Parameter Drifts, Misspecification and the Real Exchange Rate in Emerging Countries

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Abstract

This paper studies whether the structural parameters of small open economy real business cycle models are time-invariant when applied to emerging markets. Using Argentinean data, I estimate a small open economy model with trend shocks, working capital constraints and augmented with time-varying parameters. I find that “structural” technological and financial parameters are time-varying during 1935-2009. I find that time-varying parameters correlate with the real exchange rate, suggesting potential misspecification of the one-sector model. Therefore, I propose a two-sector model that accounts for real exchange rate movements and time-varying capital utilization rates and explains a significant fraction of the variability in the data.

Keywords: Emerging Markets, Real Business Cycle, Parameter Drift, Bayesian Estimation, Real Exchange Rate.

JEL Classification: C32, C51, C52, C63, F41, F34.

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1 Introduction

The business cycle in emerging markets differs from the business cycle in developed economies. The emerging markets’ business cycle tends to be more volatile than that of developed economies; consumption volatility tends to be larger than the volatility of output; and the trade balance to output ratio tends to be strongly countercyclical. Conversely, developed economies exhibit consumption smoothing and acyclical trade balance to output ratio.\(^1\) There is no agreement, however, on the theoretical framework with which to rationalize these facts. Influential articles, such as Kydland and Zarazaga (2003) and Bergoeing et al. (2002), study the dynamics of emerging markets driven by stationary technology shocks.\(^2\) Other authors, alternatively, highlight the importance of non-stationary shocks or explicitly introduce frictions to the standard open economy real business cycle model.\(^3\)

The objective of this paper is to review the basic theoretical framework for the analysis of emerging economies. First, I study whether the structural parameters of the real business cycle small open economy model are time-invariant when we estimate them using emerging markets data. Second, I use the evidence from the time-varying parameters to identify potential sources of the misspecification. To pursue these objectives, I estimate a real business cycle model with stochastic trend, working capital constraint and time-varying parameters using annual Argentinean data for the period 1935-2009.

I find that the data favor the model with time-varying parameters when compared to the standard business cycle model with trend shocks and working capital constraints. Moreover, I find that technology and financial parameters change significantly during the period 1935-2009 and that they play a key role in explaining the variability of the data.

Furthermore, the time-varying parameters suffer sudden changes in times of large real exchange rate corrections that leads to high and significant correlation between time-varying parameters and the real exchange rate in levels and at high and low frequencies. Moreover, a principal components analysis shows that three principal components explain up to 90% of the joint variability in the time-varying parameters and the real exchange rate, and these principal components are highly correlated with the real exchange rate.

\(^1\)Aguiar and Gopinath (2007) and Neumeyer and Perri (2005) present a detailed study of business cycle facts for a large number of developed and emerging small open economies.

\(^2\)Kydland and Zarazaga (2003) study Argentina’s recent macroeconomic behavior and find that real business cycle models appropriately describe its business cycle up to a puzzle regarding the lack of investment recovery in the 1990s. On the other hand, Bergoeing et al. (2002) implements a growth accounting strategy in an open economy real business cycle model to describe the behavior of Mexico and Chile during the so-called “lost decade”.

\(^3\)For example, Aguiar and Gopinath (2007) present a model with stationary technology shocks and permanent shocks and conclude that the volatility of the trend shocks is the key difference between developed and emerging economies, i.e., it is larger for emerging markets than for developed small open economies, inducing the facts observed in the data. In contrast, Boz et al. (2008) arrives at different conclusions following an alternate estimation strategy and argues that the trend shocks’ volatility in developing small open economies and developed small open economies do not differ from each other. Instead, different dynamics are due to informational frictions. Garcia-Cicco et al. (2010) reinforce the idea that standard real business cycle models with trend shocks might not be an appropriate representation of emerging economies using a large sample of annual data for Argentina. In turn, Neumeyer and Perri (2005) highlight the importance of working capital constraints and interest rate shocks to generate the observed facts and to rationalize the way real interest rates correlate with output and other macroeconomic variables.
The economics behind the strong correlations between real exchange rate and time-varying parameters goes as follows. During periods of crisis, the real exchange rate increases dramatically. In a model in which the real exchange rate is not modeled, this can be captured by a change in parameters associated to the financial frictions these economy faces, i.e. financial parameters; and also by technological parameters that regulate the capital and labor shares and the intensity of capital utilization. Hence, I interpret this as evidence towards the misspecification of the one-sector real business cycle model. For this reason, in the rest of the article I develop and estimate a small open economy model with a tradable and a non-tradable sectors. I find that the two-sectors model is able to explain a large share of the variability of national account variables and the real exchange rate once this variable is included in the vector of observables. Moreover, in line with the findings in Garcia-Cicco et al. (2010), my estimates suggest that financial frictions play a key role in the observed dynamics.

This paper is related to the literature on business cycles in emerging countries. In recent articles, Aguiar and Gopinath (2007), Garcia-Cicco et al. (2010) and Boz et al. (2008) explore the effects of permanent shocks. Neumeyer and Perri (2005) and Uribe and Yue (2006) also study the role of working capital constraints and interest rate shocks in emerging markets. My paper borrows these two key components to build the benchmark model both with and without parameter changes.

In addition to these features, my model allows for time-varying parameters. Therefore, this paper is also related to a growing literature on the estimation of models with parameter instabilities. Cogley and Sargent (2005), Sims (1999) and Primiceri (2005) estimate vector autoregression models with coefficient instabilities and time-varying volatilities for the US to study monetary policy during the Great Moderation, while King (2006), Justiniano and Primiceri (2008) and Fernández-Villaverde and Rubio-Ramirez (2007), among others, estimate dynamic stochastic general equilibrium models with parameter instabilities to study similar questions from a general equilibrium approach.

In this paper, I assume time-varying parameters follow autoregressive processes of order one, as in Fernández-Villaverde and Rubio-Ramirez (2007). My paper also follows Fernández-Villaverde and Rubio-Ramirez (2007) in assuming that volatilities of the exogenous shocks are time invariant. As pointed out by Sims (2001), this might be an important assumption. I work under this assumption because the estimation of nonlinear models using full information methods is still under study.4,5

This paper is also related to an increasing body of literature that supports parameter drifts from an empirical point of view. For example, Harrison (2002) argues, using a panel of countries, that in the period 1960-1997, the trend of labor share decreased in both developed and developing countries. Similar results are obtained by Krueger (1999) for the U.S. economy. Conversely, at business cycle frequencies and imposing a Cobb-Douglas production function, Young (2004) shows the countercyclical nature of labor share in the U.S. In

4A recent paper, Andreasen (2012), reviews the features and caveats of nonlinear Bayesian estimation using a particle filter.

5An option this paper does not explore is to introduce stochastic volatility together with a linear solution method as in Justiniano and Primiceri (2008). Under this strategy, we would still be able to implement standard Bayesian estimation. However, this strategy is undesirable because households in the model will not be able to respond to volatility changes, given that the linear approximation is certainty equivalent.
the literature concerned with measuring sources of growth, Coremberg (2002) also considers time-varying labor and capital shares in the case of Argentina. Additionally, substantial work has also been conducted on the case of depreciation rates of installed capital, as in Dueker et al. (2006) and Ambler and Paquet (1994).

This paper is also related to the study of the real exchange rates in small open economies and their importance as a transmission mechanism of foreign shocks, as those studies conducted by Mendoza (1995) and Aguirre (2011).

My paper is the first one, to my knowledge, to introduce parameter instabilities in a DSGE model to understand the recent macroeconomic behavior of emerging economies and to use their smoothed estimates to highlight the role of the real exchange rate in emerging economies. Therefore, the contributions of this paper are threefold: First, I investigate whether deep parameters in the small open economy real business cycle model are time-invariant when studying emerging markets. Second, I study the role of time-varying parameters and provide evidence that suggests that there is a correlation between their smoothed estimates and the real exchange rate, and third, I develop a general equilibrium model that intends to provide a microfoundation to these findings and to highlight the importance of the discipline imposed in the model by considering the real exchange rate dynamics.

The remainder of the paper proceeds as follows: in section 2, I discuss the benchmark one-sector model and the time-varying parameters assumption. In section 3, I review the solution and estimation procedures used in this study and discuss the main estimation results. Section 4, studies the features of time-varying parameters and technology shocks in the time-varying parameters model and provides evidence supporting the misspecification hypothesis. Section 5 introduces and estimates a two-sector model. Section 6 provides concluding remarks and discusses promising directions for future research.

2 Small open economy model with parameter drifts

This section discusses the benchmark model. I present a version of the small open economy real business cycle model with trend shocks as in Aguiar and Gopinath (2007) and Garcia-Cicco et al. (2010) and working capital constraints as in Neumeyer and Perri (2005) augmented with parameter drifts. First, I present the optimization problems of the households and the firms. Then I introduce the stochastic processes of the time-varying parameters. The model in this section builds on Garcia-Cicco et al. (2010); hence, my notation closely follows theirs. In particular, I use capital letters to denote variables in levels and lowercase letters to denote variables in effective units.

2.1 Households

Let us assume that the economy is populated by households that maximize the present discounted value of expected utility. Households consume a unique consumption good $C_t$, rent labor $h_t$, and capital $K_t$ to the firm, and are able to lend or borrow $D_t$ in international markets at an interest rate $R_t$, which is exogenously given to the domestic economy.

Given this setup, we can formalize the households’ optimization problem as follows:
\[
\max \ E_0 \sum_{t=0}^{\infty} \beta^t u \left( C_t, h_t \right),
\]

subject to,
\[
\frac{D_{t+1}}{R_t} + R_t^k K_t + W_t h_t = D_t + C_t + K_{t+1} - (1 - \delta_t) K_t + \frac{\phi}{2} \left( \frac{K_{t+1}}{K_t} - g \right)^2 K_t.
\]

Here \( g \) is the steady state growth rate of the economy. \( \frac{\phi}{2} \left( \frac{K_{t+1}}{K_t} - g \right)^2 K_t \) are the adjustment costs of capital, with \( \phi > 0 \). Convex adjustment costs of capital are standard in the open economy literature because they prevent capital from instantaneously adjusting to the differences between the international interest rate and the marginal product of capital. Without these costs, the ultimate implication would be that investment is too volatile, and a counterfactual behavior of trade balance would result. The interest rate on foreign debt, \( D_t \), is given by
\[
R_t = R + \psi_t \exp \left\{ \frac{\bar{D}_{t+1}}{X_t d} \right\}.
\]

Here \( R \) is the steady state level of gross interest rate, which is typically associated with the risk free rate. The second term in the right side of the equation is an endogenous risk premium that depends on the aggregate level of foreign debt \( \bar{D}_t \) with \( d \) as the steady state level of foreign debt in effective units and \( X_t \) as a non-stationary productivity shock that will be explained in the following section.

Following Greenwood et al. (1988) and Garcia-Cicco et al. (2010), I specify the following utility function that is commonly used in the open economy literature
\[
u(C_t, h_t) = \frac{(C_t - \theta \omega^{-1} (X_{t-1} h_t)^{\omega})^{1-\sigma}}{1-\sigma}.
\]

An important departure from this approach, compared to other work in this body of literature, is that the depreciation rate, as well as the elasticity of the interest rate and the debt rate are time-varying. In section 2.3, I specify stochastic processes for time-varying parameters.

### 2.2 Firms

I assume firms operate in competitive factors and goods markets. They rent capital and labor from households and combine them using a Cobb-Douglas technology to produce a unique type of good that can be traded internationally, used for investment or, used in consumption. I follow Neumeyer and Perri (2005) and Uribe and Yue (2006) in assuming that firms need to advance a share of the total wages before starting the production process at any period \( t \). However, while these authors assume that producers must always advance the same share of the total wages, I allow for the possibility that these shares could be time-varying.

The second key assumption regarding the firms’ setup is that firms are subject to a stationary, total factor productivity shock and a trend shock, as discussed by Aguiar and
Gopinath (2007) and Garcia-Cicco et al. (2010). The profit maximization problem of the firm is, hence, given by

$$\max \Pi = Q_t - \kappa_t (R_t - 1) W_t h_t - W_t h_t - R^k_t K_t.$$  

Where,

$$Q_t = A_t K_t^{\alpha_t} (X_t h_t)^{1-\alpha_t}.$$  

Here, $A_t$ is the total factor productivity shock that follows a mean reverting AR(1) processes

$$\log \left( \frac{A_t}{A} \right) = \rho^a \log \left( \frac{A_{t-1}}{A} \right) + \epsilon^a_t,$$

and $X_t$ is the level of labor augmenting technology that grows at the rate $g_t$ and follows a mean reverting AR(1) process,

$$\frac{X_t}{X_{t-1}} = g_t,$$

$$\log \left( \frac{g_t}{g} \right) = \rho^g \log \left( \frac{g_{t-1}}{g} \right) + \epsilon^g_t.$$  

I assume that innovations to these shocks follow a normal distribution, with $\epsilon^a_t \sim N(0, \sigma^a)$ and $\epsilon^g_t \sim N(0, \sigma^g)$. Importantly, as seen from the production function, I allow the capital share to be time-varying.

### 2.3 Introducing parameter instabilities

I allow $\psi_t$, $\kappa_t$, $\delta_t$ and $\alpha_t$ to be time-varying. For simplicity, I assume that these parameters follow autoregressive stochastic processes of order one:

$$\log \left( \frac{\psi_t}{\psi} \right) = \rho^\psi \log \left( \frac{\psi_{t-1}}{\psi} \right) + \epsilon_\psi_t,$$

$$\log \left( \frac{\delta_t}{\delta} \right) = \rho^\delta \log \left( \frac{\delta_{t-1}}{\delta} \right) + \epsilon_\delta_t,$$

$$\log \left( \frac{\alpha_t}{\alpha} \right) = \rho^\alpha \log \left( \frac{\alpha_{t-1}}{\alpha} \right) + \epsilon_\alpha_t,$$

$$\log \left( \frac{\kappa_t}{\kappa} \right) = \rho^\kappa \log \left( \frac{\kappa_{t-1}}{\kappa} \right) + \epsilon_\kappa_t.$$  

I assume that all processes are mean reverting, i.e. $|\rho^\psi| < 1$, $|\rho^\delta| < 1$, $|\rho^\alpha| < 1$, $|\rho^\kappa| < 1$, and $\epsilon^\psi_t \sim N(0, \sigma^\psi)$, $\epsilon^\delta_t \sim N(0, \sigma^\delta)$, $\epsilon^\alpha_t \sim N(0, \sigma^\alpha)$ and $\epsilon^\kappa_t \sim N(0, \sigma^\kappa)$. This is a convenient assumption to have a well-defined steady state to solve the model using a linear
approximation. The stochastic processes are specified in logarithms to guarantee that the parameters take only non-negative values.\(^6\)

Given the setup of the firms’ and households’ problems, I implicitly assume that agents are aware of the parameter instabilities. This means that agents know the law of motion for the time-varying parameters and the probability distributions of the innovations. For this reason, the time-varying parameters are state variables for the agents’ optimization problem.

Additionally, it is clear that there can be multiple sources for parameter changes. Furthermore, this model does not provide an explicit microfoundation for the time-variation found in the parameters, and hence, we cannot rule out an alternative interpretation of these changes. One of the objectives of this paper, however, is to understand what kind of implicit behavior is captured by time-varying parameters. Therefore, in section 4.2, I study the smoothed estimates of the time-varying parameters to infer which behavior they model.

Note that I assume \(\rho, \phi, \sigma^a, \sigma^g, \beta, \sigma\) and \(\omega\) are constant. The first four parameters are constant because they do not affect decision rules up to first order.\(^7\) Conversely, \(\beta, \sigma\) and \(\omega\) are time independent to focus on the potential instabilities that arise from technological and financial sources rather than preferences.

### 3 Estimating time-varying parameters model

I solve the model using log-linear approximation around the steady state.\(^8\) As discussed previously, the choice of log-linear solution methods is not without a loss of generality as it conditions which parameters are allowed to change. Yet, given that Bayesian model estimation and comparison is at the core of this exercise, it remains a good starting point to study time-varying parameters in emerging economies.

The parameters presented in Table 1 are calibrated following the literature.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\sigma)</td>
<td>2</td>
</tr>
<tr>
<td>(\theta)</td>
<td>1</td>
</tr>
<tr>
<td>(\alpha)</td>
<td>0.32</td>
</tr>
<tr>
<td>(\delta)</td>
<td>0.1255</td>
</tr>
<tr>
<td>(\omega)</td>
<td>1.6</td>
</tr>
</tbody>
</table>

Note: The parameters in this table are calibrated using existing literature.

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\(^6\)I follow Fernández-Villaverde and Rubio-Ramírez (2007) in assuming AR(1) processes for time-varying parameters. The main reason for this assumption is that AR(1) processes are flexible and parsimonious.\(^7\) Their calibration, however, can significantly affect the model dynamics. \(^8\)Log-linear approximations are commonly used in open macroeconomics literature: hence, we skip a detailed explanation of this procedure and refer the reader to standard references, i.e., Blanchard and Kahn (1980), Sims (2002), Schmitt-Grohé and Uribe (2004). In this paper, I use the method in Schmitt-Grohé and Uribe (2004).
In particular $\sigma$, $\omega$, $\alpha$, and $\delta$ are from Garcia-Cicco et al. (2010). For $\theta$ I follow Aguirre (2011). $\beta$ and $R$ are such that the model will match a domestic interest rate of 1.05, which corresponds to the historical averages of interest rate. Debt in steady state of 0.007, as in Garcia-Cicco et al. (2010). Following these authors, I calibrate the steady state of trend growth to 1.005.

I estimate the remaining parameters using Bayesian methods. I use 3 observables shown in Figure 1, the growth rate of private consumption, $\gamma^c$, the growth rate of output, $\gamma^y$, measured as the log differences of consumption, and output at fixed prices base year 1993, respectively. The third variable is trade balance to output ratio ($tby_t = TB_t/Y_t$). I do not include the growth rate of investment because it will not provide additional information. This is the case because without measurement errors, the growth rate of investment is determined as a residual from the resource constraint of the economy. Notice that the sample includes several episodes of strong output drops and sudden stops, as captured by the sharp trade balance to output ratio reversals during the 1940s, 1980s, 1990s and after 2002.

![Figure 1: Observables Argentina 1935-2009](image)

Note: Growth rate of output and consumption are the natural log difference of output and private consumption measured at 1993 prices. Details on data sources are in Appendix A.

I denote the vector of observables by

$$\text{obs} = [\gamma^c, \gamma^y, tby].$$

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9Given that I do not model the behavior of the Government, I followed the standard procedure of removing government consumption from the definition of output.
Following standard notation, as in An and Schorfheide (2007) and Garcia-Cicco (2008) the set of parameters to estimate is

\[ \Theta = \{ \phi, \psi, \kappa, \rho^a, \rho^g, \rho^\delta, \rho^\psi, \rho^\alpha, \rho^\kappa, \sigma^a, \sigma^g, \sigma^\delta, \sigma^\psi, \sigma^\alpha, \sigma^\kappa \}. \]

The goal is to characterize the posterior distribution of the parameters given the data and prior information, \( p(\Theta|\text{obs}) = \frac{L(\text{obs}|\Theta)p(\Theta)}{p(\text{obs})} \propto L(\text{obs}|\Theta)p(\Theta). \)

Here \( p(\Theta|\text{obs}) \) is the posterior density of parameters conditional on the observed data, \( L(\text{obs}|\Theta) \) is the probability that the observed data have been generated by the set of parameters given by \( \Theta \), while \( p(\Theta) \) stands for the prior distribution that summarizes econometricians’ beliefs concerning the unknown parameters and \( p(\text{obs}) \) is the marginal likelihood given by

\[ p(\text{obs}) = \int L(\Theta|\text{obs})p(\Theta)d\Theta \]

I assume independent priors for each parameter that follow the distribution specified in Table 2.\(^{11}\)

As table 2 shows, I assume the same priors for volatilities and autocorrelations for time-varying parameters. As priors are assumed to be independent, the prior distribution, \( p(\Theta) \), is given by the product of each parameter’s probability distribution function.

Given that the state space is linear and the innovations are normally distributed, we can use the Kalman filter to compute the likelihood function. I maximize the posterior mode and then implement a Random Walk Metropolis-Hastings algorithm, starting from the maximized mode. I keep the last 500 thousand draws to evaluate the posterior densities.

Even though most of the procedure is standard, an important modification must be implemented. The standard Metropolis-Hastings algorithm must be modified when working with time-varying parameters because of the parameters’ bounds. For example, even though \( \alpha_t \) is time dependent, it has to be between 0 and 1 for all \( t \). The same is true for depreciation rates and for the working capital constraint parameter. However, \( \psi_t \) is required to be positive for all \( t \). For this reason, for each draw of the Metropolis-Hastings algorithm, after evaluating \( L(\text{obs}|\Theta) \) I compute smoothed paths for \( \alpha_t, \kappa_t, \delta_t, \psi_t \), using smoothed Kalman filter. I discard the draws that imply that smoothed estimates of these parameters violate their bounds for any \( t \).\(^{12}\)

\(^{10}\)For details on Bayesian estimation procedures, see An and Schorfheide (2007).

\(^{11}\)It has been pointed out by Garcia-Cicco et al. (2010) and Seoane (2012) that \( \psi \) is a key parameter in capturing emerging market dynamics. For this reason, in the case of this parameter I check the robustness of my findings using a Gamma prior with mean 2.5, standard deviation of 1.11 and 95% confidence interval of [0.8117 - 5.1208] and results do not change significantly, both in terms of point estimates, smoothed estimates and dispersion measures.

\(^{12}\)I follow the efficient smoother as in Durbin and Koopman (2002).
Table 2: Priors

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Distribution</th>
<th>Mean</th>
<th>Mode</th>
<th>Std Dev.</th>
<th>95% C. I.</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\phi$</td>
<td>Gamma</td>
<td>0.15</td>
<td>0</td>
<td>0.15</td>
<td>0.004 - 0.55</td>
</tr>
<tr>
<td>$\psi$</td>
<td>Gamma</td>
<td>0.15</td>
<td>0</td>
<td>0.15</td>
<td>0.004 - 0.55</td>
</tr>
<tr>
<td>$\kappa$</td>
<td>Beta</td>
<td>0.8</td>
<td>0.82</td>
<td>0.07</td>
<td>0.63 - 0.93</td>
</tr>
<tr>
<td>$\rho^a$</td>
<td>Beta</td>
<td>0.75</td>
<td>0.75</td>
<td>0.07</td>
<td>0.61 - 0.87</td>
</tr>
<tr>
<td>$\rho^g$</td>
<td>Beta</td>
<td>0.75</td>
<td>0.75</td>
<td>0.07</td>
<td>0.61 - 0.87</td>
</tr>
<tr>
<td>$\rho^d$</td>
<td>Beta</td>
<td>0.75</td>
<td>0.75</td>
<td>0.07</td>
<td>0.61 - 0.87</td>
</tr>
<tr>
<td>$\rho^\psi$</td>
<td>Beta</td>
<td>0.75</td>
<td>0.75</td>
<td>0.07</td>
<td>0.61 - 0.87</td>
</tr>
<tr>
<td>$\rho^\alpha$</td>
<td>Beta</td>
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<td>0.75</td>
<td>0.07</td>
<td>0.61 - 0.87</td>
</tr>
<tr>
<td>$\sigma^a$</td>
<td>Gamma</td>
<td>0.15</td>
<td>0.05</td>
<td>0.12</td>
<td>0.01 - 0.47</td>
</tr>
<tr>
<td>$\sigma^g$</td>
<td>Gamma</td>
<td>0.15</td>
<td>0.05</td>
<td>0.12</td>
<td>0.01 - 0.47</td>
</tr>
<tr>
<td>$\sigma^d$</td>
<td>Gamma</td>
<td>0.15</td>
<td>0.05</td>
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</tr>
<tr>
<td>$\sigma^\psi$</td>
<td>Gamma</td>
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<td>0.05</td>
<td>0.12</td>
<td>0.01 - 0.47</td>
</tr>
<tr>
<td>$\sigma^\alpha$</td>
<td>Gamma</td>
<td>0.15</td>
<td>0.05</td>
<td>0.12</td>
<td>0.01 - 0.47</td>
</tr>
<tr>
<td>$\sigma^{\kappa}$</td>
<td>Gamma</td>
<td>0.15</td>
<td>0.05</td>
<td>0.12</td>
<td>0.01 - 0.47</td>
</tr>
</tbody>
</table>

Note: The last column displays the 95 percent confidence interval implied by the prior distribution.

3.1 Time-varying parameters: The case of Argentina

Table 3 presents posterior means and 95% credible sets for the estimated parameters.

As table 3 shows, the parameter estimates are in line with the findings in the related literature. Note that the working capital constraint parameter in the steady state is estimated to 80% of the wage bill, which is a high number but is significantly smaller than the calibration in Neumeyer and Perri (2005). The persistence of stationary technological and trend shocks is in line with previous findings for different sets of Argentinean data. Finally, note that the data imply a high capital adjustment cost, which is in line with Garcia-Cicco et al. (2010), for a similar data set.

As seen, using annual data, all time-varying parameters are highly persistent, with $\alpha_t$ being slightly less persistent than the rest. Additionally, the variability of time-varying parameters is substantial; in particular, it is much larger than the variability of technology shocks, suggesting that for the simple real business cycle model, time-variation in the parameters plays a substantive role in capturing the characteristics of the data. Specifically, as can be seen in the table, the standard deviation of $\psi$ is 0.21, the largest of the standard deviations of all the shocks. This parameter represents a financial friction, as discussed in Garcia-Cicco et al. (2010). A key implication of the estimation results of the time-varying simple small open economy model is that the financial frictions experienced by emerging economies exhibits a strong time variation.
Table 3: Posterior estimates and Credible Sets

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Posterior Mean</th>
<th>2.5 percentile</th>
<th>97.5 percentile</th>
</tr>
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<tbody>
<tr>
<td>$\phi$</td>
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<td>1.6</td>
<td>2.5</td>
</tr>
<tr>
<td>$\psi_{ss}$</td>
<td>0.0005</td>
<td>0.0002</td>
<td>0.001</td>
</tr>
<tr>
<td>$\kappa_{ss}$</td>
<td>0.8</td>
<td>0.63</td>
<td>0.93</td>
</tr>
<tr>
<td>$\rho_g$</td>
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<td>0.7</td>
<td>0.86</td>
</tr>
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<td>$\rho_a$</td>
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<td>0.83</td>
</tr>
<tr>
<td>$\rho_\psi$</td>
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<td>0.61</td>
<td>0.87</td>
</tr>
<tr>
<td>$\rho_\kappa$</td>
<td>0.75</td>
<td>0.6</td>
<td>0.87</td>
</tr>
<tr>
<td>$\rho_\alpha$</td>
<td>0.66</td>
<td>0.56</td>
<td>0.76</td>
</tr>
<tr>
<td>$\rho_\delta$</td>
<td>0.77</td>
<td>0.68</td>
<td>0.85</td>
</tr>
<tr>
<td>$\sigma_g$</td>
<td>0.0015</td>
<td>0.0007</td>
<td>0.003</td>
</tr>
<tr>
<td>$\sigma_a$</td>
<td>0.0007</td>
<td>0.0004</td>
<td>0.001</td>
</tr>
<tr>
<td>$\sigma_\psi$</td>
<td>0.21</td>
<td>0.016</td>
<td>0.6</td>
</tr>
<tr>
<td>$\sigma_\kappa$</td>
<td>0.0035</td>
<td>0.003</td>
<td>0.004</td>
</tr>
<tr>
<td>$\sigma_\alpha$</td>
<td>0.012</td>
<td>0.009</td>
<td>0.014</td>
</tr>
<tr>
<td>$\sigma_\delta$</td>
<td>0.08</td>
<td>0.06</td>
<td>0.1</td>
</tr>
</tbody>
</table>

Note: Posterior means are computed using the last 500,000 draws of the MCMC.

3.1.1 Model comparison

The objective of this section is to investigate whether the data support the time-varying parameter small open economy model rather than the fixed parameter model using Argentinean data. To answer this question, I compute the modified harmonic mean estimator following Geweke (1999) and Gelfand and Dey (1994). The main task in this comparison of models is to construct the marginal data density, which is conditional on the model, \(^{13}\)

\[
p(\text{obs}|M) = \int_{\tilde{\Theta}} p(\text{obs}|\Theta, M)p(\Theta|M)d(\Theta).
\]

Here $M$ indexes the model and $\tilde{\Theta}$ denotes the parameter space with respect to which we integrate. It can be shown\(^{14}\),

\[
\frac{1}{p(\text{obs}|M)} = \frac{\int_{\tilde{\Theta}} f(\Theta)d(\Theta)}{\int_{\Theta} p(\text{obs}|\Theta, M)p(\Theta|M)d(\Theta)},
\]

where

\[
f(\Theta) = \frac{1}{p(2\pi)^{k/2}}|\Sigma_m|^{-1/2}exp(-0.5(\Theta - \Theta_m)\Sigma_m^{-1}(\Theta - \Theta_m))I(\Theta \in \tilde{\Theta}).
\]

\(^{13}\)This section follows the notation style used in Geweke (1999) and An and Schorfheide (2007). Note that the fixed parameter model is a particular case in which the volatilities of the parameters are equal to zero and the autocorrelations are equal to 1.

\(^{14}\)See Geweke (1999).
Here $\Theta_m$ is the posterior mean, $\Sigma_m$ is the variance covariance matrix from the posterior simulator and $I(\Theta \in \Theta)$ is an indicator function that is zero if the condition in parentheses does not hold. To compute the marginal data density, we approximate expression 1 using posterior simulation methods.\(^{15}\)

Table 4 presents marginal data densities for time-varying parameters model and for the fixed parameters model with 3 measurement errors.\(^{16}\)

\begin{table}[h]
\centering
\begin{tabular}{lcccccccc}
Model & 0.1 & 0.2 & 0.3 & 0.4 & 0.5 & 0.6 & 0.7 & 0.8 & 0.9 \\
\hline
TVP & 365.4 & 365.4 & 365.5 & 365.5 & 365.6 & 365.7 & 365.7 & 365.8 & 365.8 \\
TIP & 359.5 & 359.4 & 359.4 & 359.4 & 359.4 & 359.4 & 359.5 & 359.5 & 359.6 \\
\end{tabular}
\caption{Model Comparison}
\end{table}

Note: Marginal posteriors are computed using modified harmonic mean estimator as in Geweke (1999). TVP stands for “Time-varying parameters model” and TIP denotes “Time-invariant parameters model”. Each column presents the marginal posteriors for different $p$ (the fraction of draws used for the approximation). $E[\cdot]$ denotes the exponential operator.

As seen in table 4, the marginal density of the time-varying parameter model is significantly larger than the marginal density of the time-invariant parameter model. Therefore, the data strongly support the time-varying parameter model when fitting Argentinean data. This evidence suggests that the structural parameters of small open economy models are time-varying when matching the features of Argentina’s business cycles.

In the remainder of this paper, I investigate the behavior of time-varying parameters to inquire what time-varying parameters account for. Then, I develop a two-sector model that provides a microfoundation for the time-varying parameters and I show that this model is capable of capturing substantial variability in the model’s observables.

4 Parameter drifts, shocks and misspecification

The previous section shows that the data favor the model with time-varying parameters compared to the model with time-invariant parameters. This section studies the smoothed estimates of time-varying parameters and technology shocks to understand the dynamics of the model. This is a key step in understanding the macroeconomic features to which the shocks accommodate.

\(^{15}\)For a detailed description of the method see Geweke (1999) and Gelfand and Dey (1994).

\(^{16}\)Given that the number of shocks is larger than the number of observables, the time-varying parameter model is estimated without measurement errors. The fixed parameter model requires the inclusion of at least one measurement error to avoid stochastic singularity. To allow the model to have more flexibility, I estimate a version with 3 measurement errors. I report the marginal posterior of this model in Table 4.
4.1 Evolution of technology shocks and time-varying parameters

Figure 2 shows the smoothed path of permanent and transitory technology shocks. As seen in the figure, the variability of both the permanent and the stationary shocks have been substantially large during the last 75 years, with particularly large deviations during the 1940s, 1970s and at the beginning of the new century. In fact, strong changes in the stationary and trend shocks occur in periods of macroeconomic distress and also in the vicinity of policy changes. These shocks are highly volatile, and negative realizations of these shocks are associated with macroeconomic crisis, while the opposite occurs during recoveries. However, these shocks are not the only driving forces in this model. Figure 3 presents the smoothed estimates of time-varying parameters.

As can be seen, the time-varying parameters are highly volatile. The sensibility of interest rate to debt, $\psi_t$, increases substantially during the 1940s, the early 1980s, the Tequila Crisis and during the recent Argentinean Crisis, indicating that foreign investors are particularly sensitive to foreign debt accumulation during these periods, which as we saw in the previous section, are also associated with technology deterioration and macroeconomic distress. The variability of the working capital constraint sensitivity, $\kappa_t$, also changes significantly in a way that resembles $\psi_t$. Although the economy fluctuates around a mean of 79% for a prolonged period of time beginning in the 1940s, this variable increases significantly during the late 1950s, the mid 1970s and at the beginning and middle of the 1980s and 1990s. The largest increase occurs, however, during the latest macroeconomic crisis, when it gets over 81%. This variable also tends to increase during macroeconomic distress, which suggests that the cost of the working capital constraint is countercyclical and, as discussed in Neumeyer and Perri (2005) exacerbates the response of endogenous variables to interest rate adjustments.

Additionally, note that $\alpha_t$ changes mainly during the 1950s, the late 1970s and the debt
crisis in 2002. These large movements occur during times of current account reversals. This can be the case because during crises, firms are more likely to change their levels of labor intensities of production technologies.

The capital depreciation rates also react substantially to times of crisis. Depreciation rates tend to rise before a crisis and to decrease during it. In particular, depreciation decreases suddenly during the hyperinflation in early 1990s, the Tequila crisis in 1995 and the Asian crisis in 1998 and exhibits strong changes during the 2002 crisis. This variable, therefore, captures reductions in the utilization rate during crisis and increases substantially when the economy recovers.

In sum, this section discusses how all parameters show substantial change during the sample period. Moreover, these parameters exhibit a large, sudden change in several episodes, particularly during the macroeconomic crisis during the 1940s, the early 1980s and 1990 and in relation to the debt crisis in 2002. These episodes coincide with strong corrections of the real exchange rate. Specifically, note that as can be seen in figure 4, these episodes the real exchange rate increases suggesting that during crisis the burden of foreign debt, denominated in foreign currency, and the cost of capital, in the form of imported goods, increase. Under these dynamics, the behavior of investors can be captured by a higher sensitivity to debt changes and higher working capital constraints, whereas a natural response of domestic firms can be captured by a switch to labor intensive technologies, as well as a larger use of capital inputs. In other words, given that this model lacks of real exchange rate adjustments, time-varying parameters capture sources of misspecification of the one sector model.

In the next section, I provide statistical evidence supporting episodes of large changes in parameters being associated with corrections to the real exchange rate. This suggests that the time-varying parameter model’s superiority arises from the fact that it overcomes
a source of model misspecification of the one-sector model. In the remainder of the paper, I provide an interpretation of those shocks and propose a richer dynamic stochastic general equilibrium model that accounts for both the real exchange rate behavior and the variability of time-varying parameters.

4.2 Misspecification of the model with time-invariant parameters

This section investigates whether time-varying parameters contain relevant information regarding the behavior of the real exchange rate. Figure 4 presents the log of smoothed estimates of the time-varying parameters with the log of the real exchange rate. This figure shows that large swings in time-varying parameters are associated with corrections in the real exchange rate. The standard one-sector model is not able to capture this behavior and its consequences. In other words, the relevance and the covariation of time-varying parameters suggest that the real exchange rate adjustment might be associated with important transmission mechanisms that are absent in the standard one-sector real business cycle model.

![Figure 4: Smoothed parameters and the real exchange rate](image)

Note: Smoothed series (solid lines) of time varying parameters are measured on the left hand side axis. Real exchange rate (dashed lines) is measured in the right hand side axis. All variables are in logarithms.

Table 5 computes the correlations between time-varying parameters and the real exchange rate. The first column presents the correlation between the logarithm estimates of time-varying parameters and the logarithm of the real exchange rate; the second column presents the correlations between their low frequency movements; and the third column presents the
correlations at medium and higher frequencies. As the table shows, all smoothed estimates are positively correlated to the real exchange rate. Specifically, $\alpha_t$ and $\psi_t$ exhibits a correlation of approximately 30%. For these two variables the correlation is very strong at different frequencies, going up to 60% at low frequencies. On the other hand, capital depreciation rates and the working capital constraint elasticity exhibit a smaller correlation with the real exchange rate. Their correlation, however, is strong at low frequencies.

Table 5: Correlation between Smoothed Estimates and Real Exchange Rate

<table>
<thead>
<tr>
<th></th>
<th>Levels</th>
<th>Levels-HP(100)</th>
<th>HP(100)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\rho(\text{rer}_t, \delta_t)$</td>
<td>3.8 (1.2)</td>
<td>19.1 (2.2)</td>
<td>-10.4 (1.3)</td>
</tr>
<tr>
<td>$\rho(\text{rer}_t, \alpha_t)$</td>
<td>27.8 (3.1)</td>
<td>55.7 (6.3)</td>
<td>12.3 (1.4)</td>
</tr>
<tr>
<td>$\rho(\text{rer}_t, \psi_t)$</td>
<td>33.5 (3.9)</td>
<td>58.6 (6.7)</td>
<td>27.1 (3.1)</td>
</tr>
<tr>
<td>$\rho(\text{rer}_t, \kappa_t)$</td>
<td>7.8 (0.9)</td>
<td>29.1 (3.4)</td>
<td>-1.4 (0.2)</td>
</tr>
</tbody>
</table>

Note: $\rho(i,j)$ denotes the contemporaneous correlation between variables $i$ and $j$. Standard errors computed by GMM are in parenthesis. Both correlations and standard errors are in percentage terms.

To provide more evidence, Table 6 presents a principal component analysis for a dataset that includes the real exchange rate, $\delta_t$, $\alpha_t$, $\psi_t$ and $\kappa_t$. As it is well known, the principal components analysis provides a decomposition of a dataset in a set of orthogonal factors that are likely to generate the variability of the variables.

Table 6: Principal Components Analysis

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>PC1</td>
<td>45.9</td>
<td>28.7 (5.2)</td>
</tr>
<tr>
<td>PC2</td>
<td>75.4</td>
<td>68.5 (7.2)</td>
</tr>
<tr>
<td>PC3</td>
<td>89.9</td>
<td>64.8 (6.6)</td>
</tr>
<tr>
<td>PC4</td>
<td>98.3</td>
<td>16.5 (2.5)</td>
</tr>
<tr>
<td>PC5</td>
<td>100</td>
<td>-0.8 (1.2)</td>
</tr>
</tbody>
</table>

Note: Variance share, correlations and standard deviations are in percentage terms.

The first column indicates the share of cumulative variance in terms of total variance explained by the 5 principal components. As seen in the table, the first principal component explains 46% of the total variance of the dataset, while the first 2 principal components explain up to 75%. In other words, a large share of the variability of the matrix composed by the real exchange rate, $\delta_t$, $\alpha_t$, $\psi_t$ and $\kappa_t$, can be explain by the first two components, and almost 90% of the variability can be explained by 3 components. The second column indicates that these components strongly correlates with the real exchange rate. The following figure plots the real exchange rate together with the first four principal components.
Figure 5: Principal components and the real exchange rate

Note: This picture shows the real exchange rate and the first 4 principal components scores, that is the representation of the matrix composed by real exchange rate $\delta_t$, $\alpha_t$, $\psi_t$ and $\kappa_t$, in the principal components space. The real exchange rate is in green dashed lines and the principal components scores are in blue solid lines.

As seen in figure 5, the real exchange rate has a strong comovement with the first three principal components that explain almost 90% of the common variability of this variable, $\delta_t$, $\alpha_t$, $\psi_t$ and $\kappa_t$. Specifically, principal components two and three exhibit a large correlation with the real exchange rate. Moreover, all four first principal components share similar behavior to the real exchange rate during macroeconomic crisis.

Additionally, it is important to point out that the strong correlation of the real exchange rate and the $\psi_t$ is of major importance at the light of existing literature. As suggested by Garcia-Cicco et al. (2010), financial frictions in the one sector small open economy model is key to understand the dynamics of emerging economies. The authors, however, consider this parameter as time invariant implying the response of interest rate to debt is constant. This section shows that the response of interest rates to debt is actually time-varying. Moreover, it is strongly related to the real exchange rate dynamics.

In sum, this section provides evidence suggesting that smoothed estimates of time-varying parameters capture the dynamics of the non-modeled real exchange rate in the one-sector small open economy model. In what follows, I present a two-sectors model that microfundates the previous time-varying parameters model and aims to take into account the transmission mechanisms associated with real exchange rate adjustments.
A two sectors model with financial frictions

This section introduces a two-sector model to take into account the behavior of the real exchange rate. To model the real exchange rate behavior, I define a consumption good as an aggregator of tradable and non-tradable goods. This assumption requires defining the capital and labor used in the tradable and the non-tradable sector. Second, I introduce differentiated capital utilization rates for both sectors to have endogenously time-varying depreciation rates explained by time-varying utilization rates.

To account for the time-varying interest rate elasticity of debt, I follow Garcia-Cicco et al. (2010) in estimating a fixed interest rate elasticity of debt and allowing for exogenous interest rate shocks.\footnote{17} Finally, as in Garcia-Cicco et al. (2010) I introduce a preference shock that seeks to complement foreign interest rate shocks and that has proven to be useful in their one-sector model.\footnote{18} Given that we use the real exchange rate as an observable, we will be able to identify the exchange rate dynamics from those of exogenous shocks to the interest rate and preferences.

5.1 Households

I assume that households maximize the present value of expected utility defined over an aggregate consumption bundle and leisure. Assume preferences are given by

$$\max \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \nu_t u\left(C_t, h_t\right),$$

and the optimal plan is subject to a sequence of budget constraints,

$$\frac{D_{t+1}}{R_t} = D_t + w_t h_t + r_t^N u_t^N K_t^N + r_t^T u_t^T K_t^T - p_t^C C_t - I_t^N - I_t^T.$$

Here $\nu_t$ denotes a preference shock, $h_t$ denotes labor supply, and $C_t$ is a consumption aggregator of tradable and nontradable consumption goods, given by

$$C_t = \left(\left(\gamma^T\right)^{\frac{1}{\sigma}}\left(C_t^T\right)^{\frac{\sigma-1}{\sigma}} + \left(\gamma^N\right)^{\frac{1}{\sigma}}\left(C_t^N\right)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}},$$

with $p_t^C$, the price of consumption goods in terms of tradable goods, implicitly defined by

$$p_t^C C_t = C_t^T + p_t^N C_t^N.$$

Here, $u_t^N$ and $u_t^T$ are the utilization rates of capital in the non-tradable and the tradable goods production sectors, respectively. I allow households to accumulate and rent utilized capital allocated to non-tradable goods production and tradable goods production. Following

\footnote{17This assumption also gives the model more flexibility to capture the behavior of interest rate. The sharp drops in the growth rate of technology and depreciation rate of capital in 2005 clearly reflects the correction of interest rate, and might be better captured by an interest rate shock.}

\footnote{18I will later show that in the two sector model, this shock is less relevant to explain the variability of the observables.}
Garcia-Cicco et al. (2010) the model assumes that the preference shock follows a mean reverting AR(1) process, given by

$$\ln \left( \frac{\nu_t}{\nu} \right) = \rho \ln \left( \frac{\nu_t - 1}{\nu} \right) + \varepsilon_t^\nu,$$

where $$\varepsilon_t^\nu \sim N(0, \sigma^\nu)$$.

Under these conditions, the intratemporal allocation problem between tradable and non-tradable consumption gives

$$C_t^T = \gamma^T \left( \frac{1}{p_t^T} \right)^{-\theta} C_t,$$

$$C_t^N = \gamma^N \left( \frac{p_t^N}{p_t^T} \right)^{-\theta} C_t,$$

and

$$p_t^T = \left[ \gamma^T + \gamma^N (p_t^N)^{1-\theta} \right]^{\frac{1}{1-\theta}}.$$

I assume capital accumulation in the tradable and the non-tradable sectors evolves according to

$$K_{t+1}^N = (1 - \delta (u_t^N)) K_t^N + I_t^N - \frac{\phi^N}{2} \left( \frac{K_{t+1}^N}{K_t^N} - g \right)^2 K_t^N,$$

and

$$K_{t+1}^T = (1 - \delta (u_t^T)) K_t^T + I_t^T - \frac{\phi^T}{2} \left( \frac{K_{t+1}^T}{K_t^T} - g \right)^2 K_t^T.$$

Furthermore, the depreciation rates are assumed to change endogenously depending on sectoral utilization rates

$$\delta (u_t^N) = \delta^N + \Phi_1 (u_t^N - 1) + \frac{\phi_2^N}{2} (u_t^N - 1)^2,$$

in the non-tradable sector, and

$$\delta (u_t^T) = \delta^T + \Phi_1 (u_t^T - 1) + \frac{\phi_2^T}{2} (u_t^T - 1)^2,$$

in the tradable sector. That is, depreciation rates in each sector are larger when the utilization of capital $$u_t^i$$, in each sector is larger. We assume the same utility function assumed in the first part of the paper

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

I introduce this assumption, because, as I show in a previous section, the evolution of capital depreciation rates does not co-move with the real exchange rate.
5.2 Firms

As in the one-sector model, firms rent capital and labor from households at given prices. I assume they produce two types of goods, tradable goods that can be used for consumption, investment or traded internationally and non-tradable goods that can only be consumed domestically. Firms operate according to a Cobb-Douglas technology

\[ Y^T_t = z^T_t \left( K^{s,T}_t \right)^{\alpha_T} \left( X_t h^T_t \right)^{1-\alpha_T}, \]

and

\[ Y^N_t = z^N_t \left( K^{s,N}_t \right)^{\alpha_N} \left( X_t h^N_t \right)^{1-\alpha_N}. \]

Here \( K^{s,T}_t \) and \( K^{s,N}_t \) are the total capital services demanded by firms. \( X_t \) denotes the non-stationary technology shock that evolves according to the following process

\[ X_t = g_t X_{t-1}, \]

Furthermore, I assume the growth rate of \( X_t \) follows a mean reverting autoregressive process of order one

\[ \ln \left( \frac{g_{t+1}}{g_t} \right) = \rho g \ln \left( \frac{g_t}{g} \right) + \epsilon^g_{t+1}. \]

As opposed to the one-sector model, I assume there are two independent shocks to the total factor productivity in the tradable and non-tradable sectors. Transitory technological shocks are given by

\[ \ln \left( \frac{z^N_t}{z^{N-1}_t} \right) = \rho^N \ln \left( \frac{z^N_{t-1}}{z^N_t} \right) + \epsilon^N_t, \]

in the non-tradable sector and

\[ \ln \left( \frac{z^T_t}{z^{T-1}_t} \right) = \rho^T \ln \left( \frac{z^T_{t-1}}{z^T_t} \right) + \epsilon^T_t, \]

in the tradable sector.

Additionally, firms are subject to two working capital constraints that might have different elasticities to account for the time variation in the tightness of working capital constraint in the previous section. Hence, the firms’ problem is to maximize profits given by

\[ \Pi^f_t = p^N_t \left[ z^N_t \left( K^{s,N}_t \right)^{\alpha_N} \left( X_t h^N_t \right)^{1-\alpha_N} \right] + z^T_t \left( K^{s,T}_t \right)^{\alpha_T} \left( X_t h^T_t \right)^{1-\alpha_T} - r^N_t K^{s,N}_t - r^T_t K^{s,T}_t - W_t (h^N_t + h^T_t) - (R_t - 1) W_t h^N_t \eta^N - (R_t - 1) W_t h^T_t \eta^T. \]

Finally, I model the domestic interest rate in a similar manner as that found in the previous section,
\[ R_t = R + \psi \exp \left\{ \frac{\widetilde{D}_{t+1}}{X_id} \right\} + \exp \{ \xi_t \} - 1. \]

Here \( \xi_t \) is an interest rate shock given by

\[ \ln (\xi_t) = \rho \ln (\xi_{t-1}) + e^\xi. \]

This shock accounts for a multiplicity of foreign shocks, such as contagion effects from other emerging economies and shocks to world economic conditions and financial frictions in world asset markets, as discussed in Garcia-Cicco et al. (2010).

5.3 Accounting for real exchange rate variability

In taking this model to the data, I follow the same procedure as for the one sector model. I solve the model using a log-linear approximation around the steady state. I calibrate some parameters according to the previous literature and estimate the remaining ones using Bayesian techniques. Table 7 presents the calibrated parameters.

I calibrate \( \alpha^N, \alpha^T, \gamma^N \) and \( \gamma^T \) according to Mendoza (1995) and Aguirre (2011). Following the calibration for the one-sector model, the interest rate in the steady state is 1.05, while the debt in the steady state is calibrated to 0.007. Finally, the steady state of the trend growth rate is also calibrated to 1.005. The prior distributions for the two-sector model are presented in Table 8.

Table 7: Calibrated Parameters for the Microfundated Model

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \sigma )</td>
<td>2</td>
</tr>
<tr>
<td>( \theta )</td>
<td>1.25</td>
</tr>
<tr>
<td>( \alpha^N )</td>
<td>0.36</td>
</tr>
<tr>
<td>( \alpha^T )</td>
<td>0.49</td>
</tr>
<tr>
<td>( \gamma^N )</td>
<td>0.70</td>
</tr>
<tr>
<td>( \gamma^T )</td>
<td>0.15</td>
</tr>
<tr>
<td>( \delta^N )</td>
<td>0.1255</td>
</tr>
<tr>
<td>( \delta^T )</td>
<td>0.1255</td>
</tr>
<tr>
<td>( \omega )</td>
<td>1.6</td>
</tr>
</tbody>
</table>

To study the role and importance of the real exchange rate, I estimate the two-sector model using two different data sets. First, I use the growth rate of output, the growth rate of consumption and the trade-balance to output ratio, as I did in the one-sector model; then I add the real exchange rate.

The objective of this section is to understand whether the model is appropriate to fit the data and to determine up to what extent it can account for the variability observed in the data. To account for it, the strategy I follow in this section is to introduce measurement errors in both estimation exercises. The variability that is left unexplained by the model is
Table 8: Priors for the 2 Sector Model

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Distribution</th>
<th>Mean</th>
<th>Mode</th>
<th>Std Dev.</th>
<th>95% C. I.</th>
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<tr>
<td>$\kappa^N$</td>
<td>Beta</td>
<td>0.8</td>
<td>0.8</td>
<td>0.08</td>
<td>0.62 - 0.9</td>
</tr>
<tr>
<td>$\kappa^T$</td>
<td>Beta</td>
<td>0.8</td>
<td>0.8</td>
<td>0.08</td>
<td>0.62 - 0.9</td>
</tr>
<tr>
<td>$\psi$</td>
<td>Gamma</td>
<td>0.825</td>
<td>0.68</td>
<td>0.35</td>
<td>0.29 - 1.6</td>
</tr>
<tr>
<td>$\phi^N$</td>
<td>Gamma</td>
<td>0.825</td>
<td>0.68</td>
<td>0.35</td>
<td>0.29 - 1.6</td>
</tr>
<tr>
<td>$\phi^T$</td>
<td>Gamma</td>
<td>0.825</td>
<td>0.68</td>
<td>0.35</td>
<td>0.29 - 1.6</td>
</tr>
<tr>
<td>$\phi_2^N$</td>
<td>Gamma</td>
<td>0.825</td>
<td>0.68</td>
<td>0.35</td>
<td>0.29 - 1.6</td>
</tr>
<tr>
<td>$\phi_2^T$</td>
<td>Gamma</td>
<td>0.825</td>
<td>0.68</td>
<td>0.35</td>
<td>0.29 - 1.6</td>
</tr>
<tr>
<td>$\rho^g$</td>
<td>Beta</td>
<td>0.75</td>
<td>0.75</td>
<td>0.07</td>
<td>0.6 - 0.87</td>
</tr>
<tr>
<td>$\rho^z^N$</td>
<td>Beta</td>
<td>0.75</td>
<td>0.75</td>
<td>0.07</td>
<td>0.6 - 0.87</td>
</tr>
<tr>
<td>$\rho^z^T$</td>
<td>Beta</td>
<td>0.75</td>
<td>0.05</td>
<td>0.12</td>
<td>0.6 - 0.87</td>
</tr>
<tr>
<td>$\rho^r$</td>
<td>Beta</td>
<td>0.75</td>
<td>0.05</td>
<td>0.12</td>
<td>0.6 - 0.87</td>
</tr>
<tr>
<td>$\rho^\nu$</td>
<td>Beta</td>
<td>0.75</td>
<td>0.05</td>
<td>0.12</td>
<td>0.6 - 0.87</td>
</tr>
<tr>
<td>$\sigma^g$</td>
<td>Gamma</td>
<td>0.1</td>
<td>0.1</td>
<td>0.03</td>
<td>0.05 - 0.17</td>
</tr>
<tr>
<td>$\sigma^z^N$</td>
<td>Gamma</td>
<td>0.1</td>
<td>0.1</td>
<td>0.03</td>
<td>0.05 - 0.17</td>
</tr>
<tr>
<td>$\sigma^z^T$</td>
<td>Gamma</td>
<td>0.1</td>
<td>0.1</td>
<td>0.03</td>
<td>0.05 - 0.17</td>
</tr>
<tr>
<td>$\sigma^r$</td>
<td>Gamma</td>
<td>0.1</td>
<td>0.1</td>
<td>0.03</td>
<td>0.05 - 0.17</td>
</tr>
<tr>
<td>$\sigma^\nu$</td>
<td>Gamma</td>
<td>0.1</td>
<td>0.1</td>
<td>0.03</td>
<td>0.05 - 0.17</td>
</tr>
</tbody>
</table>

Note: This table presents the distribution mean, mode, standard deviation and 95 percent confidence band implied by prior distributions.

captured by the measurement errors. Hence, if the model is not appropriate to capture the main features of the data, the contribution of the measurement errors would be substantial. Table 9 presents the posterior means and 95% credible sets of the estimated parameters for the estimation with both 3 and 4 observables.

As seen from the table, the posterior means and the confidence bands for most parameters do not change substantially after including the real exchange rate in the set of observables. However, the volatilities of driving forces are substantially larger when we use the real exchange rate as an observable. This increase in the shocks' standard deviation is an expected result of including the real exchange rate in the set of observables because the real exchange variability is extremely large, and hence, the model needs larger realizations of innovations to match its observed behavior. Note, additionally, that the inclusion of the real exchange rate as an observable introduces changes in parameters associated with the non-tradable side of the economy, specifically $\phi^N$ that regulates changes in the depreciation rate of capital, and $\rho^z^N$ that regulates the persistence of non-tradable sector technology shocks.

A natural question is whether the two-sector model can generate the observed variability of the real exchange rate. The left plot on Figure 6 displays the real exchange rate in the model together with the one in the data when this variable is not included in the set of observables, that is when we estimate using only 3 observables. As shown, the model is not able to generate an accurate behavior of the real exchange rate from the information contained in the national account variables. This means that when smoothed shocks are fit
Table 9: Posterior estimates and credible sets for the two sector model

<table>
<thead>
<tr>
<th>Params</th>
<th>3 observables</th>
<th>4 observables</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Post. M.</td>
<td>2.5pct</td>
</tr>
<tr>
<td>$\kappa^N$</td>
<td>0.83</td>
<td>0.67</td>
</tr>
<tr>
<td>$\kappa^T$</td>
<td>0.77</td>
<td>0.62</td>
</tr>
<tr>
<td>$\psi$</td>
<td>1.5</td>
<td>0.79</td>
</tr>
<tr>
<td>$\phi^N_1$</td>
<td>0.81</td>
<td>0.41</td>
</tr>
<tr>
<td>$\phi^T_1$</td>
<td>1.2</td>
<td>0.62</td>
</tr>
<tr>
<td>$\phi^N_2$</td>
<td>2.4</td>
<td>1.6</td>
</tr>
<tr>
<td>$\phi^T_2$</td>
<td>2.1</td>
<td>1.4</td>
</tr>
<tr>
<td>$\rho^g$</td>
<td>0.63</td>
<td>0.51</td>
</tr>
<tr>
<td>$\rho^z^N$</td>
<td>0.83</td>
<td>0.69</td>
</tr>
<tr>
<td>$\rho^z^T$</td>
<td>0.88</td>
<td>0.81</td>
</tr>
<tr>
<td>$\rho^r$</td>
<td>0.76</td>
<td>0.62</td>
</tr>
<tr>
<td>$\rho^\nu$</td>
<td>0.81</td>
<td>0.68</td>
</tr>
<tr>
<td>$\sigma^g$</td>
<td>0.0007</td>
<td>0.0003</td>
</tr>
<tr>
<td>$\sigma^z^N$</td>
<td>0.026</td>
<td>0.011</td>
</tr>
<tr>
<td>$\sigma^z^T$</td>
<td>0.004</td>
<td>0.001</td>
</tr>
<tr>
<td>$\sigma^r$</td>
<td>0.048</td>
<td>0.018</td>
</tr>
<tr>
<td>$\sigma^\nu$</td>
<td>0.042</td>
<td>0.02</td>
</tr>
<tr>
<td>m.e.1</td>
<td>0.002</td>
<td>0.0007</td>
</tr>
<tr>
<td>m.e.2</td>
<td>0.001</td>
<td>0.0006</td>
</tr>
<tr>
<td>m.e.3</td>
<td>0.0006</td>
<td>0.0003</td>
</tr>
<tr>
<td>m.e.4</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

Note: “Post. M.” stands for Posterior Mean and “pct” stands for percentiles. Computed using 500,000 draws of the MH procedure.

to capture the behavior of the observables, they fail in capturing the behavior of the real exchange rate. In particular, the variability of the real exchange rate generated by the model is much smaller than the one that should actually be generated.

The strategy, therefore, is now to impose more discipline in the model by incorporating information concerning the real exchange rate and to investigate what implications are modified. The right plot on Figure 6 shows the smoothed real exchange rate implied by model estimates together with the observed real exchange rate. As can be seen, the real exchange rate behavior imposes strong discipline to the model. The model captures the main aspects of the behavior of the real exchange rate. Even though the model is able to fit most of its variability, it is not able to match the outliers observed in several episodes, such as the early 1980s, the 1990s and in 2002. If we discard the measurement errors and re-estimate the model, we would require huge realizations of exogenous shocks to accommodate those observations. It is clear, therefore, that the model requires additional transmission mechanisms to account for the extreme dynamics in times of macroeconomic distress. Implementing a
Figure 6: Observed and smoothed real exchange rate

Note: This picture compares the observed real exchange rate in Argentina for the period 1935 to 2009 in solid line and the smoothed real exchange rate implied by the model estimated with 3 observables, in dashed line. The smoothed estimate is computed without using measurement errors, hence the dashed line captures the explained variability of the real exchange rate.

procedure that perfectly matches the behavior of the real exchange rate is beyond the scope of this paper. A promising research direction to consider is the possibility of policy changes in monetary and fiscal policy design. Recent developments with Markov Switching and time varying parameters in a monetary policy model make the analysis of these questions feasible, as shown in research by Bianchi (2010) and Seoane (2011).

We just studied the impact of including the real exchange rate as an observable in the point estimates of deep parameters. The following section studies a variance decomposition exercise for the two set of results.

5.4 Variance decomposition

Table 10 presents the variance decomposition of the two-sector model estimated using three and four observables. As seen in the table, the two-sector model explains a significant share of the variability of the growth rate of output, consumption and the trade balance to output ratio in both cases. The first line of the table, presents the $\frac{\sigma^e}{\sigma^T}$, that is the explained variability of the model over the total variability of each observable. Recall the estimation is done including measurement errors and consequently, what is not captured by the model, is explained by measurement errors. With 3 observables, however, the model works slightly worst in all the dimensions as compared to the 4 observables estimation. Hence, including the real exchange rate in the set of observables improves the fit of the model for all variables.

In line with the findings in Garcia-Cicco et al. (2010), in the two-sector model, the permanent technology shock plays a minor role in explaining the variability of all variables.
Table 10: Variance Decomposition: a two-sector model with 3 and 4 observables

<table>
<thead>
<tr>
<th></th>
<th>3 observables</th>
<th></th>
<th></th>
<th>4 observables</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model</td>
<td>$\gamma^y$</td>
<td>$\gamma^c$</td>
<td>tby</td>
<td>$\gamma^y$</td>
<td>$\gamma^c$</td>
</tr>
<tr>
<td>$\sigma^e/\sigma^t$</td>
<td>88.8</td>
<td>82.4</td>
<td>98</td>
<td>91.6</td>
<td>90.2</td>
<td>99.6</td>
</tr>
<tr>
<td>$\sigma^{N}/\sigma^e$</td>
<td>50.1</td>
<td>51.5</td>
<td>3.1</td>
<td>51.9</td>
<td>67.6</td>
<td>21.7</td>
</tr>
<tr>
<td>$\sigma^{T}/\sigma^e$</td>
<td>31.1</td>
<td>10.2</td>
<td>72.2</td>
<td>37.5</td>
<td>12.7</td>
<td>70.2</td>
</tr>
<tr>
<td>$\sigma^{r}/\sigma^e$</td>
<td>16.4</td>
<td>15</td>
<td>3.4</td>
<td>9.02</td>
<td>7</td>
<td>1</td>
</tr>
<tr>
<td>$\sigma^{u}/\sigma^e$</td>
<td>0.5</td>
<td>19.1</td>
<td>6.7</td>
<td>0.6</td>
<td>10.6</td>
<td>2.7</td>
</tr>
<tr>
<td>$\sigma^{g}/\sigma^e$</td>
<td>1.9</td>
<td>4.3</td>
<td>14.6</td>
<td>1.03</td>
<td>2.1</td>
<td>4.4</td>
</tr>
</tbody>
</table>

Note: shares are in percentage of total explained variability. Given that we do not have measurement errors, explained variability is total variability of the data. $\sigma^i$ represents the share of variability generated by shock “i” over total variability.

once the financial friction is in place. This is the case both using 3 or 4 observables. Also in line with this paper, stationary technology shocks are important. Specifically, the stationary non-tradable shock accounts for about 50% of the explained variability of consumption and output growth, and it accounts for a 20% fraction of the variability of the trade balance to output ratio, once the real exchange rate is used. In contrast, the stationary tradable technology shock is less important to generate the variability of output growth; however, it is key to capture the variability of the trade balance to output ratio. On the other hand, once the two sectors are modeled separately and the real exchange rate dynamics are considered endogenously, compared to the findings in Garcia-Cicco et al. (2010), the importance of both spread shocks and preference shocks decrease. This is an important contribution of the two sector model as the model now is able to explain larger share of the dynamics without relying on preference shocks, which is a disturbance that is hard to confront with the data.

### 6 Conclusions

This paper studies whether business cycle small open economy models are useful for understanding the macroeconomic behavior of emerging economies. I estimate the standard real business cycle small open economy model with working capital constraints and trend shocks for Argentina with two specifications: a time-invariant parameter version and a time-varying parameter version. I find that the data favor the time-varying parameter model. In fact, the technological and financial parameters of a standard real business cycle model exhibit substantial variation during the last 70 years, and drifting parameters are important to explain the variability of the data.

The comparison exercise suggests that a one-sector real business cycle model might be severely misspecified even after including trend shocks and working capital constraints, features that are among the most influential recent advances in the literature. I find that changes in the time-varying parameters are substantial during corrections of the real exchange rate, such as during 1940s, the period 1989-1990, during the hyperinflationary process, and during
2001-2002, the largest macroeconomic and financial crisis in the last 70 years in Argentina.

Next, I provide evidence suggesting that an important source of misspecification is associated with the real exchange rate behavior that is absent in the one-sector model. Specifically, the real exchange rate exhibits a strong correlation with time-varying parameters at different frequencies and with the most important scores in a principal component analysis. Therefore, I design a two-sector model with tradable and non-tradable goods that includes capital utilization rates, differentiated working capital constraints and allows for preference shocks and financial international frictions as in Garcia-Cicco et al. (2010).

I take this model to the data and show that it can successfully account for the variability of national account variables and the real exchange rate dynamics. I find that the role of trend shocks is relatively mild in accounting for the volatility of observables but the stationary productivity shocks play a major role. This finding is in line with existing literature as shown in Garcia-Cicco et al. (2010). Moreover, also in line with existing literature the estimates support the importance of financial frictions also in the two-sectors model.

Hence, this paper contributes to the existing literature that aims to understand the macroeconomic dynamics in emerging economies. Specifically, this paper uses a novel approach, the time-varying parameters, to show that the real exchange rate dynamics matters, even when the models include the latest devices suggested in literature, such as working capital constraints, trend shocks and financial frictions.
A Appendix


- From 2005 to 2009 data are from Ministry of Finance (MECON).

- Original data are nominal and are deflated by GDP deflator base year 1993.

- Real exchange rate is the bilateral rate with respect to US Dollar. The domestic price index is the GDP deflator, while the US price index is the CPI, from Ferreres, Orlando J. 2005. Dos siglos de Economía Argentina, 1810–2004. Buenos Aires, Argentina: Fundacion Norte y Sur. Data since 2005 are from FRED St. Louis FED.
References


