Productivity Shocks, Financial Frictions, and Business Cycles in Emerging Market Economies*

Bira Zhahadai†

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Abstract

This paper studies the extent to which business cycles in emerging market economies (EMEs) are explained by permanent shocks to total factor productivity (TFP). I build a small open economy (SOE) real business cycle (RBC) model with a permanent TFP shock. Two financial frictions are added to the SOE-RBC model. The financial frictions are a Kiyotaki and Moore (1997) collateral constraint and an endogenous risk premium in the world real interest rate. The goal is to examine whether these financial frictions create a business cycle propagation mechanism for the permanent TFP shock that matches aggregate fluctuations in a Brazilian sample from 1999Q1 to 2018Q4 and a Mexican sample from 1997Q1 to 2018Q4. Bayesian prior predictive analysis is applied to evaluate the SOE-RBC model fit on Brazilian and Mexican impulse response functions (IRFs) and forecast error variance decompositions (FEVDs) estimated by structural vector autoregressions (SVARs). This paper shows a permanent TFP shock is the primary driving force of the business cycle in the SOE-RBC model. Next, the SOE-RBC model yields theoretical IRFs and FEVDs that replicate the ones produced from samples of Brazil and Mexico. The findings of this paper support the hypothesis that a permanent TFP shock is the main source of business cycle fluctuations in EMEs.

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Keywords: Business cycle propagation; emerging market economies; financial frictions.

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†Department of Economics, North Carolina State University, Campus Box 8110, Raleigh, NC 27695-8110. e-mail: bila@ncsu.edu.

1. Introduction

This paper studies business cycles in emerging market economies (EMEs). My focus is on the debate started by Aguiar and Gopinath (2007). They argue permanent total factor productivity (TFP) shocks dominate business cycle fluctuations in EMEs. Additional evidence on the permanent TFP shock hypothesis on business cycles in EMEs is provided by Boz, Daude, and Durdu (2011), Flemming, L'Huillier, and Piguillem (2019), Seoane and Yurdagul (2019), and Zhahadai (2021). The other side of the debate is taken by Cao, L'Huillier, and Yoo (2016), García-Cicco, Pancrazi, and Uribe (2010), and Chang and Fernández (2013). Their position is financial frictions in EMEs make financial shocks responsible for generating business cycles in EMEs.

Critics of the permanent TFP shock explanation of business cycles in EMEs point out many small open economy (SOE) real business cycle (RBC) models cannot propagate a permanent TFP shock into movements in output that replicate fluctuations in real GDP at the business cycle horizons produced by actual EMEs. Cao et al. (2016) show a problem when household preferences are separable in consumption and leisure in a SOE-RBC model. That preference empowers transitory financial shocks to take part as main drivers of the business cyclein their SOE-RBC model. The SOE-RBC models in García-Cicco et al. (2010) and Chang and Fernández (2013) indicate that financial frictions open channels for financial shocks to cause swings in aggregate movements while a permanent TFP shock has a negligible role in producing business cycles in EMEs.

I report evidence in this paper that combining two financial frictions creates a business cycle propagation mechanism for the permanent TFP shock of a SOE-RBC model. The financial frictions are a Kiyotaki and Moore (1997) collateral constraint and a country-specific endogenous risk premium in the world real interest rate similar to Nason and Rogers (2006). In addition, the SOE-RBC model has adjustment costs in investment and a permanent TFP shock that is a random walk with drift. Transitory shocks to the risk premium, price of capital, and collateral constraint also contribute to fluctuations in the SOE-RBC model.

The business cycle propagation mechanism of the SOE-RBC model is grounded in the interaction of the Kiyotaki-Moore (KM) collateral constraint and the endogenous risk premium of the world real interest rate. The KM collateral constraint is a function of the market value of capital. The endogenous risk premium is linear in the foreign debt-output ratio. Since capital is a factor input into producing output, a permanent TFP shock ties these financial frictions together.

The interaction of the KM collateral constraint and the endogenous risk premium starts with the contemporaneous impact of a permanent TFP shock. Suppose the shock is negative. In response, representative household in the SOE-RBC model sells capital to finance the debt it owes to the rest of the world. Since the demand of capital is fixed within a period, its price falls to clear the market. The result is additional capital has to be transferred from the household to the rest of the world as the value of collateral shrinks. This tightens the KM collateral constraint in the SOE during the current period. The negative TFP shock also lowers current output, which leads to an increase in the endogenous risk premium of the world real interest rate. This forces the household to sell more capital to finance the higher interest payments on the foreign debt issued by the SOE.

The impact of the negative permanent TFP shock on business cycle fluctuations is propagated by the interaction of financial frictions in future periods. The rest of the world anticipates that output of the SOE will decline in the future due to less capital available for production. This leads to an increasingly higher endogenous risk premium in the world real interest rate that forces the representative household to relinquish more capital to make interest payments. This further tightens the KM collateral constraint, and the household is more constrained in borrowing internationally during the upcoming periods. Hence, the permanent TFP shock hypothesis relies on the KM collateral constraint interacting with the endogenous risk premium in the world real interest rate.

I apply the prior predictive analysis from Geweke (2010) to assess the fit of the SOE-RBC model on a Brazilian sample from 1999Q1 to 2018Q4 and a Mexican sample from 1997Q1 to 2018Q4. The prior predictive analysis produces a range of the SOE-RBC model's possible predictions, then confronts the predictions to an extent of possible moments derived from actual data. The SOE-RBC model needs to pass the prior predictive analysis in order to receive any type of support from sample data as a credible data generating process.

The prior predictive analysis assigns priors to the parameters of the SOE-RBC model. Second, $J = 5000$ synthetic samples are simulated from the SOE-RBC model, given draws from the priors and the distributions of shock innovations. Next, I estimate two structural vector autoregressions (SVARs) on the synthetic sample, as well as the Brazilian and Mexican samples, to construct moments of data. One SVAR is identified by recursive short-run restrictions, and the other is grounded on a recursive long-run identification. The moments of data are impulse response functions (IRFs) and forecast error variance decompositions (FEVDs). Distributions of theoretical IRFs and FEVDs associated with the SOE-RBC model is obtained by estimating SVARs on the 5000 synthetic samples. A Bayesian Monte Carlo integration method outlined in Doan (2010) is used to acquire the distributions of Brazilian and Mexican IRFs and FEVDs with the help of SVARs. All samples consist of output, the world real interest rate, Tobin's Q, and the trade balance-output ratio.

I use the confidence interval criterion (CIC) of DeJong, Ingram, and Whiteman (1996) as the econometric statistic to judge the fit of SOE-RBC models on Brazilian and Mexican samples. The CIC statistic measures the overlap of the distributions of theoretical and sample moments. The multidimensional IRFs and FEVDs are first collapsed into scalar Quasi-Lagrange Multiplier (Q-LM) statistics as in Nason and Cogley (1994). Then the CIC statistics are computed on the theoretical and sample distributions of Q-LM statistics.

This paper finds evidence that supports the argument of the interaction of financial frictions propagates the permanent TFP shock in a SOE-RBC model. Aggregate fluctuations of my SOE-RBC model is primarily driven by the permanent TFP shock. The theoretical FEVDs estimated under the short-run restrictions show the TFP shock explains about two-third of movements in output, half of variations in the world real interest rate and Tobin's Q, and one-third of fluctuations in the trade balance throughout the business cycle horizon. The long-run FEVDs reveal more than three quarters of output movement, and around half of variations in Tobin's Q and the trade balance are explained by the TFP shock.

Theoretical IRFs display shapes that are in line with the business cycle propagation mechanism created by the KM collateral constraint and the endogenous risk premium. A positive permanent TFP shock loosens the KM collateral constraint and lowers the endogenous risk premium. Consequently, the price of capital increases while the world real interest rate and the trade balance both decrease. The theoretical IRFs of output, the world real interest rate, Tobin's Q, and the trade balance display this pattern of movements.

The CIC statistics confirm that aggregate movements of the SOE-RBC model resemble the business cycle fluctuations in Brazil and Mexico. The SOE-RBC model yield theoretical IRFs and FEVDs that replicate the ones computed on the Brazilian and Mexican samples. However, the drawback of the SOE-RBC model is at producing large swings in the theoretical world real interest rate and Tobin's Q that duplicate their sample counterparts. Nonetheless, these evidence support the permanent TFP hypothesis on business cycles in EMEs.

The SOE-RBC model is outlined in the next section. Section 3 describes the Brazilian, Mexican, and synthetic samples. The SVARs are presented in Section 4. Section 5 discusses results and section 6 concludes.

2. The SOE-RBC Model

This section constructs the SOE-RBC model. The SOE-RBC model is a one-sector growth model that incorporates a KM collateral constraint, an endogenous risk premium in the world real interest rate, and costly adjustments in investment. A permanent shock to TFP and transitory shocks to the country-specific endogenous risk premium of the world real interest rate, price of capital, and collateral constraint drive the SOE-RBC model.

Consider a SOE that has a single representative household. Its period utility function is

$$U_t(C_t, N_t) = \phi lnC_t + (1-\phi)ln(1-N_t), \tag{1}$$

which is separable in consumption, C_t, and leisure, L_t. The weight of consumption in period utility function is measured by $\phi \in (0,1)$. A unit of time endowment is allocated by the household between labor, N_t, and leisure, $L_t + N_t = 1$. Lifetime utility is additive separable in discounted expected period utilities, where the discount factor is $\beta \in (0,1)$.

The household's budget constraint is

$$C_t + I_t + (1+r_t)D_t + G \leq Y_t + D_{t+1}, \tag{2}$$

where D_t is the foreign debt paid off at date t plus interest payments at the world real interest rate, r_t. The household borrows new foreign debt, D_{t+1}, from the international bond market at the end of date t. Output, investment, and constant government spending are denoted as Y_t, I_t, and G, respectively.

The output technology is owned by the household

$$Y_t = (a_t N_t)^{1-\theta} K_t^{\theta}, \tag{3}$$

where a_t is a labor augmented TFP shock, K_t is capital, and $\theta \in (0,1)$ is capital's share of production. The TFP shock has permanent effects because it follows a random walk with drift

$$\ln a_t = \mu + \ln a_{t-1} + \varepsilon_t, \tag{4}$$

where $\mu > 0$ and $\varepsilon_t \sim N(0, \sigma_\varepsilon^2)$.

The household accumulates capital, K_{t+1}, through investment, I_t, with costly adjustments as in Jermann and Quadrini (2012)

$$K_{t+1} \leq (1-\delta)K_t + \Big[\frac{\alpha_1 \gamma^{*\alpha_2}}{1-\alpha_2}\left(\frac{I_t}{K_t}\right)^{1-\alpha_2} \nu_t + \alpha_3\Big] K_t, \tag{5}$$

where $\delta \in (0,1)$ is the depreciation rate of capital, and ν_t is a shock to the price of capital. The installation costs of new capital is measured by $\alpha_1 \in (0,1)$, and $\alpha_2 \in (0,1)$ determines the sensitivity of adjustment costs to investment. The steady state value of Tobin's Q is set by $\{\gamma^*, \alpha_3\} \in (-\infty, +\infty)$. The price of capital shock follows a AR(1) process

$$\ln\nu_t = \rho_\nu \ln\nu_{t-1} + \eta_t, \tag{6}$$

where $|\rho_\nu| < 1$ and $\eta_t \sim N(0, \sigma_\eta^2)$.

The adjustment cost in investment creates a wedge between the relative price of capital to consumption and the cost of replacing capital. Dividing this price by the cost defines Tobin's Q

$$q_t = \frac{Market\ \ price\ \ of\ \ capital}{Replacement\ \ cost\ \ of\ \ capital}.$$

The market price of capital is the shadow price of investment, $\lambda_{2,t}$, which is the Lagrangian multiplier tied to the law of motion of capital (5). The replacement cost of capital is the shadow price of a unit of utility, $\lambda_{1,t}$. This Lagrangian multiplier is associated with the household's budget constraint (2). The first-order necessary conditions of the household optimization problem yield

$$q_t = \frac{\lambda_{2,t}}{\lambda_{1,t}} = \frac{1}{\alpha_1 \gamma^{*\alpha_2} \nu_t} \left(\frac{I_t}{K_t} \right)^{\alpha_2}. \tag{7}$$

As a result, Tobin's Q represents the price of capital in the SOE.

The household's foreign debt is limited by the amount of collateral it can offer valued at the current price of capital at the end of date t. The rest of the world can recover their loans by claiming collateral from the household. The KM collateral constraint takes the form

$$D_{t+1} \leq \kappa_t q_t K_{t+1}, \tag{8}$$

where κ_t is the collateral constraint shock. It follows a AR(1) process

$$\ln\kappa_t = (1 - \rho_\kappa)\ln(\kappa^*) + \rho_\kappa \ln\kappa_{t-1} + \zeta_t, \tag{9}$$

where $\kappa^* \in (0, 1)$ is the collateral constraint parameter, $|\rho_\kappa| < 1$, and $\zeta_t \sim N(0, \sigma_\zeta^2)$.

The world real interest rate consists of an exogenous stochastic return, ω_t. This shock evolves as a AR(1) process

$$\ln(\omega_t) = (1 - \rho_\omega)\ln(\omega^*) + \rho_\omega \ln(\omega_{t-1}) + \xi_t, \tag{10}$$

where ω^* is the fixed world real interest rate, $|\rho_\omega| < 1$, and $\xi_t \sim N(0, \sigma_\xi^2)$. I borrow from Nason and Rogers (2006) to specify the endogenous risk premium component as a linear function of the foreign debt-output ratio, $\varphi\left(\frac{D_t}{Y_t}\right)$. Hence, the world real interest rate is the risk premium shock plus the endogenous risk premium component

$$r_t = \omega_t + \varphi\left(\frac{D_t}{Y_t}\right), \tag{11}$$

where $\varphi > 0$ is the risk premium parameter.[1]

[1] The endogenous risk premium negates a unit root in the solution of the SOE-RBC model. See, for

The household maximizes lifetime utility (1) subject to equations (2)-(11), taking K_0, D_0, a_0, ν_0, ω_0, and κ_0 as given. The optimality and equilibrium conditions characterize any candidate equilibrium path of the endogenous variables of the SOE by necessity. The transversality conditions are $\lim_{j\to\infty}\beta^j E_t[\lambda_{2,t+j}K_{t+1+j}] = 0$ and $\lim_{j\to\infty}\beta^j E_t[\lambda_{3,t+j}D_{t+1+j}] = 0$, which provide sufficient conditions for any equilibrium path of the SOE. Brock (1982) shows when the optimality, equilibrium, and transversality conditions are satisfied, the equilibrium of the SOE is unique.[2]

The KM collateral constraint and the endogenous risk premium in the world real interest rate impose financial frictions on the SOE-RBC model. I assume the KM collateral constraint binds and the household internalizes the endogenous risk premium. These assumptions enable household decisions on investing and borrowing to take into account shifts in the KM collateral constraint and fluctuations in the endogenous risk premium component.

The two financial frictions restrict the optimal paths of the two state variables, K_t and D_t, of the SOE-RBC model. The Euler equation for capital is

$$\begin{aligned} q_t\left(1 - s_t\kappa_t\right) = E_t\Lambda_{t,t+1}\Bigg\{\theta\frac{Y_{t+1}}{K_{t+1}}\left[1+\varphi\left(\frac{D_{t+1}}{Y_{t+1}}\right)^2\right] + q_{t+1}\Big[(1-\delta+\alpha_3) \\ + \frac{\alpha_1\alpha_2\gamma^{*\alpha_2}}{1-\alpha_2}\left(\frac{I_{t+1}}{K_{t+1}}\right)^{1-\alpha_2}\nu_{t+1}\Big]\Bigg\}, \end{aligned} \tag{12}$$

example, Schmitt-Grohé and Uribe (2003) and Lubik (2007).

[2]Details about the optimality and equilibrium conditions of the SOE-RBC model are in the appendix.

and the Euler equation for foreign debt is

$$1 - s_t = E_t \Lambda_{t,t+1} \left(1 + \omega_{t+1} + 2\varphi \frac{D_{t+1}}{Y_{t+1}} \right), \tag{13}$$

where s_t is the price of liquidity specified as $s_t = \dfrac{\lambda_{3,t}}{\lambda_{1,t}}$, and $\lambda_{3,t}$ is the Lagrangian multiplier associated with the KM collateral constraint (8). The stochastic discount factor (SDF), $\Lambda_{t,t+1}$, is defined as $\Lambda_{t,t+1} = \beta \dfrac{\lambda_{1,t+1}}{\lambda_{1,t}}$.

The Euler equations (12) and (13) demonstrate how the interaction of the KM collateral constraint and the endogenous risk premium propagates a permanent TFP shock. At impact, a permanent TFP shock affects the income of the representative household, and thereby changes the investment directed for building new capital, K_{t+1}. Therefore, the permanent TFP shock shifts the KM collateral constraint (8). As the KM collateral constraint (8) tightens, there are less liquidity in the international bond market. The result is the price of liquidity, s_t, is higher. The increase in s_t lowers the cost of the marginal unit of K_{t+1}, which is on the left side of Euler equation (12). Equality of Euler equation (12) demands the expected discounted value of an extra unit of K_{t+1} also is lower. A drop in the right hand side of the Euler equation can be produced by declines in $\Lambda_{t,t+1}$, D_{t+1}, q_{t+1}, and/or I_{t+1}. Nonetheless, the source of movement in these variables is a change in the KM collateral constraint (8) because of a permanent shock to TFP.

The increase in price of liquidity, s_t, also implies the cost of an additional unit of D_{t+1} in units of the marginal utility of consumption is lower on the left side of the equality of Euler equation (13). Consequently, the expected discounted value of the marginal unit of D_{t+1} has to decrease in order to maintain the equality in Euler equation (13). Interaction of the KM collateral constraint and the internalized endogenous risk premium creates a business cycle propagation mechanism for the permanent TFP shock in the SOE-RBC model.

3. Sample and Artificial Data

This section describes the Brazilian and Mexican samples followed by a discussion of the priors of the parameters of the SOE-RBC model. Information about generating artificial data from the SOE-RBC model simulation is also provided.

3.1. Sample Data

The Brazilian and Mexican samples are quarterly, seasonally adjusted, and measured in constant local currency units. The samples include real GDP, investment, government spending, and the trade balance. The Brazilian sample runs from 1999Q1 to 2018Q4, T_B=81. There are T_M=89 observations in the Mexican sample, which runs from 1997Q1 to 2018Q4. Investment is measured by gross fixed capital formation. Government spending is consumption at all levels of government. The trade balance is the net exports of goods and services produced by the two economies. The data are found in the International Financial Statistics (IFS), Brazilian Institute of Geography and Statistics (IBGE), and Federal Reserve Economic Data (FRED) databases.

A world real interest rate and Tobin's Q are also part of the Brazilian and Mexican samples. I follow Neumeyer and Perri (2005) and Uribe and Yue (2006) to construct the world real interest rate as the global interest rate adding the emerging market bond index plus (EMBI+) spread. The EMBI+ spread data is provided by the Global Economic Monitor (GEM) database. The global interest rate is the ex-post U.S. real interest rate, which is constructed as the 3-month U.S. treasury bill rate minus the U.S. inflation rate measured by the percentage change in the U.S. GDP deflator. The U.S. data are drawn from the FRED database. Tobin's Q is measured by the ratio of the equity price index to the producer price index. These data are obtained from the IFS database. Except for the investment- and government spending-output ratios, sample data are the same from Zhahadai (2021).[3]

Table 1 summarizes several moments of the Brazilian and Mexican samples. The unconditional first moments of real GDP growth, investment-output ratio, government spending-output ratio, the world real interest rate, Tobin's Q, and the trade balance-output ratio guide the calibration of priors for some parameters of the SOE-RBC model.

Figure 1 and 2 plot the Brazilian and Mexican samples, respectively. Visual inspections suggest it is likely the log levels real GDP, the world real interest rate, and Tobin's Q are non-stationary in the Brazilian and Mexican samples. I borrow the unit root test results from Zhahadai (2021) to conclude that the first differences of log real GDP, the log world real interest rate, and log Tobin's Q plus the level of the trade balance-output ratio are stationary in both samples.

[3]The appendix has more information about the sources and construction of data.

3.2. Prior Distributions

The parameters, $\{\beta, \theta, \phi, \delta\}$, are chosen without prior distributions. I assign dogmatic priors to these parameters because of two reasons. First, the discount factor, β, share of capital in the production function, θ, share of consumption in the utility function, ϕ, and capital depreciation rate, δ, are not associated with the financial frictions of the SOE-RBC model. These parameters are not key interests of this paper. Second, values of these parameters are borrowed from the EME-RBC literature. I take from Boz et al. (2011) to set $\beta = 0.98$. Neumeyer and Perri (2005) is the reference for $\theta = 0.38$. Seoane and Yurdagul (2019) aid in determining $\phi = 0.31$, and Aguiar and Gopinath (2007) help to decide $\delta = 0.05$. These parameters appear in table 2.

Priors for $\{\alpha_1, \alpha_2, \alpha_3, \mu, g^*\}$ are obtained according to sample moments of Brazil and Mexico. The means of these priors are calibrated to match the steady state ratios and rates of the SOE-RBC model with the sample averages.[4] Prior means of the parameters associated with the adjustment costs in investment, α_1 and α_2, are calibrated to the sample mean of the investment-output ratio in Brazil and Mexico. I use the sample average of Tobin's Q to fix the mean of Tobin's Q adjustment parameter, α_3. To my knowledge, there is little information from the EME-RBC literature for assigning values to the parameters of Jermann and Quadrini (2012) style adjustment costs in investment. Uncertainty about $\{\alpha_1, \alpha_2, \alpha_3\}$ is shown by the 95% coverage intervals, which are non-informative and wide.

[4]Details on the steady state equations of the SOE-RBC model are in the appendix.

I calibrate the drift in TFP, μ, and the constant government spending-output ratio, g^*, to the average Brazilian and Mexican real GDP growth and government spending-output ratio. The 95% coverage intervals of $\{\mu, g^*\}$ capture the standard deviations of real GDP growth and government spending-output ratio in Brazil and Mexico. Table 3 contains these priors.

Prior of the collateral constraint parameter, κ^*, is centered at 0.3 with a 95% coverage interval, $\kappa^* \in [0.061, 0.583]$. This range contains values of κ^* from Mendoza (2010) and Korinek and Mendoza (2014). Aguiar and Gopinath (2007) and Schmitt-Grohé and Uribe (2003) restrict the world real interest rate in their SOE-RBC models to be insensitive to the changes in foreign debt. However, Cao et al. (2016) point out a moderate value of the interest rate sensitivity parameter in the SOE-RBC model of Aguiar and Gopinath (2007) overturns the permanent TFP shock explanation.[5] I incorporate stances of Aguiar and Gopinath (2007) and Cao et al. (2016) regarding the interest rate sensitivity parameter into my calibration of φ. I set the mean of φ at 0.3 with a 95% coverage interval of $[0.001, 0.585]$. Priors of $\{\kappa^*, \varphi\}$ are used in all SOE-RBC models. Table 4 gathers these priors.

Priors governing the impulse dynamics of the SOE-RBC model, $\{\omega^*, \rho_\omega, \rho_\nu, \rho_\kappa, \sigma_\varepsilon, \sigma_\xi, \sigma_\eta, \sigma_\varsigma\}$, are based on empirical observations of sample data and references from the EME-RBC literature. Since the fixed global interest rate, ω^*, is common to all small open economies, I use the mean and standard deviation of the ex-post U.S. real interest rate from 1999Q1

[5]Cao et al. (2016) report an increase in the responsiveness of the world real interest rate to foreign debt movements results in excess smoothness in consumption. Consequently, volatilities of consumption and net exports in a SOE-RBC model fall, making the model fails to match the moment of data from EMEs.

to 2018Q4 to calibrate the mean and 95% coverage interval of this prior.[6] The means of the AR(1) parameters of the risk premium and price of capital shocks, ρ_ω and ρ_ν, are set to 0.95. The 95% coverage intervals of $\{\rho_\omega, \rho_\nu\}$ are assumed to be $[0.80, 0.99]$. The tight coverage intervals of $\{\rho_\omega, \rho_\nu\}$ generate synthetic samples that are observationally equivalent to random walk movements in the risk premium and price of capital shocks. The prior of ρ_κ is centered at 0.4 with a 95% coverage intervals of $[0.071, 0.8]$. This assumption is based on the belief the impact of collateral constraint shock is not persistent to the Brazilian and Mexican business cycles. I follow Seoane and Yurdagul (2019) to determine the prior of the standard deviation of TFP shock, σ_ε. Uribe and Yue (2006) and Neumeyer and Perri (2005) guide the prior of the standard deviation of risk premium shock, σ_ξ. Priors of the standard deviation of price of capital and collateral constraint shocks, σ_η and σ_ζ, are based on Letendre and Luo (2007) and Bahadir and Gumus (2016), respectively. These priors are applied to all SOE-RBC models and are collected in table 5.

3.3. Creating Synthetic Sample

I obtain synthetic samples by simulating the SOE-RBC models. A SOE-RBC model is stochastically detrended due to the permanent TFP shock, its steady state is computed, linearized around the steady state, and solved using methods described in Sims (2002). Artificial output, the world real interest rate, Tobin's Q, and the trade balance are simulated

[6]The ex-post U.S. real interest rate is computed by subtracting the U.S. inflation rate, which is the percentage change in the U.S. GDP deflator, from the 3-month U.S. treasury bill rate.

from the linearized SOE-RBC model.[7]

Samples of artificial data are generated from the linearized SOE-RBC model. Sequences of TFP, risk premium, price of capital, and collateral constraint shocks are fed into a SOE-RBC model along with draws from prior parameters to produce $J = 5000$ synthetic samples. The length of a synthetic sample is $S = 1000$. Each simulation of the linearized SOE-RBC model produces a samples of length S of which the first 919 (911) observations are tossed out to remove dependence on initial conditions. The length of the synthetic samples is $S_B = 81$ ($S_M = 89$) for exploring the fit of the SOE-RBC models on the Brazilian (Mexican) sample moments, which are computed on $T_B = 81$ ($T_M = 89$).

4. SVARs

The prior predictive analysis requires a range of possible values of sample moments, in order to evaluate the SOE-RBC model. The Bayesian Monte Carlo integration method of Doan (2010) produces the distributions of IRFs and FEVDs from SVAR estimates. This method involves assigning priors to the slope coefficient and covariance matrices of a reduced-form VAR. Then posterior distributions of the slope coefficient and covariance matrices are derived from the priors and the likelihood function of a VAR. Obtaining posterior slope coefficient and covariance matrices are key for the computations of the distributions of IRFs and FEVDs from the Brazilian and Mexican samples.

[7]The appendix has details about solving and simulating the SOE-RBC model.

This section introduces the SVARs. First, I present a reduced-form VAR followed by an outline of its distributional properties. Next, two SVARs identified by the short- and long-run restrictions are discussed. Finally, construction of sampling distributions of IRFs and FEVDs using the Bayesian Monte Carlo integration algorithm is reviewed.

4.1. Reduced-form VAR

Consider a VAR with Gaussian errors $\boldsymbol{u_t}$ that describes the reduced-form dynamics of a vector of endogenous variables $\boldsymbol{y_t}$

$$\boldsymbol{y_t} = v + C(L)\boldsymbol{y_{t-1}} + \boldsymbol{u_t}, \quad \boldsymbol{u_t} \sim N(0, \Sigma_u), \tag{14}$$

where v is a $n \times 1$ vector of intercepts, n is the dimension of $\boldsymbol{y_t}$, L is the lag operator defined such that $L\boldsymbol{y_t} = \boldsymbol{y_{t-1}}$, $C(L) = \sum_{i=1}^{p} C_i L^{i-1}$ are the $n \times n$ slope coefficient matrices associated with lags of the reduced-form VAR, and Σ_u is the covariance matrix of $\boldsymbol{u_t}$. The reduced-form VAR (14) is Gaussian conditional on the errors of the VAR, $\boldsymbol{u_t}$, are Gaussian.

The reduced-form VAR (14) can be written as a system of static regressions

$$\boldsymbol{Y} = \boldsymbol{X}\mathbb{C} + \boldsymbol{U},$$

where $\boldsymbol{Y} = [\boldsymbol{y}_1\ \boldsymbol{y}_2\ ...\ \boldsymbol{y}_T]'$ and T is the size of sample. Define $\boldsymbol{x}_t = [\boldsymbol{y}_{t-1}\ ...\ \boldsymbol{y}_{t-p}\ 1]$ so that $\boldsymbol{X} = [\boldsymbol{x}_1\ \boldsymbol{x}_2\ ...\ \boldsymbol{x}_T]'$. The coefficient matrix is $\mathbb{C} = [C_1\ ...\ C_p\ v]'$ and Gaussian errors $\boldsymbol{u_t}$ are collected in $\boldsymbol{U} = [\boldsymbol{u}_1\ \boldsymbol{u}_2\ ...\ \boldsymbol{u}_T]'$.

The system of static regression can be stacked into the single regression

$$y = (I_n \otimes \boldsymbol{X})c + \nu, \quad \nu \sim N(0, \Sigma_u \otimes I_T),$$

where $y = vec(\boldsymbol{Y})$ and $\nu = vec(\boldsymbol{U})$ are $nT \times 1$ vectors, I_n is a n dimension identity matrix, and $c = vec(\mathbb{C})$ is a $n(np+1) \times 1$ vector. Since the VAR is Gaussian, $y \sim N\big((I_n \otimes \boldsymbol{X})c, \Sigma_u \otimes I_T\big)$, I follow Doan (2010) to write the likelihood of y as

$$\begin{aligned} \mathcal{L}(y|c, \Sigma_u) &\propto |\Sigma_u|^{-\frac{k}{2}} exp\big[-\frac{1}{2}(c - \hat{c})'(\Sigma_u \otimes (\boldsymbol{X}'\boldsymbol{X})^{-1})^{-1}(c - \hat{c})\big] \\ &\times |\Sigma_u|^{-\frac{(T-k-n-1)+n+1}{2}} exp\big[-\frac{1}{2}tr\{(\boldsymbol{Y} - \boldsymbol{X}\hat{\mathbb{C}})'\Sigma_u^{-1}(\boldsymbol{Y} - \boldsymbol{X}\hat{\mathbb{C}})\}\big], \end{aligned} \tag{15}$$

where tr denotes the trace of a matrix, $k = np + 1$, $\hat{c}$ and $\hat{\mathbb{C}}$ are OLS estimates of c and $\mathbb{C}$, respectively.[8] Conditional on the Gaussian errors, $\nu \sim N(0, \Sigma_u \otimes I_T)$, the $|\Sigma_u|^{-\frac{k}{2}} exp\big[-\frac{1}{2}(c - \hat{c})'(\Sigma_u \otimes (\boldsymbol{X}'\boldsymbol{X})^{-1})^{-1}(c - \hat{c})\big]$ component is the kernel of a normal distribution, and the $|\Sigma_u|^{-\frac{(T-k-n-1)+n+1}{2}} exp\big[-\frac{1}{2}tr\{(\boldsymbol{Y} - \boldsymbol{X}\hat{\mathbb{C}})\Sigma_u^{-1}(\boldsymbol{Y} - \boldsymbol{X}\hat{\mathbb{C}})'\}\big]$ term is the kernel of an inverse Wishart distribution. Hence, the likelihood function (15) is the product of a normal density for c

$$c \sim N\big(\hat{c}, \Sigma_u \otimes (\boldsymbol{X}'\boldsymbol{X})^{-1}\big),$$

[8] The appendix contains details about deriving the likelihood function (15).

and an inverse Wishart density for Σ_u

$$\Sigma_u \ \sim \ IW\big((\boldsymbol{Y} - \boldsymbol{X}\hat{\mathbb{C}})'(\boldsymbol{Y} - \boldsymbol{X}\hat{\mathbb{C}}), T - k - n - 1\big).$$

4.2. SVARs and Short- and Long-Run Identifications

A SVAR is constructed from the reduced-form VAR (1) as

$$\boldsymbol{y_t} = v + C(L)\boldsymbol{y_{t-1}} + D\boldsymbol{\epsilon_t}, \quad \boldsymbol{\epsilon_t} \sim N(0, I), \tag{16}$$

where D is a $n \times n$ structural matrix of the SVAR. The mapping from the reduced-form errors to the structural shocks is $\boldsymbol{u_t} = D\boldsymbol{\epsilon_t}$. A long-run structural matrix, $\Gamma(1)$, is constructed from D as $\Gamma(1) = [I_{n\times n} - C(1)]^{-1}D$, where $C(1) = C_1 + C_2 + ... + C_p$. The SVAR estimates on the vector of endogenous variables

$$\boldsymbol{y_t} = \begin{bmatrix} \Delta lnY_t & \Delta lnR_t & \Delta lnQ_t & \dfrac{TB_t}{Y_t} \end{bmatrix}',$$

where ΔlnY_t is output growth, ΔlnR_t is the first difference of the log world real interest rate, ΔlnQ_t is the first difference of log Tobin's Q, and $\dfrac{TB_t}{Y_t}$ is the trade balance-output ratio.

For the first SVAR, I impose recursive short-run restrictions to identify TFP, risk premium, price of capital, and collateral constraint shocks, $\boldsymbol{\epsilon_t} = [\epsilon_{y,t} \ \epsilon_{r,t} \ \epsilon_{p,t} \ \epsilon_{d,t}]'$, given the ordering of $\boldsymbol{y_t}$. The permanent TFP shock hypothesis argues for placing output at the top of the ordering, which is consistent with my SOE-RBC model. Next, the endogenous risk premium is a linear function of the foreign debt-output ratio in the SOE-RBC model. This makes the world real interest rate respond to the TFP and risk premium shocks at impact, and therefore it is placed second. Hayashi (1982) views the market value of capital is the present discounted value of profit generated by a unit of investment. Computing the present discounted value relies on the SDF. The Euler equation for foreign debt (13) suggests a channel running from changes in the world real interest rate through the SDF to the market value of capital and Tobin's Q. As a result, Tobin's Q growth is ordered third in $\boldsymbol{y_t}$. The trade balance-output ratio stands last in $\boldsymbol{y_t}$ because TFP, risk premium, price of capital, and collateral constraint shocks disturb the trade balance and output at impact.

I apply the Blanchard and Quah (1989) decomposition to restrict $\Gamma(1)$ as a lower triangular matrix. Given $\Gamma(1)$ is a 4×4 matrix, its identification requires six long-run zero restrictions. The long-run identification also depends on the ordering of $\boldsymbol{y_t}$. Real GDP growth is ordered first because the SOE-RBC model is driven by a permanent TFP shock that guarantees the long-run neutrality of output. Since the endogenous risk premium of the world real interest rate is a linear function of foreign debt-output ratio, only TFP and risk premium shocks drive the world real interest rate in the long run. This explains placing the first difference of the log world real interest rate second. The world real interest rate affects the SDF in an EME is key to the long-run identification. According to this assumption, it is the world real interest rate moves Tobin's Q, not the converse. This gives one long-run zero restriction, meaning that the price of capital shock does not drive the world real interest rate in the long run. The assumption that the collateral constraint shock is transitory places no long-run restrictions on output, the world real interest rate, Tobin's Q, and the trade balance-output ratio. This yields the remaining three long-run zero restrictions for identifying TFP, risk premium, price of capital, and collateral constraint shocks.

4.3. Priors, Posteriors, and Bayesian Monte Carlo Integration

I choose the non-informative priors from Doan (2010) for c and Σ_u of the VAR. The non-informative priors do not impose any prior predictions to the movements of IRFs and FEVDs. I believe acquiring a distribution of IRFs and FEVDs without presumptions fits the spirit of the prior predictive analysis.

The non-informative priors make the posterior distributions of slope efficient matrices and the intercept equivalent to the sampling distribution of its OLS estimator. Posterior distribution of c follows

$$\underline{c} \sim N\big(\hat{c}, \Sigma_u \otimes (\boldsymbol{X}'\boldsymbol{X})^{-1}\big),$$

and the posterior for Σ_u is

$$\underline{\Sigma}_u \sim IW\big((\boldsymbol{Y} - \boldsymbol{X}\hat{\mathbb{C}})'(\boldsymbol{Y} - \boldsymbol{X}\hat{\mathbb{C}}), T - k\big),$$

conditional on the assumption that the errors of the VAR is Gaussian.[9]

[9]Refer to the appendix for derivations of the posterior distributions.

Estimation of the SVAR under the short-run identification is straight forward. The lag length of the SVARs are set to two, $p = 2$.[10] Estimates of the coefficient matrix, $\hat{\mathbb{C}}$, and the covariance matrix, $\hat{\Sigma}_u$, are done by the OLS. I take the Cholesky decomposition to find $\hat{D} = \hat{\Sigma}_u^{0.5}$. The next objective is to acquire posterior distributions of IRFs and FEVDs. Doan (2010) proposes a Bayesian Monte Carlo integration algorithm that first draws $\underline{c}$ and $\underline{\Sigma}_u$ from their posterior distributions. Then calculate IRFs and FEVDs using $\underline{c}$ and $\underline{D}$, where $\underline{D} = \underline{\Sigma}_u^{0.5}$. Repeat the calculations for J times to acquire the sampling distributions of IRFs and FEVDs for twelve quarters.[11]

Under the long-run restrictions, SVAR estimation involves several more steps. The structural infinite-order vector moving average (VMA) representation of the SVAR (16) is

$$\boldsymbol{y_t} = \mu + \sum_{j=0}^{\infty} \Gamma_j \boldsymbol{\epsilon_{t-j}}, \tag{17}$$

where $\mu = [I_{n\times n} - C(1)]^{-1}v$ is a $n \times 1$ vector of unconditional mean of $\boldsymbol{y_t}$, and Γ_j are the $n \times n$ structural moving average coefficient matrices that follow

$$\Gamma_0 = D, \;\; \boldsymbol{u_t} = \Gamma_0 \boldsymbol{\epsilon_t}, \;\; \Gamma(L) = \sum_{j=0}^{\infty} \Gamma_j L^j, \;\; \Gamma(L) = [I_{n\times n} - C(L)]^{-1} D.$$

The long-run structural matrix, $\Gamma(1)$, is computed as $\Gamma(1) = [I_{n\times n} - C(1)]^{-1}D$. The recursive long-run restrictions specify a lower triangular long-run structural matrix, $\tilde{\Gamma}(1)$. Computa-

[10] It is common in the EME empirical literature to estimate SVARs with two lags. References are Akinci (2013), Bruno and Shin (2015), and Kim et al. (2020).

[11] Detailed steps of the Bayesian Monte Carlo integration algorithm are shown in the appendix.

tion of $\tilde{\Gamma}(1)$ begins at multiplying $\Gamma(1)\boldsymbol{\epsilon_t}$ by $[\Gamma(1)\boldsymbol{\epsilon_t}]'$ to obtain

$$\Gamma(1)\boldsymbol{\epsilon_t}\boldsymbol{\epsilon_t}'\Gamma(1)' = [I_{n\times n} - C(1)]^{-1}\boldsymbol{u_t}\boldsymbol{u_t}'\Big([I_{n\times n} - C(1)]^{-1}\Big)'.$$

Since $E_t[\boldsymbol{\epsilon_t}\boldsymbol{\epsilon_t}'] = I_{n\times n}$ and $E_t[\boldsymbol{u_t}\boldsymbol{u_t}'] = \Sigma_u$, rewrite the above equation as

$$\Gamma(1)\Gamma(1)' = [I_{n\times n} - C(1)]^{-1}\Sigma_u\Big([I_{n\times n} - C(1)]^{-1}\Big)'.$$

The long-run structural matrix, $\tilde{\Gamma}(1)$, is found by taking the Cholesky decomposition of $\Gamma(1)\Gamma(1)'$, $\tilde{\Gamma}(1) = \Big[\Gamma(1)\Gamma(1)'\Big]^{0.5}$. Because of $\Sigma_u = DD'$, the Cholesky decomposition of $\Gamma(1)\Gamma(1)'$ also yields

$$\Big[\Gamma(1)\Gamma(1)'\Big]^{0.5} = \Big\{[I_{n\times n} - C(1)]^{-1}DD'\Big([I_{n\times n} - C(1)]^{-1}\Big)'\Big\}^{0.5} \Rightarrow \tilde{\Gamma}(1) = [I_{n\times n} - C(1)]^{-1}D.$$

Finally, the structural matrix, D, is recovered by computing $D = [I_{n\times n} - C(1)]\tilde{\Gamma}(1)$. The long-run Bayesian Monte Carlo integration method first draws $\underline{c}$ and $\underline{\Sigma}_u$, then follows the above steps to acquire $\underline{D}$. Estimates of $\underline{c}$ and $\underline{D}$ pin down the IRFs and FEVDs generated from the SVAR governed by the long-run identification.[12]

[12]More details on the long-run Bayesian Monte Carlo integration algorithm can be found in the appendix.

5. Results

This section starts with reporting the econometric measure of fit between the synthetic sample and data samples of Brazil and Mexico. Main findings of this paper are discussed next.

5.1. Test Statistics

A Q-LM statistic similar to Nason and Cogley (1994) measures the distance between IRFs and FEVDs. The Q-LM statistic collapses the multidimensional IRFs and FEVDs into a scalar statistic by computing

$$\text{Q-LM(m)} = [\hat{F} - F(j)]V^{-1}[\hat{F} - F(j)]',$$

where m is the forecast horizon of the IRFs (FEVDs), $\hat{F}$ is the mean of sample IRFs (FEVDs), and $F(j)$ is an IRF (FEVD) from the theoretical and sample distributions of IRFs (FEVDs). The forecast horizon is set at twelve quarters, $m = 12$. The covariance matrix, V, of theoretical and sample IRFs (FEVDs) is specified as

$$V = J^{-1}\sum_{j=1}^{J}[F(j) - F][F(j) - F]',$$

where F is the mean of the theoretical and sample IRFs (FEVDs). There are J numbers of IRFs and FEVDs produced by the SVARs to form distributions of Q-LM statistics. I denote Q-LM$_{Theo}$, Q-LM$_{Braz}$ and Q-LM$_{Mexi}$, as the theoretical, Brazilian, and Mexican Q-LM statistics, respectively.

I use the CIC statistic of DeJong et al. (1996) to measure the overlap of Q-LM$_{Theo}$ and Q-LM$_{Braz}$ (Q-LM$_{Mexi}$) distributions. The CIC statistics judge the ability of the SOE-RBC model at producing a business cycle that matches the one from Brazil and Mexico. For example, the CIC of Q-LM$_{Theo}$ and Q-LM$_{Braz}$ is computed as

$$CIC = \frac{1}{1-\alpha} \int_a^b \text{Q-LM}_{Theo}(j) dj,$$

where $1 - \alpha$ is the percentage confidence interval, a and b are the lower 0.5α and upper $1 - 0.5\alpha$ quantile and is normalized by $1 - \alpha$ to equal $\int_a^b \text{Q-LM}_{Braz}(j) dj$.

5.2. Findings from Short-Run Restrictions

Figure 3 contains the theoretical and sample IRFs of output, the world real interest rate, Tobin's Q, and the trade balance with respect to a TFP shock generated by the SVAR under the short-run restrictions. In response to a positive TFP shock, theoretical output rises at impact and remains above zero throughout the twelve-quarter horizon. The TFP shock produces a theoretical IRF for the world real interest rate that drops at impact and returns to zero after the two-quarter horizon. The theoretical IRF of Tobin's Q with respect to the

TFP shock increases at impact then stays slightly above zero across the three-year horizon. The artificial trade balance increases at impact, falls below zero at the next quarter, then jumps above zero again in the following quarter. This pattern of fluctuating movements in the trade balance continues across the business cycle horizon in response to the TFP shock.

Under the short-run restrictions, dynamic movements of the theoretical IRFs match the predictions of the SOE-RBC model with the KM collateral constraint and the internalized endogenous risk premium of the world real interest rate. A positive TFP shock leads the growth of future flow of output. This increase in output lowers the endogenous risk premium causing the world real interest rate to fall. The TFP shock drives the representative household to accumulate more capital. Consequently, Tobin's Q appreciates. However, there is an anomaly in the theoretical IRFs generated from the short-run restrictions. The IRF of the trade balance in figure 3 shows a rise at impact when the SOE-RBC model predicts the trade balance should fall. The SOE-RBC model predicts expansions in output and capital enable the SOE to borrow more from the rest of the world because the TFP shock grows the collateral. The upshot is the theoretical trade balance deteriorates. One possible explanation to the anomaly is that the exports benefit from the positive TFP shock, which drives up the trade balance at impact. On the other hand, the growing foreign debt quickly offsets the increase in export that cause the trade balance to fall below zero at the one-quarter horizon.

Table 6 and 7 present the FEVDs estimated on the synthetic samples simulated from the SOE-RBC models. The FEVDs estimated on the Brazilian and Mexican samples are also included in table 6 and 7, respectively. These FEVDs uncover that the permanent TFP shock dominates the aggregate fluctuations in the SOE-RBC model. The TFP shock accounts for about three quarters of the variation in output, anywhere between half to one-third of the movements in the world real interest rate and Tobin's Q, and more than one-third of the fluctuation in the trade balance throughout the three-year horizon.[13] Furthermore, the price of capital shock is important to the SOE-RBC model. This shock drives about one-third of the fluctuation in output, about a quarter of the variation in the world real interest rate, and one-third to a quarter of the trade balance across the business cycle horizon. The short-run restrictions reveal a rich dynamic of business cycle produced by the SOE-RBC model.

5.3. Findings from Long-Run Restrictions

Figure 4 displays the theoretical and sample IRFs estimated by the SVAR grounded on the long-run identification. These IRFs show a similar pattern of movements with the short-run theoretical IRFs in figure 3. For example, a positive TFP shock causes the theoretical world real interest rate to fall at impact and to revert back to zero at the one-quarter horizon. There is a small increase in the theoretical IRF of Tobin's Q with respect to the TFP shock at impact. Then it remains slightly above zero throughout the twelve-quarter horizon. In response to the TFP shock, the theoretical trade balance decreases at impact and fluctuates around zero throughout the twelve-quarter horizon.

The long-run identification produces theoretical IRFs that are fully consistent with the

[13] Point estimates of FEVDs greater than 20% are deemed economically important.

business cycle propagation mechanism created by the interaction of the KM collateral constraint and the internalized endogenous risk premium in the world real interest rate. In response to a positive TFP shock, the representative household invests to grow capital, which drives up the price of capital. The price of capital appreciation raises the value of collateral. This loosens the KM collateral constraint that enables the SOE to borrow more from the rest of the world. This explains the increase in the price of capital and the fall in the trade balance with respect to the TFP shock in figure 4. The TFP shock also decreases the world real interest rate by expanding the output to lower the endogenous risk premium. Movements of output, the world real interest rate, Tobin's Q, and the trade balance in response to a TFP shock match the predictions of the business cycle propagation mechanism of the SOE-RBC model.

As shown in table 8 and 9, the FEVDs estimated on synthetic samples confirm the permanent TFP is the primary driving force of the SOE-RBC model. The TFP shock explains more than three quarters of the variation in output at the one- to twelve-quarter horizon. In addition, about a quarter of the movement in the trade balance, and half of the fluctuations in Tobin's Q and the trade balance are generated by the TFP shock across the three-year horizon. Also note that the risk premium and collateral constraint shocks are important for explaining variations in the world real interest rate and the trade balance. These evidence support the hypothesis that the interaction of financial frictions propagates the permanent TFP shock of the SOE-RBC model.

5.4. SOE-RBC Model Fit

The CIC statistics quantify the fit of the SOE-RBC model on the sample data from Brazil and Mexico. The CIC of the Q-LM statistics computed on IRFs in table 10 and 11 show the SOE-RBC model can in part replicate the Brazilian and Mexican IRFs. The theoretical IRFs of output and the trade balance highly overlap with the Brazilian and Mexican IRFs across the short- and long-run restrictions. However, the SOE-RBC model fails to generate large swings in the world real interest rate and Tobin's Q. Figure 5 and 6 show the theoretical world real interest rate and Tobin's Q move slightly after hit by the TFP, risk premium, price of capital, and collateral constraint shocks. These theoretical IRFs match poorly with the Brazilian and Mexican IRFs. As the result, the CIC of the Q-LM statistics computed on IRFs of the world real interest rate and Tobin's Q in table 10 and 11 are near zero.

Table 12 and 13 exhibit the CIC of the Q-LM statistics computed on FEVDs. At least fourteen out of sixteen CIC statistics in table 12 and 13 are above 0.5. Under short- and long-run restrictions, theoretical FEVDs match incredibly well with the Brazilian and Mexican FEVDs. These statistics show the SOE-RBC model produces a business cycle propagation mechanism that resembles the business cycles in Brazil and Mexico.

6. Conclusion

This paper builds a SOE-RBC model. The SOE-RBC model rests on four key elements. First, the real price of capital is Tobin's Q in the SOE-RBC model because of adjustment costs in investment. Second, household expectation about the present discounted value of the future flow of output are affected in the price of capital, which shifts the KM collateral constraint in the current period. Third, capital is more valuable in production to the household than it is to the rest of the world holding the debt of the SOE. Fourth, an increase in the endogenous risk premium reinforces the business cycle propagation mechanism of a permanent TFP shock. Thus, the permanent TFP shock hypothesis relies on the KM collateral constraint interacting with the endogenous risk premium in the world real interest rate to create a business cycle propagate mechanism of the SOE-RBC model. There are also transitory shocks to the risk premium, price of capital, and collateral constraint that drive the SOE-RBC model.

Model evaluation is a multi-step process. First, the linearized SOE-RBC model is simulated 5000 times to build synthetic samples. Next, SVARs under short- and long-run restrictions estimate synthetic, Brazilian, and Mexican samples to generate distributions of theoretical and sample IRFs and FEVDs. The multi-dimensional IRFs and FEVDs are collapsed into scalar Q-LM statistics. Finally, the CIC statistics is introduced to measure the overlap of the distributions of theoretical and sample Q-LM statistics. I use the CIC statistics to confront the SOE-RBC model, in terms of the model's ability to explain the business cycles in Brazil and Mexico.

This paper finds the SOE-RBC model is dominated by the permanent TFP shock, which is evidence the interaction of financial frictions propagates a permanent TFP shock. In addition the SOE-RBC model generates a business cycle that duplicats the aggregate fluctuations in Brazil and Mexico. The SOE-RBC model is successful at replicating the movements of real GDP and the trade balance in Brazil and Mexico at the business cycle horizon. The only caveat is that the SOE-RBC model is limited at creating large movements in the world real interest rate and Tobin's Q that fails to match the movements in the Brazilian and Mexican sample counterparts. Nevertheless, findings of this paper support the permanent TFP shock explanation of business cycles in EMEs.

For future work, I plan to apply the prior predictive analysis to three versions of the SOE-RBC model: one with the KM collateral constraint and not internalized endogenous risk premium, one without the KM collateral constraint and internalized endogenous risk premium, and one without financial frictions. This exercise yields more insights on business cycle propagation mechanism of the SOE-RBC model.

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Table 1: Brazilian and Mexican Sample Moments

Brazilian Sample Moment	ΔlnY	$\frac{I}{Y}$	$\frac{G}{Y}$	R	Q	$\frac{TB}{Y}$
Value	0.006	0.181	0.193	0.059	0.634	-0.001
	(0.012)	(0.019)	(0.006)	(0.047)	(0.204)	(0.020)
Mexican Sample Moment	ΔlnY	$\frac{I}{Y}$	$\frac{G}{Y}$	R	Q	$\frac{TB}{Y}$
Value	0.006	0.214	0.109	0.044	0.650	-0.015
	(0.010)	(0.011)	(0.012)	(0.029)	(0.302)	(0.006)

Notes: This table reports unconditional means of ratios and rates in the Brazilian sample from 1999Q1 to 2018Q4 and the Mexican Sample from 1997Q1 to 2018Q4. Standard deviations appear in parenthesis. Real GDP growth, investment-output ratio, government spending-output ratio, the world real interest rate, Tobin's Q, and the trade balance-output ratio are denoted as ΔlnY, $\frac{I}{Y}$, $\frac{G}{Y}$, R, Q, and $\frac{TB}{Y}$, respectively.

Table 2: Fixed Parameters of SOE-RBC Models

Parameter	β	θ	ϕ	δ
Value	0.98	0.38	0.31	0.05

Notes: This table gives the parameters with dogmatic priors. The discount factor, share of capital in production, share of consumption in utility, and depreciation rate are denoted as β, θ, ϕ, and δ, respectively. Boz et al. (2011), Neumeyer and Perri (2005), Aguiar and Gopinath (2007), and Seoane and Yurdagul (2019) are the sources for dogmatic calibration of these parameters.

Table 3: Priors Calibrated to Brazilian and Mexican Sample Moments

Brazil	Prior Distribution	Mean	Standard Deviation	95% Coverage Interval
α_1	Truncated[Normal(28.542, 3.841)| 0, 1]	0.65	0.3	[0.070, 0.989]
α_2	Truncated[Normal(-12.156, 2.511)| 0, 1]	0.34	0.3	[0.011, 0.925]
α_3	Normal(-0.121, 0.3)	-0.121	0.3	[-0.709, 0.467]
μ	Normal(0.006, 0.012)	0.006	0.012	[-0.018, 0.029]
g^*	Beta(834.772, 3490.473)	0.193	0.006	[0.181, 0.205]
Mexico	Prior Distribution	Mean	Standard Deviation	95% Coverage Interval
α_1	Truncated[Normal(21.207, 2.905)| 0, 1]	0.687	0.3	[0.096, 0.990]
α_2	Truncated[Normal(-12.543, 2.568)| 0, 1]	0.342	0.3	[0.011, 0.926]
α_3	Normal(-0.167, 0.3)	-0.167	0.3	[-0.755, 0.421]
μ	Normal(0.006, 0.01)	0.006	0.01	[-0.014, 0.026]
g^*	Beta(73.404, 600.032)	0.109	0.012	[0.087, 0.134]

Notes: The priors of the parameters of the SOE-RBC model are calibrated to match its steady state ratios and rates with the sample means of Brazilian variables from 1999Q1 to 2018Q4 and Mexican variables from 1997Q1 to 2018Q4. The installation costs of new capital and sensitivity of adjustment costs to investment parameters, α_1 and α_2, are calibrated to the sample mean of investment-output ratio in Brazil and Mexico. Tobin's Q adjustment parameters, α_3, are calibrated to the Brazilian and Mexican sample average of Tobin's Q. The 95% coverage intervals of $\{\alpha_1, \alpha_2, \alpha_3\}$ reflect the belief that these priors are non-informative. The drift in TFP shock, μ, is set to the sample average of sample real GDP growth. The constant government spending-output ratio, g^*, is the sample average of the Brazilian and Mexican government spending-output ratio. Standard deviations of real GDP growth and government spending-output ratio guide the 95% coverage intervals of $\{\mu, g^*\}$.

Table 4: Priors of Financial Friction Parameters

	Prior Distribution	Mean	Standard Deviation	95% Coverage Interval
κ^*	Truncated[Normal(-15.417, 4.271)| 0.05, 0.6]	0.3	0.158	[0.061, 0.583]
φ^*	Truncated[Normal(115.185, 26.746)| -0.015, 0.6]	0.3	0.177	[0.001, 0.585]

Notes: The priors linked to the KM collateral constraint, κ^*, and the endogenous risk premium, κ^*, are applied to the SOE-RBC model. Mendoza (2010) and Korinek and Mendoza (2014) guide the prior of κ^*. Prior of φ^* reflects the views of Aguiar and Gopinath (2007) and Cao et al. (2016) about the sensitivity of the world real interest rate to changes in foreign debt.

Table 5: Priors of Exogenous Shock Process Parameters

	Prior Distribution	Mean	Standard Deviation	95% Coverage Interval
ω^*	Beta(0.463, 34.619)	0.013	0.019	[0.004, 0.042]
ρ_ω	Beta(13.967, 0.735)	0.950	0.055	[0.800, 0.999]
ρ_ν	Beta(13.967, 0.735)	0.950	0.055	[0.800, 0.999]
ρ_κ	Beta(2.073, 3.110)	0.4	0.197	[0.071, 0.800]
σ_ε	IGamma(6, 0.1)	0.02	0.01	[0.001, 0.045]
σ_ξ	IGamma(2.159, 0.046)	0.04	0.1	[0.008, 0.158]
σ_η	IGamma(10.999, 0.299)	0.03	0.01	[0.016, 0.055]
σ_ζ	IGamma(6, 0.1)	0.02	0.01	[0.001, 0.045]

Notes: This table summarizes the priors that define the impulse dynamics of the SOE-RBC model. The first and second moments of the ex-post U.S. real interest rate decides the prior of the fixed global interest rate, ω^*. The AR(1) parameters of the risk premium and price of capital shocks, ρ_ω and ρ_ν, are determined such that the impact of both shocks is persistent. Contrary, the AR1 parameter of the collateral constraint shock, ρ_κ, is decided such that the collateral constraint shock is transitory. Seoane and Yurdagul (2019), Uribe and Yue (2006), Neumeyer and Perri (2005), Letendre and Luo (2007), Bahadir and Gumus (2016) are the references for the priors of the standard deviations of shocks $\{\sigma_\varepsilon, \sigma_\xi, \sigma_\eta, \sigma_\zeta\}$.

Table 6: FEVDs Estimated on Brazilian and Synthetic Samples Under Short-Run Restrictions

Variable	Shocks \ Horizons	Q1	Q2	Q4	Q8	Q12
Y_t	TFP	$0.94_{Brazil}, 0.63_{Model}$	$0.87_{Brazil}, 0.65_{Model}$	$0.82_{Brazil}, 0.63_{Model}$	$0.74_{Brazil}, 0.62_{Model}$	$0.69_{Brazil}, 0.61_{Model}$
	Risk Premium	$0.03_{Brazil}, 0.04_{Model}$	$0.06_{Brazil}, 0.04_{Model}$	$0.07_{Brazil}, 0.05_{Model}$	$0.07_{Brazil}, 0.05_{Model}$	$0.06_{Brazil}, 0.06_{Model}$
	Price of Capital	$0.02_{Brazil}, 0.29_{Model}$	$0.05_{Brazil}, 0.26_{Model}$	$0.08_{Brazil}, 0.27_{Model}$	$0.08_{Brazil}, 0.27_{Model}$	$0.08_{Brazil}, 0.27_{Model}$
	Collateral Constraint	$0.01_{Brazil}, 0.04_{Model}$	$0.02_{Brazil}, 0.05_{Model}$	$0.03_{Brazil}, 0.05_{Model}$	$0.11_{Brazil}, 0.06_{Model}$	$0.17_{Brazil}, 0.06_{Model}$
R_t	TFP	$0.02_{Brazil}, 0.49_{Model}$	$0.04_{Brazil}, 0.47_{Model}$	$0.04_{Brazil}, 0.45_{Model}$	$0.04_{Brazil}, 0.41_{Model}$	$0.04_{Brazil}, 0.39_{Model}$
	Risk Premium	$0.84_{Brazil}, 0.14_{Model}$	$0.80_{Brazil}, 0.16_{Model}$	$0.79_{Brazil}, 0.17_{Model}$	$0.74_{Brazil}, 0.19_{Model}$	$0.72_{Brazil}, 0.20_{Model}$
	Price of Capital	$0.13_{Brazil}, 0.23_{Model}$	$0.15_{Brazil}, 0.23_{Model}$	$0.15_{Brazil}, 0.23_{Model}$	$0.14_{Brazil}, 0.23_{Model}$	$0.14_{Brazil}, 0.22_{Model}$
	Collateral Constraint	$0.01_{Brazil}, 0.14_{Model}$	$0.01_{Brazil}, 0.14_{Model}$	$0.02_{Brazil}, 0.15_{Model}$	$0.08_{Brazil}, 0.17_{Model}$	$0.10_{Brazil}, 0.19_{Model}$
Q_t	TFP	$0.04_{Brazil}, 0.51_{Model}$	$0.05_{Brazil}, 0.47_{Model}$	$0.08_{Brazil}, 0.42_{Model}$	$0.11_{Brazil}, 0.37_{Model}$	$0.12_{Brazil}, 0.34_{Model}$
	Risk Premium	$0.07_{Brazil}, 0.06_{Model}$	$0.06_{Brazil}, 0.06_{Model}$	$0.05_{Brazil}, 0.06_{Model}$	$0.05_{Brazil}, 0.06_{Model}$	$0.05_{Brazil}, 0.06_{Model}$
	Price of Capital	$0.88_{Brazil}, 0.39_{Model}$	$0.88_{Brazil}, 0.42_{Model}$	$0.81_{Brazil}, 0.44_{Model}$	$0.67_{Brazil}, 0.46_{Model}$	$0.60_{Brazil}, 0.46_{Model}$
	Collateral Constraint	$0.01_{Brazil}, 0.04_{Model}$	$0.01_{Brazil}, 0.05_{Model}$	$0.06_{Brazil}, 0.08_{Model}$	$0.17_{Brazil}, 0.11_{Model}$	$0.23_{Brazil}, 0.14_{Model}$
TB_t	TFP	$0.01_{Brazil}, 0.30_{Model}$	$0.01_{Brazil}, 0.33_{Model}$	$0.03_{Brazil}, 0.37_{Model}$	$0.04_{Brazil}, 0.40_{Model}$	$0.05_{Brazil}, 0.40_{Model}$
	Risk Premium	$0.03_{Brazil}, 0.12_{Model}$	$0.04_{Brazil}, 0.14_{Model}$	$0.05_{Brazil}, 0.17_{Model}$	$0.06_{Brazil}, 0.19_{Model}$	$0.06_{Brazil}, 0.19_{Model}$
	Price of Capital	$0.01_{Brazil}, 0.38_{Model}$	$0.01_{Brazil}, 0.34_{Model}$	$0.01_{Brazil}, 0.29_{Model}$	$0.02_{Brazil}, 0.24_{Model}$	$0.02_{Brazil}, 0.22_{Model}$
	Collateral Constraint	$0.95_{Brazil}, 0.20_{Model}$	$0.94_{Brazil}, 0.19_{Model}$	$0.91_{Brazil}, 0.17_{Model}$	$0.88_{Brazil}, 0.17_{Model}$	$0.87_{Brazil}, 0.19_{Model}$

Notes: The table summarizes the contributions of TFP, risk premium, price of capital, and collateral constraint shocks to the fluctuations of output, Y_t, the world real interest rate, R_t, Tobin's Q, Q_t, and the trade balance, TB_t. A SVAR under the short-run restrictions estimates the synthetic sample and a Brazilian sample from 1999Q1 to 2018Q4 to produce these FEVDs.

Table 7: FEVDs Estimated on Mexican and Synthetic Samples Under Short-Run Restrictions

Variable	Horizons / Shocks	Q1	Q2	Q4	Q8	Q12
Y_t	TFP	$0.86_{Mexico}, 0.64_{Model}$	$0.69_{Mexico}, 0.65_{Model}$	$0.54_{Mexico}, 0.64_{Model}$	$0.50_{Mexico}, 0.63_{Model}$	$0.49_{Mexico}, 0.62_{Model}$
	Risk Premium	$0.01_{Mexico}, 0.04_{Model}$	$0.01_{Mexico}, 0.04_{Model}$	$0.02_{Mexico}, 0.05_{Model}$	$0.03_{Mexico}, 0.05_{Model}$	$0.03_{Mexico}, 0.05_{Model}$
	Price of Capital	$0.05_{Mexico}, 0.28_{Model}$	$0.12_{Mexico}, 0.26_{Model}$	$0.19_{Mexico}, 0.26_{Model}$	$0.21_{Mexico}, 0.27_{Model}$	$0.22_{Mexico}, 0.27_{Model}$
	Collateral Constraint	$0.08_{Mexico}, 0.04_{Model}$	$0.18_{Mexico}, 0.05_{Model}$	$0.25_{Mexico}, 0.05_{Model}$	$0.26_{Mexico}, 0.05_{Model}$	$0.26_{Mexico}, 0.06_{Model}$
R_t	TFP	$0.02_{Mexico}, 0.48_{Model}$	$0.06_{Mexico}, 0.46_{Model}$	$0.10_{Mexico}, 0.44_{Model}$	$0.11_{Mexico}, 0.41_{Model}$	$0.12_{Mexico}, 0.39_{Model}$
	Risk Premium	$0.88_{Mexico}, 0.14_{Model}$	$0.82_{Mexico}, 0.16_{Model}$	$0.78_{Mexico}, 0.17_{Model}$	$0.78_{Mexico}, 0.19_{Model}$	$0.78_{Mexico}, 0.20_{Model}$
	Price of Capital	$0.08_{Mexico}, 0.23_{Model}$	$0.09_{Mexico}, 0.22_{Model}$	$0.08_{Mexico}, 0.22_{Model}$	$0.07_{Mexico}, 0.22_{Model}$	$0.07_{Mexico}, 0.22_{Model}$
	Collateral Constraint	$0.02_{Mexico}, 0.15_{Model}$	$0.03_{Mexico}, 0.16_{Model}$	$0.04_{Mexico}, 0.17_{Model}$	$0.04_{Mexico}, 0.18_{Model}$	$0.03_{Mexico}, 0.19_{Model}$
Q_t	TFP	$0.01_{Mexico}, 0.53_{Model}$	$0.02_{Mexico}, 0.48_{Model}$	$0.03_{Mexico}, 0.43_{Model}$	$0.03_{Mexico}, 0.37_{Model}$	$0.03_{Mexico}, 0.34_{Model}$
	Risk Premium	$0.02_{Mexico}, 0.06_{Model}$	$0.04_{Mexico}, 0.06_{Model}$	$0.06_{Mexico}, 0.06_{Model}$	$0.07_{Mexico}, 0.06_{Model}$	$0.07_{Mexico}, 0.06_{Model}$
	Price of Capital	$0.93_{Mexico}, 0.38_{Model}$	$0.89_{Mexico}, 0.41_{Model}$	$0.86_{Mexico}, 0.44_{Model}$	$0.86_{Mexico}, 0.46_{Model}$	$0.85_{Mexico}, 0.47_{Model}$
	Collateral Constraint	$0.04_{Mexico}, 0.03_{Model}$	$0.05_{Mexico}, 0.05_{Model}$	$0.05_{Mexico}, 0.07_{Model}$	$0.04_{Mexico}, 0.11_{Model}$	$0.05_{Mexico}, 0.13_{Model}$
TB_t	TFP	$0.01_{Mexico}, 0.30_{Model}$	$0.01_{Mexico}, 0.33_{Model}$	$0.02_{Mexico}, 0.36_{Model}$	$0.02_{Mexico}, 0.40_{Model}$	$0.02_{Mexico}, 0.40_{Model}$
	Risk Premium	$0.01_{Mexico}, 0.12_{Model}$	$0.02_{Mexico}, 0.14_{Model}$	$0.03_{Mexico}, 0.17_{Model}$	$0.03_{Mexico}, 0.19_{Model}$	$0.04_{Mexico}, 0.20_{Model}$
	Price of Capital	$0.03_{Mexico}, 0.38_{Model}$	$0.06_{Mexico}, 0.34_{Model}$	$0.08_{Mexico}, 0.28_{Model}$	$0.09_{Mexico}, 0.23_{Model}$	$0.09_{Mexico}, 0.22_{Model}$
	Collateral Constraint	$0.95_{Mexico}, 0.20_{Model}$	$0.91_{Mexico}, 0.19_{Model}$	$0.87_{Mexico}, 0.19_{Model}$	$0.88_{Mexico}, 0.18_{Model}$	$0.87_{Mexico}, 0.18_{Model}$

Notes: The table summarizes the contributions of TFP, risk premium, price of capital, and collateral constraint shocks to the fluctuations of output, Y_t, the world real interest rate, R_t, Tobin's Q, Q_t, and the trade balance, TB_t. A SVAR under the short-run restrictions estimates the synthetic sample and a Mexican sample from 1997Q1 to 2018Q4 to produce these FEVDs.

Table 8: FEVDs Estimated on Brazilian and Synthetic Samples Under Long-Run Restrictions

Variable	Horizons / Shocks	Q1	Q2	Q4	Q8	Q12
Y_t	TFP	$0.47_{Brazil}, 0.74_{Model}$	$0.50_{Brazil}, 0.77_{Model}$	$0.55_{Brazil}, 0.83_{Model}$	$0.67_{Brazil}, 0.89_{Model}$	$0.73_{Brazil}, 0.91_{Model}$
	Risk Premium	$0.12_{Brazil}, 0.09_{Model}$	$0.10_{Brazil}, 0.08_{Model}$	$0.08_{Brazil}, 0.06_{Model}$	$0.06_{Brazil}, 0.04_{Model}$	$0.05_{Brazil}, 0.04_{Model}$
	Price of Capital	$0.26_{Brazil}, 0.06_{Model}$	$0.24_{Brazil}, 0.05_{Model}$	$0.20_{Brazil}, 0.03_{Model}$	$0.15_{Brazil}, 0.02_{Model}$	$0.12_{Brazil}, 0.02_{Model}$
	Collateral Constraint	$0.15_{Brazil}, 0.11_{Model}$	$0.16_{Brazil}, 0.10_{Model}$	$0.17_{Brazil}, 0.08_{Model}$	$0.12_{Brazil}, 0.05_{Model}$	$0.10_{Brazil}, 0.03_{Model}$
R_t	TFP	$0.09_{Brazil}, 0.24_{Model}$	$0.11_{Brazil}, 0.24_{Model}$	$0.11_{Brazil}, 0.22_{Model}$	$0.14_{Brazil}, 0.19_{Model}$	$0.16_{Brazil}, 0.18_{Model}$
	Risk Premium	$0.61_{Brazil}, 0.45_{Model}$	$0.58_{Brazil}, 0.47_{Model}$	$0.63_{Brazil}, 0.52_{Model}$	$0.67_{Brazil}, 0.59_{Model}$	$0.68_{Brazil}, 0.63_{Model}$
	Price of Capital	$0.17_{Brazil}, 0.07_{Model}$	$0.17_{Brazil}, 0.07_{Model}$	$0.14_{Brazil}, 0.06_{Model}$	$0.10_{Brazil}, 0.05_{Model}$	$0.09_{Brazil}, 0.05_{Model}$
	Collateral Constraint	$0.13_{Brazil}, 0.24_{Model}$	$0.14_{Brazil}, 0.22_{Model}$	$0.12_{Brazil}, 0.20_{Model}$	$0.09_{Brazil}, 0.17_{Model}$	$0.07_{Brazil}, 0.14_{Model}$
Q_t	TFP	$0.11_{Brazil}, 0.56_{Model}$	$0.10_{Brazil}, 0.56_{Model}$	$0.10_{Brazil}, 0.54_{Model}$	$0.13_{Brazil}, 0.52_{Model}$	$0.16_{Brazil}, 0.51_{Model}$
	Risk Premium	$0.16_{Brazil}, 0.10_{Model}$	$0.16_{Brazil}, 0.09_{Model}$	$0.16_{Brazil}, 0.08_{Model}$	$0.15_{Brazil}, 0.07_{Model}$	$0.15_{Brazil}, 0.07_{Model}$
	Price of Capital	$0.13_{Brazil}, 0.23_{Model}$	$0.19_{Brazil}, 0.26_{Model}$	$0.32_{Brazil}, 0.30_{Model}$	$0.46_{Brazil}, 0.35_{Model}$	$0.50_{Brazil}, 0.37_{Model}$
	Collateral Constraint	$0.60_{Brazil}, 0.11_{Model}$	$0.55_{Brazil}, 0.09_{Model}$	$0.42_{Brazil}, 0.08_{Model}$	$0.26_{Brazil}, 0.06_{Model}$	$0.19_{Brazil}, 0.05_{Model}$
TB_t	TFP	$0.48_{Brazil}, 0.39_{Model}$	$0.46_{Brazil}, 0.44_{Model}$	$0.43_{Brazil}, 0.49_{Model}$	$0.41_{Brazil}, 0.54_{Model}$	$0.40_{Brazil}, 0.55_{Model}$
	Risk Premium	$0.08_{Brazil}, 0.31_{Model}$	$0.08_{Brazil}, 0.28_{Model}$	$0.08_{Brazil}, 0.24_{Model}$	$0.09_{Brazil}, 0.21_{Model}$	$0.09_{Brazil}, 0.19_{Model}$
	Price of Capital	$0.23_{Brazil}, 0.06_{Model}$	$0.24_{Brazil}, 0.06_{Model}$	$0.25_{Brazil}, 0.05_{Model}$	$0.25_{Brazil}, 0.05_{Model}$	$0.25_{Brazil}, 0.05_{Model}$
	Collateral Constraint	$0.21_{Brazil}, 0.24_{Model}$	$0.22_{Brazil}, 0.22_{Model}$	$0.24_{Brazil}, 0.22_{Model}$	$0.25_{Brazil}, 0.20_{Model}$	$0.26_{Brazil}, 0.21_{Model}$

Notes: The table summarizes the contributions of TFP, risk premium, price of capital, and collateral constraint shocks to the fluctuations of output, Y_t, the world real interest rate, R_t, Tobin's Q, Q_t, and the trade balance, TB_t. A SVAR under the long-run restrictions estimates the synthetic sample and a Brazilian sample from 1999Q1 to 2018Q4 to produce these FEVDs.

Table 9: FEVDs Estimated on Mexican and Synthetic Samples Under Long-Run Restrictions

Variable	Horizons / Shocks	Q1	Q2	Q4	Q8	Q12
Y_t	TFP	$0.70_{Mexico}, 0.74_{Model}$	$0.82_{Mexico}, 0.78_{Model}$	$0.90_{Mexico}, 0.84_{Model}$	$0.95_{Mexico}, 0.90_{Model}$	$0.96_{Mexico}, 0.92_{Model}$
	Risk Premium	$0.03_{Mexico}, 0.09_{Model}$	$0.03_{Mexico}, 0.08_{Model}$	$0.02_{Mexico}, 0.06_{Model}$	$0.01_{Mexico}, 0.04_{Model}$	$0.01_{Mexico}, 0.03_{Model}$
	Price of Capital	$0.14_{Mexico}, 0.05_{Model}$	$0.08_{Mexico}, 0.04_{Model}$	$0.04_{Mexico}, 0.03_{Model}$	$0.02_{Mexico}, 0.02_{Model}$	$0.02_{Mexico}, 0.03_{Model}$
	Collateral Constraint	$0.13_{Mexico}, 0.12_{Model}$	$0.07_{Mexico}, 0.10_{Model}$	$0.04_{Mexico}, 0.07_{Model}$	$0.02_{Mexico}, 0.04_{Model}$	$0.01_{Mexico}, 0.02_{Model}$
R_t	TFP	$0.04_{Mexico}, 0.24_{Model}$	$0.04_{Mexico}, 0.23_{Model}$	$0.07_{Mexico}, 0.21_{Model}$	$0.08_{Mexico}, 0.18_{Model}$	$0.09_{Mexico}, 0.17_{Model}$
	Risk Premium	$0.86_{Mexico}, 0.46_{Model}$	$0.88_{Mexico}, 0.49_{Model}$	$0.88_{Mexico}, 0.54_{Model}$	$0.89_{Mexico}, 0.61_{Model}$	$0.89_{Mexico}, 0.64_{Model}$
	Price of Capital	$0.06_{Mexico}, 0.07_{Model}$	$0.05_{Mexico}, 0.07_{Model}$	$0.03_{Mexico}, 0.06_{Model}$	$0.02_{Mexico}, 0.05_{Model}$	$0.01_{Mexico}, 0.04_{Model}$
	Collateral Constraint	$0.04_{Mexico}, 0.23_{Model}$	$0.03_{Mexico}, 0.21_{Model}$	$0.02_{Mexico}, 0.19_{Model}$	$0.01_{Mexico}, 0.16_{Model}$	$0.01_{Mexico}, 0.15_{Model}$
Q_t	TFP	$0.34_{Mexico}, 0.58_{Model}$	$0.32_{Mexico}, 0.58_{Model}$	$0.29_{Mexico}, 0.56_{Model}$	$0.27_{Mexico}, 0.53_{Model}$	$0.27_{Mexico}, 0.52_{Model}$
	Risk Premium	$0.08_{Mexico}, 0.09_{Model}$	$0.07_{Mexico}, 0.08_{Model}$	$0.06_{Mexico}, 0.07_{Model}$	$0.05_{Mexico}, 0.06_{Model}$	$0.05_{Mexico}, 0.06_{Model}$
	Price of Capital	$0.54_{Mexico}, 0.24_{Model}$	$0.58_{Mexico}, 0.26_{Model}$	$0.63_{Mexico}, 0.31_{Model}$	$0.66_{Mexico}, 0.36_{Model}$	$0.67_{Mexico}, 0.38_{Model}$
	Collateral Constraint	$0.04_{Mexico}, 0.09_{Model}$	$0.03_{Mexico}, 0.08_{Model}$	$0.02_{Mexico}, 0.06_{Model}$	$0.02_{Mexico}, 0.05_{Model}$	$0.01_{Mexico}, 0.04_{Model}$
TB_t	TFP	$0.35_{Mexico}, 0.39_{Model}$	$0.39_{Mexico}, 0.44_{Model}$	$0.42_{Mexico}, 0.49_{Model}$	$0.43_{Mexico}, 0.54_{Model}$	$0.43_{Mexico}, 0.55_{Model}$
	Risk Premium	$0.11_{Mexico}, 0.32_{Model}$	$0.09_{Mexico}, 0.29_{Model}$	$0.07_{Mexico}, 0.25_{Model}$	$0.06_{Mexico}, 0.21_{Model}$	$0.06_{Mexico}, 0.19_{Model}$
	Price of Capital	$0.04_{Mexico}, 0.06_{Model}$	$0.03_{Mexico}, 0.05_{Model}$	$0.03_{Mexico}, 0.05_{Model}$	$0.03_{Mexico}, 0.04_{Model}$	$0.03_{Mexico}, 0.04_{Model}$
	Collateral Constraint	$0.50_{Mexico}, 0.23_{Model}$	$0.49_{Mexico}, 0.22_{Model}$	$0.48_{Mexico}, 0.21_{Model}$	$0.48_{Mexico}, 0.21_{Model}$	$0.48_{Mexico}, 0.22_{Model}$

Notes: The table summarizes the contributions of TFP, risk premium, price of capital, and collateral constraint shocks to the fluctuations of output, Y_t, the world real interest rate, R_t, Tobin's Q, Q_t, and the trade balance, TB_t. A SVAR under the long-run restrictions estimates the synthetic sample and a Mexican sample from 1997Q1 to 2018Q4 to produce these FEVDs.

Table 10: CIC of Q-LM Statistics Computed on IRFs Under Short-Run Restrictions

Brazil	TFP Shock	Risk Premium Shock	Price of Capital Shock	Collateral Constraint Shock
Output	1.005	1.012	0.998	0.949
World real interest rate	0.000	0.000	0.000	0.000
Tobin's Q	0.000	0.000	0.000	0.000
Trade balance	0.542	0.974	0.669	0.986
Mexico	TFP Shock	Risk Premium Shock	Price of Capital Shock	Collateral Constraint Shock
Output	1.005	1.020	1.010	1.011
World real interest rate	0.000	0.000	0.000	0.000
Tobin's Q	0.004	0.000	0.004	0.000
Trade balance	0.629	0.810	0.691	1.013

Notes: This table gathers the CIC of the Q-LM statistics computed on the distributions of theoretical and sample IRFs under the short-run restrictions. The Brazilian sample runs from 1999Q1 to 2018Q4, and the Mexican sample runs from 1997Q1 to 2018Q4.

Table 11: CIC of Q-LM Statistics Computed on IRFs Under Long-Run Restrictions

Brazil	TFP Shock	Risk Premium Shock	Price of Capital Shock	Collateral Constraint Shock
Output	1.018	1.009	0.953	0.956
World real interest rate	0.000	0.000	0.000	0.000
Tobin's Q	0.000	0.000	0.000	0.000
Trade balance	1.018	0.670	1.014	0.610
Mexico	TFP Shock	Risk Premium Shock	Price of Capital Shock	Collateral Constraint Shock
Output	1.005	1.006	1.014	1.004
World real interest rate	0.000	0.000	0.000	0.000
Tobin's Q	0.000	0.000	0.000	0.000
Trade balance	1.009	0.741	0.699	0.787

Notes: This table gathers the CIC of the Q-LM statistics computed on the distributions of theoretical and sample IRFs under the long-run restrictions. The Brazilian sample runs from 1999Q1 to 2018Q4, and the Mexican sample runs from 1997Q1 to 2018Q4.

Table 12: CIC of Q-LM Statistics Computed on FEVDs Under Short-Run Restrictions

Brazil	TFP Shock	Risk Premium Shock	Price of Capital Shock	Collateral Constraint Shock
Output	0.920	0.978	0.843	1.021
World real interest rate	0.760	0.132	0.938	0.636
Tobin's Q	0.833	0.814	0.740	0.985
Trade balance	0.860	0.915	0.829	0.121

Mexico	TFP Shock	Risk Premium Shock	Price of Capital Shock	Collateral Constraint Shock
Output	1.050	0.586	0.972	0.291
World real interest rate	0.818	0.125	0.866	0.513
Tobin's Q	0.820	0.988	0.674	0.958
Trade balance	0.857	0.790	0.929	0.138

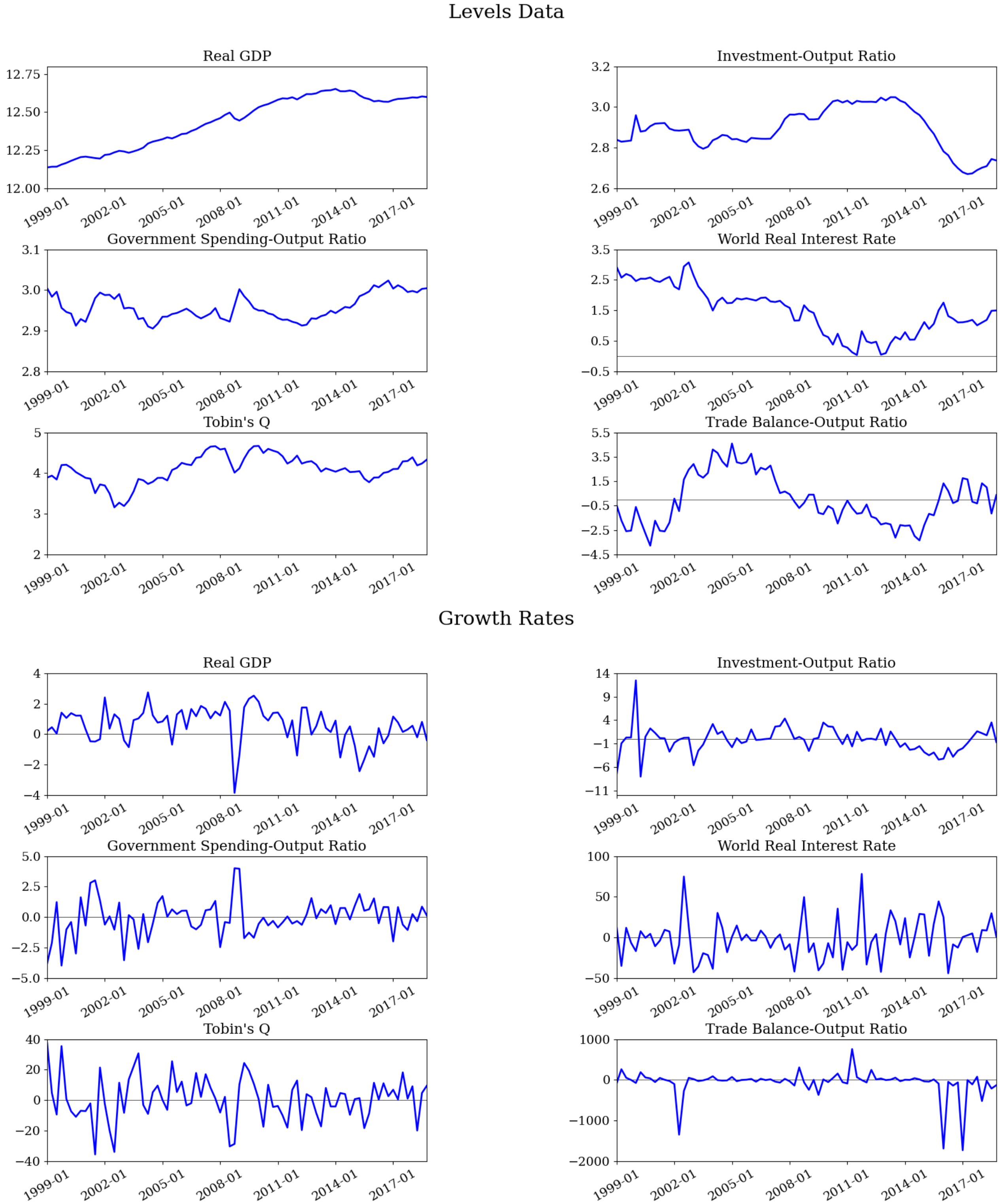
Notes: This table gathers the CIC of the Q-LM statistics computed on the distributions of theoretical and sample FEVDs under the short-run restrictions. The Brazilian sample runs from 1999Q1 to 2018Q4, and the Mexican sample runs from 1997Q1 to 2018Q4.

Table 13: CIC of Q-LM Statistics Computed on FEVDs Under Long-Run Restrictions

Brazil	TFP Shock	Risk Premium Shock	Price of Capital Shock	Collateral Constraint Shock
Output	0.974	1.018	0.986	0.990
World real interest rate	1.020	1.017	1.017	1.024
Tobin's Q	1.027	1.000	1.013	0.114
Trade balance	0.990	0.969	0.992	0.998
Mexico	TFP Shock	Risk Premium Shock	Price of Capital Shock	Collateral Constraint Shock
Output	0.996	0.521	1.012	0.993
World real interest rate	1.026	1.026	0.985	0.770
Tobin's Q	1.017	0.994	1.016	0.800
Trade balance	1.010	0.886	1.010	1.007

Notes: This table gathers the CIC of the Q-LM statistics computed on the distributions of theoretical and sample FEVDs under the long-run restrictions. The Brazilian sample runs from 1999Q1 to 2018Q4, and the Mexican sample runs from 1997Q1 to 2018Q4.

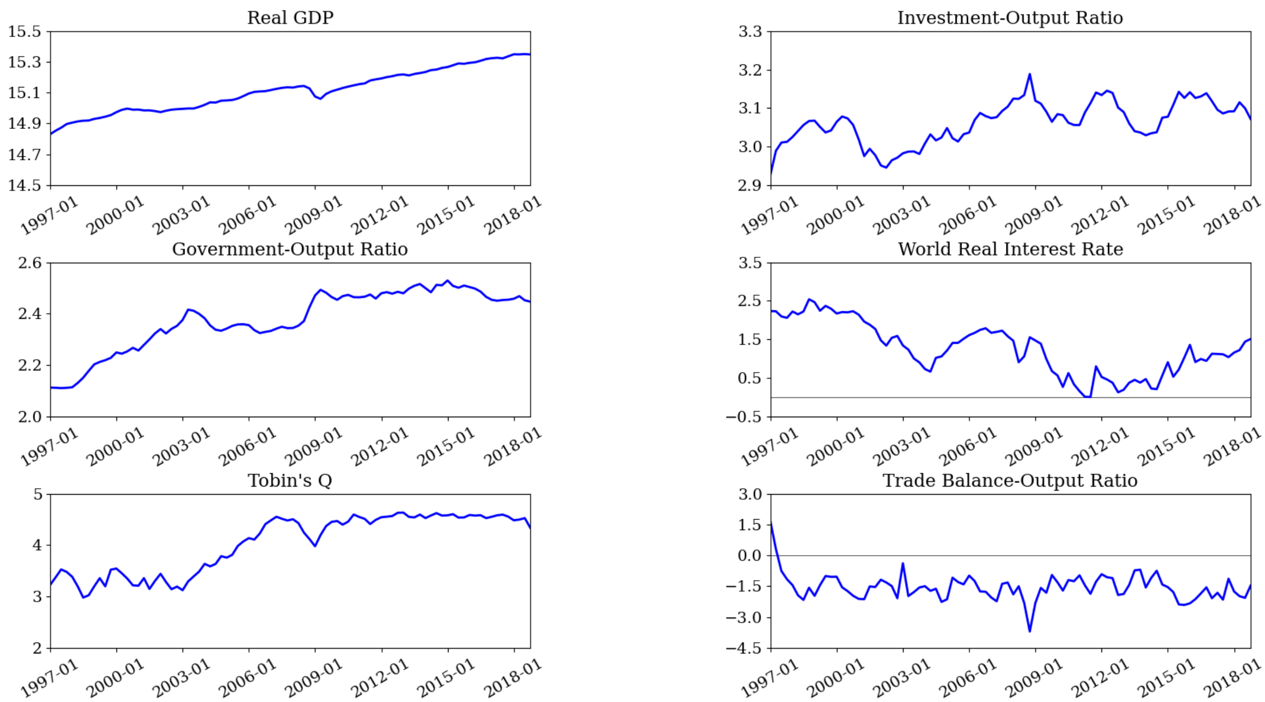
Figure 1: Brazilian Sample from 1999Q1 to 2018Q4



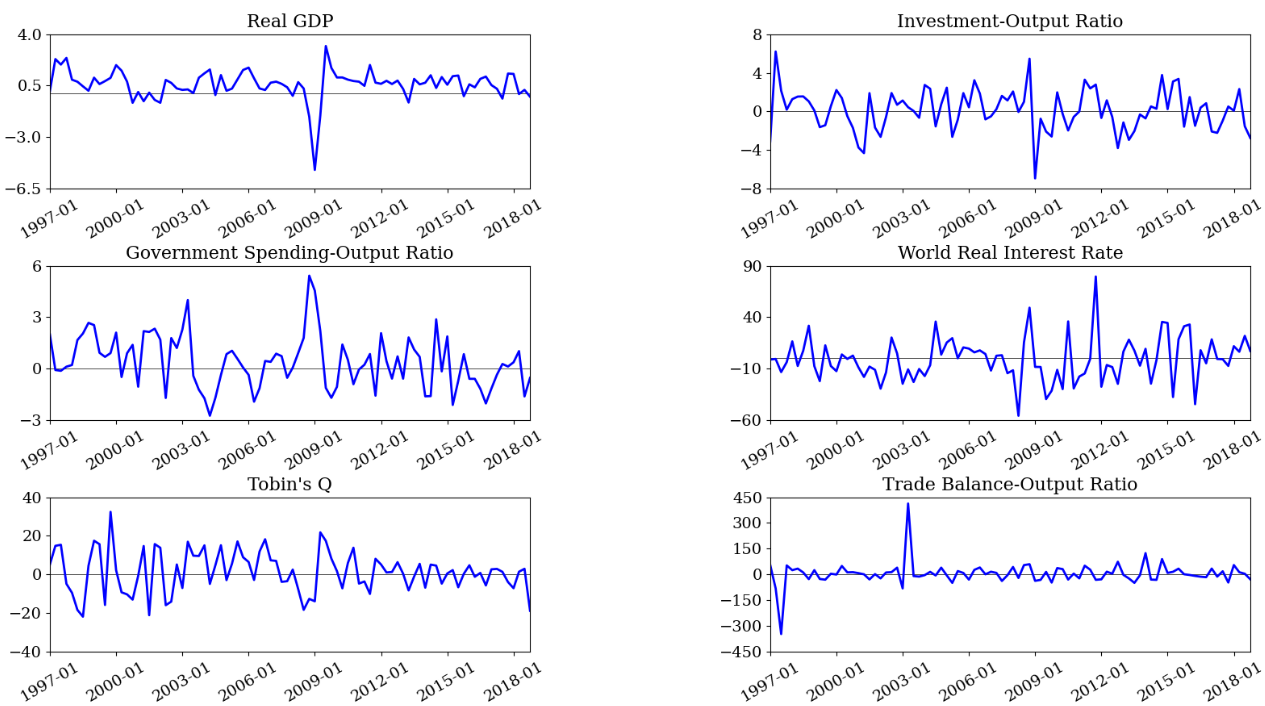
Notes: The top six graphs present log real GDP, log investment-output ratio, log government spending-output ratio, log world real interest rate, log Tobin's Q, and the trade balance-output ratio. Growth rates are the first differences of the log levels. The first difference of the trade balance-output ratio is computed as $100{*}(\frac{TB_t}{Y_t}\text{-}\frac{TB_{t-1}}{Y_{t-1}})/\frac{TB_{t-1}}{Y_{t-1}}$.

Figure 2: Mexican Sample from 1997Q1 to 2018Q4

Levels Data

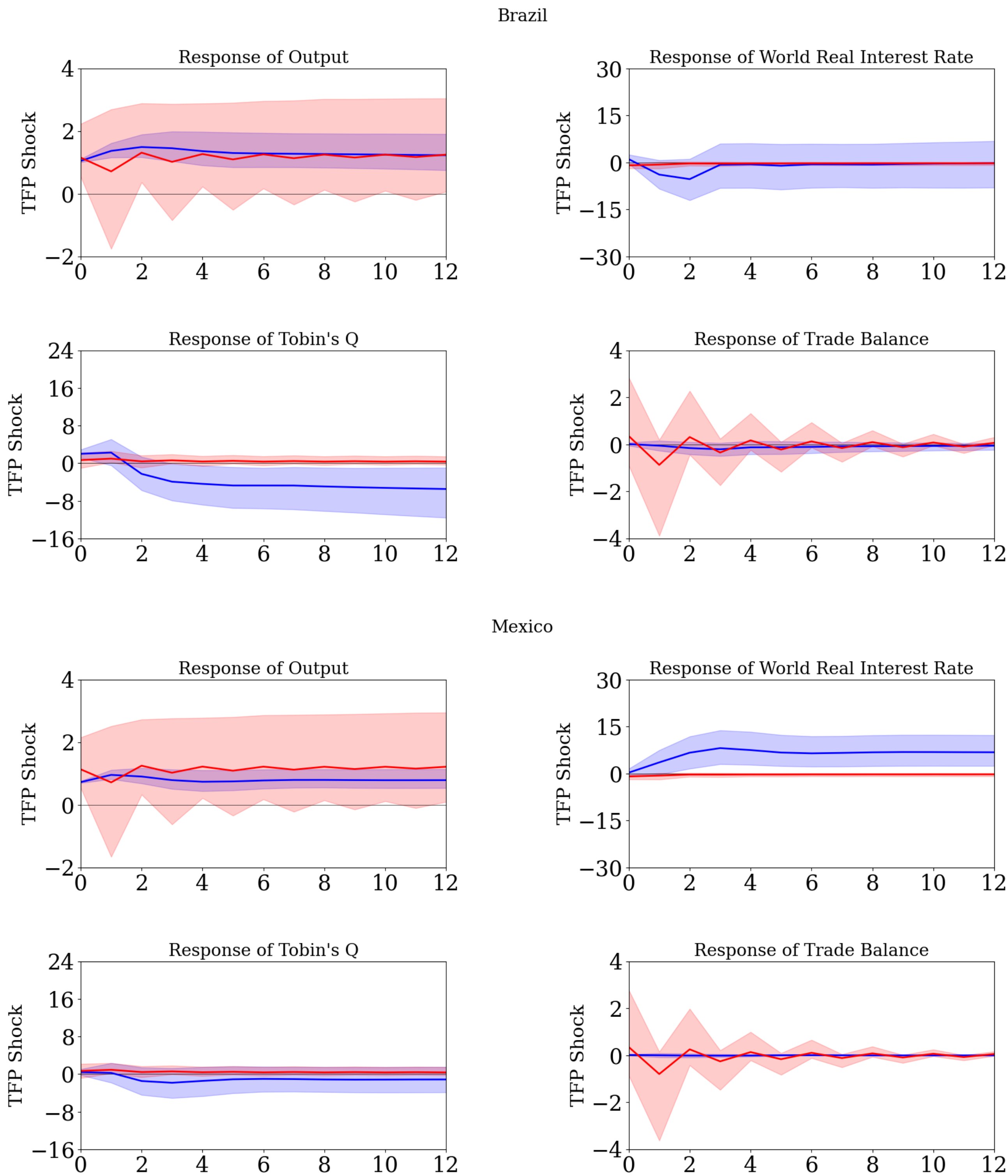


Growth Rates



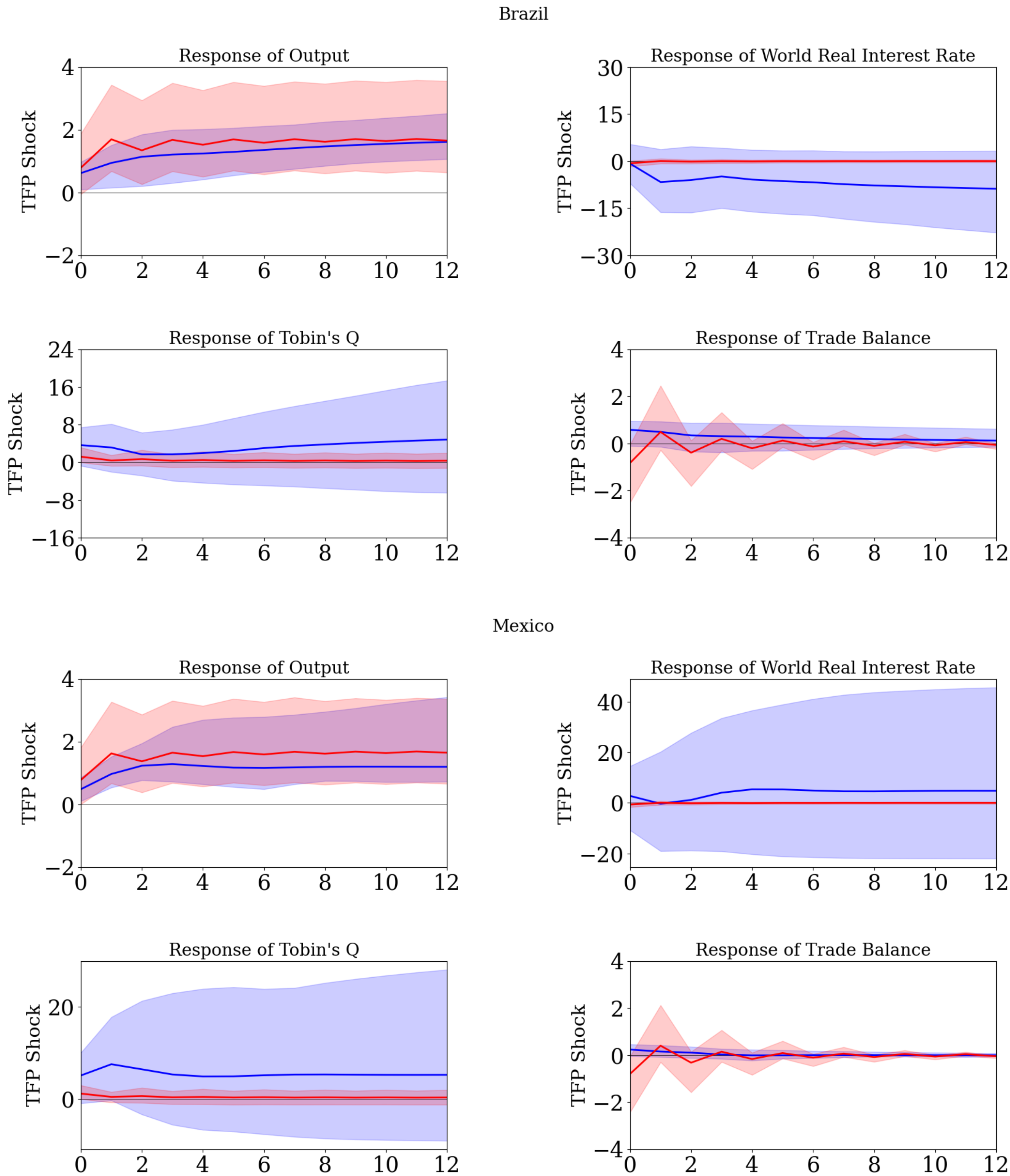
Notes: The top six graphs present log real GDP, log investment-output ratio, log government spending-output ratio, log world real interest rate, log Tobin's Q, and the trade balance-output ratio. Growth rates are the first differences of the log levels. The first difference of the trade balance-output ratio is computed as $100^*(\frac{TB_t}{Y_t}\text{-}\frac{TB_{t-1}}{Y_{t-1}})/\frac{TB_{t-1}}{Y_{t-1}}$.

Figure 3: IRFs with Respect to a TFP Shock Under Short-Run Restrictions



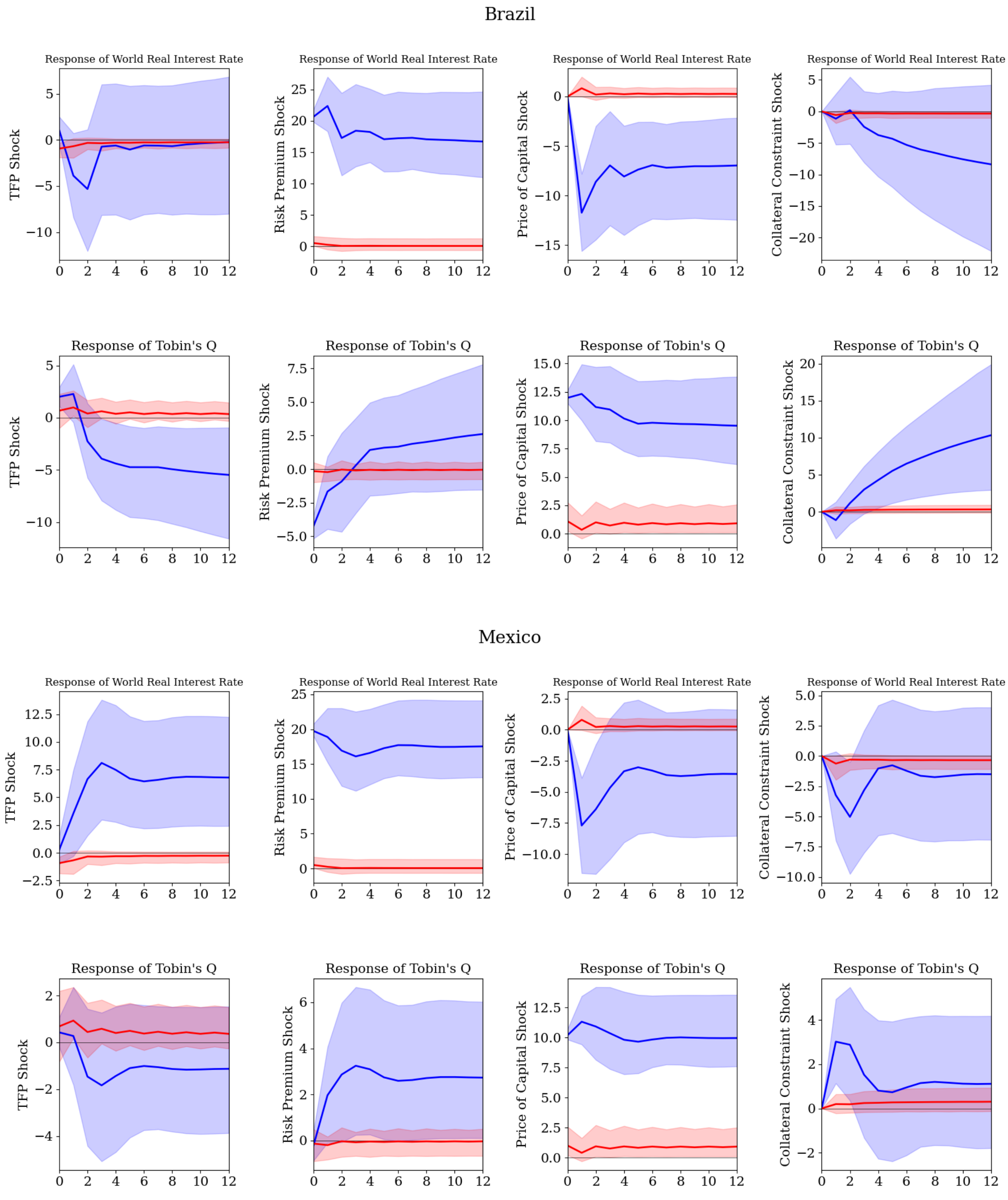
Notes: The red solid lines trace the theoretical IRFs. The red shadings are the 90% quantile distribution of theoretical IRFs. Theoretical IRFs are estimated on the synthetic sample simulated from the SOE-RBC model. The blue solid lines trace the sample IRFs. The blue shadings are the 90% Bayesian Monte Carlo confidence bands. Samples IRFs estimated on the Brazilian data from 1999Q1 to 2018Q4, and the Mexican data from 1997Q1 to 2018Q4.

Figure 4: IRFs with Respect to a TFP Shock Under Long-Run Restrictions



Notes: The red solid lines trace the theoretical IRFs. The red shadings are the 90% quantile distribution of theoretical IRFs. Theoretical IRFs are estimated on the synthetic sample simulated from the SOE-RBC model. The blue solid lines trace the sample IRFs. The blue shadings are the 90% Bayesian Monte Carlo confidence bands. Samples IRFs estimated on the Brazilian data from 1999Q1 to 2018Q4, and the Mexican data from 1997Q1 to 2018Q4.

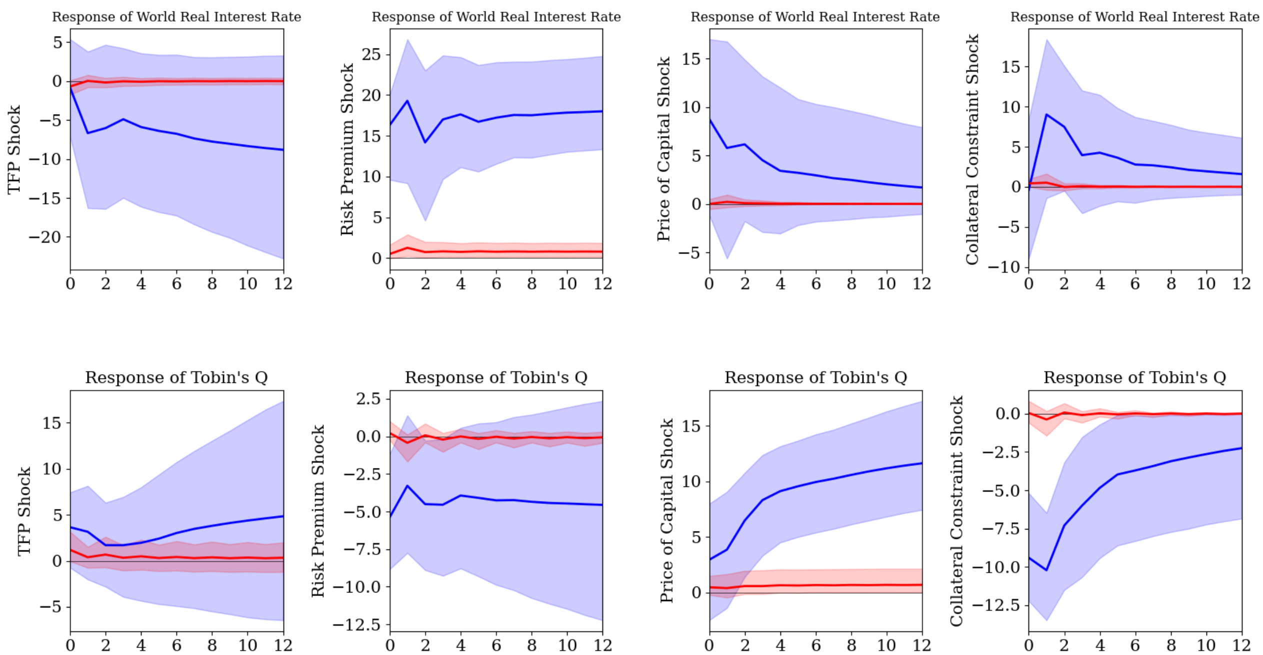
Figure 5: IRFs of World Real Interest Rate and Trade Balance Under Short-Run Restrictions



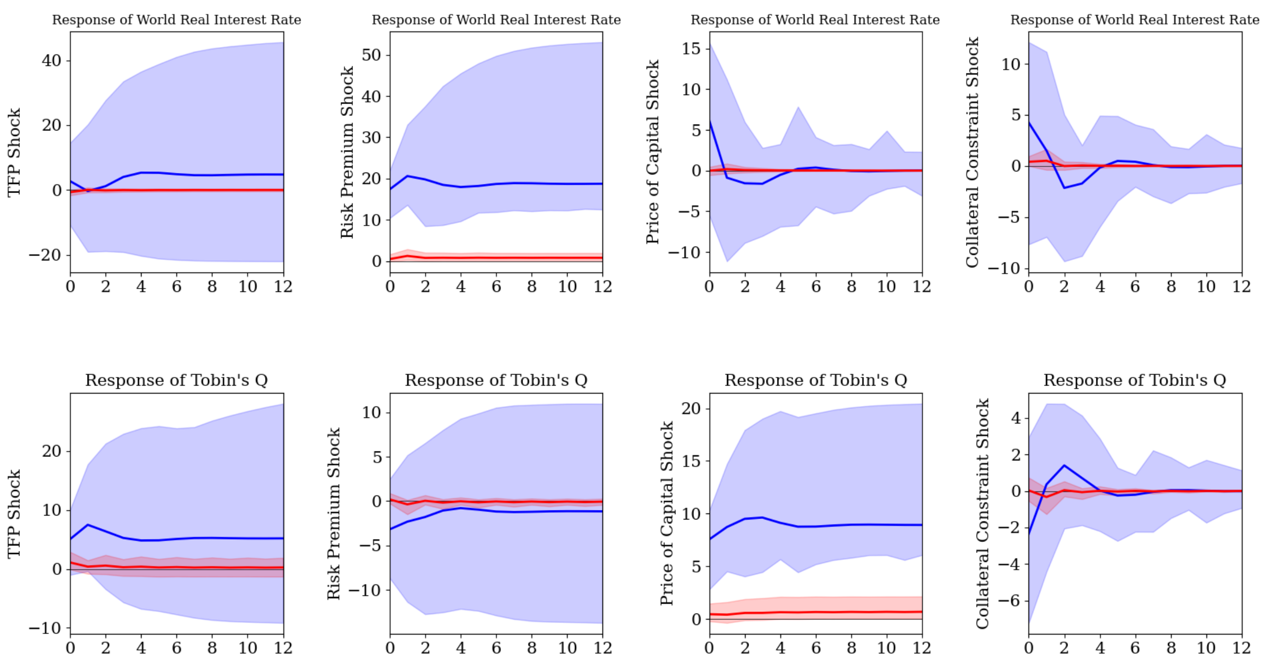
Notes: The red solid lines trace the theoretical IRFs. The red shadings are the 90% quantile distribution of theoretical IRFs. Theoretical IRFs are estimated on the synthetic sample simulated from the SOE-RBC model. The blue solid lines trace the sample IRFs. The blue shadings are the 90% Bayesian Monte Carlo confidence bands. Samples IRFs estimated on the Brazilian data from 1999Q1 to 2018Q4, and the Mexican data from 1997Q1 to 2018Q4.

Figure 6: IRFs of World Real Interest Rate and Trade Balance Under Long-Run Restrictions

Brazil



Mexico



Notes: The red solid lines trace the theoretical IRFs. The red shadings are the 90% quantile distribution of theoretical IRFs. Theoretical IRFs are estimated on the synthetic sample simulated from the SOE-RBC model. The blue solid lines trace the sample IRFs. The blue shadings are the 90% Bayesian Monte Carlo confidence bands. Samples IRFs estimated on the Brazilian data from 1999Q1 to 2018Q4, and the Mexican data from 1997Q1 to 2018Q4.