Estimating Models for Monetary Policy Analysis in Emerging Countries*

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Abstract

We estimate a DSGE model of an emerging country containing many frictions that, as has been recently argued, impose non-trivial constraints for monetary-policy design in these economies. In particular, our framework features a sectorial decomposition of the productive sector, the use of intermediate inputs, incomplete pass-through, endogenous premium to finance capital accumulation, balance sheets effects due to liability dollarization, currency substitution, price and wage rigidities, and dynamics are driven by eleven shocks. We use a Bayesian approach to Mexican data to address three main questions. First, can the model satisfactorily fit the data? Our answer is generally yes, with some caveats. Second, are the estimated parameters similar to those usually calibrated in policy-related studies? The answer is negative, particularly for those describing financial frictions, price stickiness and money demand. Finally, which of the emerging-markets frictions are more relevant in fitting the data? We found that including intermediate inputs is most important, while currency substitution does not seem to play a major role. Moreover, financial frictions and liability dollarization are also relevant.

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1 Introduction

What makes the job of the monetary authority in an emerging country different from that in a more developed economy? The literature has analyzed many distinctive characteristics of these markets that are relevant for policy analysis.[1] For instance, they are subject to shocks to international interest rates and prices, for they heavily rely on foreign trade and/or financing but they are generally price takers in the rest of the world. Additionally, financial frictions are usually in place, generating countercyclical costs of financing which tend to amplify business cycles fluctuations. Moreover, if an important part of their debt is denominated in foreign currency, they might face a liability dollarization problem that can exacerbate any financial constraint. Another feature of these countries is the coexistence of both domestic and foreign currency (currency substitution). All these impose non-trivial restrictions on policy-related decisions like exchange-rate regimes, stabilization policies and inflation management.

Part of the literature that has emerged after the sequence of emerging-markets crisis since the mid-90's has re-evaluated the design of monetary policy in these countries by explicitly acknowledging these characteristics.[2] In terms of financial frictions and liability dollarization, for instance, Cespedes et al. (2004) and Cook (2004) have studied the optimal exchange-rate regime by adapting the financial accelerator framework of Bernanke et al. (1999) to a small-open economy with dollar-denominated debt. More recently, Devereux et al. (2006) extended these studies by considering these frictions in a richer model, Elekdag and Tchakarov (2007) evaluate the robustness of exchange-rate recommendations in terms of debt-to-GDP differences across countries, and Gertler et al. (2007) use this framework to explore the connection between exchange rate regimes and financial distress during the 1997 Korean crisis.

Also in this literature, the link between currency substitution and monetary policy, albeit its long tradition,[3] has been recently revisited in the context of DSGE models by Felices and Tuesta (2007) and Batini et al. (2007, 2008). On the other hand, in terms of the domestic propagation of international prices, Calvo et al. (2008) have highlighted the importance of accounting for the use of intermediate inputs (particularly those imported) in analyzing exchange-rate regimes. Additionally, the study by Devereux et al. (2006) also addresses this issue by considering the role of incomplete pass-through for monetary policy. To summarize the importance of this line of work, in Calvo's words,

> "[...] the research that has taken place in the last decade –while still short of earth-shaking results– has laid the ground for a major revision of the way we think about financial crises and policymaking in Emerging Market economies." (Calvo, 2005, p. xii)

Nevertheless, the relevance of any policy-related study strongly depends on whether the specific model (and its parameterization) used to draw recommendations is empirically sound or not. This issue is of particular importance for these aforementioned papers for at least two reasons. First, this line of research usually apply calibration techniques to assign values for the relevant parameters, many times using as reference studies from developed countries. Second, regardless of how is the model parameterized, these papers do not analyze if the model can adequately fit the data. Moreover, given

[1] Calvo (2005), for example, provides an excellent book-length treatment of many of these distinctive features of emerging economies and how they have played a role in explaining their experience in the last two decades.

[2] Another feature distinguishing this new wave of research from the older related literature is methodological, for they have been able to exploit the recent developments in the so-called New-Open-Economy Macroeconomics (NOEM), as well as the progress in tools for policy analysis for dynamic stochastic general equilibrium (DSGE) models.

[3] See, for instance, the survey by Calvo and Végh (1992).

this methodological approach, the question of which of the emerging-countries frictions are empirically more relevant is not addressed, even though it is of great interest for policy design.

Given these empirical concerns, our contribution is to set up and estimate a comprehensive DSGE model that takes into account these defining characteristics of emerging countries. In particular, our framework features a sectorial decomposition of the productive sector, the use of intermediate inputs, incomplete pass-through, endogenous premium to finance capital accumulation, balance sheets effects due to liability dollarization, currency substitution, as well as price and wage rigidities. Additionally, eleven driving forces, both from domestic and international origin, are considered. We follow a Bayesian approach to estimate the model using a quarterly data set from Mexico –from 1980 to 2007– that includes a large number of observables.

Our goal is to address three main quantitative questions. First, can the estimated model fit the data? Our answer is generally yes, but with some caveats (for instance, the fit of real wages is not satisfactory). Second, are the estimated parameters similar to those calibrated in policy-related studies? The results show many significant differences, particularly for those describing financial frictions, price stickiness and money demand. Finally, which of the emerging-markets frictions are more relevant in fitting the data? We found that including intermediate inputs is most relevant, while currency substitution does not seem to play a relevant role. Moreover, the financial accelerator mechanism and liability dollarization are also important.

Additionally, we use our preferred specifications to study which of the included driving forces are more important in explaining the data. We found that, while foreign shocks play an non negligible role (especially export prices), the most important sources of fluctuations have a domestic origin. In particular, sectorial (stationary) technology shocks account for more than 40% of the variance of most domestic observables. Country premium disturbances are also relevant to explain real variables, while shocks related with monetary policy are helpful in describing the dynamics of inflation.

From a methodological perspective, we depart from the usual implementation of the Bayesian estimation of DSGE models in two aspects. First, our approach to assign the prior distribution for the estimated parameters modifies the methodology proposed by Del Negro and Schorfheide (2006), which provides a more transparent procedure (particularly for parameters describing driving forces) of translating our *a priori* beliefs into a probability density. On the other hand, in addition to the usual model comparison according to the marginal likelihood, we perform a more thorough analysis by applying the loss function-based approach developed by Schorfheide (2000), which allow us to rank models according to their ability to fit the data in many different dimensions.

This paper is also related with studies estimating DSGE models in emerging countries. For instance, NOEM models featuring frictions like sticky prices and wages are estimated by Caputo et al. (2006) and Medina and Soto (2005) for Chile and da Silveira (2006) for Brazil. In terms of the financial frictions and liability dollarization, Elekdag et al. (2005) and Tovar (2006b) estimate a simplified version of the financial accelerator using data from Korea, while Tovar (2006a) does it for Chile, Colombia and Mexico. Additionally, the work by Castillo et al. (2006) estimates a model featuring currency substitution for Peru.

Our approach differs, however, from these empirical studies in several relevant aspects. All these papers use models with a single domestically-produced good that is fully tradable, while our framework displays a richer production structure that also includes non-traded goods. In addition, with the exception of Castillo et al. (2006), cash-less economies are generally consider. Finally, only a few number of observables are frequently used for estimation. In particularly, although foreign prices and interest rates are usually considered as driving forces in these models, most of the times they are not included in the data set. On the other hand, we match the likelihood of 14 variables, both domestic and foreign.

The rest of the paper is organized as follows. Section 2 describes the model, while Section 3 presents the details of the estimation procedure. The results under the Baseline model are studied in Section 4, in which we analyze the posterior of the parameters, as well as the extent to which the model can fit the data. Section 5 evaluates the role of several emerging-countries frictions in replicating the data, comparing also the estimation results of the preferred specifications in terms of posterior distributions and variance decompositions. Finally, Section 6 summarizes the findings and discusses suggested directions for future research.

2 The Model

This section presents the Baseline model. We start with a brief overview, describing then the problems faced by all agents, as well as the driving forces affecting the economy. A separate Technical Appendix provides the details regarding optimality conditions, definition of the stationary equilibrium and computation of the non-stochastic steady state.[4]

The small open economy is populated by households, firms, entrepreneurs and a consolidated government. There are three consumption goods: exportables (x, sold both domestically and in the rest of the world), non-tradeables (n) and imported goods (f). The first two are produced domestically, while the latter is produced abroad and sold domestically trough import agents. The production of x and n uses labor, capital, and other consumption goods as inputs, taking their prices as given. While exportable firms sell at a price determined in the rest of the world, both non-traded firms and import agents have market power and face price adjustment costs.

Capital goods are produced in three steps. First, competitive firms combine entrepreneurs labor with both non-traded and foreign goods to produce final investment goods. In a second stage, a group of competitive firms produce unfinished capital goods for each sector combining final investment goods and used capital, which they buy from entrepreneurs. Finally, entrepreneurs transform these into finished capital goods using a linear technology. This production process is subject to an idiosyncratic productivity shock, revealed privately to entrepreneurs ex-post. Because they have to borrow to produce, this informational asymmetry introduces an endogenous finance premium. In addition, they are subject to balance-sheet effects originated by movements in the nominal exchange rate, for they borrow in foreign currency but their income is denominated in local currency.

Households derive utility from consumption (subject to habit formation), leisure and holdings of real balances of domestic (pesos) and foreign currency (dollars). The demand for both types of currency reflects a non-trivial degree of substitutability, and real balances are partially complements of consumption. In terms of other financial assets, they have access to both domestic and foreign non-contingent nominal bonds. Additionally, households are assumed to have monopoly power in setting wages, facing adjustment costs.

The government consumes an exogenous stream of final goods and collects lump sum taxes. They also print domestic currency and set the interest rate on domestic bonds according to a Taylor-type

[4]This appendix can be found at www.duke.edu/~jg55/research/TechnicalAppendix.pdf

rule with time-varying targets (inflation and output).

This economy is subject to a multitude (11) of shocks affecting the following variables: non-stationary labor augmenting productivity, stationary TFP (sector specific), domestic nominal interest rate, targets in the Taylor rule, government purchases, country premium, world interest rate and international prices (exports and imports).

2.1 Households

The economy is populated by continuum of households in the unit interval, indexed by h, seeking to maximize $E_0 \sum_{t=0}^{\infty} \beta^t \frac{\left[V_t^h(1-l_t^h)^{\phi}\right]^{1-\sigma}}{(1-\sigma)}$, with $\phi > 0$ and $\sigma > 0$, where

$$V_t^h \equiv \left[b(X_t^h)^{1-1/\zeta} + (1-b)(Z_t^h)^{1-1/\zeta}\right]^{\frac{\zeta}{\zeta-1}},$$

with $b \in [0,1]$ and $\zeta > 0$. $X_t^h \equiv \left(C_t^h - \rho_c C_{t-1}\right)$ is habit adjusted consumption, where C_t^h is final consumption by household h, $C_t = \int_0^1 C_t^h dh$ is aggregate household consumption (i.e. the utility function exhibits *external* habit formation), and $\rho_c \in [0,1)$. Labor effort is denoted by l_t^h. We follow the notation that lower case letters represent stationary variables while those in capital letters contain a stochastic trend in equilibrium.

The variable Z_t^h is a liquidity-service index, defined as

$$Z_t^h \equiv \left[\nu\left(\frac{M_{t+1}^h}{P_t}\right)^{1-1/\chi} + (1-\nu)\left(\frac{D_{t+1}^h S_t}{P_t}\right)^{1-1/\chi}\right]^{\frac{\chi}{\chi-1}},$$

with $\nu \in [0,1]$ and $\chi > 0$. The holdings of pesos and dollars (decided at t) are denoted by, respectively, M_{t+1}^h and D_{t+1}^h, S_t is the nominal exchange rate (measured as pesos per dollar) and P_t is the price of final consumption goods (with $\pi_t \equiv P_t/P_{t-1}$ denoting inflation). This particular way of introducing currency substitution is due to Felices and Tuesta (2007). The parameter ν governs the importance of the liquidity services provided by domestic currency: if $\nu = 1$ dollars are not useful for transaction purposes while $\nu = 0$ represents the case of full transaction dollarization. Notice also that we allow for non-trivial complementarities between habit-adjusted consumption and liquidity services (governed by ζ). This interaction, as emphasized by Felices and Tuesta (2007), is particularly important for the design of monetary policy, for it introduces an endogenous tradeoff between output and inflation stabilization as the marginal utility of consumption depends on money holdings.

Each household h sells labor services in a monopolistically competitive market, charging a nominal wage denoted by W_t^h (in pesos), and facing a demand given by $(W_t^h/W_t)^{-\theta_w} l_t^d$, with $\theta_w > 1$. The variable l_t^d denotes aggregate labor demand and $W_t \equiv [\int_0^1 \left(W_t^h\right)^{1-\theta_w} dh]^{1/(1-\theta_w)}$ is the aggregate nominal wage index. Given that workers supply labor in order to meet their demand, we have $l_t^h = l_t^d(W_t^h/W_t)^{-\theta_w}$. Additionally, changing wages is costly, with adjustment costs given by (in pesos)

$$AC_t^{w,h} \equiv W_t \frac{\psi_w}{2}\left(\frac{W_t^h}{\hat{\pi}_t W_{t-1}^h} - 1\right)^2,$$

where $\psi_w > 0$. $\hat{\pi}_t$ (defined below) is the inflation target, to which nominal wages are indexed.[5]

Additionally, households have access to two types of non-contingent one-period debt: one denominated in pesos (B_t^h), with nominal rate given by i_t, and the other is dollar denominated (B_t^{*h}) with a rate of $i_t^* \xi_t$. The variable ξ_t denotes the country premium and is defined as

$$\xi_t = \psi_d \left[\exp\left(\frac{S_t B_{t+1}^*}{P_t GDP_t} - \bar{b} \right) - 1 \right] + \xi_t^*, \tag{1}$$

with $\psi_d > 0$.[6] As can be seen, this premium is determined by an endogenous component that depends on the aggregate level of households international debt ($B_{t+1}^* = \int_0^1 B_{t+1}^{*h} dh$) relative to aggregate output (GDP_t, to be defined), and by a stochastic component (ξ_t^*).

Overall, each household h faces, at period t, the following nominal budget constraint

$$\begin{aligned} P_t C_t^h + AC_t^{w,h} + M_{t+1}^h + S_t D_{t+1}^h - B_{t+1}^h - S_t B_{t+1}^{*h} = \\ W_t^h l_t^h - B_t^h i_{t-1} - S_t B_t^{*h} i_{t-1}^* \xi_{t-1} + M_t^h + S_t D_t^h + \Pi_t^h + T_t^h. \end{aligned} \tag{2}$$

As households own the monopolistic firms, part of their income comes from aggregate profits $\Pi_t \equiv \sum_j \Pi_t^j$ for $j = n, f$ (defined below), with $\Pi_t = \int_0^1 \Pi_t^h dh$. Finally, each household receives a lump-sum transfer from the government in the amount of T_t^h pesos.

2.2 Supply of Consumption Goods

Firms operating in each consumption-goods market x, n and f differ across sectors along two dimensions: available technology and price setting ability. We describe first production in each sector, discussing then the pricing problem in the different markets. In addition, there are two packer sectors, combining different consumption goods into a final consumption basket.

Production

The technology available for the domestic production of goods x and n uses as inputs labor and capital rented from households, as well as intermediate inputs from other sectors. Firms are price takers in input markets. The typical firm, indexed by i, in sector j uses the following production function

$$Y_t^{j,i} = A_j z_t^j \left(K_t^{j,i} \right)^{\alpha_j^k} \left(\Gamma_t l_t^{j,i} \right)^{\alpha_j^l} \left(IC_t^{x,j,i} \right)^{\alpha_j^x} \left(IC_t^{n,j,i} \right)^{\alpha_j^n} \left(IC_t^{f,j,i} \right)^{\alpha_j^f}, \tag{3}$$

with $A_j \equiv \prod_\iota (\alpha_j^\iota)^{-\alpha_j^\iota}$ and $\sum_\iota \alpha_j^\iota = 1$ for $\iota = k, l, x, n, f$ and $j = x, n$. In addition, we assume $\alpha_j^j = 0$. Intermediate consumption of good $\iota = x, n, f$ by a firm i in sector $j = x, n$ is given by $IC_t^{\iota,j,i}$.

[5]This target will be used for price indexation also (see below). Emerging countries have many times implemented inflation-stabilization programs. Most of these attempts have been successful, at least in the short-run, in the sense that inflation was indeed reduced after their implementation (see, for instance, Mendoza and Uribe, 2000, for an analysis of the Mexican case). To the extent that these policies will be reflected in changes in the inflation target, it seems appropriate to use it as the indexation variable. If, alternatively, prices and wages were indexed to past inflation, they will not adjust after the policy is implemented as in the data. Moreover, we have estimated the Baseline Model allowing the indexation variable to be a combination of the target and past inflation. The results in terms of the parameter governing this combination strongly suggest to use only the target.

[6]This is as a possible way to "close" this small open economy model. See Schmitt-Grohé and Uribe (2003) for details and alternatives.

The variable z_t^j denotes a sector-specific technology shifter, assumed to be stationary. On the other hand, Γ_t is a labor-augmenting technology shock common to all sectors, driven by a non-stationary process. The idea behind this specification is that changes affecting the production possibilities of the economy as a whole are captured by Γ_t, whereas z_t^j will reflect shocks having a differential impact in the technology of each sector.

Given the constant-return-to-scale technology and the price-taking assumption in factor's markets, each firm in sector j will face the same nominal marginal cost given by

$$MC_t^j = \left(z_t^j\right)^{-1}\left(R_t^j\right)^{\alpha_j^k}\left(\frac{W_t}{\Gamma_t}\right)^{\alpha_j^l}\left(P_t^x\right)^{\alpha_j^x}\left(P_t^n\right)^{\alpha_j^n}\left(P_t^f\right)^{\alpha_j^f},$$

for $j = x, n$, where P_t^ι is the domestic price of good $\iota = x, n, f$ and R_t^j is the rental rate of capital.

Finally, consumption goods of type f are produced in the rest of the world and sold domestically by import agents. The nominal marginal cost in pesos (MC_t^f, common to all firms in this sector) is simply the international dollar price of these goods (P_t^{*f}, determined by an exogenous process) adjusted by the nominal exchange rate. Thus, $MC_t^f = P_t^{*f} S_t$.

Price Setting and Profits

Firms also differ across markets in terms of price setting ability and the demand they face. On one hand, firms producing exportable goods x are assumed to behave competitively, taking the international price as given. This implies that $P_t^x = S_t P_t^{*x}$, with P_t^{*x} being the (exogenous) international dollar price of exports.[7]

On the other hand, firms selling only domestically do have price setting power. We assume that all buyers of goods n demand part of an homogeneous aggregate defined as

$$Y_t^{d,n} \equiv \left[\int_0^1 \left(Y_t^{d,n,i}\right)^{\frac{\theta_n - 1}{\theta_n}} di\right]^{\frac{\theta_n}{\theta_n - 1}},$$

with $\theta_n > 1$. Therefore, a firm i in sector n, charging a price $P_t^{n,i}$, will face a demand given by $Y_t^{d,n,i} = Y_t^{d,n}(P_t^{n,i}/P_t^n)^{-\theta_n}$, where $P_t^n = [\int_0^1 (P_t^{n,i})^{1-\theta_n} di]^{1/(1-\theta_n)}$. As we assumed for wages, changing prices is costly due to quadratic adjustment costs given by (in pesos)

$$AC_t^{n,i} \equiv \frac{\psi_n}{2}\left(\frac{P_t^{n,i}}{\hat{\pi}_t P_{t-1}^{n,i}} - 1\right)^2 P_t^n \Gamma_t,$$

where $\psi_p > 0$. Additionally, these firms incur in fixed operational costs, in terms of their own output, given by $\Gamma_t \kappa^n y^n$, where y^n denotes output of sector n in the non-stochastic (stationary) steady state.[8]

[7] Here we are departing from many studies estimating DSGE models in emerging economies, which usually assume that exporters face a negatively-sloped demand curve and have enough market power internationally to set prices (either in pesos or dollars). See, for instance, Elekdag et al. (2005), da Silveira (2006), Tovar (2006a,b), Caputo et al. (2006) and Castillo et al. (2006). It is not clear, however, that this is an appropriate assumption for these countries, for most of them are mainly exporters of some commodities for which they are clearly price takers (e.g. oil in Mexico, copper in Chile, agricultural goods in Argentina, etc.).

[8] Variables without time subscript represent steady state values

Therefore, the profits of a firm i in sector n are given by

$$\Pi_t^{n,i} = \left[P_t^{n,i} - MC_t^n\right] Y_t^{d,n,i} - P_t^n \Gamma_t \kappa^n y^n - AC_t^{n,i}.$$

Finally, import agents (sector f) face a similar situation than firms in sector n, differing only in terms of parameter values for the elasticity of substitution, adjustment costs and fixed costs. Thus, a firm i in sector f faces a demand given by $Y_t^{d,f,i} = Y_t^{d,f}(P_t^{f,i}/P_t^f)^{-\theta_f}$, with $\theta_f > 1$ and $P_t^f = [\int_0^1 (P_t^{f,i})^{1-\theta_f} di]^{1/(1-\theta_f)}$. The cost associated with price changes is

$$AC_t^{f,i} \equiv \frac{\psi_f}{2}\left(\frac{P_t^{f,i}}{\hat{\pi}_t P_{t-1}^{f,i}} - 1\right)^2 P_t^f \Gamma_t,$$

and profits are $\Pi_t^{f,i} = \left[P_t^{f,i} - MC_t^f\right] Y_t^{d,f,i} - P_t^f \Gamma_t \kappa^f y^f - AC_t^{f,i}$.

Final Consumption Goods

Final consumption goods are a combination of non-traded (n) and traded (x and f) goods. The later are produced competitively according to

$$C_t^T = A_T \left(C_t^x\right)^{\eta_x} \left(C_t^f\right)^{1-\eta_x}, \tag{4}$$

where $A_T \equiv (\eta_x)^{-\eta_x}(1-\eta_x)^{-(1-\eta_x)}$. Aggregate final consumption of each type is denoted by C_t^j for $j = x, n, f$.[9] In equilibrium, the price for this aggregate will be $P_t^T = (P_t^x)^{\eta_x}(P_t^f)^{1-\eta_x}$.

On the other hand, the production of final consumption goods is given by

$$Y_t^C = \left[a^{1/\varphi}\left(C_t^N\right)^{1-1/\varphi} + (1-a)^{1/\varphi}\left(C_t^T\right)^{1-1/\varphi}\right]^{\frac{\varphi}{\varphi-1}}. \tag{5}$$

and thus the domestic price index is $P_t = \left[a\left(P_t^N\right)^{1-\varphi} + (1-a)\left(P_t^T\right)^{1-\varphi}\right]^{\frac{1}{1-\varphi}}$.

2.3 Capital Goods and Financial Frictions

The stock of capital that will be available for next's period production is accumulated in three steps. First, competitive firms produce final investment goods, Y_t^k, combining non-traded ($IC_t^{k,n}$) and foreign goods ($IC_t^{k,f}$),[10] as well as entrepreneurial labor (L_t^e, supplied inelastically). In particular, the production function in this sector is

$$Y_t^k = A_k \left(IC_t^{n,k}\right)^{\alpha_k^n} \left(IC_t^{f,k}\right)^{\alpha_k^f} \left(\Gamma_t l_t^e\right)^{\alpha_k^e}. \tag{6}$$

[9] Because we assume that households and the government share the same preference for different goods and varieties, C_t^j is the aggregate consumption of good j. The other part of the demand for these goods is given by intermediate demand by firms (and exports for good x).

[10] Calvo et al. (2008) highlight the importance for monetary policy design of considering that the production of capital goods uses imported goods as inputs.

where $A_k \equiv \prod_\iota (\alpha_k^\iota)^{-\alpha_k^\iota}$ and $\sum_\iota \alpha_k^\iota = 1$ for $\iota = n, f, e$. Letting W_t^e denote entrepreneurial wage, perfect competition implies that the equilibrium price of these goods is $P_t^k = (P_t^n)^{\alpha_k^n} (P_t^f)^{\alpha_k^f} (W_t^e/\Gamma_t)^{\alpha_k^e}$.

In a second stage, after the production of consumption and final investment goods is finished, a group of competitive firms produce unfinished capital goods for each sector (selling at a price Q_t^j) combining final investment goods and used capital, which they buy from entrepreneurs (paying $Q_t^{old,j}$ per unit). Specifically, for each sector $j = x, n$ they operate the following technology

$$K_{t+1}^j = (1-\delta) K_t^j + I_t^j - \frac{\psi_k^j}{2} \left[\frac{I_t^j}{K_t^j} - (\gamma - 1 + \delta) \right]^2 K_t^j, \tag{7}$$

where δ represents the depreciation rate. Prices of unfinished and old capital are determined by the optimality conditions of these firms.

Finally, a continuum of risk-neutral entrepreneurs buy unfinished capital goods for all sectors, transforming them into final capital goods using a linear technology.[11] In particular, given K_{t+1}^j units of unfinished capital of sector $j = x, n$, they produce $\omega_{t+1} K_{t+1}^j$ units of finished capital; where $\ln(\omega_t) \sim \mathcal{N}\left(-.5\sigma_\omega^2, \sigma_\omega^2\right)$. This idiosyncratic productivity shock is revealed to entrepreneurs ex-post (i.e. after paying the cost of production), and it might be also observed by a third party paying a fraction μ of the total value of production (monitoring cost).

The total cost of this operation ($KC_t \equiv \sum_{j=x,n} Q_t^j K_{t+1}^j$) is financed in part by entrepreneurs net worth (NW_t, defined below) and by borrowing from foreign lenders in dollars (B_{t+1}^{*e}). On the other hand, in the following period they obtain a payoff given by $KI_{t+1} \equiv \sum_{j=x,n} (R_{t+1}^j + Q_{t+1}^{old,j}) K_{t+1}^j$, i.e. the sum of the rental income from firms and the proceeding from selling the used capital to unfinished capital producers. Because entrepreneurs income is denominated in pesos but they borrow in dollars, they are exposed to a balance-sheet effect generated by movements in the nominal exchange rate.

Given the informational asymmetry, foreign lenders will charge a premium (rp_t, a.k.a external finance premium) for these loans, satisfying

$$E_t \left\{ rp_{t+1} \left(R_{t+1}^j + Q_{t+1}^{old,j} \right) / Q_t^j \right\} = i_t^* \xi_t, \tag{8}$$

for $j = n, x$. As can be seen, this premium –which will be an increasing function of the leverage ratio KC_t/NW_t under the optimal contract– represents a wedge between the opportunity cost for foreign lenders (i.e. return on households lending) and the expected return of entrepreneurs operation.

At the beginning of each period, a fraction ϑ of surviving entrepreneurs collect the returns on capital and repay their debt. Therefore, as shown in the Technical Appendix, the net worth available to finance a project in period t is given by

$$NW_t = \vartheta \left[KI_t (1 - \upsilon_t) - i_{t-1}^* \xi_{t-1} S_t B_t^{*e} \right] + W_t^e, \tag{9}$$

where υ_t (defined in the Technical Appendix) represents monitoring costs. Therefore, an unexpected nominal depreciation will reduce entrepreneurs net worth, which will in turn increase the external

[11] This specification is similar to Bernanke et al. (1999), adapted to an open economy and a multi-sector framework. Cespedes et al. (2004), Cook (2004) and Gertler et al. (2007) pioneered the used of this framework to analyze monetary policy in a one-sector small open economy model, while Devereux et al. (2006) use it in a two-sector model closer to ours. The details of the entrepreneurs problem and the financial contract, as well as the differences with these previous papers, are presented in the Technical Appendix.

finance premium generating the aforementioned balance-sheet effect.

2.4 Government

We assume that government bonds remain in zero net supply at all time (i.e. $B_t = 0$, $\forall t$). The period t government budget constraint is then given by

$$P_t G_t + \int_0^1 T_t^h dh = M_{t+1} - M_t, \tag{10}$$

where government consumption of final goods (G_t) is exogenously given.

Monetary policy is carried by Taylor-type rule for the nominal interest rate in pesos, with time varying targets. In particular,

$$\frac{i_t}{i} = \left(\frac{i_{t-1}}{i}\right)^{\alpha_i} \left[\left(\frac{\pi_t}{\hat{\pi}_t}\right)^{\alpha_\pi} \left(\frac{g_t^y}{\hat{g}_t^y}\right)^{\alpha_y}\right]^{1-\alpha_i} \hat{i}_t, \tag{11}$$

with $\alpha_i \in [0, 1)$ and $\alpha_\pi, \alpha_y > 0$.[12] The growth rate of GDP is denoted by $g_t^y \equiv GDP_t/GDP_{t-1}$ and $\hat{i}_t$ is a policy disturbance. $\hat{\pi}_t$ and $\hat{g}_t^y$ denote, respectively, the policy targets for aggregate inflation and output growth, which are assumed be stochastic. In particular,

$$\ln(\hat{\pi}_t/\pi) = \rho_\pi \ln(\hat{\pi}_{t-1}/\pi) + \epsilon_t^\pi, \tag{12}$$

$$\ln(\hat{g}_t^y/g^y) = \rho_y \ln(\hat{g}_{t-1}^y/g^y) + \epsilon_t^y, \tag{13}$$

where $\rho_\pi, \rho_\pi \in [0, 1)$.

It might seem odd that we have not included the nominal exchange rate in this rule, for many emerging countries have (particularly in the 80's and 90's) explicitly targeted this variables in implementing monetary policy. Moreover, many times they have experienced some abrupt (sometimes dramatic) changes in their exchange-rate regime. To properly model these policy fluctuations, however, it would require not only to include the nominal depreciation rate in the rule but to additionally consider a time-varying coefficient describing how the interest rate adjusts to changes in the exchange rate. For instance, under fixed exchange rates, the coefficient will be extremely high, while different levels of softs pegs or pre-announced devaluations should be represented by lower values for this parameter. However, dealing with a model with such a rule is computationally more difficult.[13] Moreover, it is important to highlight that none of the previous papers estimating DSGE models for emerging countries has dealt with these issues, for they constrain themselves to floating periods (which clearly limits the size of the sample and, thus, the inference power).

Our approach to deal with this situation is to replace the exchange rate regime represented with a time-varying coefficient with a time-varying target for inflation; which can instead be solved up to

[12] These parameters are further constrained by the requirement of equilibrium determinacy.

[13] On one hand, it is easy to show that this additional variable (i.e. the time-varying coefficient) will not appear in the first-order approximation of the rule. Unfortunately, relaying on a higher order of approximation, while feasible, is computational more intensive, both to solve the model and to compute its likelihood. On the other hand, we could consider discrete changes of regimes (i.e. the exponent in the rule following a discrete Markov process). However, perturbation methods would not be appropriate under this alternative and other solution techniques (such as value function iterations, parameterized expectations or collocations methods) are almost impractical given the dimension of our model.

first order. The motivation behind this alternative is based on observing that, for most emerging countries, policy changes associated with exchange rates have generally led to similar changes in inflation. Therefore, we might be able capture policy changes that were actually implemented targeting the exchange rate trough changes in the inflation target, as if they were observationally equivalent. While this is certainly not the most accurate representation of the actual policy, it will be enough if we obtain a good fit for policy-related variables using this alternative, which we will analyze after estimating the model. Therefore, although we acknowledge the potential limitations, we choose this approach that is computationally simpler, and leave the alternative based on higher-order-perturbation methods for future research.[14]

2.5 Driving Forces

The model includes 11 driving forces: eight domestic and three determined in the rest of the world. In terms of technology, define $\gamma_t \equiv \Gamma_t/\Gamma_{t-1}$ to be the growth rate of labor-augmenting technology. We assume

$$\ln(\gamma_t/\gamma) = \rho_\gamma \ln(\gamma_{t-1}/\gamma) + \epsilon_t^\gamma. \tag{14}$$

All error terms are assumed to be i.i.d. normal with mean zero and variance to be estimated. The sector-specific technology follows

$$\ln(z_t^j) = \rho_{z^j} \ln(z_t^j) + \epsilon_t^{z^j}, \quad \text{for} \quad j = x, n. \tag{15}$$

We include three monetary policy shocks. Those associated with the time-varying targets were already described in (12) and (13). Additionally, the residuals in the Taylor rule are determined by

$$\ln(\hat{i}_t/i) = \rho_i \ln(\hat{i}_{t-1}/i) + \epsilon_t^i. \tag{16}$$

Government expenditures also follow an exogenous process given by

$$\ln(g_t/g) = \rho_g \ln(g_{t-1}/g) + \rho_{g,gdp} \ln(gdp_{t-1}/gdp) + \epsilon_t^g, \tag{17}$$

where $g_t \equiv G_t/\Gamma_{t-1}$ and $gdp_t \equiv GDP_t/\Gamma_{t-1}$ are the detrended versions of government expenditures and GDP, respectively. We allow government purchases to react to the level of economic activity, for it is generally argued that fiscal policy is procyclical in emerging countries (see, for instance, Talvi and Végh, 2005). The final domestic driver is the shock to the country premium, for which we assume

$$\ln(\xi_t^*) = \rho_{\xi^*} \ln(\xi_{t-1}^*) + \epsilon_t^{\xi^*}, \tag{18}$$

The world variables are jointly determined by an exogenous stochastic process. Alternatively, some papers in the literature explicitly model the rest of the world, generally using a simplified version of the small economy model.[15] In principle, it is not clear which of the two approaches should be preferred. The advantage of modeling the rest of the world is that we can "name" the foreign shocks (for instance,

[14] Moreover, given the lack of such a comprehensive study tackling this issue, we consider that this simpler approach is still a clear step forward.

[15] For instance, see Elekdag et al. (2005), Castillo et al. (2006), Tovar (2006a,b), Caputo et al. (2006) and da Silveira (2006)

technology or monetary policy). However, it is not clear how the particular model choice will impact the estimation of the small open economy model. Therefore, we choose a more agnostic approach given that our main goal is to characterize the parameters describing the emerging country. Moreover, it is likely that a reduced form specification will provide a better fit to the behavior of the international variables that a highly stylized model of the rest of the world.

Let the vector $x_t^* \equiv [\pi_t^{*f}, \pi_t^{*x}, i_t^*]'$ collect the stationary rest-of-the-world variables, where $\pi_t^{*f} \equiv P_t^{*f}/P_{t-1}^{*f}$ and $\pi_t^{*x} \equiv P_t^{*x}/P_{t-1}^{*f}$ are, respectively, the foreign inflation of imported and exported goods. Notice that we cannot simply model them as a VAR process, for the terms of trade ($tot_t \equiv P_t^{*x}/P_t^{*f}$) have to be stationary.[16] An error-correction representation is then appropriate for these foreign variables, in which lagged values of terms of trade are included as regressors. In particular,

$$A_0 \ln(x_t^*/x^*) = B \ln(tot_{t-1}/tot) + A(L) \ln(x_{t-1}^*/x^*) + \epsilon_t^{rw},$$

where A_0 is a 3x3 matrix, B is 3x1 and $A(L)$ is a matrix in the lag operator.[17] The vector $\epsilon_t^{rw} \equiv [\epsilon_t^{f^*}, \epsilon_t^{x^*}, \epsilon_t^{i^*}]'$ is i.i.d. normal with mean zero and diagonal variance-covariance matrix. In order to identify these three shocks we impose

$$A_0 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ a_i^f & a_i^x & 1 \end{bmatrix}.$$

In particular, this assumption implies that the nominal interest rate may react to contemporaneous shocks to prices, but prices will not react contemporaneously to changes in the interest rate; an assumption in line with the literature identifying monetary shocks in the U.S. (see, for instance, Christiano et al., 1999).[18] This error-correction process is estimated by maximum likelihood, ahead of estimating the other parameters in the model.[19] Results are presented in Table 1. It is relevant to highlight that the identified shock to export prices is significantly more volatile than the other two, which mainly reflects the observed path of oil prices in our sample.

2.6 Aggregation and Market Clearing

Given that adjustments costs parameters for both prices and wages are the same across firms of each type and households, and that marginal cost are also equal across firms in each sector, the equilibrium will be symmetric. Therefore, we can drop the indices i and h from allocations and prices of different firms and households. In equilibrium, the following market clearing conditions must hold:

- Labor market for households and entrepreneurs: $l_t = l_t^d = l_t^x + l_t^n$ and $l_t^e = 1$.
- Exportables: $Y_t^x = C_t^x + IC_t^{x,n} + EXP_t$, with EXP_t denoting exports.

[16] On one hand, this restriction needs to hold in the model for the equilibrium's stationary representation to exist. Additionally, unit root tests reject the hypothesis that terms of trade are I(1) in the data.

[17] The optimal lag length is selected by Bayesian and Hannan-Quinn information criteria; both suggesting for Mexico to include only one lag.

[18] Using Likelihood Ratio tests, this specification cannot be rejected against others, particularly a triangular representations for A_0.

[19] This helps to reduce the dimensionality of the estimation procedure for the DSGE model. As a robustness check, we have estimated the Baseline specification including all the parameters in one step, but the results are not significantly different from this alternative two-steps approach.

- Non-tradeables: $Y_t^n = C_t^n + \sum_{j=x,k} IC_t^{j,n} + \Gamma_t \kappa^n y^n + AC_t^n / P_t^n$.
- Imported: $IMP_t \equiv Y_t^f = C_t^f + \sum_{j=x,n,k} IC_t^{j,f} + \Gamma_t \kappa^f y^f + AC_t^f / P_t^f$, where IMP_t are imports.
- Investment: $Y_t^k = \sum_{j=x,n} I_t^j$.
- Final consumption: $Y_t^c = C_t + G_t$.

Finally we introduce several helpful measures to confront the model with the data. The trade balance, in terms of domestic consumption, is given by $TB_t = \frac{P_t^x}{P_t} EXP_t - \frac{P_t^f}{P_t} IMP_t$, while gross domestic product at domestic prices is defined as $GDP_t = C_t + G_t + \frac{P_t^k}{P_t} I_t + TB_t$.[20] and $TBY_t = TB_t / GDP_t$. The inflation rate in the non-traded sector is $\pi_t^n \equiv P_t^n / P_{t-1}^n$, the share of non-traded value added is $s_t^n \equiv \left(P_t^n Y_t^n - P_t^x IC_t^{n,x} - P_t^f IC_t^{n,f} - P_t^n \Gamma_t \kappa^n y^n - AC_t^n \right) / (P_t GDP_t)$, and $M1_t \equiv M_{t+1} + S_t D_{t+1}$ is the money aggregate outstanding at the end of period t.

3 Empirical Strategy

In order to evaluate the performance of the model we use a combination of calibrated and estimated parameters. We chose to calibrate some of them mainly because, although we are using a large number of variables for the estimation, the data set is not rich enough to identify all of them; particularly those from production functions. This section first describes our calibration approach, presenting then the details regarding the estimation procedure.

3.1 Calibrated Parameters

The parameters describing the production function for sectors n, x and k are calibrated, following Calvo et al. (2008), using the input-output matrix. We present the values in Table 2, while a detailed explanation of the criteria used is included in Appendix B. Comparing the exportable and non-traded sectors, we can see that the later is more labor intensive, while the use of capital is similar in both. Also, a significant share of inputs in the exportable sector are non-traded goods. On the other hand, while most of the inputs used for investment-goods production come from the non-traded sector, the share of imported inputs is around 16%.

The time unit is meant to be a quarter. We set the steady state inflation to be equal to 6%, which is the average for the quarterly GDP deflator inflation in our sample. Also, the steady state values for the foreign and domestic interest rate, as well as the terms of trade, are equal to their sample mean (i.e. $i^* = 1.01$, $i = 1.08$ and $tot = 0.6$). In addition, the steady state value for the trend of TFP is $\gamma = 1.007$, equal to the average (quarterly) growth rate of GDP. These will determine the value for the discount factor β. It is important to highlight that we are departing here from the common strategy in previous studies estimating models for emerging countries, which generally assumes zero steady state inflation. Given that, up to first order, the steady state represent the unconditional mean of the variables, our approach has the advantage of "centering" the model closer to the unconditional mean in the data.

Four parameters are calibrated to standard values, for preliminary estimations indicate that they are weakly identified given our data set. We set the depreciation rate $\delta = 0.025$, a common value

[20] Given the market clearing conditions, GDP_t is also equal to real value added.

used in the literature. In addition, we follow Tovar (2006a,b), Caputo et al. (2006) and Castillo et al. (2006) to assign values for the elasticities of substitution between variates of labor and goods: $\theta_w = 2$ and $\theta_n = \theta_f = 6$. Given these, the values for κ^n and κ^f are chosen to make the steady state profits equal to zero. Also, we set the risk aversion coefficient $\sigma = 2$.

Finally, the parameters ϕ, η^x, a, $\bar{b}$ and g (the steady state value of government expenditures) are set to match the following steady state values: a share of time devotes to work equal to 20%, a 10% of the total labor suply working in the exportable sector,[21] and shares of exports, imports and government expenditures over GDP to match their sample averages (22, 23 and 10%, respectevely).

3.2 Bayesian Approach

The other parameters, collected in the vector Θ, are estimated using a Bayesian approach (see, for instance, Ann and Schorfheide, 2007). Given the sample $X^T = \{x_1, ..., x_T\}$, the object of interest is the joint posterior distribution of the parameters given the data,

$$p\left(\Theta|X^T\right) = \frac{L\left(X^T|\Theta\right)p\left(\Theta\right)}{\int L\left(X^T|\Theta\right)p\left(\Theta\right)d\Theta},$$

where $L\left(X^T|\Theta\right)$ denotes the likelihood function, $p\left(\Theta\right)$ is the prior distribution. and the denominator is known as the marginal likelihood of the data.

In order to compute the likelihood, we first solve for the log-linear approximation to the policy functions around the non-stochastic steady state (in particular, we implement the method described in Schmitt-Grohé and Uribe, 2004). Given the linear solution, and the assumption of normally-distributed shocks, the Kalman filter can be used to compute $L\left(X^T|\Theta\right)$.

The vector of observables used for estimation includes the growth rates of output, consumption and government expenditures per capita, the trade-balance-to-output ratio, the overall and non-traded inflation rates, the share of traded value-added in total GDP, the growth rate of the real wage and of M1, the nominal depreciation, the domestic nominal interest rate, foreign inflation of imported and exported goods, and the foreign nominal interest rate (see Appendix B for data sources and definitions). Thus, in terms of the model's notation,

$$\begin{aligned} x_t \;=\; & \{\Delta\ln(GDP_t),\ \Delta\ln(C_t),\ \Delta\ln(G_t),\ TBY_t,\ \ln(\pi_t),\ \ln(\pi_t^n),\ \ln(s_t^n), \\ & \left.\Delta\ln(W_t/P_t),\ \Delta\ln(M1_t),\ \Delta\ln(S_t),\ \ln(i_t),\ \ln(\pi_t^{*f}),\ \ln(\pi_t^{*x}),\ \ln(i_t^*)\right\}, \end{aligned}$$

where Δ denotes the first-difference operator. In addition, we include i.i.d. measurement errors for domestic variables. The data is quarterly, from 1980:I to 2007:IV.[22]

It is relevant to notice that our set of observables includes more variables than most previous DSGE estimations for emerging countries. On one hand, we consider series that are of general interest for policy analysis –such as output, consumption, the trade balance, inflation, real wages, the exchange

[21] This value is infered from the fact that, according to the 2003 Input-Output Matrix, 10% of total wage payments correspond to the exportable sector. If wages are the same across sectors, as assumed in the model, this share is also the fraction of total labor in the sector. Additionally, this value implies that the share of non-traded value added on total value added is equal to 92%, close to the mean of this variable in the data (96%).

[22] Series are demeaned and the X-12 filter was applied to those showing significant seasonal behavior. Additionally, we have performed unit-root tests for these variables, generally rejecting the hypothesis of non-stationarity for these variables. Moreover, for those measured in differences these tests do not reject the null of unit root in levels.

rate and the nominal interest rate– which are those generally used in the literature. On the other hand, our data set also includes variables that may *a priori* help us identify several features of the model. Clearly, government expenditures and the three variables in the foreign block will be useful in characterizing their associated stochastic processes and disturbances. Additionally, our measure of the stock of money includes the holdings of both domestic and foreign currency, which contains information that may improve the identification of the parameters associated with the preference for liquidity and currency substitution.[23] The price of non-tradeables is included to help the model tell apart the price-adjustment parameters in both sectors. Finally, we use the share of non-tradeables value added on GDP, for it may contain relevant information to separately identify the parameters describing the sectorial technology shocks.

Given the likelihood and the prior (described below), we characterize the posterior distribution in two steps. First, the posterior is maximized[24] and the resulting mode is used as the starting value of a Random Walk Metropolis-Hastings algorithm, using a $\mathcal{N}(0, c\Sigma)$ as the proposal distribution.[25] The parameter c is calibrated to obtain an acceptance ratio close to 30% and the convergence of the chain is analyzed by checking recursive means. For each estimated alternative we generate two million draws from the posterior, eliminating the first million to reduce the dependence from initial values.

3.2.1 Priors

Our approach to assign the prior distribution for the parameters modifies the one proposed by Del Negro and Schorfheide (2006). While a detailed explanation of our method (as well as the differences with the original) is included in Appendix C, we describe here the general idea of the procedure and its implementation.

The advantage of using priors is to take our *a priori* beliefs into account in estimating the parameters of the model. However, it is not always clear how we should elicit these beliefs, expressing them in terms of statistical distributions. For some parameters, we can use information coming from previous studies (e.g. from micro-evidence, studies related with other countries or samples, or estimations performed using a different approach). This is the case, for instance, for those describing preferences, technology, frictions or policy rules. But this task is less straight forward for some other parameters, particularly those describing the driving forces of the model, for our beliefs are generally expressed in terms of certain stylized facts (moments). For instance, given that is well known that consumption is more volatile than output and that the trade balance tends to be countercyclical in emerging countries, *a priori* we may conjecture that shocks able to generate those features (such as, interest rate fluctuations or shocks to the trend of technology) are likely to be more important. The method proposed by Del Negro and Schorfheide (2006), and the modifications included here, give us

[23] Two comments are in order here. First, while Castillo et al. (2006) estimate a model with currency substitution, they do not use a measure of money as an observable. Second, it would be preferable to also include the peso/dollar decomposition of the total stock of money, which may in principle contain additional information to describe the currency-substitution block of the model. Unfortunately, a long series of such a decomposition is not available, either because central banks started to produce these series only recently, or because there have been significant methodological changes in computing this decomposition that makes the construction of such a long series a difficult task.

[24] This was implemented by combining two optimization algorithms: `csminwel` developed by Chris Sims (available at http://sims.princeton.edu/yftp/optimize/) and `CMAES-DSGE` by Martin Andreasen (available at http://www.econ.au.dk/DCSC/DCSC_mma2.htm).

[25] Σ is the inverse of the posterior's Hessian evaluated at the mode computed in the first step. This matrix is computed numerically, and it is updated after the first 500K draws if a new maximizer is found by the Metropolis-Hastings.

a way to translate those beliefs collected in a set of moments into a distribution for the parameters.

Formally, let the vector of parameters Θ be decomposed in two groups, i.e. $\Theta = [\Theta_1', \Theta_2']'$. The subset Θ_1 contains parameters for which we can assign standard distributions as priors based on parameter constraints and on previous studies (preferences, technology, policy, etc), while Θ_2 collects the ones for which this task is not easy to implement (in our case, those describing the evolution of the driving forces and measurement errors). Our prior distribution takes the following form

$$p(\Theta|\Omega^*) \equiv c_1(\Omega^*) L(\Theta_1, \Theta_2|\Omega^*)\pi(\Theta_2)p(\Theta_1).$$

The distribution $p(\Theta_1)$ is the prior that we choose based on previous studies, while $\pi(\Theta_2)$ is an initial prior for Θ_2, which might be uninformative (i.e. flat). The sufficient statistics of interest are collected in Ω^* and the function $L(\theta_1, \Theta_2|\Omega^*)$ can be interpreted as a measure of how well can the model replicate, *a priori*, the target moments collected in Ω^*. In particular, we specify this as a transformation of a minimum-distance objective function that seeks to match a collection of data moments (specified below) with those generated by the model, in the spirit of the Laplace-type estimator suggested by Chernozhukov and Hong (2003). Finally, the constant $c_1(\Omega^*)$ is chosen to make the prior $p(\Theta|\Omega^*)$ proper (see Appendix C for details).

It is important to notice that under this approach the parameters will generally not be independent (although according to $p(\Theta_1)$ and $\pi(\Theta_2)$ they might be). The usual practice in estimating DSGE models is to specify independent priors, which is generally assumed for simplicity. However, our goal is to choose a distribution that makes our model as close to the moments that represent our beliefs as possible; which may perfectly require a distribution in which parameters are dependent. Moreover, while the targeted moments Ω^* and the functions $p(\Theta_1)$ and $\pi(\Theta_2)$ are the same regardless of the particular model, the distribution $p(\Theta|\Omega^*)$ will change as we estimate different versions of the model. Therefore, for each estimated model we will report the final implied prior.

Columns three to five in Table 3 describe the initial prior distributions $p(\Theta_1)$ and $\pi(\Theta_2)$. In terms of the preference parameters for both types of currency, our main reference is the estimation for Peru in Castillo et al. (2006). They calibrate $\zeta = 2$, $\chi = 1$ and $b = 0.83$, while estimating values for ν between 0.6 and 0.7. On the other hand, Batini et al. (2007) calibrate $\chi = 4$, while Felices and Tuesta (2007) set $b = .83$, $\zeta = 4.1$, $\nu = .5$ and $\chi = \{0.9, 2\}$. Therefore, we center the priors for these parameters around the values from Castillo et al. (2006) and set the dispersion according to the calibrations used in these other studies.

In terms of habit persistence, previous studies show mixed evidence for ρ_c. While Castillo et al. (2006) estimate it to be large (in the range of $[0.7, 0.9]$ for Peru), Medina and Soto (2005) found a value close to 0.3 for Chile and the results in Uribe and Yue (2006) indicate $\rho_c = 0.2$ for a panel emerging countries. Thus, we chose a Beta distribution with mean similar to that from Castillo et al. (2006), given that their utility specifications is closer to ours.

The wage adjustment cost coefficient, ψ_w, is estimated by Tovar (2006a) to be between 0.24 and 0.86 for three Latin American countries, while Tovar (2006b) obtains a value of 1.35 for Korea. Our prior includes these values in the 95% confidence band. In terms of price adjustment costs, we are not aware of emerging-countries studies estimating a model with pricing parameters that differ across sectors. Using a one-sector model, Tovar (2006a) estimates values between 4.6 and 7.13 for his sample of Latin American countries and 5.7 for Korea in Tovar (2006b). Therefore, we assign the same prior for both ψ_n and ψ_f, with a mean of 5.25.[26]

The coefficient in the country premium faced by households ψ_d is a parameter usually calibrated to low values ranging from 0.001 to 0.1, and the evidence from estimated exercises is mixed: while Castillo et al. (2006) find it to be almost zero in Peru, Caputo et al. (2006) obtain values between 0.1 and 0.9 for Chile. Conservatively, our initial prior assigns most of the probability mass to low values. The capital adjustment cost is also generally calibrated, an exception being Castillo et al. (2006) that obtains a values between 0.34 and 0.98 for Peru. Additionally, the previous literature do not make a sectorial distinction for capital adjustment costs. Thus, we assign the same prior for both parameters, with a 95% confidence region wider then the estimated values mentioned before.

In terms of the elasticity of substitution between traded and non-traded good, φ, Mendoza (1995) uses a value close to 1.3 for emerging countries, while Gonzalez-Rozada and Neumeyer (2003) estimate it to be around 0.4 for Argentina. Other studies assuming that all goods are tradeables use a related measure: the elasticity of substitution between domestic and foreign goods. Medina and Soto (2005) estimate a value of 0.6, while Castillo et al. (2006) obtain values between 1.07 and 2.5. Given this dispersion in the literature, we assign an Inverse Gamma distribution with a wide confidence region.

The estimated parameters describing the entrepreneurs problem are the external finance premium in steady-state (rp), the variance of the idiosyncratic shock (σ_ω) and the monitoring cost (μ).[27] Choosing priors for these based on previous research is however difficult. On one hand, as mentioned before, there are few studies estimating models that include these type of financial frictions (e.g. Tovar, 2006a, 2006b, and Elekdag et al., 2005). However, they use a simpler version of the financial accelerator, making their results hard to interpret under the more general framework.[28] Therefore, our prior is based on emerging-countries papers that calibrate models of the financial accelerator compatible with ours, even though these values are generally chosen based on U.S.-related studies. Cook (2004) and Gertler et al. (2007) use $rp = 1.035$, $\sigma_\omega = 0.28$ and $\mu = 0.12$, while Devereux et al. (2006) set them to be, respectively, 1.02, 0.2 and 0.5. Additionally, from Elekdag et al. (2005) we can infer an estimate for rp for Korea in a range between 1.02 and 1.05. The chosen distributions include these values within the 95% confidence band.

Previous estimates of the smoothing coefficient in the Taylor rule (α_i) show mixed results. According to Tovar (2006a,b), it ranges from 0.03 to 0.71 for his sample, Medina and Soto (2005) found values around 0.3 for Chile, Elekdag et al. (2005) estimates a value of 0.68 for Korea and Castillo et al. (2006) found it to be small for Peru (around 0.04). We then choose a uniform prior for this parameter. Additionally, the evidence in terms of the response to inflation and to output growth is also disperse: α_π ranges from 1.27 in Castillo et al. (2006) to 2.6 in Tovar (2006b), while α_y is almost zero in Castillo et al. (2006) and Elekdag et al. (2005) but Tovar (2006b) found a value of 1.4 for Korea. We thus choose a normal prior centered in the average of these previous estimates and with enough variance to include this previous results with significant mass.

For the parameters describing the exogenous stochastic processes in the model (i.e. the driving forces and measurement errors) we assign uninformative initial priors. The autocorrelation of the

[26]Other studies estimating models with price and/or wage rigidities for emerging countries generally use staggering *a la* Calvo, making their results difficult to interpret in our framework. See, for instance, Medina and Soto (2005), Elekdag et al. (2005), Castillo et al. (2006), Caputo et al. (2006) and da Silveira (2006).

[27]In steady-state, these three will determine the survival rate ϑ.

[28]These studies generally estimate two parameters: the steady state leverage ratio and the elasticity of the premium with respect to this ratio. However, these two "reduced form" coefficients are a complicated function of the three parameters describing the financial accelerator, and thus the later cannot be computed from the former.

shocks have a uniform prior between zero and one, with the exception of ρ_γ for which we use a Beta distribution with mean of 0.3, for it is generally estimated to be small. The feedback of GDP to government expenditures $\rho_{g,gdp}$ has a uniform prior in the range [-1,1]. The standard errors of shocks also have a uniform prior: for driving forces is in the [0,0.15] range, while for measurement errors it is limited by 25% of the standard deviation of the particular variable in the data.

After setting the initial priors $p(\Theta_1)$ and $\pi(\Theta_2)$, we continue by describing the minimum-distance function that determines $L(\Theta_1, \Theta_2|\Omega^*)$. In particular, this function measures the difference between the following data and model moments related with the 11 domestic observables: the standard deviations, the correlations of all variables with output growth, the trade-balance-to-output ratio and inflation, as well as all the first order autocorrelations; obtaining a total of 49 distinct moments. In addition, the weighting matrix that completes this function is set to the optimal one (see Appendix C for further details).[29]

Columns six and seven on Table 3 report the mean and the 95% confidence band from the final prior under the Baseline model. Draws from this distribution are obtained with a Metropolis-Hastings algorithm analogous to the one specified before. As we can see, the information contained in the selected moments significantly updates the initial prior. In some cases, this additional information helps to narrow the prior's confidence bands (e.g. the smoothing and output-growth coefficients in the Taylor rule, or the risk premium in steady state), while for others it also significantly changes the center of the distribution.

To conclude, the final prior allow us to have an *a priori* rank of the variances of the shocks: in order to replicate the targeted moments, the model requires a relatively large variance for the inflation target shock, followed by, in order of importance, the country premium shock and by disturbances to government expenditures, the non-stationary productivity and the TFP in the exportable sector. Of course, this order might change under the posterior (and indeed it will), for the likelihood may contain additional information allowing a better characterization of the parameters' distribution.

4 The Fit of the Baseline Model

In this section we first describe the estimated posterior distribution, paying particular attention to those parameters describing the frictions that are characteristic of emerging countries. We then perform a posterior predictive analysis to establish the extent to which the Baseline model can fit the data.

4.1 Posterior Distribution

The last two columns of Table 3 describe the estimated posterior distribution. In terms of the demand for money, we can see that b is estimated to be close to one, with a tight confidence band, and that the elasticity of substitution ζ has a posterior mean of 0.08. Putting this result in the context of the related literature, on one hand, the key channel relating currency substitution with monetary policy according to Felices and Tuesta (2007) (i.e. the marginal utility of consumption depending on money holdings) is estimated to be irrelevant for Mexico. On the other hand, the estimation exercise in

[29]These moments are computed from the same sample used for the estimation. Alternatively, Del Negro and Schorfheide (2006) use a pre-sample to compute their sufficient statistics. This approach will be unfortunately too costly in our case because we only have a short sample available.

Castillo et al. (2006) calibrates $b = 0.83$. While results are not comparable as they use Peruvian data, this finding at least suggests that it might be important to estimate this parameter as well.[30]

While the role of currency substitution is reduced given the value of b, the parameters ν and χ might still play a role (as long as $b < 1$) in determining the demand of pesos relative to dollars. The elasticity of substitution has a wide confidence region, with values from 1.4 to 6.9, while the confidence band for the share of dollars in the liquidity index indicates a significance range between almost zero and 0.2. The last parameter in the utility function, ρ_c, indicates a strong degree of habit persistence.

The wage adjustment cost, ψ_w, has a posterior mean of 0.4, which is somehow bigger than the value of 0.24 estimated for Mexico by Tovar (2006a). Looking at price adjustment costs, the estimation indicates that this friction is significantly more severe for imported goods. This is not surprising given that the correlation between aggregate and non-traded inflation is extremely high in the data (see Table 4): the model requires prices in the f sector to be more sticky in order to obtain such a strong correlation. In addition, this distinction puts a warning sign in interpreting the estimation of price stickiness in the literature. As commented before, previous studies do not allow for sectorial decomposition of inflation and all goods are assumed to be tradables. The case of Mexico thus shows that these assumptions are likely inappropriate.[31]

The posterior mean for the country premium coefficient implies an elasticity with respect to the debt-to-GDP ratio (equal to $\psi_d\bar{b}$)[32] of around 0.08 and significantly greater than zero (the implied lower bound is 0.05). Additionally, capital adjustment costs seem to be similar in both sectors, although the confidence band for these parameters includes a wide range of values. Finally, the estimated elasticity of substitution between traded and non-traded good is high (between 2.6 and 3.4), which is significantly bigger than the values usually calibrated in the literature –generally based in reduced-form estimations.

Turning to the parameters describing financial frictions, it is relevant to compare the initial prior and the posterior. Recall, from the discussion above, that the initial prior was set to reflect the calibrated values used in policy exercises which, as discussed, are generally drawn from U.S.-related studies. As we can see, the estimated parameters are completely different, particularly indicating that financial frictions are more severe that what is generally assumed. Moreover, the posterior confidence band does not even include the initial prior mean. This represents a significant drawback for the related literature, and gives additional support to our original motivation about the empirical relevance of these studies.

The estimated Taylor rule displays a mild smoothing coefficient, while the responses to inflation and output growth (with posterior means of 2.08 and 0.46, respectively) are in the range of previous studies. In terms of the three monetary-related disturbance, the shocks to GDP-growth target seems to be more volatile and persistent. On the other hand, σ_i and σ_π display similar posterior means, while the inflation target seems to be more persistent than $\hat{i}$.

The volatility of the country premium shock is comparable with that of the GDP target and it is also significantly persistent. The disturbances to government purchases display high volatility as well

[30] Particularly in terms of currency substitution, Mexico and Peru seem to be really different. For instance, Levy-Yeyati (2006) documents that the annual share of dollar-denominated deposits was, on average, 67% for Peru between 1991 and 2004 but only 7.3% for Mexico in that same period.

[31] While Devereux et al. (2006) use a model with a sectorial decomposition similar to ours, they calibrate the price stickiness parameter to be the same across sectors.

[32] At the posterior mean, the debt-to-GDP ratio in steady state, $\bar{b}$, is 0.04.

and the posterior confidence bands for its persistence indicate values from 0.2 to 0.7. Additionally, government expenditures display a significant procyclical response to lagged output.

Finally, in terms of technology, the shock to the stationary productivity in the exportables sector is the most volatile, with a posterior mean of 0.08, which is even higher than that estimated for the foreign price of exports (around 0.06). Both stationary TFP shocks display high persistence (the posterior means for ρ_{z^x} and ρ_{z^n} are, respectively, near 0.8 and 0.9). A more illustrative analysis of the relative importance of each driving force will be presented in the next section, when we perform the variance decomposition exercise.

4.2 Posterior Predictive Analysis

In order to asses the goodness of fit of the model, we start with a visual inspection of the estimated path of the observables. Figures 1 and 2 display the actual series for the domestic variables, as well as the posterior mean of their smooth version according to the Baseline model.[33] As can be seen, the fit in terms output and consumption growth, as well as for both inflations, is almost perfect. The model does a good job also for the trade balance, the share of non-tradables and M1. The fit seems also appropriate for the nominal depreciation, although the model seems to overestimate its volatility for relatively stable periods. Overall, the model seems able to replicate the reduction in volatility that can be observed from most of the variables after the Tequila crisis.

The predicted path for the nominal interest rate is also close to the actual series, with some minor caveats. First, the model seems to underestimate it for the first year of the sample, while it implies higher-then-observed values from 1983 and 1985. Additionally, the interest rate in the last five years of the sample is somehow more volatile than in the data. On the other hand, the variable for witch the model clearly provides a very limited fit is the real wage.

Table 4 compares a number of moments computed from the data and those (unconditional) implied by the model. The Baseline specification closely replicates the standard deviation of the real variables as well as that of both inflations and the nominal interest rate, although it mildly overestimate those of output and consumption. In particular, the model predicts consumption being more volatile than output, a feature that is characteristic of most emerging countries. Also, in line with the evidence presented before, while the volatility of the monetary aggregate and the exchange rate is over estimated (especially for the former), the implied standard error of real wages is predicted to be smaller in the model.

In terms of the cyclical behavior of the variables –measured by their correlation with GDP growth– the model provides an adequate approximation to the data. While the posterior mean of these moments is somehow smaller (in absolute value) to their empirical counterpart, most of the posterior confidence regions generally overlap with the error bands computed from the data. In particular, the model is able to replicate the countercyclicality of the trade balance, inflations, interest rates and nominal depreciation. Important mismatches can be observed, however, in terms of the correlation of the share of non-tradables and real wages with GDP (the later was expected given the poor fit in this dimension

[33]In general, the goal of a posterior predictive analysis is to characterize a vector of interest z (in this case, the smoothed series of observables) which is a function of the parameters of the model (i.e. $z = h(\Theta)$). Given draws from the posterior of the parameters, $p\left(\Theta|X^T\right)$, we can easily characterize moments associated with the posterior of the vector of interest $p\left(z|X^T\right)$. For instance, if we have M random draws from the posterior of parameters Θ_i for $i = 1, ..., M$, an estimate of $E\left(z|X^T\right)$ can be computed as $M^{-1}\sum_{i=1}^{M} h(\Theta_i)$.

described before).

On the other hand, the fit is significantly better in terms of the correlation of the variables with aggregate inflation. Two minor exemptions are the correlations with GDP and consumption growth: in the model, the first is smaller while the latter is somehow bigger. The fit is good also in terms of of the autocorrelation of the variables. While, as expected, the match is not good for real wages, most of the posterior means and point estimates in the data are similar. Additionally, the confidence bands in the data and in the model tend to overlap.

We conclude the section by summarizing the findings. Overall, the model seems to provide a good fit to the data, particularly in terms of output, inflations and the nominal exchange rate. A major exception is the ability of the model to account for the dynamics of the real wage. Additionally, the fit in terms of the nominal interest rate seems appropriate, with some minor limitations. Given these results, in the next section we investigate the role of the frictions that are characteristic of emerging countries in obtaining these results.

5 On the Importance of Emerging-Countries Frictions

We now turn to study which features of the model are more relevant in explaining the data. While the Baseline model contains many nominal and real frictions, we are particularly interested in assessing the role of those that are characteristic of Emerging countries. In particular, four different versions of the Baseline model are estimated.[34] First, we will shut down the currency substitution channel, keeping the demand for real balances. This specification (denoted as No C.S.) is obtained by setting $\nu = 1$.[35] Given the estimated value of b close to one for the Baseline model, it is likely that this alternative will improve the overall fit of the model.

A second variant eliminates the liability dollarization friction (No L.D.), while still maintaining the financial accelerator mechanism. In this case, entrepreneurs borrow in pesos using the domestic bond market, making the domestic interest rate the relevant opportunity cost for lenders. Therefore, surprises in the nominal exchange rate will have no first-order effect on entrepreneurs net worth, although they may have an indirect impact.

In addition, a version without the financial accelerator is estimated (No F.A.). Under this alternative, entrepreneurs are no longer part of the economy and capital is instead owned (and accumulated) by households. While the endogenous country premium in equation (1) is maintained, changes in the cost of borrowing will produce no direct effects in the supply side of the economy.

The final specification eliminates the use of intermediate inputs for production (No I.I.). In particular, we set $\alpha_x^n = \alpha_x^f = \alpha_n^x = \alpha_n^f = \alpha_k^f = 0$ and adjust the other coefficients to maintain the homogeneity of degree one in the production functions. Given the calibrated values for these parameters presented in Table 2, this alternative will most likely have an impact by eliminating the transmission of import price shocks to the price of investment goods.

In the rest of the section, we first address the goodness of fit of these specifications by means of both informal and formal model comparison tools. After determining which of them are more useful in explaining the data, we compare the results in terms of the estimated posterior of the parameters for these preferred specifications and perform a variance decomposition exercise.

[34] The Technical Appendix contains also the equilibrium conditions for each of these cases.

[35] Under this restriction, the parameter χ becomes irrelevant.

5.1 Model Comparison

As we did before, we start by comparing the smoothed series of observables implied by each alternatives with the actual data, presented in figures 3 and 4. For most of the variables, this visual inspection does not help to tell models apart. The only noticeable difference seems to be in terms of the nominal interest rate. While the model that excludes currency substitution generates a similar path for this variables as in the Baseline, albeit still less volatile than the data, the fit of this variables in the other three alternatives is even worst. Additionally, neither of them seems to produce and improvement in terms of the real wage.

In order to quantify the differences across models, we begin by comparing them according to same set of moments previously analyzed. Table 5 shows the posterior mean and confidence regions for the selected moments, reproducing also those from the Baseline and their data counterparts to facilitate the comparison. In terms of standard deviations, the fit of the No C.S. alternative is similar to that of the Baseline. The only significant difference seems to be in the volatility of the interest rate, which is estimated to be smaller. On the other hand, the performance of the other three alternatives is less satisfactory. In particular, neither of these is able to generate more volatility for consumption compared to GDP. Additionally, these three specifications imply even smoother interest rates and real wages.

While the Baseline and No C.S. models have similar predictions in terms of volatility, the latter does not perform as well in terms of correlations with GDP growth. Counterfactually, inflation and the nominal interest rate are estimated to be procyclical. Additionally, the negative correlation of trade balance with output is milder under this specification. On the other hand, while most of these correlations under the other alternatives have the correct sign, they are not as close to the data as the Baseline model. The only apparent improvement is in terms of the cyclical behavior of consumption.

Regarding the correlation with inflation, none of the alternatives produce a significant improvement relative to the Baseline. For instance, on one hand, the No L.D., No F.A. and No I.I. specifications generate a comovement between inflation and the nominal devaluation that is closer to the data. However, these three produce a significantly smaller correlation with money growth. Additionally, the correlation of both consumption growth and the trade-balance-to-output ratio with inflation are underestimated by No C.S., No L.D. and No I.I.. Finally, a similar pattern can be observed in terms of the first order autocorrelations.

The next step is to compare the alternatives using formal tools. One of the most widely used methods under a Bayesian framework is the marginal likelihood, which allows to compare models in terms of their relative one-step-ahead forecasting ability (see, for instance, Geweke, 1999). Table 6 present the log marginal likelihood of the four alternatives relative to that of the Baseline. As can be see, according to this criteria, eliminating the demand for dollars from the utility function produces the most significant improvement to the overall fit of the model. The No L.D. alternative also seems to adjust the data better that the Baseline, but it is worst than the No C.S. model. On the other hand, eliminating either the financial accelerator mechanism and the intermediate demand for consumption goods provides a worst fit to the data, particularly the No I.I. alternative.

While the marginal likelihood is a useful tool to compare models in terms of their overall fit, it is also of interest to determine in which particular dimensions different models can perform better. To this end, we implement the loss function-based evaluation proposed by Schorfheide (2000), who provides a formal way to compare models in terms of their ability to match certain data features of interest. A detailed description of this procedure, as well as our implementation, is presented in Appendix D.[36] The general idea is, for a given set of targeted moments, to compare the performance of each DSGE relative to a reference model that is more densely parameterized and that provides a good fit to the data (in our case, Bayesian VAR with a Minnesota prior). In addition, a loss function that penalizes deviations of the DSGE model prediction in terms of the moments of interest relative to the reference model is specified (we use a quadratic loss). The alternative DSGE models are then ranked in terms of their posterior risk, defined as the expected loss incured in using the particular model.

We compare the different specifications based on their ability to match several covariances functions: the autocovariance of each domestic variable and their contemporaneous and lagged covariance with output growth and aggregate inflation, all of them up to eight quarters. Table 7 displays the ratio of the risk of the particular set of moments for each model, relative to the Baseline (if the ratio is bigger than one, the Baseline is preferred).[37] The first general conclusion that can be drawn is that, in line with the marginal-likelihood-based results, the specification that exclude intermediate inputs generally provides the worst fit relative to all other specifications. Such a clear difference cannot be found in the other alternatives, for which we analyze each set of moments separately.

In terms of autocovariances, the Baseline model clearly outperforms the others for output growth and, to a less extent, the nominal interest rate. It also better approximates the autocovariance of the nominal exchange rate compared with No C.S., although it seems inferior in this dimension relative to No L.D. and No F.A.. On the other hand, these three alternatives seem to outperform the Baseline for the other variables. Additionally, among these specifications, shutting down the currency substitution channel improves the fit in terms of the autcovariances of trade balance, both inflations and the share of non-tradables, while the No F.A. alternative seems more appropriate in terms of consumption and the No L.D. better accounts for the dynamics of the nominal depreciation.

Looking at the lagged covariances of the variables with respect to output growth, the Baseline model generally provides a better fit. Two exceptions are the covariance with TBY, in which the No I.I. and No C.S. are preferred, and with $M1$, where No C.S. seems to be preferable. Finally, either the Baseline or the No C.S. specification appear superior in terms of the lagged covariances with inflation.

After this detailed model comparison exercise, we can draw the following conclusions. First, of the four evaluated frictions that are of special relevance for policy analysis in emerging countries, the inclusion of intermediate inputs is the one that appears more important. On the other hand, currency substitution does not seems to be consequential, although eliminating this channel counterfactually induces a procyclical inflation. Additionally, the No L.D. and No F.A. specifications, while improving the fit along a few dimensions, are generally inferior relative to either the Baseline or the No C.S. specification, which seems to indicate that both play a relevant role.

5.2 Posterior Distribution

Given the results from the previous analysis, we now present the parameter's posterior for the No C.S. specification. The goal is to see if the estimated parameters are similar to those from the Baseline model. Table 8 displays the posterior mean and confidence for the parameters under this alternative

[36] As described in the Appendix D, this method is more general and flexible that our particular application.

[37] Real wages are omitted from the table as we already saw that the fit is not good.

and the Baseline.[38] In terms of utility-related coefficients, b is estimated to be close to one as in the Baseline. Thus, in spite of its denomination, money appears to have no significant influence in the marginal utility of consumption. Additionally, while the estimate of ζ is bigger in the No C.S. specification, this value is still significantly smaller than in previous studies.

While the posterior mean for wage and price adjustment-costs parameters are somehow smaller if we exclude the currency substitution channel, the confidence bands significantly overlap for both specifications. In particular, it is still the case that prices of imported goods appear to be more sticky than for non-tradeables.

The elasticity the country premium is smaller in this case, around 0.03, but still significantly positive (the implied lower bound is near 0.02). On the other hand, the estimated elasticity of substitution between traded and non-traded goods is similar under No C.S., while the capital adjustment costs are estimated to be less important.

In terms of the financial accelerator mechanism, the absence of currency substitution preserves the previous findings: while the posterior means are somehow different, the confidence bands are similar for both specifications. Moreover, it is still the case that financial frictions are estimated to be more severe than what is usually calibrated in policy-related studies. Results are also similar in terms of the coefficients in the Taylor rule.

Finally, there are some discrepancies in terms of the parameters describing the evolution of the driving forces. However, it is more illustrative to study how different are the exogenous processes by analyzing how they propagate to the rest of the economy, which we analyze in what follows.

5.3 Variance Decomposition

Table 9 presents the decomposition of the unconditional variance for the domestic variables under the Baseline model. In line with the previous discussion, the model provides a good overall fit: the contribution of measurement errors in explaining the variability of the observables is generally small. The exception is, as before, the real wages (the measurement error explains almost 80% of the variances).

A second general observation is that the (stationary) sectorial technology shocks play an important role in explaining the behavior of all variables, in particular that for exportables. Regarding real variables, each of them account for near 30% of output fluctuations and they togheter generate around 40% of the variance of consumption and the trade balance. In addition, the shock in the exportable sector accounts for near 30% of the variance of both inflations and between 35 and 45% of policy-related variables, while the shock in the other sector only have a minor contribution for these. On the other hand, the non-stationary productivity shock seems to play no significant role, with the exception of consumption for which it explains around 35% of the variance.

Among the foreign driving forces, the price of exportables appears to have the biggest impact, although it is of second order relative to the sectorial technology disturbances. Around 10% of the variability of inflation, consumption and the nominal interest rate is explained by this shocks, and it seems even more important for the trade balance, the nominal exchange rate and the stock of money.

Another driver with a relevant contribution is the shock to the country premium, explaining around 40% of the variance of the non-traded share and close to 20% of the variance of GDP, the

[38] For completeness, the table also includes those for the other three specifications, even though we regard them as inferior. Additionally, the final prior for each alternative can be found in Table C.1 in Appendix C.

trade balance and M1. Additionally, it has a smaller impact in terms of inflation, the nominal interest rate and depreciation, contributing to at most 10% of their variability.

In terms of policy-related shocks, unexpected changes in both targets together explain almost 40% of the fluctuations in inflation, but only around 10% of money, nominal depreciation and the interest rate. On the contrary, shocks to government expenditure and the Taylor-rule residuals have a negligible impact.

Turning to Table 10, which presents the variance decomposition for the No C.S. specification, we can see that many of the previous conclusion are maintained, with some important caveats. On one hand, while both sectorial shocks still have an important role, their influence in both inflations is significantly smaller. External shocks, country premium disturbances and non-stationary TFP appear to be of similar importance compared with the Baseline model. Moreover, measurement errors for the interest rate are more relevant for this alternative.

The main difference across these two specifications is in terms of monetary policy shocks. First, the residual of the Taylor rule seems to be more important under No C.S.: it explains almost 20% of output fluctuations and near 10% of inflation volatility. Additionally, shocks to both targets play significantly bigger role in explaining prices, for combined they now account for almost 70% of the variance of both inflations.

As a final exercise, Figure 5 present a historical decomposition of aggregate inflation, the nominal depreciation and the domestic interest rate in both preferred specifications. While the variance decomposition give us an idea of the average contribution of each shock, this approach is useful to understand if the impact of the driving forces has change over time. To facilitate the exposition, we have clustered the sources of fluctuations in three groups: monetary policy shocks are those appearing in the Taylor rule, other domestic shocks include the three technology disturbances, government expenditure and country premium shocks, and the rest are international shocks.

In terms of inflation, it seems that monetary shocks have been an important determinant of the two major peaks experienced in the 80's. Nevertheless, other domestic shocks appear to have played an additional relevant role in the first of these episodes, while international disturbances (particularly the drop in oil prices in 1986) have also contributed to the second.[39] On the other hand, non-policy domestic shocks are estimated to be the main factor during the Tequila crisis. This can partially be explained by the fact that the estimated model seems to assign an important part of the sudden stop to a negative productivity shock in the exportable sector. Lastly, the observed stabilization in the level of inflation experienced since 1996 appears to be mostly explained by the evolution of international variables.

On the other hand, regarding the fluctuations in the nominal depreciation rate, the historical decomposition is less clear, for it seems complicated to attribute the episodes of large fluctuations in this variable to a particular set of shocks. Finally, in line with the variance decomposition exercise, most nominal interest rate movements were mainly originated by the endogenous response to other real and international shocks. Moreover, it seems that these two groups of shocks have historically pushed this variable in opposite directions.

[39] In the model, a drop in the price exportables generates inflation through the implied nominal depreciation.

6 Conclusions and Future Research

This work presents a quantitative evaluation of the empirical relevance of several frictions that, as has been argued, constrain the design of monetary policy in emerging countries. We were motivated by the fact that the recent literature does not provide a satisfactory assessment of the goodness of fit of models used to draw policy recommendations, which might potentially limit the relevance of their conclusions.

Our framework included a sectorial decomposition of the productive sector, the use of intermediate inputs, incomplete pass-through, endogenous premium to finance capital accumulation, balance sheets effects due to liability dollarization, currency substitution, price and wage rigidities, as well as eleven driving forces. The model was estimated using a Bayesian approach with a quarterly data set from Mexico, including more observables than what is typically used in estimations of emerging-market models.

Our findings carry both good and bad news. On one hand, a model that includes these distinctive characteristics of emerging economies can indeed provide a good approximation to the data, which makes its use for policy analysis appealing. Moreover, we have been able to identify which of these frictions appear to be more important in fitting Mexican data. In particular, accounting for intermediate inputs seems to be most relevant, while the currency substitution channel has a negligible estimated role.

On the other hand, however, our results also suggest that many of the parameterizations chosen in the policy literature are significantly different from what arises after a meticulous estimation exercise, placing a warning sign in interpreting these previous conclusions. This seems to be the case particularly for financial frictions, prices stickiness and money demand. Additionally, many of these policy-related papers exclusively consider foreign shocks as driving forces. Nonetheless, according to our findings these appear to be relatively less important compared with domestic sources of fluctuations for the Mexican case.

We conclude by suggesting several potential venues for future research. First, while results based on up-to-first-order solutions are encouraging, it seems relevant to also estimate the model using a higher order of approximation. As discussed before, this solution technique will allow a better characterization of changes in exchange-rate regimes. Additionally, given that the degree of uncertainty (measured, for instance, by the volatility of variables like GDP, inflation, etc.) in these countries has been considerable, a higher order of approximation might be more appropriate to account for endogenous responses to uncertainty (e.g. precautionary savings cannot be captured with a first-order approximation).

A second relevant study would be an international comparison, for evidence suggests that the role of these emerging-countries frictions are significantly different across countries. For instance, Levy-Yeyati (2006) documents that, for a sample of 15 Latin American countries in 2000, while the mean of the share of dollar-denominated deposits was close to 32%, the observed values ranged from 1.5% to around 90%. He also reports ratios of total dollar liabilities over GDP for these countries from near 20% to almost 150%; with mean and median of, respectively, 63% and 50%. Clearly, the role of both currency substitution and liability dollarization is expected to vary for different emerging countries, which will provide an additional empirical test for the model.

Additionally, in this paper we have just evaluated the in-sample goodness of fit of the model. It could be of interest to also investigate the out-of-sample performance of the model, by comparing its forecasting ability with BVAR models or by using a DSGE-VAR approach. Finally, given that our findings indicate that the parameter values of models previously used for policy analysis are not in line with estimated results, it seems important to re-evaluate issues like exchange-rate regimes and optimal stabilization policies using a model that is more empirically sound.

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A Tables and Figures

Table 1: Estimated VECM(1) for the rest-of-the-world variables.

	Coefficients						Std. Dev.
Equation	π_t^{*f}	π_t^{*x}	π_{t-1}^{*f}	π_{t-1}^{*x}	i_{t-1}^*	tot_{t-1}	σ_j
π_t^{*f}	–	–	0.397	0.031	0.007	-0.021	0.008
			(0.09)	(0.02)	(0.03)	(0.01)	(0.00)
π_t^{*x}	–	–	0.597	0.085	-0.156	-0.347	0.057
			(0.67)	(0.09)	(0.25)	(0.08)	(0.01)
i_t^*	0.065	-0.009	0.063	-0.003	0.925	0.002	0.002
	(0.03)	(0.00)	(0.03)	(0.00)	(0.04)	(0.00)	(0.00)

Note: The table shows the MLE estimates and their respective standard errors in parenthesis (computed by Boostrap, based on randomly drawing 5000 series of reduced-form errors).

Table 2: Calibrated values for α_j^i, Mexico.

	Sector (j)		
Input (i)	x	n	k
x	—	0.039	—
n	0.310	—	0.835
f	0.056	0.072	0.162
l	0.116	0.302	0.001
k	0.519	0.587	—

Note: Based on the 2003 Input-Output Matrix, according to the methodology described in Appendix B.

Table 3: Prior and Posterior Distributions, Baseline Model.

Para-			Initial Prior		Final Prior		Posterior	
meter	Description	Dist.	Mean	95% C.B.	Mean	95% C.B.	Mean	95% C.B.
b	Share of X in V	B	0.71	[0.4,1]	0.51	[0.4,0.6]	0.99	[0.99,1]
ζ	E.o.S. between X and Z	IG	2	[0.2,9.3]	1	[0.9,1.2]	0.08	[0.06,0.1]
ρ_c	Habit persistence	B	0.6	[0.2,0.9]	0.44	[0.2,0.6]	0.83	[0.81,0.86]
ν	Share of M in Z	B	0.67	[0.3,0.9]	0.44	[0.4,0.5]	0.1	[0.03,0.21]
χ	E.o.S. between M and D	IG	2	[0.2,9.3]	2.84	[2.4,3.6]	3.9	[1.38,6.86]
ψ_w	Wage adj. cost	G	1	[0.1,2.8]	0.02	[0,0.05]	0.44	[0.12,0.79]
ψ_d	Country premium coef.	IG	0.01	[0,0.01]	0.07	[0,0.1]	1.91	[1.19,2.79]
φ	E.o.S. n and T	IG	2	[0.4,8.3]	0.75	[0.3,1.3]	2.96	[2.59,3.44]
ψ_n	Price adj. cost in n	G	5.25	[1.1,13]	5.32	[4.5,5.8]	1.07	[0.2,2.88]
ψ_f	Price adj. cost in f	G	5.25	[1.1,13]	8.62	[8,9.2]	14.2	[10.1,18.5]
ψ_k^n	Capital adj. cost. in n	IG	0.5	[0.1,1.6]	0.42	[0.2,0.8]	1.92	[0.66,4.11]
ψ_k^x	Capital adj. cost. in x	IG	0.5	[0.1,1.6]	3.16	[2.7,3.5]	1.86	[0.39,6]
rp-1	Risk Premium in SS	G	0.01	[0,0.05]	0.01	[0,0.02]	0.06	[0.05,0.1]
σ_ω	Std.Dev. of $\ln(\omega)$	IG	0.43	[0.2,0.9]	1.7	[1.4,1.9]	2.37	[1.93,2.81]
μ	monitoring cost	B	0.25	[0,0.6]	0.6	[0.3,0.8]	0.54	[0.45,0.68]
α_i	Coef. of i_{t-1}	U	0.5	[0,1]	0.56	[0.5,0.7]	0.08	[0,0.24]
α_π	Coef. of π	N	2	[1.6,2.4]	1.35	[1.2,1.5]	2.08	[1.91,2.29]
α_y	Coef. of g^y	N	0.5	[0.3,0.7]	0.54	[0.4,0.7]	0.46	[0.27,0.66]
ρ_i	Autocorr. of $\hat{i}$	U	0.5	[0,1]	0.37	[0,0.9]	0.34	[0.02,0.89]
ρ_π	Autocorr. of $\hat{\pi}$	U	0.5	[0,1]	0.26	[0.1,0.4]	0.69	[0.52,0.85]
ρ_y	Autocorr. of $\hat{g^y}$	U	0.5	[0,1]	0.44	[0,0.9]	0.94	[0.9,0.98]
ρ_{ξ^*}	Autocorr. of ξ^*	U	0.5	[0,1]	0.35	[0,0.6]	0.97	[0.96,0.99]
ρ_g	Autocorr. of g	U	0.5	[0,1]	0.66	[0.4,0.9]	0.43	[0.18,0.71]
$\rho_{g,gdp}$	Response of g_t to gdp_{t-1}	U	0	[-1,1]	0.55	[0.3,0.7]	0.17	[0.02,0.34]
ρ_γ	Autocorr. of γ	B	0.33	[0.1,0.7]	0.5	[0.3,0.7]	0.07	[0.02,0.16]
ρ_{z^x}	Autocorr. of z^x	U	0.5	[0,1]	0.24	[0,0.7]	0.79	[0.74,0.82]
ρ_{z^n}	Autocorr. of z^x	U	0.5	[0,1]	0.56	[0,0.98]	0.89	[0.84,0.95]
σ_i	Std.Dev. of $\hat{i}$	U	0.08	[0,0.1]	0.00	[0,0.01]	0.01	[0,0.02]
σ_π	Std.Dev. of $\hat{\pi}$	U	0.08	[0,0.1]	0.04	[0.03,0.05]	0.01	[0.01,0.02]
σ_y	Std.Dev. of $\hat{g}^y$	U	0.08	[0,0.1]	0.00	[0,0.01]	0.02	[0.01,0.04]
σ_{ξ^*}	Std.Dev. of ξ^*	U	0.08	[0,0.1]	0.02	[0.01,0.04]	0.02	[0.02,0.03]
σ_g	Std.Dev. of g	U	0.08	[0,0.1]	0.01	[0,0.03]	0.03	[0.03,0.04]
σ_γ	Std.Dev. of γ	U	0.08	[0,0.1]	0.01	[0,0.01]	0.01	[0.01,0.01]
σ_{z^x}	Std.Dev. of z^x	U	0.08	[0,0.1]	0.01	[0,0.02]	0.08	[0.07,0.09]
σ_{z^n}	Std.Dev. of z^x	U	0.08	[0,0.1]	0.00	[0,0.01]	0.01	[0.01,0.01]

Note: B, U, G, IG and N denote, respectively, Beta, Uniform, Gamma, Inverse Gamma and Normal distributions. Priors are truncated at the boundary of the determinacy region. C.B. denotes confidence band.

Table 4: Selected Moments, Baseline Model.

	σ_x		$\rho_{x,\Delta\ln(GDP)}$		$\rho_{x,\ln(\pi)}$		$\rho_{x_t,x_{t-1}}$	
Variable	Data	Model	Data	Model	Data	Model	Data	Model
$\Delta\ln(GDP)$	1.5	1.6	—		-0.32	-0.16	0.11	0.02
	(0.2)	[1.5,1.7]			(0.1)	[-0.24,-0.07]	(0.15)	[-0.06,0.11]
$\Delta\ln(C)$	1.8	2	0.77	0.43	-0.35	-0.42	0.15	0.47
	(0.2)	[1.9,2.2]	(0.19)	[0.36,0.49]	(0.1)	[-0.49,-0.35]	(0.15)	[0.39,0.53]
TBY	3.8	3.2	-0.24	-0.14	0.67	0.73	0.94	0.77
	(0.2)	[3,3.4]	(0.11)	[-0.24,-0.04]	(0.1)	[0.67,0.79]	(0.1)	[0.74,0.8]
$\ln(\pi)$	6.1	5.9	-0.32	-0.16	—		0.88	0.83
	(0.5)	[5.8,6]	(0.1)	[-0.24,-0.07]			(0.16)	[0.8,0.86]
$\ln(\pi^n)$	6.1	6	-0.29	-0.13	0.98	0.99	0.9	0.83
	(0.6)	[5.9,6.1]	(0.1)	[-0.22,-0.04]	(0.18)	[0.99,0.99]	(0.17)	[0.8,0.86]
$\ln(s^n)$	1.5	1.5	0.13	-0.04	-0.71	-0.7	0.93	0.74
	(0.2)	[1.4,1.6]	(0.09)	[-0.13,0.06]	(0.11)	[-0.75,-0.63]	(0.19)	[0.7,0.78]
$\Delta\ln(W/P)$	5	2.2	0.16	0.57	-0.24	-0.21	-0.1	0.41
	(0.7)	[1.9,2.6]	(0.14)	[0.44,0.67]	(0.12)	[-0.36,-0.04]	(0.15)	[0.23,0.53]
$\Delta\ln(M1)$	6.5	11.1	0.02	0.22	0.54	0.37	0.57	0.49
	(0.7)	[10.1,12]	(0.12)	[0.09,0.32]	(0.14)	[0.3,0.44]	(0.14)	[0.42,0.59]
$\Delta\ln(S)$	10.5	11.5	-0.29	-0.35	0.61	0.49	0.41	0.16
	(1.4)	[10.6,12.4]	(0.13)	[-0.45,-0.25]	(0.13)	[0.42,0.55]	(0.11)	[0.13,0.2]
$\ln(i)$	4.5	4.2	-0.26	-0.19	0.9	0.92	0.92	0.87
	(0.3)	[3.9,4.5]	(0.09)	[-0.29,-0.1]	(0.15)	[0.9,0.94]	(0.13)	[0.85,0.89]

Note: For each moment, the table shows the one from the data (GMM standard errors in parenthesis) and the corresponding posterior mean (computed using 50,000 draws from the posterior) of the unconditional moment using the Baseline Model (95% confidence bands in brackets). Standard Deviations (σ_x) in percentage points. The contribution of measurement errors to the variance is not included.

Table 5: Model Comparison, Moments.

Variable	Data	Baseline		No C.S.		No L.D.		No F.A.		No I.I.	
	σ_x										
$\Delta\ln(GDP)$	1.5	1.6	[1.5,1.7]	1.8	[1.7,2]	2.2	[2.1,2.3]	2.3	[2.2,2.4]	2.1	[1.9,2.2]
$\Delta\ln(C)$	1.8	2	[1.9,2.2]	2	[1.9,2.2]	2.1	[1.9,2.3]	1.9	[1.7,2.1]	2.1	[1.9,2.2]
TBY	3.8	3.2	[3,3.4]	3.1	[2.8,3.3]	2.9	[2.7,3.1]	3	[2.9,3.2]	3	[2.7,3.2]
$\ln(\pi)$	6.1	5.9	[5.8,6]	5.9	[5.8,6]	6.2	[6.1,6.3]	6.3	[6.2,6.4]	6.3	[6.2,6.5]
$\ln(\pi^n)$	6.1	6	[5.9,6.1]	6	[5.9,6.1]	6.2	[6.1,6.3]	6.2	[6.1,6.3]	6.1	[6,6.2]
$\ln(s^n)$	1.5	1.5	[1.4,1.6]	1.5	[1.4,1.6]	1.5	[1.4,1.6]	1.4	[1.3,1.5]	1.7	[1.6,1.8]
$\Delta\ln(W/P)$	5	2.2	[1.9,2.6]	2.1	[1.8,2.5]	1.9	[1.8,2.2]	1.6	[1.4,1.8]	1.8	[1.4,2.2]
$\Delta\ln(M1)$	6.5	11.1	[10,12]	10	[9,11]	9.6	[9,11]	8.9	[8,10]	8.2	[7,10]
$\Delta\ln(S)$	10	11.5	[11,12]	12.1	[11,13]	9.9	[9,10]	10.6	[10,11]	11.1	[10,12]
$\ln(i)$	4.5	4.2	[3.9,4.5]	2.8	[2.5,3.2]	1.9	[1.7,2.3]	1.7	[1.6,2]	1.8	[1.6,2]
	$\rho_{x,\Delta\ln(GDP)}$										
$\Delta\ln(C)$	0.77	0.43	[0.4,0.5]	0.48	[0.4,0.5]	0.73	[0.6,0.8]	0.8	[0.7,0.9]	0.64	[0.5,0.7]
TBY	-0.24	-0.14	[-0.2,0]	-0.04	[-0.1,0]	-0.04	[-0.1,0]	-0.09	[-0.2,0]	-0.01	[-0.1,0.1]
$\ln(\pi)$	-0.32	-0.16	[-0.2,-0.1]	0.08	[0,0.2]	-0.09	[-0.2,0]	-0.09	[-0.2,0]	-0.02	[-0.1,0.1]
$\ln(\pi^n)$	-0.29	-0.13	[-0.2,0]	0.12	[0,0.2]	-0.02	[-0.1,0.1]	-0.03	[-0.1,0]	0.1	[0,0.2]
$\ln(s^n)$	0.13	-0.04	[-0.1,0.1]	-0.18	[-0.2,-0.1]	-0.13	[-0.2,-0.1]	-0.11	[-0.2,0]	-0.19	[-0.3,-0.1]
$\Delta\ln(W/P)$	0.16	0.57	[0.4,0.7]	0.54	[0.4,0.6]	0.81	[0.6,0.9]	0.65	[0.4,0.8]	0.68	[0.5,0.8]
$\Delta\ln(M1)$	0.02	0.22	[0.1,0.3]	0.25	[0.1,0.3]	0	[-0.1,0.1]	0.02	[-0.1,0.1]	0.27	[-0.1,0.4]
$\Delta\ln(S)$	-0.29	-0.35	[-0.4,-0.3]	-0.26	[-0.4,-0.2]	-0.57	[-0.6,-0.5]	-0.55	[-0.6,-0.5]	-0.33	[-0.4,-0.2]
$\ln(i)$	-0.26	-0.19	[-0.3,-0.1]	0.06	[0,0.1]	0.03	[0,0.1]	-0.02	[-0.1,0]	-0.03	[-0.1,0]
	$\rho_{x,\ln(\pi)}$										
$\Delta\ln(C)$	-0.35	-0.42	[-0.5,-0.3]	-0.11	[-0.2,0]	-0.07	[-0.1,0]	-0.11	[-0.2,0]	-0.35	[-0.4,-0.2]
TBY	0.67	0.73	[0.7,0.8]	0.47	[0.4,0.6]	0.26	[0.2,0.4]	0.25	[0.2,0.3]	0.59	[0.5,0.7]
$\ln(\pi^n)$	0.98	1	[1,1]	1	[1,1]	0.99	[1,1]	1	[1,1]	0.97	[1,1]
$\ln(s^n)$	-0.71	-0.7	[-0.8,-0.6]	-0.56	[-0.6,-0.5]	-0.26	[-0.4,-0.2]	-0.22	[-0.3,-0.2]	-0.43	[-0.5,-0.4]
$\Delta\ln(W/P)$	-0.24	-0.21	[-0.4,0]	-0.09	[-0.2,0]	-0.07	[-0.3,0.1]	-0.24	[-0.3,-0.1]	-0.31	[-0.5,-0.1]
$\Delta\ln(M1)$	0.54	0.37	[0.3,0.4]	0.51	[0.4,0.6]	0.22	[0,0.4]	0.31	[0.2,0.4]	0.11	[-0.1,0.3]
$\Delta\ln(S)$	0.61	0.49	[0.4,0.5]	0.45	[0.4,0.5]	0.69	[0.7,0.7]	0.69	[0.7,0.7]	0.74	[0.7,0.8]
$\ln(i)$	0.9	0.92	[0.9,0.9]	0.74	[0.7,0.8]	0.7	[0.6,0.8]	0.72	[0.7,0.8]	0.58	[0.5,0.7]
	$\rho_{x_t,x_{t-1}}$										
$\Delta\ln(GDP)$	0.11	0.02	[-0.1,0.1]	0.03	[0,0.1]	-0.05	[-0.1,0]	-0.01	[0,0]	-0.15	[-0.2,-0.1]
$\Delta\ln(C)$	0.15	0.47	[0.4,0.5]	0.46	[0.4,0.5]	0.13	[0,0.2]	0.06	[0,0.1]	0.23	[0.1,0.3]
TBY	0.94	0.77	[0.7,0.8]	0.83	[0.8,0.9]	0.74	[0.7,0.8]	0.78	[0.8,0.8]	0.83	[0.8,0.8]
$\ln(\pi)$	0.88	0.83	[0.8,0.9]	0.58	[0.5,0.7]	0.41	[0.3,0.5]	0.42	[0.4,0.5]	0.57	[0.5,0.6]
$\ln(\pi^n)$	0.9	0.83	[0.8,0.9]	0.58	[0.5,0.7]	0.42	[0.4,0.5]	0.43	[0.4,0.5]	0.53	[0.4,0.6]
$\ln(s^n)$	0.93	0.74	[0.7,0.8]	0.8	[0.7,0.8]	0.7	[0.7,0.7]	0.69	[0.7,0.7]	0.7	[0.7,0.7]
$\Delta\ln(W/P)$	-0.1	0.41	[0.2,0.5]	0.39	[0.3,0.5]	0.07	[0,0.1]	0.05	[0,0.1]	0.11	[0,0.2]
$\Delta\ln(M1)$	0.57	0.49	[0.4,0.6]	0.38	[0.3,0.5]	0.16	[0.1,0.2]	0.17	[0.1,0.2]	0.34	[0.3,0.4]
$\Delta\ln(S)$	0.41	0.16	[0.1,0.2]	0.02	[0,0.1]	0.09	[0.1,0.1]	0.08	[0.1,0.1]	0.26	[0.2,0.3]
$\ln(i)$	0.92	0.87	[0.9,0.9]	0.9	[0.9,0.9]	0.93	[0.9,1]	0.92	[0.9,0.9]	0.96	[0.9,1]

Note: See Table 4

Table 6: Model Comparison, Marginal Likelihood.

Model	Difference with Baseline
No Currency Substitution (No C.S.)	112
No Liability dollarization (No L.D.)	64.4
No Financial Accelerator (No F.A.)	-19.5
No Intermediate Inputs (No I.I.)	-187.2

Note: The table shows the log Marginal Likelihood for each model minus that for the Baseline model. These were computed using the modified harmonic mean proposed by Geweke (1999). In performing this comparison, the priors have been re-scaled to account for the possibly different uniqueness regions in each specification.

Table 7: Model Comparison based on Loss-Function.

Variable	No C.S.	No L.D.	No. F.A.	No I.I.
$cov(x_t, x_{t-h}), h = 0, .., 8$				
$\Delta \ln(GDP)$	3.58	11.79	15.02	248.62
$\Delta \ln(C)$	0.97	0.56	0.23	17.51
TBY	0.63	0.75	0.62	0.89
$\ln(\pi)$	0.75	0.87	0.83	9.44
$\ln(\pi^n)$	0.74	0.85	0.82	1.79
$\ln(s^n)$	0.61	0.87	0.96	52.38
$\Delta \ln(M1)$	0.36	0.29	0.19	2.77
$\Delta \ln(S)$	1.31	0.78	0.84	8.99
$\ln(i)$	1.06	1.1	1.13	1.07
$cov(\Delta \ln(GDP_t), x_{t-h}), h = 0, .., 8$				
$\Delta \ln(C)$	1.94	4.79	6.06	191.19
TBY	0.5	15.21	22.11	0.16
$\ln(\pi)$	3.77	2.54	1.7	350.63
$\ln(\pi^n)$	4.11	2.94	2.02	93.4
$\ln(s^n)$	1.78	1.95	1.11	345.65
$\Delta \ln(M1)$	0.87	0.13	0.1	37.04
$\Delta \ln(S)$	1.59	2.73	3.37	50.32
$\ln(i)$	2.89	3.86	3.3	0.4
$cov(\ln(\pi_t), x_{t-h}), h = 0, .., 8$				
$\Delta \ln(GDP)$	1.39	0.81	0.48	62.86
$\Delta \ln(C)$	0.77	0.28	0.2	14.99
TBY	0.83	1.27	1.38	1.07
$\ln(\pi^n)$	0.75	0.87	0.83	9.44
$\ln(s^n)$	0.59	1.29	1.64	10.3
$\Delta \ln(M1)$	0.1	0.33	0.26	19.44
$\Delta \ln(S)$	0.71	0.64	0.65	6.4
$\ln(i)$	1.06	1.11	1.16	0.8

Note: The table shows the ratio of the Risk factor of each model relative to the Baseline (if the ratio is bigger than 1, the Baseline is preferred). See the Appendix for details.

Table 8: Model Comparison, Posterior Distribution.

Para-meter	Baseline mean	Baseline 95% C.B.	No C.S. mean	No C.S. 95% C.B.	No L.D. mean	No L.D. 95% C.B.	No F.A. mean	No F.A. 95% C.B.	No I.I. mean	No I.I. 95% C.B.
b	0.99	[0.99,1]	0.99	[0.99,1]	0.29	[0.1,0.5]	0.38	[0.2,0.5]	0.27	[0.2,0.4]
ζ	0.08	[0.1,0.1]	0.25	[0.2,0.3]	0.76	[0.6,0.9]	0.67	[0.6,0.7]	0.85	[0.6,0.9]
ρ_c	0.83	[0.8,0.9]	0.7	[0.6,0.8]	0.19	[0,0.4]	0.13	[0,0.3]	0.38	[0.2,0.5]
ν	0.1	[0,0.2]			0.91	[0.8,1]	0.89	[0.8,0.9]	0.81	[0.8,0.8]
χ	3.9	[1.4,6.9]			2.93	[1.7,4.4]	2.98	[2.1,4]	7.04	[6.2,8.1]
ψ_w	0.44	[0.1,0.8]	0.34	[0.2,0.7]	0.08	[0,0.2]	0.45	[0.1,0.9]	0.07	[0,0.1]
ψ_d	1.91	[1.2,2.8]	0.72	[0.5,1]	0.94	[0.8,1.1]	1.12	[0.7,2]	1.04	[0.7,1.4]
φ	2.96	[2.6,3.4]	2.9	[2.5,3.3]	2.79	[2.5,3.2]	2.92	[2.6,3.3]	2.13	[2,2.3]
ψ_n	1.07	[0.2,2.9]	0.63	[0.1,1.8]	7.3	[5.9,8.8]	3.36	[0.8,5.4]	4.01	[1,7.4]
ψ_f	14.2	[10,19]	13.4	[9,19]	6.5	[6,7]	25	[20,30]	25	[23,27]
ψ_k^n	1.92	[0.7,4.1]	0.85	[0.3,1.7]	1.08	[0.2,3.6]	6.87	[4.3,9.8]	36	[38,40]
ψ_k^x	1.86	[0.4,6]	0.74	[0.2,1.7]	1.14	[0.2,5]	2.49	[1.5,3.3]	37	[34,40]
rp-1	0.06	[0.05,0.1]	0.07	[0.05,0.1]	0	[0,0]			0.02	[0,0.05]
σ_ω	2.37	[1.9,2.8]	2.1	[1.7,2.5]	1.48	[1.2,1.8]			0.41	[0.4,0.4]
μ	0.54	[0.5,0.7]	0.68	[0.5,0.8]	0.29	[0.1,0.6]			0.73	[0.4,0.9]
α_i	0.08	[0,0.2]	0.06	[0,0.2]	0.46	[0,0.7]	0.47	[0.3,0.6]	0.84	[0.7,0.9]
α_π	2.08	[1.9,2.3]	2.12	[1.8,2.5]	1.8	[1.5,2.1]	1.57	[1.3,1.9]	1.57	[1.4,1.8]
α_y	0.46	[0.3,0.7]	0.55	[0.4,0.7]	0.73	[0.6,0.9]	0.75	[0.6,0.9]	0.59	[0.4,0.9]
ρ_i	0.34	[0,0.9]	0.13	[0,0.3]	0.11	[0,0.2]	0.96	[0.9,1]	0.99	[1,1]
ρ_π	0.69	[0.5,0.9]	0.06	[0,0.2]	0.13	[0,0.3]	0.15	[0,0.2]	0.12	[0,0.5]
ρ_y	0.94	[0.9,1]	0.95	[0.9,1]	0.94	[0.9,1]	0.1	[0,0.4]	0.02	[0,0.1]
ρ_{ξ^*}	0.97	[1,1]	0.97	[0.9,1]	0.98	[1,1]	0.98	[1,1]	0.72	[0.3,1]
ρ_g	0.43	[0.2,0.7]	0.46	[0.2,0.7]	0.26	[0,0.6]	0.33	[0.1,0.6]	0.52	[0.3,0.7]
$\rho_{g,gdp}$	0.17	[0,0.3]	0.11	[-0.1,0.3]	0.18	[-0.1,0.5]	0.29	[0.1,0.5]	-0.03	[-0.2,0.2]
ρ_γ	0.07	[0,0.2]	0.07	[0,0.1]	0.1	[0,0.3]	0.11	[0,0.2]	0.08	[0,0.1]
ρ_{z^x}	0.79	[0.7,0.8]	0.73	[0.7,0.8]	0.8	[0.8,0.9]	0.78	[0.7,0.8]	0.74	[0.7,0.8]
ρ_{z^n}	0.89	[0.8,0.9]	0.92	[0.8,1]	0.96	[0.9,1]	0.97	[0.9,1]	0.97	[1,1]
σ_i	0.01	[0,0.02]	0.03	[0,0.04]	0.03	[0,0.07]	0.00	[0,0.01]	0.00	[0,0.0]
σ_π	0.01	[0,0.02]	0.03	[0,0.04]	0.03	[0,0.04]	0.04	[0,0.04]	0.02	[0,0.04]
σ_y	0.02	[0,0.04]	0.03	[0,0.03]	0.01	[0,0.02]	0.04	[0,0.07]	0.1	[0,0.14]
σ_{ξ^*}	0.02	[0,0.03]	0.01	[0,0.02]	0.03	[0,0.04]	0.03	[0,0.05]	0.05	[0,0.14]
σ_g	0.03	[0,0.04]	0.03	[0,0.04]	0.03	[0,0.03]	0.03	[0,0.03]	0.03	[0,0.03]
σ_γ	0.01	[0,0.01]	0.01	[0,0.01]	0.01	[0,0.01]	0.01	[0,0.01]	0.01	[0,0.01]
σ_{z^x}	0.08	[0.07,0.09]	0.09	[0.1,0.1]	0.05	[0,0.05]	0.05	[0,0.06]	0.06	[0.05,0.07]
σ_{z^n}	0.01	[0,0.01]	0.01	[0,0.01]	0.01	[0,0.01]	0.01	[0,0.01]	0.01	[0,0.01]

Table 9: Variance Decomposition, Baseline Model.

	Shock											
Variable	$\hat{i}$	$\hat{\pi}$	$\hat{g}^y$	ξ^*	g	γ	z^x	z^n	π^{*f}	π^{*x}	i^*	m.e.
$\Delta \ln(GDP)$	3	1	1	17	1	4	30	28	2	5	3	7
	[0,10]	[0,2]	[0,2]	[13,21]	[1,2]	[2,5]	[22,37]	[21,34]	[1,2]	[3,7]	[2,5]	[5,8]
$\Delta \ln(C)$	0	0	0	4	0	36	35	7	0	11	0	6
	[0,0]	[0,0]	[0,0]	[2,6]	[0,1]	[29,45]	[28,42]	[5,10]	[0,0]	[9,14]	[0,1]	[5,8]
TBY	0	0	1	22	0	0	40	0	2	20	3	11
	[0,1]	[0,1]	[0,2]	[17,28]	[0,0]	[0,0]	[34,48]	[0,1]	[1,2]	[17,23]	[2,5]	[9,12]
$\ln(\pi)$	2	20	22	8	1	1	29	4	0	9	1	2
	[0,6]	[12,30]	[8,35]	[5,11]	[1,2]	[1,1]	[22,39]	[3,7]	[0,1]	[6,12]	[0,2]	[1,4]
$\ln(\pi^n)$	2	19	22	8	1	1	29	5	0	10	1	3
	[0,6]	[11,30]	[8,34]	[5,11]	[1,2]	[1,1]	[22,38]	[3,7]	[0,1]	[7,13]	[0,2]	[2,4]
$\ln(s^n)$	2	3	7	40	1	0	14	3	3	13	6	8
	[0,7]	[1,5]	[2,14]	[32,47]	[0,2]	[0,0]	[10,19]	[2,6]	[2,3]	[10,17]	[3,9]	[7,10]
$\Delta \ln(W/P)$	0	0	0	1	0	1	12	5	0	2	0	79
	[0,1]	[0,0]	[0,0]	[0,1]	[0,0]	[1,2]	[8,18]	[3,8]	[0,0]	[1,3]	[0,0]	[71,84]
$\Delta \ln(M1)$	1	6	7	17	1	0	40	6	1	16	2	3
	[0,2]	[4,10]	[2,10]	[12,22]	[1,2]	[0,1]	[33,49]	[4,9]	[1,1]	[13,19]	[1,3]	[3,4]
$\Delta \ln(S)$	1	5	6	6	0	0	48	1	0	24	1	7
	[0,2]	[3,9]	[2,9]	[4,8]	[0,1]	[0,0]	[41,57]	[1,2]	[0,0]	[21,28]	[1,1]	[6,8]
$\ln(i)$	0	4	9	12	1	1	43	6	1	14	1	8
	[0,1]	[1,9]	[2,14]	[7,16]	[1,2]	[0,1]	[36,54]	[4,10]	[0,1]	[11,17]	[1,2]	[7,9]

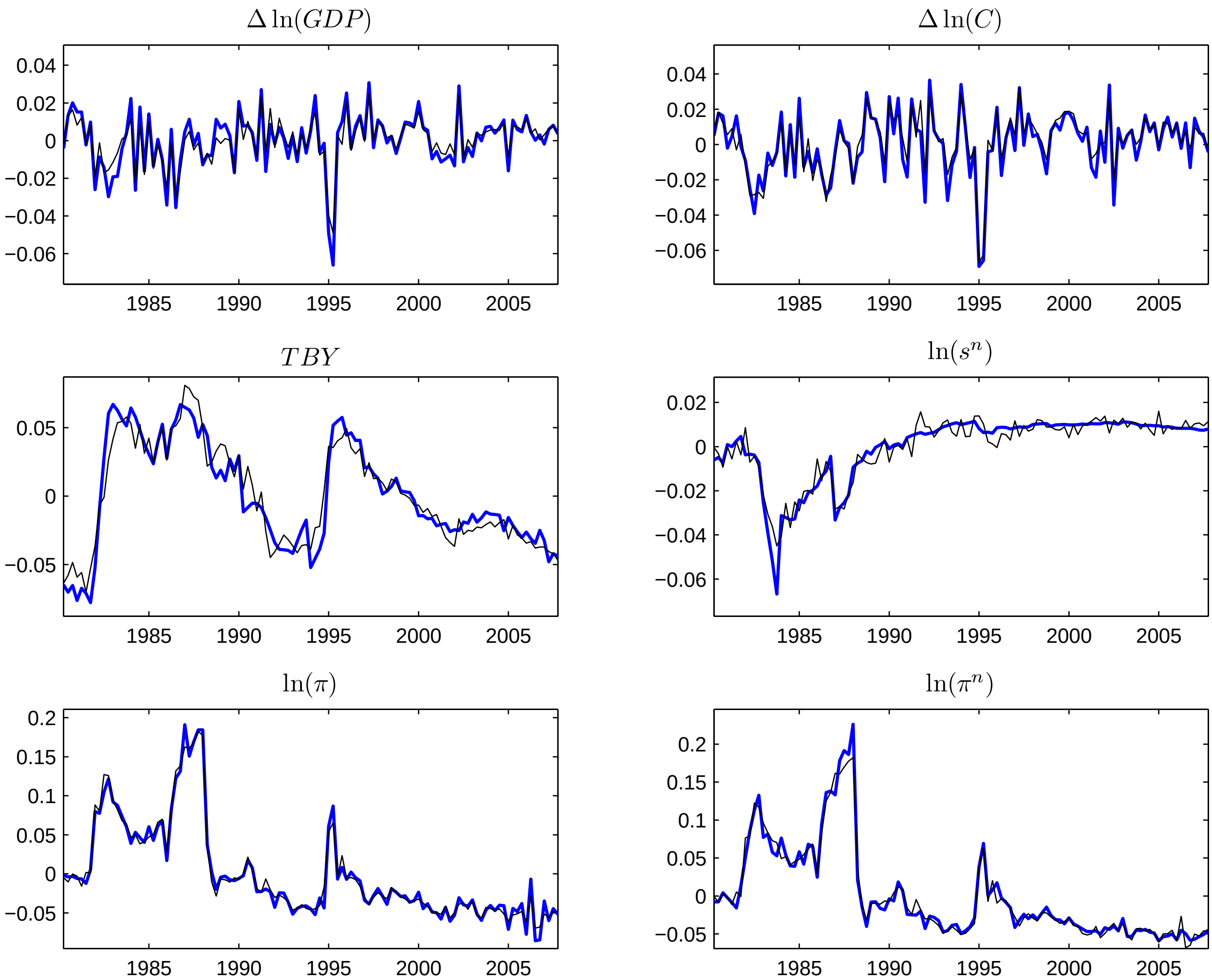
Note: Each entry denotes the posterior means of the unconditional variance decomposition (in percentage) under the Baseline Model (computed using 50,000 draws from the posterior), as well as its 95% confidence bands in brackets. m.e. denotes measurement error.

Table 10: Variance Decomposition, No C.S. Model.

	Shock											
Variable	$\hat{i}$	$\hat{\pi}$	$\hat{g}^y$	ξ^*	g	γ	z^x	z^n	π^{*f}	π^{*x}	i^*	m.e.
$\Delta\ln(GDP)$	17	0	1	10	0	2	33	25	1	3	4	4
	[9,25]	[0,0]	[0,1]	[6,14]	[0,0]	[2,3]	[26,40]	[19,32]	[1,2]	[2,4]	[3,6]	[2,6]
$\Delta\ln(C)$	1	0	0	5	0	27	40	9	0	9	2	6
	[0,2]	[0,0]	[0,0]	[3,8]	[0,1]	[20,33]	[34,48]	[7,12]	[0,0]	[7,11]	[1,2]	[3,8]
TBY	2	0	2	21	0	0	39	0	2	16	7	10
	[1,3]	[0,0]	[1,4]	[15,28]	[0,0]	[0,0]	[31,46]	[0,0]	[1,3]	[14,19]	[5,9]	[7,13]
$\ln(\pi)$	8	33	40	4	0	1	9	1	0	3	1	0
	[4,11]	[23,43]	[31,55]	[2,7]	[0,0]	[0,1]	[3,15]	[1,2]	[0,0]	[1,4]	[1,2]	[0,0]
$\ln(\pi^n)$	8	31	37	4	0	1	9	1	0	3	1	5
	[5,11]	[22,40]	[29,51]	[2,6]	[0,0]	[1,1]	[3,15]	[1,2]	[0,0]	[1,4]	[1,2]	[4,6]
$\ln(s^n)$	10	0	16	37	0	0	5	2	3	7	13	7
	[5,16]	[0,0]	[8,27]	[28,46]	[0,1]	[0,1]	[2,9]	[1,3]	[2,4]	[4,10]	[9,17]	[4,9]
$\ln(W/P)$	1	0	0	1	0	1	11	4	0	2	0	79
	[0,3]	[0,0]	[0,0]	[1,2]	[0,0]	[1,2]	[6,16]	[2,6]	[0,0]	[1,3]	[0,1]	[72,86]
$\Delta\ln(M1)$	5	9	17	20	1	1	22	5	1	6	8	4
	[2,8]	[6,13]	[12,24]	[15,27]	[1,2]	[1,3]	[13,33]	[3,7]	[1,2]	[5,7]	[5,10]	[3,4]
$\Delta\ln(S)$	3	8	9	3	0	0	46	0	0	23	1	6
	[2,5]	[5,10]	[7,13]	[2,5]	[0,0]	[0,0]	[39,52]	[0,0]	[0,0]	[20,26]	[1,2]	[5,7]
$\ln(i)$	0	0	30	13	0	1	25	1	0	7	4	16
	[0,0]	[0,1]	[21,43]	[9,18]	[0,1]	[1,1]	[13,37]	[1,3]	[0,1]	[6,10]	[3,6]	[14,18]

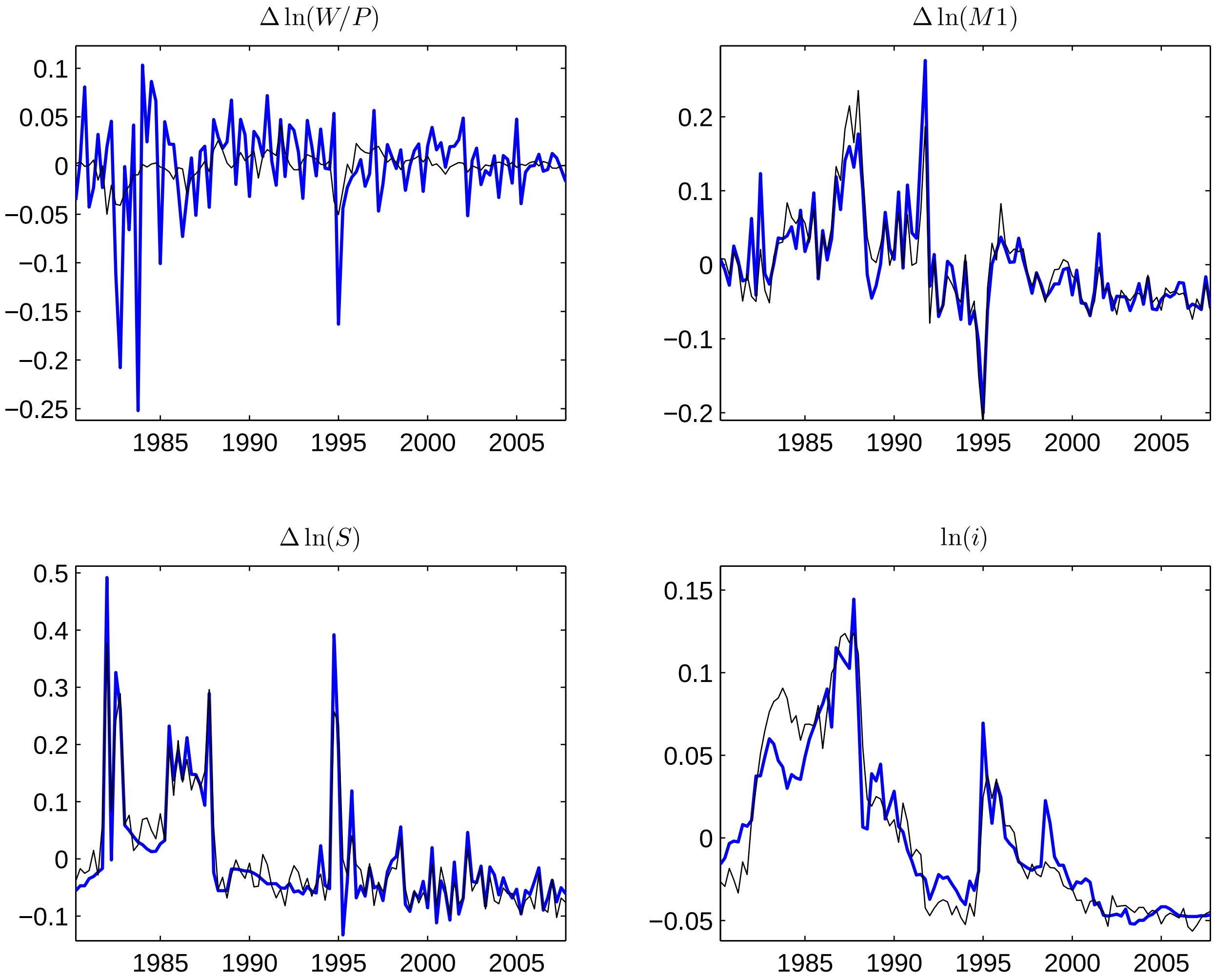
Note: See table 9.

Figure 1: Data vs. Baseline Model



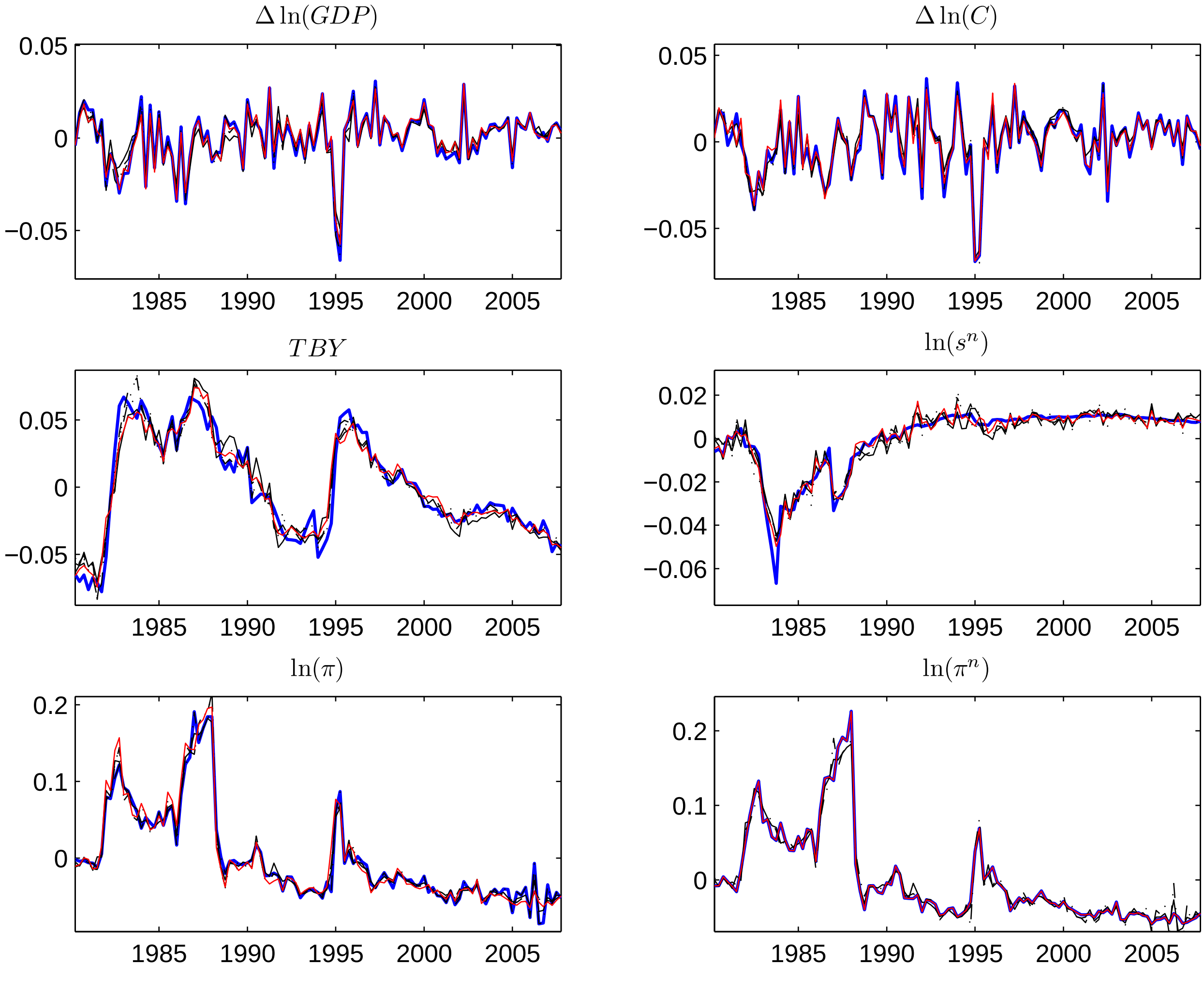
Note: The blue thick line is the data (measured as deviations from the mean) and the black line posterior mean of the smooth version of the same series form the Baseline Model (computed using 50,000 draws from the posterior).

Figure 2: Data vs. Baseline Model, cont.



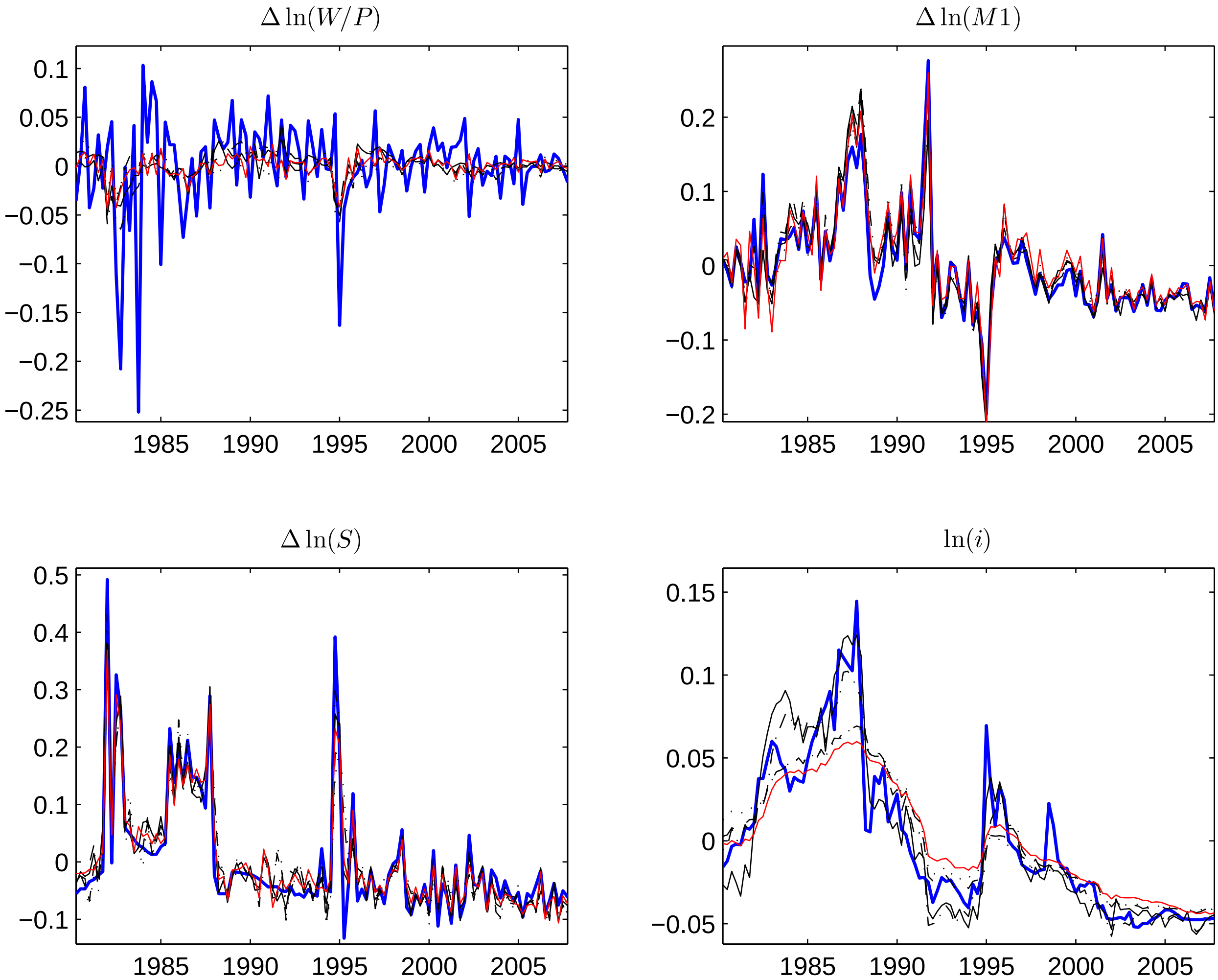
Note: See Figure 1.

Figure 3: Data vs. Different Models



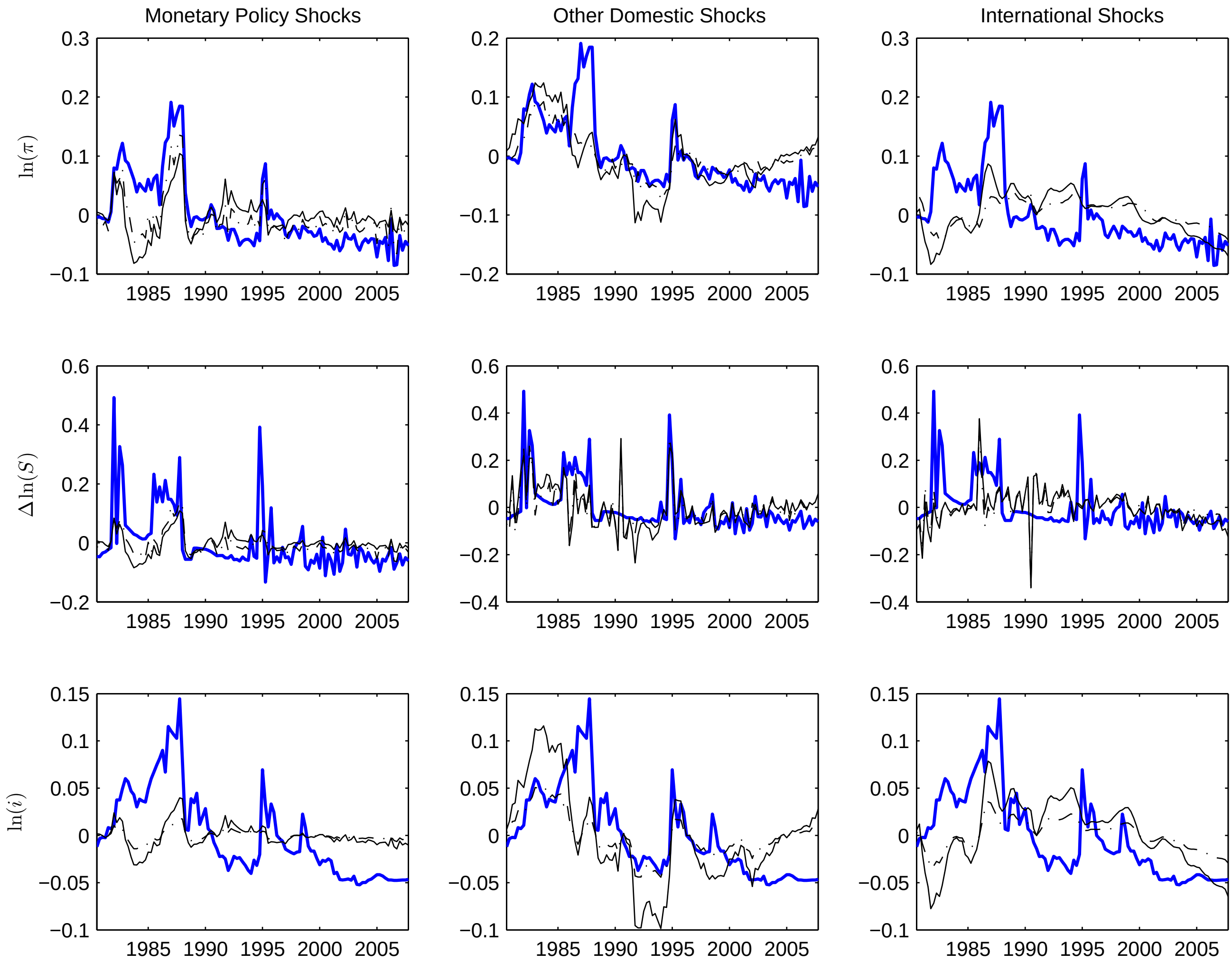
Note: The blue thick line is the data (measured as deviations from the mean), the black line is the Baseline Model, the black dashed-doted line is the model without Currency Substitution, the black doted line is the model without Liability dollarization, the black dashed line is the model without Financial Accelerator, and the red line is the model without Intermediate Inputs.

Figure 4: Data vs. Different Models, cont.



Note: See Figure 3.

Figure 5: Historical Decomposition, Selected variables.



Note: The thick blue line is the data (measured as deviations from the mean), the thin black line shows the model series if only the shocks in the particular group are active under the Baseline (measured as deviations from the steady state) and the dashed-dotted line is the analogous for the No C.S. model. The values for each shock are computed from the smooth Kalman filter evaluated at the posterior mean.

B Data Sources and Definitions

Real GDP, private and public consumption and the trade balance are from Banco de Mexico.[40] These were transformed in per-capita terms using an annual population series from ECLAC,[41] transformed to quarterly using linear interpolation. On the other hand, the series of sectorial value added and total GDP (both nominal and real) are from INEGI.[42] Our measure of aggregate inflation is the change in the GDP deflator. Inflation in the non-traded sector is a weighted average of the deflators of the industries included in the non-trade sector (see next subsection), were the weights are the nominal share of each sector in total nominal value added. Finally, the sum of these shares is equal to the share of non-tradeables in total value added.

The real wage is an index from the Manufacturing sector, computed by INEGI. The nominal exchange rate is also from INEGI. The series from M1 is from Banco de Mexico from 1986, extended backwards using the series from INEGI. The nominal interest rate is the CETES91.

In terms of international variables, the foreign inflation of exportables and importables is computed from the indices of foreign price of exports and imports from INEGI. Finally, the world nominal interest rate is the 3-month T-bill from FRED.[43]

B.1 Calibrating the Production Function

The parameters describing the production function for sectors n, x and k are calibrated, following Calvo et al. (2008), using the input-output matrix from 2003, constructed by INEGI. First, the 18 industries are collected in two groups: exportable and non-traded.[44] An industry is considered to be exportable if the share of exports in the gross value of production is at least 20%. In the case of Mexico, the Mining sector (which includes oil production) is the only industry satisfying this condition;[45] the rest are grouped in the non-traded sector.

Given this distinction, a reduced input-output matrix of two sectors is constructed, allowing to compute to the coefficient characterizing the demand for intermediate goods in each of these two sectors, including the use of imported inputs. The share of labor is computed from the share of wage payments, and the rest of value added (minus taxes and subsidies) is attributed to capital.

On the other hand, the shares of imported and non-traded intermediate goods in the production of capital are calibrated from the total demand devoted to gross capital formation. Finally, we set the

[40] Their statistical website is http://www.banxico.org.mx/tipo/estadisticas/index.html.

[41] Available at http://www.eclac.cl/celade/proyecciones/basedatos_BD.htm.

[42] Their statistical website is http://dgcnesyp.inegi.org.mx/bdiesi/bdie.html.

[43] Available at http://research.stlouisfed.org/fred2/.

[44] Calvo et al. (2008) collect industries at a more disaggregated level. However, because we wanted to construct a time series of sectorial production, we choose to work with a higher level of aggregation in order to be consistent with the available sectorial time series.

[45] While it is possible to distinguish from the 2003 Mexican input-output matrix the part of the manufacturing production attributed to the Maquila industries (which in 2003 constitutes almost 50% of total exports), such a decomposition is not available in the NIPA time series of sectorial production that we use for estimation (this data starts in 1993). Therefore, we do not include the Maquila industry in the exportable sector. While this is clearly a limitation, two comments are in order. First, the implied coefficients for the non-tradeables production function are almost identical regardless of the inclusion of the Maquila. On the other hand, the coefficients for the exportable sector do change depending on the treatment of the Maquila, for these Manufacturing industries are more labor intensive. However, due to the structure of the Maquila industry, they will be less dependent on fluctuations of international prices relative to the Mining sector; a point that supports our choice given the data limitation.

share of entrepreneur labor is set to a low value, 0.1%, given that this is just introduced for technical reasons.

C Forming Priors

Our approach to assign priors for the parameters modifies the procedure proposed by Del Negro and Schorfheide (2006). The vector of parameters θ is decomposed in two groups, i.e. $\theta = [\theta_1', \theta_2']'$. The subset θ_1 contains parameters for which we can assign standard distribution as prior based on parameter constraints and on previous studies (preferences, technology, policy, etc), while θ_2 collects the ones for which this task is more complicated (for instance, those describing the evolution of the driving forces). The general idea of this procedure is to choose a distribution for θ_2 capable to generate several characteristics (moments) that we observe in the data. Here, we describe the general approach and the implementation suggested by Del Negro and Schorfheide (2006), as well as the modifications we introduced relative to their work.

The general structure proposed by Del Negro and Schorfheide (2006) is

$$p(\theta|\Omega^*) = c_1(\theta_1|\Omega^*) L(\theta_1, \theta_2|\Omega^*)\pi(\theta_2)p(\theta_1),$$

where $p(\theta_1)$ is the prior that we choose based on previous studies and $\pi(\theta_2)$ is an initial prior for θ_2, which might be uninformative (i.e. flat). The sufficient statistics of interest are collected in Ω^* and the function $L(\theta_1, \theta_2|\Omega^*)$ (to be specified) measures the probability that the model can accurately replicate the characteristics collected in Ω^*. Additionally, the normalization constant $c_1(\theta_1|\Omega^*)$ is set such that

$$\frac{1}{c_1(\theta_1|\Omega^*)} = \int L(\theta_1, \theta_2|\Omega^*)\pi(\theta_2)d\theta_2.$$

In this way, we can interpret $p(\theta_2|\theta_1, \Omega^*) \equiv c_1(\theta_1|\Omega^*) L(\theta_1, \theta_2|\Omega^*)\pi(\theta_2)$ as the conditional probability of θ_2 given θ_1, implying that we are factorizing the overall prior using the Bayes Theorem. Moreover, the normalization constant ensure that $p(\theta_2|\theta_1, \Omega^*)$ is proper and thus, if $p(\theta_1)$ also integrates to one, $p(\theta|\Omega^*)$ will be proper as well; the later being a most relevant requirement for model comparison porpoises.

Del Negro and Schorfheide (2006) suggest to implement this approach as follows. First, recognizing that to calculate the constant is computationally cumbersome, they propose to evaluate $p(\theta_2|\theta_1, \Omega^*)$ at a given value $\bar{\theta}_1$. Therefore, the actual prior they use is

$$p(\theta|\Omega^*) = c_1\left(\bar{\theta}_1|\Omega^*\right) L(\bar{\theta}_1, \theta_2|\Omega^*)\pi(\theta_2)p(\theta_1).$$

Under this simplification, the prior for θ_2 is independent from $p(\theta_1)$. In order to compute the constant $c_1\left(\bar{\theta}_1|\Omega^*\right)$, the Metropolis-Hastings algorithm can be used to randomly draw from $L(\bar{\theta}_1, \theta_2|\Omega^*)\pi(\theta_2)$, calculating then the constant using the modified harmonic mean proposed by Geweke (1999).

On the other hand, their choice for $L(\bar{\theta}_1, \theta_2|\Omega^*)$ works as follows. In general, a VAR of order p with Gaussian errors can be written in compact form as $y_t' = x_t'\Phi + u_t'$, where the relevant parameters are collected in the matrices Φ and Σ, the latter being the variance-covariance matrix of the error term. Let $\Phi(\theta)$ and $\Sigma(\theta)$ be the analogous matrices coming from the VAR approximation of the model.[46] Additionally, suppose that we have T^* observations and we compute the associated sufficient statistics, i.e. $\sum y_t^* y_t^{*\prime} = T^*\Gamma_{yy}^*$, $\sum y_t^* x_t^{*\prime} = T^*\Gamma_{yx}^*$ and $\sum x_t^* x_t^{*\prime} = T^*\Gamma_{xx}^*$. Then, the quasi-likelihood of the parameters (premultiplied by $|\Sigma(\theta)|^{-(n+1)/2}$) is given by

$$L(\theta|\Omega^*) = |\Sigma(\theta)|^{-(T^*+n+1)/2} \exp\left\{-\frac{T^*}{2} tr\left[\Sigma(\theta)^{-1}\left(\Gamma_{yy}^* - \Phi(\theta)'\Gamma_{yx}^{*\prime} - \Gamma_{yx}^*\Phi(\theta) + \Phi(\theta)'\Gamma_{xx}^*\Phi(\theta)\right)\right]\right\},$$

where $\Omega^* = \left\{\Gamma_{yy}^*, \Gamma_{yx}^*, \Gamma_{xx}^*, T^*\right\}$. Thus, using this quasi-likelihood as a component of the prior would imply that we are "centering" our beliefs around the moments collected in the sufficient statistics. The lag length p in the VAR will determine which moments to match: for instance, if $p = 1$ we are matching *all* the covariances and first auto-covariances. Additionally, the parameter T^* will govern the precision of the quasi-likelihood, for it determines how concentrated $L(\theta|\Omega^*)$ is around the targeted moments.

Our approach differs from Del Negro and Schorfheide (2006) in two aspects: the treatment of the normalizing constant and the choice of $L(\theta|\Omega^*)$. First, while fixing a value $\bar{\theta}_1$ solves the computational problem, it is not clear what value should be chosen or how it will affect the results.[47] Moreover, "bad" choices for $\bar{\theta}_1$ may result in the model not being able to match the targeted moments. Therefore, we propose to replace $c_1\left(\bar{\theta}_1|\Omega^*\right)$ with $\tilde{c}_1\left(\Omega^*\right)$, where

$$\frac{1}{\tilde{c}_1\left(\Omega^*\right)} = \int L(\theta_1, \theta_2|\Omega^*)\pi(\theta_2)p(\theta_1)d\theta.$$

Several comments are in order. First, notice that, given this choice of normalization constant, the prior $\tilde{p}\left(\theta|\Omega^*\right) \equiv \tilde{c}_1\left(\Omega^*\right) L(\theta_1, \theta_2|\Omega^*)\pi(\theta_2)p(\theta_1)$ is proper. Second, while $\tilde{c}_1\left(\Omega^*\right) L(\theta_1, \theta_2|\Omega^*)\pi(\theta_2)$ it is not the conditional probability of θ_2 given θ_1, it is proportional to it and, in particular, not proper. Nevertheless, what is important for model comparison is for the overall prior to be proper, which is the case for $\tilde{p}\left(\theta|\Omega^*\right)$. Finally, this constant can also be computed with the procedure outlined before, the only difference being that now we should use the Metropolis-Hastings algorithm to draw from $L(\theta_1, \theta_2|\Omega^*)\pi(\theta_2)p(\theta_1)$.[48]

In terms of the choice of $L(\theta|\Omega^*)$, using the quasi-likelihood has two limitations. First, the only degree of freedom that we have available in selecting which moments to match is the parameter p, and given this value we ask the model to match *all* the auto-covariances up to order p. However, this might be to restrictive and we may want to choose fewer moments to match. Second, even if we want to match all the moments for a given p, the procedure proposed by Del Negro and Schorfheide (2006) will weight which moments are more important according to the model, through the matrix $\Sigma(\theta)$. Alternatively, we may want to assign more weight to certain moments, or to let the data tell us which moments should be weighted more. Thus, we replace the quasi-likelihood $L(\theta|\Omega^*)$ with the minimum-distance objective function

$$\tilde{L}(\theta|\Omega^*) = \exp\left\{-\left[m^* - m(\theta)\right]' W^* \left[m^* - m(\theta)\right]\right\},$$

[46] These are related with the population covariances under the model ($\Gamma_{yy}(\theta) \equiv E_\theta\left(y_t y_t'\right)$, $\Gamma_{yx}(\theta) \equiv E_\theta\left(y_t x_t'\right)$ and $\Gamma_{xx}(\theta) \equiv E_\theta\left(x_t x_t'\right)$) by the least-square population regression $\Phi(\theta) = \left[\Gamma_{xx}(\theta)\right]^{-1}\left[\Gamma_{yx}(\theta)\right]'$ and $\Sigma(\theta) = \Gamma_{yy}(\theta) - \Gamma_{yx}(\theta)\Phi(\theta)$.

[47] Del Negro and Schorfheide (2006) do not specify which particular parameter values they use.

[48] This alternative has an additional advantage in terms of computational time. In the original, for each draw from the posterior we need to solve the model twice: for parameters $\left[\bar{\theta}_1', \theta_2'\right]'$ to compute the prior and for $\left[\theta_1', \theta_2'\right]'$ to compute the likelihood. Under the alternative, we only need to solve the model once for each draw.

where m^* is the vector of moments that we want to match, $m(\theta)$ are those same moments generated by the model for a given parameterization θ, W^* is a positive-definite weighting matrix,[49] and $\Omega^* = \{m^*, W^*\}$. Additionally, in the same way that T^* was a measure of concentration of the prior around the targeted moments, we can always multiply the matrix W^* by an arbitrary constant which will serve the same goal as T^*. Finally, notice that, although $\tilde{L}$ is not a likelihood function, $\tilde{p}(\theta|\Omega^*)$ is indeed a probability distribution. In fact, it is a particular case of a quasi-posterior distribution as defined by Chernozhukov and Hong (2003).

D Comparing Models Using a Loss-Function

In this section be briefly describe the implementation of the procedure developed by Schorfheide (2000). The goal is to compare a collection of DSGE models $\mathcal{M}_i$ for $i = 1, ..., N$ (in our case, all the variants of the Baseline Model) based on their ability to match certain population characteristics collected in the vector z (moments in our case) of size n_z. Let $\mathcal{M}_0$ be a reference model (in our case, the BVAR). For each model, we can compute z as a function of its parameters. Therefore, given random draws from the parameters' posterior distribution of model i, $p\left(\theta_i|X^T, \mathcal{M}_i\right)$, we can easily obtain draws from the moments' posterior $p\left(z|X^T, \mathcal{M}_i\right)$.

The choice of models is based on a loss function $L(z, \hat{z})$ that penalizes deviations of the DSGE model prediction $\hat{z}$ from the population characteristics z. Based on a general loss function, the optimal predictor under model i, denoted by $\hat{z}_i$, is defined as

$$\hat{z}_i \equiv \arg\min_{\tilde{z} \in R^{n_z}} \int L(z, \tilde{z})\, p\left(z|X^T, \mathcal{M}_i\right) dz.$$

Given this prediction, the DSGE models are judged according to the risk (expected loss) of $\hat{z}_i$ under the posterior distribution $p\left(z|X^T, \mathcal{M}_0\right)$,[50] defined as

$$R\left(\hat{z}_i|X^T\right) \equiv \int L(z, \hat{z}_i)\, p\left(z|X^T, \mathcal{M}_0\right) dz.$$

This posterior risk provides an absolute measure of how well model i predicts the population characteristics z, and it the can be used to compare models: model i is preferred to j if $R\left(\hat{z}_i|X^T\right) < R\left(\hat{z}_j|X^T\right)$.

If the loss function is quadratic (i.e. $L(z, \hat{z}) = (z - \hat{z})' W (z - \hat{z})$, with W being a $n_z \times n_z$ positive definite weighting matrix), the risk function simplifies to

$$R\left(\hat{z}_i|X^T\right) = \left[\hat{z}_i - E\left(z|X^T, \mathcal{M}_0\right)\right]' W \left[\hat{z}_i - E\left(z|X^T, \mathcal{M}_0\right)\right],$$

and the optimal predictor under model i is simply the posterior mean $\hat{z}_i = E\left(z|X^T, \mathcal{M}_i\right)$. These expectations can be computed from the random draws from the posterior.

In our case, we use as the reference model a BVAR(1) with a Minnesota prior, with tightness and

[49] A possible choice for W^* is the optimal weighting matrix (i.e. $W^* = (S^*)^{-1}$ where S^* is an estimate of the spectral density of m^*).

[50] In the more general framework, this expectation is computed with respect to the overall posterior $p\left(z|X^T\right) = \sum_{i=0}^{N} \pi_{i,T}\, p\left(z|X^T, \mathcal{M}_i\right)$, where $\pi_{i,T}$ is the posterior probability of model i. However, as indicated by Schorfheide (2000), if the DSGE has less structural shocks than observables (as it is the case here) these probabilities are equal to zero (i.e. $\pi_{i,T} = 0$ for $i = 1, ..., N$) and therefore $p\left(z|X^T\right) = p\left(z|X^T, \mathcal{M}_0\right)$.

weight coefficients equal to 0.2 and 0.5 respectively (see, for instance Kadiyala and Karlson, 1997).[51] The posterior is then normal and we can draw from it using a simple random number generator. Additionally, we set the weighting matrix to be diagonal, with elements equal to the inverse of the variance of each moment under the BVAR (also computed from the random draws).

[51] The lag length was chosen according to both Bayesian and Hannan-Quinn information criterion.

Table C.1: Model Comparison, Prior Distribution.

Para-	No C.S.		No L.D.		No F.A.		No I.I.	
meter	mean	95% C.B.	mean	95% C.B.	mean	95% C.B.	mean	95% C.B.
b	0.62	[0.62,0.62]	0.62	[0.56,0.66]	0.67	[0.5,0.83]	0.79	[0.74,0.83]
ζ	0.26	[0.26,0.26]	0.66	[0.65,0.67]	1.17	[0.89,1.49]	2.53	[2.19,2.93]
ρ_c	0.997	[0.995,0.998]	0.48	[0.46,0.51]	0.76	[0.64,0.86]	0.61	[0.5,0.74]
ν			0.83	[0.82,0.84]	0.83	[0.76,0.87]	0.26	[0.08,0.44]
χ			2.19	[2.17,2.22]	1.86	[1.75,1.97]	5.6	[2.26,11.01]
ψ_w	0.01	[0.008,0.01]	1.22	[1.09,1.3]	0.07	[0.01,0.2]	0.04	[0.01,0.12]
ψ_d	0.18	[0.17,0.18]	0.49	[0.45,0.53]	0.55	[0.43,0.67]	0.29	[0.18,0.51]
φ	1.25	[1.24,1.25]	0.95	[0.91,0.99]	1.07	[0.93,1.14]	1.21	[0.84,1.62]
ψ_n	8.02	[8.02,8.02]	5.39	[5.37,5.42]	7.15	[6.79,7.75]	5.36	[2.09,11.9]
ψ_f	2.47	[2.46,2.47]	5.26	[5.21,5.31]	7.03	[6.85,7.18]	13.71	[8.84,19.1]
ψ_k^n	0.73	[0.73,0.73]	0.93	[0.91,0.95]	1.59	[1.49,1.71]	0.39	[0.15,0.86]
ψ_k^x	1.34	[1.34,1.34]	0.42	[0.37,0.46]	0.61	[0.46,0.7]	0.39	[0.16,0.69]
rp-1	0.1	[0.1,0.11]	0	[0,0]			0.26	[0.17,0.4]
σ_ω	1.25	[1.25,1.25]	0.52	[0.49,0.57]			3.21	[2.09,4.1]
μ	0.76	[0.76,0.76]	0.18	[0.16,0.2]			0.67	[0.5,0.84]
α_i	0.13	[0.1,0.17]	0.28	[0.25,0.31]	0.37	[0.07,0.61]	0.51	[0.29,0.69]
α_π	3.08	[2.97,3.24]	1.85	[1.8,1.89]	1.48	[1.27,1.64]	2.06	[1.69,2.49]
α_y	0.46	[0.3,0.63]	0.38	[0.35,0.41]	0.54	[0.37,0.68]	0.42	[0.27,0.59]
ρ_i	0.34	[0.02,0.87]	0.3	[0.23,0.35]	0.74	[0.57,0.89]	0.43	[0.02,0.93]
ρ_π	0.36	[0.01,0.86]	0.47	[0.44,0.52]	0.13	[0.06,0.22]	0.32	[0.03,0.59]
ρ_y	0.36	[0.01,0.89]	0.79	[0.77,0.81]	0.33	[0.01,0.83]	0.96	[0.94,1]
ρ_{ξ^*}	0.47	[0.02,0.95]	0.5	[0.11,0.88]	0.4	[0.04,0.82]	0.38	[0.01,0.91]
ρ_g	0.83	[0.83,0.83]	0.45	[0.4,0.5]	0.76	[0.61,0.94]	0.89	[0.83,0.94]
$\rho_{g,gdp}$	0.17	[0.17,0.17]	0.56	[0.52,0.6]	-0.25	[-0.36,-0.15]	0.5	[0.26,0.69]
ρ_γ	0.34	[0.15,0.53]	0.33	[0.2,0.41]	0.24	[0.05,0.55]	0.28	[0.07,0.58]
ρ_{z^x}	0.98	[0.98,0.99]	0.07	[0,0.2]	0.2	[0.01,0.75]	0.07	[0,0.23]
ρ_{z^n}	0.97	[0.93,1]	0.53	[0.07,0.97]	1	[1,1]	0.22	[0.01,0.83]
σ_i	0.02	[0,0.05]	0.02	[0.02,0.02]	0.01	[0,0.01]	0.01	[0,0.01]
σ_π	0.01	[0,0.02]	0.04	[0.03,0.04]	0.05	[0.03,0.06]	0.04	[0.03,0.05]
σ_y	0.05	[0,0.11]	0.04	[0.03,0.04]	0.02	[0,0.07]	0.02	[0.01,0.03]
σ_{ξ^*}	0	[0,0.01]	0.02	[0,0.03]	0.01	[0,0.02]	0.01	[0,0.02]
σ_g	0.02	[0.01,0.03]	0.02	[0.02,0.03]	0.04	[0.03,0.06]	0	[0,0.01]
σ_γ	0.01	[0.01,0.01]	0.01	[0.01,0.01]	0	[0,0.01]	0	[0,0]
σ_{z^x}	0.05	[0.05,0.06]	0.02	[0.02,0.02]	0.03	[0.01,0.04]	0.03	[0.02,0.04]
σ_{z^n}	0.01	[0,0.01]	0	[0,0]	0.01	[0.01,0.02]	0.01	[0,0.01]

Note: C.B. denotes confidence band.