage of recent developments in the theory and implementation of Bayesian methods. The encompassing model assigns a substantial role to interest rate shocks and financial frictions as amplifying mechanisms, but not to trend shocks, in generating aggregate fluctuations. Formal model comparison exercises favor models with financial frictions over the stochastic trend model, although this is sensitive to the inclusion of measurement errors. Our results are inconclusive in terms of which of the financial frictions we consider, working capital versus endogenous spreads, is a superior choice, and both appear to be required for a reasonable approximation to the data.

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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 strong counter cyclical behavior of the trade surplus and the higher volatility of consumption relative to output's.

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 build an encompassing model that combines both stochastic trends, interest rate shocks and financial frictions. We then estimate the parameters of the exogenous shocks processes, along with a few other crucial parameters. Our Bayesian estimation procedure has the advantage that a natural comparison of different models' predictive performance is given by their marginal likelihoods. Using this tool we develop restricted versions of the encompassing model in the form of a 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 also estimate the parameters of the exogenous shocks processes, and assess their relative performance by comparing their marginal likelihood as well as the matching of a subset of selected moments relative to the data.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 highest probability region of the posterior distribution is characterized by strong financial frictions; volatile shocks in interest rates and transient technology, and modest trend shocks. In fact the random walk component is less than a fifth of what other studies found where they did not take into account financial frictions. Consequently, when we evaluate the relative contribution of temporary productivity shocks, trend shocks, and interest rate shocks to aggregate fluctuations, we find that, while temporary productivity shocks are responsible for the bulk of the variance of aggregates, interest rate shocks have a sizeable role as well, generating about ten percent of the variance of output and consumption, one fifth the variance of investment, and one third the variance of the trade balance/output ratio. In contrast, the share of those variances due to trend shocks is ten percent or less. These results are robust along many dimensions such as the use of uninformative priors and the various parameterization of preferences. In addition, the financial frictions model beats the stochastic trends model in nearly every comparison based on likelihood or marginal likelihood, although this result is sensitive to the inclusion of measurement errors.

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 financial frictions can enhance significantly the performance of models with stochastic interest rates. 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

Currently competing views on the sources of shocks to emerging countries can be regarded as elaborations on 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 standard model has notable empirical shortcomings, which have motivated several extensions and amendments. In this paper we are concerned with two dominant extensions: one which we will call the *stochastic trend model,* which features permanent shocks to technology, as advocated by Aguiar and Gopinath (2007); and another, the *financial frictions model,* which introduces foreign interest rate shocks that interact with financial imperfections, as discussed by Neumeyer and Perri (2005) and Uribe and Yue (2006). This section discusses these alternatives and also describes an *encompassing* model that embeds both stochastic trends and financial frictions.

2.1. The standard small open economy model

The standard model of a small open 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 with 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:

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

where $|\rho_a| < 1$, and ε_t^a is an i.i.d. shock with mean zero and variance σ_a^2. In the standard 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 standard 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 has access to a world capital market for noncontingent debt.

[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.

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 $t+1$, while 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 so far 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 standard 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

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

$|\rho_g| < 1$, ε_t^g is an i.i.d. process with mean zero and variance σ_g^2, and μ represents the mean value of labor productivity growth. A positive realization of ε_t^g 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_t^g, 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 for a theoretical framework where business cycles in emerging economies are driven by random world interest rates that interact with financial frictions. An empirical motivation for this view is what Calvo (1998) has called "sudden stops", defined by abrupt and exogenous halts to the flow of international credit to the economy, which force a violent turnarounds in the current account.

To develop this view, one can modify the standard 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 world interest rate is now assumed to be random, and fluctuates around its long run value R^* according to the 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 future productivity 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.

2.4. An Encompassing Model

While the literature has naturally considered stochastic trends and financial frictions separately, it is relatively straightforward to specify a model in which both extensions of the standard model are present. In this subsection we indeed describe our preferred version of such an *encompassing* model, which will be a focus of our empirical analysis below.

Our encompassing model follows the spirit of Aguiar and Gopinath (2008), which extend the stochastic trend model to allow for shocks to the consumption and investment Euler equations that operate through the interest rate. But we differ from Aguiar and Gopinath (2008) in two fundamental dimensions. First, our encompassing model includes both financial frictions, endogenous spreads and working capital requirements, embedded in the parameters η and θ. Aguiar and Gopinath (2008) did consider endogenous spreads but not working capital which 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) only allowed the spread to be affected by transient technology shocks, our encompassing model allows for permanent shocks to also affect the spread. This is more 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 idea, however, we need to modify the assumption (2.12) on country risk. So, in our 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 below.

Our encompassing model is then given by the combination of one of the preceding two assumptions for the spread together with the assumptions of 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).

With this formulation, one way to evaluate the relative merits of the hypotheses of stochastic trends and financial frictions is to analyze the contribution to different macro aggregates of trend shocks versus shocks to the foreign interest rate. A different but complementary perspective is to compare directly the stochastic trend model against the financial frictions model. Clearly, each of the two can be seen as suitably restricted versions of the encompassing model, but none is a special version of the other.

3. Empirical Approach

3.1. Bayesian Analysis, in a nutshell

We adopt a Bayesian viewpoint because of its conceptual simplicity and 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.

Additionally, it is useful for our purposes 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. This is particularly appealing if the models to be compared are not nested.

Given this framework, we conduct two complementary exercises. First, we 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. Second, we estimate the stochastic trend model and the financial frictions models separately and compare their marginal likelihoods, which amounts to a direct comparison of the two versions in terms of their predictive power.

3.2. Functional forms, and calibrated versus estimated parameters

We follow the current literature on emerging market business cycles when choosing the functional forms for preferences and technology. For the most part, we impose a utility function of the Greenwood, Hercowitz and Huffman (1988) form:

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

As discussed by Neumeyer and Perri (2005) and others, 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, which explains their popularity. It may be noted, however, that Aguiar and Gopinath (2007) focused on their results with Cobb Douglass preferences instead (in spite of the fact that, in the working paper version, they also estimated their model with GHH preferences and found very little difference). Accordingly, in one of our robustness exercises we examine a more flexible preference specification due to Jaimovich and Rebelo (2008), which embed both GHH and Cobb Douglass as special cases.

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:

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

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 standard, Mendoza-type model, allowing for 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 1 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%[2]. Following Aguiar and Gopinath (2007) 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 percent. As it is common in the literature on closing small open economy models, we set the parameter ψ, determining the interest rate elasticity to debt, to a minimum value that guarantees the equilibrium solution to be stationary (Schmitt-Grohe and Uribe, 2003). Lastly, we calibrate the long-run productivity growth, μ, equal to 1.006 following the point estimate reported by Aguiar and Gopinath (2004) and consistent with a yearly growth rate of 2.4 percent.

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

[2]Note that in the model with financial frictions, α is not exactly equal to labor share in the Financial Frictions model but it is rather calibrated as $\alpha = LaborShare * [1 + (R-1)\,\theta]$.

period 1980:I to 2003:II.

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

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 i.i.d. 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:

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

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 (rather than log-linear) to the model-based measure of trade balance share, tby, the mapping in terms of first differences is

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

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. First, note that neither the encompassing model nor any of its restrictions exhibit more structural shocks than the number of time series we observe. To overcome the well-known stochastic singularity problem that arises in cases like these two options are available to the applied researcher: one can either base estimation on as many observed variables as there are shocks; or one can artificially augment the space of shocks by adding measurement error shocks, completing the probability space of each model so as to render the theoretical covariance matrix of the variables in X_t no longer singular[3]. Within the context of our investigation each alternative

[3] A third option, known in the literature as the multiple-shock approach, is to include additional structural shocks. This option, however, would take us further away from the scope of this paper so we discard it.

offers advantages and disadvantages. While the addition of measurement errors may be warranted given the well-known measurement issues surrounding macroeconomic data from emerging economies, it is still an arbitrary decision which variables will have errors and which will not. On the other hand, given that one of the central goals is to compare the performance of two restricted versions of the encompassing model, one would also like to know how this comparison looks like when each version is directly mapped to the data without any artificial statistical errors. Of course, the latter alternative brings the tougher question of which of the four time series considered should be used when estimating the models without measurement errors. In light of this trade-off we choose to combine both methods. We estimate both the encompassing model and the two restricted versions using all four time series vectors and adding measurement errors to all four. In addition, when conducting the model comparison between the stochastic trend and financial frictions models we also report the results when no measurement errors are added. In this latter case, we explore the implications of using different pairs of observable vector time series, given that the two models exhibit only two structural shocks.

The third issue is how to sample from the posterior distribution. We follow, for the most part, the Random Walk Metropolis algorithm presented in An and Schorfheide (2007) to generate draws from the posterior distribution $p_M(\theta^M|X)$. 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. It proved useful to repeat the maximization algorithm using random starting values for the parameters drawn from their prior support in order to gauge the possible presence of many modes in the posterior distribution[4]. Once this step is completed, the algorithm is used to make $150,000$ draws from the posterior distribution of each case. The initial $50,000$ draws are burned.

A key part in this step is to use a properly scaled version of the covariance matrix for the proposal distribution in order to allow for an efficient exploration of the mode(s) in the

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

posterior distribution (see An and Schorfheide for details). In addition, to overcome the high serial correlation of the draws, we use every 100^{th} draw and posterior distributions are generated with the resulting 1000 draws. Convergence of the Markov chains was mainly verified informally through graphical methods, although we also computed the Geweke and Chib (1998)'s separated mean test.

4. Results

This section presents our baseline results. We first summarize our prior beliefs and present the parameters' posterior distributions and the distribution of other key moments. We estimate the encompassing model as well as its two restricted versions of interest, the stochastic trend model and the financial frictions model. For the most part we report results obtained with and without measurement errors. We conclude the section with an assessment of the relative fit of the two competing approaches to business cycles in emerging economies.

4.1. Priors

Our prior beliefs over the estimated parameters are described in Table 2 and were based, to the extent possible, upon earlier studies on emerging market business cycles.

Key parameters are the ones governing the temporary and permanent technology processes: $\sigma_a, \sigma_g, \rho_a, \rho_g$. Unfortunately, estimates available from other studies on the relative importance of each of these parameters are ambiguous. While Aguiar and Gopinath (2004)[5] estimate a ratio $\sigma_a/\sigma_g = 0.41/1.09 = 0.4$ for Mexico, Garcia-Cicco et.al. (2009) find for Argentina the much higher ratio $\sigma_a/\sigma_g = 3.3/0.71 = 4.6$. Given this, we chose our prior beliefs to have a mean of 0.74 for both σ_a and σ_g. The mean value of 0.74 mimics the average between the two point estimates found by Aguiar and Gopinath (2004). We did so using a

[5]The reader should note that we use the working paper version of Aguiar and Gopinath's work (Aguiar and Gopinath, 2004) when forming our priors, instead of the published version (Aguiar and Gopinath, 2007). This is because only in the working paper version the estimation is done using the same GHH preferences we use in our work whereas in the published version the authors 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. In the next sections we explore the robustness of our results to other set of preferences.

Gamma function with parameters (2.06, 0.0036).

Our prior for ρ_a, the autoregressive coefficient of the temporary productivity shock, was a Beta function with parameters $(356, 19)$, implying a mean of 0.95 and a standard deviation of 1.1 percent. The mean is close to the point estimate found by Aguiar and Gopinath (2004), and was the same calibrated value used by Neumeyer and Perri (2005). The prior for the autoregressive coefficient of permanent productivity shocks, ρ_g, was also formed using a Beta function with parameters $(285, 111)$, yielding a mean of 0.72, and a standard deviation of 2.3 percent. This follows the point estimate found by Aguiar and Gopinath (2004).

Similarly, we based our priors over parameters governing the world interest rate process and the degrees of financial frictions $(\rho_R, \sigma_R, \eta, \theta)$ upon earlier studies. Our prior for ρ_R, was a Beta function with parameters (44.3, 9.06), consistent with beliefs that the mean value was 0.83, the point estimate found by Uribe and Yue (2006), and 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 and a standard deviation of 0.31 percent, formed using a Gamma function with parameters (5.6, 0.0013).

Previous studies provide little statistical information on the size of the elasticity of the spread to the country's fundamentals, η, and the fraction of the wage bill held as working capital, θ. We use a prior with mean of 1.0 and a standard deviation of 10 percent for η, close to the value calibrated by Neumeyer and Perri (2005) to match the volatility of the interest rate faced by Argentina's residents in international capital markets. As for θ, we decided to specify a fairly diffuse prior, with the only restriction that it must lie between zero and one. For this purpose we used a Beta$(2, 2)$ function with mean 0.5, and a considerable standard deviation of 22.4 percent to reflect the little information we have *a priori* on this parameter.

Lastly, our prior on ϕ was a Gamma function with parameters (3, 2). This is a considerably diffuse prior, as given by the large 90 percent confidence interval, reflecting that previous studies have found different values for this parameter when trying to mimic the investment volatility.

4.2. Posteriors

We estimated various scenarios. On one hand, we estimated the encompassing model as well as the two restricted versions of it - the stochastic trend version and the financial frictions version- under a flexible framework allowing for measurement errors in the four time series observed. On the other hand, under a more restricted framework, the stochastic trend and financial frictions models were separately estimated without any measurement errors using several alternative pairs of observable time series.

The posterior distribution results for the estimations allowing for measurement errors are reported in Table 3. While the third and fourth column report posterior modes and means of the parameters of the encompassing model, the next two columns report the posterior modes for the two restricted models. As a benchmark, the last column reports the GMM estimates in Aguiar and Gopinath (2005). In addition, Table 4 reports the variance decomposition experiments undertaken with the encompassing model.

Several results deserve attention:

- The data are fairly informative in all cases, in particular with respect to the volatilities of the shocks, in the sense that the estimated posteriors appear much more precise than the priors, as measured by the size of the 90 percent highest posterior density intervals. Perhaps the only exception is the standard deviation of the permanent shock, a subject that will be looked in further detail bellow.

- Interestingly, in the encompassing model, the role of permanent shocks does not appear to be as important as our prior beliefs suggested. The estimated posterior mode ratio of volatilities is $\sigma_a/\sigma_g = 0.54/0.25 = 2.2$, which is clearly at odds with Aguiar and Gopinath's (2007) finding that volatility of innovations appears to be much stronger in the permanent technology process than in the transient one. While this ratio suggests a minor role of trend shocks in the Mexican business cycle, 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 which, following Aguiar and

Gopinath (2007), is defined as follows:

$$RWC = \frac{\alpha^2\sigma_g^2/\left(1-\rho_g\right)^2}{\left[2/\left(1+\rho_z\right)^2\right]\sigma_a^2 + \left[\alpha^2\sigma_g^2/\left(1-\rho_g^2\right)\right]}$$

The mode and mean of the posterior distribution of the RWC for the encompassing model is given at the bottom of Table 3. It is immediate to see that, 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, the posterior of the random walk component is largely reduced relative to the prior. Indeed, we obtain a RWC whose posterior mode is close to unity, 1.05; this is far below the value recovered by Aguiar and Gopinath of 5.3. Therefore, a full-information method that incorporates the entire information in the data does not assign such a relevant role to trend shocks as a method that only looks at a selected subset of moments.

- To a large extent, the minor role of trend shocks is explained by the relevance of interest rate shocks as well as by the financial frictions amplifying them. We find that the posterior distributions of the parameters θ and η governing the degree of financial frictions are far away from zero. The posterior mode for θ is 0.77, signaling that close to three quarters of the wage bill is kept as working-capital needs. The tight posterior mode for η, with its mean centered around 0.79, reveals a significant elasticity of the spread to expected movements in the country fundamentals, embedded in the Solow residual. While this is lower than our prior beliefs, which were 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 do not observe here. It is also remarkable to see how the relative importance of trend shocks increases when the stochastic trend model is estimated, that is, when we shut down both interest rate shocks and financial frictions.

- To assess the relative role of each structural shock in explaining macroeconomic fluctuations, we computed the posterior distribution of the variance decompositions implied by the encompassing model. The results over a time horizon of 40 quarters are reported in the top panel of Table 4. The most remarkable result is the small role played by trend shocks when accounting for the variance of the observed macroeconomic aggregates. The largest share of permanent shocks is only 10%, when explaining the variance of output and it shrinks further when looking at the other three variables. On the other hand, world interest rate shocks play a nontrivial role, particularly when explaining the variance in the trade balance-to-GDP ratio (35%), investment (21%), and to a lesser extent in consumption (9%). Their role accounting for the variance of output (8%) falls within the estimates from other studies. For example, Neumeyer and Perri (2005) find that the percentage standard deviation of Argentina's GDP in a model with financial frictions but no shocks to international rates is 3% smaller than the one in a model with interest rate shocks; and Uribe and Yue (2006) find that US interest rate shocks explain about 20% of movements in aggregate activity in a pool of emerging market economies. The largest share of the variance in all four aggregates is however largely explained by transient shocks to the technology process.

- The lower panel in Table 4 presents the counterfactual experiment of shutting down the amplifying mechanism of technology shocks through movements in the spread, $\eta = 0$. The results of this experiment suggest that the large role of transient technology shocks in accounting for fluctuations in investment and the trade balance, and to a lesser extent in consumption, is driven by their impact on spreads. Still, surprisingly, output's variability continues to be explained by "pure" technology shocks, independent of the effect that fundamentals may have over the spread.

- We mainly considered convergence diagnostics for the MCMC from the Metropolis-Hastings algorithm based upon informal graphical methods[6]. Following An and Schorfheide (2007) we compared draws and recursively computed means from multiple chains. For this purpose we chose six vectors of initial parameters by randomly drawing from their prior support; each vector was used to run six independent Markov chains. The results

[6] Convergence of the Markov chains was also verified in each case by running the Geweke and Chib (1998)'s separated mean test. Results can be provided upon request.

of these experiments are reported in Figure 1 for the estimation of the encompassing model. Despite different initializations, the parameters' means converge in the long-run with two notable exceptions for the parameters governing the standard deviation of the two technology shocks, σ_a and σ_g. In two of the six chains the means appear to converge to a second (lower) mode where the ratio σ_a/σ_g is lower. We digged deeper into this issue by exploring the posterior along the dimensions in these two parameters. We set the other eleven parameters equal to their posterior mode levels and examined the posterior along the support for the two parameters. The results of this experiment are reported in Figure 2. While the posterior mode lies at a high value of the ratio σ_a/σ_g, it is clear that there is another region with high posterior value where the ratio is low. This explains why two of the chains in Figure 1 deviated to this region. Importantly, however, the Metropolis-Hastings algorithm was tuned so that this region was also explored in the estimation. This explains the fact that the posterior means somewhat differ from the modes for both parameters (Table 3). In light of these findings, an important robustness check that we conduct in the next section, is to assess the extent to which our priors are driving these results. In particular, we check the extent to which the posterior mode with a high ratio σ_a/σ_g is sensitive to the shape of our priors, and whether or not the region of the posterior with a lower ratio becomes more important as less informative priors are used.

- Another noteworthy result in Table 3 is that measurement errors appear to be quantitatively significant. This is robust across the three cases in Table 3 and signals that a large fraction of the volatility in the main macro aggregates, particularly consumption and investment, is left unexplained by all three models. Nonetheless, one could ask how the posterior results would differ for the two restricted models if we estimated them without any measurement error. The results of this experiment, using three separate pairs of observables, are given in Table 5. What we observe across the three pairs of results is that the size of the shocks increases in order to account for the volatility that was soaked up before by the measurement errors. In two of the three cases considered for the stochastic trend model, the RWC increases with respect to the benchmark case with measurement errors. In the case of the financial frictions model, however, most of the volatility is now soaked up by increasing the size of the parameter governing the capital adjustment cost. This may signal another explanation as to why our results differ from Aguiar and Gopinath (2007), given that they did not consider the possibility of measurement errors.

4.3. Model Comparison

4.3.1. Marginal Data Densities

We turn next to formal model comparisons of the models considered above; the results are reported in Table 6. For each case considered, we report the values of the likelihood and posterior (in logs) computed at the posterior mode, ($\ln L_M(\theta^M|X)$ and $p_M(\theta^M|X)$ in terms of our previous discussion) and the values of the marginal data density ($\ln p_M(X)$).

Before turning to the results it should be noted that, following An and Schorfheide (2008) the log-marginal likelihood can be rewritten as

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

thereby implying that model comparisons based on marginal data densities capture the relative one-step-ahead predictive performance of each model considered.

Overall, the results, reported in Table 6 are ambiguous as to which model dominates from a one-step-ahead forecasting performance. While a more flexible framework that allows for measurement errors points to a superiority of the stochastic trend model, we get the opposite ranking when there are no measurement errors. Indeed, in all three cases when only pairs of time series are used in estimation, the extension of the small open economy-RBC model that features a stochastic interest rate coupled with financial frictions appears to have a better relative fit than the stochastic trend model. This obtains both in terms of achieving a higher log-likelihood value and, more markedly, in terms of marginal data densities and, hence, predictive performance. Indeed, the posterior odds of the financial frictions model against the stochastic trend model (the ratios of their respective marginal likelihoods) are in the order of $1 : \exp(10)$ or higher, well above the thresholds considered as "decisive evidence" in favor of the financial frictions model (see DeJong and Dave, 2007).

Note that the two restricted models, the stochastic trend and financial frictions models, exhibit higher likelihood and marginal likelihood levels than the encompassing model. This result can be explained by the different priors used implicitly when estimating the two restricted models. As an illustration, consider the case of ρ_R, the AR(1) parameter in the process of R^*. When estimating the encompassing model, the 90 percent prior distribution over this parameter lies in the interval $[0.74, 0.91]$, so values close to zero are highly penalized by the prior. Yet, when estimating the stochastic trend model as a restricted version of the encompassing model this parameter is set to zero, or, more precisely, a unit mass prior is defined over zero. A similar case occurs with all the other parameters that are set equal to zero in the restricted models, $\{\sigma_R, \theta, \eta\}$ for the case of the stochastic trend model and $\{\rho_g, \sigma_g\}$ for the case of the financial frictions model. These differences in the priors imply that areas of the posterior distribution that were not explored before in the estimation of the encompassing model are now explored in the two restricted models. This analysis make it more urgent to further explore the role of the priors, as we do in the next section.

For comparison purposes, we report in Table 6 the log-likelihood value for the stochastic trend model evaluated at the point GMM estimates of the parameters reported by Aguiar and Gopinath (2004)[7]. The log-likelihood value implied by the GMM-estimated parameters is far below the levels obtained when using a full-information 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 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.

[7] The parameters are reported in Table 3. When computing the log-likelihood value at this vector, we use the posterior mode of the four measurement errors.

4.3.2. Selected Moments

It could be argued that for macroeconomists, predictive performance may not be the only relevant metric to evaluate the relative merits of alternative models. As mentioned above, the literature on emerging market business cycle has emphasized some key moments when evaluating the performance of models of the business cycle. Two moments have drawn much attention: the high countercyclicality of the trade balance compared to the data from developed countries as well as the higher volatility of consumption and investment relative to output. In this section we compare the performance of the models under analysis along a particular subset of moments, including the two just mentioned. In doing so we are implicitly conducting a more stringent test of each model's extension as the estimation was not designed to match this particular set of moments. We continue to distinguish our results between the cases where measurement errors are included and those when they are not.

The results of these experiments are gathered in Tables 7.1 and 7.2, where the filtered sample moments of the Mexican quarterly data, in terms of standard deviations, correlations with output and the trade balance, and serial correlations are compared to the theoretical moments from the encompassing model as well as the two restricted models. Consistent with the measurement equations used in the above section, 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[8]. For comparison purposes, the moments obtained in Aguiar and Gopinath (2004)'s GMM estimation are reported in the last column of Table 7.1[9].

The main findings are as follows:

- The encompassing model delivers a reasonably close match to the facts emphasized in the literature: it delivers a more volatile path for consumption with respect to output and reproduces the strong countercyclicality of the trade balance share observed in the data. Recall that this is obtained without resorting to high values of trend shocks.

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

[9] 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 7.1. 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.

This is further confirmed when looking at the moments of the financial frictions model, which are quite similar to those obtained for the encompassing model. This indicates 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. This result was obtained previously by Neumeyer and Perri (2005) for Argentina. Our results clearly confirm that their findings extend to Mexico 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.

- A salient failure of the stochastic trend model in matching some of the key moments lies in the model's inability to reproduce a more volatile consumption with respect to output. This failure occurs consistently both when measurement errors are added and when they are not. In addition, when measurement errors are not included the model counterfactually reproduces a high variance of the main macro aggregates exhibited, notably gY and gC.

- A comparison between the model-based moments from the estimated stochastic trend model and the ones replicated using the GMM point estimates 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 Tables 7.1 and 7.2, will be better matched too in a full-information approach.

5. Robustness Checks

In this section we assess the robustness of our baseline results presented in the previous section along four dimensions. First, we gauge the robustness of the results when using less informative priors. Second, we investigate the role played by each of the two financial frictions considered by shutting each one of them separately. Third, we assess the extent to which our results are the product of assuming GHH preferences. And, fourth, we estimate long-run productivity growth.

5.1. Robustness Case 1: Uninformative Priors

It was documented in Figure 2 how the estimated posterior exhibits a region of relatively similar (although slightly lower) probability with predominance of trend shocks, as given by a low ratio σ_a/σ_g. It is therefore of interest to document how the shape of the posterior distribution is influenced by the shape of the prior, and whether or not the region of the posterior with a low σ_a/σ_g ratio becomes more important if less informative priors are assumed.

Our robustness check is reported in the first five columns of Table 8. For almost all parameters we choose flat priors given by uniform distributions. In the other cases, the AR(1) coefficients for the driving forces' processes, we choose a quasi flat prior depicted by a Beta function with parameters (2,2), implying a mean of 0.5 and a large standard deviation of 22.4 percent.

The first result of interest is the presence of two local modes in the posterior distribution, where each mode favors one of the two approaches to business cycles in emerging economies. Contour plots around the two modes are given in Figure 3. On one hand, the higher mode, with a likelihood and posterior values of 961 and 973 respectively, is characterized by the virtual disappearance of trend shocks - the posterior mode for σ_g is 0.01-, while the transitory technology and interest rate shocks exhibit values larger than the ones obtained under the initial priors. As a consequence of this, the value of the random walk component is negligible. On the other hand, a lower posterior mode, with a likelihood and posterior values of 959 and 970 respectively, is characterized by the predominance of trend shocks: its technology shocks ratio is $\sigma_a/\sigma_g = 0.43/1.10$, and the parameters governing the degree of financial frictions, θ and η, exhibit lower values than those observed in the high mode.

A challenge for the Bayesian estimation is therefore to fine tune the Metropolis-Hasting algorithm so as to properly sample from each of the two modes. As we report in the fifth column of Table 8, we were able to make the Markov chain cross over the two modes with enough regularity as to obtain mean values in between the two modes. The Markov chain explored more the posterior around the high mode, and hence the mean values are closer to those of the high posterior mode. Interestingly, the mean posteriors are fairly close to the results reported for the encompassing model under the initial priors. This explains why the results from the variance decomposition exercise under the less informative priors, reported in the upper panel of Table 9, are quantitatively similar to the ones presented before. Indeed, we continue to observe a small role played by trend shocks as opposed to transitory technology shocks when accounting for the variance of the observed macroeconomic aggregates. We view these results as evidence that our baseline results are robust to assuming less informative priors.

5.2. Robustness Case 2: Shutting Down One Financial Friction at a Time

The results presented thus far indicate that the estimation of a structural model encompassing the two approaches to modeling business cycles in emerging economies favors one in which financial frictions amplify shifts in market fundamentals through endogenous spreads and, through the presence of working-capital needs, have supply side effects following exogenous interest rate perturbations. It is therefore of interest to investigate the extent to which each of the two financial frictions considered is responsible for these results. We address this question by sequentially shutting down one of the two frictions at a time.

We start by estimating the encompassing 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 by expected changes in the Solow residual and estimating the parameter η governing the elasticity of the spread. Next, we run the estimation by considering the opposite: we shut down the assumption of an endogenous spread, $\eta = 0$, while we allow for the possibility of working capital needs, estimating the parameter θ. Last, we consider the case where none of the two financial frictions is present, $\theta = \eta = 0$.

The results of these experiments, in terms of the new posterior distributions, are reported in Table 10; and the results in terms of variance decompositions and selected second moments are presented in Tables 11 and 12. Two results are worth mentioning. First, when shutting down either of the two financial frictions the exploration of the posterior focuses more on the mode that favors the presence of stochastic trend shocks as leading driving forces. In fact, when the endogenous spread is shut down, the posterior exploration focuses entirely on that mode. This is further emphasized by the variance decomposition, where in both experiments the role of growth shocks accounts now for the lion's share of output: 60% in the case where $\theta = 0$ and 76% when $\eta = 0$. Second, the moments presented in Table 12 show that if working capital needs are the only financial friction in place, the model fails to generate a consumption path more volatile than output's, and this in turn prevents the model from generating a strong countercyclical trade balance-to-GDP ratio. This result is in line with Oviedo (2005) who argues that the presence of an endogenous spread is a necessary ingredient when building models that aim at replicating emerging market business cycles.

Taken together, these two results are indicative that both financial frictions are rather complementary to each other and should both be considered when building business cycles models for emerging economies.

5.3. Robustness Case 3: Jaimovich-Rebelo preferences

The parameterization for preferences used in the analysis so far has been of the one first suggested by Greenwood, Hercowitz and Huffman (1988). Many authors have noted that GHH preferences improve the ability of business cycles models to reproduce some of the stylized facts both in advanced open economies as in Mendoza (1991) and Correia et.al. (1995) and developing market economies as in Neumeyer and Perri (2005) and Garcia-Cicco et.al. (2009).

A well documented reason for the empirical success of GHH preferences is the fact that they allow for labor supply to be independent of consumption levels. This leads to high substitutability between leisure and consumption, low income effect on labor supply, and large responses of consumption and labor to productivity shocks. In contrast, in the case of Cobb-Douglas preferences, the income effect mitigates labor's response to productivity shocks because labor supply is no longer independent of consumption levels. Compared to the case of GHH preferences, leisure and consumption are not easily substituted because the income effect is strong. As a consequence, there is an incentive to smooth consumption excessively over the business cycle by saving, in response to a positive shock. As shown in Aguiar and Gopinath (2004), however, the main result concerning the relative importance of trend shocks is robust to these two alternative parameterizations of preferences.

The robustness to alternative preference specifications has also been investigated within business cycle models driven by interest rate shocks and financial frictions. Neumeyer and Perri (2005) show that, under GHH preferences, a positive shock to interest rates that reduces consumption and shifts down the labor demand curve will not generate a shift of the labor supply curve because labor supply is independent of consumption levels. As a result, in equilibrium, employment will fall together with output, hence delivering the significantly high and negative correlation between interest rates and output observed in developing economies. In the case of Cobb-Douglas preferences, a rise in the interest rate induces an outward shift in the labor supply curve that may potentially offset the initial drop in labor demand leading to a counterfactual increase in employment (and output) following interest rate increases. Neumeyer and Perri (2005) document how the only way possible to make the results following an interest rate shock qualitatively robust across the two types of preferences is to assume a low intertemporal elasticity of substitution, $1/\sigma$, that can dampen the labor supply response. In fact, Neumeyer and Perri (2005) find that only implausible values for σ equal or higher than 50 are sufficient enough to reduce the elasticity of substitution so as to dampen the labor supply response. Hence, it appears that, given plausible values of intertemporal substitution, GHH preferences are a key ingredient for business cycles models driven by interest rate shocks coupled with financial frictions.

In light of these findings by previous studies, it is of interest to investigate the robustness of our results to more flexible preference specifications. To address this question, we repeated our estimations with preferences introduced by Jaimovich and Rebelo (2008), which embed both GHH and Cobb Douglass as special cases:

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

where the representative household internalizes in her maximization problem the dynamics of X_t given by:

$$X_t = C_t^{\gamma} X_{t-1}^{1-\gamma}, \qquad 0 \leq \gamma \leq 1$$

The presence of X_t makes preferences non-time-separable in consumption and hours worked. As shown in Jaimovich and Rebelo (2008), these preferences nest as special cases the two classes of utility functions mentioned above. When $\gamma = 1$ we obtain preferences of the Cobb-Douglas type. Conversely, when $\gamma = 0$ we obtain GHH preferences. Therefore, lower values of γ will render the income effect of technology and interest rate shocks milder, producing short-run responses to shocks that are similar to those obtained under GHH preferences. Conversely, higher values of γ will have the opposite effect, as shifts in the labor supply will likely offset changes in labor demand. In the latter case, and according to the findings in Aguiar and Gopinath (2004), it is more likely that business cycles will be driven by trend shocks, and interest rate shocks coupled with financial frictions will play a minor role.

The experiment that we conduct in this section consist in re-estimating the encompassing model under Jaimovich-Rebelo-type of preferences. A key parameter to be estimated in this experiment will be γ. Our approach was agnostic in that we did not impose strong prior beliefs on the shape of the distribution of this parameter. To this end we use a uniform distribution over the support $\gamma \in (0, 1]$. Note that, by excluding the case $\gamma = 0$, hours worked are stationary so we don't need to introduce the trend in the utility function.

The results of this experiment are reported in the second-to-last column in Table 8. It is immediate to see that, unambiguously, the estimation favors very low levels of γ, as the posterior is tightly concentrated toward zero with a mean of 0.07. Moreover, the role of permanent shocks is even less important relative to our baseline results: before the estimated posterior mode ratio of volatilities was $\sigma_a/\sigma_g = 0.54/0.25 = 2.2$, while now it increases to $\sigma_a/\sigma_g = 0.75/0.08 = 9.4$ and the posterior mean for the random walk component falls from 1.5 to 0.1. In addition the role of trend shocks when recomputing the variance decomposition of the main macro aggregates is now negligible, as trend shocks do not account more than 3 percent of the overall variance (middle panel in Table 9).

Taken together these results are indicative that our baseline results, favoring a model with financial frictions and interest rate shocks do not hinge on the assumption of GHH preferences. Instead, what they show is that the data is indeed consistent with GHH-type preferences where the wealth elasticity of labor supply is near zero and where transitory technology and interest rate shocks coupled with financial frictions are the main driving forces of the business cycles. To our knowledge Schmitt-Grohe and Uribe (2009) is the only work that has previously implemented an estimation of γ within a fully-fledged DSGE model for open and developed economies and their findings point to even lower posterior means for γ. Our results clearly extend theirs for developing economies.

5.4. Robustness Case 4: Estimating Long-Run Growth

A key parameter in the hypothesis that business cycles in emerging economies are driven by stochastic productivity shocks is the long-run productivity growth, μ, because it is around this value that the random shocks drive the productivity process. In the baseline encompassing model we calibrated the value of this parameter to match a yearly net growth rate of 2.4 percent, or $\mu = 1.006$, using the GMM-point estimate reported by Aguiar and Gopinath (2004). However, it is clear from the evidence presented so far that GMM estimates may differ from the values obtained by full-information methods. Thus, it is important to assess whether the results found so far in terms of the minor role of trend shocks in driving business cycles in Mexico are sensitive to this value.

To this end, we reestimated the encompassing model including net yearly growth, ζ, as one of the estimated parameters. We specified a diffuse prior over that parameter, with a Gamma function with parameters $(25, 0.1)$ in accordance with our beliefs that long-run yearly net growth has a mean equal to 2.5 percent but allowing for substantial uncertainty, a standard deviation of 50 percent [10]. The results are reported in the last column of Table 8 and indicate a slightly higher posterior mean of 2.7 percent, although with substantial uncertainty as 90 percent of the distribution lies between 1.96 and 3.53. Importantly, however, the baseline results from the encompassing model appear to be robust. Notably, the posterior ratio among volatilities is now $\sigma_a/\sigma_g = 0.5/0.27 = 1.9$, and the random walk component posterior

[10] The link between the gross quarterly growth rate, μ, and ζ is thus: $\zeta = 100 * \left(\mu^4 - 1\right)$.

mean is 1.43, both quite close to the baseline results. Likewise, the variance decomposition presented in the bottom panel of Table 9 still assign a minor role of trend shocks.

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] Jaimovich, N., and S. Rebelo (2008), "Can News About the Future Drive the Business Cycle?". Manuscript.

[13] 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.

[14] 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.

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

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

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

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

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

[20] 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.

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

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

[23] 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.

[24] Schmitt-Grohe, S. and M. Uribe, (2009) "What's News in Business Cycles", Manuscript, Columbia University.

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

TABLES AND FIGURES

Table 1. Calibrated Parameters

Variable	*Description*	*Value*
σ	Intertemporal Elasticity of Substitution $[1/\sigma]$	**2.000**
ω	Labor Supply Elasticity $\left[\frac{1}{\omega-1}\right]$	**1.600**
α	Labor Share of Income	**0.680**
$\boldsymbol{R}^*$	Gross Foreign Interest Rate	**1.032**
μ	Long-run Productivity Growth	**1.006**
τ	Labor Parameter so that $\boldsymbol{h}^{ss} = 1/3$	**Varies**
ψ	Debt Elastic Interest Rate Parameter	**0.001**
β	Discount Factor	**Varies**
$\boldsymbol{S}$	Long-run Gross Country Interest Rate Premium	**Varies**
δ	Depreciation Rate of Capital	**0.050**
$\boldsymbol{d}$	Debt-to-GDP Ratio (***D/Y***)	**0.100**

Note: A period is taken to be a quarter in the calibration. Most values taken from Aguiar and Gopinath (2007). In the encompassing and financial friction models, the discount factor is assumed to be 0.93 as in Neumeyer and Perri (2005), consistent with a gross spread of 1.054. Note also that α is not exactly equal to labor share in the Financial Frictions model but it is rather $\alpha = \boldsymbol{h\text{-}Share} * \left[1+(\boldsymbol{R}-1)\theta\right]$. In contrast, in the Stochastic Trend model we follow Aguiar and Gopinath (2007) and set $\beta = 0.98$ and $\boldsymbol{S} = 1$.

Table 2. Prior Distributions

Parameter		Range	Density	Mean	S.D (%)	90% Conf. Interval
Parameters Common to Both Models						
ρ_a	AR(1) Coeff. Transitory Tech. Process.	[0,1)	Beta [356.2 ; 18.753]	0.95	1.12	[0.92 ; 0.97]
σ_a	S.D. of Transitory Tech. Shock (%)	R^+	Gamma [2.060 ; 0.0036]	0,74	0.56	[0.12 ; 1.67]
ϕ	Capital Adjustment Cost Fct. Parameter	R^+	Gamma [3.000 ; 2.0000]	6.00	346	[1.62 ; 12.6]
σ_X	S.D. (%) of Measurement Error in ***X = Y,C,I,TB/Y***	R^+	Gamma [4.000 ; 0.0050]	2.00	1.00	[0.67 ; 3.86]
Parameters Specific to the Stochastic Trend Model						
ρ_g	AR(1) Coeff. Permanent Tech. Process.	[0,1)	Beta [285.1 ; 110.88]	0.72	2.25	[0.68 ; 0.76]
σ_g	S.D. of Permanent Tech. Shock (%)	R^+	Gamma [2.060 ; 0.0036]	0,74	0.56	[0.12 ; 1.67]
Parameters Specific to the Financial Frictions Model						
ρ_R	AR(1) Coeff. Foreign Interest Rate Process.	[0,1)	Beta [44.26 ; 9.0655]	0.83	5.10	[0.74 ; 0.91]
σ_R	S.D. of Foreign Interest Rate Shock (%)	R^+	Gamma [5.552 ; 0.0013]	0,72	0.31	[0.30 ; 1.29]
θ	Working Capital Parameter	[0,1]	Beta [2.000 ; 2.0000]	0.50	22.4	[0.13 ; 0.87]
η	Spread Elasticity	R^+	Gamma [99.22 ; 0.0101]	1.00	10.1	[0.84 ; 1.17]

Table 3. Posterior Distributions. Encompassing and Separate Models

Parameter	Prior	Encompassing Model		Separate Models: Posterior Modes		AG-GMM Estimates
		Mode	Mean	Stochastic Trend M.	Fin. Frictions M	
ρ_a	0.95 [0.92, 0.97]	0.91	0.92 [0.89, 0.94]	0.95	0.91	0.94
$100\sigma_a$	0.74 [0.12, 1.67]	0.54	0.52 [0.36, 0.69]	0.61	0.58	0.41
ϕ	6.00 [1.62, 12.6]	10.47	10.49 [8.40, 13.16]	4.45	10.59	3.79
$100\sigma_Y$	2.00 [0.67, 3.86]	0.77	0.77 [0.51, 0.98]	0.54	0.75	
$100\sigma_C$	2.00 [0.67, 3.86]	1.23	1.24 [1.07, 1.43]	1.17	1.23	
$100\sigma_I$	2.00 [0.67, 3.86]	2.43	2.48 [1.71, 3.24]	3.01	2.42	
$100\sigma_{TB/Y}$	2.00 [0.67, 3.86]	0.90	0.91 [0.74, 1.08]	0.98	0.90	
ρ_g	0.72 [0.68, 0.76]	0.71	0.71 [0.67, 0.75]	0.73		0.72
$100\sigma_g$	0.74 [0.12, 1.67]	0.25	0.29 [0.03, 0.69]	0.88		1.09
ρ_R	0.83 [0.74, 0.91]	0.80	0.81 [0.71, 0.89]		0.78	
$100\sigma_R$	0.72 [0.30, 1.29]	0.39	0.38 [0.22, 0.55]		0.41	
θ	0.50 [0.13, 0.87]	0.77	0.76 [0.43, 0.98]		0.73	
η	1.00 [0.84, 1.17]	0.80	0.79 [0.65, 0.92]		0.80	
RWC	3.15 [0.18, 6.37]	1.05	1.52 [0.01, 4.19]	4.21	0.00	5.33

Note: Estimates obtained using four observables, {gY, gC, gI, dTB/Y} from the Mexican Data, 1980.1-2003.2. For the separate models standard errors are omitted for brevity but are available upon request. All estimations were done using measurement errors in all four variables. AG-GMM Estimates refer to the generalized method of moment estimates reported by Aguiar and Gopinath (2004) which we present here as benchmark. RWC refers to the random walk component, see text for details.

Table 4. Forecast Error Variance Decompositions in the Encompassing Model

Structural Shock	*gY*	*gC*	*gI*	*dTB/Y*
ε^{a}	82,32	83,93	73,84	62,16
ε^{g}	10,09	7,12	5,11	3,09
ε^{R^*}	7,60	8,96	21,05	34,75
Counterfactual, No Endogenous Spread: $\eta = 0$				
ε^{a}	81,95	64,38	12,59	5,20
ε^{g}	9,89	12,27	6,88	0,92
ε^{R^*}	8,17	23,35	80,52	93,88

Note: gX denotes log-differences, dX denotes first differences. Variance decompositions computed from the estimation using four observables and measurement errors in all variables. Numbers reported using posterior means estimates. Standard Errors are omitted for brevity but are available upon request. In the variance decomposition computations only the role of the structural shocks was taken into account. In the counterfactual exercise, all parameters are set equal to their posterior mode levels except for $\eta = 0$. A time horizon of 40 quarters was used when computing the variance decomposition.

Table 5. Posterior Distributions. Estimations Without Measurement Errors

Parameter	Observables:{g^Y, dTB/Y}		Observables:{g^Y, g^I}		Observables:{g^Y, g^C}	
	Stochastic Trend M.	Financial Frictions M.	Stochastic Trend M.	Financial Frictions M.	Stochastic Trend M.	Financial Frictions M.
ρ_a	0.91	0.91	0.92	0.95	0.92	0.89
$100\sigma_a$	1.12	0.75	1.19	0.83	1.16	0.88
ϕ	8.86	24.32	3.63	24.33	10.97	15.74
ρ_g	0.75		0.77		0.82	
$100\sigma_g$	1.59		1.13		1.42	
ρ_R		0.89		0.92		0.90
$100\sigma_R$		0.68		0.85		0.85
θ		0.80		0.21		0.38
η		0.79		0.91		0.73
RWC	4.83	0.00	3.85	0.00	6.66	0.00

Note: Estimates obtained using pairs of observables, from the Mexican Data, 1980.1-2003.2 and no measurement errors. Numbers reported are posterior modes, which are very similar to the posterior means. Standard errors are omitted for brevity but are available upon request.

Table 6. Bayesian Model Comparison

Models	Log-Likelihood	Log-Posterior	Marginal Log-Likelihood
Observables: {gY, gC, gI, dTB/Y}; Measurement Errors in all Variables			
Encompassing Model	951,33	978,90	927,70
Stochastic Trend Model	955,84	981,54	941,01
Financial Frictions Model	955,18	974,54	931,25
AG - GMM	41.70		
Observables: {gY, dTB/Y}; No Measurement Errors			
Stochastic Trend Model	371,15	366,93	352,41
Financial Frictions Model	517,74	518,34	497,52
Observables: {gY, gI}; No Measurement Errors			
Stochastic Trend Model	371,75	377,44	358,71
Financial Frictions Model	412,17	417,33	395,97
Observables: {gY, gC}; No Measurement Errors			
Stochastic Trend Model	480,22	475,93	459,02
Financial Frictions Model	494,10	491,84	472,61

Note: Log-Likelihood levels computed in the posterior mode. Results on marginal data densities are approximated by Geweke's harmonic mean estimator with truncation parameter 0.5. 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 all variables. AG-GMM stands for the log-likelihood value evaluated using the estimated parameters in Aguiar and Gopinath (2004).

Table 7.1. Second Moments. Encompassing and Separate Models

Variable	Mexican Data	Encompassing Model	Stochastic Trend Model	Financial Frictions Model	Aguiar-Gopinath GMM
Standard Deviations (%)					
gY	1,53	1,13	1,56	1,13	1,58
gC	1,94	1,64	1,58	1,65	1,71
gI	5,66	5,32	4,54	5,32	5,52
dTB/Y	1,38	1,13	0,86	1,13	1,12
S.D. (*X*) / S.D. (*gY*)					
gC	1,27	1,45	1,01	1,45	1,08
gI	3,71	4,72	2,90	4,70	3,49
dTB/Y	0,91	1,00	0,55	1,00	0,71
Correlation with *gY*					
gC	0,76	0,94	0,98	0,94	0,98
gI	0,75	0,76	0,89	0,77	0,88
dTB/Y	-0,44	-0,62	-0,62	-0,64	-0,71
Correlation with *dTB/Y*					
gC	-0,50	-0,85	-0,76	-0,86	-0,82
gI	-0,67	-0,98	-0,90	-0,98	-0,95
Serial Correlation					
gY	0,27	0,28	0,19	0,25	0,27
gC	0,20	0,20	0,15	0,18	0,19
gI	0,44	-0,05	-0,01	-0,06	-0,01
dTB/Y	0,33	-0,05	-0,02	-0,05	-0,02

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. All estimations were done using measurement errors in all four variables. 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 7.1. 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.

Table 7.2. Second Moments. Estimations Without Measurement Errors

Variable	Mexican Data	Observables:{g^Y, dTB/Y}		Observables:{g^Y, g^I}		Observables:{g^Y, g^C}	
		Stochastic Trend	Financial Frictions	Stochastic Trend	Financial Frictions	Stochastic Trend	Financial Frictions
Standard Deviations (%)							
gY	1,53	2,86	1,49	2,61	1,51	2,87	1,64
gC	1,94	2,91	2,38	2,44	3,14	3,08	2,49
gI	5,66	5,77	4,10	7,65	5,84	5,71	6,64
dTB/Y	1,38	1,32	1,51	1,53	2,42	1,61	2,03
S.D. (*X*) / S.D. (*gY*)							
gC	1,27	1,02	1,59	0,93	2,07	1,07	1,52
gI	3,71	2,02	2,74	2,93	3,86	1,99	4,05
dTB/Y	0,91	0,46	1,01	0,59	1,60	0,56	1,24
Correlation with *gY*							
gC	0,76	0,96	0,88	0,96	0,82	0,94	0,81
gI	0,75	0,85	0,65	0,84	0,73	0,80	0,59
dTB/Y	-0,44	-0,30	-0,44	-0,41	-0,53	-0,24	-0,30
Correlation with *dTB/Y*							
gC	-0,50	-0,54	-0,81	-0,63	-0,92	-0,55	-0,80
gI	-0,67	-0,75	-0,95	-0,83	-0,95	-0,78	-0,94
Serial Correlation							
gY	0,27	0,16	0,21	0,16	0,16	0,22	0,12
gC	0,20	0,14	0,21	0,14	0,04	0,16	0,09
gI	0,44	0,01	-0,04	-0,02	-0,02	0,03	-0,04
dTB/Y	0,33	-0,02	-0,02	-0,03	-0,01	-0,03	-0,03

Note: gX denotes log-differences, dX denotes first differences. Model-based moments using different pairs of observables and no measurement errors 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 8. Posterior Distributions. Robustness Cases 1-3-4

Parameter	Robustness 1: Uninformative Priors					Robustness 3 and 4		
	Prior Distribution	Prior Mean	High Posterior Mode	Low Posterior Mode	Posterior Mean	Prior Distribution	Robustness 3: Posterior Mean	Robustness 4: Posterior Mean
ρ_a	Beta (2,2)	0.50	0.87	0.90	0.90 [0.85, 0.96]	0.95 [0.92, 0.97]	0.90 [0.88, 0.92]	0.92 [0.90, 0.94]
$100\sigma_a$	Uniform (0.01,10)	5.00	0.77	0.43	0.75 [0.51, 0.92]	0.74 [0.12, 1.67]	0.75 [0.57, 0.93]	0.50 [0.35, 0.66]
ϕ	Uniform (0.0,40)	20.0	8.76	7.15	8.17 [5.65, 10.84]	6.00 [1.62, 12.6]	10.49 [8.38, 12.74]	10.27 [8.17, 12.51]
$100\sigma_Y$	Uniform (0.01,10)	5.00	0.32	0.01	0.17 [0.01, 0.52]	2.00 [0.67, 3.86]	0.63 [0.34, 0.87]	0.81 [0.61, 1.01]
$100\sigma_C$	Uniform (0.01,10)	5.00	1.23	1.24	1.26 [1.10, 1.44]	2.00 [0.67, 3.86]	1.27 [1.09, 1.47]	1.24 [1.06, 1.45]
$100\sigma_I$	Uniform (0.01,10)	5.00	2.33	2.42	2.36 [1.62, 3.04]	2.00 [0.67, 3.86]	2.43 [1.68, 3.13]	2.50 [1.72, 3.21]
$100\sigma_{TB/Y}$	Uniform (0.01,10)	5.00	0.93	0.96	0.95 [0.79, 1.11]	2.00 [0.67, 3.86]	0.86 [0.68, 1.04]	0.89 [0.74, 1.05]
ρ_g	Beta (2,2)	0.50	0.58	0.57	0.53 [0.16, 0.81]	0.72 [0.68, 0.76]	0.72 [0.69, 0.76]	0.71 [0.67, 0.75]
$100\sigma_g$	Uniform (0.01,10)	5.00	0.01	1.10	0.28 [0.01, 0.90]	0.74 [0.12, 1.67]	0.08 [0.01, 0.20]	0.27 [0.02, 0.67]
ρ_R	Beta (2,2)	0.50	0.72	0.74	0.76 [0.57, 0.94]	0.83 [0.74, 0.91]	0.77 [0.68, 0.88]	0.80 [0.72, 0.89]
$100\sigma_R$	Uniform (0.01,10)	5.00	0.47	0.39	0.38 [0.19, 0.61]	0.72 [0.30, 1.29]	0.40 [0.25, 0.55]	0.37 [0.21, 0.53]
θ	Beta (2,2)	0.50	0.49	0.39	0.45 [0.07, 0.89]	0.50 [0.13, 0.87]	0.63 [0.28, 0.94]	0.77 [0.42, 0.98]
η	Uniform (0.0,5.0)	2.50	0.51	0.36	0.40 [0.09, 0.78]	1.00 [0.84, 1.17]	0.74 [0.62, 0.87]	0.81 [0.68, 0.96]
γ	Uniform (0.001,1.0)					0.50 [0.05, 0.95]	0.07 [0.01, 0.14]	
ξ	Gamma (25,0.1)					2.50 [1.72, 3.35]		2.71 [1.96, 3.53]
RWC		1.01	0.00	2.95	0.44 [0.00, 1.98]		0.11 [0.00, 0.42]	1.43 [0.01, 4.10]
Log-Posterior at Mode			972.8	969.9			976.3	978.9
Log-Likelihood at Posterior Mode			961.4	958.8			954.5	952.0

Note: All robustness cases were estimated using observables {gY, gC, gI, dTB/Y} from the Mexican Data, 1980.1-2003.2 using measurement errors in all four variables.

Table 9. Forecast Error Variance Decompositions. Robustness Cases 1-3-4

Structural Shock	*gY*	*gC*	*gI*	*dTB/Y*
Robustness 1: Uninformative Priors				
ε^{a}	85,18	85,01	66,72	35,14
ε^{g}	12,14	8,58	4,73	1,95
ε^{R^*}	2,69	6,41	28,55	62,91
Robustness 3: Jaimovich-Rebelo Preferences				
ε^{a}	88,58	92,87	82,15	62,32
ε^{g}	2,35	2,07	1,42	2,74
ε^{R^*}	9,07	5,07	16,43	34,94
Robustness 4: Estimating Long-Run Growth				
ε^{a}	75,54	79,16	71,44	63,20
ε^{g}	16,87	12,09	8,84	5,08
ε^{R^*}	7,60	8,76	19,72	31,72

Note: gX denotes log-differences, dX denotes first differences. Model-based moments using different pairs of observables and no measurement errors from the Mexican Data, 1980.1-2003.2. Moments are computed using posterior means. Standard Errors are omitted for brevity but are available upon request.

Table 10. Posterior Distributions. Robustness Case 2

Parameter	Prior	No Working Capital $\theta = 0$			No Endogenous Spread $\eta = 0$		No Financial Frictions $\theta = \eta = 0$	
		Low Posterior Mode	High Posterior Mode	Mean	Posterior Mode	Mean	Posterior Mode	Mean
ρ_a	0.95 [0.92, 0.97]	0,94	0,90	0.93 [0.89, 0.96]	0.95	0.95 [0.94, 0.97]	0.95	0.95 [0.94, 0.97]
$100\sigma_a$	0.74 [0.12, 1.67]	0,30	0,68	0.35 [0.08, 0.77]	0.42	0.34 [0.05, 0.71]	0.48	0.39 [0.04, 0.81]
ϕ	6.00 [1.62, 12.6]	11,69	11,49	11.37 [9.43, 13.5]	6.16	6.41 [4.73, 8.29]	6.09	6.39 [4.49, 8.60]
$100\sigma_Y$	2.00 [0.67, 3.86]	0,68	0,72	0.64 [0.27, 0.97]	0,43	0.42 [0.17, 0.67]	0,42	0.40 [0.18, 0.64]
$100\sigma_C$	2.00 [0.67, 3.86]	1,19	1,24	1.22 [1.02, 1.42]	1,22	1.24 [1.07, 1.43]	1,23	1.25 [1.08, 1.42]
$100\sigma_I$	2.00 [0.67, 3.86]	2,87	2,56	2.71 [1.92, 3.36]	2,02	2.05 [1.30, 2.82]	2,11	2.18 [1.36, 2.94]
$100\sigma_{TB/Y}$	2.00 [0.67, 3.86]	0,89	0,94	0.91 [0.73, 1.08]	0,96	0.97 [0.83, 1.13]	0,97	0.98 [0.83, 1.14]
ρ_g	0.72 [0.68, 0.76]	0,68	0,72	0.69 [0.64, 0.74]	0.71	0.71 [0.68, 0.75]	0.71	0.71 [0.68, 0.75]
$100\sigma_g$	0.74 [0.12, 1.67]	0,98	0,25	0.78 [0.11, 1.30]	1.00	1.00 [0.67, 1.26]	1.01	1.01 [0.51, 1.33]
ρ_R	0.83 [0.74, 0.91]	0,84	0,81	0.85 [0.73, 0.93]	0.81	0.83 [0.73, 0.91]	0.82	0.83 [0.74, 0.90]
$100\sigma_R$	0.72 [0.30, 1.29]	0,38	0,38	0.37 [0.24, 0.51]	0.31	0.31 [0.21, 0.42]	0.30	0.30 [0.20, 0.44]
θ	0.50 [0.13, 0.87]				0.28	0.35 [0.02, 0.85]		
η	1.00 [0.84, 1.17]	0,85	0,77	0.81 [0.67, 0.95]				
RWC	3.15 [0.18, 6.37]	4,67	0,67	3.37 [0.13, 5.38]	5.02	5.04 [2.92, 6.32]	4.75	4.70 [1.78, 6.32]

Table 11. Forecast Error Variance Decompositions. Robustness Case 2

Structural Shock	*gY*	*gC*	*gI*	*dTB/Y*
No Working Capital Needs: $\theta = 0$				
ε^{a}	39,07	40,70	37,25	33,27
ε^{g}	59,95	52,37	40,49	22,43
ε^{R^*}	0,98	6,93	22,26	44,30
No Endogenous Spread: $\eta = 0$				
ε^{a}	21,61	18,41	7,90	0,88
ε^{g}	76,47	75,96	55,34	26,23
ε^{R^*}	1,93	5,63	36,77	72,89
No Financial Frictions: $\theta = \eta = 0$				
ε^{a}	27,28	23,79	11,26	1,60
ε^{g}	71,86	71,85	54,12	27,34
ε^{R^*}	0,86	4,36	34,63	71,06

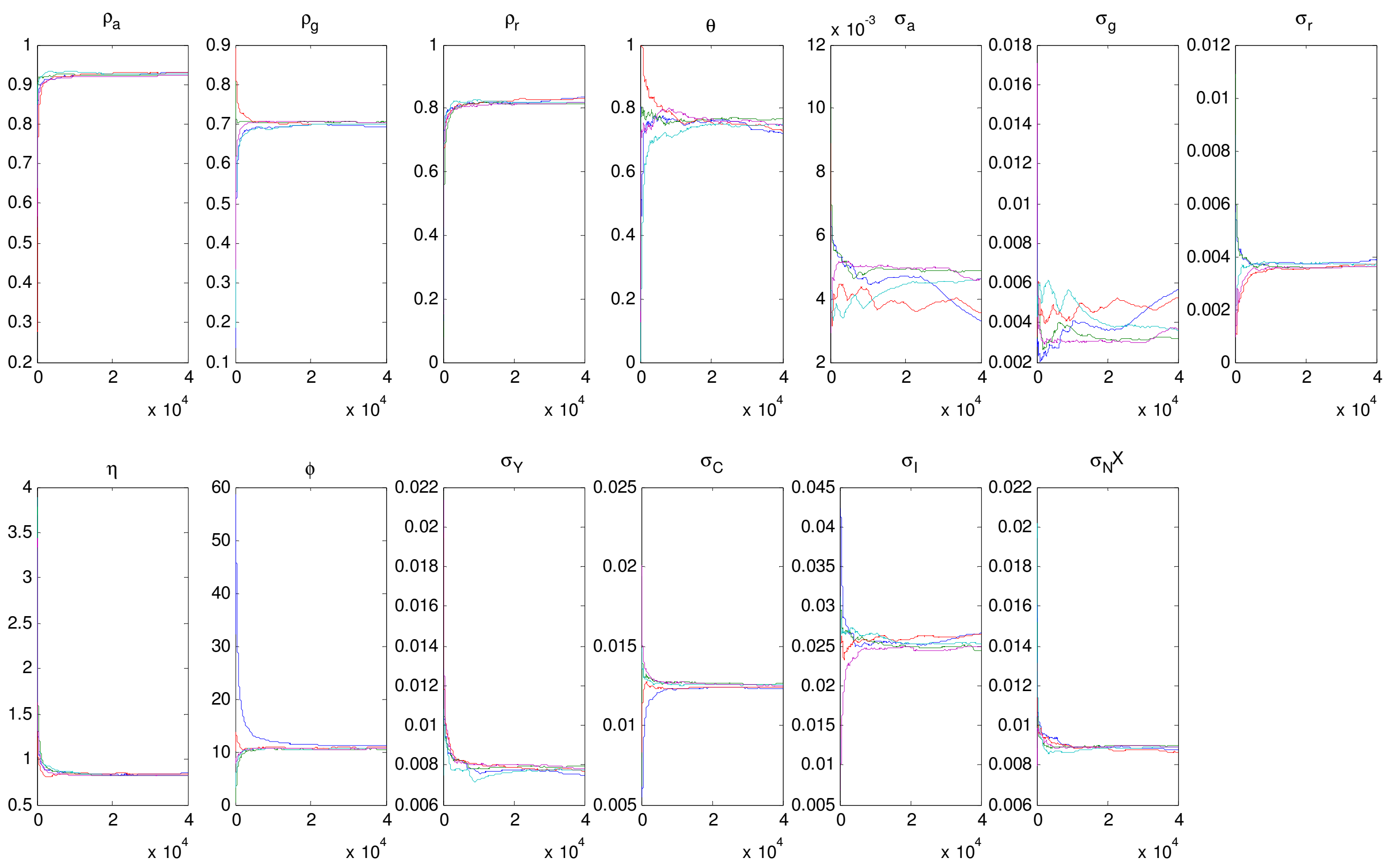
Note: gX denotes log-differences, dX denotes first differences. Variance decompositions computed from the estimation using four observables and measurement errors in all variables. Numbers reported using posterior means estimates. Standard Errors are omitted for brevity but are available upon request. In the variance decomposition computations only the role of the structural shocks was taken into account.

Table 12. Second Moments. Robustness Case 2

Variable	Mexican Data	No Working Capital $\theta = 0$	No Endogenous Spread $\eta = 0$	No Financial Frictions $\theta = \eta = 0$
Standard Deviations (%)				
gY	1,53	1,16	1,47	1,46
gC	1,94	1,60	1,53	1,50
gI	5,66	4,81	5,05	4,88
dTB/Y	1,38	1,11	0,84	0,82
S.D. (*X*) / S.D. (*gY*)				
gC	1,27	1,38	1,04	1,03
gI	3,71	4,16	3,43	3,35
dTB/Y	0,91	0,96	0,57	0,56
Correlation with *gY*				
gC	0,76	0,92	0,96	0,96
gI	0,75	0,78	0,71	0,73
dTB/Y	-0,44	-0,55	-0,31	-0,32
Correlation with *dTB/Y*				
gC	-0,50	-0,83	-0,55	-0,56
gI	-0,67	-0,95	-0,89	-0,88
Serial Correlation				
gY	0,27	0,20	0,23	0,22
gC	0,20	0,03	0,19	0,17
gI	0,44	-0,06	-0,03	-0,03
dTB/Y	0,33	-0,05	-0,04	-0,04

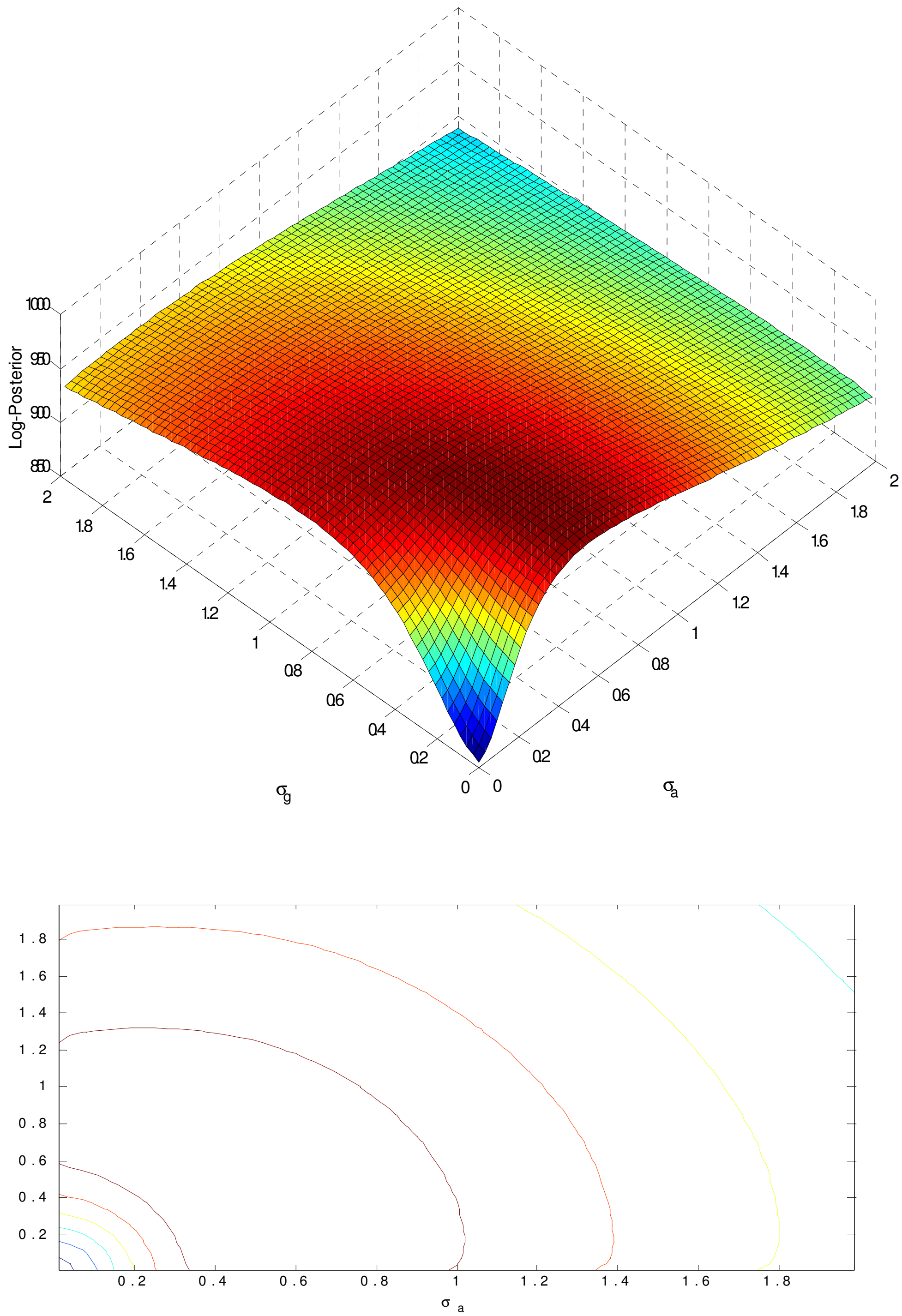
Note: gX denotes log-differences, dX denotes first differences. Model-based moments using observables {gY, gC, gI, dTB/Y} from the Mexican Data, 1980.1-2003.2. Moments are computed using posterior mode estimates. Standard Errors are omitted for brevity but are available upon request. All estimations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

Figure 1. Convergence Analysis



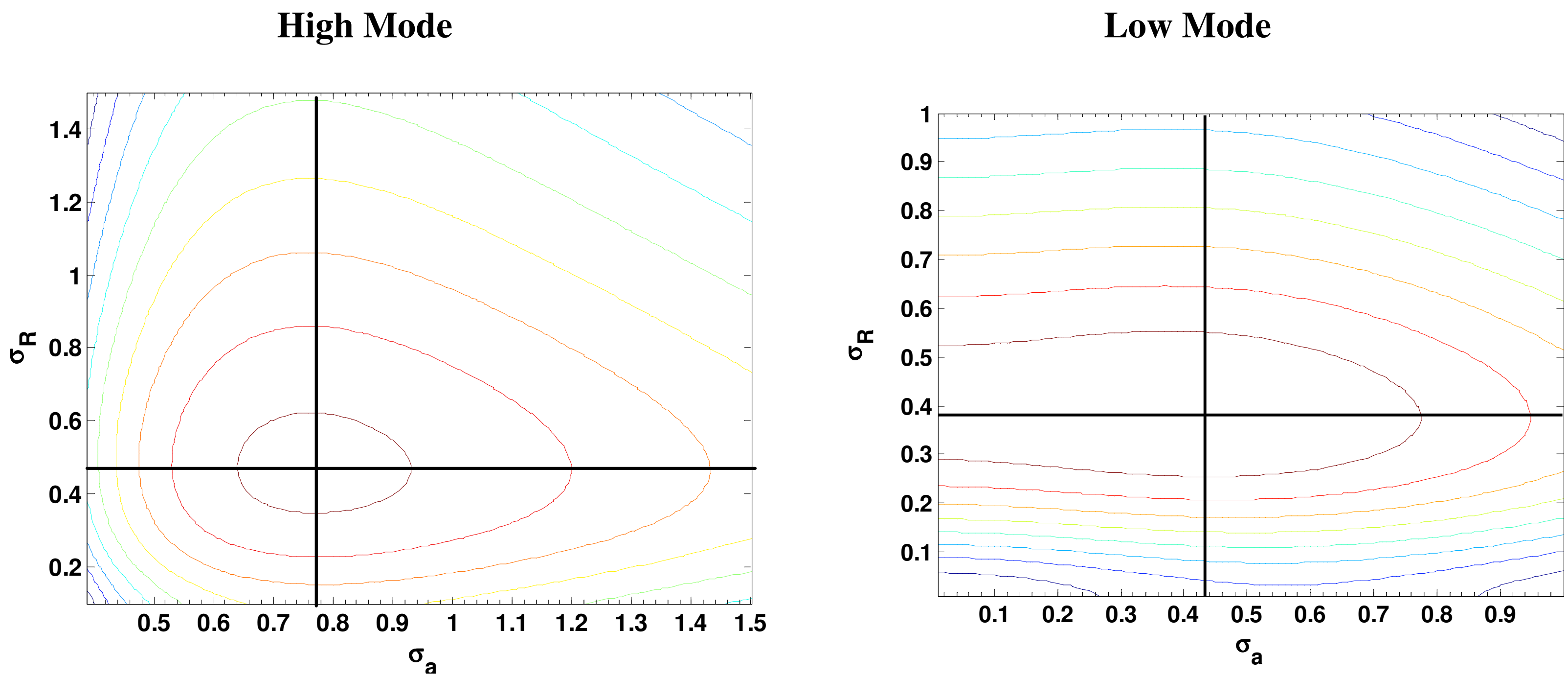
Note: Each line corresponds to recursive means for the 13 parameters as a function of the number of draws, computed from 6 independent MCMC chains using random starting values.

Figure 2. Posterior. Encompassing Model



Note: Posterior mesh and contours as a function of the volatility of the two technology shocks. The other 11 parameters were fixed at their posterior mode values.

Figure 3. Posterior, Robustness Case 1



Note: Posterior contours as a function of the volatility of the transitory technology and foreign interest rate shocks. The other 11 parameters were fixed at their high posterior mode values.