NBER WORKING PAPER SERIES

ON THE SOURCES OF AGGREGATE FLUCTUATIONS IN EMERGING ECONOMIES

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Working Paper 15938
http://www.nber.org/papers/w15938

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
April 2010

We are immensely indebted to John Landon Lane for teaching us on Bayesian tools and for providing us with the appropriate code. We also received very useful comments from Mark Aguiar, Peter Benczur, Bora Durdu, Dave DeJong, Pat Kehoe, Federico Mandelman, Andy Neumeyer, Martin Uribe, Tao Zha, and seminar participants at the NBER IFM Summer Institute, MIT, Rutgers, the Federal Reserve Board, the IMF, Universidad di Tella, Atlanta Fed, Magyar Nemzeti Bank, and the University of Pittsburgh. Of course, any errors or shortcomings are ours. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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NBER Working Paper No. 15938
April 2010
JEL No. E3,F4

ABSTRACT

Recent research on macroeconomic fluctuations in emerging economies has focused in two leading approaches: introducing a stochastic productivity trend, in addition to 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 them, taking advantage of recent developments in the theory and implementation of Bayesian methods. The encompassing model assigns a significant role to interest rate shocks and financial frictions, but not to trend shocks, in generating and amplifying 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. Of the two financial frictions we consider, working capital versus spreads linked to expected future productivity, the latter emerges as key 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 stochastic trends with interest rate shocks and financial frictions. We then estimate the parameters of the exogenous shock processes, along with a few other crucial parameters. The stochastic trend model and the random interest rates/financial frictions model can be then regarded as restricted versions of the encompassing model. The relative performance of these alternative models is evaluated by comparing their marginal likelihoods as well as their ability to match a subset of selected moments of 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. In our benchmark estimations, the mode of the posterior distribution of the estimated parameters of the encompassing model is characterized by strong financial frictions, volatile shocks to the processes for interest rates and transient technology, and modest trend shocks. The random walk component, a measure of the relative importance of trend shocks, is less than a fifth of what Aguiar and Gopinath (2007) obtained using a model with no financial frictions. Consequently, when we evaluate the relative contribution of the different 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 six to ten percent of the variance of output and consumption, one fourth the variance of investment, and close to half the variance of the trade balance/output ratio. In contrast, the share of those variances due to trend shocks is three percent or less.

In formal, likelihood based, model comparisons, the financial frictions model beats the stochastic trends model more often than not, although the results are not decisive. This reflects that the likelihood has several local modes, and indeed we find that assuming less informative priors than in the benchmark implies a posterior parameter distribution with two local modes, each favoring one of the two approaches (although the one associated with financial frictions is the highest mode). In other words, this perspective on the data appear not to speak very loudly about which approach is empirically better.

In other ways, however, the data are quite informative. In particular, the benchmark model allows for two kinds of financial frictions: a working capital requirement (as in Uribe and Yue 2006) and an endogenous spread (as in Neumeyer and Perri 2005). Our estimations strongly indicate that it is the latter, not the former, that is crucial for a financial frictions view to be a reasonably good approximation to the data. Notably, this confirms previous analysis by Oviedo (2005).

Likewise, our estimations clearly imply that temporary productivity shocks cannot be dispensed with in the models under study, even if interest rate shocks and trend shocks are included, if these models are to match the volatility and persistence of output and other major macroeconomic aggregates. However, we show that the role of temporary productivity shocks is greatly enhanced by the presence of financial frictions.

We show our results to be robust to a number of departures from our benchmark assumptions, such as preference specification, or the addition of data on interest rates to the

Aguiar-Gopinath dataset. Finally, we estimate the contribution of temporary productivity shocks, trend shocks, and interest rate shocks in explaining the dynamics of the Mexican 1995 Tequila crisis. We argue that temporary productivity shocks appear to have dominated the episode but, again, that financial frictions were crucial to amplify their effects.

Overall, our results are supportive of the view that explaining fluctuations in emerging economies requires assuming financial imperfections that amplify conventional productivity shocks and, perhaps less crucially, interest rate shocks. Trend shocks add relatively little, although they become quantitatively relevant if financial frictions are assumed away.

Our study is closely related to the recent paper of García-Cicco, Pancrazi, and Uribe (forthcoming), who examined 1900-2005 data from Mexico and Argentina to probe the empirical soundness of the stochastic trend hypothesis. They find that an estimated dynamic stochastic model with trend shocks performs poorly along several dimensions, most markedly the behavior of the trade balance to GDP ratio. For the case of Argentina, they also estimated a version of the model augmented with stochastic shocks to the cost of foreign credit, and found that version to be much more satisfactory. Also, they found that such an extension implied that the role of trend shocks in explaining aggregate fluctuations became negligible. Hence Garcia Cicco et al.'s work and findings clearly have similar flavor as ours. However, there are significant differences as well. One difference is that Garcia-Cicco et al.'s findings appear strongly driven by their use of very long run data. In contrast, we use the same data as in Aguiar and Gopinath (2007), and are still able to argue in favor of the role of financial frictions and against that of stochastic trends. More importantly, we study deeper specifications of financial frictions (working capital requirements and endogenous spreads), as opposed to the exogenously stochastic spreads that represent the main financial frictions in Garcia Cicco et al. Finally, we complement the review of impulse responses and variance decompositions with formal Bayesian model evaluation and comparison methods.

Our emphasis on the role of financial frictions is, of course, not new. In addition to the papers by Neumeyer-Perri and Uribe-Yue, financial imperfections have been stressed by the literature on balance sheet effects (Cespedes, Chang and Velasco 2004) and sudden stops (Calvo 1998, Mendoza 2006). A main contribution of this paper is to provide a quantitative perspective on the empirical accuracy of financial frictions models relative to their main competitor, the stochastic trend hypothesis.

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), and Rabanal and Tuesta (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 $t = 0, 1, 2, \ldots$ 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 the process:

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

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.

[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.

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. 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

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

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

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

2.3. Financial frictions models

Neumeyer and Perri (2005) and Uribe and Yue (2006) have argued 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:

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

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 assumptions of a spread linked to expected productivity (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 a spread process determined by expected productivity, 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 three fundamental dimensions. First, our encompassing model includes both financial frictions, spreads that react to fundamentals and working capital requirements, embedded in the parameters η and θ, respectively. Aguiar and Gopinath (2008) considered the former but did not allow for a working capital requirement. 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

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

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.

Third, and perhaps most importantly, Aguiar and Gopinath (2008) considered only Cobb-Douglass preferences, which have been shown to reduce the extent to which business cycles can be driven by interest rate shocks (Neumeyer and Perri, 2005). We assume preferences of the Greenwood-Hercowitz-Huffman type; later, we explore the robustness of this choice with a more flexible specification due to Jaimovich and Rebelo (2008).

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. One the other hand, 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 a 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, as in some of the cases examined below.

Given this framework, we conduct two complementary exercises. First, we estimate the encompassing model and focus on the posterior distribution of the 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 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 help reproducing some emerging economies' business cycles facts by allowing the labor supply to be independent of consumption levels. Note that, in contrast, Aguiar and Gopinath (2007) focused on their results with Cobb Douglass preferences instead [2]. Accordingly, one of our robustness exercises later explores 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:

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

[2] Although, in the working paper version, they also estimated their model with GHH preferences and found very little difference.

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

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

For each model, we estimate some parameters and calibrate the rest. The choice of which parameters to estimate or calibrate is guided by the objectives of our investigation as 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 introduces 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 the parameter ϕ governing the capital adjustment function.

We calibrate the remaining parameters of each model. A period is taken to be a quarter in our calibration. 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 1.66 and a third of time spent working in the long run. The labor's share of income, α, is set to be 68%[3]. We calibrate the debt-to-GDP ratio to 0.1, the value used in Aguiar and Gopinath (2007).

In the models with financial frictions, we set the long-run levels of the annualized foreign and country specific gross real interest rates to 1.06 and 1.01, respectively. These values were

[3] Note that in the models with financial frictions, α is not exactly equal to labor share in but it is rather calibrated as $\alpha = LaborShare * [1 + (R - 1)\theta]$. Thus, it will have an entire distribution determined by the posterior distribution of θ.

calibrated according to the data provided by Uribe and Yue (2006) on Mexican interest rates and are consistent with a five hundred basis points spread observed in Mexican sovereign bonds, and with the long-run mean of the real risk-free rate measured by the 3-month gross Treasury bill rate. In the stochastic trend model we set the spread to zero and use the value reported by Aguiar and Gopinath (2007) as the mean long run foreign interest rate.

The quarterly depreciation rate is assumed to be 5 percent. As common in the literature on 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 period 1980:I to 2003:II.

Our empirical implementation 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.

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, ν_t the vector of structural shocks, and P and Q system matrices that may depend on the model parameters. The Kalman filter then requires specifying a measurement equation,

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

mapping the elements in Z_t to a vector of observed data X_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 how to deal with data on aggregate output in levels, Y_t. In this case, the observed data can be directly linked to its theoretical stationary 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. 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 a trend 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., forthcoming).

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 resulting stochastic singularity two options are available: either basing estimation on as many observed variables as there are shocks; or 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[4]. Within the context of our investigation each alternative 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 ones will not. On the other hand, given that one of our central goals is to compare the performance of restricted versions of the encompassing model, we also want to know how this comparison looks like when each version is directly mapped to the data, without the addition of artificial statistical errors. Of course, under the latter alternative the tougher question arises of which of the four available time series to use[5]. In light of this trade-off we choose to combine both methods. We estimate both the encompassing model and its two restricted versions using all four time series vectors and adding measurement errors to all four. In addition, for comparing the stochastic trend and financial frictions models, we also report results when no measurement

[4] 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. See Fernandez (forthcoming) for an expanded version of the encompassing model with more structural shocks.

[5] This choice is indeed not a trivial one. Guerron (2009) has shown that, in the estimation of DSGE models by Bayesian methods, posterior distributions may significantly vary according to which set of observables is used.

errors are added. In the latter case we explore the implications of using different pairs of observable vector time series.

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 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. We found it 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 multiple modes in the posterior distribution[6]. Once this step was completed, we used the algorithm to make $150,000$ draws from the posterior distribution in each case. The initial $50,000$ draws were burned. To overcome the high serial correlation of the draws, we used every 100^{th} draw and posterior distributions were generated with the resulting 1000 draws. Finally, convergence of the Markov chains was assessed by recursively computing means from multiple chains as illustrated in An and Schorfheide (2007).

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 the 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.

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

4.1. Priors

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

Key parameters are those governing the temporary and permanent technology processes: $\sigma_a, \sigma_g, \rho_a, \rho_g$. Unfortunately, existing evidence on the relative importance of each of these parameters is ambiguous. While Aguiar and Gopinath (2004)[7] estimated a ratio $\sigma_a/\sigma_g = 0.41/1.09 = 0.4$ for Mexico, Garcia-Cicco et.al. (forthcoming) found the much higher ratio $\sigma_a/\sigma_g = 3.3/0.71 = 4.6$ for Argentina. Given this, we chose our prior to be a Gamma function with parameters (2.06, 0.0036). This prior has a mean of 0.74 for both σ_a and σ_g, which lies between the two point estimates found by Aguiar and Gopinath (2004) and Garcia-Cicco et.al. (forthcoming).

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 equals the value calibrated by Neumeyer and Perri (2005). Our prior for the autoregressive coefficient of permanent productivity shocks, ρ_g, was also 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 as prior a Gamma function with parameters (5.6, 0.0013), which is centered at 0.72 percent, the value reported by Uribe and Yue, and has a standard deviation of 0.31 percent.

[7] 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.

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 reflecting the little information we have *a priori* on this parameter.

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.

Lastly, for the standard errors of the four measurement errors we chose a Gamma prior centered at 2.0 and a 90 percent confidence interval ranging between 0.67 and 3.86. This relatively diffuse prior reflected our lack of information about the size of measurement errors, and also our belief that measurement issues may potentially be large in emerging economies.

4.2. Posteriors

We estimated various scenarios. 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. We also estimated the stochastic trend and financial frictions models without any measurement errors using several alternative pairs of observable time series.

Estimated posterior distributions, allowing for measurement errors, are summarized in Table 3. The third and fourth columns report posterior modes and means of the parameters of the encompassing model, while the next two columns report posterior modes for the two restricted models. As a benchmark, the last column reports the GMM estimates of Aguiar and Gopinath (2004). In addition, Table 4 reports variance decompositions and Figure 1 plots priors and posterior distributions for the encompassing model.

Several results deserve attention:

- The data are fairly informative, 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.

- Interestingly, in the encompassing model, the role of permanent shocks does not appear to be as dominant as suggested by our prior beliefs. The estimated posterior mode ratio of volatilities is $\sigma_a/\sigma_g = 0.66/0.12 = 5.5$, 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, an overall assessment can be based on the random walk component of the Solow residual 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 only 0.20, far below the 5.3 value recovered by Aguiar and Gopinath. Therefore, a full-information method 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 and 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 0.69, signaling that a little less than three quarters of the wage bill is kept as working-capital needs. This value is in line with those calibrated for other emerging economies[8]. The tight posterior mode for η, with its mean centered around 0.73, reveals a significant elasticity of the spread to expected movements in the country fundamentals, embedded in 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. Notably also, the relative importance of trend shocks increases when the stochastic trend model is estimated and we shut down both interest rate shocks and financial frictions (fifth column).

- 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 3%, when explaining the variance of consumption, 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 (43%), investment (24%), and to a lesser extent in consumption (11%). Their role accounting for the variance of output (6%) 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. This will be further analyzed below.

[8] Using data on net aggregate interest payments to GDP in Korea, Benjamin and Meza (2009) calibrate working capital requirements in a multi sector model between 0.50 and 0.82.

- Following An and Schorfheide (2007), we checked for convergence of the MCMC algorithm by recursively computing means from multiple chains. For this purpose we chose six vectors of initial parameters by drawing randomly from their prior support, and then used each vector to run independent Markov chains. The results are reported in Figure 2 for the estimation of the encompassing model. Despite different initializations, the parameters' means converge in the long-run.

- The lower panel in Table 4 presents the counterfactual experiment of shutting off the limk between technology shocks and spreads, $\eta = 0$. The results 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. This is better illustrated by looking at the impulse response functions in Figures 3 and 4. The responses of the main macroeconomic aggregates to a transitory technology shock depend strongly on whether the financial friction embedded in η is included or not. With $\eta > 0$ transitory technology shocks are greatly amplified, which explains the large share of interest rate shocks when this channel is turned off in the lower panel of Table 4 and in the impulse responses plotted in Figure 4. Still, surprisingly, output's variability continues to be explained by "pure" technology shocks even if $\eta = 0$.

- Another result in Table 3 is that measurement errors appear to exhibit large standard deviations similar to those in the structural shocks. This is robust across the three cases in Table 3. While this signals that still a non trivial fraction of the volatility in the main macro aggregates, particularly consumption and investment, is left unexplained by the model, the role of measurement errors in the dynamics of these aggregates should not be compared to that of the structural shocks given that, by construction, these shocks are serially uncorrelated. Indeed, over the time horizon of the forecast error variance decompositions in Table 4 (40 quarters) their role in accounting for the variance of the variables considered is virtually negligible.

- 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 all 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 a complementary explanation as to why our results differ from Aguiar and Gopinath (2007), given that they did not consider the possibility of measurement errors. Overall these results are also consistent with Guerron (2009)'s findings that posterior distributions may significantly vary according to which set of observables is used.

4.3. Model Comparison

4.3.1. Marginal Data Densities

We turn next to formal comparisons of the models considered above. Table 6 reports values of the likelihood and posterior (in logs) computed at the posterior mode, ($\log L_M(\theta^M|X)$ and $\log p_M(\theta^M|X)$ in terms of our previous discussion) and the values of the marginal data density ($\log p_M(X)$) for each model.

Overall, the results reported in Table 6 tend to mildly favor the financial frictions model. All values for the log-likelihood evaluated at each model's posterior mode are highest for the financial frictions model. When judging by the log-marginal likelihood, the results are a little bit more ambiguous. Allowing for measurement errors implies superiority for the stochastic trend model, yet this is probably because the likelihood of the financial frictions model peaks at a value that is at odds with the information used to construct the prior distribution (An and Schorfheide, 2007).

With no measurement errors, in two of the three cases the financial frictions model attains a better relative fit than the stochastic trend model, both in terms of a higher log-likelihood 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 e.g. DeJong and Dave, 2007). In the third case, when only consumption and output are observed, the log-marginal likelihood favors the stochastic trend model, but only with a posterior odds in the order of $1 : 2$, which constitutes only "very slight evidence" in favor of that model.

Note that the two restricted models, the stochastic trend and financial frictions models, can attain 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 R^* process. When estimating the encompassing model, the 90 percent prior distribution over this parameter lies in the interval $[0.74, 0.91]$, so that 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, ρ_R 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 makes it essential to explore further 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)[9]. The log-likelihood value implied by the GMM-estimated parameters is far below the levels we obtain. This gives further quantitative evidence that, within the context of the models analyzed here, a full-information method can deviate substantially from an estimation method that, like GMM, only looks at a selected subset of moments. And from the evidence just discussed, we learn that this deviation takes mainly the form of

[9] 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.

a significantly higher variance of the transient technology shock.

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 in model evaluation. Two moments have drawn much attention: the marked countercyclicality of the trade balance and the high volatility of consumption and investment relative to output. This section compares the models under study 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, as the estimation was not designed to match this particular set of moments.

The results are gathered in Tables 7.1 and 7.2, where the filtered sample moments of the 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 at posterior mode estimates[10]. For comparison purposes, the moments associated with Aguiar and Gopinath (2004)'s GMM estimation are reported in the last column of Table 7.1[11].

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 and investment 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 significant trend shocks. This is further confirmed by the moments of the financial frictions model

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

[11] 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 in that work refer to Hodrick-Prescott filtered moments which we don't present here given that we don't use this filtering technique.

which are quite similar to those of the encompassing model, indicating that financial frictions can amplify interest rate and transient technology shocks to the point of causing a response of consumption that exceeds the response in output leading to countercyclical net exports, a result obtained previously by Neumeyer and Perri (2005) for Argentina.

- A salient failure of the stochastic trend model is its inability to reproduce a significantly more volatile consumption with respect to output. This failure occurs consistently both with and without measurement errors. In addition, when measurement errors are not included, the model's implied variance of the main macro aggregates is excessively high, notably for gY and gC.

- A comparison between the moments implied by the the estimated stochastic trend model and the ones derived from the GMM point estimates suggests why our 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 also better matched in a full-information approach.

5. Robustness Checks

In this section we assess the robustness of our baseline results along five dimensions. First, we gauge the robustness of the results when using less informative priors. Second, we investigate the separate role of the two financial frictions under consideration. Third, we examined the role of GHH preferences. Fourth, we assess whether our results change if we estimate the rate of long-run productivity growth. Finally, we include the country specific and foreign interest rates into the vector of observables and use the reestimated model and smoothed shocks to simulate the macro dynamics during the Tequila Crisis.

5.1. Less Informative Priors

The first six columns of Table 8 examine the implications of less informative priors. To do this, for almost all parameters we choose flat priors given by uniform distributions. The exceptions are the AR(1) coefficients of the driving forces' processes, for which we choose a quasi flat priors given 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. Each mode favors one of the two approaches to business cycles in emerging economies. The higher mode, with a likelihood and posterior values of 1004.6 and 1014.6 respectively, is characterized by the virtual disappearance of trend shocks -the posterior mode for σ_g is 0.02 percent-, while the transitory technology shocks exhibit values larger than the ones obtained under the initial priors. The parameters estimated for the interest rate process characterize a lower volatility but a higher persistence relative to the benchmark case. 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 997.8 and 1009 respectively, is characterized by the predominance of trend shocks: its technology shocks ratio is $\sigma_a/\sigma_g = 0.46/1.12$, and the parameters governing the the elasticity of the spread, η, is virtually zero.

A challenge for the Bayesian estimation is, therefore, to fine tune the Metropolis-Hasting algorithm so as to properly sample from the regions surrounding each of the two modes. For the results reported in the sixth column of Table 8, we were able to make the Markov chain cross over the two modes with enough regularity. 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 not too far from the mode 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 in Table 4. Indeed, we observe a much smaller 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. One Financial Friction at a Time

The results presented thus far favor the view that financial frictions amplify shifts in market fundamentals through spreads that react to fundamentals 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 is responsible for these results. We address this question by shutting down one of the two frictions at a time.

We start by estimating the encompassing model without the assumption of working capital needs, $\theta = 0$, but still allowing for the spread to be affected 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 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, relative to the benchmark case in Table 3, the results are virtually unaltered when the working-capital assumption is dropped, $\theta = 0$. Indeed, the posterior mode continues to be characterized, as in the encompassing model, by a strong elasticity of the spread to fundamentals, volatile shocks in interest rates and transient technology, and modest trend shocks. A sharply different outcome is obtained when $\eta = 0$. In this case the exploration of the posterior favors the mode where stochastic trend shocks are the leading driving forces. This is further emphasized by the variance decompositions in Table 11. The results in the upper panel, where $\theta = 0$, are virtually unchanged relative to the benchmark case in Table 4. However the variance decompositions change drastically when $\eta = 0$. In this case, the lion's share of the variance of most of the macro variables is explained by growth shocks. 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 process more volatile than the output process, and this in turn prevents the model from generating a strong countercyclical trade balance-to-GDP ratio.

These results are 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 and that the presence of working capital requirements is not a necessary requirement in getting business cycles models closer to emerging economies' macroeconomic data.

5.3. Jaimovich-Rebelo preferences

Our baseline parameterization for preferences has been of the kind first suggested by Greenwood, Hercowitz and Huffman (1988). This is because GHH preferences improve the ability of business cycles models to reproduce some stylized facts both in advanced open economies (Mendoza (1991), Correia et.al. (1995)) and developing market economies (Neumeyer and Perri (2005), Garcia-Cicco et.al. (forthcoming)).

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 the response of labor 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 substitutable 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. Aguiar and Gopinath (2004), however, suggested that the role of preferences was minor, and in particular that their main result concerning the relative importance of trend shocks was robust to these alternative assumptions on preferences.

To investigate this issue, and more generally to test the robustness of our results to our specification of preferences, we repeated our estimations with preferences of the form 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.

A key parameter to be estimated is γ. Our approach was agnostic in not imposing strong prior beliefs on the distribution of this parameter. To this end we used a uniform distribution over the support $\gamma \in (0, 1]$. Note that, by excluding the case $\gamma = 0$, hours worked were stationary so we did not need to introduce the trend in the utility function.

The results are reported in the second-to-last column in Table 8. It is immediate to see that the estimation strongly favors very low levels of γ, as the posterior is tightly concentrated toward zero with a mean of 0.05. Moreover, the role of permanent shocks is even less important relative to our baseline results: before, the estimated posterior mode ratio of volatilities was $\sigma_a/\sigma_g = 0.66/0.12 = 5.5$; now, it increases to $\sigma_a/\sigma_g = 1.02/0.06 = 17$, and the posterior mean for the random walk component falls from 0.28 to 0.04. In addition, re-computing variance decompositions implies that trend shocks are now negligible, accounting for at most 2 percent of the overall variance (upper-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. To our knowledge Schmitt-Grohe and Uribe (2009) is the only work that has previously estimated γ within a fully-fledged DSGE model, for open developed economies, finding even lower posterior means for γ. Our results clearly extend theirs to developing economies.

5.4. Estimating Long-Run Growth

A key parameter in the hypothesis that business cycles in emerging economies are driven by stochastic productivity shocks is 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.

To check the significance of this issue, 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 [12]. The results are reported in the last column of Table 8 and indicate a slightly higher posterior mean of 2.51 percent, and the uncertainty is somewhat reduced relative to the prior beliefs. Importantly, the baseline results from the encompassing model appear to be robust. Notably, the posterior ratio among volatilities, σ_a/σ_g, and the random walk component posterior mean are both quite close to the baseline results. Likewise, the variance decomposition presented in the lower-middle panel of Table 9 continues to assign a minor role of trend shocks.

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

5.5. Observing interest rate processes and simulating the Tequila Crisis

Our estimations have been based on the dataset of Aguiar and Gopinath (2007) and, accordingly, have not exploited observable data on interest rates. We proceeded in that way in order to maximize comparability with Aguiar and Gopinath's work, but also because of data availability. Data series of interest rates for emerging economies are not easy to obtain, and most times they are constructed from data on sovereign spreads, like the J.P. Morgan EMBI, which starts only after 1994. In contrast, Aguiar and Gopinath's data set starts in 1980.

In spite of these considerations, it may be of interest to check how our results change if we add interest rate data. Hence we estimated the encompassing model adding measures of the domestic and foreign interest rates, R and R^*, respectively, in the set of observable time series for estimation. As the country specific risky interest rate we used Uribe and Yue (2006)'s Mexican interest rate in international capital markets, computed as the sum of the J.P. Morgan's EMBI+ stripped spread for Mexico and the US real interest rate. As the foreign interest rate we used the sum the US real interest rate and a global index of eight emerging market economies[13]. This definition of R^* may be somewhat unusual, but is the appropriate one if we are to regard the spread between R and R^* as a *country specific* one, which is the only view consistent with the theoretical model (and, in particular, with the assumption that the spread may depend on expected *domestic* productivity).

As noted already, data on sovereign spreads is available only since 1994. The two measures of interest rates are plotted in Figure 5. The plot also presents the implied spread, computed as the ratio of the Mexican and foreign interest rates. The two interest rates exhibit a high but not perfect correlation, (equal to 0.78) and present two particular peaks around the Mexican Tequila Crisis in the mid 1990s and the Russian and Asian financial crises of the late 1990s.

We added the interest rate series to the four observables in the Aguiar-Gopinath dataset, and reestimated the encompassing model (for the subsample after 1994). The results of are

[13] For the period 1998 onward the EMBI+Emerging Market index was used. For the period 1994 to 1997, the index was interpolated using countries for which data on sovereign yields spreads was available. These countries (and the first year for which data on spreads was available) are: Argentina (1994), Brazil (1994), Ecuador (1995), Mexico (1994), Peru (1997), Korea (1994), Thailand (1997) and South Africa (1995).

presented in the bottom of Table 9[14]. Shocks to the transitory component of the technology process continue to account for most of the variability in the Mexican macro variables. Notably, however, the significance of growth shocks in explaining the variability of output and consumption increases relative to our previous cases. In contrast, interest rate shocks become less relevant. In this sense, the inclusion of interest rate data appears to favor the stochastic trends hypothesis.

One should realize, however, that these results do not mean that financial frictions are unimportant, since financial frictions may be amplifying the impact of any of the exogenous shocks. To examine this, and also to have an alternative view of model performance, we attempted to quantify the accuracy of the encompassing model in reproducing the Mexican dynamics during the 1994-5 Tequila Crisis.

We computed a historical decomposition of the structural shocks, exploiting the smoothing properties of the Kalman filter, following Hamilton (1994) and DeJong and Dave (2007). From the state space representation (3.1) and the measurement equation (3.2) we backed out the state variables and innovations, using the information contained in the entire sample:

$$\{Z_{1t|T}, \nu_{t|T}\}_{t=1994:1}^{T=2003:4}$$

Next, we independently used each of the three structural shocks to simulate the evolution of the four Mexican macroeconomic aggregates during the 1995 Tequila Crisis and its aftermath.

Figure 6 shows the results. Each row tracks the observed and model-based simulated time series of the Mexican macro aggregates between 1994 and 1997. The model based simulations were obtained using only the smoothed shocks to the technology growth (first row), the foreign interest rate (second row), and the transitory technology processes (third row). It is immediate to see that neither growth shocks nor shocks to the foreign interest rate can reproduce the observed dynamics. The only shock that comes close to reproducing the deep fall in economic activity and the sharp reversal of the trade balance during the

[14] For the sake of brevity, the posterior estimates are omitted but the tabulated results are available upon request.

crisis is the one that transiently affects total factor productivity.

Here, again, we have to remember that these perturbations may also be largely amplified by the financial frictions embedded in the model. To evaluate this possibility, Figure 7 reproduces the simulation of the Tequila Crisis using only transitory technology shocks but varying the severity of the two financial frictions embedded in the parameters η and θ. The first row reports the simulation shutting down both financial frictions by setting $\eta = \theta = 0$. The second and third rows set, separately, $\theta = 0$ and $\eta = 0$ respectively, while leaving the other one equal to its estimated value. It is quite clear after looking at these plots that the success of transitory technology shocks in reproducing the Tequila crisis comes, by and large, from the presence of financial frictions, particularly embedded in η, the parameter that governs the elasticity of the spread to expectations of future productivity. [15]

6. Concluding Remarks

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.

[15] A similar experiment was conducted by Fernandez (forthcoming) using data for other developing countries and a wider spectrum of shocks. His results point also to the need for financial frictions in closing the gap between observed and simulated dynamics.

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.

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TABLES AND FIGURES

Table 1. Calibrated Parameters

Parameter	Description	Models		
		Encompassing	Stochastic Trend	Financial Frictions
σ	Intertemporal Elasticity of Substitution $\left[1/\sigma\right]$	2.000	2.000	2.000
ω	Labor Supply Elasticity $\left[\frac{1}{\omega-1}\right]$	1.600	1.600	1.600
α	Labor Share of Income	0.6868	0.6800	0.6867
R^*	Gross Foreign Interest Rate	1.0025	1.0323	1.0025
μ	Long-run Productivity Growth	1.006	1.006	1.006
τ	Labor Parameter so that $h^{ss}=1/3$	1.7168	1.5662	1.7169
ψ	Debt Elastic Interest Rate Parameter	0.001	0.001	0.001
β	Discount Factor	0.9976	0.9804	0.9976
S	Long-run Gross Country Interest Rate Premium	1.0120	1.0000	1.0120
δ	Depreciation Rate of Capital	0.050	0.050	0.050
d	Debt-to-GDP Ratio (*D/Y*)	0.100	0.100	0.100
R	Gross Country-specific Interest Rate	1.0145	1.0323	1.0145

Note: A period is taken to be a quarter in the calibration. Note that in the encompassing and financial friction models α is not exactly equal to labor share (h-$Share$) but it is rather $\alpha = h\text{-}Share * \left[1+(R-1)\theta\right]$. In the Table, values are computed using the posterior mode of θ.

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 & 90% C.I	Stochastic Trend M.	Fin. Frictions M	
ρ_a	0.95 [0.92, 0.97]	0.89	0.89 [0.87, 0.92]	0.94	0.89	0.94
$100\sigma_a$	0.74 [0.12, 1.67]	0.66	0.66 [0.51, 0.82]	0.69	0.66	0.41
ϕ	6.00 [1.62, 12.6]	14.78	14.86 [11.99, 18.81]	3.69	14.77	3.79
$100\sigma_Y$	2.00 [0.67, 3.86]	0.64	0.62 [0.32, 0.88]	0.48	0.64	
$100\sigma_C$	2.00 [0.67, 3.86]	1.13	1.16 [0.99, 1.35]	1.15	1.14	
$100\sigma_I$	2.00 [0.67, 3.86]	3.04	3.09 [2.58, 3.66]	3.08	3.03	
$100\sigma_{TB/Y}$	2.00 [0.67, 3.86]	0.78	0.78 [0.54, 0.99]	0.92	0.78	
ρ_g	0.72 [0.68, 0.76]	0.72	0.72 [0.68, 0.75]	0.73		0.72
$100\sigma_g$	0.74 [0.12, 1.67]	0.12	0.11 [0.01, 0.29]	0.73		1.09
ρ_R	0.83 [0.74, 0.91]	0.81	0.81 [0.70, 0.88]		0.81	
$100\sigma_R$	0.72 [0.30, 1.29]	0.42	0.41 [0.26, 0.57]		0.42	
θ	0.50 [0.13, 0.87]	0.69	0.69 [0.25, 0.98]		0.69	
η	1.00 [0.84, 1.17]	0.73	0.73 [0.61, 0.85]		0.73	
RWC	3.15 [0.18, 6.37]	0.20	0.28 [0.00, 1.14]	3.25	0.00	5.33

Note: Estimates obtained using four observables, {gY, gC, gI, dTB/Y} from the Mexican Data, 1980.1-2003.2. 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, Encompassing Model

Structural Shock	*gY*	*gC*	*gI*	*dTB/Y*
ε^{a}	91.52	86.36	74.95	55.22
ε^{g}	2.38	3.12	1.32	1.78
ε^{R^*}	6.10	10.52	23.72	43.01
Counterfactual, No Endogenous Spread: $\eta = 0$				
ε^{a}	93.04	66.84	5.95	17.38
ε^{g}	1.53	5.08	1.47	0.82
ε^{R^*}	5.43	28.08	92.59	81.81

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. Posteriors Without Measurement Errors

Parameter	Observables:{gY,dTB/Y}		Observables:{gY,gI}		Observables:{gY,gC}	
	Stochastic Trend M.	Financial Frictions M.	Stochastic Trend M.	Financial Frictions M.	Stochastic Trend M.	Financial Frictions M.
ρ_a	**0.93**	**0.90**	**0.91**	**0.93**	**0.93**	**0.89**
$100\sigma_a$	**0.87**	**0.76**	**1.21**	**0.84**	**1.03**	**0.87**
ϕ	**5.66**	**31.45**	**3.59**	**27.81**	**10.87**	**18.37**
ρ_g	**0.76**		**0.77**		**0.78**	
$100\sigma_g$	**1.04**		**1.15**		**1.09**	
ρ_R		**0.88**		**0.92**		**0.91**
$100\sigma_R$		**0.58**		**0.72**		**0.63**
θ		**0.77**		**0.24**		**0.59**
η		**0.79**		**0.88**		**0.75**
RWC	**4.46**	**0.00**	**3.92**	**0.00**	**4.67**	**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. Model Comparison

Models	Likelihood	Posterior	Marginal Likelihood
Observables: {gY, gC, gI, dTB/Y}; Measurement Errors in all Variables			
Encompassing Model	991.5	1010.1	956.2
Stochastic Trend Model	989.7	1015.0	973.8
Financial Frictions Model	991.9	1003.4	960.4
AG - GMM	975.2		
Observables: {gY. dTB/Y}; No Measurement Errors			
Stochastic Trend Model	516.1	525.0	506.8
Financial Frictions Model	540.1	535.7	514.9
Observables: {gY, gI}; No Measurement Errors			
Stochastic Trend Model	387.0	391.7	372.9
Financial Frictions Model	430.1	432.6	408.0
Observables: {gY, gC}; No Measurement Errors			
Stochastic Trend Model	512.7	517.0	499.9
Financial Frictions Model	524.4	519.5	499.3

Note: Results are in logs. 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) and the measurement errors from the posterior mode.

Table 7.1. Second Moments. Encompassing and Separate Models

Variable	Mexican Data	Encompassing	Stochastic Trend	Financial Frictions	Aguiar-Gopinath
Standard Deviations (%)					
gY	1.53	1.23	1.54	1.22	1.58
gC	1.94	1.68	1.62	1.65	1.71
gI	5.66	4.63	4.47	4.60	5.52
dTB/Y	1.38	1.46	0.98	1.44	1.12
S.D. (*X*) / S.D. (*gY*)					
gC	1.27	1.36	1.05	1.36	1.08
gI	3.71	3.76	2.90	3.77	3.49
dTB/Y	0.91	1.18	0.64	1.18	0.71
Correlation with *gY*					
gC	0.76	0.95	0.95	0.95	0.98
gI	0.75	0.79	0.90	0.79	0.88
dTB/Y	-0.44	-0.65	-0.54	-0.64	-0.71
Correlation with *dTB/Y*					
gC	-0.50	-0.83	-0.78	-0.83	-0.82
gI	-0.67	-0.97	-0.85	-0.97	-0.95
Serial Correlation					
gY	0.27	0.19	0.15	0.19	0.27
gC	0.20	0.18	0.08	0.18	0.19
gI	0.44	-0.06	-0.02	-0.06	-0.01
dTB/Y	0.33	-0.08	-0.05	-0.08	-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 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:{gY, dTB/Y}		Observables:{gY, gI}		Observables:{gY, gC}	
		Stochastic Trend	Financial Frictions	Stochastic Trend	Financial Frictions	Stochastic Trend	Financial Frictions
Standard Deviations (%)							
gY	1.53	2.06	1.43	2.66	1.52	2.32	1.63
gC	1.94	2.33	2.25	2.78	3.17	2.63	2.43
gI	5.66	5.07	3.57	7.71	6.08	3.94	6.39
dTB/Y	1.38	1.37	1.58	1.93	2.89	1.33	2.56
S.D. (*X*) / S.D. (*gY*)							
gC	1.27	1.13	1.57	1.05	2.08	1.13	1.49
gI	3.71	2.46	2.50	2.90	4.00	1.69	3.93
dTB/Y	0.91	0.67	1.10	0.72	1.90	0.57	1.57
Correlation with *gY*							
gC	0.76	0.92	0.90	0.91	0.84	0.91	0.82
gI	0.75	0.86	0.70	0.84	0.73	0.84	0.59
dTB/Y	-0.44	-0.41	-0.45	-0.38	-0.57	-0.20	-0.34
Correlation with *dTB/Y*							
gC	-0.50	-0.73	-0.80	-0.72	-0.92	-0.59	-0.81
gI	-0.67	-0.82	-0.95	-0.82	-0.98	-0.71	-0.96
Serial Correlation							
gY	0.27	0.17	0.19	0.16	0.15	0.14	0.17
gC	0.20	0.08	0.21	0.09	0.05	0.07	0.17
gI	0.44	-0.29	-0.04	-0.02	-0.03	0.02	-0.04
dTB/Y	0.33	-0.05	-0.06	-0.05	-0.04	-0.05	-0.05

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 Analysis: Less Informative Priors; Other Preferences; and Estimation of Long-Run Growth

Parameter	Less Informative Priors					Jaimovich-Rebelo Preferences and Estimating Long-Run Growth		
	Prior Distribution	**Prior Mean**	**High Posterior Mode**	**Low Posterior Mode**	**Posterior Mean**	**Prior Distribution**	**Jaimovich-Rebelo Preferences**	**Estimating Long-Run Growth**
ρ_a	Beta (2,2)	0.50	0.89	0.67	0.91 [0.83, 0.98]	0.95 [0.92, 0.97]	0.88 [0.87, 0.90]	0.89 [0.87, 0.92]
$100\sigma_a$	Uniform (0.01,10)	5.00	0.82	0.46	0.84 [0.74, 0.96]	0.74 [0.12, 1.67]	1.02 [0.82, 1.25]	0.66 [0.50, 0.83]
ϕ	Uniform (0.0,40)	20.0	8.75	2.30	7.92 [4.02, 11.95]	6.00 [1.62, 12.6]	16.40 [12.40, 20.79]	14.87 [11.92, 18.01]
$100\sigma_Y$	Uniform (0.01,10)	5.00	0.01	0.01	0.09 [0.01, 0.31]	2.00 [0.67, 3.86]	0.43 [0.16, 0.68]	0.59 [0.20, 0.90]
$100\sigma_C$	Uniform (0.01,10)	5.00	1.19	1.19	1.20 [1.05, 1.37]	2.00 [0.67, 3.86]	1.19 [1.04, 1.36]	1.18 [1.00, 1.38]
$100\sigma_I$	Uniform (0.01,10)	5.00	2.89	2.82	3.02 [2.47, 3.54]	2.00 [0.67, 3.86]	2.96 [2.44, 3.47]	3.08 [2.57, 3.66]
$100\sigma_{TB/Y}$	Uniform (0.01,10)	5.00	0.64	0.81	0.48 [0.03, 0.84]	2.00 [0.67, 3.86]	0.65 [0.37, 0.90]	0.71 [0.18, 0.97]
ρ_g	Beta (2,2)	0.50	0.50	0.50	0.52 [0.06, 0.96]	0.72 [0.68, 0.76]	0.72 [0.68, 0.75]	0.72 [0.68, 0.76]
$100\sigma_g$	Uniform (0.01,10)	5.00	0.02	1.12	0.03 [0.01, 0.08]	0.74 [0.12, 1.67]	0.06 [0.00, 0.16]	0.11 [0.01, 0.30]
ρ_R	Beta (2,2)	0.50	0.93	0.87	0.94 [0.86, 0.99]	0.83 [0.74, 0.91]	0.82 [0.72, 0.89]	0.82 [0.72, 0.90]
$100\sigma_R$	Uniform (0.01,10)	5.00	0.17	0.04	0.16 [0.07, 0.30]	0.72 [0.30, 1.29]	0.36 [0.25, 0.49]	0.41 [0.26, 0.57]
θ	Beta (2,2)	0.50	0.65	0.76	0.62 [0.13, 0.96]	0.50 [0.13, 0.87]	0.56 [0.18, 0.88]	0.69 [0.26, 0.96]
η	Uniform (0.0,5.0)	2.50	0.32	0.00	0.25 [0.01, 0.52]	1.00 [0.84, 1.17]	0.67 [0.56, 0.79]	0.73 [0.60, 0.87]
γ	Uniform (0.001,1.0)					0.50 [0.05, 0.95]	0.05 [0.00, 0.13]	
ξ	Gamma (25,0.1)					2.50 [1.72, 3.35]		2.51 [1.97, 3.06]
RWC		1.01	0.00	2.48	0.33 [0.00, 0.40]		0.04 [0.00, 0.16]	0.28 [0.00, 1.18]
Log-Posterior at Mode			1014.6	1009.0			1011.3	1009.9
Log-Likelihood at Posterior Mode			1004.6	997.8			1000.5	991.6

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. Results for Jaimovich-Rebelo Preferences and Estimating Long-Run Growth are posterior means and 90 percent confidence intervals for posterior distributions.

Table 9. Forecast Error Variance Decompositions. Robustness Analysis: Less Informative Priors; Other Preferences; and Estimation of Log-Run Growth

Structural Shock	*gY*	*gC*	*gI*	*dTB/Y*
Less Informative Priors				
ε^{a}	97.56	87.37	64.59	22.11
ε^{g}	0.16	0.68	0.17	0.78
ε^{R^*}	2.28	11.95	35.24	77.11
Jaimovich-Rebelo Preferences				
ε^{a}	87.57	94.91	85.64	58.68
ε^{g}	1.09	1.82	0.66	2.05
ε^{R^*}	11.34	3.27	13.71	39.27
Estimating Long-Run Growth				
ε^{a}	91.38	85.74	73.72	53.37
ε^{g}	2.46	3.19	1.34	1.76
ε^{R^*}	6.16	11.07	24.94	44.87
Observing Interest Rates {R*,R}				
ε^{a}	61.72	53.16	76.70	67.45
ε^{g}	37.96	46.20	17.98	16.01
ε^{R^*}	0.32	0.65	5.32	16.55

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 Analysis: One Financial Friction at a Time.

Parameter	Prior	No Working Capital $\theta = 0$		No Endogenous Spread $\eta = 0$		No Financial Frictions $\theta = \eta = 0$	
		Posterior Mode	Mean	Posterior Mode	Mean	Posterior Mode	Mean
ρ_a	0.95 [0.92, 0.97]	0.89	0.89 [0.87, 0.91]	0.96	0.96 [0.94, 0.97]	0.96	0.96 [0.94, 0.97]
$100\sigma_a$	0.74 [0.12, 1.67]	0.78	0.78 [0.64, 0.91]	0.71	0.73 [0.58, 0.85]	0.73	0.74 [0.61, 0.89]
ϕ	6.00 [1.62, 12.6]	15.14	15.41 [12.43, 18.8]	4.11	4.28 [2.90, 5.92]	4.02	4.13 [2.94, 5.51]
$100\sigma_Y$	2.00 [0.67, 3.86]	0.53	0.54 [0.26, 0.80]	0.35	0.34 [0.15, 0.58]	0.35	0.31 [0.11, 0.54]
$100\sigma_C$	2.00 [0.67, 3.86]	1.17	1.18 [1.00, 1.39]	1.12	1.14 [0.98, 1.32]	1.13	1.15 [1.01, 1.33]
$100\sigma_I$	2.00 [0.67, 3.86]	2.87	2.99 [2.51, 3.54]	2.65	2.68 [2.15, 3.21]	2.66	2.70 [2.16, 3.22]
$100\sigma_{TB/Y}$	2.00 [0.67, 3.86]	0.79	0.80 [0.56, 1.03]	0.73	0.74 [0.54, 0.94]	0.72	0.73 [0.52, 0.94]
ρ_g	0.72 [0.68, 0.76]	0.72	0.72 [0.68, 0.75]	0.71	0.71 [0.67, 0.75]	0.71	0.71 [0.68, 0.75]
$100\sigma_g$	0.74 [0.12, 1.67]	0.12	0.10 [0.01, 0.26]	0.62	0.57 [0.27, 0.81]	0.62	0.59 [0.29, 0.84]
ρ_R	0.83 [0.74, 0.91]	0.84	0.84 [0.75, 0.91]	0.86	0.85 [0.77, 0.92]	0.86	0.86 [0.78, 0.93]
$100\sigma_R$	0.72 [0.30, 1.29]	0.37	0.37 [0.22, 0.53]	0.14	0.15 [0.09, 0.22]	0.14	0.14 [0.09, 0.20]
θ	0.50 [0.13, 0.87]			0.65	0.61 [0.10, 0.96]		
η	1.00 [0.84, 1.17]	0.71	0.71 [0.60, 0.83]				
RWC	3.15 [0.18, 6.37]	0.13	0.14 [0.00, 0.57]	2.62	2.31 [0.69, 3.60]	2.38	2.20 [0.61, 3.49]

Table 11. Forecast Error Variance Decompositions. Robustness Analysis: One Financial Friction at a Time

Structural Shock	*gY*	*gC*	*gI*	*dTB/Y*
No Working Capital Needs: $\theta = 0$				
ε^{a}	97.97	91.62	78.79	56.52
ε^{g}	1.38	2.09	0.88	1.34
ε^{R}	0.65	6.29	20.33	42.14
No Endogenous Spread: $\eta = 0$				
ε^{a}	72.67	47.53	32.11	3.50
ε^{g}	25.84	49.65	30.55	39.22
ε^{R}	1.50	2.82	37.34	57.28
No Financial Frictions: $\theta = \eta = 0$				
ε^{a}	73.23	47.78	33.99	4.16
ε^{g}	25.98	50.41	31.66	41.57
ε^{R}	0.79	1.81	34.35	54.28

See Note in Table 9.

Table 12. Second Moments. Robustness Analysis: One Financial Friction at a Time

Variable	Mexican Data	No Working Capital $\theta = 0$	No Endogenous Spread $\eta = 0$	No Financial Frictions $\theta = \eta = 0$
Standard Deviations (%)				
gY	1,53	1,38	1,49	1,51
gC	1,94	1,79	1,50	1,51
gI	5,66	4,76	4,58	4,64
dTB/Y	1,38	1,44	1.24	1.26
S.D. (*X*) / S.D. (*gY*)				
gC	1,27	1,30	1,00	1,00
gI	3,71	3.45	3,07	3,07
dTB/Y	0,91	1.04	0,83	0,83
Correlation with *gY*				
gC	0,76	0,96	0,94	0,94
gI	0,75	0,87	0,72	0,73
dTB/Y	-0,44	-0,70	-0,35	-0,36
Correlation with *dTB/Y*				
gC	-0,50	-0,88	-0,60	-0,61
gI	-0,67	-0,96	-0,88	-0,88
Serial Correlation				
gY	0,27	0,00	0,11	0,11
gC	0,20	-0,04	0,08	0,07
gI	0,44	-0,06	-0,04	-0,04
dTB/Y	0,33	-0,07	-0,07	-0,07

Figure 1. Priors and Posteriors: Encompassing Model

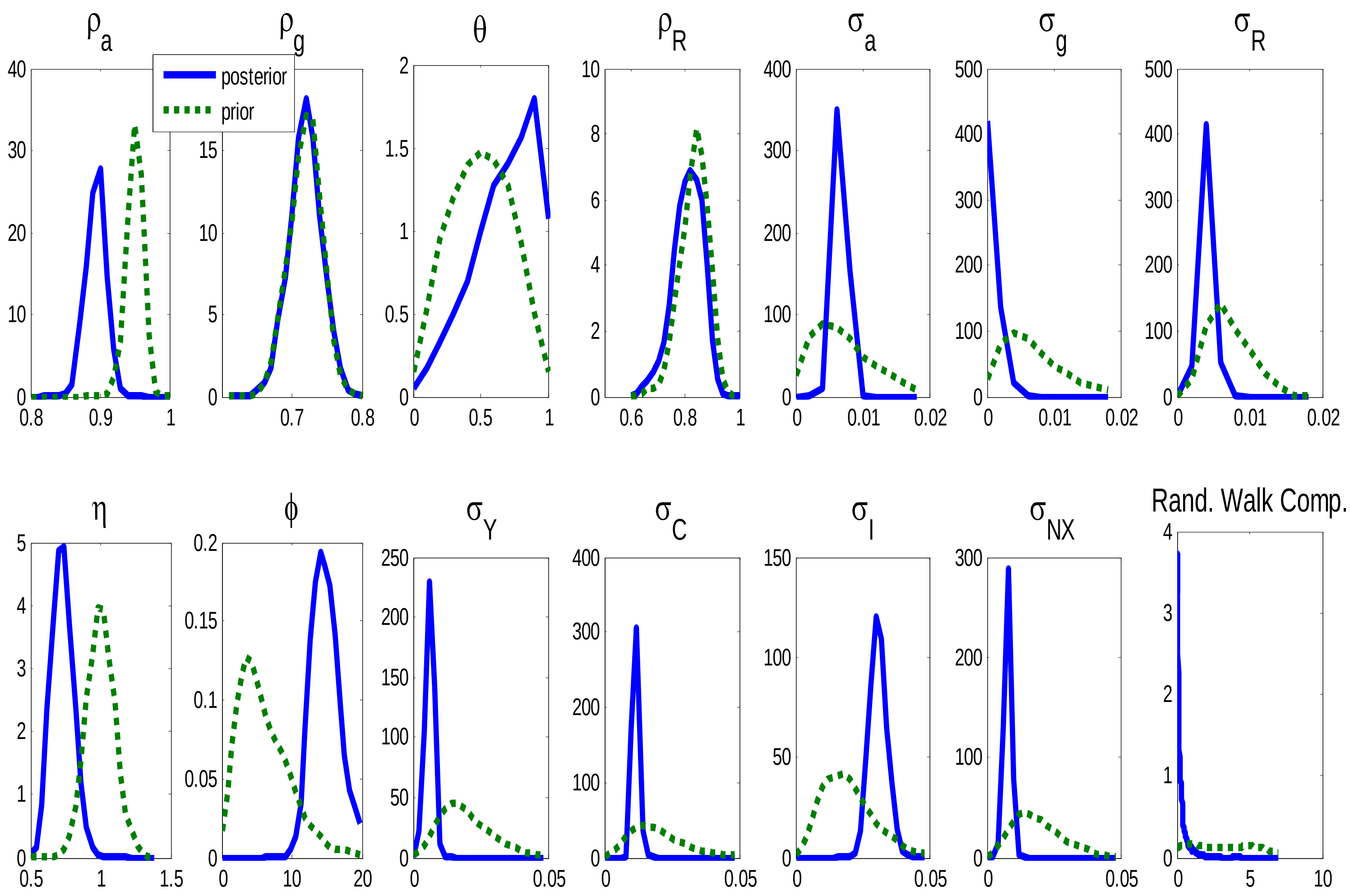
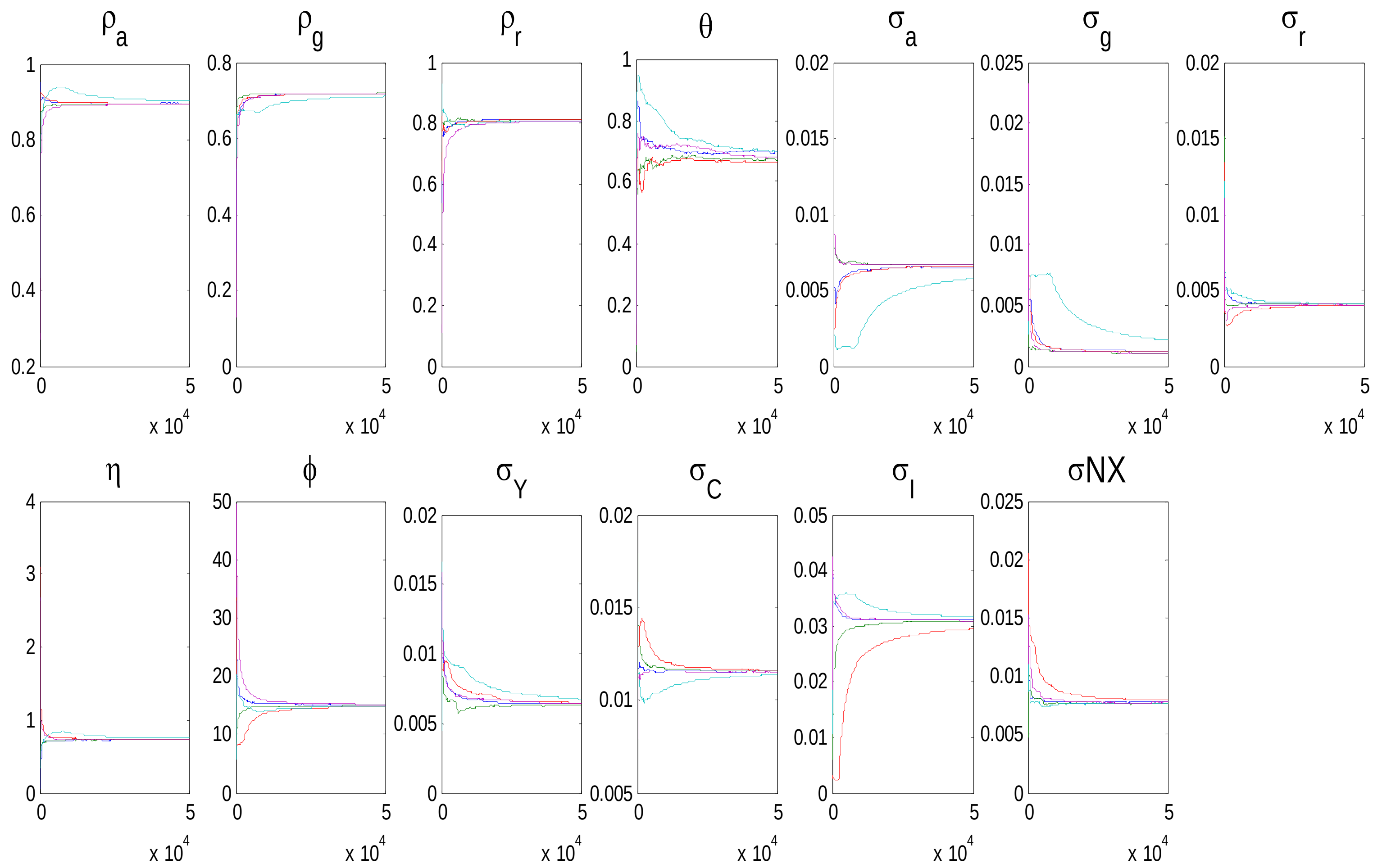
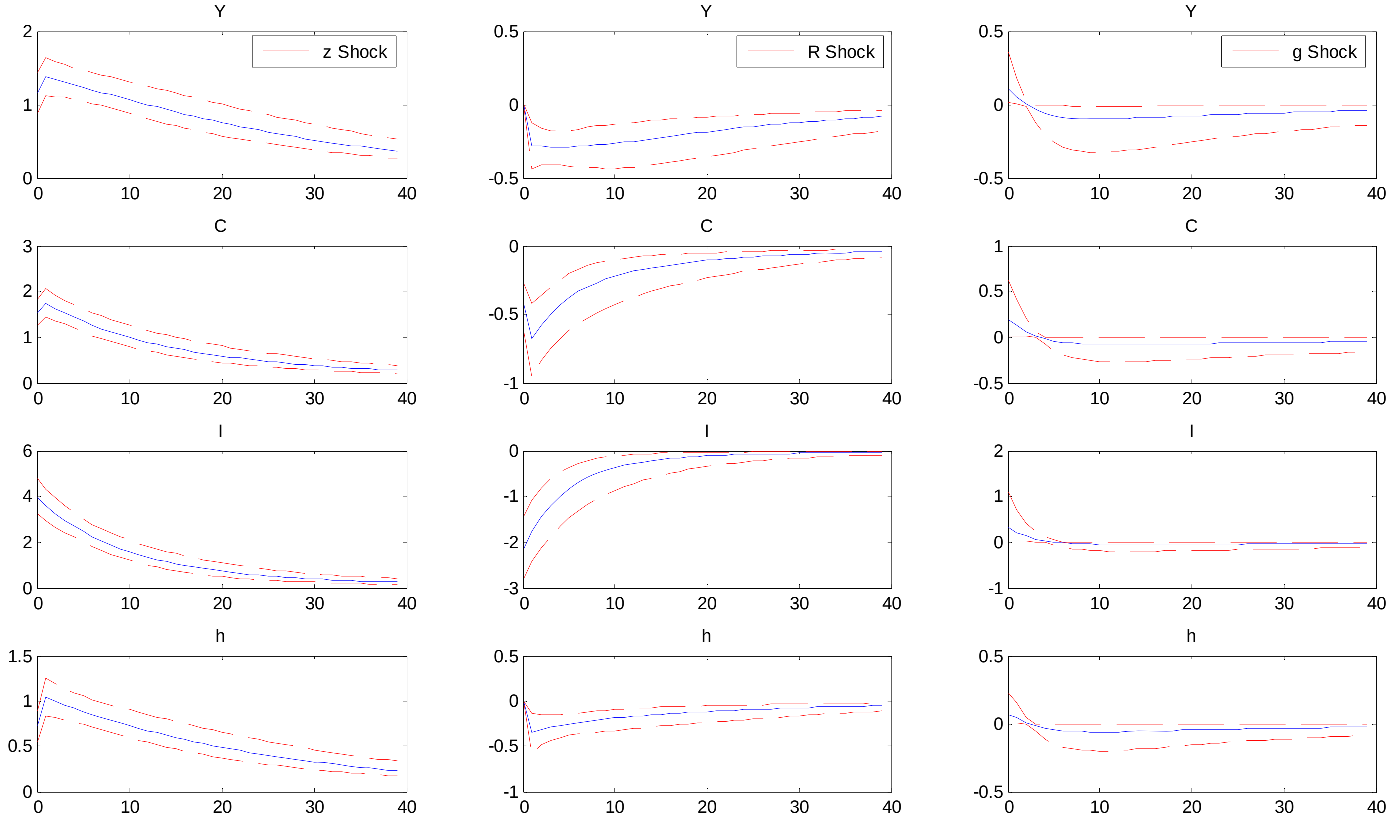


Figure 2. Convergence



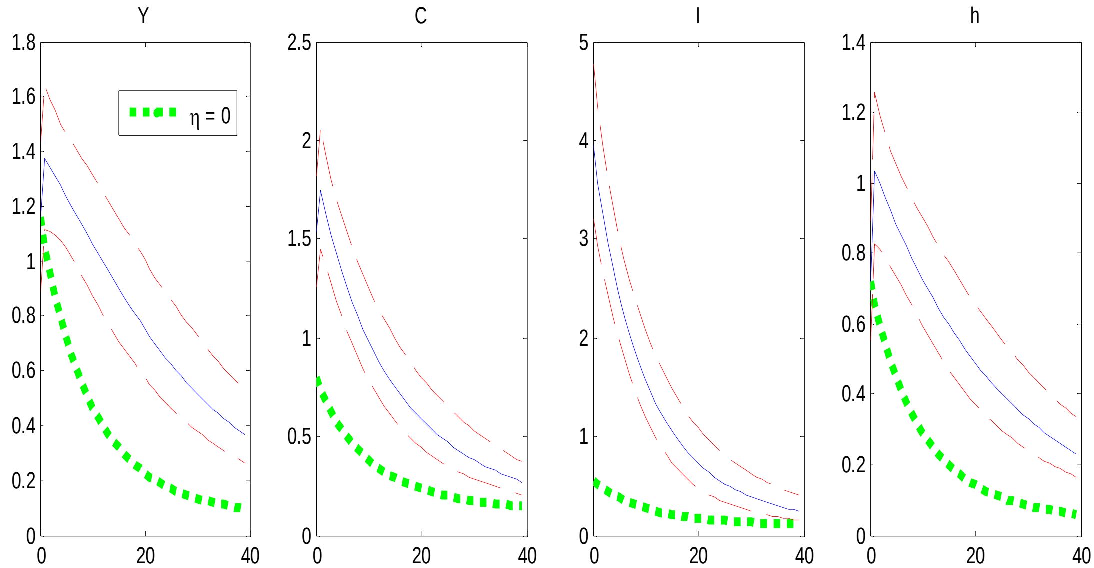
Note: Each line corresponds to recursive means for the 13 parameters as a function of the number of draws, computed from 6 independent MCMC chains using random starting values.

Figure 3 Impulse Response Functions, Encompassing Model



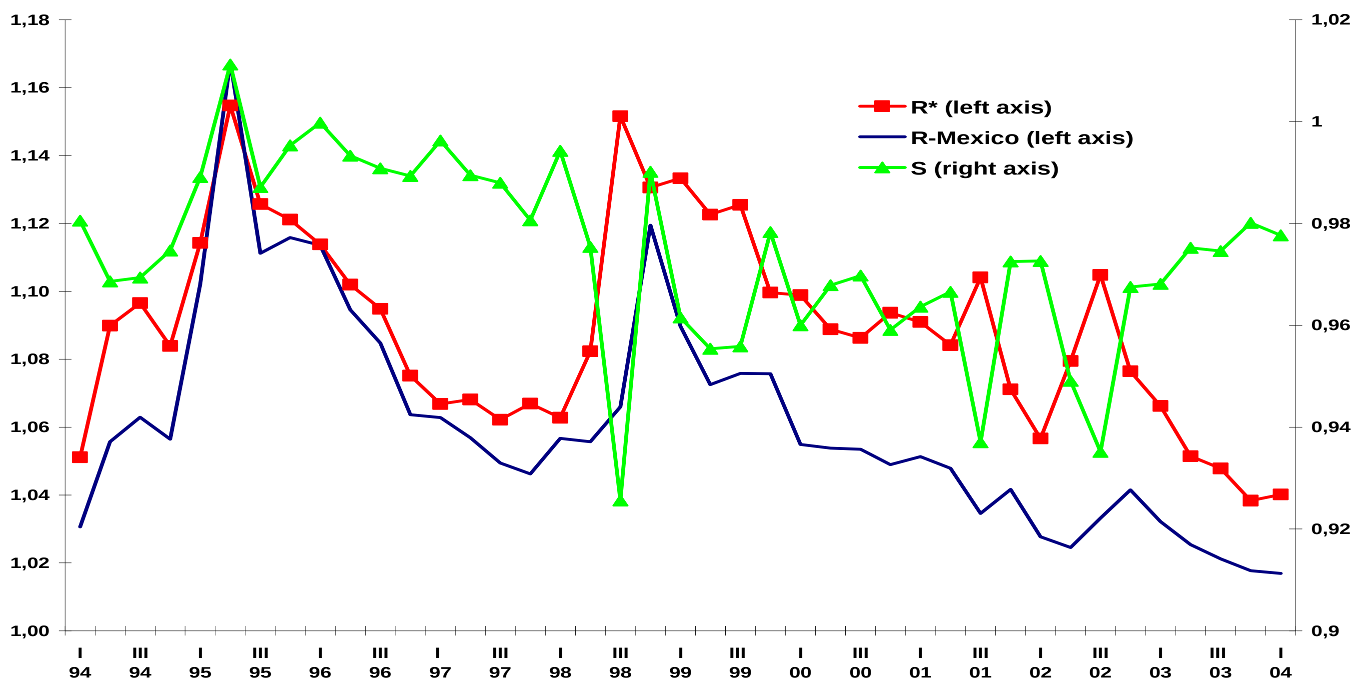
Note: Each column tracks the response of output (Y); consumption (C); investment (I), and employment (h) as deviations from steady states, after an **estimated** 1 S.D. shock to the transitory technology process (Column 1); the foreign interest rate process (Column 2); and the growth process (Column 3). Dashed lines depict 90% confidence interval based upon the posterior distribution.

Figure 4. Impulse Response Functions after a transitory technology Shock: A Counterfactual Experiment



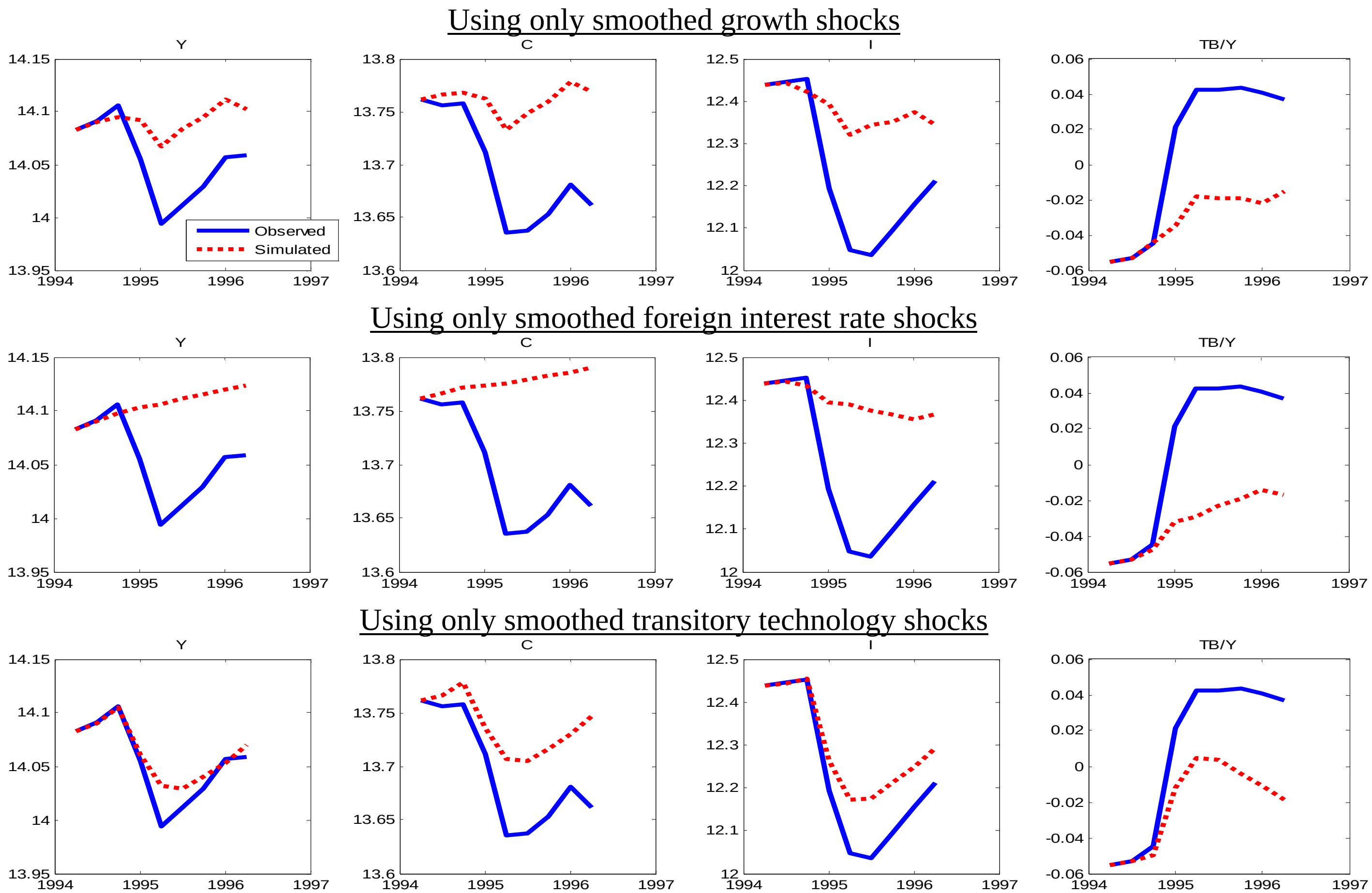
Note: The green dotted line depicts the mean posterior distribution of the same impulse response function following an **estimated** 1 S.D. shock to the transitory technology process except that we counterfactually assume the parameter η to be zero.

Figure 5. Time Series for Domestic and Foreign Interest Rates



Note: R* is the risky world interest rate measured as the safe interest rate (taken from the TBills rate) plus the EMBI+ for a pool of developing emerging market economies; R is the Mexican interest rate measured as the safe interest rate plus the EMBI+ Mexico; S is the implied spread between the two interest rates. Sources: Uribe and Yue (2006) and Global Financial Data.

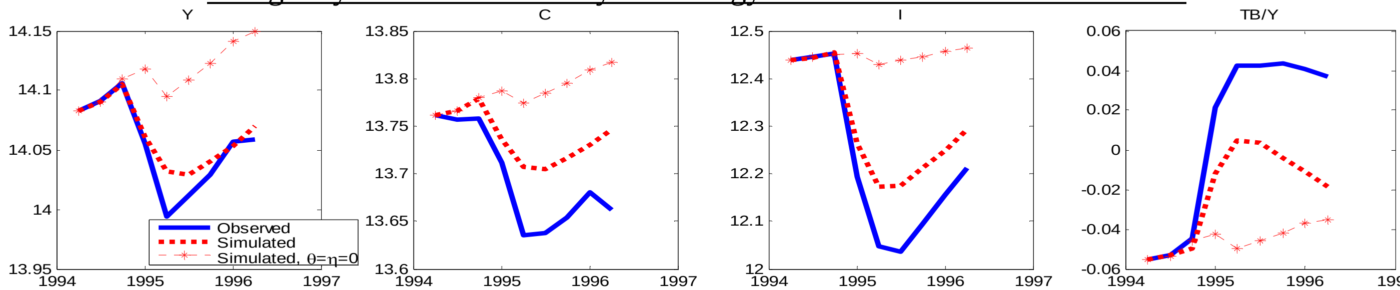
Figure 6. Simulating The Tequila Crisis



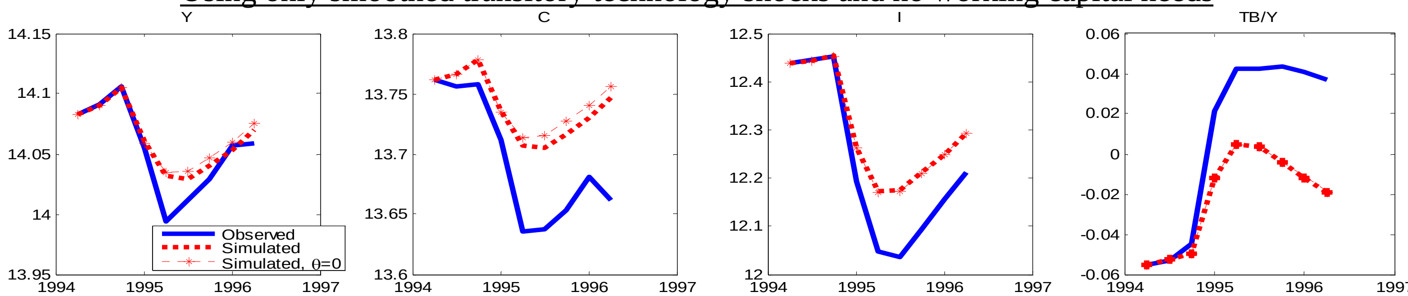
Note: Each row tracks the observed (solid line) and model-based simulated (dashed line) time series of log-output (Y); log-consumption (C); log-investment (I), and the trade balance-to-GDP (TB/Y). The model-based simulations were obtained using the smoothed state shocks. Simulations do not include measurement errors.

Figure 7. Simulating The Tequila Crisis Using Only Transitory Technology Shocks and Various Degrees of Financial Frictions

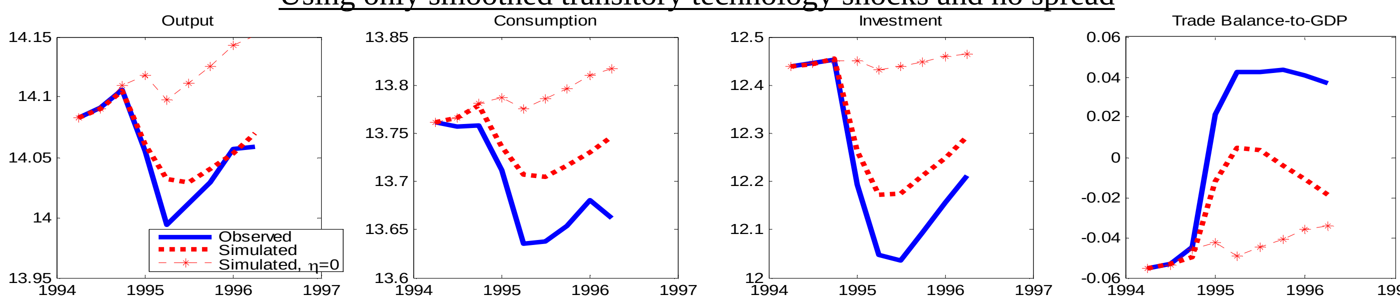
Using only smoothed transitory technology shocks and no financial frictions



Using only smoothed transitory technology shocks and no working capital needs



Using only smoothed transitory technology shocks and no spread



Note: Each row tracks the observed (solid line) and model-based simulated (dashed and starred lines) time series of log-output (Y); log-consumption (C); log-investment (I), and the trade balance-to-GDP (TB/Y). The model-based simulations were obtained using the smoothed state transitory technology shocks.