On the Sources of Aggregate Fluctuations in Emerging Economies*

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This Version: September 2012

Abstract

Recent research on macroeconomic fluctuations in emerging economies has advocated introducing a stochastic productivity trend, in addition to temporary productivity shocks, or allowing for foreign interest rate shocks coupled with financial frictions. This paper develops a model that encompasses both approaches and estimates it via Bayesian methods. This exercise sheds light on the relative merit of the two approaches and on how financial frictions affect the transmission of shocks. The estimated model accounts for aggregate fluctuations by assigning a dominant role to financial frictions in amplifying conventional productivity shocks and, less markedly, interest rate shocks; trend shocks, in contrast, play a very minor role. Of the two financial frictions we consider, working capital versus spreads linked to expected future productivity, the latter emerges as essential for a reasonable approximation to the data.

*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 four anonymous referees, Mark Aguiar, Peter Benczur, Bora Durdu, Dave DeJong, Jesus Fernandez-Villaverde, Pat Kehoe, Federico Mandelman, Andy Neumeyer, Martin Uribe, Tao Zha, and seminar participants at the NBER IFM Summer Institute, MIT, the Federal Reserve Board, the St. Louis Fed, the IMF, Universidad di Tella, the Atlanta Fed, Magyar Nemzeti Bank, and University of Pittsburgh. We thank Sergio Castellanos Gamboa for excellent research assistance. Of course, any errors or shortcomings are ours.

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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 one, 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 long way towards addressing well known 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.

This paper develops and estimates a model that encompasses both approaches, combining stochastic trends with interest rate shocks and financial frictions. We push the exercise in several directions intended to cast light on the relative merits of the two approaches and on the role of financial frictions in amplifying shocks to arrive to a reasonable characterization of the data.

We exploit recent advances in Bayesian methods to estimate the posterior distributions of the parameters of the encompassing model, and of functions of those parameters such as variance decompositions. We can then measure the relative importance of temporary productivity shocks, trend shocks, and interest rate shocks when all of them can contribute to fluctuations. In addition, we estimate separately the stochastic trend and the random interest rates/financial frictions models, regarded as restricted versions of the encompassing model; this allows for the analysis of the marginal contribution of each approach to the overall model. 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 also use interest rate and spreads data from Uribe and Yue (2006).

In the benchmark estimation of the encompassing model, the posterior distribution of the estimated parameters is characterized by strong financial frictions, volatile shocks to the processes for interest rates and transient technology, and small 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. We find that temporary productivity shocks are responsible for the bulk of the variance of aggregates, although interest rate shocks have a sizeable role as well. In contrast, the share of the variances due to trend shocks is three percent or less.

We find that the encompassing model does a good job in matching the data moments that have been emphasized in existing studies. Success in this regard is largely due to the interaction between conventional productivity shocks and financial frictions. Indeed, the financial frictions model yields virtually the same values for the data moments as the encompassing model, while the stochastic trend model delivers notable counterfactual implications.

The results, therefore, support the view that explaining fluctuations in emerging economies requires financial imperfections to amplify conventional productivity shocks and, perhaps less crucially, interest rate shocks. Trend shocks add relatively little, and become quantitatively relevant only if financial frictions are assumed away.[1]

To further understand the transmission mechanism, we investigate the role of the two financial frictions assumed in the encompassing model: a working capital requirement and an endogenous spread. 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).

Finally, to check for the robustness of the previous results and for additional detail, we estimate the contribution of temporary productivity shocks, trend shocks, interest rate

[1]Boz, Daude, and Durdu (2012) estimate a model similar to Aguiar and Gopinath's and, like us, find that the volatility of the temporary technology shock is larger than the volatility of trend shocks. But their explanation relies not on financial frictions but on learning effects. In their model, agents observe directly innovations to total factor productivity but not whether they are temporary or permanent in nature. The economy may then respond to temporary shocks as if they were permanent; interestingly, this can be the case even if productivity innovations are dominated by the temporary component.

shocks and financial frictions in explaining the dynamics of the Mexican 1995 Tequila crisis. We find that temporary productivity shocks appear to have dominated the episode but, again, that financial frictions were crucial to amplify their effects.

Our study is closely related to García-Cicco, Pancrazi, and Uribe (2010), who examined 1900-2005 data from Mexico and Argentina to probe 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 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; in that extension, the role of trend shocks turned out to be negligible. Hence Garcia-Cicco et.al.'s findings and ours have much in common. 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 and high debt elastic interest rate premia that represent the main financial frictions in Garcia-Cicco et al.

Our work is related to a long standing debate of whether fluctuations in emerging economies are dominated by domestic shocks or foreign shocks. Several years ago now, Calvo, Leiderman, and Reinhart (1993) challenged 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.

Likewise, emphasizing the role of financial frictions is of course not new. In addition to the papers by Neumeyer-Perri and Uribe-Yue, financial imperfections in open economies have been stressed by the literature on balance sheet effects (Cespedes, Chang and Velasco 2004) and sudden stops (Calvo 1998, Mendoza 2010). A main contribution of this paper is to provide a quantitative perspective on the empirical accuracy of financial frictions models relative to their main alternative, the stochastic trend hypothesis.

Our focus on estimating the macroeconomic implications of financial frictions is similar to that of a recent literature on the importance of agency costs and net worth effects in developed country fluctuations. Most of that literature (which includes De Graeve (2008), Nolan and Thoenissen (2009), Gilchrist, Ortiz, and Zakrajsek (2009), Christiano, Motto, and Rostagno (2010), and Fuentes-Albero (2012)) studies empirical implementations of the influential Bernanke, Gertler, and Gilchrist (1999) framework, and generally finds that financial frictions significantly improve the empirical plausibility of standard models. Our study's empirical likelihood-based approach as well as its results have the same flavor, although its details are quite different. Specifically, our model does not include a financial accelerator, which is crucial in the Bernanke et al. framework. Instead, our model's financial channels are those emphasized in previous emerging countries studies.[2]

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. Models

2.1. The Standard Small Open Economy Model

The standard model of a small open economy, first developed by Mendoza (1991) and discussed by Schmitt-Grohe and Uribe (2003), is well known. Time is discrete and indexed by $t = 0, 1, 2, ...$ There is only one final good in each period, which can be produced with the technology

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

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[3]. Also, a_t is a shock to

[2] Likelihood based methods are also being becoming more frequent in open economy macroeconomics. Leading studies include Lubik and Schorfheide (2005), Rabanal and Tuesta (2006), and Adolfson, Laséen, Lindé, and Villani (2008).

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

total factor productivity, assumed to follow

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

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

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

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

Capital accumulation is given by a conventional equation:

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

where I_t denotes investment, δ the rate of depreciation, and Φ costs of installing capital.

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

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

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

The representative agent has access to a world capital market for noncontingent debt. 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 RHS 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 be given by

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

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 country's debt to ensure that there is a well defined nonstochastic steady state. [4]

The standard model is completed by the equality of factor payments and marginal productivities: $u_t = a_t F_1(K_t, \Gamma_t h_t)$ and

$$W_t = a_t F_2(K_t, \Gamma_t h_t)\Gamma_t \tag{2.6}$$

2.2. The Stochastic Trend Model

Aguiar and Gopinath (2007) 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

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

$|\rho_g| < 1$, ε_t^g is an i.i.d. process with mean zero and variance σ_g^2, and μ represents the mean value of labor productivity growth. A positive realization of ε_t^g implies that the growth

[4] As shown by Schmitt-Grohe and Uribe (2003), this device is one of several possible ones to ensure a well define steady state and can be chosen to have negligible effects on the business cycle properties of the model.

of labor productivity is temporarily above its long run mean. Such a shock, however, is incorporated in Γ_t and, hence, results in a permanent productivity improvement.

That the addition of permanent productivity shocks has the potential to eliminate the departures between the model and the data is intuitive and explained by a permanent income view of consumption. After a favorable realization of ε_t^g, productivity increases permanently. Accordingly, permanent income, and therefore consumption, can increase more than current income; this explains why consumption may be more volatile than income in emerging economies. By the same reasoning, 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. The Financial Frictions Model

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) termed "sudden stops", defined by abrupt and exogenous halts to the flow of international credit to the economy, which force violent current account reversals.

To develop this view, one can modify the standard model along the lines suggested by Neumeyer and Perri (2005). First, instead of (2.5), the price of the household's debt is assumed to be given by

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

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. Second, the world interest rate is assumed to be random, fluctuating around its long run value R^* according to

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

where $|\rho_R| < 1$ and ε_t^R is an i.i.d. innovation with mean zero and variance σ_R^2.

Third, 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 [5]. 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.[6]

An additional friction, developed by Neumeyer and Perri (2005) and Uribe and Yue (2006), is to assume that firms must finance a fraction of their 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). This says that the typical firm hires workers to the point at which the marginal product of labor equals the wage rate inclusive of financing costs. Firms are assumed to borrow from households and forced to pay 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 and Uribe and Yue's imposing both. Indeed, they emphasize different avenues for improving the performance of the basic model. With the working cap-

[5] See, for instance, Mendoza (1991) and Aguiar and Gopinath (2008).

[6] To be precise, our formulation is motivated by Neumeyer and Perri's "induced country risk" case. In a related fashion Uribe and Yue (2006) effectively assumed that the spread depended on world interest rates, output, investment, and the trade balance/GDP ratio. Uribe and Yue also provided supporting evidence from an identified VAR.

ital 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, as in (2.12), a favorable productivity shock not only increases output via the usual channels but also, and because the shock is persistent, reduces the interest rate applicable to the representative household's debts, thus boosting consumption and investment further. A countercyclical trade balance may then emerge, as with working capital, but due to a different mechanism.

2.4. An Encompassing Model

While the literature has naturally considered stochastic trends and financial frictions separately, it is straightforward to specify a model that includes both extensions of the standard model. In this subsection we 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 extended 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) along three key dimensions. First, our encompassing model includes the two aforementioned financial frictions, spreads linked to fundamentals and working capital requirements, embedded in the parameters η and θ, respectively. Aguiar and Gopinath (2008) considered the first friction but not the second. Second, Aguiar and Gopinath (2008) allowed the spread to be affected only by transient technology shocks. Instead, our encompassing model allows for permanent shocks to also affect the spread. This is natural, since the logic behind an endogenous spread is often based on the idea that default risk falls with expected productivity, regardless of whether shocks to the latter are permanent or transitory. To implement this idea, however, we need to modify the assumption (2.12) on country risk. So, our encompassing model assumes a country spread given by

$$\log(S_t/S) = -\eta_1 E_t \log a_{t+1} - \eta_2 E_t \log(g_{t+1}/\mu) \tag{2.14}$$

One particular version of this, which we will adopt for most of the paper, assumes that the spread is given by (2.12), except that the temporary productivity shock a_{t+1} is replaced by total factor productivity (i.e. the normalized Solow residual):

$$\log(S_t/S) = -\eta E_t \log(SR_{t+1}/SR) \tag{2.15}$$

where $SR_t = a_t g_t^a$ and $SR = \mu^\alpha$ according to the Cobb-Douglas technology specified below. To check for robustness, nonetheless, we explore later the more general case where the two elasticities, η_1 and η_2, differ.

Third, Aguiar and Gopinath (2008) restricted their focus to Cobb-Douglas 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 instead assume preferences of the Greenwood, Hercowitz and Huffman (1988, GHH henceforth) type. As discussed by Neumeyer and Perri (2005) and others, GHH preferences help reproducing emerging economies' business cycles facts by allowing the labor supply to be independent of consumption levels[7].

Our encompassing model is then given by the spread process in (2.15) 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).

3. Empirical Approach

Given our formulation, we conduct several empirical exercises intended to evaluate the relative merits of the hypotheses of stochastic trends and financial frictions as well as the nature of the transmission mechanism. To implement these exercises, we adopt a Bayesian framework 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

[7] While Aguiar and Gopinath (2007) restricted discussion to the case with Cobb Douglas preferences, in the working paper version Aguiar and Gopinath also estimated their model assuming GHH preferences and found very little difference. It is also worth mentioning that we explored a more flexible preference specification, due to Jaimovich and Rebelo (2009), which embeds both GHH and Cobb Douglas as special cases. The results, reported in the working paper versions of this paper and others available on request, overwhelmingly favor GHH preferences. Schmitt Grohe and Uribe (2012) report very similar results for the case of the U.S.

trend model and the financial frictions model. We draw on recent theoretical and computational advances, usefully summarized by An and Schorfheide (2007), Canova (2007), DeJong and Dave (2007), Fernandez-Villaverde (2010), Geweke (2005), and others.

3.1. Functional Forms, Calibrated and Estimated Parameters

As mentioned, our baseline preferences come from GHH:

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

The production function is assumed to be Cobb Douglas:

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

where α is the labor's share of income.

The capital adjustment cost function is assumed to be quadratic:

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

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

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

where d is the normalized steady state value of debt.

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. Since the relative importance of the various sources of fluctuations is a key question, in each case we estimate the parameters of the exogenous shocks. 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 ρ_g and σ_g, the corresponding parameters 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 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 one quarter. The calibrated parameters are given in Table 1 and set at 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 percent [8]. We calibrate the debt-to-GDP ratio to 0.1, the value used in Aguiar and Gopinath (2007).

Our calibration of the steady state interest rate and spread is based on Uribe and Yue (2006), who made their data publicly available. Uribe and Yue measured foreign real interest rates by dividing the 3-month gross U.S. Treasury Bill rate by the gross US inflation over the previous four quarters. They also provide the J.P. Morgan's EMBI+ stripped spread for Mexico. Given the Uribe-Yue sample means, we set the long run values of the (annualized) foreign interest rate, R^*, and of the country specific gross real interest rate, R, to 1.01 and 1.06, respectively. For the stochastic trend model we set the spread to zero, and kept R at 1.06[9].

The quarterly depreciation rate is assumed to be 5 percent as in Aguiar and Gopinath (2007). Following the literature on small open economy models, we set the parameter ψ, which pins down the elasticity of interest rates to debt, to a very small value that guarantees the equilibrium solution to be stationary (Schmitt-Grohe and Uribe, 2003).

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

[9] This implies a lower level of the steady state interest rate relative to that used by Aguiar and Gopinath (2007). Results using the same interest rate as in that paper are very similar to the ones reported here and are available upon request.

3.2. Data and Implementation

For comparability, we used the Mexican data from Aguiar and Gopinath (2007) as our observed data. 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.[10]

Our empirical implementation requires a number of other decisions. The first one is how to deal with trends. We decided to estimate the model using log differences of C, I, and Y, and differences of TB/Y.[11] One reason for this choice is that the mapping from model variables to observables, needed for Kalman filtering, is then straightforward[12].

A second issue is the treatment of measurement errors. Neither the encompassing model nor its restrictions exhibit more structural shocks than the number of time series we observe. The resulting stochastic singularity can be dealt with by either basing estimation on as many observed variables as shocks, or adding measurement error shocks, thus completing the probability space of each model so as to render the theoretical covariance matrix of observed variables no longer singular[13]. We chose to add measurement errors to all the variables we observe. This is warranted given well-known measurement issues surrounding macroeconomic data from emerging economies, and the fact that the restricted models have fewer structural shocks than the encompassing model[14].

To sample from the posterior distribution, we implemented a Random Walk Metropolis

[10] The sample period is the same as in Aguiar and Gopinath (2007), hence it has the advantage of comparability. But the period includes the Mexican default in 1982, which can be seen as problematic as the theoretical framework we use does not explicitly model sovereign default. However, note that our specification of endogenous spreads does accommodate (admittedly in an imperfect way) the impact of sovereign default on the cost of capital. Also, in a later section we show that our main results remain when the "lost decade " is excluded from the sample period.

[11] While TB/Y has no trend, we chose to work with first differences of TB/Y instead of levels, because small open economy models typically and counterfactually deliver a quasi-random walk process in the trade balance level, inherited by the nature of the endowment process (see Garcia-Cicco, Pancrazi, and Uribe 2010).

[12] See our working paper version, Chang and Fernandez (2010), for details.

[13] A third option, known 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. But see Fernandez (2010) for an effort in this direction.

[14] It should be noted that the choice of which variables to use in the estimation and the use or not of measurement errors 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 across various sets of observables used. In the working paper version of this work, Chang and Fernandez (2010), we assess the robustness of our results to cases where no measurement errors are used.

algorithm, described in An and Schorfheide (2007) and elsewhere, to generate draws from the posterior distribution. This procedure constructs a Gaussian approximation around the posterior mode, which we found via a numerical optimization, 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[15]. Once this step was completed, we used the algorithm to make one million draws from the posterior distribution in each case. The initial two hundred thousand draws were burned. To overcome the high serial correlation of the draws, we used every hundredth draw to form a set to compute posterior distributions[16].

The last issue is whether or not to include interest rate data in the set of observables. One can argue that including such data may yield valuable information, particularly in terms of the parameters that govern the strength of financial frictions. However, in the benchmark case we decided against this option. One reason is that, as discussed in more detail later, satisfactory series on Mexico's interest rates start only in 1994. Including interest rate data, therefore, would reduce comparability with Aguiar and Gopinath's work, which was based on series dating to the early 1980s. Also, given that one of the objectives in our investigation is to compare the restricted models, including interest rates data would automatically put the stochastic trend models at a disadvantage since that model implies zero fluctuations of interest rates (other than those implied by the debt elastic interest rate). Thus any likelihood based comparison would reject such model against any alternative. This being said, to check for robustness later we explore the implications of including the Uribe-Yue interest rate data in estimation.

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

[16] In the working paper version, Chang and Fernandez (2010), we assess the convergence of the Markov chains by recursively computing means from multiple chains, as illustrated in An and Schorfheide (2007).

4. Results

This section discusses our benchmark findings. After summarizing our priors, we describe the posterior distributions of the parameters of the encompassing model and the two restricted versions of interest, the stochastic trend model and the financial frictions model. We analyze the relative fit of these models, both in terms of likelihood based measures and of their ability to account for data moments of interest. We conclude the section with a discussion of the role of financial frictions in amplifying exogenous shocks.

4.1. Priors

Our priors over the estimated parameters are described in Table 2. They were based, to the extent possible, on earlier studies on emerging markets' 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)[17] estimated a ratio $\sigma_a/\sigma_g = 0.41/1.09 = 0.4$ for Mexico, Garcia-Cicco et.al. (2010) found higher ratios for Mexico ($\sigma_a/\sigma_g = 1.9/1.7 = 1.1$) and Argentina ($\sigma_a/\sigma_g = 3.3/0.71 = 4.6$). Given this, we chose our priors for σ_a and σ_g both to be Gamma distributions with mean of 0.74 and standard deviation 0.56. The common mean lies between the point estimates of σ_a and σ_g in Aguiar and Gopinath (2004).

Our prior for ρ_a, the autoregressive coefficient of the temporary productivity shock, was a Beta distribution with mean 0.95 and standard deviation 1.1 percent. The mean is close to the point estimate of 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, with mean 0.72, and standard deviation 2.3 percent. This follows the point estimate found by Aguiar and Gopinath (2004).

Similarly, our priors over the parameters of the world interest rate process and the strength of the financial frictions followed earlier studies. Our prior for ρ_R was Beta with

[17] When forming priors we used the working paper version of Aguiar and Gopinath's study (Aguiar and Gopinath 2004) instead of the published version (Aguiar and Gopinath 2007). This is because only the former presents results with GHH preferences,which we assume here.

a mean value of 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 centered at 0.72 percent, the value reported by Uribe and Yue (2006), and a standard deviation of 0.31 percent.

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. For η we used a Gamma prior with mean of 1.0 and a standard deviation of 10 percent. The mean is 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. Accordingly, we used a Beta distribution with mean 0.5, and a considerable standard deviation (22.4 percent) reflecting our little *a priori* information on this parameter.

Our prior on ϕ was a Gamma 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. For the standard errors of the four measurement errors we chose a Gamma prior centered at 2.0 percent and a 90 percent confidence interval between 0.67 and 3.86. This relatively diffuse prior reflected our lack of information about the size of measurement errors and our belief that measurement issues may be quite large in emerging economies.

Lastly, our priors over the long-run productivity growth, μ, were based upon estimates reported by Aguiar and Gopinath (2004). Our prior over net yearly growth, ζ, was a Gamma distribution reflecting 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 [18].

4.2. Parameter Posteriors

Estimated posterior distributions of the parameters of the encompassing model and its two restricted versions, the stochastic trend version and the financial frictions version, are summarized in Table 3. The first three number columns report priors and posterior modes, means, and 90 percent confidence intervals of the parameters in the encompassing model,

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

while the next four columns report posterior statistics for the two restricted models. For comparison purposes, the last column reports the GMM estimates of Aguiar and Gopinath (2004). Figure 1 plots priors and posterior distributions for the encompassing model[19].

Several results deserve mention:

- 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 width of the 90 percent highest posterior density intervals. This is also the case for ρ_a and ρ_R, the parameters that govern the persistence of stationary technology and foreign interest rate processes. On the other hand, the data has little to say about ρ_g, the persistence of the permanent technology process, so that the posterior for ρ_g basically reproduces the prior. The latter finding is in line with Garcia-Cicco et.al. (2010) who also weakly identified the persistence of the trend shock to productivity in an estimated real business cycle model with trend shocks and financial frictions using data for Argentina in the twentieth century.

- The role of permanent shocks in the encompassing model does not appear to be as dominant as implied by our prior. The estimated posterior mode ratio of volatilities, $\sigma_a/\sigma_g = 0.66/0.12 = 5.5$, is clearly at odds with Aguiar and Gopinath's (2007) finding that the volatility of innovations is much stronger in the permanent technology process than in the transient one. More to the point, an overall assessment can be based on the random walk component (RWC) of the Solow residual defined as in Aguiar and Gopinath (2007):

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

  The mode and mean of the posterior distribution of the RWC for the encompassing model are given at the bottom row of Table 3. The posterior of the RWC falls steeply

[19]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 Chang and Fernandez (2010). Despite different initializations, the parameters' means converge in the long-run.

relative to the prior and its mode, 0.18, is far below the value estimated by Aguiar and Gopinath (2004).

- In contrast with the minor role of trend shocks, interest rate shocks and the financial frictions amplifying them appear quite significant. The posterior distributions of the parameters that govern 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[20]. The tight posterior distribution for η, with a mode and mean of 0.73, reveals a significant elasticity of the spread to expected movements in the Solow residual. While the mode and mean are lower than our prior ones, which were centered around Neumeyer and Perri's calibrated value of 1.0, it is still remarkable to obtain high values since Neumeyer and Perri's calibration was based on the observed process of the country interest rate, which we do not use in this estimation exercise.

- That trend shocks add very little to the encompassing model can also be seen by comparing that model's parameter estimates against those of the financial frictions restriction (number columns 2/3 and 6/7 in Table 3): they are virtually the same.

- Conversely, the relative importance of trend shocks increases when we estimate the stochastic trend model, shutting off both interest rate shocks and financial frictions (number columns 4 and 5).

- The posterior distribution over the long run productivity growth parameter ζ indicates a posterior mode of 2.53 percent, slightly higher than the prior mode. Uncertainty around ζ is greatly reduced, as judged by the significantly tighter posterior distribution relative to the prior.

- Finally, the estimated values of ϕ differ substantially between the stochastic trend model and the others. The difference reflects the alternative propagation mechanisms of the models. In particular, in the encompassing and financial frictions models pro-

[20] For instance, 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.

ductivity shocks affect investment not only directly through the marginal product of capital but also indirectly their effect on interest rates. The latter effect is absent in the stochastic trend model. Hence capturing investment dynamics in the presence of financial frictions requires higher capital adjustment costs.[21]

4.3. Model Evaluation

4.3.1. Marginal Data Densities

For each model, Table 4 reports standard measures of predictive accuracy: log values of the likelihood and the posterior, both computed at the posterior mode, as well as the marginal data density. Overall, the results do not single out a clear winner. Values for the log-likelihood are highest for the financial frictions model. However, when judging by the log-marginal likelihood the ranking is reversed, and the stochastic trend model outperforms the other models in terms of its forecasting performance[22].

To understand these results, note first that the two restricted models, the stochastic trend and financial frictions models, can attain higher likelihood and marginal likelihood levels than the less restricted encompassing model. This can, in principle, be explained by the different priors used implicitly when estimating the two restricted models. 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 $[0.71, 0.89]$, 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. This occurs with all the other parameters that are set to zero in the restricted models. These differences in the priors imply that areas of the posterior distribution that were not explored in the estimation of the encompassing model were explored in the two restricted models. Hence it is possible that the relative inferiority of the financial frictions model comes from the likelihood of this

[21] Thus, for example, Neumeyer and Perri (2005) reported that matching Argentina's investment volatility required values of ϕ as low as 8 and as large as 40. The macro literature has employed many different specifications and parametrizations of investment adjustment costs, and so it does not provide much guidance about the plausibility of different values of ϕ.

[22] The log-marginal data density can be interpreted as a predictive score in terms of the relative one-step-ahead predictive performance. See An and Schorfheide (2007) for further details.

model peaking at a value that is at odds with the information used to construct the prior distribution (An and Schorfheide, 2007).

A second factor is that the inclusion of financial frictions requires estimating at least two additional parameters. This is relevant because marginal likelihood comparisons are known to generally favor models with fewer parameters.[23] In our case, this means that the stochastic trend model has an automatic advantage in terms of its marginal likelihood.

Hence, we take the results of Table 4 as inconclusive. In the next section we attempt to cast some more light on these results, by exploring the role of alternative priors.

Finally, for comparison purposes, Table 4 reports the log-likelihood value of the stochastic trend model evaluated at the GMM parameter estimates of Aguiar and Gopinath (2004)[24]. That value is far below the levels we obtain for the other estimates.

4.3.2. Matching Moments

It can be argued that, for macroeconomists, predictive performance is not 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 moments in model evaluation, especially: (i) the marked countercyclicality of the trade balance; (ii) the high volatility of consumption and investment relative to output; and (iii) the countercyclicality of interest rates. In this vein, this section evaluates the models under study along a particular subset of moments, including the three just mentioned.

Results are gathered in Table 5, where the 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 and its two restrictions. For comparison purposes, the moments associated with Aguiar and Gopinath (2004)'s estimation are also reported.[25] Consistent with our estimation, the table uses data in log

[23] This is captured e.g. by the fact that a large sample approximation to the Bayes factor of a model, say model 1, relative to model 2 is the Bayes Information Criterion or Schwartz criterion, which is proportional to $n^{(k_2-k_1)/2}$, where n is the sample size and k_1, k_2 the number of parameters estimated for models 1 and 2. See, for instance, Lancaster (2004, p. 100).

[24] 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 in the stochastic trend model.

[25] To be precise, Aguiar and Gopinath (2004) conduct the GMM estimation based upon 11 moments of which only two, the standard deviation and serial correlations of gY, are reported in Table 6. The other 9

differences except for the trade balance share where level differences are used. Model-based moments are computed at posterior mode estimates[26]. Note that the table summarizes the Uribe-Yue interest rate data in addition to the Aguiar-Gopinath data.

Table 5 shows that the encompassing model delivers a reasonably close match to the facts emphasized in the literature. It delivers more volatility in consumption and investment than in output and also a strongly countercyclical trade balance share, as in the data. Also, while the encompassing model delivers a real interest rate that is less volatile relative to its empirical counterpart, its dynamics reproduce surprisingly well the strong countercyclicality observed in practice. The correlation between filtered output and interest rates in the data is -0.61, and its model counterpart is -0.63. Likewise, the model delivers an almost zero first autocorrelation of interest rate changes, as in the data. This is remarkable given that this version of the encompassing model is not estimated using real interest rates.

To explore this issue further, we used the Kalman filter to back out the smoothed time series for the gross Mexican interest rates implied by the state space representation of the encompassing model. Then we compared the simulated series to the empirical time series. The results are displayed in Figure 2. The plot reveals that the encompassing model tracks closely the evolution of the Mexican interest rate, particularly around the beginning of the empirical sample, which coincides with the Tequila crisis episode.[27]

Table 5 also reveals that the moments implied by the financial frictions model are virtually the same as those of the encompassing model. This is a reflection of the fact that the estimated parameters of two models are almost indistinguishable. More importantly, it indicates that financial frictions can amplify interest rate and transient technology shocks enough so as to match the stylized facts, echoing Neumeyer and Perri's (2005) and Uribe and Yue's (2006) results. [28] Notably, again, financial frictions can achieve this without help

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.

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

[27]While sovereign default is not model explicitly, note that our specification can replicate the financial turbulence associated with default. This is captured by the large spike displayed by the model-based interest rate in Figure 4 around 1982, the year of Mexico's public default. The spike can only be compared in size to the large increase in interest rates experienced during the Tequila crisis.

[28]As suggested by our discussion, the key parameter in helping the encompassing model account for the dynamics in the data is the high elasticity of the spread to fundamentals, η. This can be seen by examining model moments under the assumption that η or θ are zero. The results of such experiment are reported in

from trend shocks.

The converse is not true: trend shocks alone lead to a much less satisfactory characterization of the data. Indeed, Table 5 says that the stochastic trend model has at least two salient failures: it is unable to reproduce a significantly more volatile consumption with respect to output; and it delivers counterfactual dynamics for the interest rate process. The latter follows since the interest rate process inherits the dynamics of the debt elastic premium, which is procyclical, too smooth, and highly persistent. In contrast, observed interest rates in Mexico and other emerging economies are countercyclical, volatile, and moderately persistent.

4.4. The Role of Financial Frictions

For a complementary perspective on the relative role of each shock, 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 6.[29]

The most noteworthy finding is the small role played by trend shocks. The largest share of permanent shocks is 2.1 percent, when accounting for the variance of consumption. In contrast, world interest rate shocks play a nontrivial role, particularly when explaining the variance of the trade balance-to-GDP ratio (41.2 percent), of investment (22.2 percent), and to a lesser extent of consumption (9.2 percent). Their role in accounting for the variance of output (5.1 percent) falls within the estimates from other studies.[30] The variance of all four aggregates is, however, mostly explained by transitory shocks to technology.

Altogether, our results favor the view that the estimated encompassing model provides an adequate approximation to the Mexican data. Fluctuations are chiefly generated by transitory technology shocks, and to a smaller extent interest rate shocks, which are amplified by financial frictions. Trend shocks appear to play a minor role.

In view of these findings, it is of interest to investigate which of the two financial frictions,

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the working paper version (Chang and Fernandez, 2010).

[29] For brevity, Table 4 reports only the means of the distributions. Standard errors are available on request.

[30] Neumeyer and Perri (2005) found that the percentage standard deviation of Argentina's GDP in a model with financial frictions but no shocks to international rates is 3 percent smaller than in a model with interest rate shocks. Uribe and Yue (2006) found that US interest rate shocks explain about 20 percent of movements in aggregate activity in a pool of emerging market economies.

spreads that react to fundamentals or working-capital needs, is responsible for these results. We address this question in the three lower panels in Table 6 which present the variance decompositions of three counterfactual experiments of shutting off each or both of the frictions, i.e. setting $\eta = 0$ (no endogenous spread), $\theta = 0$ (no working capital requirements), or $\theta = \eta = 0$.

The results indicate 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: the results are virtually unaltered when the working-capital assumption is dropped ($\theta = 0$). In contrast, when η is set to zero, interest rate shocks have a much greater role in accounting for the variance of C, I and TB/Y. Notably, the variability of output continues to be dominated by "pure" technology shocks even if $\eta = 0$.

Further illustration is given by impulse response analysis. Figure 3 displays responses of the estimated encompassing model to a one standard deviation shock to each of its driving processes. Figure 4 depicts how the responses of the main macro aggregates to a transitory technology shock, the main driving force, depend on whether the financial friction embedded in η is included or not. Two aspects of Figure 4 are especially revealing. First, transitory technology shocks are amplified more strongly in the estimated model than if η were set to zero. Hence, if the link between spreads and productivity is turned off, some other shock must pick up some of the macro variance; Table 6 tells that that shock is the one to interest rates [31]. Second, the figure clearly illustrates the mechanisms at work. Without financial frictions, a positive but transitory productivity shock increases current consumption less than current output, essentially along the lines of the permanent income theory of consumption. This also leads to a positive trade balance at impact. When η is positive, however, the relevant interest rate falls with the shock. This leads to a steeper consumption response, which allows consumption to be more volatile than income. Also, it enhances the response of investment. Finally, since both consumption and investment respond more strongly, the trade balance becomes negative, which helps matching the countercyclicality of the TB/Y

[31] In Chang and Fernandez (2010) we undertake a complementary experiment to this one where we estimate three versions of the encompassing model where $\theta = 0$, $\eta = 0$, and $\theta = \eta = 0$. Summing up, the results of such longer experiments continue to show the relevance of η for the dynamics of the model. Interestingly, the case when the model is estimated with $\eta = 0$ has a much more important role of growth shocks.

ratio.

These results are in line with Oviedo (2005) and Aguiar and Gopinath (2008), who argue that a link between domestic productivity and the interest rate is a necessary ingredient when building models that aim at replicating emerging market business cycles. Conversely, Oviedo (2005) emphasizes that the presence of working capital requirements is not essential. Also, our counterfactual exercises and results agree with similar ones in Uribe and Yue (2006). [32]

5. Robustness

5.1. Less Informative Priors

Tables 7, 8, and 9 examine the implications of less informative priors. To do this, for almost all parameters we chose priors given by Uniform distributions. The exceptions were the autocorrelation coefficients of the shock processes, for which we chose a quasi flat prior given by a Beta distribution with mean 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. Interestingly, each mode favors one of the two leading approaches to business cycles in emerging economies. The "higher" mode, with a likelihood and posterior values of 1004.7 and 1013.3, respectively, is characterized by the virtual disappearance of trend shocks - the posterior mode for the random walk component is negligible. The "lower" mode, with a likelihood and posterior values of 1002.4 and 1009.9 respectively, is characterized by the predominance of trend shocks, and implies a RWC equal to 4.69.

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 last column of Table 7 we were able to make the Markov chain cross over the two modes with enough regularity. The Markov chain explored more often the posterior around the high mode, and hence the mean values are closer to those of the high posterior mode. Interestingly, for most of the parameters, although not for all, the mean

[32] In the context of their model, Uribe and Yue (2006) studied the impact of turning off the effect on spreads of, in turn, world interest rates and domestic variables. From the second exercise, in particular, they found that the fact that spreads respond to business conditions significantly accentuates aggregate instability, a result that clearly agrees with ours.

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 top panel of Table 8, are quantitatively similar to the ones presented earlier (top panel of Table 6).

Table 9 presents the corresponding model comparison likelihood based statistics. Now the encompassing and financial frictions models both attain a higher likelihood and posterior mode values. But the marginal likelihood of the stochastic trend model is still higher than that of the other two models. Since table 9 is based on flatter priors, it is less likely that the last result comes from the congruence between the likelihood and the prior, which was one of our conjectures before. Instead, the relative dominance of the stochastic trend model in terms of marginal likelihood seems to reflect the fact that two fewer parameters are estimated, which gives that model a forecasting advantage in that comparison.

5.2. Observing Interest Rate Processes and Simulating the Tequila Crisis

Our estimations so far have been based on the dataset of Aguiar and Gopinath (2007) and, accordingly, did not use observable data on interest rates. As argued earlier, we proceeded in that way in order to maximize comparability with Aguiar and Gopinath's work, and also because of data availability. In spite of these considerations, it may be of interest to check how our results change if we use interest rate data. This subsection does so, and in addition it discusses if and how the encompassing model can reproduce Mexican dynamics around the Tequila Crisis.[33]

To this end, we used the series for interest rates and spreads from Uribe and Yue (2006), which we described earlier. As mentioned, those series start in 1994. This is as good as one can obtain since data on sovereign spreads, like the J.P. Morgan EMBI for Mexico, are available only after 1994. Figure 5 plots the Uribe-Yue series for the foreign interest rate (R^*) and the spread (S), as well as the implied process for the country specific interest rate, R, that results from these two variables. As it is evident from the plot, most of the variation in R comes from variation in S, particularly during the turbulent episodes of the Tequila

[33] One more reason for this exercise is to assess how our benchmark results change when the period around Mexico's 1982 default is excluded from the sample.

Crisis in the mid 1990s and the Russian and Asian crises of the late 1990s.

We added the two Uribe-Yue series for R^* and S to the four observables in the Aguiar-Gopinath dataset, and reestimated the encompassing model for the subsample after 1994. In addition to this, and given that several studies show that a significant amount of variation in country spreads is not driven by fundamentals, to better account for the spreads data we also considered an alternative to the spread equation (2.15) obtained by adding shocks to country spreads:

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

where ε_t^S is an i.i.d. process with mean zero and variance σ_S^2 that is assumed to capture movements in the spread that emanate from reasons other than changes in fundamentals (the Solow residual). This follows, among others, Neumeyer and Perri (2005) and Uribe and Yue (2006). For this reason, our prior for σ_S was a Gamma distribution with a mean of 2.4 percent, the average of the point estimates for the standard deviation of the spread shocks found in those two works. Last, we added a measurement error to each of the two new observables and set the priors over these errors as the other priors over the other measurement errors[34].

Posterior distribution results, with and without spread shocks, are presented in Table 10, while the variance decomposition for the case with spread shocks is reported in the second panel of Table 8. Overall, the results continue to indicate that transitory shocks to technology account for most of the variability in the Mexican macro variables, and that the importance of growth shocks is low. The RWC in each of the two Table 10 cases is almost identical to that of the estimated encompassing model. In addition, foreign interest rate shocks become less relevant, while spread shocks contribute to about 6% of output variability.

As argued before, 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, we attempted to quantify the accuracy of the encompassing model in reproducing the

[34] Here we treat interest rates like the other variables in assuming errors in the corresponding observation equation. Our main justification is twofold: first, there are well known problems associated with computing *real* rates; second, it is not clear to us that the Uribe-Yue interest rates map perfectly into the corresponding variables in the model. In case, we have checked that our results remain qualitatively when interest rate data is assumed to be free of measurement errors. These results are available upon request.

Mexican dynamics during the 1994-5 Tequila Crisis. We obtained a historical decomposition of the structural shocks via Kalman filtering. We then backed out the state variables and innovations using the information contained in the entire sample. Finally, we used each of the structural shocks separately to simulate the evolution of the Mexican macro aggregates during the 1995 Tequila Crisis and its aftermath.

Figure 6 shows the results. Each row tracks, for each kind of shock, the simulated time series of the Mexican aggregates against the observed series between 1994 and 1997. The figure reveals that the only shock that comes close to reproducing by itself the deep fall in economic activity and the sharp reversal of the trade balance during the crisis is the temporary one to productivity.

Here again, we recall that these shocks must have been amplified by the financial frictions embedded in the model. To evaluate this, Figure 7 recomputes the simulation of the Tequila Crisis using only the smoothed transitory technology shocks, but varying the severity of the two financial frictions. The plots indicate that the success of transitory technology shocks in reproducing the Tequila crisis is only possible because of the presence of financial frictions, particularly embedded in η, the parameter that governs the elasticity of the spread to expected future productivity. [35]

The results in this subsection can be related to those in Fernandez-Villaverde, Guerron-Quintana, Rubio-Ramírez, and Uribe (2011). They estimated interest rate processes using data on interest rates and spreads for Argentina, Brazil, Ecuador, and Venezuela. Allowing for time varying volatility, they concluded that the variability of interest rates was dominated by innovations to spreads and also that stochastic volatility was strong. Then they fed the estimated interest rate processes into an otherwise standard calibrated small open economy model and showed, in particular, that stochastic volatility shocks could help accounting for some features of the data, especially the volatility of consumption and investment relative to output. While these findings are similar to ours, the mechanisms are different. Our model does not allow for time varying volatility. But, in contrast with Fernandez-Villaverde et al.,

[35] A similar experiment was conducted by Fernandez (2010) 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.

who take the process for spreads as exogenous, our model postulates that spreads may be endogenous, responding to expected productivity.[36] Thus we see Fernandez-Villaverde et al.'s study and ours as complementary at this point. Clearly, it may be of interest to investigate whether stochastic volatility or endogenous spreads gives a better approximation, but this would raise substantial technical issues (as discussed in Fernandez-Villaverde et al.'s paper) and best left for future research.

5.3. Two Elasticities

Thus far we imposed equal elasticities of the spread with respect to temporary and permanent productivity shocks, i.e. $\eta_1 = \eta_2 = \eta$ in (2.14). It could be argued, however, that this restriction may have a significant impact on the dynamics of the model. Also, while Neumeyer and Perri (2005) stressed the relevance of temporary shocks on spreads (η_1), little is known about the effect of trend shocks on spreads.

To address these issues, we reestimated the encompassing model allowing for the two elasticities to differ in (2.14). Moreover, because we wanted to assess specifically the contribution of each shock to the spread, we included data on Mexican spreads and foreign interest rates in the estimation.

The spread equation we estimated was

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

The results are reported in Table 11. We assumed uninformative Uniform priors (on $[0, 5]$) over η_1 and η_2. For the other parameters, the left hand side of the table was based on the same priors as in the benchmark estimation. Notably, the posterior distribution over η_2 collapses over zero, indicating that trend shocks do not have a significant effect on the spread at business cycle frequencies. Also, trend shocks continue to play a minor role in the overall dynamics of the model, which is confirmed by the low level of the RWC and the variance decomposition in the bottom panel of Table 8. The last three columns of Table

[36]It bears mentioning that an online extension of Fernandez-Villaverde et al. (2011) features a working capital requirement and finds that it does not make substantial difference to their results.

11 display results based on less informative priors. Here the RWC is still small, but the posterior distribution for η_2 is now much more disperse: the posterior mode for η_2 is still zero but its distribution, with a 90 percent confidence interval between zero and 2.68, allows for some more room for growth shocks to affect the cyclical component of the spread process.

Overall, it seems fair to conclude that the effect of productivity shocks on spreads is mostly due to their temporary component. Notably, this is consistent with Neumeyer and Perri (2005).

6. Concluding Remarks

Observed aggregate fluctuations in emerging economies differ from those in developed economies. The search for a model that can account for such differences has led to two approaches, one based on stochastic trend shocks and another relying on foreign interest rate shocks and financial frictions. In this paper we have incorporated the two approaches into an encompassing model embedding both stochastic trends, interest rate shocks and financial frictions. Our findings support the view that explaining fluctuations in emerging economies requires financial imperfections that amplify conventional productivity shocks and interest rate shocks. Trend shocks add relatively little except perhaps increase the out-of-sample forecasting performance of models; they become quantitatively relevant only if financial frictions are assumed away. Our analysis also sheds light on the mechanisms by which shocks, especially conventional ones to technology, are amplified by financial frictions to account for major macro regularities, not only in normal times but also in crisis periods such as the Tequila episode.

Some may question the relevance of our analysis on the basis that deeper distortions in an economy may well manifest themselves in the Solow residual, so that the stochastic trend approach could be seen as relying on market imperfections as well, blurring the distinction with financial frictions models. We do not believe, however, that the argument is compelling. The stochastic trend may be a shortcut to model frictions in an economy, but it is silent as to what form do these frictions take and how they operate. In contrast, the financial frictions approach is specific as to what kind of frictions matter and how they modify the propagation of shocks. Hence a comparison between the two alternative approaches does provide useful information as to whether and how a certain type of frictions, financial in nature, can enhance the performance of business cycle models in emerging economies or, instead, one needs to resort to other kind of frictions.

At least two areas emerge for future research. First, we have followed the financial frictions literature in our modeling of endogenous spreads and working capital requirements. The precise specifications are, however, ultimately suggested by but not derived from first principles. This indicates a need for more work seeking true microfoundations. Second, in terms of policy, our results lend support to the idea that attempts to ameliorate financial imperfections may reduce aggregate volatility. They are likely too to lead to increases in welfare, but that inference is not obvious and remains to be confirmed.

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TABLES AND FIGURES

Table 1. Calibrated Parameters and Steady State Levels

Parameter	***Description***	***Encompassing Model***
σ	Intertemporal Elasticity of Substitution $\left[1/\sigma\right]$	**2.000**
ω	Labor Supply Elasticity $\left[\frac{1}{\omega-1}\right]$	**1.600**
α	Labor Share of Income	**0.6868**
R^*	Gross Foreign Interest Rate	**1.0025**
τ	Labor Parameter so that $h^{ss}=1/3$	**1.7168**
ψ	Debt Elastic Interest Rate Parameter	**0.001**
β	Discount Factor	**0.9976**
s	Long-run Gross Country Interest Rate Premium	**1.0120**
δ	Depreciation Rate of Capital	**0.050**
d	Debt-to-GDP Ratio (***D/Y***)	**0.100**
R	Gross Country-specific Interest Rate	**1.0145**

Notes: A period is taken to be a quarter. Note that in the encompassing and financial friction models α is not equal to labor share ($h\text{-}Share$) but it is rather $\alpha = h\text{-}Share * \left[1+(R-1)\theta\right]$. Table values are computed using the posterior mode of θ. These parameters pin down the steady state of the encompassing model that is the same for the two restricted models (Stochastic Trend and Financial Frictions models).

Table 2. Prior Distributions

Parameter		Range	Density	Mean	S.D (%)	90% Conf. Interval
Parameters Common to All 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]
ζ	Gross Annual Growth Rate of Productivity	R^+	Gamma [25.00 ; 0.1000]	2.50	50	[1.72 ; 3.35]
σ_χ	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 Restricted Models

Parameter	Prior	Encompassing Model		Restricted Models: Posterior Modes, Mean and 90% C.I.				AG-GMM Estimates
		Mode	Mean & 90% C.I	Stochastic Trend M.		Fin. Frictions M.		
ρ_a	**0.95** [0.93, 0.97]	**0.89**	**0.90** [0.87, 0.92]	**0.94**	**0.94** [0.92, 0.96]	**0.89**	**0.89** [0.87, 0.92]	**0.94**
$100\sigma_a$	**0.75** [0.14, 1.76]	**0.66**	**0.66** [0.51, 0.81]	**0.72**	**0.72** [0.59, 0.86]	**0.66**	**0.67** [0.52, 0.82]	**0.41**
ρ_g	**0.72** [0.68, 0.76]	**0.72**	**0.72** [0.68, 0.75]	**0.73**	**0.73** [0.69, 0.76]			**0.72**
$100\sigma_g$	**0.74** [0.14, 1.71]	**0.12**	**0.11** [0.01, 0.29]	**0.69**	**0.70** [0.52, 0.88]			**1.09**
ρ_R	**0.83** [0.74, 0.91]	**0.81**	**0.81** [0.71, 0.89]			**0.81**	**0.81** [0.71, 0.89]	
$100\sigma_R$	**0.72** [0.30, 1.29]	**0.42**	**0.41** [0.25, 0.57]			**0.42**	**0.41** [0.26, 0.58]	
ϕ	**6.00** [1.71, 12.6]	**14.76**	**14.97** [11.89, 18.60]	**3.45**	**3.55** [2.62, 4.71]	**14.76**	**14.97** [11.89, 18.54]	**3.79**
θ	**0.50** [0.14, 0.87]	**0.69**	**0.69** [0.26, 0.97]			**0.69**	**0.68** [0.25, 0.97]	
η	**1.00** [0.84, 1.18]	**0.73**	**0.73** [0.61, 0.86]			**0.73**	**0.73** [0.61, 0.86]	
ζ	**2.51** [1.72, 3.42]	**2.53**	**2.50** [1.96, 3.07]	**2.33**	**2.32** [1.66, 3.06]	**2.53**	**2.51** [2.00, 3.05]	
$100\sigma_Y$	**2.01** [0.67, 3.90]	**0.64**	**0.64** [0.37, 0.89]	**0.41**	**0.40** [0.16, 0.65]	**0.64**	**0.63** [0.36, 0.88]	
$100\sigma_C$	**2.01** [0.67, 3.90]	**1.13**	**1.15** [0.98, 1.35]	**1.15**	**1.16** [1.00, 1.34]	**1.14**	**1.16** [0.99, 1.34]	
$100\sigma_I$	**2.01** [0.67, 3.90]	**3.04**	**3.09** [2.57, 3.64]	**3.13**	**3.17** [2.73, 3.66]	**3.04**	**3.08** [2.57, 3.63]	
$100\sigma_{TB/Y}$	**2.01** [0.67, 3.90]	**0.78**	**0.78** [0.53, 1.00]	**0.86**	**0.87** [0.67, 1.07]	**0.78**	**0.77** [0.53, 1.00]	
RWC	**3.06** [0.15, 3.21]	**0.18**	**0.88** [0.12, 3.43]	**2.93**	**2.96** [2.02, 3.93]	**0.00**		**5.33**

Note: Results are posterior modes, means and 90 percent confidence intervals for posterior distributions. 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). RWC refers to the random walk component, see text for details.

Table 4. Model Comparison

Models	Likelihood	Posterior	Marginal Likelihood
Encompassing Model	991.6	1009.9	957.2
Stochastic Trend Model	991.1	1015.6	974.3
Financial Frictions Model	992.0	1003.3	960.4
AG – GMM	966.0		

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. 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 of the stochastic trend model.

Table 5. Second Moments, Encompassing and Restricted Models

Variable	Mexican Data	Encompassing M.	Stochastic Trend M.	Financial Frictions M.	Aguiar-Gopinath
Standard Deviations (%)					
gY	1.53	1.23	1.55	1.23	1.58
gC	1.94	1.68	1.59	1.66	2.07
gI	5.66	4.61	4.26	4.60	5.16
dTB/Y	1.38	1.45	1.08	1.44	1.57
gR	1.81	0.63	0.00	0.63	0.00
S.D. (*X*) / S.D. (*gY*)					
gC	1.27	1.36	1.03	1.35	1.31
gI	3.71	3.75	2.75	3.75	3.27
dTB/Y	0.91	1.18	0.70	1.18	1.00
gR	1.04	0.51	0.00	0.51	0.00
Correlation with *gY*					
gC	0.76	0.95	0.93	0.96	0.95
gI	0.75	0.80	0.90	0.80	0.89
dTB/Y	-0.44	-0.65	-0.54	-0.65	-0.72
gR	-0.61	-0.63	0.47	-0.63	0.65
Correlation with *dTB/Y*					
gC	-0.50	-0.83	-0.80	-0.83	-0.89
gI	-0.67	-0.97	-0.85	-0.97	-0.95
gR	0.53	0.99	-0.18	1.00	-0.19
Serial Correlation					
gY	0.27	0.19	0.13	0.19	0.25
gC	0.20	0.18	0.08	0.18	0.10
gI	0.44	-0.06	-0.02	-0.06	-0.01
dTB/Y	0.33	-0.08	-0.05	-0.08	-0.06
gR	-0.05	-0.08	0.92	-0.08	0.91

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 provided by Aguiar and Gopinath (2007). Data for the growth rate of Mexican interest rates, gR, starts from 1994.1 and is taken from Uribe and Yue (2006). Moments are computed using posterior mode. All estimations were done using measurement errors in all four variables.

Table 6. Forecast Error Variance Decompositions, Encompassing Model

Structural Shock	*gY*	*gC*	*gI*	*dTB/Y*
Benchmark, Encompassing Model				
ε^{a}	93.5	88.7	76.9	57.6
ε^{g}	1.5	2.1	0.8	1.2
ε^{R^*}	5.1	9.2	22.2	41.2
Counterfactual, No Endogenous Spread: $\eta = 0$				
ε^{a}	93.5	68.0	6.3	18.2
ε^{g}	1.4	4.6	1.4	0.8
ε^{R^*}	5.1	27.3	92.3	81.1
Counterfactual, No Working Capital:				
ε^{a}	97.8	91.2	77.1	57.1
ε^{g}	1.5	2.2	0.8	1.2
ε^{R^*}	0.7	6.6	22.0	41.7
Counterfactual, No Endogenous Spread and No Working Capital:				
ε^{a}	97.9	75.0	6.8	18.8
ε^{g}	1.4	5.1	1.4	0.8
ε^{R^*}	0.7	19.9	91.8	80.4

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 modes. 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 mean levels except for the parameters governing the elasticity of the spread and/or the working capital needs. A time horizon of 40 quarters was used for the variance decomposition.

Table 7. Posterior Distributions with Less Informative Priors

Parameter	Less Informative Priors				
	Prior Distribution	Prior Mean	High Posterior Mode	Low Posterior Mode	Posterior Mean & 90% C.I.
ρ_a	Beta (2,2)	0.50 [0.14, 0.86]	0.88	0.87	0.92 [0.78, 0.99]
$100\sigma_a$	Uniform (0.01,10)	5.00 [0.51, 9.49]	0.82	0.80	0.70 [0.37, 0.94]
ρ_g	Beta (2,2)	0.50 [0.14, 0.86]	0.50	0.96	0.52 [0.11, 0.87]
$100\sigma_g$	Uniform (0.01,10)	5.00 [0.51, 9.50]	0.01	0.10	0.59 [0.02, 1.23]
ρ_R	Beta (2,2)	0.50 [0.14, 0.86]	0.94	0.20	0.96 [0.85, 0.99]
$100\sigma_R$	Uniform (0.01,10)	5.00 [0.51, 9.50]	0.17	0.45	0.08 [0.04, 0.15]
ϕ	Uniform (0.0,40)	20.00 [2.02, 38.02]	8.71	7.46	4.14 [2.23, 7.65]
θ	Beta (2,2)	0.50 [0.14, 0.87]	0.65	0.76	0.57 [0.07, 0.97]
η	Uniform (0.0,5.0)	2.50 [0.25, 4.75]	0.33	0.37	0.03 [0.00, 0.22]
ξ	Uniform (0.5,5.0)	2.75 [0.72, 4.78]	2.63	2.59	2.37 [0.98, 3.72]
$100\sigma_Y$	Uniform (0.01,10)	5.00 [0.51, 9.50]	0.01	0.06	0.09 [0.01, 0.31]
$100\sigma_C$	Uniform (0.01,10)	5.00 [0.51, 9.49]	1.19	1.06	1.19 [1.05, 1.36]
$100\sigma_I$	Uniform (0.01,10)	5.00 [0.51, 9.49]	2.90	2.93	2.91 [2.37, 3.46]
$100\sigma_{TB/Y}$	Uniform (0.01,10)	5.00 [0.51, 9.49]	0.62	0.67	0.52 [0.02, 0.89]
RWC		2.50 [0.01, 8.56]	0.00	4.69	0.31 [0.11, 1.00]
Log-Posterior at Mode			1013.3	1009.9	
Log-Likelihood at Posterior Mode			1004.7	1002.4	

Note: Encompassing model estimated using observables {gY, gC, gI, dTB/Y} from the Mexican Data, 1980.1-2003.2 using measurement errors in all four variables. Results are posterior modes, means and 90 percent confidence intervals for posterior distributions.

Table 8. Variance Decompositions of Extensions

Structural Shock	*gY*	*gC*	*gI*	*dTB/Y*
Less Informative Priors				
ε^{a}	97.91	90.28	66.97	24.50
ε^{g}	0.01	0.01	0.00	0.00
ε^{R^*}	2.08	9.71	33.03	75.50
Observing Interest Rates				
ε^{a}	92.19	91.20	90.81	80.11
ε^{g}	1.38	2.16	1.03	1.79
ε^{R^*}	0.59	1.71	5.06	11.77
ε^{S}	5.84	4.93	3.11	6.33
Two Spread Elasticities				
ε^{a}	93.97	90.69	83.99	62.67
ε^{g}	1.55	2.89	0.92	1.73
ε^{R^*}	0.58	1.50	8.77	21.70
ε^{S}	3.90	4.91	6.31	13.89

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 except in the two lower panels where, due to availability of interest rate data, the sample is 1994.1-2003.2. Moments are computed using posterior modes.

Table 9. Model Comparison – Less Informative Priors

Models	Likelihood	Posterior	Marginal Likelihood
Encompassing Model	1004.7	1013.3	958.4
Stochastic Trend Model	996.8	1005.9	968.3
Financial Frictions Model	1004.7	1010.6	965.0

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. 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.

Table 10. Encompassing Model Observing Interest Rate Data

Parameter	Prior	Without Spread Shocks		With Spread Shocks	
		Mode	Mean & 90% C.I	Mode	Mean & 90% C.I
ρ_a	0.95 [0.93, 0.97]	0.88	0.89 [0.86, 0.91]	0.88	0.89 [0.87, 0.91]
$100\sigma_a$	0.75 [0.14, 1.76]	0.79	0.80 [0.62, 1.01]	0.79	0.78 [0.58, 1.00]
ρ_g	0.72 [0.68, 0.76]	0.72	0.72 [0.68, 0.76]	0.72	0.72 [0.68, 0.76]
$100\sigma_g$	0.74 [0.14, 1.71]	0.14	0.13 [0.01, 0.33]	0.13	0.12 [0.01, 0.32]
ρ_R	0.83 [0.74, 0.91]	0.88	0.87 [0.80, 0.93]	0.87	0.87 [0.79, 0.93]
$100\sigma_R$	0.72 [0.30, 1.29]	0.15	0.15 [0.09, 0.22]	0.15	0.15 [0.09, 0.22]
$100\sigma_s$	2.43 [0.97, 4.46]			0.52	0.53 [0.28, 0.82]
ϕ	6.00 [1.71, 12.6]	14.44	14.62 [11.30, 18.56]	14.13	14.38 [11.16, 18.24]
θ	0.50 [0.14, 0.87]	0.68	0.67 [0.26, 0.97]	0.62	0.67 [0.28, 0.97]
η	1.00 [0.84, 1.18]	0.78	0.78 [0.66, 0.92]	0.77	0.78 [0.65, 0.91]
ξ	2.51 [1.72, 3.42]	2.55	2.52 [1.81, 3.29]	2.54	2.51 [1.81, 3.28]
$100\sigma_Y$	2.01 [0.67, 3.90]	0.56	0.58 [0.34, 0.83]	0.55	0.59 [0.32, 0.88]
$100\sigma_C$	2.01 [0.67, 3.90]	1.04	1.07 [0.84, 1.35]	0.93	0.94 [0.67, 1.23]
$100\sigma_I$	2.01 [0.67, 3.90]	2.10	2.14 [1.43, 2.86]	2.00	2.09 [1.39, 2.83]
$100\sigma_{TB/Y}$	2.01 [0.67, 3.90]	0.69	0.71 [0.51, 0.95]	0.65	0.68 [0.47, 0.92]
$100\sigma_{R*}$	2.01 [0.67, 3.90]	0.18	0.18 [0.13, 0.24]	0.17	0.17 [0.11, 0.24]
$100\sigma_s$	2.01 [0.67, 3.90]	1.47	1.50 [1.24, 1.82]	1.41	1.45 [1.14, 1.80]
RWC	3.06 [0.15, 3.21]	0.16	0.22 [0.00, 0.88]	0.16	0.22 [0.00, 0.88]
Log-Posterior at Mode		717.0		719.0	
Log-Likelihood at Posterior Mode		697.6		698.7	

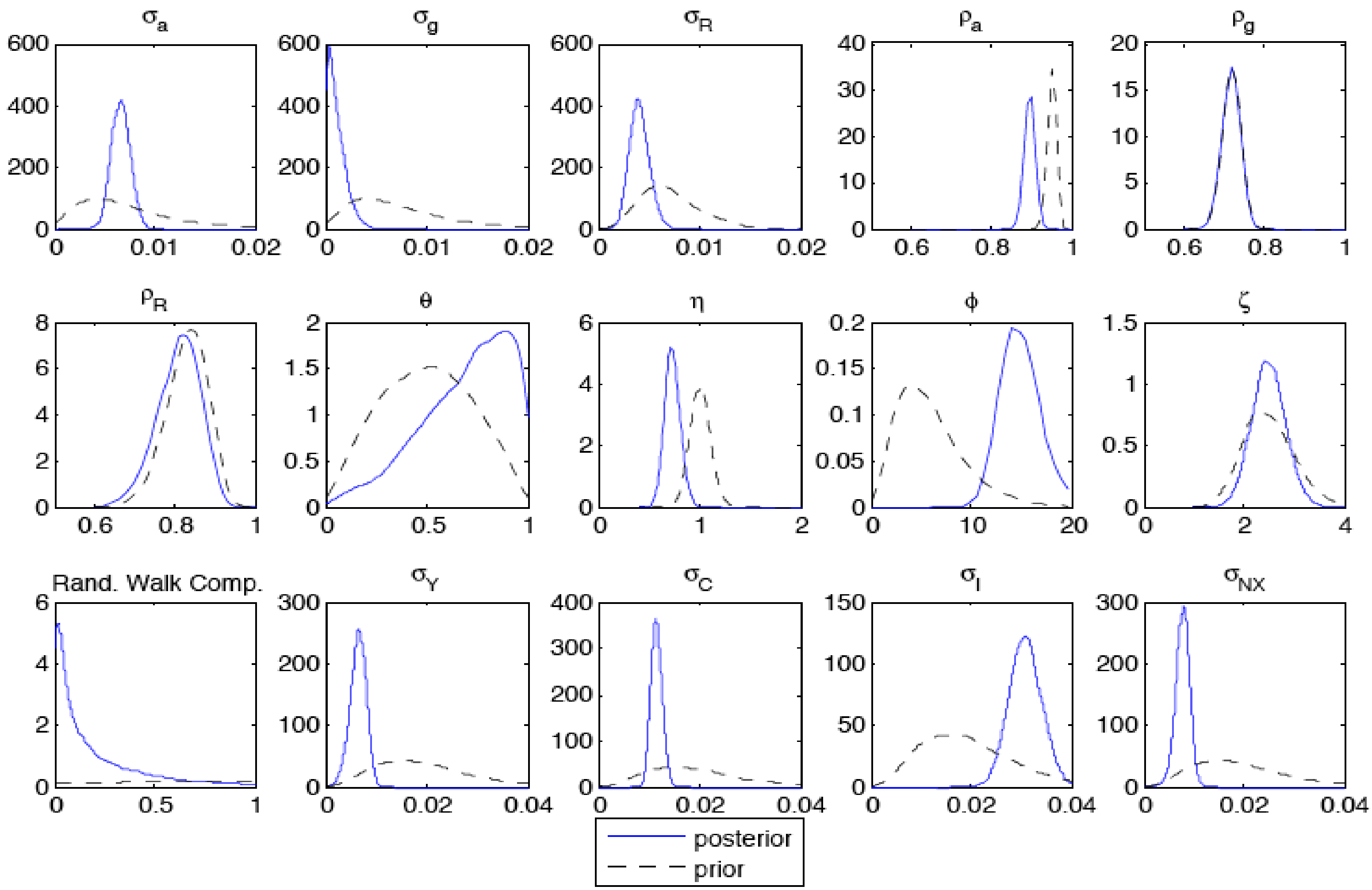
Note: Results are posterior modes, means and 90 percent confidence intervals for posterior distributions. Estimates obtained using six observables, {gY, gC, gI, dTB/Y, gR*, gS} from the Mexican Data, 1994.1-2003.2. All estimations were done using measurement errors in all six variables. RWC refers to the random walk component, see text for details.

Table 11. Encompassing Model with two Spread Elasticities

Parameters	BENCHMARK PRIORS			LESS INFORMATIVE PRIORS		
	Prior	Mode	Mean & 90% C.I	Prior	Mode	Mean & 90% C.I
ρ_a	0.95 [0.93, 0.97]	0.94	0.94 [0.92, 0.96]	0.50 [0.14, 0.86]	0.71	0.75 [0.61, 0.87]
$100\sigma_a$	0.75 [0.14, 1.76]	0.91	0.93 [0.75, 1.14]	5.00 [0.51, 9.49]	0.93	0.96 [0.75, 1.21]
ρ_g	0.72 [0.68, 0.76]	0.72	0.72 [0.68, 0.76]	0.50 [0.14, 0.86]	0.44	0.46 [0.08, 0.92]
$100\sigma_g$	0.74 [0.14, 1.71]	0.16	0.15 [0.01, 0.40]	5.00 [0.51, 9.50]	0.35	0.25 [0.01, 0.78]
ρ_R	0.83 [0.74, 0.91]	0.87	0.87 [0.79, 0.93]	0.50 [0.14, 0.86]	0.96	0.94 [0.73, 0.99]
$100\sigma_R$	0.72 [0.30, 1.29]	0.13	0.13 [0.08, 0.19]	5.00 [0.51, 9.50]	0.09	0.08 [0.04, 0.13]
$100\sigma_{\boldsymbol{s}}$	2.43 [0.97, 4.46]	0.43	0.43 [0.24, 0.69]	5.00 [0.51, 9.49]	0.22	0.19 [0.01, 0.47]
ϕ	6.00 [1.71, 12.6]	7.74	7.45 [5.25, 10.22]	20.00 [2.02, 38.00]	9.95	9.49 [6.36, 13.04]
θ	0.50 [0.14, 0.87]	0.66	0.67 [0.25, 0.97]	0.50 [0.14, 0.87]	0.47	0.56 [0.13, 0.95]
η_1	2.50 [0.25, 4.75]	0.20	0.18 [0.09, 0.30]	2.50 [0.25, 4.75]	1.41	1.17 [0.46, 2.09]
η_2	2.50 [0.25, 4.75]	0.00	0.00 [0.00, 0.00]	2.50 [0.25, 4.75]	0.00	0.41 [0.00, 2.68]
ξ	2.51 [1.72, 3.42]	2.39	2.38 [1.69, 3.14]	2.75 [0.72, 4.78]	3.33	3.14 [1.72, 4.32]
$100\sigma_Y$	2.01 [0.67, 3.90]	0.44	0.45 [0.19, 0.71]	5.00 [0.51, 9.50]	0.01	0.13 [0.01, 0.44]
$100\sigma_C$	2.01 [0.67, 3.90]	0.90	0.92 [0.71, 1.15]	5.00 [0.51, 9.49]	0.95	0.98 [0.77, 1.21]
$100\sigma_I$	2.01 [0.67, 3.90]	1.56	1.58 [0.91, 2.25]	5.00 [0.51, 9.49]	2.05	2.12 [1.51, 2.77]
$100\sigma_{TB/Y}$	2.01 [0.67, 3.90]	0.58	0.59 [0.40, 0.79]	5.00 [0.51, 9.49]	0.43	0.36 [0.04, 0.72]
$100\sigma_{\boldsymbol{R}^*}$	2.01 [0.67, 3.90]	0.19	0.20 [0.15, 0.25]	5.00 [0.51, 9.49]	0.19	0.20 [0.16, 0.24]
$100\sigma_{\boldsymbol{s}}$	2.01 [0.67, 3.90]	1.61	1.65 [1.34, 2.03]	5.00 [0.51, 9.49]	1.32	1.41 [1.13, 1.75]
RWC	3.06 [0.15, 3.21]	0.18	0.13 [0.00, 0.66]	2.55 [0.02, 8.71]	0.17	0.14 [0.00, 0.45]
Log-Posterior at Mode		728.2			725.8	
Log-Likelihood at Posterior Mode		701.5			711.6	

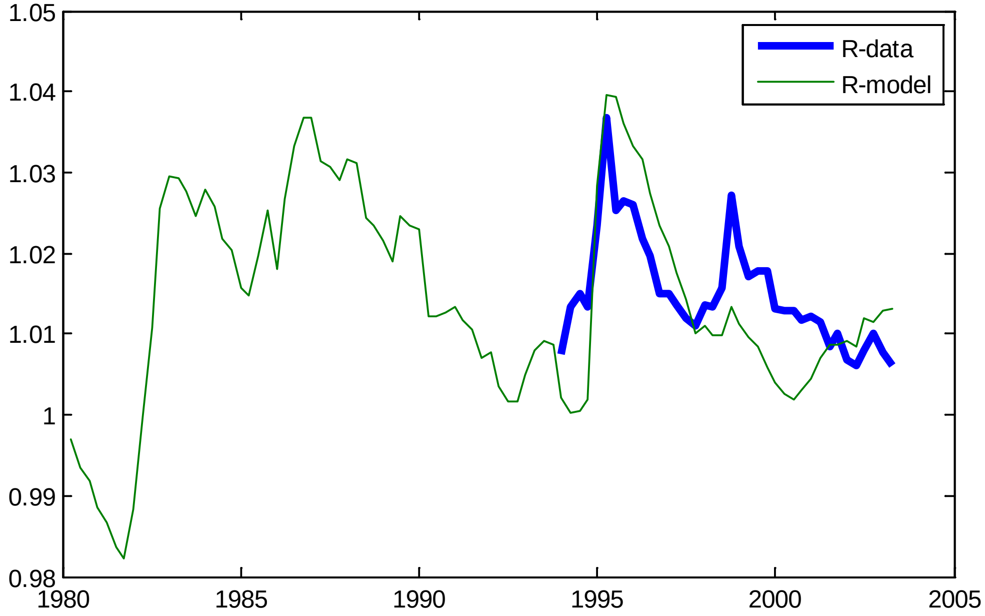
Note: Results are posterior modes, means and 90 percent confidence intervals for posterior distributions. Estimates obtained using six observables, {gY, gC, gI, dTB/Y, gR*, gS} from the Mexican Data, 1994.1-2003.2. All estimations were done using measurement errors in all six variables. RWC refers to the random walk component, see text for details.

Figure 1. Priors and Posteriors: Encompassing Model



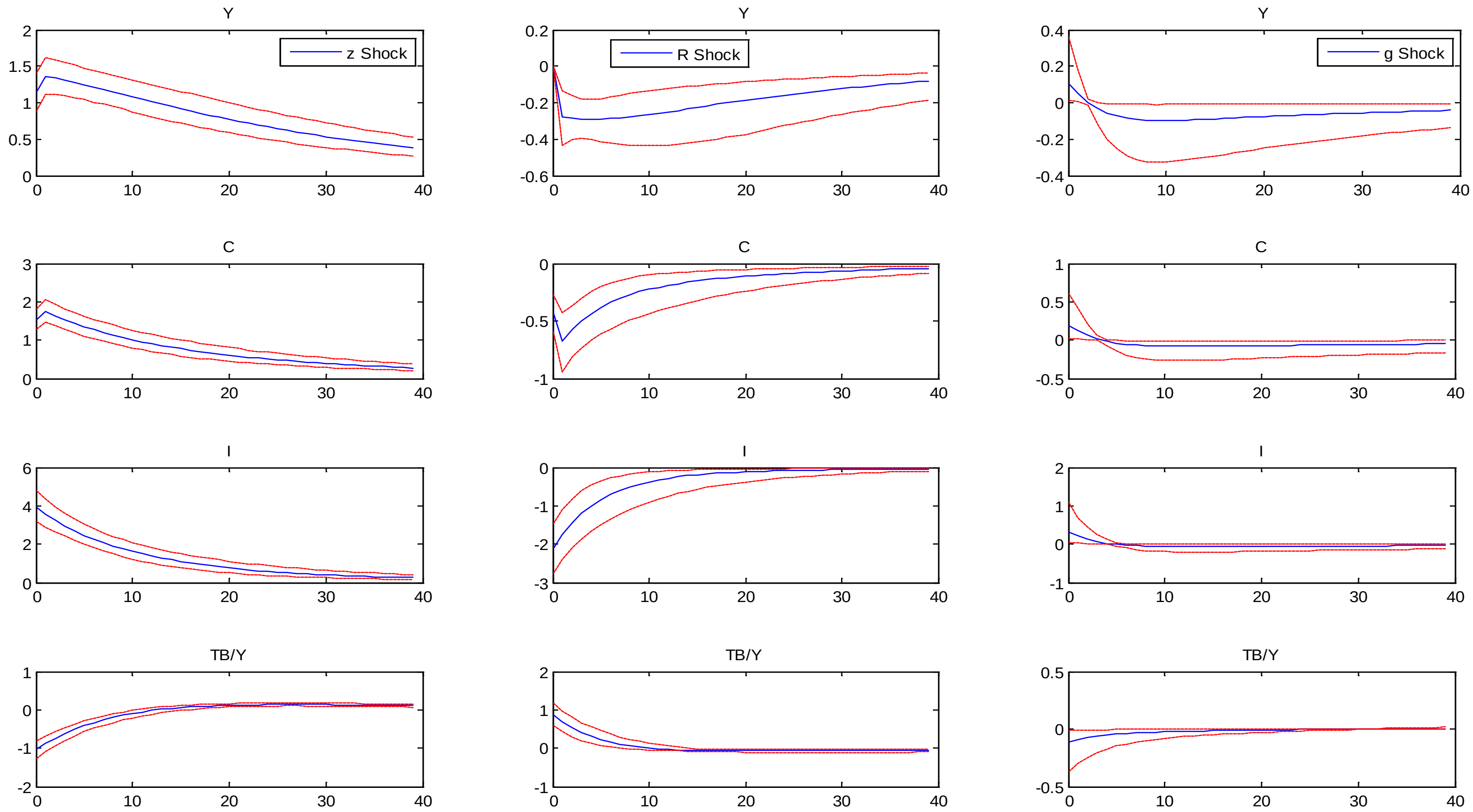
Note: The plots in this figure report the prior/posterior distributions of the parameters in the Encompassing Model. Plots are generated using the MCMC draws of the Metropolis Hastings algorithm.

Figure 2. Observed and model-based dynamics of the interest rate



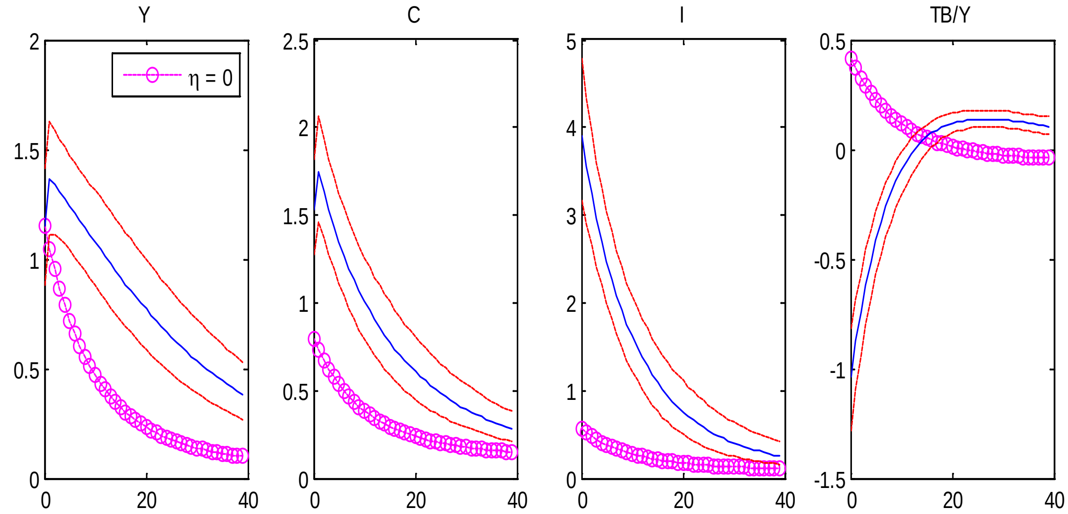
Note: The blue (shorter/thicker) line depicts the gross real Mexican interest rate computed as in Uribe and Yue (2006) using the US Tbills rate and the Mexican EMBI spread. The green (longer/thinner) time series are the model-based dynamics implied by the encompassing model computed using the Kalman smoother.

Figure 3. Impulse Response Functions, Encompassing Model



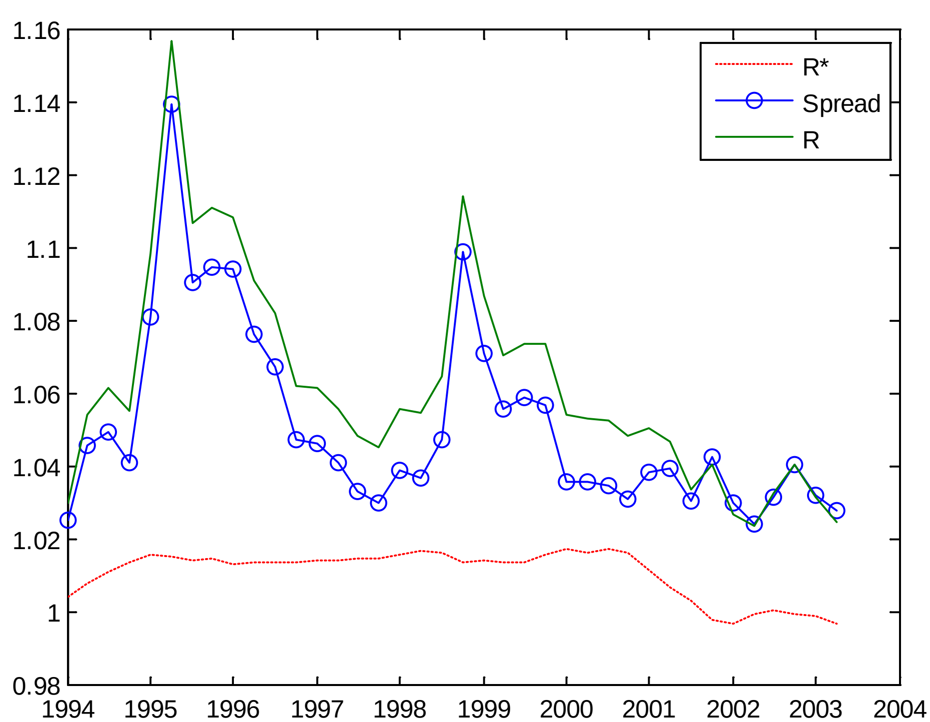
Note: Each column tracks the response of output (Y); consumption (C); investment (I), and employment (h) as deviations from steady states, after an estimated 1 S.D. shock to the transitory technology process (Column 1); the foreign interest rate process (Column 2); and the growth process (Column 3).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

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



Note: The 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. The other lines reproduce the first column in Figure 3.

Figure 5. Time Series for Domestic and Foreign Interest Rates



Note: R* is the world interest rate (taken from the TBills rate); Spread is the EMBI+ Mexico; R is the Mexican interest rate implied by multiplying R* and S. Sources: Uribe and Yue (2006).

Figure 6. Simulating The Tequila Crisis

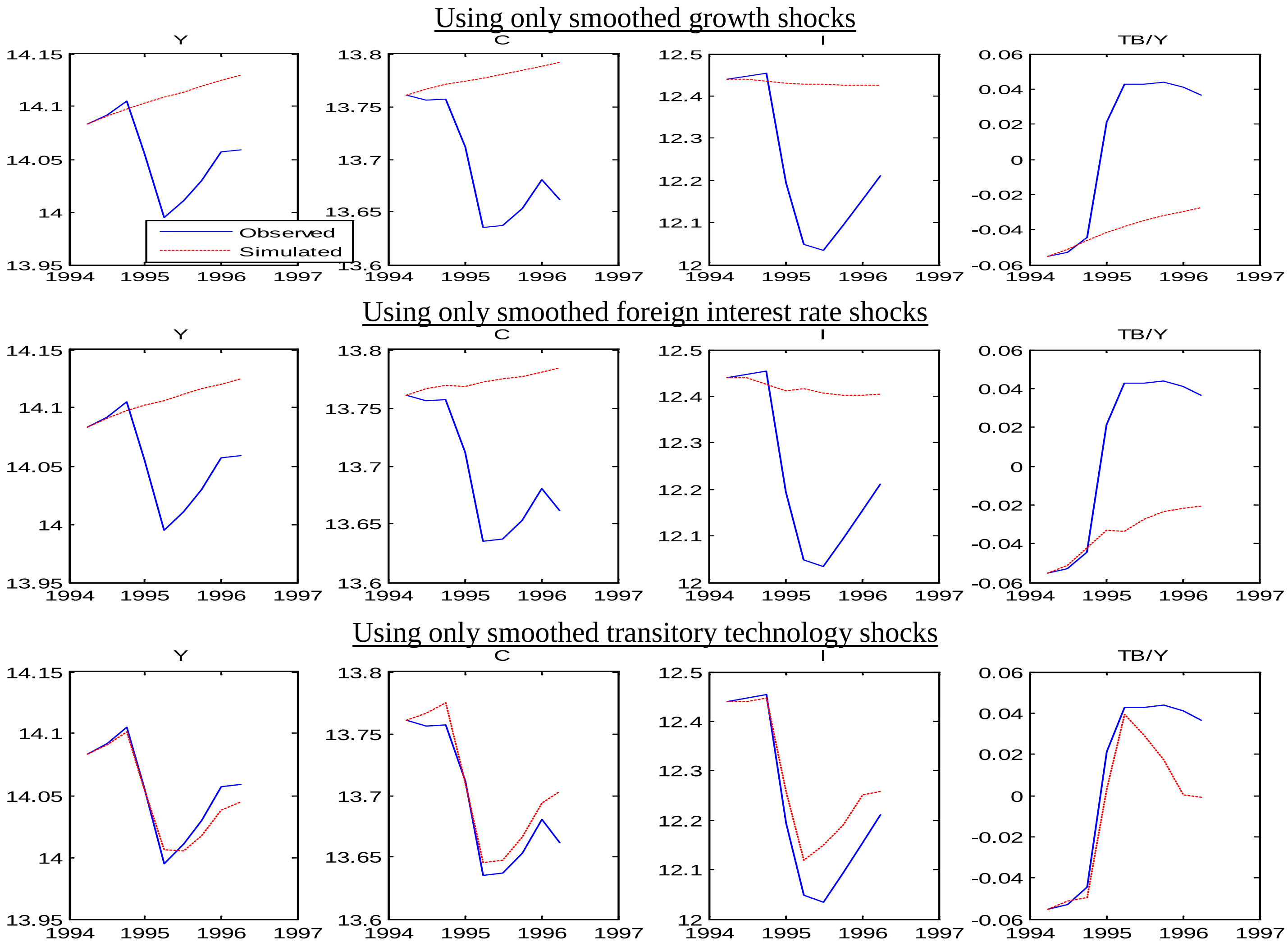
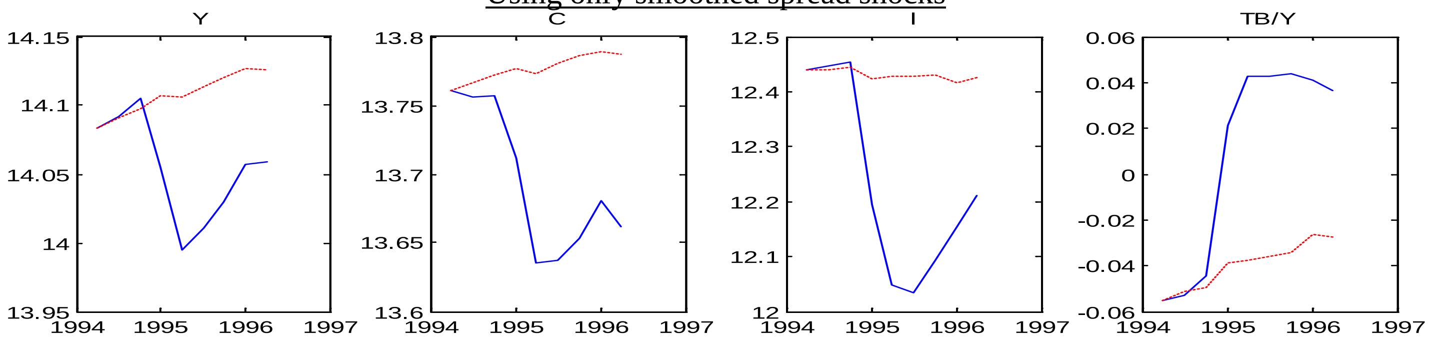


Figure 6 (cont). Simulating The Tequila Crisis

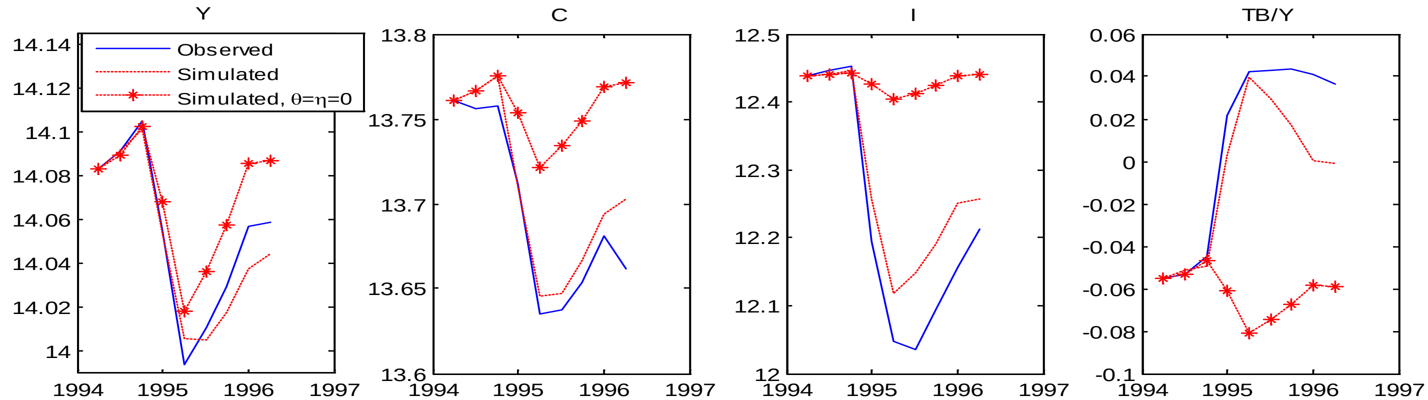
Using only smoothed spread shocks



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

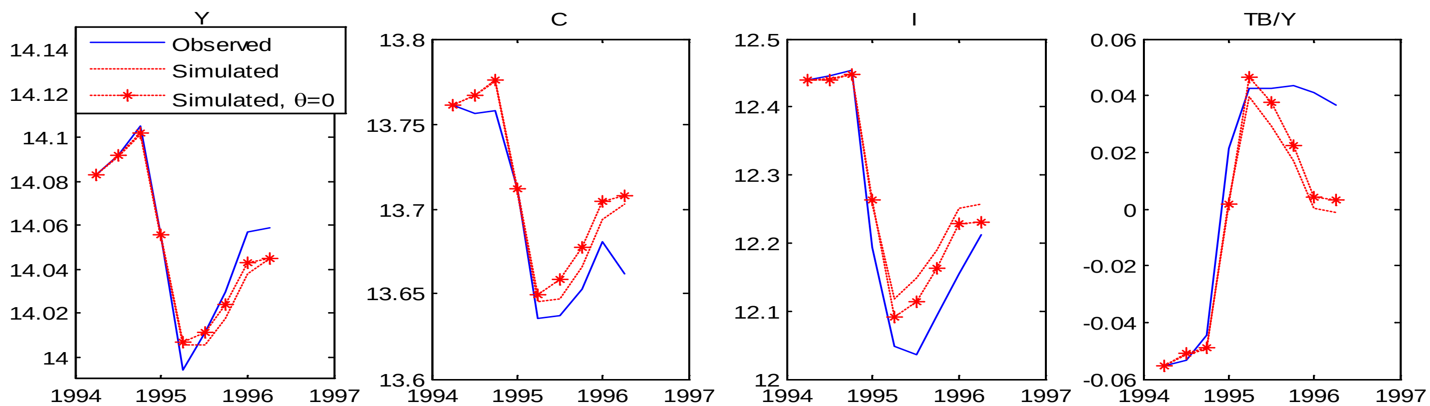
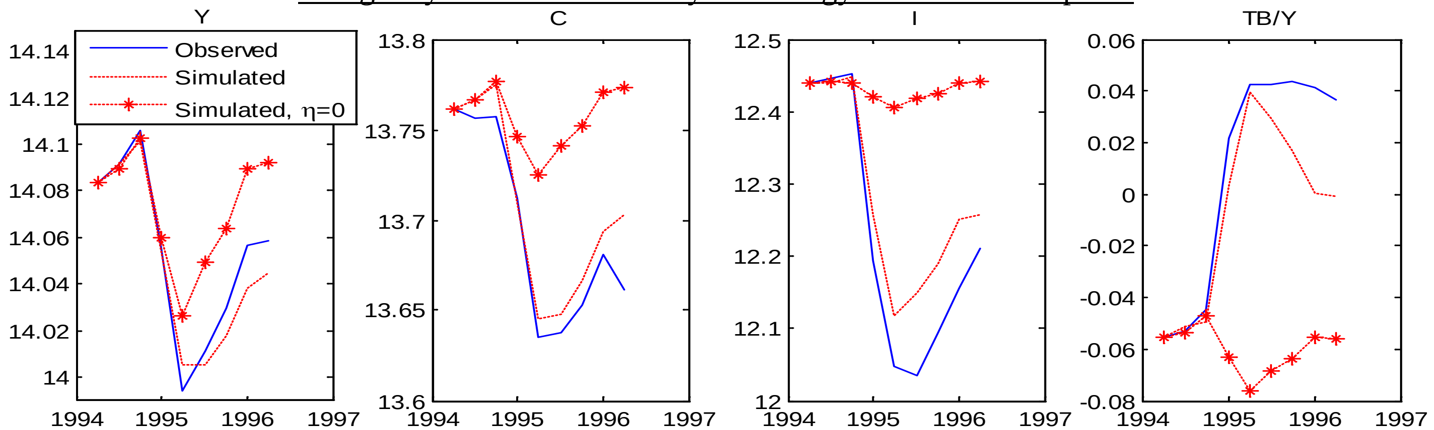


Figure 7(cont). Simulating The Tequila Crisis Using Only Transitory Technology Shocks and Various Degrees of Financial Frictions

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.