Sources of Fluctuations in Emerging Markets: DSGE Estimation with Mixed Frequency Data

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ABSTRACT

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by

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In this dissertation, I assess sources of aggregate fluctuations in emerging markets using a small open economy model. I focus on the importance of permanent versus transitory technology shocks. Notably, emerging countries present short quarterly national accounts data, usually since the late eighties, but longer annual series, since 1950. To use this information efficiently, I estimate the model implementing a Bayesian mixed frequency strategy that combines quarterly and annual data for 1950-2010. The mixed strategy allows us to extend the sample period 40 years back with annual data, which helps to identify permanent versus transitory shocks. And at the same time, it keeps the information of shorter quarterly series, addressing potential temporal-aggregation bias of estimation with annual data.

In Chapter I, I outline the DSGE Bayesian mixed frequency estimation methodology. Then, I estimate a small open economy model featuring financial frictions for twelve emerging countries under the baseline mixed frequency estimation. I find that transitory technology shocks are the main driver of fluctuations in emerging markets, accounting for 48% of output growth variance on average, while permanent productivity shocks explain 35%. For comparison, I also estimate the model using alternative single frequency estimators based either on quarterly or annual data. Interestingly, these estimators assign a larger role to permanent shocks than the mixed frequency strategy.

In Chapter II, I perform a Monte Carlo experiment for a representative emerging economy to

assess the relative merits of the mixed frequency strategy. Strikingly, estimations based on short quarterly series exhibit large upward bias for the contribution of permanent technology shocks, yielding an incorrect ranking of shocks importance. Further, I find that the mixed frequency estimation drastically reduces this bias, sorting the shocks in the right order. Finally, the mixed strategy also does a better job than annual estimation along several dimensions. Interestingly, the predictions of the Monte Carlo experiment are in line with the different role assigned to permanent shocks across alternative estimation strategies in Chapter I. Also, I show that the magnitude and sign of these biases are sensitive to the true parameter values in the data generating process, especially with respect to the relative volatility of technology shocks. Overall, the proposed mixed frequency strategy presents large efficiency gains compared with alternative single frequency estimators.

In Chapter III, in turn, I analyze the ability of a simpler RBC model driven only by technology shocks to explain emerging markets' business cycles. I find that a frictionless RBC does a poor job at reproducing main business cycle facts. However, the model fit presents a remarkable improvement if I assume a moderate degree of financial frictions by calibrating a larger debt-elasticity of the interest rate. Finally, using artificial data for a representative emerging economy, I find that the mixed frequency estimations deliver significant efficiency gains compared with quarterly estimations, but the gains are not as large as for the financial frictions model of Chapter I and II.

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Dedication

I dedicate this dissertation to my family, that stimulated my curiosity since I was a child, and especially to my wife for her unconditional support.

Acknowledgments

First, I would like to thank my advisor, Martin Uribe for his invaluable support and effective guidance. I would also like to express my gratitude to the other members of my dissertation defense committee, Geert Bekaert, Serena Ng, Jon Steinsson and Stephanie Schmitt-Grohe, that contributed with excellent comments and suggestions. I am also indebted to Ozge Akinci, Pablo Ottonello and participants of the Economics Fluctuations Colloquium at Columbia University for valuable comments.

Chapter 1

Sources of Fluctuations in Emerging Markets

1.1 Introduction

The main goal of this paper is to explore sources of fluctuations in emerging markets (henceforth, EM) in a small open economy model, addressing some data limitations. In general, emerging countries present short quarterly national accounts data, usually since the late eighties, but much longer annual series, in most cases since 1950. To use this data more efficiently, I propose a Bayesian mixed frequency estimation (MF) strategy that combines quarterly and annual data for the period 1950-2010. The mixed strategy allows us to extend the sample back with annual data, which helps to identify permanent versus transitory shocks. At the same time, it keeps the information of quarterly series, which is likely to alleviate potential temporal-aggregation bias of alternative estimation using only annual data.

There is a body of empirical literature documenting salient features of economic fluctuations in EM (see e.g., Neumeyer and Perri [2005], Uribe and Yue [2006], Calvo, Izquierdo and Mejia [2004]). Specifically, these countries are characterized by the excess volatility of macroeconomic variables with respect to developed countries (henceforth, DC), the countercyclicality of the trade balance, the excess volatility of consumption with respect to output and sudden stops.

This paper is related to a line of research that proposes and estimates DSGE models to account for economic fluctuations in emerging markets in the tradition of real business cycle models (see e.g. Aguiar and Gopinath [2007], Garcia-Cicco, et.al. [2010], Chang and Fernandez [2010], Akinci [2011]). These models usually do a reasonable job to reproduce most salient EM facts. However, there is an open debate about the importance of competing sources of fluctuations, in particular regarding the relative contribution of permanent and transitory technology shocks. This debate is clearly illustrated by a couple of important papers I describe below.

On the one hand, in a highly influential paper, Aguiar and Gopinath (2007) (henceforth, AG) propose a real business cycle model augmented with a shock to productivity trend (permanent technology shock).[1] In this framework, they argue that the countercyclicality of the trade balance and the excess volatility of consumption indicate that permanent technology shocks are much more important in EM than in DC. Then, the authors estimate the model for Mexico and Canada, finding evidence in favor of their hypothesis.[2]

On the other hand, in a more recent paper, Garcia-Cicco, Pancrasi and Uribe (2010) (henceforth, GPU) estimate a model including a broader set of shocks than AG and reduced form financial frictions, using more than one hundred years of data for Argentina. In contrast to the AG results, they find a negligible contribution of permanent technology shocks to economic fluctuations. Moreover, they conclude that transitory shocks are the most important driver of output volatility and that other non-technology shocks and financial frictions play a key role to explain EM facts.

This paper attempts to shed some light on this debate by addressing some data limitations in EM. In short, my main contribution is to implement a Bayesian mixed frequency estimation of a DSGE, using annual and quarterly series. This estimation methodology contrasts with the most standard practice in the related literature that uses only quarterly data (see e.g., AG, Chang, et.al.

[1] In this chapter, I also mention an earlier NBER version of the paper, Aguiar and Gopinath (2004) that uses a model closer to the one estimated in this paper, which considers GHH preferences.

[2] They estimate the model using GMM with quarterly data for the period 1980-2003.

[2010]). Unfortunately, EM quarterly national accounts are normally available for relatively short periods of time, typically since the late eighties, which may lead to small sample bias and imprecise estimates. The proposed mixed frequency strategy allows us to extend the sample period back to 1950 for most countries while keeping the rich information present in shorter quarterly series. In effect, using longer series may help to distinguish between permanent and very persistent transitory shocks.

Aware of these small sample issues, GPU propose an alternative coarser estimation using a longer annual dataset for Argentina (since 1900). However, their strategy also presents some potential limitations. First, they assume that the model period is a year, which may lead to mis-specification problems if the true decision period is a quarter (or higher frequency). Second, model estimates may suffer from temporal-aggregation bias as emphasized by Christiano, Eichenbaum and Marshall (1991), Aadland (2001) and Galles and Portier (2005).[3] Last but not least, many EM countries simply do not present reliable annual data for such a long period.[4] The mixed strategy proposed here allows us to keep the rich information of higher frequency quarterly series, which is likely to reduce potential temporal-aggregation bias of alternative annual estimation.

One of the main contributions of this paper is of an empirical nature. I explore sources of fluctuations in EM using an estimated small open economy - real business cycle model. The theoretical framework is basically the financial frictions model presented in GPU and features two technology

[3] For more mechanical temporal-bias on autoregressive process see Working (1960) seminal paper, Rossana and Seater (1995) for univariate series and Marcellino (1999) for multivariate processes. More recently, Kim (2010) shows that assuming a model period of lower frequency than the true one leads to upward-biased estimates of the Calvo price-adjustment parameter in a New Keynesian model.

[4] In fact, for most countries national accounts series are available since the 1950s. When data are available before the 1950s in many cases present long periods of missing observations (typically associated with war periods) and/or substantial structural breaks. In particular, developed countries pre-war data is about two times more volatile than post-war data.

shocks (transitory and permanent) and three non-technology shocks (to time preference, government spending and interest rate). I estimate the model with Bayesian methods for 12 EM (and 6 DC for comparison), using mixed frequency data (annual and quarterly) for the period 1950-2010.[5] This study pays special attention to the relative importance of permanent and transitory technology shocks and to differences between EM and DC. I also explore whether alternative estimation strategies (MF, annual and quarterly estimations) lead to different results.

The main empirical findings can be summarized as follows. First, under the baseline MF strategy in EM, transitory technology shocks (TTS) are the most important driver of output and consumption fluctuations, accounting on average for 48% and 33% of the variance of each variable respectively. Meanwhile, permanent technology shocks (PTS) come in second place, explaining around 35% of output fluctuations, far above the negligible contribution assigned by GPU estimation for Argentina. In turn, interest rate shocks are the primary source of investment and trade balance fluctuations in EM.

Second, I find that alternative estimation strategies yield significantly different results about sources of fluctuations in EM. In effect, annual and quarterly estimation strategies tend to assign a larger role to PTS than MF estimations in EM.[6] Similarly, for a given estimation strategy, the importance of PTS tends to fall as we increase the data span with annual data. Interestingly, the differences between mixed frequency estimates and alternative strategies, in particular about the role of PTS, are in line with many predictions of a Monte Carlo experiment I perform in chapter II.[7] There, I show that MF estimation may present important advantages over alternative single

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[5] The model period is assumed to be a quarter. The dataset used in estimation is an unbalanced panel for each country.

[6] For the sake of comparison, I re-estimate the model using only shorter quarterly series, which assign a similar role to PTS and TTS in EM, in contrast with mixed frequency estimates. I find similar results estimating an annual model with annual data.

[7] In effect, in chapter II, I assess the relative merits of the mixed frequency strategy, using a Monte Carlo experiment

frequency strategies. In sum, the selection of the estimation strategy seems to be crucial to assess sources of fluctuations in EM.

Third, in the baseline estimation strategy PTS are relatively less important in EM than in DC. For instance, PTS contribution to output variance falls from 55% in DC to 35% in EM. However, I find that the estimated role of PTS in DC is extremely sensitive to the calibration strategy (with respect to the government spending-to-gdp ratio). In effect, under an alternative strategy, I find that the share of PTS in DC may fall below 30%. In any case, I do not find support for the AG results that the permanent shock is several times more important in EM than in DC.

Another noteworthy result is that estimations display a wide variation across EM countries, in particular regarding the contribution of PTS. This underscores the importance of considering many countries to assess sources of fluctuations in EM as a whole, as in this study, unlike most related papers that implement Bayesian estimation with one or two countries (see e.g., GPU, Chang, et.al. [2010]).

I also explore potential links between empirical business cycle moments and the estimated contribution of permanent technology shocks to output fluctuations. Surprisingly, I do not find a positive relation between PTS importance and the countercyclicality of the trade balance or the excess volatility of consumption, showing lack of support for the AG hypothesis (these moments are indeed more closely related to non-technology shocks). I argue that this lack of information about the permanent shock makes it harder to identify permanent versus transitory shocks in the financial frictions model.[8] Instead, I find that the contribution of PTS is positively associated with

for a representative emerging economy. Strikingly, estimations based on short quarterly series exhibit large upward bias for the contribution of permanent technology shocks, yielding an incorrect ranking of shocks importance. Further, I find that the mixed frequency estimation drastically reduces this bias, sorting the shocks in the right order. I find similar results using annual estimation as GPU.

[8] In contrast, in chapter III, for an RBC model with just technology shocks, I find that these moments are in fact informative about the importance of PTS vs. TTS, suggesting that these results are model-dependent.

the persistence of output, consumption and investment growth (first order autocorrelations).

The mixed frequency estimation technique employed here is primarily based on well-known state-space methods (see e.g., Durbin and Koopman [2001]). In this regard, there is a large body of empirical literature implementing mixed frequency estimation to assess business cycle conditions (see e.g., Aruoba, et.al. [2009], Mariano, et.al. [2003]). However, the approach in this study presents some distinctive features that are worth highlighting here. While the existing literature presents estimates for reduced form models and focuses on forecasting performance, this paper performs structural estimation of a DSGE model and is primarily focused on estimation efficiency.[9,10] This study also presents a relevant methodological contribution specific to DSGE estimation. That is, to obtain a mixed frequency state-space representation, I find a first order approximation of annual variables in the model as a function uniquely of their quarterly counterparts. This step allows us to keep the size of the state space as small as possible, which makes a huge difference in computing time.

The remainder of the paper is organized as follows. Section 2 presents the small open economy model. Section 3, in turn, describes the Bayesian estimation strategy that accommodates mixed frequency time series. Subsequently, it presents main estimation results, including variance decompositions and the model fit. In section 4, I study the sensitivity of main estimation results to alternative estimation strategies and data span. Finally, section 5 concludes.

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[9] An exception of mixed frequency estimation of a DSGE model is Kim (2010), who estimates a new Keynesian model using quarterly and monthly data, and Kim (2010b).

[10] Another motivational difference is that while most papers start with quarterly series (e.g., gdp series) and attempt to exploit higher frequency series available (e.g., monthly, weekly, daily), this paper starts with quarterly data but, instead, extends the sample by incorporating lower frequency (annual) series.

1.2 Model

The theoretical framework considered is the financial frictions model presented in GPU (2010). The framework is essentially a standard small open economy model augmented with permanent technology shocks and financial frictions. The model economy is buffeted by a total of five shocks: two technology shocks (transitory and permanent) and three non-technology shocks (time preference, government spending and interest rate spread). I select this model to assess sources of fluctuations, as it does a much better job at explaining EM business cycles than a model with only technology shocks, as shown in GPU and in chapter III.

The representative household faces the following sequential budget constraint:

$$\frac{D_{t+1}}{1+r_t} + Y_t = D_t + C_t + S_t + I_t + \frac{\varphi}{2}\left(\frac{K_{t+1}}{K_t} - g\right)^2 K_t, \tag{1.1}$$

where D_{t+1} denotes the stock of external debt issued at period t and r_t is the corresponding interest rate. The variables Y_t, C_t and I_t denote output, consumption and investment in real terms, respectively, while S_t is an exogenous government spending shock. The last term of the right hand side represents a quadratic capital adjustment cost with $\varphi > 0$, while g denotes the constant long-run rate of growth. Households produce an homogeneous good according to the following Cobb-Douglas technology:

$$Y_t = a_t K_t^{\alpha} \left(x_t h_t\right)^{1-\alpha}, \tag{1.2}$$

where h_t denotes hours worked, a_t is a transitory productivity shock and x_t is a labor-augmenting permanent technology shock (non-stationary). The stock of capital dynamics are governed by the following law of motion:

$$K_{t+1} = (1-\delta) K_t + I_t, \tag{1.3}$$

with depreciation rate $\delta \in [0,1)$. The country interest rate is assumed to be elastic to aggregate debt-to-gdp ratio (gdp trend), a feature that induces stationarity of debt-to-gdp ratio as shown in

Schmitt-Grohe and Uribe (2003). The interest rate is also affected by an exogenous country premium μ_t. Thus, the country interest rate is the result of the sum of the exogenous and endogenous components as follows:

$$r_t = r^* + \psi \left(\exp(\frac{\bar{D}_{t+1}}{\bar{y}x_t} - \bar{d}) - 1 \right) + \exp(\mu_t - 1) - 1,$$

where r^* denotes the steady state interest rate, ψ denotes the elasticity of the interest rate with respect to debt-to-gdp ratio, $\bar{d}$ and $\bar{y}$ indicate steady state values of debt-to-gdp ratio and de-trended output respectively and, thus, $\bar{y}x_t$ denotes the output trend.[11] The variable $\bar{D}_t$ denotes the aggregate level of external debt in the economy, which is taken as exogenous by households. In equilibrium, $D_t = \bar{D}_t$. Consumers are also subject to the following no-Ponzi-game condition:

$$\lim_{j\to\infty} E_t \frac{D_{t+j}}{\Pi_{i=0}^{j}\left(1 + r_{t+i}\right)} \leq \infty.$$

I assume that all five structural shocks follow a first-order autoregressive process and that are mutually uncorrelated. The transitory technology shock in logs evolves according to :

$$\ln a_{t+1} = \rho_a \ln a_t + \varepsilon_{a,t+1}; \qquad \varepsilon_{a,t} \sim N\left(0, \sigma_a^2\right).$$

Let g_t denote the rate of growth of the permanent technology shock:[12]

$$g_{t+1} \equiv \frac{x_{t+1}}{x_t}.$$

This shock is governed by the following autoregressive process:

$$\ln \frac{g_{t+1}}{g} = \rho_g \ln \frac{g_t}{g} + \varepsilon_{g,t+1}; \qquad \varepsilon_{g,t} \sim N\left(0, \sigma_g^2\right).$$

[11] The only difference with GPU model is that the interest rate here depends on debt-to-gdp trend ratio $\frac{\bar{D}_{t+1}}{\bar{y}x_t}$ instead of on the stationary debt level $\frac{\bar{D}_{t+1}}{x_t}$ used in GPU. This transformation just rescalates the interest rate-debt elasticity to make it comparable across countries and easier to interpret.

[12] From now on, each time I refer to the permanent technology shock I precisely refer to g_t, the rate of growth of x_t.

Meanwhile, the exogenous country interest rate shock evolves as follows:

$$\ln \mu_{t+1} = \rho_\mu \ln \mu_t + \varepsilon_{\mu,t+1}; \qquad \varepsilon_{\mu,t} \sim N\left(0, \sigma_\mu^2\right).$$

The preference shock presents the following law of motion:

$$\ln \nu_{t+1} = \rho_\nu \ln \nu_t + \varepsilon_{\nu,t+1}; \qquad \varepsilon_{\nu,t} \sim N\left(0, \sigma_\nu^2\right).$$

And finally, let s_t denote a detrended version of the government spending shock defined as $s_t \equiv \frac{S_t}{\bar{s}x_{t-1}}$, where $\bar{s}$ represents the government spending-to-gdp ratio in steady state. The evolution of variable s_t is given by:

$$\ln s_{t+1} = \rho_S \ln s_t + \varepsilon_{S,t+1}; \qquad \varepsilon_{S,t} \sim N\left(0, \sigma_S^2\right).$$

Households choose a plan $\{c_t, h_t, k_{t+1}\}_{t=0}^{\infty}$ that maximizes the following lifetime utility function:

$$E_0 \Sigma_{t=0}^{\infty} \nu_t \beta^t \left[\frac{\left(C_t - \theta\omega^{-1} x_{t-1} h_t^{\omega}\right)^{1-\gamma} - 1}{1-\gamma} \right],$$

subject to (1) − (3) and the no-Ponzi-game given initials conditions D_0 and K_0 and taking as given the processes for $a_t, x_t, \nu_t, s_t, \mu_t$ and r_t. Here, the parameter $\omega > 1$ implies a Frisch elasticity of $\frac{1}{\omega-1}$ and γ denotes the relative risk aversion coefficient. The period utility features GHH preferences, which removes wealth effects over hours worked. In this regard, I opt not to use a Cobb-Douglas utility function because it may lead to an unrealistic decrease of hours in response to a positive permanent productivity shock, as mentioned in AG. See the Appendix for a full set of equilibrium conditions.

1.3 Estimation

In the benchmark estimation, the model period is assumed to be one quarter. For the sake of comparison, the estimation strategy follows GPU very closely regarding the set of parameters that are calibrated and estimated, prior distributions and concepts observed in the data. Besides, this DSGE model appears to be identified following GPU estimation strategy according to Komunjer and Ng (2011) (see their supplementary appendix). The least standard features of the estimation strategy to accommodate mixed frequency data are detailed below.

A subset of parameters are calibrated as described in the following section and the remaining parameters are estimated using Bayesian methods.

1.3.1 Calibration

I calibrate the structural parameters α, β, δ, γ, θ, ω, g, $\bar{d}$ and $\bar{s}$ using either long-run ratios in the data for each country or standard values used in the related literature. Table 1 presents calibrated parameter values and moments matched.

Table 1: Calibrated Parameters

Param	Concept	Values	Param	Concept	Values
δ	Cap.depreciation	match I/Y	β	Discount factor	0.98
d	Debt to gdp	match TB/Y	γ	Risk aversion	2
s	Gov.spend to gdp	match G/Y	θ	Hours worked	2.24
g	Growth rate	match gY	ω	Frisch elasticity	1.6
α	Capital share	0.32			

Notes: Y, I, G, TB and gY denote gdp, investment, government spending, trade balance and gdp growth respectively. Capital depreciation, debt-to-gpd, government-to-gdp and gdp growth are calibrated to match correspoding long-run ratios for each country.

On the one hand, parameters $\delta, g, \bar{d}$ and $\bar{s}$ are set for each country to match long-run relations from national accounts data for the period 1950-2010. Capital depreciation rate δ is chosen to match average investment-to-output ratio for each country. The parameters g, $\bar{d}$ and $\bar{s}$ are set to match average output growth, trade balance-to-gdp and government spending-to-gdp ratios respectively. On the other hand, parameters $\alpha, \beta, \gamma, \theta$ and ω are assumed to be equal across countries and are set to the same values assigned in GPU which, in turn, are standard values in the literature of small open economies. The parameter α, which represents the capital income share, is set to 0.32 as in

GPU, AG and Mendoza (1991). In turn, parameter β, denoting the discount factor, is set to 0.98 as in AG and GPU (quarterly equivalent).[13] Relative risk aversion γ is set to 2, the same value as in AG and GPU, which lies within normal range of values used in the literature. The parameter ω is set to 1.6 as in GPU, slightly higher than in Mendoza (1991), corresponding to a Frisch elasticity of $\frac{1}{\omega-1} = 1.67$. Finally, the parameter θ is set to 2.24, which implies that households allocate 20% of their time to work in steady state.

1.3.2 Estimation Strategy

The Bayesian estimation procedure is primarily based on Markov Chain Monte Carlo methods as described in An and Schorfheide (2006). The estimation of the proposed DSGE model using mixed frequency data presents two primary challenges: accommodating annual variables in a quarterly model and dealing with missing observations. These less standard features of mixed frequency estimation are explained in detail below.

I estimate 12 structural parameters and 8 parameters representing measurement errors variance for each country at a time. More specifically, I estimate the 10 parameters characterizing structural shocks dynamics (σ_a, ρ_a, σ_g, ρ_g, σ_ν, ρ_ν, σ_s, ρ_s, σ_μ and ρ_μ) and 2 additional structural parameters associated with capital adjustment costs (φ) and interest rate-debt elasticity (ψ). I assume that all estimated parameters display uninformative uniform priors that are identical for all countries (see table 2 for details).

In the baseline mixed frequency strategy, I estimate the model using four annual series and four quarterly series. Specifically, parameters are estimated observing the rate of growth of output, consumption and investment (in log-differences) and the trade balance-to-gdp ratio, both at

[13] Unlike this paper, in which the benchmark model time unit is set to one quarter, in GPU, the model time unit is one year. They select an annual discount factor $\beta = 0.9224$, which is equivalent to a quarterly discount factor of 0.98.

quarterly and annual frequency.[14] Further, I assume that each of these variables are observed with a measurement error (independent across series) that cannot account for more than 25% of the standard deviation of the corresponding empirical series. The sample covers the period 1950-2010, but data availability for quarterly series varies from country to country (see more details below). In the baseline strategy, for the more recent period in which quarterly and annual data are available simultaneously, I use both in the estimation (henceforth, overlapping strategy).

Table 2: Prior Distributions

Param	Concept	Distribution	LB	UB
φ	Capital adj costs	Uniform	0	200
ψ	Int rate debt-elasticity	Uniform	0	0.25
ρ_a	Autocorr transitory tech	Uniform	0	0.99
ρ_g	Autocorr permanent tech	Uniform	0	0.99
ρ_ν	Autocorr preference shock	Uniform	0	0.99
ρ_s	Autocorr spending shock	Uniform	0	0.99
ρ_μ	Autocorr int rate shock	Uniform	0	0.99
σ_a	Std Dev transitory tech	Uniform	0	0.10
σ_g	Std Dev permanent tech	Uniform	0	0.10
σ_ν	Std Dev preference shock	Uniform	0	1.00
σ_s	Std Dev spending shock	Uniform	0	0.50
σ_μ	Std Dev int rate shock	Uniform	0	0.10

To estimate the proposed DSGE model with mixed frequency data we must derive a state-space representation not only for quarterly variables but also for annual variables, which is implemented as follows: First, let Z_t denote the model counterpart of observed variables, which is given by:

$$Z_t = \left[Z_t^{Q\prime}, Z_t^{A\prime}\right]',$$

where $Z_t^Q = [\Delta y_t, \Delta c_t, \Delta i_t, tby_t]'$ and $Z_t^A = \left[\Delta y_t^A, \Delta c_t^A, \Delta i_t^A, tby_t^A\right]'$ denote model variables at quarterly and annual frequency respectively, tby denotes the trade balance-to-gdp ratio and the

[14] All series used in estimation are previously demeaned.

operator Δ indicates variables in log-differences. Second, I obtain a state-space representation for quarterly variables given equilibrium conditions and a vector of parameter values Θ, solving the model up to a first-order approximation.[15] Third, I show that up to a first-order approximation the four annual variables Z_t^A may be written as a function uniquely of their quarterly counterparts (see Appendix for details).[16] This step allows us to keep the state space as small as possible, minimizing computing time. Finally, combining the previous two steps and extending the state vector appropriately, the model admits the following state-space representation that accommodates quarterly and annual variables in the measurement equation:

$$Z_t = G(\Theta) X_t,$$

$$X_{t+1} = H(\Theta) X_t + \varepsilon_{t+1}, \quad \varepsilon_{t+1} \sim N(0, V[\Theta])$$

where $G(\Theta)$, $H(\Theta)$ and $V(\Theta)$ are matrices whose entries are given by non-linear functions of the structural parameters, ε_t is a vector of structural shocks and X_t is a vector of state variables that includes lags of variables in Z_t^Q (see Appendix for details).[17]

Now, note that the observed series present missing observations both at quarterly and annual frequencies. Even if quarterly series are potentially observed every quarter, in practice they become available later than the corresponding first annual observation, leading to an early period of missing values. Annual series, in contrast, are only observed every four quarters, implying that 3 out of 4 observations are missing.[18] I deal with this issue implementing a Kalman Filter adapted to missing

[15] I use perturbation methods following Schmitt-Grohe and Uribe (2004).

[16] I provide general approximations for annual variables in levels (trade balance-to-gdp ratio) and for variables in log-differences (Δy,Δc, and Δi). Simulated data suggest that the proposed approximations exhibit a very small error of approximation for reasonable parameter values.

[17] The state vector X_t includes 6 lags of the variables in log-differences and 3 lags of tby_t.

[18] In general, it is assumed that annual series are observed at the fourth quarter every year. One exception is Australia that reports annual data for the fiscal year finished in June. For this case, I assume that annual frequency series are observed in the second quarter.

values following Aruoba, et.al. (2009), which extends Durbin-Koopman (2001) methodology. In essence, the Kalman filter is updated using only the sub-set of available observations each period (see Appendix).[19]

1.3.3 Data

I estimate the model for 12 emerging countries: six are from Latin-America (Argentina, Brazil, Chile, Colombia, Mexico and Peru), five are from Asia (Indonesia, Malaysia, Philippines, Thailand and Turkey) and one comes from Africa (South Africa). In turn, the list of developed countries is composed of Australia, Belgium, Canada, Netherlands, Norway and Sweden.

I select these countries based on the following criteria. First, to be consistent with the small open economy model, I consider countries with an absolute gdp that did not exceed 2 trillion US dollars in 2009 (Brazil is the biggest economy included). Second, in order to have a large number of observations, I only include countries with annual data available at least since 1960 and quarterly data at least since 2000Q1. Finally, an economy is considered an EM or DC according to the following criteria that removes countries that occasionally switched between categories. Specifically, a country is considered a developed economy if its annual gdp per capita (PPP adjusted) has been no less than 50% of US gdp per capita during the estimation period 1950-2010. Meanwhile, a country is considered an emerging market if its gdp per capita has never exceeded 50% of US counterpart during that period.

The dataset is an unbalanced panel for the period 1950-2010. All countries have annual data available since 1950, except for Indonesia, which starts in 1960. For most quarterly series, the first observation is available later than its annual frequency counterpart. All data series used in estimation (output, consumption, investment and trade balance) are from national accounts. Series for output, consumption and investment are expressed in per capita terms. All quarterly series used

[19] An alternative treatment of missing observations is data augmenting methodology (see Kim [2010]). However, I decided not to use this methodology, as it is likely to increase computing time by a factor of 2 to 3.

in the estimation are seasonally adjusted. Main data sources and sample periods are detailed in the Appendix.

1.3.4 Estimation Results

This section presents main estimation results under the baseline mixed frequency strategy for the period 1950-2010 (later in the Sensitivity section, I present estimates under alternative estimation strategies). While in general the focus is on EM results, I also examine the main differences between emerging and developed countries. I pay special attention to the relative importance of different structural shocks to explain macroeconomic fluctuations, especially to permanent and transitory technology shocks (henceforth, PTS and TTS respectively). I also compare main findings with the existing literature. Specifically, I attempt to answer the following questions: 1) Are PTS a negligible source of fluctuations in EM as GPU findings for Argentina? 2) Are PTS relatively more important in EM than in DC, as AG findings? 3) How does the estimated model account for EM excess volatility?

This section is organized as follows. First, I present parameter estimates country by country and associated summary statistics grouped by EM and DC. Second, I assess the fit of the model comparing empirical and model implied moments. Third, I report variance decomposition statistics and summarize main sources of economic fluctuations.

Parameter Estimates

This section reports mixed frequency estimations based on 3 million draws from the Markov Chain from which the first 1 million are discarded (reasonable convergence is achieved for each country).[20] Tables 3-4 display parameter estimates (posterior median and standard errors) for each country

[20] I conduct the estimations own code in Matlab 2010b. For each country, I run two MCMC chains from two alternative initial points and I find that the two chains converge to similar distributions. Also, within each chain, the distribution is stable for the first and second part of the chain (after discarding the first million of observations).

within EM and DC respectively. Meanwhile, table 5 presents median of parameter estimates by group of countries.

Before analyzing summary statistics for each group it is worth highlighting some general results for EM. First, note that there is a substantial dispersion of point estimates of parameters across EM countries, especially for standard deviations of shocks. Not surprisingly, this large variability will reflect in a wide heterogeneity in the sources of fluctuations for different countries, as it is shown later. Note that permanent technology shocks estimates exhibit a markedly large dispersion and standard errors compared with other shocks, suggesting that this process is likely to be relatively imprecisely estimated. These findings underscore the importance of considering a wide array of countries to assess the role of PTS in EM as a whole, in contrast with the bulk of related papers that draw conclusions based on estimations for one or two countries.[21] Also, I observe a large variability of estimates for capital adjustment costs φ and interest rate-debt elasticity ψ.

As for point estimates, it is worth noting the high persistence exhibited by preference and interest rate shocks, with median autocorrelations of about 0.97 for all countries, and to a lesser extent by TTS. In turn, PTS exhibit a persistence significantly larger than zero, of around 0.58 (relatively homogeneous across countries), well above AG(2007) estimates and in line with GPU results.[22] This indicates that a large fraction of trend shocks movements are forecastable. Another noteworthy fact is that the correlation between σ_g and σ_a across countries is negative (-0.41), while the correlation of σ_g with other non-technology shocks is positive. This appears to indicate that PTS and TTS compete intensely with each other to explain fluctuations.

Importantly, estimates assign a relevant role to financial frictions. In effect, the median estimate

[21] For instance, AG and GPU present estimations only for Mexico and Argentina within EM.

[22] Note that ρ_g standard errors are bigger (more imprecisely estimated) the smaller the relative volatility of PTS innovations $\frac{\sigma_g}{\sigma_a}$ (correlation of -0.72). This is important for explaining some results in the Monte Carlo Experiment I perform in Chapter II.

of the debt-elasticity of interest rate in EM is 0.36 (annualized), meaning that if the debt-to-annual gdp ratio increases by 1%, the annual interest rate rises by approximately 36 basis points.[23] This elasticity value lies within the range of estimates in related papers, from around 10 basis points in Akitoby, et.al. (2006) to 59 basis points in GPU.[24] The persistence of the trade balance is an extremely informative moment about different degrees of financial frictions across countries. The intuition is that when debt goes up due to a shock that deteriorates the external balance, the interest rate increases, discouraging current demand, which in turn improves the trade balance (the larger the debt-elasticity the less persistent the trade balance). In effect, estimations confirm this intuition: countries with a lower persistence of the trade balance-to-gdp ratio in the data are typically assigned a larger interest rate-debt elasticity (the correlation between these two concepts is -0.52 in the cross section of all countries).

[23]The mean estimate of this elasticity is even larger, about 51 basis points.

[24]As it will become clear in chapter III, this elasticity is very important for the RBC model performance to fit EM business cycle facts.

Table 3: Posterior Distribution Emerging Markets

Param	Arg	Bra	Chi	Col	Mex	Peru	Indo	Mal	Phil	Thai	Tur	S.Afr	**Median**
φ	5.4	28.5	7.6	2.8	4.2	8.3	6.9	3.3	4.8	4.1	14.8	15.7	**6.1**
	(0.7)	(11.9)	(2.7)	(0.7)	(0.7)	(1.8)	(2.2)	(0.7)	(1.2)	(1.0)	(4.1)	(2.7)	**(1.5)**
ψ	0.16	1.08	0.35	0.28	0.07	0.39	0.39	0.02	0.36	1.04	1.78	0.23	**0.36**
	(0.05)	(0.80)	(0.19)	(0.13)	(0.04)	(0.12)	(0.15)	(0.02)	(0.10)	(0.47)	(0.74)	(0.10)	**(0.13)**
ρ_a	0.96	0.98	0.94	0.92	0.94	0.84	0.86	0.91	0.81	0.84	0.97	0.49	**0.92**
	(0.01)	(0.03)	(0.05)	(0.02)	(0.25)	(0.25)	(0.17)	(0.04)	(0.14)	(0.13)	(0.01)	(0.28)	**(0.09)**
ρ_g	0.53	0.65	0.57	0.45	0.53	0.65	0.55	0.59	0.85	0.65	0.44	0.68	**0.58**
	(0.12)	(0.16)	(0.17)	(0.23)	(0.12)	(0.07)	(0.11)	(0.19)	(0.10)	(0.15)	(0.23)	(0.06)	**(0.14)**
ρ_v	0.98	0.89	0.97	0.94	0.89	0.99	0.98	0.85	0.99	0.98	0.96	0.98	**0.97**
	(0.01)	(0.05)	(0.02)	(0.05)	(0.06)	(0.00)	(0.01)	(0.08)	(0.01)	(0.02)	(0.02)	(0.01)	**(0.02)**
ρ_s	0.56	0.35	0.87	0.93	0.97	0.88	0.86	0.96	0.66	0.57	0.57	0.66	**0.76**
	(0.26)	(0.11)	(0.05)	(0.03)	(0.02)	(0.04)	(0.04)	(0.02)	(0.08)	(0.17)	(0.10)	(0.06)	**(0.06)**
ρ_μ	0.97	0.97	0.98	0.96	0.96	0.96	0.98	0.95	0.96	0.98	0.95	0.98	**0.97**
	(0.01)	(0.01)	(0.01)	(0.02)	(0.03)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)	(0.03)	(0.01)	**(0.02)**
σ_a	1.4	1.0	1.2	0.8	0.6	0.4	0.8	1.1	0.9	1.1	1.7	0.2	**0.9**
	(0.1)	(0.2)	(0.2)	(0.1)	(0.3)	(0.5)	(0.3)	(0.1)	(0.2)	(0.3)	(0.1)	(0.1)	**(0.2)**
σ_g	1.0	0.9	0.8	0.2	1.0	2.4	1.5	0.5	0.5	1.1	0.3	0.8	**0.9**
	(0.3)	(0.3)	(0.5)	(0.1)	(0.4)	(0.5)	(0.5)	(0.4)	(0.3)	(0.6)	(0.3)	(0.1)	**(0.4)**
σ_v	21.3	11.8	36.2	7.1	5.7	50.9	34.2	21.2	31.0	31.8	23.7	23.5	**23.6**
	(6.1)	(3.2)	(12.9)	(3.1)	(1.2)	(10.1)	(11.7)	(4.9)	(7.4)	(12.3)	(9.4)	(6.6)	**(7.0)**
σ_s	1.4	11.5	11.8	5.2	10.8	17.9	28.7	12.4	21.0	16.5	15.1	12.0	**12.2**
	(1.0)	(1.1)	(1.6)	(0.8)	(1.5)	(1.6)	(2.9)	(2.1)	(1.9)	(2.7)	(1.5)	(0.9)	**(1.5)**
σ_μ	0.19	0.45	0.32	0.22	0.12	0.55	0.31	0.43	0.38	1.04	0.92	0.33	**0.35**
	(0.03)	(0.22)	(0.10)	(0.06)	(0.03)	(0.14)	(0.08)	(0.09)	(0.09)	(0.28)	(0.29)	(0.06)	**(0.09)**

Notes: Posterior estimates are based on a 3-million MCMC chain (first 1 million draws are discarded). Each column displays posterior median and standard deviation (between parenthesis) for a given country. Interest rate-debt elasticity annualized (multiplied by 16). Last column displays median across countries of posterior medians and standard deviations Estimates of standard deviation of shocks are in percentage points.

Table 4: Posterior Distribution Developed Countries

Param	Australia	Belgium	Canada	Netherlands	Norway	Sweden	**Median**
φ	3.5	6.3	13.8	4.1	1.9	6.9	**5.2**
	(0.6)	(1.4)	(2.2)	(0.9)	(0.4)	(1.6)	**(1.2)**
ψ	1.37	0.26	0.47	0.63	0.02	0.22	**0.36**
	(0.33)	(0.09)	(0.12)	(0.15)	(0.03)	(0.06)	**(0.11)**
ρ_a	0.71	0.81	0.63	0.82	0.83	0.89	**0.81**
	(0.22)	(0.21)	(0.25)	(0.15)	(0.18)	(0.03)	**(0.19)**
ρ_g	0.58	0.64	0.70	0.55	0.60	0.24	**0.59**
	(0.04)	(0.06)	(0.04)	(0.06)	(0.18)	(0.19)	**(0.06)**
ρ_v	0.94	0.98	0.96	0.97	0.86	0.97	**0.97**
	(0.03)	(0.01)	(0.02)	(0.02)	(0.05)	(0.01)	**(0.02)**
ρ_s	0.83	0.88	0.88	0.83	0.92	0.96	**0.88**
	(0.03)	(0.02)	(0.02)	(0.09)	(0.02)	(0.02)	**(0.02)**
ρ_μ	0.94	0.95	0.97	0.98	0.86	0.97	**0.96**
	(0.02)	(0.02)	(0.02)	(0.01)	(0.04)	(0.01)	**(0.02)**
σ_a	0.2	0.2	0.2	0.4	0.7	0.6	**0.3**
	(0.2)	(0.1)	(0.1)	(0.2)	(0.2)	(0.1)	**(0.1)**
σ_g	1.1	0.6	0.7	1.0	0.7	0.5	**0.7**
	(0.1)	(0.1)	(0.1)	(0.1)	(0.3)	(0.2)	**(0.1)**
σ_v	13.6	16.9	12.6	38.1	23.3	23.4	**20.1**
	(5.6)	(4.5)	(4.0)	(13.9)	(4.3)	(7.8)	**(5.1)**
σ_s	7.0	4.9	4.5	3.6	9.0	2.8	**4.7**
	(0.4)	(0.5)	(0.2)	(0.5)	(0.9)	(0.4)	**(0.4)**
σ_μ	0.75	0.17	0.23	0.24	0.73	0.13	**0.23**
	(0.13)	(0.04)	(0.04)	(0.04)	(0.17)	(0.02)	**(0.04)**

Notes: Posterior estimates are based on a 3-million MCMC chain (first 1 million draws are discarded). Each column displays posterior median and standard deviation (between parenthesis) for a given country. Interest rate-debt elasticity annualized (multiplied by 16). Last column displays median across countries of posterior medians and standard deviations Estimates of standard deviation of shocks are in percentage points.

Now, I highlight key differences and similarities of median estimations for EM and DC. First, note that all shocks are more volatile in EM than in DC, consistent with the excess volatility of EM in the data. Notably, the differences are wider for some shocks than others. Strikingly, TTS innovation is three times as volatile in EM as in DC. Besides, the median persistence of TTS is also larger (0.92 in EM and 0.81 in DC). These two facts combined imply that the unconditional volatility of TTS shocks is almost four times larger in EM. This suggests that TTS play a key role in explaining the excess volatility in EM, intuition that is confirmed later through variance decomposition statistics.

The remainder shocks exhibit a more moderate increase in volatility. Sorted in decreasing order, the unconditional volatility of spending, interest rate and preference shocks increase about 91%, 62% and 32% respectively from DC to EM. Notably, the smallest increase is observed for PTS (24%), shock that is likely to have a smaller role in EM than in DC, in contrast with AG findings. Second, median values of ρ_g, ρ_v and ρ_μ are pretty similar for both country categories. Third, median estimates for capital adjustment costs φ and the interest rate-debt elasticity ψ turn out to be surprisingly similar for both groups.[25] Finally, note that in general EM estimates display larger

[25] The similarities of interest rate-debt elasticities between groups is somewhat unexpected considering the empirical evidence that shows that EM interest rates are usually more sensitive to fundamentals than in DC. as documented by Reinhart, et.al. (2003).

standard errors and dispersion, especially for volatilities.

Table 5: Posterior Distribution by Country Group (median)

		Emerging Markets		Developed Countries	
Param	Concept	Median	Std Dev	Median	Std Dev
φ	Capital Adj Costs	6.1	(1.5)	5.2	(1.2)
ψ	Int rate debt-elasticity	0.36	(0.13)	0.36	(0.11)
ρ_a	Autocorr transitory tech	0.92	(0.09)	0.81	(0.19)
ρ_g	Autocorr permanent tech	0.58	(0.14)	0.59	(0.06)
ρ_v	Autocorr preference shock	0.97	(0.02)	0.97	(0.02)
ρ_s	Autocorr spending shock	0.76	(0.06)	0.88	(0.02)
ρ_μ	Autocorr int rate shock	0.97	(0.02)	0.96	(0.02)
σ_a	Std Dev transitory tech	0.9	(0.2)	0.3	(0.1)
σ_g	Std Dev permanent tech	0.9	(0.4)	0.7	(0.1)
σ_v	Std Dev preference shock	23.6	(7.0)	20.1	(5.1)
σ_s	Std Dev spending shock	12.2	(1.5)	4.7	(0.4)
σ_μ	Std Dev int rate shock	0.35	(0.09)	0.23	(0.04)

Notes: Baseline mixed frequency estimation results. Posterior estimates are based on a 3-million MCMC chain (first 1 million draws are discarded). For each country group, it reports median across countries of point estimates (posterior medians) and standard errors (between parenthesis). Estimates of standard deviation of shocks are in percentage points. Interest rate-debt elasticity is annualized multiplied by 16.

Model Fit

This section explores whether the estimated model is able to reproduce main empirical facts in EM and DC for the baseline estimation period 1950-2010. To facilitate comparisons, table 6 presents empirical and model implied moments at annual frequency (median of EM and DC).[26]

Before assessing the model fit, it is useful to outline most salient empirical moments for our

[26] Given that annual data is available for the whole estimation period 1950-2010, unlike quarterly data, I decided to compute empirical and theoretical moments at annual frequency.

country sample. Consistent with the existing literature, EM used in estimation display excess volatility of consumption with respect to output, a moderate countercyclicality of the trade balance-to-gdp ratio and excess volatility with respect to DC.

In our sample, DC statistics, in contrast, present some differences with other related papers. In effect, DC exhibit a moderate negative correlation between output and trade balance-to-gdp on average, similar to EM value, and a consumption growth volatility slightly larger than that of output. These statistics contrast with most common findings for DC, indicating that consumption is less volatile than output and the trade balance is acyclical. In light of this, empirical second moments of EM and DC are closer than expected.[27]

[27] These differences are partly explained by the fact that I consider a longer sample period (1950-2010), while related papers typically consider a shorter sample period, starting after 1980 (see e.g., AG, Neumeyer and Perri [2005]). In fact, AG(2004) recognized that using a larger estimation period empirical moments between EM and DC are much closer. Moreover, if I limit the sample period to 1980-2010, the trade balance becomes acyclical and consumption growth is slightly less volatile than output in DC, but still the differences with EM are moderate.

Table 6: Second Moments (annual frequency)

	Emerging Markets				Developed Countries			
	Y	C	I	TBY	Y	C	I	TBY
Std Dev %								
- Data	4.4	4.7	14.4	3.4	2.2	2.3	7.3	2.5
- Model	4.4	5.4	11.2	3.9	2.5	3.2	5.5	2.9
	(0.3)	(0.4)	(0.6)	(0.8)	(0.2)	(0.2)	(0.3)	(0.8)
Correl w/Y								
- Data	-.-	0.76	0.70	-0.18	-.-	0.69	0.74	-0.20
- Model		0.83	0.55	-0.13		0.79	0.57	-0.12
		(0.03)	(0.03)	(0.05)		(0.02)	(0.03)	(0.05)
Correl w/TBY								
- Data	-.-	-0.14	-0.24	-.-	-.-	-0.09	-0.12	-.-
- Model		-0.17	-0.13			-0.08	-0.08	
		(0.05)	(0.05)			(0.05)	(0.05)	
Autocorrel								
- Data	0.25	0.20	0.10	0.69	0.29	0.18	0.05	0.82
- Model	0.39	0.29	0.12	0.77	0.47	0.38	0.13	0.85
	(0.05)	(0.04)	(0.03)	(0.06)	(0.05)	(0.04)	(0.04)	(0.05)

Notes: Median across countries of model and empirical moments. Model implied moments based on 500,000 draws from posterior distribution (posterior median, standard errors between parenthesis). Empirical moments for the period 1950-2010. Variables Y, C and I denote rate of growth of output, consumption and investment. TBY denotes trade balance-to-output ratio.

As shown in table 6, the estimated model does a remarkable job in reproducing main empirical facts. That is, it correctly ranks both volatility and first-order autocorrelations for output, consumption, investment and the trade balance, both for EM and DC.[28] It also reproduces the countercyclicality of the trade balance, not only with respect to output but also to consumption and investment, and the positive autocorrelation of all variables in the data.

The model also correctly predicts that the trade balance-to-gdp ratio is less persistent in EM than in DC on average, and, in both cases, the first-order autocorrelations are significantly below

[28]Further, the estimated model generates an autocorrelation function of the trade balance-to-gdp close to the one observed in the data for most countries, and for several lags.

1. The latter is mainly due to the positive estimates of the interest rate debt-elasticity, as discussed above. If we instead set this parameter to a value near zero, the trade balance autocorrelation is near a unit root, as highlighted in Schmitt-Grohe and Uribe (2003), GPU and Chapter III . Finally, the model does an outstanding job in reproducing the excess volatility of EM with respect to DC for each variable.

The model fit is satisfactory, but not perfect. For instance, it significantly underpredicts the volatility of investment and overstates the volatility of consumption (it appears to face a trade-off in fitting these two variables). Additionally, it overstates the persistence of consumption and output, especially for DC.

One question that emerges here is how the model implies a similar negative correlation of output and trade balance for both groups of countries despite the predominance of TTS in EM.[29] This is in part explained by the fact that TTS are more persistent in EM, reducing the positive impact on trade balance procyclicality.

It is interesting to explore the AG hypothesis that PTS are crucial to explain salient EM facts. To shed some light on this, I shut off the PTS shock (setting $\sigma_g = 0$) and re-compute implied moments. I find that consumption is still more volatile than output (for a similar margin) on average, indicating that PTS are not essential to generate this moment. Similarly, the trade balance is still significantly countercyclical (though correlation with output is slightly higher) and presents a similar absolute volatility, suggesting that the permanent shock has a limited impact on this variable. This implies that other non-technology shocks are very important to explain these EM stylized facts, as I confirm below.

[29] As discussed in AG, the increase in consumption levels in response to a positive transitory technology shock is less than proportional than the increase in income, which leads to an improvement in the trade balance. Therefore, TTS are associated with a procyclical trade balance.

Variance Decomposition

In this section, I assess the relative importance of shocks in explaining aggregate fluctuations. For that purpose, I compute variance decompositions for the rate of growth of output, consumption and investment and for the trade balance-to-gdp ratio (at annual frequency).[30] To facilitate comparisons, table 7 presents variance decomposition statistics grouped by EM and DC (averages across countries of point estimates and standard errors). Tables A7-A9 in the Appendix report results country by country.

I find that for EM on average, transitory technology shocks are the most important source of output and consumption fluctuations, accounting for about 48% and 33% of the variance of each variable respectively (see table 7). In turn, permanent technology shocks explain around 35% and 22% of the variance of these variables respectively. I also find that preference shocks are an important driver of consumption fluctuations (share of 33%). Conversely, interest rate shocks are the main source of variability for investment and trade balance in EM, explaining around 46% and 49% of each variable respectively. Finally, government spending shocks display a modest contribution to fluctuations, except for trade balance dynamics.

As for developed countries, PTS is relatively much more important than TTS as a driver of economic fluctuations. Strikingly, PTS account for 55% and 34% of output and consumption variability respectively. Similar to EM, interest rate shocks explain the bulk of investment volatility,

[30] These statistics are constructed based on 500,000 draws from the posterior distribution (baseline estimation) for each country.

but are in second place behind preference shocks in accounting for trade balance fluctuations.

Table 7: Variance Decomposition (average across countries, annual frequency)

	Emerging Markets				Developed Countries				Difference EM - DC			
Shocks	Y	C	I	TBY	Y	C	I	TBY	Y	C	I	TBY
Transitory tech	48.0	32.5	17.0	3.8	20.7	12.2	5.5	1.9	27.2	20.2	11.5	1.9
	(16.1)	(10.8)	(7.2)	(2.4)	(9.7)	(6.2)	(3.0)	(1.4)				
Permanent tech	34.6	22.1	13.3	3.6	55.2	33.6	24.0	4.5	-20.5	-11.5	-10.8	-0.8
	(16.6)	(11.2)	(7.5)	(2.7)	(10.8)	(7.4)	(5.5)	(2.0)				
Preference	8.5	32.8	19.3	28.0	8.0	33.5	11.9	41.1	0.5	-0.7	7.4	-13.1
	(3.1)	(4.8)	(4.9)	(9.7)	(3.2)	(4.4)	(3.4)	(11.9)				
Spending	1.1	5.8	4.9	15.6	2.7	11.1	7.5	23.5	-1.6	-5.3	-2.6	-7.9
	(0.4)	(2.2)	(1.7)	(4.5)	(0.8)	(2.7)	(2.0)	(6.0)				
Interest rate	7.9	6.9	45.5	48.9	13.4	9.6	51.0	29.0	-5.5	-2.8	-5.5	19.9
	(1.6)	(1.4)	(5.3)	(9.7)	(2.1)	(1.6)	(4.8)	(7.0)				
Technology	82.6	54.5	30.3	7.4	75.9	45.8	29.6	6.3	6.7	8.7	0.7	1.1
Non-Technology	17.4	45.5	69.7	92.6	24.1	54.2	70.4	93.7				

Notes: Posterior estimates are based on 500,000 draws from posterior distribution. Variables Y, C and I denote rate of growth of output, consumption and investment. TBY denotes trade balance-to-output ratio. Each entry displays the contribution of a given structural shock to the corresponding variable (average across countries). For each country the point estimate is the mean of the posterior distribution. Standard errors between parenthesis (average of standard errors across countries). Values are expressed in percentage terms and each column adds up to one. Variance does not include measurement errors.

Now, let me summarize the main differences between EM and DC. As it is already clear from the above results, I find huge differences in the relative importance of shocks in EM and DC, especially in regard to the role of technology shocks. In fact, while TTS are relatively more important in EM, PTS are predominant in DC. For instance, the share of output variance explained by PTS is 55% in DC, far above the 35% in EM, difference that is mirrored by an increase in the share of TTS from 21% in DC to 48% in EM.[31]

[31] In light of this, the ratio of output variance accounted for by TTS to PTS exhibits a sharp increase, from 0.38 in DC to 1.38 in EM. This is clearly at odds with AG findings about the relative predominance of PTS in EM. Note that the increase in TTS importance more than offsets the decline in PTS from DC to EM, leading to an overall increase in the share of technology shocks combined (e.g., for output, rises from 76% in DC to 83% in EM).

Now, I must highlight that the result of the predominance of PTS shocks in DC is extremely sensitive to the calibration of the government spending-to-gdp ratio (higher in DC than in EM on average). Later, in the Sensitivity section, I show that calibrating a smaller spending ratio for DC may lead to revert the previous result, yielding a smaller role for PTS (output variance share falls below 30% on average). In any case, I do not find support for AG results that PTS is several times more important in EM than in DC.

Looking at non-technology shocks, the importance of spending shocks declines substantially from DC to EM, possibly due to the smaller size of government spending in the latter. Meanwhile, interest rate shocks exhibit a significant increase in the share of trade balance fluctuations in EM of almost 20%, but present a decline for the remainder variables.

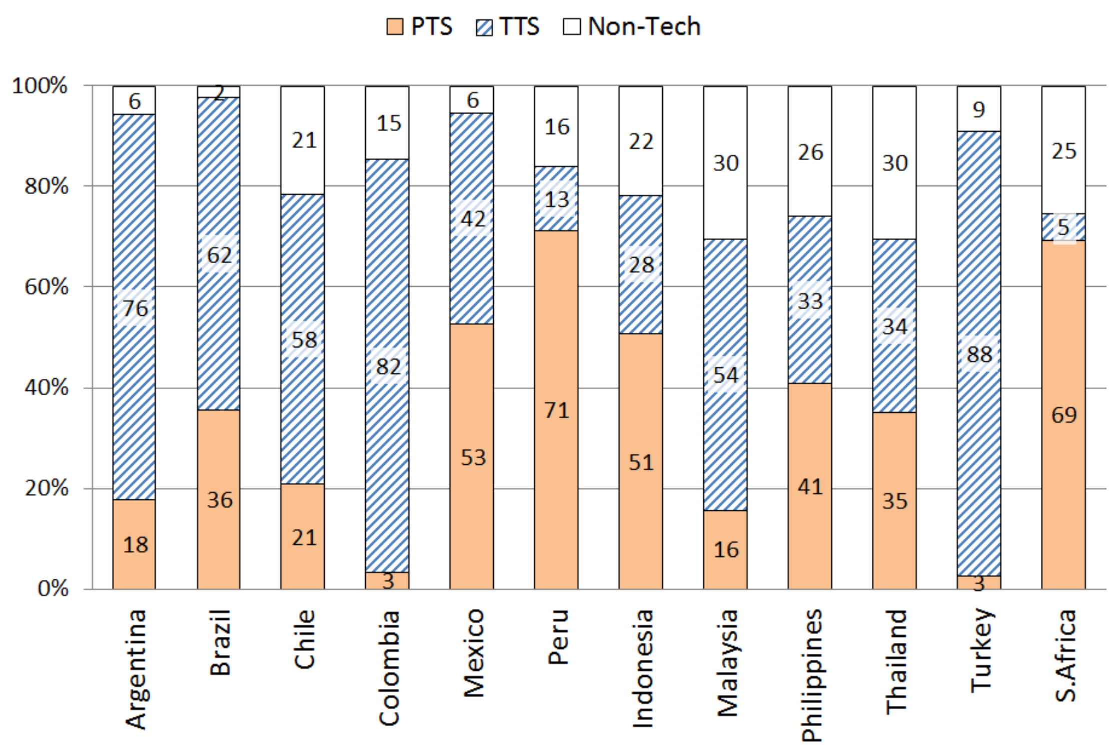
It is interesting to decompose the variance gap between EM and DC, assessing the contribution of each shock. Naturally, volatility gaps depend on differences not only on shock processes but also on the transmission mechanism, characterized here by φ and ψ. But given that these parameters estimates are similar on average for EM and DC, I focus only on the contribution of shocks. For that, I propose the following average decomposition of output growth variance. First, for each group (EM and DC) I breakdown the output variance (in variance units), multiplying the average share of each shock by the average output variance (model implied). Second, the contribution of a given shock to the variance gap is computed as the variance gap in levels between EM and DC conditional on the shock, divided by the total variance gap (note this decomposition adds up to 1). This procedure indicates that two thirds of the output variance gap is attributed to TTS, followed by PTS, preference and interest rate shocks, explaining about 21%, 9% and 4% respectively (spending shock explains a similar variance for both groups).

It is worth noting that some shares are relatively imprecisely estimated in EM, in particular the contribution of permanent and transitory technology shocks to output fluctuations (large average standard errors, of around 16% each). However, the combined contribution of technology shocks to output (82.6%) is indeed quite precisely estimated, displaying a standard error of only 5%.

This is explained by a large negative correlation between PTS and TTS within each country. These combined facts suggest potential identification issues between permanent versus transitory technology shocks but precise estimates of the joint importance of technology versus non-technology shocks.[32]

Further, country by country estimations yield a large dispersion about the relative contribution of technology shocks, especially across EM (see tables A7-A9 in the Appendix). For example, the share of output variance attributed to PTS goes from 2-3% in Turkey and Colombia to around 70% in Peru and South Africa (see figure 1). In light of this dispersion, average results for EM and DC reverse for some countries (e.g., in Peru PTS are relatively more important and in Sweden TTS are predominant).

Figure 1: Output Growth Variance Decomposition



[32] In a Monte Carlo experiment in Chapter II, I show that even if all countries' data is originated from the same data generating process, estimations yield substantial heterogeneity of the relative importance of PTS versus TTS shocks across samples, reinforcing the idea that it is difficult to identify these shocks.

The main results about sources of fluctuations so far present strong differences and some similarities with closely related papers.

First of all, the predominance of TTS in EM is qualitatively in line with GPU annual estimations for Argentina. However, the results here depict a quantitatively more substantial role for PTS (35% of output variance share in EM compared to 7% in GPU). This difference is in part explained by the fact that our estimations for Argentina assign a smaller role for PTS than the average EM (e.g., the output variance share of PTS for Argentina is around 18%, half that of EM). The rest is explained by the different estimation period.[33]

Second, I do not find support for the AG findings that indicate that permanent shocks are many times as important as transitory technology shocks to account for output fluctuations. In fact, the baseline estimation suggests that PTS are relatively more important in DC, though this result is sensitive to an alternative calibration strategy.[34]

Informative Moments about the Permanent Technology Shock

It is interesting to examine whether the heterogeneity of PTS importance across countries is associated with empirical moments in the cross section. To this end, I compute correlations in the cross section of countries (for all countries and for EM) between the fraction of output variance explained by PTS and a set of second moments (period 1950-2010), including those in table 6, together with relative volatilities with respect to output. In this regard, it is worth exploring the relevance of AG's argument that the countercyclicality of the trade balance and the excess volatility

[33] In fact, later in the sensitivity section, I re-estimated the model with a longer sample for Argentina for the period and data cosidered in GPU and the estimated share of PTS is very similar to GPU result (both under MF or annual estimation strategies).

[34] Note that PTS is relatively more important in Canada than in Mexico in our country by country estimations, even though Mexico estimate assigns a larger role for PTS than the average EM. I would like to remark that the results here are not directly comparable to AG for several reasons: differences in the model, they employ a shorter sample, etc.

of consumption in EM are informative of the presence of PTS.

Surprisingly, the only empirical moments that show a clear positive correlation with PTS share are first-order autocorrelations of output, consumption and investment growth, with values of around 0.40.[35] These correlations are even stronger if we consider only emerging markets. In other words, countries that show more persistent variables are usually assigned a more important role to PTS. Note that these empirical moments do not show a clear difference between EM and DC either (output growth is slightly more persistent in DC, but the opposite is true for consumption and investment).

Contrary to AG argument, I find that the countercyclicality of the trade balance and the excess consumption volatility do not show a positive link with PTS importance (correlations are small and of the wrong sign).[36] Interestingly, in Chapter II, I find similar results using artificial data. In other words, these moments do not convey much information about the importance of PTS shocks in the financial frictions model, which leads to a weaker identification of PTS versus TTS shocks, as I discuss in Chapters II and III.[37] Arguably, the loss of information about PTS importance is explained by the fact that other non-technology shocks have a stronger link with these moments (this fact is confirmed in Chapter II).

[35]Significant negative correlations are observed between PTS and standard deviation of output, suggesting that more volatile countries normally exhibit a bigger contribution of PTS. This is hardly a surprise, given that EM are much more volatile and display smaller contributions of PTS. However, these correlations are much smaller (closer to zero) if we consider only emerging markets.

[36]The relative volatility of consumption is indeed negatively correlated with PTS share of output variance (-0.46) including all countries. If we restrict the sample to EM, this correlation is smaller in absolute value but still negative (-0.26). The trade balance-to-gdp ratio, in turn, shows a small and positive correlation (wrong sign).

[37]In the RBC model of Chapter III (with only technology shocks), I find that these moments are much more informative about the importance of PTS versus TTS, possibly because in that model there are no demand and interest shocks that may generate these facts.

Given the similarities displayed by relevant second moments in EM and DC, it is worth exploring other possible explanations to account for the different results obtained for these two groups. One potential explanation is that EM exhibit sudden stops episodes far more often than DC (see e.g., Calvo et.al. [2004]). These episodes are characterized by current account reversals and sharp output contractions that are partly reverted in the medium term, potentially consistent with the presence of transitory technology shocks. To test this hypothesis, I remove sudden stops episodes from EM and DC samples (episodes detected following a criteria similar to Calvo et.al. (2004)) and re-estimate the model using mixed frequency series. However, I find that the main results about the sources of output fluctuations remain practically unchanged. Therefore, the main findings appear to be robust to the exclusion of sudden stops.[38]

In sum, baseline estimations assign a predominant role to TTS in EM (and to PTS in DC, but this result is not robust) for the period 1950-2010. Further, the contribution of PTS in EM is considerably larger than in GPU estimations. There is no obvious explanation for these differences in sources of fluctuations between EM and DC based only on usual second moments.

1.4 Sensitivity Analysis

This section studies the sensitivity of main empirical findings (obtained under the baseline estimation) to different estimation strategies. Specifically, I consider the alternatives of quarterly estimation, annual estimation and MF estimation with non-overlapping data. Also, I explore the sensitivity of results to different estimation periods. I concentrate on the sensitivity of variance decompositions for PTS and TTS. Notably, I find that alternative estimation strategies yield sig-

[38] Alternatively, the stronger contribution of TTS in EM may be associated with the relative importance of terms of trade in EM, as long as we considered them persistent but transitory (in our model, terms of trade shocks may be interpreted as a technology shock). In this sense, note that TTS contribution is larger in Latin-America, region characterized by a larger share of commodity exports, than in the remaining EM countries. But further analysis of this hypothesis is out of the scope of this paper.

nificantly different results about sources of fluctuations. Notably, annual and quarterly estimations tend to assign a larger role to PTS than MF estimations. Similarly, for a given estimation strategy, the share of PTS on output fluctuations tends to fall as we increase the data span with annual data.

1.4.1 Quarterly Estimation

Recall that the baseline estimation strategy uses mixed frequency series with annual data since 1950. Alternatively, here I re-estimate the model using only quarterly data (henceforth, quarterly estimation), the standard practice in related papers, that is available for much shorter periods, as described before. Table 8 presents parameter estimates with quarterly data (to facilitate comparisons, it includes baseline results MF1). At first sight, estimates seem similar across strategies; however, there are some significant differences that will reflect in the relative importance of shocks. Notably, quarterly estimation in general delivers less persistent shocks, especially for TTS. This is consistent with the bias predicted in the Monte Carlo experiment I perform in chapter II. Note also a substantial decline in the volatility of preference shocks.

Table 9 reports variance decompositions (group averages), which reveal very important differences between quarterly and MF estimation. In contrast to baseline MF, quarterly estimates assign a much more important role to permanent technology shocks, which reflects in a smaller role of transitory technology shocks (compare tables 9 and 7). As a result, quarterly estimations indicate that PTS and TTS play a similar role in explaining fluctuations in EM.[39] This contrasts with the predominance of TTS in EM obtained in the baseline MF estimation. Interestingly, these remarkable differences are in line with the upward bias for the relative importance of PTS predicted by the

[39] TTS are slightly more relevant for output and consumption fluctuations; meanwhile, PTS contribute more to investment and trade balance.

Monte Carlo experiment in chapter II.[40], [41] Note also that the contribution of preference shocks in EM falls substantially from MF to quarterly estimation.

[40] Even if the changes in results from MF to quarterly estimation are in line with the predictions of the Monte Carlo experiment, the differences may obey to diverse causes. For example, in the experiment, estimates are pretty sensitive to actual realizations of shocks and recall that MF uses a longer sample period than quarterly estimation (typically 40 more years). Additionally, we cannot rule out the possibility of structural breaks.

[41] A similar rebalance in sources of fluctuations is obtained for DC, reinforcing the predominance of PTS for this group. Consequently, the result that PTS is relatively more important in EM than in DC still holds for quarterly estimation. Keep in mind that quarterly series for DC are available for a longer period than for EM (on average about 13 years longer). Therefore, it is reasonable to expect smaller differences between MF and quarterly estimates for DC.

Table 8: Posterior Distribution by Country Group and Estimation Strategy

		Emerging Markets			Developed Countries		
Param	Concept	MF1	MFNO	Quart	MF1	MFNO	Quart
φ	Capital Adj Costs	6.1	6.6	6.0	5.2	4.9	5.8
		(1.5)	(1.5)	(1.3)	(1.2)	(1.2)	(1.3)
ψ	Int rate debt-elasticity	0.36	0.38	0.19	0.36	0.29	0.33
		(0.13)	(0.16)	(0.09)	(0.11)	(0.10)	(0.10)
ρ_a	Autocorr transitory tech	0.92	0.91	0.88	0.81	0.68	0.60
		(0.09)	(0.10)	(0.15)	(0.19)	(0.23)	(0.21)
ρ_g	Autocorr permanent tech	0.58	0.59	0.55	0.59	0.54	0.55
		(0.14)	(0.13)	(0.18)	(0.06)	(0.07)	(0.08)
ρ_v	Autocorr preference shock	0.97	0.97	0.90	0.97	0.96	0.97
		(0.02)	(0.02)	(0.13)	(0.02)	(0.02)	(0.02)
ρ_s	Autocorr spending shock	0.76	0.76	0.77	0.88	0.87	0.82
		(0.06)	(0.06)	(0.08)	(0.02)	(0.03)	(0.04)
ρ_μ	Autocorr int rate shock	0.97	0.96	0.96	0.96	0.96	0.96
		(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)
σ_a	Std Dev transitory tech	0.91	0.88	0.80	0.28	0.24	0.24
		(0.17)	(0.20)	(0.22)	(0.13)	(0.12)	(0.12)
σ_g	Std Dev permanent tech	0.88	0.79	0.75	0.70	0.77	0.72
		(0.35)	(0.34)	(0.33)	(0.12)	(0.13)	(0.11)
σ_v	Std Dev preference shock	23.6	20.4	11.4	20.1	18.4	19.0
		(7.0)	(6.5)	(5.2)	(5.1)	(5.3)	(5.9)
σ_s	Std Dev spending shock	12.2	14.8	14.1	4.7	4.8	4.9
		(1.5)	(1.7)	(2.0)	(0.4)	(0.5)	(0.6)
σ_μ	Std Dev int rate shock	0.35	0.36	0.26	0.23	0.20	0.20
		(0.09)	(0.12)	(0.10)	(0.04)	(0.04)	(0.06)

Notes: MF1 and MFNO denote mixed frequency overlapping and non-overlapping strategies respectively. Quart denotes quarterly data estimation. Each column displays posterior median and standard deviation between parenthesis (median across countries). Interest rate-debt elasticity annualized (multiplied by 16). Posterior estimates based on a 3-million MCMC chain (first 1 million draws are discarded). Estimates of standard deviation of shocks are in percentage points.

Table 9: Variance Decomposition Quarterly Estimation

	Emerging Markets				Developed Countries			
	Y	C	I	TBY	Y	C	I	TBY
Transitory tech	44.5	33.3	18.0	5.6	14.8	7.1	2.3	1.0
	(18.8)	(14.8)	(9.3)	(4.9)	(12.9)	(7.6)	(3.4)	(1.3)
Permanent tech	43.7	30.6	23.9	11.0	64.8	36.1	30.0	6.2
	(19.6)	(16.1)	(11.8)	(7.4)	(14.5)	(9.6)	(7.8)	(3.5)
Preference	2.5	21.5	4.4	19.4	8.6	39.1	13.2	38.6
	(1.8)	(5.7)	(2.8)	(12.5)	(4.1)	(6.7)	(4.3)	(16.2)
Spending	1.4	7.7	5.9	23.1	3.3	11.9	10.0	29.5
	(0.8)	(3.6)	(2.7)	(8.1)	(1.2)	(3.7)	(2.8)	(8.8)
Interest rate	8.0	6.9	47.8	41.0	8.5	5.7	44.4	24.7
	(2.2)	(2.0)	(7.6)	(13.1)	(2.8)	(1.9)	(6.4)	(7.8)

Notes: Each entry displays the contribution of a given structural shock to the corresponding variable (average across countries). Variables Y, C and I denote rate of growth of output, consumption and investment, annual frequency. TBY denotes trade balance to output ratio. For each country the point estimate is the mean of the posterior distribution. Standard errors between parenthesis (average OF standard errors across countries). Variance does not include measurement errors. Posterior estimates are based on 500,000 draws from posterior distribution.

1.4.2 Annual Estimation

Here, I estimate the financial frictions model for all EM under an alternative strategy that assumes the model period is a year (henceforth, annual estimation), as in GPU.[42] I use only annual data for the period 1950-2010, the same period covered in MF1. I focus on the variance decomposition of output growth. Table 10 displays average variance decompositions for emerging markets. Additionally, to facilitate comparisons, table 11 includes output variance decomposition for alternative estimation strategies and periods. Interestingly, annual estimations assign a predominant role to permanent shocks in EM, in contrast with baseline MF1 estimation results. In numbers, annual estimations yield a share of PTS of 46% on average, above the 41% explained by TTS. This contrasts with the PTS share of 35% obtained under baseline MF estimations. In sum, annual estimations

[42] Note that this strategy requires re-calibrating some parameters used in the MF strategy to their annual equivalents.

yield quite different results than MF estimations, assigning a larger role to permanent shocks (in chapter II, I obtain similar results using artificial data).

Table 10: Var. Decomp. EM Annual Estim. 1950-2010

	Y	C	I	TBY
Transitory tech	40.7	28.4	13.9	4.1
	(19.8)	(14.1)	(8.4)	(3.7)
Permanent tech	45.6	32.3	21.2	4.4
	(20.1)	(14.3)	(10.0)	(3.2)
Preference	5.5	28.5	16.6	22.1
	(2.5)	(5.7)	(5.1)	(10.3)
Spending	0.8	6.9	2.7	9.5
	(0.4)	(3.0)	(1.3)	(4.3)
Interest rate	7.4	3.9	45.5	59.9
	(2.0)	(1.2)	(6.9)	(9.8)

Notes: Variance decompositions for EM implied by annual estimation 1950-2010. Each entry displays the contribution of a given structural shock to the corresponding variable (average across EM countries). Variables Y, C and I denote rate of growth of output, consumption and investment, annual frequency. TBY denotes trade balance to output ratio. For each country the point estimate is the mean of the posterior distribution. Standard errors between parenthesis (average OF standard errors across countries). Variance does not include measurement errors. Posterior estimates are based on 100,000 draws from posterior distribution.

1.4.3 Latin-America Estimations 1901-2010 (MF vs Annual Estimation)

Latin-American countries (Latam) present reliable annual data for the pre-World War II period. Therefore, in this section, I analyze the sensitivity of results to estimations using 110 years of data for the period 1901-2010 for Latin-American countries. One goal is to compare with the results of GPU for Argentina (they use data for 1901-2005).[43] Further, I implement both a mixed frequency estimation using annual data for the whole period and quarterly data when available, similar to

[43] For comparison, for Argentina and Mexico for the period 1901-2005 I use exactly the same data from GPU.

the MF strategy used so far, and annual estimation (as GPU) as in the previous section. I analyze only the contribution of shocks to output variance.

First, I find that MF2 estimations assign a predominant role to TTS for Latam, accounting for 61% of output variance on average, while PTS explains just 20% (see lower panel of table 11). Similarly, annual estimations indicate that TTS are the primary driver of output fluctuations (58%) compared with a share of 27% for PTS. Note that even if both MF and annual estimations have similar qualitative implications, MF estimated contribution of PTS is 7% smaller than that under annual estimation.

To facilitate comparisons, table 11 also includes MF and annual estimations for the average of the six Latam countries for the baseline period 1950-2010 (see lower panel). The plan is to explore how the estimated sources of fluctuations change when we extend the sample back with annual data from 1950 to 1901, within the same frequency strategy Notably, under MF estimation, the share of PTS falls significantly when we extend the sample back to 1901, from 35% under MF1 to 20% under MF2. Similarly, under annual estimation, the share of PTS falls markedly from 50% for 1950-2010 to 27% for 1901-2010. These results together, suggest that when increasing the data span the share of permanent shocks goes down, which could be associated with finite sample bias. In fact, later in chapter II, the Monte Carlo experiment predicts exactly this behavior for a representative EM when we add annual data. Note that the share of non-technology shocks also goes up with the data span for both MF and annual strategies.

Finally, note that for Argentina, I obtain very similar results as GPU. In effect, MF and annual estimations for 1901-2010 here predict a PTS share of 3% and 8% respectively, compared to a 7% in GPU. Again, the role attributed to PTS for Argentina is markedly below Latam average, which suggests that one must be cautious to extract conclusions for EM only using this country. For a full set of estimations, country by country, see tables A11 (MF) and A12 (annual estimation) in the appendix.

1.4.4 Comparing Variance Decompositions across Estimation Strategies

This section attempts to summarize main changes in the predicted contribution of technology shocks across alternative estimation strategies and periods for a country group. Some of these differences, in particular about the importance of permanent shocks, have been analyzed above. For this, table 11 includes summary variance decomposition estimations for Latam and EM using MF, quarterly and annual strategies (only for output variance). For EM, estimations under MF and annual strategies are available just for the baseline period 1950-2010, while for Latam, I also present estimations for the period 1901-2010, presented in the previous section.

Notably, we can extract some patterns from average estimations for a group of countries when we switch between estimation strategies or when we change the estimation period, keeping the frequency strategy unchanged. In short, main findings may be summarized as follows: 1) for a given frequency strategy (MF, annual), estimated PTS share tends to decrease as we extend the sample back, for example from MF1 to MF2 or from A1 to A2 in Latam (that used 60 and 110 years respectively); 2) for a given data span, PTS share tends to fall if we switch from annual to MF estimation (e.g., from A1 to MF1 in EM and Latam, and from A2 to MF2 in Latam); 3) the share of PTS tends to decrease when we switch from quarterly estimation with short series to MF strategies (this holds both for EM as a whole and for Latam). Notice that the latter is similar to fact 1), in the sense that we are incorporating longer datasets.[44]

For each of these facts, note that the shares of TTS and non-technology shocks move in the exact opposite direction of PTS. More importantly, the facts documented here are predicted by the Monte Carlo experiment for a representative EM economy and are associated with finite sample bias reductions (of MF strategies compared to annual or quarterly strategies or estimations with longer time series).

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[44] The enumerated facts hold for the analyzed country groups and do not need to hold for each individual country.

Table 11: Var(Y) Decomp. Summary MF, Ann & Quart estim.

	MF2	MF1	Q	A2	A1
EM (12 countries)					
- Transitory Tech	-.-	48	44	-.-	41
- Permanent Tech	-.-	35	44	-.-	46
- Rest	-.-	17	12	-.-	14
Latam (6 countries)					
- Transitory Tech	61	55	47	58	40
- Permanent Tech	20	34	48	27	50
- Rest	19	11	6	16	10

Notes: Summary of output growth variance decomposition for different estimation strategies and periods. MF, A and Q denote mixed frequency, annual and quarterly estimation respectively. MF1 and A1 estimation period is 1950-2010. MF2 and A2 estimation period is 1901-2010. Variance decomposition at annual frequency (does not include measurement errors). Values are expressed in percentage points.

1.4.5 Sensitivity to Calibrated Parameters

Recall that in the baseline estimation some parameters ($\delta, \bar{d}, \bar{g}$ and $\bar{s}$) are calibrated using long-run ratios from the data for each country. Main estimation results do not seem to be affected by different (reasonable) calibrations of $\delta, \bar{d}$ and $\bar{g}$. However, the results are particularly sensitive to the calibration of $\bar{s}$, which matches the government spending-to-gdp ratio in the data for the period 1950-2010. This is especially important for the comparisons between, groups given that developed countries exhibit a much larger spending ratio than EM (on average $\bar{s}$ is calibrated to 12% in EM and to 19% in DC). More specifically, in the baseline MF estimation, I find that calibrating a larger value for the government spending ratio tends to generate a larger (estimated) share of PTS in aggregate fluctuations.

To study the impact of $\bar{s}$ calibration, I perform two different exercises, one for EM and the other for DC. First, to explore whether EM results are affected by a higher spending ratio as in DC, I re-calibrate $\bar{s} = 19\%$ for all EM countries (at the average spending ratio of DC) and re-estimate the model using the baseline MF strategy. In a nutshell, I find that average PTS share of output variance increases to 43% (from 35%), while TTS share falls to 41% (from 48%).[45] As a result, PTS becomes slightly more important than TTS in EM after calibrating a bigger government spending value comparable to that of DC. Still, in relative terms, the ratio of PTS to TTS shares in DC from baseline estimations is bigger than in this new EM estimation.

In a second exercise, I explore the effect of $\bar{s}$ calibration for DC. For that purpose, I re-calibrate the government spending-to-gdp ratio at a lower 12% in DC (at the average of EM, below the ratio of 19% on average in DC), constant for all countries, and re-estimate the model under the MF strategy. Strikingly, I find that the average share of output variance attributed to PTS drops to 28% from 55%, and TTS increases to 45%, reverting the baseline result.

Why a larger $\bar{s}$ tends to favor the importance of the permanent shock is far from obvious. One potential explanation is that in the model the permanent shock X_t has an immediate impact both on output (on aggregate supply) and on government spending (on aggregate demand) because spending in levels is given by $S_t = s_t X_t$ and s_t is exogenous. Therefore, the larger the share of government spending on output, the X_t tends to align aggregate supply and demand pretty well without having a substantial impact over the trade balance.

In sum, the result that PTS are predominant in DC is reversed if we calibrate a much smaller government spending level comparable to that of EM. What is more, the output variance share of PTS for DC on average falls below that obtained for EM under the baseline estimation. In any case, either on the baseline calibration or in these exercises, I do not find support for the AG results that the permanent shock is several times more important in EM than in DC (i.e., in Mexico vs. Canada).[46]

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[45] The observed increase in PTS importance is not generalized; that is, some countries are assigned a larger PTS share, but for others variance decompositions remain practically unchanged.

[46] For a more detailed explanation of AG results, see Chapter III.

1.4.6 MF Estimation with Non-Overlapping Data

Recall that the baseline estimation uses annual series for 1950-2010, including quarterly and annual data simultaneously when both are available (overlapping strategy). Instead, here I propose an alternative mixed frequency strategy that uses annual data only when quarterly series are not available (mixed frequency non-overlapping, MFNO). I find that parameter estimates are very similar under MF and MFNO (see table 8). As a result, variance decomposition statistics are also quite similar under the two strategies, both in EM and DC (see table A10 in the appendix). For instance, in EM the fraction of output variance explained by PTS is 48% and 47.4%, on average, under MF and MFNO respectively, while the contribution of TTS is 34.6% and 36% respectively. The country by country results are also quite similar.[47]

1.5 Conclusions

This study explores the sources of fluctuations in a small open economy model, estimated for twelve emerging and six developed countries using series at annual and quarterly frequency simultaneously. The proposed mixed frequency methodology has the advantage of covering a much longer sample period, using annual data, while keeping the rich information available in quarterly series, usually available for shorter periods. This is especially compelling for emerging markets, for which quarterly national accounts data is available typically since 1990, while annual data is normally available since 1950.

I find that transitory technology shocks are the main driver of output fluctuations in emerging countries. Note that even if permanent technology shocks are not predominant in emerging economies, they still account for a substantial fraction of output variance, far above the negligible role assigned by Garcia-Cicco, et. al. (2010) annual estimation for Argentina. However, other non-technology shocks seem to be crucial to explain typical EM business cycle facts.

[47] Country by country estimates are available upon request from the author.

Notably, I do not find support for the Aguiar and Gopinath (2007) findings that permanent shocks are much more relevant in emerging countries than in developed economies (based on quarterly estimations for Canada and Mexico).

Another interesting result is that estimations yield a wide dispersion for the relative importance of shocks across EM. This highlights the importance of conducting estimations with many countries to draw conclusions for EM as a whole.

Finally, for comparison, I also estimate the model using alternative single frequency estimators based either on quarterly or annual data. I find that alternative estimation strategies yield radically different results about sources of fluctuations in EM. In particular, annual and quarterly estimation strategies tend to assign a larger role to PTS than MF estimations in EM. Similarly, for a given estimation strategy, the share of PTS on output fluctuations tends to fall as we increase the data span with annual data. In light of this, in chapter II I investigate whether these differences across strategies are the result of finite sample bias and whether the MF estimator is indeed more efficient.

Chapter 2

Finite Sample Properties of the DSGE Mixed Frequency Estimator

2.1 Introduction

In this chapter, I analyze finite sample properties of the DSGE Bayesian mixed frequency estimation proposed in chapter I, in the context of the financial frictions (FF) model. In chapter I, I argue that the mixed frequency strategy may improve estimations, in particular regarding the relative contribution of permanent and transitory shocks to aggregate fluctuations. Here, I focus on the efficiency properties of the mixed frequency strategy compared with standard quarterly estimation with short time series. Additionally, I compare the performance of MF estimation and coarser annual estimation, regarding variance decompositions. I pay special attention to the relative contribution of permanent and transitory technology shocks (PTS and TTS) to aggregate fluctuations.

To assess the relative merits of the mixed frequency strategy, I conduct a Monte Carlo experiment, in which I generate artificial data assuming that the true data generating process (DGP) is governed by the FF model of Chapter I. I assume that the econometrician faces similar data availability as in a representative emerging market. That is, it observes short quarterly series (21 years) and longer annual series (typically 60 years). To generate artificial data for a representative EM, I evaluate the model at the median of parameter estimates from Chapter I (baseline strategy).

The main results for the representative economy may be summarized as follows. First, for parameter estimates, MF estimations deliver substantial efficiency gains with respect to quarterly estimation with short series (RMSE falls 30% on average under MF with 60 years of data), including large bias reductions.[1]

Second, estimations with short quarterly series present large upward bias for the share of output variance attributed to PTS (17%) (and similar downward bias for TTS) in the representative EM, incorrectly ranking PTS shock as predominant. Importantly, mixed frequency strategies deliver substantial bias and RMSE reductions for the PTS share, ranking the shocks in the right order (this bias falls to 7% under MF with 60 years and to 3% under MF using 110 years).

In turn, annual estimations also present upward-biased estimates of the PTS share, though not as large as those for quarterly series. Similarly, MF strategies exhibit smaller bias than the corresponding annual estimation. But the more severe problems of coarser annual estimation are observed for the implied contribution of interest rate and preference shocks to the trade balance. Finally, annual estimation severely underpredicts the autocorrelation of output, consumption and investment growth, moments that are, in fact, correctly reproduced by MF and quarterly estimations. These shortcomings presented by annual estimation may be related to information loss from temporal-aggregation, which typically leads to underestimation of the importance of cyclical components, as discussed in Rossana and Seater (1995), or from mis-specification problems if the true model decision period is a quarter.

Interestingly, empirical estimations from Chapter I yield some important differences in the role assigned to PTS across alternative estimation strategies. In particular, quarterly and annual

[1] In particular, quarterly estimates present large downward bias for autocorrelation coefficients of transitory shocks, especially for those that are close to unity, similar to the Dickey-Fuller effect. Quarterly estimates also present significant downard-biased estimates of the innovation of the transitory technology, understating the contribution of this shock to aggregate fluctuations.

estimations assigned a larger role to PTS compared with MF estimation. Besides, the share of PTS tends to decrease as we extend the sample backwards with annual data (for a given frequency strategy). Importantly, the Monte Carlo experiment for a representative EM predicts exactly the same facts. Therefore, the different role assigned to PTS by alternative strategies in Chapter I may be explained by small sample bias.

I also analyze the sensitivity of the results to different parameter values governing the DGP and to alternative estimation strategies. First, I assess the sensitivity of RMSE and bias regarding the technology shocks with respect to different relative volatilities of PTS and TTS in the DGP. I find that for all strategies, the bias for the share of output variance explained by PTS depends negatively on the relative volatility of the true permanent shock. More specifically, PTS share bias is positive and extremely large when the actual volatility of PTS is relatively small and, in contrast, PTS bias becomes negative if the true volatility of PTS is relatively large.[2] I argue that this is an "attenuation" effect associated with identification problems between PTS and TTS, which is more acute the shorter the sample.[3]

In this context, I find that the efficiency gains of MF strategy are, in general, robust to different relative volatilities. In other words, MF strategies present smaller absolute bias than quarterly estimation for all different relative volatilities analyzed. Moreover, in general, MF strategies also imply smaller absolute bias than the corresponding annual estimation strategy.

Strikingly, inefficiencies are extremely large if we shut off the permanent shock ($\sigma_g = 0$). In that case, PTS share is estimated at 38%, 19% and 10% under quarterly estimation, MF1 (with 60 years) and MF2 (with 110 years) respectively, despite the fact that the true share is zero.[4] This

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[2] This behavior is mirrored by a bias of opposite sign for TTS shares.

[3] Behind this bias, I find another effect associated with the downward-biased estimates of autocorrelation coefficients of transitory shocks, an effect that always generates a positive PTS bias (I call it persistence effect).

[4] This high PTS bias at $\sigma_g = 0$ is explained by the fact that the attenuation effect and the persistence effect play

indicates that quarterly estimation may be particularly misguiding about the role of permanent shocks when they are small in the true model. Moreover, using longer series appears to be crucial to obtain more precise estimates of the importance of PTS versus TTS in the FF model. However, in Chapter III, I argue that this result is model-dependent.[5]

Another interesting result is that the MF estimations of variance decompositions present efficiency properties that are pretty close to a (counterfactual) optimal situation in which we observe quarterly series for the whole estimation period. This result suggests that the data span is much more important than augmenting the number of observations in order to assess sources of fluctuations. This resembles the standard result that the key to identify permanent and very persistent (yet transitory) shocks is the length of the sample period.

Finally, I find that the efficiency gains of MF with respect to quarterly estimation are robust to the possibility that the annual data for the early period (e.g., for the first 40 years) is of poorer quality than the more recent data.[6]

This Chapter is organized as follows. Section 2 describes the main Monte Carlo experiment and presents results for the representative emerging economy. Section 3 analyzes the sensitivity of the main results to alternative parameter values and estimation strategies. Finally, Section 4 concludes.

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in the same upward direction.

[5] In a simpler RBC model presented in chapter III, identification of PTS shocks appears to be much easier than in the FF model, even for short series.

[6] In short, I assume that the first 40 years of data present measurement errors that are four times as large as in the more recent 20 years of data.

2.2 Monte Carlo Experiment

The goal of this section is to explore potential efficiency gains of mixed frequency estimation (MF) compared to alternative single frequency estimation strategies for a representative emerging economy. For that purpose, I perform a Monte Carlo experiment, generating artificial data at different frequencies, and implement alternative estimation strategies. The key difference across estimation methodologies is the observational structure used in estimation.

The Monte Carlo experiment is implemented as follows. First, I assume that the data generating process is given by the model economy presented in Chapter I, in which the time period is assumed to be one quarter. In order to focus on a representative EM, the model is evaluated at a vector of parameters equal to the median of estimated (and calibrated) parameters across EM in the baseline strategy of Chapter I (see the first column of table 1). Then, I simulate 200 samples of quarterly data with 440 observations each (110 years) for the vector of observables Z_t. More precisely, the vector of 4 annual series Z_t^A is obtained through temporal aggregation of the corresponding quarterly series, and 3 out of every 4 observations are deleted. After that, I add independent measurement errors to each time series.[7] I henceforth assume that the econometrician observes only the last 21 years of quarterly data for each sample, as is typically the case for an EM economy.[8]

In what follows, I perform a pair of comparison exercises. First, I assess efficiency gains of mixed frequency estimation compared to estimation including only short quarterly series. I pay more attention to this first comparison, as quarterly estimation is by far the most frequent strategy in the related literature. The second exercise, in turn, explores the efficiency gains of MF methodology compared to estimating a (mis-specified) annual model with only annual data, as in GPU (henceforth, annual estimation). This strategy is less frequent in the literature and has the

[7] The variance of each measurement error is assumed to be 5.4% of observed variance of the corresponding series. The value 5.4% is the median of estimated measurement errors across countries and variables from chapter I.

[8] Accordingly, the first 89 years of quarterly data are replaced by "unavailable" observations.

additional disadvantage that few countries present reliable data for about 100 years as in GPU.

The design of these experiments and main simulation results are described in detail below. I concentrate on the efficiency gains regarding the contribution of shocks for economic fluctuations, paying special attention to the relative importance of permanent and transitory productivity shocks.

2.2.1 Mixed Frequency vs Quarterly Estimation

Recall that quarterly and MF estimation methodologies correctly assume that the decision period is one quarter (quarterly model). Moreover, the estimated model is correctly specified.[9] Once we have 200 samples of simulated data, the quarterly model is estimated under alternative estimation strategies for each sample, either with quarterly data or mixed frequency series.

The first strategy follows the most standard practice in the literature of estimating the model observing only quarterly series (henceforth, quarterly estimation), and includes only the last 84 quarterly observations of each sample (21 years), as in a typical EM. The second estimation strategy, in contrast, employs mixed frequency series and assumes that only the last 60 years of annual data are observed, together with the 21 years of quarterly data (henceforth, MF1). Note this resembles the baseline estimation strategy of Chapter I. The third estimation strategy also considers MF, but assumes that all 110 years of annual data are observed (henceforth, MF2). The latter illustrates the case of some EM that present longer datasets available, as Argentina and Mexico in GPU.

For each sample, I estimate 12 structural parameters (and corresponding measurement errors) under the three alternative strategies proposed, following essentially the same Bayesian methodology described in the empirical Section.[10] Tables 1 and 2 present estimation results for MF1,

[9] By "correctly specified" I mean that the estimated model has the same form of the underlying data generating process and the subset of calibrated parameters are set to their true values.

[10] In this section, the posterior distribution is estimated based on 1 million draws from the MCMC chain from which the first half is discarded. For each sample, the MCMC chain is initiated at the true parameter vector used in the data generating process.

MF2 and quarterly estimation strategies. First, table 1 shows average parameter estimates across samples and root mean square errors (RMSE) with respect to the true parameter vector Θ.[11]

The main findings of the Monte Carlo experiment are summarized below. Before examining efficiency gains, note that using quarterly estimation parameters are, in general, quite imprecisely estimated (large RMSE) and exhibit large biases. This result underscores the potential for exploring estimation procedures that incorporate all information available. For instance, autocorrelation parameters with true values close to unity display large downward biases (see table 1). Besides, parameters that characterize interest rate dynamics, such as the debt-elasticity of interest rate (ψ) and the volatility of the country spread shock (σ_μ), exhibit large upward bias, overstating the role of financial frictions. Importantly, quarterly estimation tends to underestimate both the volatility and persistence of transitory technology shocks, unambiguously understating the importance of this process. These findings indicate that quarterly estimation with just 21 years of data for a representative EM is subject to large small-sample biases.

Now, I outline main contributions of MF strategies relative to quarterly estimation. First, I find large efficiency gains of estimating the parameters using MF series compared to standard quarterly estimation. In effect, the last two columns of table 1 show that, on average, RMSE falls about 30% when we switch from quarterly to MF1 estimation and 40% in the case of MF2. Further, MF strategies deliver a large bias reduction for most parameters (see the second panel of table 1).[12] In particular, bias associated with TTS is substantially reduced under MF, which leads to a more

[11] Given a vector of parameters (or population moments) Θ, RMSE is computed as follows:

$$RMSE\left(\Theta\right) = \sqrt{(IJ)^{-1}\sum_{i=1}^{I}\sum_{j=1}^{J}\left(\hat{\Theta}_{i,j} - \Theta\right)^2},$$

where $\hat{\Theta}_{i,j}$ denotes a draw from posterior distribution for sample i, I denotes the number of simulated samples and J is an arbitrary number of draws from the posterior (here I set $J = 100,000$) .

[12] Note that efficiency gains are unevenly distributed across parameters. Specifically, MF strategies present larger efficiency gains for the parameters that are most imprecisely estimated with quarterly data in the first place.

accurate assessment of the importance of this shock for economic fluctuations, which is verified later through variance decompositions.[13]

Table 1: Monte Carlo Experiment. MF & Quarterly Estimation

		Posterior Mean			RMSE			Gain %	
Param	True	MF2	MF1	Quart	MF2	MF1	Quart	MF2-Q	MF1-Q
φ	6.1	8.0	8.5	10.0	3.5	4.3	6.2	-43	-31
ψ	0.02	0.04	0.04	0.07	0.03	0.04	0.07	-61	-43
ρ_a	0.92	0.85	0.81	0.76	0.17	0.22	0.27	-37	-19
ρ_g	0.58	0.52	0.53	0.54	0.21	0.20	0.20	1	0
ρ_v	0.97	0.96	0.95	0.93	0.03	0.04	0.07	-64	-50
ρ_s	0.76	0.72	0.70	0.64	0.11	0.13	0.21	-48	-36
ρ_μ	0.97	0.95	0.93	0.88	0.04	0.06	0.14	-72	-58
σ_a	0.91	0.85	0.81	0.73	0.28	0.33	0.39	-28	-15
σ_g	0.88	0.83	0.88	0.98	0.47	0.50	0.53	-11	-6
σ_v	23.6	22.3	21.2	21.1	7.6	8.2	10.2	-26	-20
σ_s	12.2	12.8	13.0	13.7	1.9	2.1	2.8	-31	-23
σ_μ	0.35	0.51	0.59	0.83	0.26	0.36	0.64	-59	-44

Notes: Table displays parameter estimates (posterior mean and RMSE) under alternative estimation strategies. MF and Quart denote mixed frequency and quarterly data estimation respectively. MF1 and MF2 estimation include 60 years and 110 years of annual observations respectively. All three estimation strategies include 84 observations of quarterly series (21 years). Last two columns display the RMSE percentage change of MF strategy with respect to quarterly estimation. Monte Carlo experiment estimations based on 200 samples, 1,000,000 MCMC draws each (first 500,000 are

It is worth exploring how the efficiency results analyzed so far translate into the estimated importance of different shocks to explain economic fluctuations. To this end, table 2 displays average variance decompositions under the three estimation strategies considered so far and under the true DGP.

Before exploring efficiency properties of MF, I summarize main inefficiencies and biases of quarterly estimation. Strikingly, quarterly estimation yields a huge upward bias on the contribution of PTS to output growth variance, estimated at 46% compared to a true value of 29%.[14] This

[13]The unconditional volatility of TTS is 2.3% (true value), compared to 1.7%, 1.4% and 1.1% for MF2, MF1 and quarterly estimation respectively (unconditional volatility computed with point estimates).

[14]Similar results hold for consumption and, to a lesser extent, for investment growth.

result is mirrored by a downward bias on the importance of TTS of similar magnitude. As a result, quarterly estimation incorrectly places PTS as the most important source of output fluctuations.[15] Not surprisingly, the contribution of each technology shock to output is particularly imprecisely estimated (RMSE are in the range of 34-37 percentage points out of 100). In sum, these statistics suggest that it is really hard to identify the relative importance of the two technology shocks using a small sample of quarterly data.

[15] This implies that the estimated ratio of the contributions to output of PTS and TTS is 1.2 compared to a true value of 0.56, reversing the true order of importance.

Table 2: Monte Carlo Experiment. Variance Decomposition MF vs Quarterly estimation

		Posterior Mean			Bias			RMSE			RMSE MF-Quart	
	True	MF2	MF1	Quart	MF2	MF1	Quart	MF2	MF1	Quart	MF2	MF1
Output growth												
- Transitory Tech	51.4	49.7	46.2	38.2	-1.7	-5.3	-13.2	26.6	29.9	34.0	-7.5	-4.1
- Permanent Tech	28.8	31.7	36.3	45.7	2.9	7.5	17.0	27.3	31.1	36.9	-9.5	-5.7
- Preference	11.8	11.1	10.4	10.2	-0.7	-1.4	-1.6	5.2	5.9	7.9	-2.7	-2.0
- Spending	1.1	1.2	1.2	1.4	0.1	0.2	0.3	0.6	0.8	1.2	-0.6	-0.4
- Interest rate	7.0	6.3	5.9	4.5	-0.7	-1.1	-2.5	1.9	2.5	3.7	-1.8	-1.2
Consumption growth												
- Transitory Tech	31.2	29.9	27.5	22.2	-1.3	-3.8	-9.0	17.1	19.2	21.6	-4.5	-2.4
- Permanent Tech	17.7	19.7	22.8	29.2	2.1	5.1	11.6	17.7	20.5	25.4	-7.7	-5.0
- Preference	43.2	41.7	41.0	39.7	-1.5	-2.2	-3.5	6.7	8.1	11.1	-4.4	-3.0
- Spending	3.1	3.5	3.7	4.2	0.4	0.6	1.1	1.9	2.4	3.6	-1.7	-1.2
- Interest rate	4.8	5.1	5.0	4.6	0.3	0.3	-0.2	1.8	2.2	2.9	-1.1	-0.7
Investment growth												
- Transitory Tech	14.4	12.6	11.3	9.1	-1.8	-3.1	-5.3	8.6	9.6	11.0	-2.5	-1.4
- Permanent Tech	9.8	9.8	11.1	14.8	0.0	1.4	5.0	9.2	10.6	15.0	-5.8	-4.4
- Preference	19.1	20.3	20.2	22.0	1.1	1.1	2.8	6.9	8.0	11.3	-4.4	-3.3
- Spending	4.9	5.7	6.1	7.4	0.8	1.2	2.5	2.7	3.4	5.6	-2.9	-2.2
- Interest rate	51.8	51.6	51.3	46.8	-0.2	-0.5	-5.0	6.9	8.4	12.8	-5.9	-4.5
Trade balance (%gdp)												
- Transitory Tech	1.5	1.9	2.0	2.0	0.4	0.5	0.5	1.5	1.8	2.5	-1.0	-0.7
- Permanent Tech	2.4	2.9	3.4	5.3	0.5	1.0	2.9	3.2	4.0	7.7	-4.6	-3.7
- Preference	36.3	28.8	27.1	26.8	-7.5	-9.2	-9.4	16.4	18.2	21.4	-4.9	-3.2
- Spending	9.5	10.8	11.6	14.0	1.3	2.1	4.5	4.0	5.3	8.8	-4.8	-3.5
- Interest rate	50.4	55.7	55.9	51.9	5.3	5.6	1.6	16.7	18.6	22.5	-5.8	-4.0

Notes: Table displays variance decomposition at annual frequency (does not include measurement errors). MF and Quart denote mixed frequency and quarterly data estimation respectively. MF1 and MF2 estimation include 60 years and 110 years of annual observations respectively. All three estimation strategies include 84 observations of quarterly series (21 years). Monte Carlo experiment estimations based on 200 samples, 1,000,000 MCMC draws each (first 500,000 are discarded). Variance decompositions calculated based on 100,000 draws from posterior. Last two columns display the difference between RMSE of the corresponding MF strategy and quarterly estimation. Values are expressed in percentage points (scale 0-100%).

In general, I find large efficiency gains of MF compared to quarterly estimation regarding variance decompositions. In short, small sample biases of quarterly estimation are significantly reduced under MF methodologies, especially for the importance of technology shocks. For instance, for the contribution of PTS to output variance, the bias falls from 17% under quarterly data to about 7% under MF1 and to 3% under MF2, and a symmetric result holds for TTS (see the upper panel of table 2). This takes the PTS-to-TTS ratio from 1.2 under quarterly strategy to 0.78 and

0.64 under MF1 and MF2 respectively, closer to the true ratio of 0.56. Unlike quarterly estimation, both MF strategies yield the correct ranking of technology shocks, assigning a predominant role to TTS.

It must be stressed that the results analyzed so far (in particular the upward-biased importance of PTS) hold for a representative EM (evaluating the model at the median of parameter estimates). Later, I perform sensitivity analysis with respect to the true parameters in the DGP. There, I show that PTS bias (both the magnitude and sign) vary significantly for different parameter values, especially for different relative volatilities of PTS and TTS in the DGP.

Similarly, the RMSE of the share of output variance explained by PTS drops about 6 and 10 percentage points when we switch from quarterly to MF1 and MF2 respectively (see the last two columns of table 2). More generally, efficiency gains of mixed frequency relative to quarterly estimation is observed for all variance decomposition entries. For instance, if we look at the top two shocks for each variable, RMSE falls about 4 and 6 percentage points on average respectively. Not surprisingly, MF2 achieves further efficiency gains (for all entries) compared to MF1, which indicates that extending the sample backwards with annual data improves estimation performance.

Finally, I assess the finite sample properties of the model fit, computing the same business cycle moments as in Chapter I. Interestingly, posterior means are close to the true population moments for all three strategies (MF1, MF2 and, surprisingly, quarterly estimation), though quarterly estimation somewhat underpredicts the persistence of the trade balance. This acceptable fit presented by the quarterly estimation strategy is achieved despite its large bias for PTS and TTS shares, which reinforces the idea of identification issues between these two shocks highlighted in Chapter I, especially in short samples.

2.2.2 Mixed Frequency vs Annual Estimation

The goal of this section is to assess finite sample properties of the annual estimation procedure performed in GPU and explore potential efficiency gains of the MF strategy that allows us to incorporate more recent quarterly data.

Here, I still assume that the true data generating process is given by the quarterly model economy explained before. However, I propose an alternative strategy that estimates a mis-specified model that incorrectly assumes the decision interval is a year (annual model) using only annual data (henceforth, annual estimation). I further assume that all 110 years of annual observations are available for estimation. Note this methodology employs the same number of annual observations as in MF2.

Given that the strategies previously analyzed (MF and quarterly estimation) and annual estimation assume different model periods, it is not straightforward to compare efficiency properties of parameter estimators. In this context, to assess the relative merits of these strategies I focus on variance decompositions at the annual frequency. To facilitate comparisons, table 3 reports variance decomposition statistics not only for annual estimation but also for MF2 (it only shows entries with shares of at least 10%).

The main question here is whether by pursuing MF2 strategy (i.e. incorporating a short period of quarterly data) we achieve efficiency gains with respect to estimation only with annual series. Overall, the answer to this question is yes, but the size of the gains on average are somewhat less spectacular than those obtained when we switch from quarterly to MF estimation. Still, there are substantial bias reductions in some particular dimensions.

First, note that annual estimation yields similar bias, qualitatively speaking, to the other estimation procedures. For instance, it overstates the fraction of output variance explained by PTS by almost 9 percentage points. Certainly, the largest inefficiencies of annual estimation are observed for the breakdown of the trade balance-to-gdp ratio, as it overstates the contribution of preference shocks by 16.2%, to the detriment of interest rate shocks.

Comparing across strategies, I find that mixed frequency estimation provides more accurate results than annual estimations. In fact, MF2 presents bias that are in all cases smaller than those obtained under annual estimation. For example, the bias for the interest rate shock share of trade balance falls 11% in absolute terms and that of PTS contribution to output falls about 6%. In this context, MF2 presents RMSE generally smaller than annual estimation (RMSE for top 2 shocks for each variable decreases by 2 percentage points on average).[16]

The larger upward-biased estimate of the permanent shock under annual estimation than under MF may potentially be an indication that annual estimation suffers from temporal-aggregation bias, as the one described in Rossana and Seater (1995). In this regard, they find that for many economic series in the US annual aggregation of quarterly (or monthly) data produces a severe loss of information about cyclical components (that last more than a year), leading to an overestimation of the importance of stochastic trends.

The shortcomings of annual estimation, regrettably, are not limited to variance decompositions bias. Notably, annual estimation significantly underpredicts the first order autocorrelation of output, consumption and investment growth (implied values of just 0.18, 0.09 and -0.06 below the true DGP implied moments of 0.33, 0.28 and 0.12 respectively), despite the fact it uses a long data sample of 110 years. Instead, MF and even quarterly estimation correctly predict these moments. Notably, a similar problem with the implied autocorrelations of these variables are observed in empirical results of Chapter I and in GPU (especially for investment growth). This phenomenon may be associated with the time-aggregation bias mentioned before, which is typically associated with a loss of information about cyclical components, or it may also be the result of a mis-specification

[16] Note that when we move from annual to MF estimation, in general, RMSE falls much more than bias, which reflects the fact than MF estimates are, in some cases, more disperse.

issue. In short, if the true DGP is a quarterly model and there is a stochastic trend process (PTS), then annual aggregation gives rise to MA(1) terms in the shock and in aggregate variables, as shown in Rossana, et.al. (1995). The annual model with shocks that are just AR(1) will struggle to fit actual data dynamics due to these mis-specifications problems, and, in particular, it may fall short of predicting the first order autocorrelation of the variables in differences as observed here.

Finally, the annual model obviously has the practical problem that we cannot perform business cycle analysis for frequencies higher than a year, for which the typical unit is a quarter (or even a month). And, certainly, the annual model is unable to incorporate information that typically arrives at much higher frequencies than a year to timely infer the state of the economy, to generate more accurate predictions and formulate optimal policy.

The markedly poor relative performance of annual estimation to account for trade balance fluctuations could be related to implied moments for investment, in particular, to the downward bias for the first order autocorrelation mentioned above.[17], [18]

[17]Further, for this moment, RMSE under annual estimation is 4 times as high as under MF2.

[18]This may suggest that annual estimation is underestimating capital adjustment costs, since investment autocorrelation is strongly positively associated with this parameter, which, in turn, may reflect temporal-aggregation bias. For instance, to obtain a serial correlation of investment growth of -0.06 in the quarterly model (measured at annual frequency), the capital adjustment cost parameter must be 1/3 of the baseline calibration value. This, in turn, may potentially contribute to the upward bias of PTS, since a lower perceived capital adjusment cost reduces the implied persistence of output after a transitory technology shock. Accordingly, annual estimation may be incorrectly assigning to PTS part of the observed persistence in output growth actually driven by the combined effect of TTS and higher (true) capital adjustment costs.

Table 3: Monte Carlo Experiment. Variance Decomp. MF vs Annual Estim.

		Posterior Mean		Bias		RMSE
	True	MF2	Annual	MF2	Annual	MF2-A
Output growth						
- Transitory Tech	51.4	49.7	44.9	-1.7	-6.5	-0.8
- Permanent Tech	28.8	31.7	37.6	2.9	8.8	-0.7
- Preference	11.8	11.1	10.1	-0.7	-1.7	0.3
Consumption growth						
- Transitory Tech	31.2	29.9	27.0	-1.3	-4.2	-0.7
- Permanent Tech	17.7	19.7	25.0	2.1	7.3	-1.7
- Preference	43.2	41.7	40.8	-1.5	-2.4	-0.7
Investment growth						
- Transitory Tech	14.4	12.6	12.3	-1.8	-2.1	-1.4
- Permanent Tech	9.8	9.8	17.0	0.0	7.2	-5.3
- Preference	19.1	20.3	17.4	1.1	-1.7	0.0
- Interest rate	51.8	51.6	47.7	-0.2	-4.1	-2.1
Trade balance (%gdp)						
- Preference	36.3	28.8	52.5	-7.5	16.2	-6.6
- Spending	9.5	10.8	8.0	1.3	-1.5	0.0
- Interest rate	50.4	55.7	34.2	5.3	-16.2	-4.5

Notes: Table displays variance decomposition at annual frequency (does not include measurement errors). MF2 and Annual (A) denote mixed frequency and annual estimation respectively (both include 110 years of annual observations). MF2 strategy includes 84 observations of quarterly series (21 years). Monte Carlo experiment estimations based on 200 samples, 1,000,000 MCMC draws each (first 500,000 are discarded). Variance decompositions calculated based on 100,000 draws from posterior. Last column displays the difference between RMSE of MF2 vs Annual. Values are expressed in percentage points.

Even if it is not the goal of this paper, it is interesting to note that, in general, annual estimation performs much better than quarterly estimation in terms of efficiency.

In sum, mixed frequency estimations deliver more efficient estimates and large bias reductions compared to alternative single frequency estimators, especially about the importance of permanent versus stationary technology shocks.

2.2.3 Finite Sample Bias and Empirical Results across Strategies

One of the most interesting results of Chapter I and II about the importance of technology shocks is that there is a tight link between empirical results and the predictions of the Monte Carlo experiment for alternative estimation strategies. Interestingly, in Chapter I, empirical estimations under different strategies (short quarterly series or MF or annual estimation) presented very different implications about the importance of the permanent shock. To refresh the main results, the upper panel of table 4 reproduces empirically estimated PTS and TTS shares of output variance from Chapter I for 12 EM and 6 Latin-American economies respectively (the distinction is because Latam economies present reliable pre-World War II data).[19]

The main empirical results of Chapter I may be summarized as follows: 1) estimations with short quarterly series predicted a larger share of PTS compared to MF1 or MF2 strategies (this holds both for EM and for Latam); 2) for a given frequency strategy (MF, annual or quarterly), estimated PTS share tends to decrease as we extend the sample back, for example from MF1 to MF2 or from A1 to A2 in Latam (which uses 60 and 110 years respectively); 3) for a given data span, PTS share tends to increase if we switch from MF to annual estimation (e.g., from MF1 to A1 in EM and Latam, and from MF2 to A2 in Latam). I also observe similar movements in the TTS share in the exact opposite direction for all three facts mentioned.

[19] In Latam, unlike DC, empirical business cycle moments are similar considering pre-war and post-war data.

Table 4: Monte Carlo Experiment. Variance Decomp. MF & Annual Estim.

	True	MF2	MF1	Q	A2	A1
Empirical Estim Ch. I						
EM (12 countries)						
- Transitory Tech	-.-	-.-	48	44	-.-	41
- Permanent Tech	-.-	-.-	35	44	-.-	46
Latam (6 countries)						
- Transitory Tech	-.-	61	55	47	58	40
- Permanent Tech	-.-	20	34	48	27	50
Monte Carlo Experiment						
- Transitory Tech	51	50	46	38	45	41
- Permanent Tech	29	32	36	46	38	41

Notes: Table displays average contribution of permanent and transitory technology shocks to output growth variance. Upper Panel presents empirical estimates from Chapter I for 12 EM and 6 Latam economies respectively. Lower panel displays Monte Carlo experiment estimates (average across 200 samples simulated for a representative EM). MF1 and MF2 denote mixed frequency estimation with 60 and 110 years of data respectively. A1 and A2 denote annual estimation with 60 and 110 years of data respectively. Q denotes quarterly estimation. Variance decomposition at annual frequency.

More interestingly, the predictions of the Monte Carlo experiment (for the representative EM) imply exactly these three facts about differences in PTS shares along alternative strategies, at least qualitatively (see the lower panel of table 4). That is, Q and A1 present larger upward biases for the share of PTS than MF1, while A2 overstates the share of PTS compared with MF2.

Therefore, the Monte Carlo experiment suggests that the relative predominance of PTS implied by A1 and Q empirical estimations for EM and Latam may be just the result of small sample (upward) bias of PTS highlighted before (although obviously this is just one potential explanation). Conversely, note that TTS is predicted to be the primary source of output fluctuations under MF1, both for EM and Latam, and A2 and MF2 for Latam. According to the Monte Carlo predictions, the latter is likely to be closer to the true importance of shocks in the DGP than quarterly or A1 estimations.

2.2.4 MF versus Full Information Quarterly Estimation

In reality, EM present short quarterly series, typically from the late eighties and longer annual data sets, normally since 1950, as detailed in Chapter I. Let me suppose for a moment that the econometrician actually has access to quarterly data since 1950 and estimate the model using standard quarterly estimation (I henceforth call this counterfactual scenario "full information" quarterly estimation). This is clearly an optimal situation because we have all the information available and, thus, it is likely to deliver much more precise estimates than estimation with shorter quarterly series. The question I want to answer with this alternative exercise is how good is the more realistic MF strategy compared to the full information estimation. For that, table 5 displays variance decompositions for the full information quarterly estimation (Q-Full) and, to facilitate comparisons, reproduces MF1 results obtained above (note that the data span is 60 years for both strategies).

Surprisingly, MF1 presents variance decompositions with RMSE quite similar to those implied by Q-Full. Precisely, Q-Full RMSE are in general smaller but the differences are modest (on average 0.5% and 1% for PTS and TTS shares of output). Compared with more realistic quarterly estimations with 21 years of data, MF1 achieves an 88% of the RMSE reduction attained under Q-Full, a fairly large proportion. Similarly, Q-full variance decompositions are closer to true values, but on average just about 0.5% closer than MF1, implying that mixed frequency estimation achieves the bulk of bias reductions obtained in the full information case. Overall, these results suggest that for variance decompositions MF estimations get quite close to the full information case in terms of efficiency.

In contrast with previous results for variance decompositions, Q-full, in fact, delivers significant efficiency gains relative to MF1 for parameter estimates (RMSE go down 21% on average, see table B1 in the appendix). In this dimension, MF1 achieves 68% of the RMSE gains of Q-Full with respect to quarterly estimation, which is not bad, but not as good as for variance decompositions. These apparently contradictory results is explained by the fact that the more impressive gains of Q-Full are concentrated in some parameters and are more moderate for the technology shocks processes (this leads to modest gains for PTS and TTS bias).

Table 5: Variance Decomp. MF vs Full Information Quarterly Estim.

		Posterior Mean		Bias		RMSE
	True	MF1	Q-Full	MF1	Q-Full	Q-Full - MF1
Output growth						
- Transitory Tech	51.4	46.2	46.8	-5.3	-4.6	-0.8
- Permanent Tech	28.8	36.3	35.3	7.5	6.6	-1.2
- Preference	11.8	10.4	10.6	-1.4	-1.2	-0.4
Consumption growth						
- Transitory Tech	31.2	27.5	27.9	-3.8	-3.3	-0.4
- Permanent Tech	17.7	22.8	22.3	5.1	4.6	-0.8
- Preference	43.2	41.0	41.8	-2.2	-1.4	-0.3
Investment growth						
- Transitory Tech	14.4	11.3	12.4	-3.1	-2.1	-0.2
- Permanent Tech	9.8	11.1	11.8	1.4	2.0	-0.3
- Preference	19.1	20.2	19.1	1.1	0.0	-0.5
- Interest rate	51.8	51.3	51.3	-0.5	-0.5	-0.2
Trade balance (%gdp)						
- Preference	36.3	27.1	32.8	-9.2	-3.4	-0.3
- Spending	9.5	11.6	11.0	2.1	1.5	-0.9
- Interest rate	50.4	55.9	50.9	5.6	0.5	-0.4

Notes: Table displays variance decomposition at annual frequency (does not include measurement errors). MF1 and Q-Full denote mixed frequency and full information- quarterly estimation respectively. MF1 strategy includes 84 observations of quarterly series (21 years) and 61 years of annual data. Full-Q includes 61 years of quarterly data (244 observations). Monte Carlo experiment estimations based on 200 samples, 1,000,000 MCMC draws each (first 500,000 are discarded). Variance decompositions calculated based on 100,000 draws from posterior. Last column displays the difference between RMSE of Full-Q vs MF1. Values are expressed in percentage points.

2.2.5 Further Comments about Identification of Permanent vs Transitory Technology Shocks

As highlighted so far, it is hard to identify the relative importance of PTS versus TTS in the baseline (financial frictions model) in light of the large RMSE and bias of the contribution of each shock to output variance. As shown in this Chapter, in this model, extending the sample backwards with annual data is key to more precisely estimate these concepts, and especially to reduce small sample bias. Here, I provide further insights about the reasons behind these identification issues.

Recall that in the context of an RBC model (with only technology shocks), AG argue that the excess volatility of consumption with respect to output and the countercyclicality of the trade balance are informative of the presence of permanent shocks (AG hypothesis), which holds for estimates with Mexican and Canadian data as representatives EM and DC countries respectively. However, empirical estimates in Chapter I do not support this hypothesis in the context of the more complex financial frictions model which, aside from technology shocks, includes preference, interest rate and government spending shocks. Specifically, estimations do not assign a larger role of PTS for countries with larger excess consumption volatility or countercyclical trade balances (the correlations are actually small and of the wrong sign), which suggests that these moments are not informative of the predominance of this shock.

To reinforce the idea that AG hypothesis does not hold in the financial frictions model, I perform the same analysis for the 200 samples of artificial data in the Monte Carlo experiment. In short, I compute correlations across samples for the estimated share of output variance assigned to PTS and the AG moments. I find that excess volatility of consumption does not present a positive correlation with the share of PTS; in fact, the correlation is small and of the wrong sign, extremely similar to the empirical result from Chapter I (the correlation with the trade balance, in turn, is of the right sign but small). These results suggest that excess consumption volatility is no longer informative about the presence of PTS in this more complex model, which makes it harder to identify these shocks. This is explained by the fact that in the FF model PTS compete with other non-technology shocks that are also able to generate excess volatility of consumption (in fact, excess consumption volatility is positively correlated with these estimated shocks).[20]

[20] To further explore the plausibility of this hypothesis, in Chapter III, I find that in an RBC model similar to the one used in AG these moments are quite informative about the relative importance of permanent shocks, unlike in the FF model.

In light of the results above, it is worth exploring which empirical moments are informative about the role of PTS across countries In Chapter I, I find a large positive correlation between PTS share of output and the first order autocorrelation of output, consumption and, to a lesser extent, of investment. These correlations are even higher in the Monte Carlo experiment (across samples) which reinforces the idea that autocorrelations are highly informative of the role of permanent shocks. Notably, these autocorrelations are highly imprecisely estimated in short samples, and it is crucial to have a larger data span to obtain more reliable estimates. This provides one potential explanation for why it is so important to have a larger data span to better identify PTS and TTS and, thus, to explain the substantial efficiency and bias gains of MF over short quarterly series estimation.[21]

2.3 Sensitivity Analysis

This section analyzes the sensitivity and robustness of main results with respect to alternative estimation strategies and parameter values. I focus on the robustness of efficiency gains of MF estimation with respect to quarterly estimation, in particular regarding the importance of permanent and transitory technology shocks.

2.3.1 Sensitivity to Parameter Values

First, I explore the sensitivity of results to different calibrations of the true data generating process, focusing on the relative important of PTS and TTS.

[21] In contrast, in Chapter III, I find that in a simpler RBC there are more business cycle moments informative about PTS importance, which leads to much more precise estimations (including substantially smaller biases), even in small samples.

Sensitivity to σ_g/σ_a

I study the sensitivity of the results to different values of the relative volatility of the permanent shock with respect to the transitory technology shock, but keeping constant the joint contribution of technology shocks to output variance. To this end, I calibrate σ_a and σ_g so as to: (i) target different values of the share of output variance explained by PTS, and (ii) keep the sum of PTS and TTS contributions unchanged at around 80% (similar to baseline results).

Table 6 presents the share of output growth variance attributed to PTS under MF1 and quarterly estimation (and corresponding bias and RMSE gains) for different true values of σ_a and σ_g, implying true PTS shares in the interval 0-80% as follows: [0, 15, 28.8, 40, 50, 70 and 80%]. To facilitate comparisons, figure 1 shows the same information in a scatter plot with the true PTS share in the horizontal axis and the estimated bias of PTS shares in the vertical axis, both under MF1 (solid blue line, square markers) and quarterly estimation (solid orange line, circular markers). Note that PTS share lines are surprisingly linear considering that variance decompositions are highly non-linear functions of the parameters.

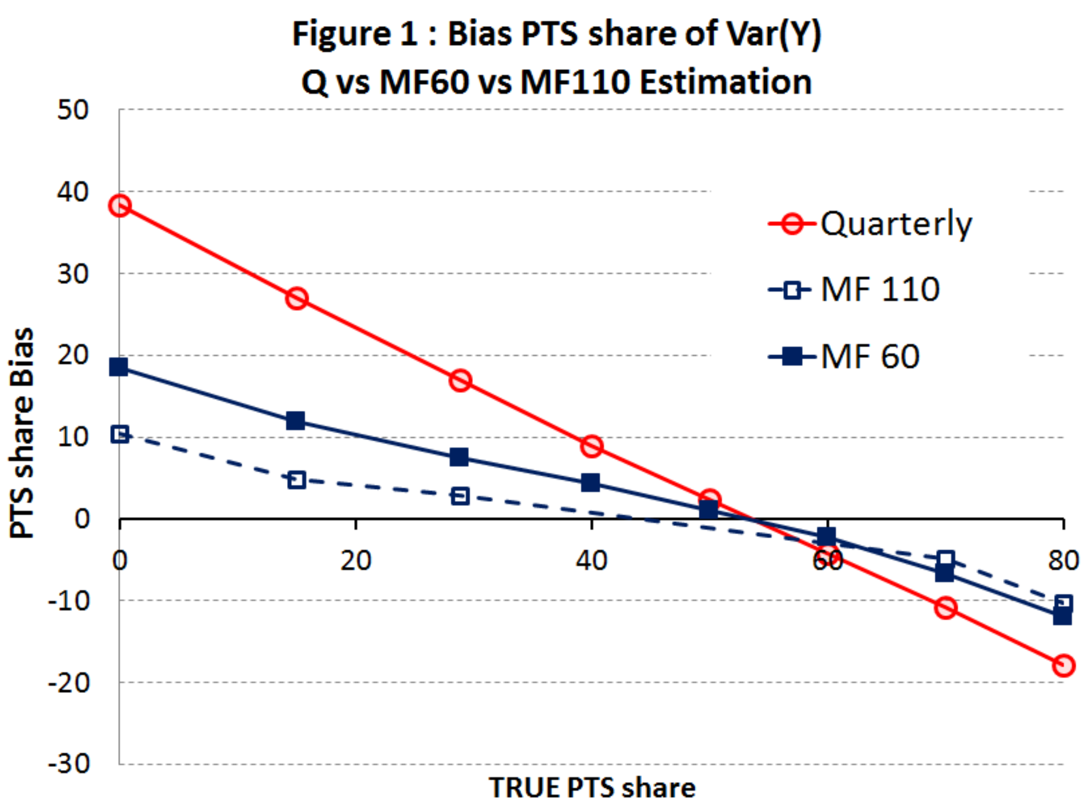
Table 6: Share of Output Var Explained by PTS

PTS Mean			Baseline					
- True value	0	15	28.8	40	50	60	70	80
- MF1 estim	18.5	26.9	36.3	44.3	51.0	57.7	63.3	68.1
- Quarterly estim	38.4	42.1	45.7	48.9	52.4	55.7	59.2	62.2
PTS Bias								
- MF1 estim	18.5	11.9	7.5	4.3	1.0	-2.3	-6.7	-11.9
- Quarterly estim	38.4	27.1	17.0	8.9	2.4	-4.3	-10.8	-17.8
- Bias gain (abs)	**19.9**	**15.2**	9.4	**4.6**	**1.4**	**2.0**	**4.1**	**5.9**
RMSE gain MF1-Q	-20.6	-12.5	-5.7	-2.6	-2.0	-3.3	-5.6	-5.6
PTS-TTS Mean								
- True value	-80	-50	-23	0	20	40	60	80
- MF1 estim	-45.6	-28.6	-9.9	**6.4**	19.9	33.4	44.7	54.4
- Quarterly estim	-7.4	**0.1**	**7.5**	**14.2**	21.3	28.0	35.1	41.2

Notes: Each column displays true and estimated share of output growth variance explained by PTS. Each column corresponds to a different calibration of the relative variance of PTS to TTS (increasing from left to right). PTS and TTS shocks volatility are calibrated to keep the sum of PTS and TTS share of output in 80%. MF1 and Quart denote mixed frequency and quarterly data estimation respectively. Lower panel shows the difference between PTS and TTS shares. Variance decomposition at annual frequency (does not include measurement errors). Monte Carlo experiment estimations based on 200 samples, 1,000,000 MCMC draws each (first 500,000 are discarded). Variance decompositions calculated based on 100,000 draws from posterior.

Ideally, PTS bias lines in figure 1 should be close to zero (unbiased estimator of PTS shares) and insensitivity to the σ_g/σ_a. Instead, the two PTS share lines exhibit a positive intersect in the vertical axes (38% and 19% for quarterly and MF1 respectively) and significantly large negative slopes (about -7/10 and -3/8 for quarterly and MF1 respectively). These two lines appear to cross the horizontal axis (zero bias) at around 53%; therefore, PTS share bias is positive for true shares of less than 53% and negative for larger values. Given that the quarterly estimation slope is bigger in absolute terms, MF1 is always closer to the horizontal axis, and thus presents smaller (absolute) bias than quarterly estimation for all values of σ_g/σ_a considered (see also table 6). The bias gain (absolute terms) of MF1 is convex, presenting larger gains for extreme values of the true PTS share away from the crossing point (similar for RMSE gains; see table 6). Figure 1 also includes some points of MF2 strategy with 110 years, which lies, in general, closer to the horizontal axis, reducing PTS bias even further.

How can we explain the shape of the PTS contribution bias? First, notice that there is a sort of attenuation effect; that is, the PTS share is upward-biased for small values of the true PTS volatility and downward-biased for large true values (i.e. a centripetal force). This attenuation effect seems to be related to the identification issues between PTS and TTS in small sample bias discussed above (the relative shares of these shocks are extremely sensitive to the realization of shocks, in particular for short series). This explains why the quarterly estimation bias is always bigger. If the only effect present were a pure identification effect between PTS and TTS, the estimated PTS share lines should cross the horizontal axis at 40%, just in the middle of the 80% explained by the sum of PTS and TTS. However, PTS lines cross the diagonal at about 53%. Therefore, there are additional forces at play generating an upward PTS bias.

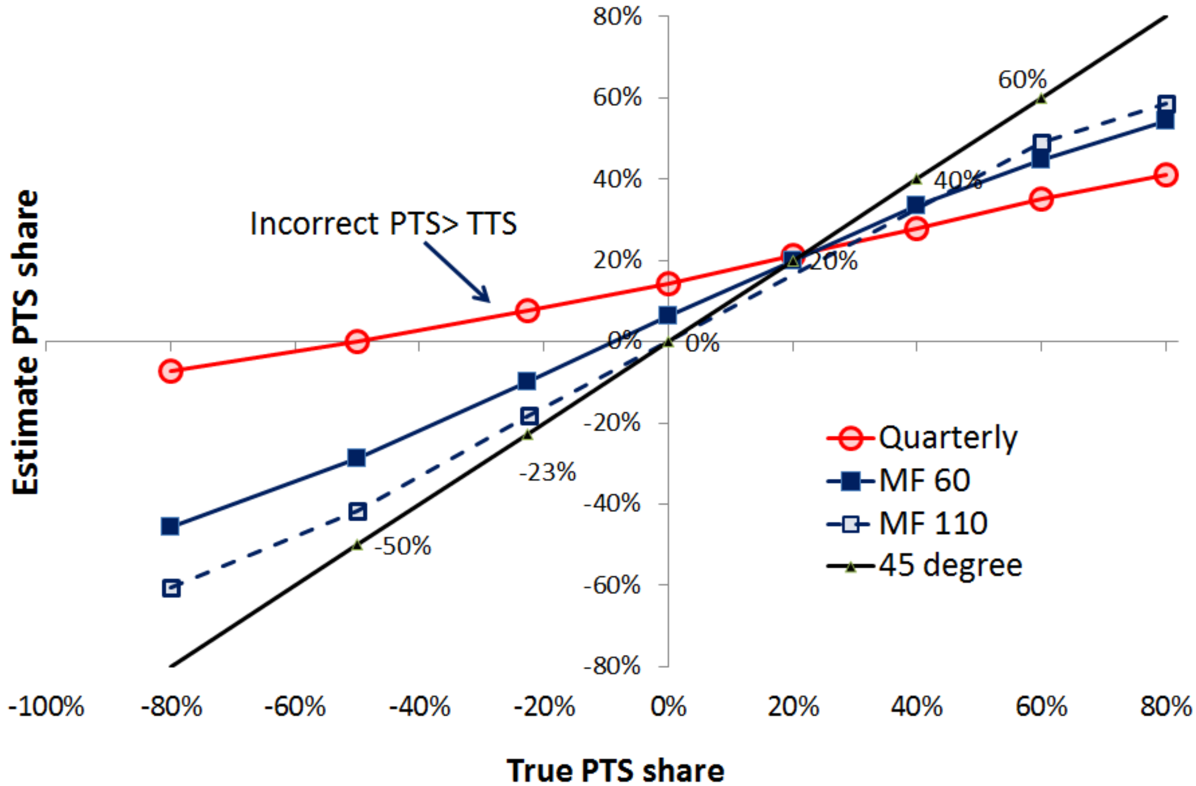


Arguably, there is a second effect related to the downward-biased estimates of transitory shocks persistence (henceforth, persistence effect) contributing to an upward bias of PTS in all cases. More specifically, the shorter the sample, the larger the downward bias estimate of autocorrelation parameters of transitory shocks. As a result, transitory shocks die out quickly with time, and thus a larger variance of PTS is needed to explain lower frequency fluctuations. Probably, at the crossing point, of 53%, the attenuation (downward bias in this case) and persistence effect (upward bias) offset each other exactly. To investigate the plausibility of the presence of a persistence effect, I repeat the Monte-Carlo experiment but, instead, I calibrate all $\rho's$ coefficients to the true values. Precisely, figure 3 shows the estimated PTS bias curves for MF1 and quarterly (dashed blue and dotted orange lines respectively), excluding the persistence effect, which cross the 45 degree line at about 38% and 40% respectively, much closer to the middle point (40%) (for comparison, it also reproduces the curve including the persistence effect from figure 1). Further, both curves are located below the corresponding PTS lines, including the persistence effect (i.e., under baseline strategy that estimated all parameters), indicating that the persistence effect unambiguously implies an upward PTS bias.

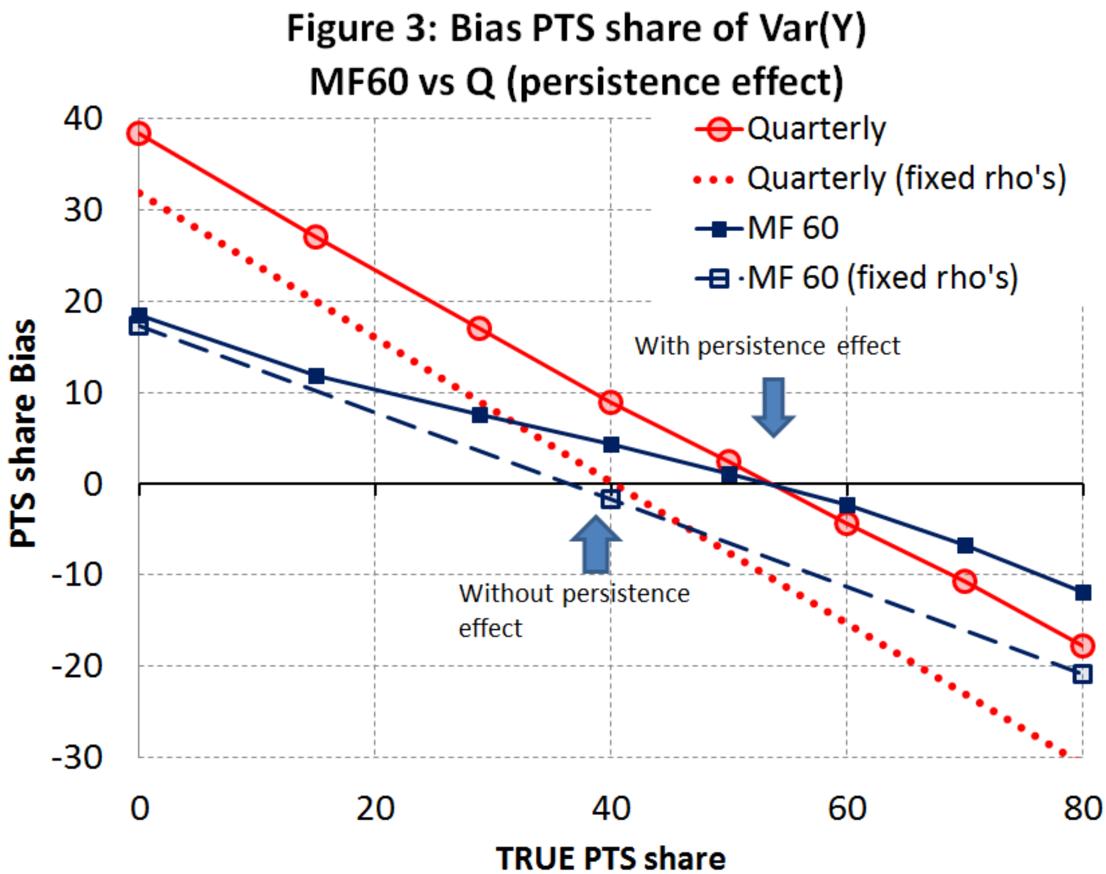
It must be stressed the extremely poor performance of quarterly estimation for low values of PTS. In effect, when we shut off PTS (set $\sigma_g = 0$), quarterly estimate assigns 38% of output variance to it, wrongly identifying a significant (and spurious) trend shock. The huge size of this bias is explained by the fact that both the attenuation and persistence effects play in the same direction at $\sigma_g = 0$, and that the attenuation intensity is maximum, since PTS true volatility is at the longest distance from the middle. In conclusion, quarterly estimation may be especially misguiding about sources of fluctuations when the true model is characterized by a small importance of permanent technology shocks, and MF1 may yield large efficiency gains.

In the opposite corner with a maximum σ_g, that is, at $\sigma_a = 0$, quarterly estimation bias is smaller, around 17%, because, in this case, identification bias is partly offset by the persistence effect that, this time, plays in the opposite direction.

Figure 2: PTS-TTS share of Output Variance



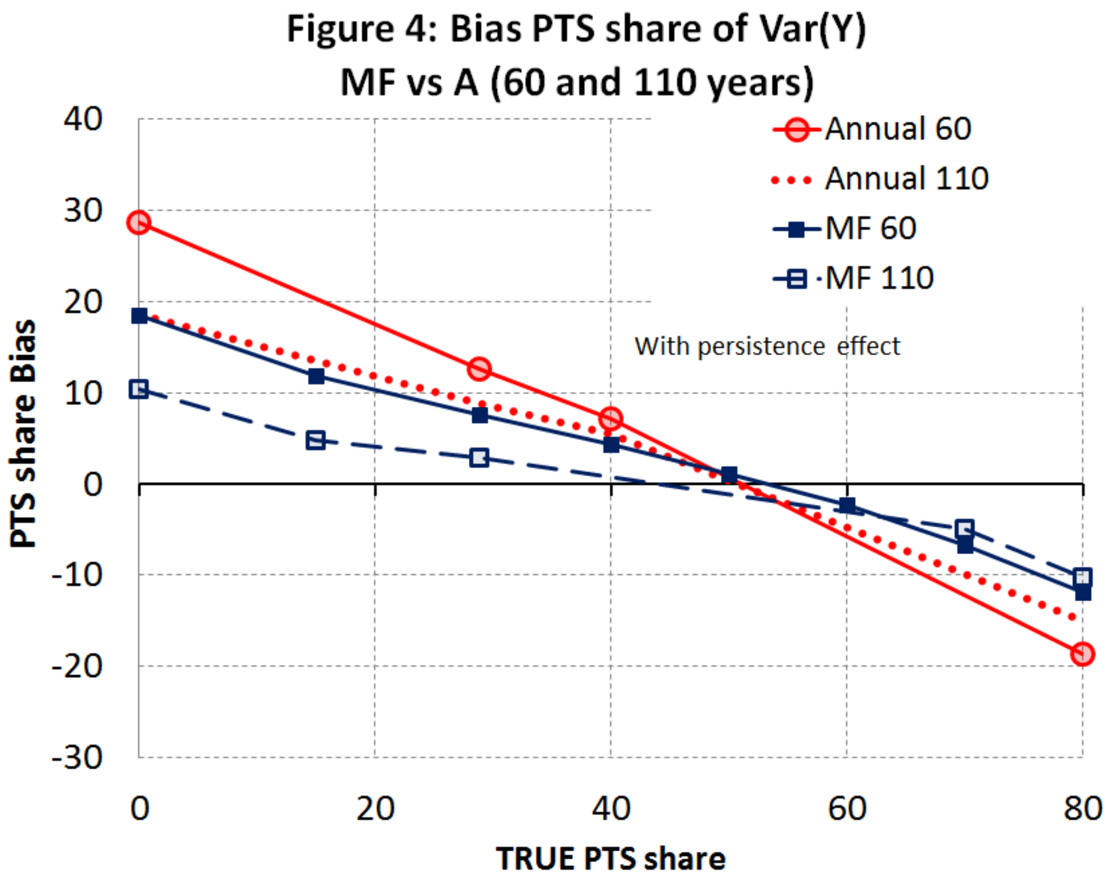
An important question is: Are the alternative estimation strategies ranking the technology shocks correctly? To this end, the lower panel of table 6 shows the differences between PTS and TTS shares (true and estimated) corresponding to different values of σ_g/σ_a (a positive value indicates PTS share is larger). Similarly, figure 2 provides a scatter plot with the true PTS-TTS share in the horizontal axis and the estimated PTS-TTS share in the vertical axis for quarterly and MF strategies. Strikingly, quarterly estimation incorrectly predicts that PTS is larger than TTS for the wide interval [-50%, 0%] of the true PTS-TTS (see circled red line). Surprisingly, even when the TTS share is as much as 50 percentage points larger that PTS's, quarterly strategy assigns a predominant role to PTS. In contrast, mixed MF1 estimates are always closer to the true difference and incorrectly rank PTS in first place only for the interval [-10%,0%] (see squared solid blue line). What is more, MF2 that uses 110 years is very close to the zero bias 45 degree line for most of the support and correctly ranks the shocks all the time (see dashed blue line). This reinforces the idea that using longer annual data samples is crucial to achieving a better identification of the relative importance of permanent and transitory shocks.[22]



Finally, to compare MF and annual strategies, figure 4 presents PTS bias for different relative volatilities of σ_g. Interestingly, in general, MF estimation strategies (squared lines) present smaller PTS bias than corresponding annual strategies (circled and dotted lines), using 60 and 110 years of data respectively. Interestingly, MF with 60 years produces a similar, or even smaller bias, than

[22] A subtlety in figure 2: note that both MF strategies exhibit a sort of saddle point approximately when crossing the 45 degree line and are convex to the left and concave to the right of that point. Therefore, the bias in absolute terms increases more than proportionally when the true PTS minus TTS ratio approaches the extremes. In other words, identification between PTS-TTS gets more difficult when one of the shocks gets very small.

annual estimation with 110 years.



Sensitivity to ρ_a

Here I analyze the sensitivity of results to values of ρ_a. Presumably, a larger ρ_a makes it harder to distinguish permanent from very persistent transitory technology shocks, for which it is reasonable to expect more imprecise estimates.

I generate artificial data calibrating the DGP with $\rho_a = 0.95$ (high persistence) and $\rho_a = .8$ (low persistence). For these two economies, I recalibrate the corresponding σ_a so as to keep the unconditional variance of the TTS unchanged at its baseline value. First, for the high persistence case, as expected, I find larger RMSE and absolute biases of the shares of output variance explained by technology shocks for both quarterly and MF strategies. However, the efficiency gains from quarterly to MF are similar to the one obtained in the baseline case.

Symmetrically, the low persistence case yields smaller biases and RMSE, both for quarterly and MF estimations. Interestingly, the PTS share of output present a bias of almost zero under MF1 and of 8% under quarterly estimation (much smaller than in the baseline case). Still, the efficiency gains of MF with respect to quarterly estimation are of similar magnitude than in the baseline case.

2.3.2 MF Estimation with Non-Overlapping Data

This section analyzes the robustness of results to using non-overlapping data. Recall that the baseline estimation uses annual series for the period 1950-2010, considering quarterly and annual data when both are available (overlapping strategy). Consequently, efficiency gains of MF with respect to quarterly estimation may come from using annual data for the early period for which quarterly series are not available (extended sample) or from the overlapping period. In order to isolate the contribution of the extended sample, here I follow the MFNO strategy described in chapter I, which uses annual data only when quarterly series are not available. More specifically, I keep the length of the sample period in 61 years, but use annual series for the first 40 years and only quarterly series for the last 21 years.[23]

I find that the bulk of the efficiency gains of mixed frequency estimation (with respect to quarterly estimation) is achieved through the extended period. In effect, parameter estimates RMSE fall 27% on average from quarterly to MFNO estimation, which represents almost 90% of the efficiency gains achieved under overlapping MF.[24] Further, variance decomposition estimates are very similar for MFNO and MF, and both strategies deliver efficiency gains and bias reductions of similar magnitude. This suggests that the better performance of MF strategies is mainly the

[23] The artificial data is exactly the same as used previously.

[24] Parameter estimates and variance decomposition using MFNO are available upon request from the author.

result of extending the sample backwards.

2.3.3 MF Estimation and Measurement Errors

In the baseline MF estimation, I extend the sample period backwards using annual data, but the measurement error variance (as a fraction of each series variance) is assumed to be the same for annual and quarterly series and constant for the whole period. However, in practice, it can be argued that annual data from earlier periods may be of poorer quality due to smaller survey coverage, etc. To reflect this possibility, I perform an alternative experiment in which I simulate data assuming that the variance of measurement errors for the first 40 years of annual data is three times as large as for the last 21 years. Then, I implement the same MF estimation strategy, but with this new data. Main results indicate that efficiency gains of MF versus quarterly estimation still hold. For instance, new MF (with noisier data) achieves 90% of parameters RMSE gains (on average) obtained with baseline MF (homogeneous measurement errors). Similarly, new MF attains 88% of RMSE reduction for variance decompositions on average (and 82% for PTS share of output). In turn, new MF exhibits a bias for the PTS share of output 6 percentage points smaller than quarterly estimation (achieves roughly two thirds of the gains of baseline MF). In sum, the efficiency gains of MF with respect to quarterly estimation are robust to noisier early annual data.

2.4 Conclusions

I show that the Bayesian mixed frequency estimation proposed in Chapter I may present substantial efficiency gains compared to alternative single frequency estimators, in particular to assess sources of fluctuations within the financial frictions model.

Strikingly, standard quarterly estimation with short time series may be severely misguiding in terms of the role played by the permanent technology shocks in aggregate fluctuations in EM. In particular, this strategy incorrectly assigns a large role to PTS when the shock is, in fact, very small in the DGP. Importantly, mixed frequency estimations deliver substantial efficiency gains, including bias reductions, with respect to quarterly estimation, yielding a correct ranking of technology shocks most of the time.

On the other hand, MF strategies also present a better performance than corresponding annual estimation in several dimensions, though the bias reduction for the role of technology shocks is not as impressive at the one obtained with quarterly estimation.

I show that within the FF model, the main efficiency results for the MF strategy hold for different parameter values governing the DGP and under alternative conditions. However, I argue that the improved identification of PTS versus TTS under MF strategies is model-dependent, as I will illustrate in Chapter III.

In future research, it would be interesting to investigate whether this efficiency gains are robust to structural breaks in the DGP, especially for the rate of growth of output.

Chapter 3

The Performance of the RBC Model in Emerging Markets

3.1 Introduction

The main goal of this chapter is to assess the ability of the real business cycle (RBC) paradigm to account for salient business cycle facts in emerging markets (EM). For that purpose, I estimate a standard small open economy RBC model with permanent and transitory technology shocks for 12 emerging markets for the period 1950-2010. I implement the same Bayesian mixed frequency estimation strategy described in Chapter I, that combines quarterly and annual data. This mix strategy allows us to extend the data span with annual data, which helps to better estimate persistent shock processes, using, at the same time, the shorter quarterly series. I find that the performance of the RBC to fit the data is intimately linked to the assumed degree of financial frictions.

As discussed in Chapter I, macroeconomic fluctuations in EM are characterized by the excess volatility of consumption with respect to output and countercyclical trade balance (see e.g. Neumeyer and Perri (2005), Uribe and Yue (2006)). Besides, Garcia-Cicco, Pancrazi and Uribe (2010) (henceforth GPU) emphasize that the trade balance-to-gdp ratio (*tby*) exhibits an autocorrelation function significantly below one and rapidly decaying to zero and a volatility similar to that of output growth.

The approach in this paper is closest to GPU analysis. In this regard, to evaluate the ability of the RBC paradigm to account for EM facts, GPU estimate a standard RBC small open economy model driven by transitory and permanent technology shocks for Argentina and Mexico, using annual data since 1900.[1] Importantly, their model specify an extremely small debt-elasticity of the country spread just for the sake of inducing stationarity of the system.[2] They find that the estimated RBC model does an extremely poor job at explaining business cycles in EM, in particular, regarding trade balance and consumption dynamics. In short, the RBC model predicts an excessively persistent and volatile trade balance-to-gdp ratio and falls short of generating the excess consumption volatility over output observed in the data. Finally, they show the financial frictions model (henceforth, FF) detailed in Chapter I, which estimates the debt-elasticity and includes other non-technology shocks, does a much better job at fitting the data.

One of the contributions of this paper is to analyze whether the failure of the RBC documented in GPU for Argentina and Mexico is also observed for a wider set of countries and different periods. For comparison, I consider the same RBC model as in GPU keeping exactly the same small calibrated value of the debt-elasticity of the country premium (henceforth, baseline RBC). Further, I estimate the model for a total of 12 EM for the period 1950-2010 using the Bayesian mixed frequency strategy proposed in Chapter I. Importantly, I find that the shortcomings of the RBC model also hold for this wider array of EM countries. Notably, the estimated RBC model counterfactually predicts a *tby* several times more volatile than in the data with an autocorrelation flat and close to one for all 12 countries. Besides, the baseline RBC does not generate enough volatility of consumption relative to output as in the data (mainly because it overstates the volatility of output).[3], [4] Overall,

[1] The model is estimated using Bayesian methods for Argentina and GMM for Mexico. The observables are output, consumption, investment and the trade balance-to-gdp ratio.

[2] GPU refere to this calibrated model as the "frictionless" RBC.

[3] The model generates an absolute standard deviation of consumption close to the data but it clearly overstates the volatility of output (by 1.3% on average).

[4] The RBC also presents some limitations to reproduce other EM facts, though the failure is not as dramatic as

these results appear to be robust to different time periods.[5]

The excessively persistent trade balance-to-output ratio predicted by the baseline RBC is explained by the extremely small calibrated debt-interest rate elasticity which results in consumption and debt-to-gdp processes that are very close to a random walk, typical of a small open economy with incomplete markets (see Schmitt-Grohe Uribe (2003)). More generally, as I will discuss here, the calibration of the parameter denoting the debt-interest rate semi-elasticity turns out to be crucial for the ability of the RBC model to fit the data.

In contrast with GPU results, Aguiar and Gopinath (2004) estimate the same RBC model as GPU for Canada and Mexico for the period 1980-2003 and find that it does a fairly good job at explaining aggregate fluctuations in EM and DC.[6] Their estimations assign a central role to the permanent technology shocks in EM. Further, they argue that, in their model, the permanent shock is key to generate the excess consumption volatility and countercyclical tby observed in EM.[7] I will show that this apparent contradiction between the RBC performance in GPU versus AG is to a

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for the facts mentioned above. For example, the RBC implies that tby is countercyclical on average, but the median correlation with output growth is just -0.05, smaller in absolute value than the median of -0.18 observed in the data. Similarly, the model does not generate enough negative correlation between consumption and investment with the trade balance. Besides, the RBC overstates the correlation of consumption with output, arguably because the economy is uniquely driven by technology shocks.

[5] Many of the model fitting problems also hold for developed countries.

[6] GPU argue that the reasonable fit implied by AG model estimates is because the model does an acceptable job for the AG short period (1980-2003) for Mexico but, in contrast, it is unable to reproduce data facts for a longer period, 1900-2005. For this, GPU provide GMM estimates for Mexico using the same data as AG for the period 1980-2003. To check this possibility, I re-estimate the baseline RBC model with quarterly data for the period used in AG, for 4 EM and 6 DC, and find, unlike GPU, that the main flaws of the model also hold for this shorter period, in particular, those related to the trade balance.

[7] They find that PTS shocks are much more important in EM than in DC, result that they attribute to the relatively larger excess volatility of consumption and tby countercyclicality in EM.

large extent explained by differences in the assumed degree of financial frictions. In this regard, I show that AG calibrate an elasticity of the interest rate that is as much as 160 times larger than that used in GPU, but still small relative to empirical estimates.[8] Accordingly, I interpret this AG assumption as a small departure from the frictionless RBC paradigm.

Motivated by the different results of GPU and AG, I analyze the robustness of the failures of the RBC to relatively small departures from the frictionless RBC paradigm. Specifically, I re-estimate the RBC model with a moderately higher degree of financial frictions calibrating a larger debt-elasticity of the interest rate (yet empirically small) equivalent to that used in AG(2004) (henceforth RBC-AG model). Interestingly, I find that after this modification the model exhibits a remarkable improvement in fitting the data in some dimensions that are problematic in the frictionless RBC. In particular, the tby exhibits a model implied volatility similar to that of output and its autocorrelation function is downward sloping and much closer to the data, though the fit is not as good as in the FF model.[9] Nonetheless, the RBC-AG still does not generate enough excess volatility of consumption over output, which may be reflecting the absence of demand shocks.

Despite the significant improvements compared to the baseline RBC, the RBC-AG performance

[8] GPU calibration implies that after an increase in external debt of 100% of gdp the country interest rate increases only by 2 basis points, an extremely small value compared with estimates in the literature. For example, GPU estimations of the FF model for Argentina yield an elasticity of about 5,900 basis points, while chapter I presents a median estimate of 3,600 for EM. In turn, Akytobi and Stratmann (2008) provide an empirical estimate of around 1,000 in a panel data model. In turn, the calibration used in AG(2004) implies an elasticitiy of around 363 basis points.

[9] As these results suggest, one way to achieve a downard-sloping tby autocorrelation function in the small open economy model is to set a larger interest rate debt-elasticity. The intuition for this result is that when economy is running a trade balance deficit, the external debt increases, leading to higher borrowing costs. This, in turn, discourages domestic demand, producing and improvement in the external balance that gradually reverts to its mean.

is not as good as that of the FF model. As shown in Chapter I, the FF is able to generate enough excess volatility of consumption over output and implies a smaller correlation between consumption and output closer to the data, solving two shortcomings of the RBC-AG. This is most likely the result of the inclusion of other sources of fluctuations, namely, preference and interest rate shocks, not considered in the RBC. Besides, the FF model implies a tby with an autocorrelation function that is even closer to the actual data and always inside confidence intervals. This is basically explained by the fact that in the FF the debt-elasticity of the country premium is directly estimated (and, in general, turns out to be much larger than the calibrated values in GPU and AG).

In the spirit of AG, it is of interest to analyze the importance of permanent technology shocks in EM and DC within the RBC paradigm. In this regard, main estimates for the baseline RBC indicate that the permanent shock explains about 48% of output growth fluctuations in emerging markets. Thus, permanent and transitory technology shocks play a similar role in output movements. However, the permanent shock plays a predominant role for consumption, investment growth and the *tby*, accounting for 66%, 62% and 64% of their variance respectively.[10] In contrast, estimates for DC suggest that, in general, transitory shocks are predominant in these countries, similar to the results of AG.

Finally, in order to assess the contribution of the mixed frequency strategy I perform a Monte Carlo experiment for a representative EM assuming that the data is generated from the RBC-AG model. I find that the MF estimations deliver large efficiency gains (fall in RMSE) with respect to estimation with short quarterly series, both for parameters and variance decompositions. Interestingly, both strategies present bias and RMSE that are much smaller than those obtained in Chapter II for the FF model, in particular for the relative contribution of the technology shocks. Thus, I argue that the PTS shock is better identified in the RBC model than in the FF model, even in short samples.

[10] For robustness, I also computed variance decompositions implied by the RBC-AG estimations, which yield very similar results both for EM and DC on average.

The remainder of the chapter is organized as follows. Section 2, presents the small open economy RBC model. Section 3 outlines the estimation strategy and reports main estimation results. There, I assess the ability of the estimated model to reproduce main EM facts. Section 4, in turn, presents the Monte Carlo experiment. Finally, section 5 concludes.

3.2 Model

The theoretical framework considered is the RBC model presented in GPU (2010) and AG (2004). The framework is a standard RBC small open economy model augmented with a permanent technology shock. The model economy is buffeted by a total of two technology shocks (transitory and permanent).

The representative household faces the following sequential budget constraint:

$$\frac{D_{t+1}}{1+r_t} + Y_t = D_t + C_t + I_t + \frac{\varphi}{2}\left(\frac{K_{t+1}}{K_t} - g\right)^2 K_t, \tag{3.1}$$

where D_{t+1} denotes the stock of external debt issued at period t and r_t is the corresponding interest rate. The variables Y_t, C_t and I_t denote output, consumption and investment in real terms respectively.[11] The last term of the right hand side represents a quadratic capital adjustment cost with $\varphi > 0$, while g denotes the constant long-run rate of growth. Households produce an homogeneous good according to the following Cobb-Douglas technology:

$$Y_t = a_t K_t^{\alpha} \left(X_t h_t\right)^{1-\alpha}, \tag{3.2}$$

where h_t denotes hours worked, a_t is a transitory productivity shock and X_t is a labor-augmenting permanent technology shock (non-stationary). The stock of capital dynamics are governed by the following law of motion:

$$K_{t+1} = (1-\delta) K_t + I_t, \tag{3.3}$$

[11] Unlike the financial frictions model, I do not consider a government spending shock S_t here, as in AG model.

with depreciation rate $\delta \in [0,1)$. The country interest rate is assumed to be elastic to the debt-to-gdp ratio (gdp trend):

$$r_t = r^* + \psi\left(\exp\left[\frac{\bar{D}_{t+1}}{\bar{y}X_t} - \bar{d}\right] - 1\right)$$

where r^* denotes the steady state interest rate, ψ denotes the elasticity of the interest rate with respect to debt-to-gdp ratio, $\bar{d}$ and $\bar{y}$ indicate steady state values of debt-to-gdp ratio and de-trended output respectively and, thus, $\bar{y}X_t$ denotes the output trend.[12] The variable $\bar{D}_t$ denotes the aggregate level of external debt in the economy, which is taken as exogenous by households. In equilibrium, $D_t = \bar{D}_t$.

The debt-elastic interest rate feature is introduced just to induce stationarity of debt-to-gdp ratio as shown in Schmitt-Grohe and Uribe (2003). Accordingly, the debt-elasticity parameter is set to a very small value so that the model is as close as possible to a frictionless RBC, as in GPU. However, what is considered a small value of this parameter will be key for the performance of the RBC in emerging markets as it is discussed in depth later.

Consumers are also subject to the following no-Ponzi-game condition:

$$\lim_{j\to\infty} E_t \frac{D_{t+j}}{\Pi_{i=0}^{j}\left(1 + r_{t+i}\right)} \leq \infty$$

The transitory technology shock in logs evolves according to:

$$\ln a_{t+1} = \rho_a \ln a_t + \varepsilon_{a,t+1}; \qquad \varepsilon_{a,t} \sim N\left(0, \sigma_a^2\right)$$

Let g_t denote the rate of growth of the permanent technology shock:

$$g_{t+1} \equiv \frac{X_{t+1}}{X_t}.$$

[12] The only difference with GPU model is that the interest rate here depends on debt-to-gdp trend ratio $\frac{\bar{D}_{t+1}}{\bar{y}X_t}$ instead of on the stationary debt level $\frac{\bar{D}_{t+1}}{X_t}$ used in GPU. This transformation just rescalates the interest rate-debt elasticity to make it comparable across countries and easier to interpret.

This shock is governed by the following autoregressive process:

$$\ln \frac{g_{t+1}}{g} = \rho_g \ln \frac{g_t}{g} + \varepsilon_{g,t+1}; \qquad \varepsilon_{g,t} \sim N\left(0, \sigma_g^2\right).$$

Households choose a plan $\{c_t, h_t, k_{t+1}\}_{t=0}^{\infty}$ that maximizes the following lifetime utility function:

$$E_0 \Sigma_{t=0}^{\infty} \beta^t \left[\frac{\left(C_t - \theta\omega^{-1} X_{t-1} h_t^{\omega}\right)^{1-\gamma} - 1}{1-\gamma} \right],$$

subject to (1) – (3) and the no-Ponzi-game given initials conditions D_0 and K_0 and taking as given the processes for a_t, X_t and r_t.[13] Note that the RBC model considered is a particular case of the financial frictions model presented in Chapter I (shutting off the three non-technology shocks and setting government spending to 0 in steady state). See the Appendix for a full set of equilibrium conditions.

3.3 Estimation

The baseline estimation strategy in this chapter is identical to the baseline strategy used in Chapter I. Some parameters are calibrated and the remainder are estimated using the Bayesian mixed frequency methodology implemented in Chapter I.

I calibrate the structural parameters $\alpha, \beta, \delta, \gamma, \theta, \omega, \psi, g$ and $\bar{d}$. (see table 1, baseline calibration for details). The parameters g, δ and $\bar{d}$ are calibrated to match long-run ratios (output growth, and investment-to-gdp and trade balance-to-gdp ratios respectively) for each country for the period 1950-2010 . Meanwhile, the parameters $\alpha, \beta, \gamma, \theta,$ and ω are assigned the same values as in Chapter I and GPU and are assumed to be identical for all countries.

As it will become clear later, the calibration of the parameter ψ denoting the debt-interest rate elasticity is crucial for the ability of the model to fit the data. In the baseline strategy, this

[13] Here, the parameter $\omega > 1$ implies a Frisch elasticity of $\frac{1}{\omega-1}$ and γ denotes the relative risk aversion coefficient. The period utility features GHH preferences, which removes wealth effects over hours worked. In this regard, I opt not to use a Cobb-Douglas utility function because it may lead to an unrealistic decrease of hours in response to a positive permanent productivity shock, as mentioned in AG.

elasticity is calibrated to a very small value of 0.00022 in annual terms (equivalent to GPU, RBC model calibration), so as to remain as close as possible to the frictionless RBC while inducing stationarity (RBC baseline).[14] This value implies that after an increase in external debt of 100% of gdp the country interest rate increases only by 2 basis points, an extremely small value compared to estimates in the related literature. For example, within theoretical models, GPU estimations of the FF model for Argentina yield an elasticity of about 5,900 basis points, while Chapter I presents a median estimate of 3,600 for EM. In turn, Akytobi and Stratmann (2008) provide an empirical estimate of around 1,000 in a (reduced form) panel data model for several countries. Interestingly, GPU-RBC elasticity value is also much smaller (160 times) than the calibration used in AG(2004), of around 363 basis points, which is already a low elasticity.[15] Later, I also consider an alternative calibration-estimation strategy setting this elasticity to the value used in AG(2004) to explore the

[14] As discussed above, in GPU and AG(2004) the interest rate equation is written in terms of debt levels, unlike this paper that writes it in terms of debt-to-steady state gdp. Accordingly, to obtain the ψ value in this paper equivalent to GPU and AG values, I evaluate GPU and AG models in steady state and multiply their elasticity values by steady state gdp. Besides, to convert an elasticity from quarterly to annual units I multiplied by 16, given than in the quarterly model the interest rate is roughly 1/4 of its annual counterpart and the debt-to-gdp ratio is 4 times its annual counterpart.

[15] In the FF model estimations in chapter I, all EM countries but Malaysia exhibit a larger interest rate elastiticy than the AG(2004) calibration equivalent to 363 basis points.

sensitivity of main results.

Table 1: Calibrated Parameters

Param	Concept	Values	Param	Concept	Values
Baseline Calibration					
δ	Cap.depreciation	match I/Y	β	Discount factor	0.98
d	Debt to gdp	match TB/Y	γ	Risk aversion	2
g	Growth rate	match gY	θ	Hours worked	2.24
α	Capital share	0.32	ω	Frisch elastiticy	1.6
ψ	Int rate debt-elast	0.00022			
AG(2004) Strategy					
δ	Cap.depreciation	0.03	ψ	Int rate debt-elast	0.03633
d	Debt to gdp	0.1	θ	Hours worked	1.4

Notes: Table displays baseline calibration strategy and alternative AG strategy following AG (2004). Y, I, TB and gY denote gdp, investment, trade balance and gdp growth respectively. Capital depreciation, debt-to-gdp and gdp growth are calibrated to match correspoding long-run ratios for each country. Interest rate elasticity to debt-to-gdp ratio is annualized multilplied by 16. Lower panel displays only parameters presenting a calibration in AG (2004) different from the baseline calibration.

I estimate 5 structural parameters ($\sigma_a, \sigma_g, \rho_a, \rho_g$ and φ) and 8 measurement error variances. I assume uniform priors for all estimated parameters (see table 2 for details) as in Chapter I. The model is estimated observing the rate of growth of output, consumption and investment and the trade balance-to-gdp ratio at quarterly and annual frequency for the period 1950-2010 as in previous chapters (baseline mixed frequency strategy).[16] The methodology to accommodate mixed frequency series in the DSGE Bayesian estimation is identical to the baseline strategy methodology followed in Chapter I.

The dataset is the same used in Chapter I and the countries considered are Argentina, Brazil, Chile, Colombia, Mexico, Peru, Indonesia, Malaysia, Philippines, Thailand, Turkey, South Africa

[16]Measurement errors are assumed not to explain more than 25% of the standard deviation of the corresponding observed series. When quarterly and annual series are simultaneously available, I use both in the estimation (overlapping strategy).

from EM and Australia, Belgium, Canada, Netherlands, Norway and Sweden representing small DC. Again, I selected the sample period 1950-2010 because annual data is available for most countries over that span and offers a good trade-off between country coverage and time series length.

Table 2: Prior Distributions

Param	Concept	Distribution	LB	UB
φ	Capital adj costs	Uniform	0	200
ρ_a	Autocorr transitory tech	Uniform	0	0.99
ρ_g	Autocorr permanent tech	Uniform	0	0.99
σ_a	Std Dev transitory tech	Uniform	0	0.10
σ_g	Std Dev permanent tech	Uniform	0	0.10

3.3.1 Estimation Results

This section presents main estimation results for emerging markets under the MF baseline strategy for the period 1950-2010. I analyze to which extent the estimated RBC model is able to explain main EM facts, paying special attention to the dynamics of the trade balance and relative consumption volatility. The main findings are that the shortcomings of the RBC model documented in GPU for Argentina (and Mexico) also hold for a wider array of countries and using the mixed frequency dataset. I also compare the performance of the RBC with that of the financial frictions model (FF) estimated in Chapter I. Finally, I analyze the robustness of these results to relatively small departures from the frictionless RBC paradigm. Specifically, I re-estimate the model calibrating a larger debt-elasticity of the interest rate comparable to that used in AG(2004). I find that after this modification the model exhibits a remarkable improvement in fitting the data in some dimensions compared with the frictionless RBC.

In this section, I also provide variance decomposition statistics, focusing on the importance of the permanent technology shock, both for EM and DC.

RBC Baseline Estimation

This section reports mixed frequency estimations for the period 1950-2010 based on 2 million draws from the Markov Chain (first 1 million is discarded). Table 3 displays main parameter estimates for emerging markets country by country (baseline RBC). Table 4, in turn, shows median of parameter estimates across countries both for EM and DC.[17] Notably, main estimates yield a substantial heterogeneity across countries (see table 3). Both shocks present innovations with similar median standard deviations, of around 1.5%, but its relative volatility vary a lot from country to country. However, the overall contribution of each shock to fluctuations depends also on other parameters values (see variance decompositions in the next section). The transitory technology shock is quite persistent for some countries but its median is about 0.86, substantially below the unit root.[18] On the other hand, the permanent shock persistence is substantially larger than zero for most countries and its median is 0.42, but it displays a larger dispersion than in the estimated financial frictions model. Interestingly, the standard errors of σ_g are smaller than those obtained for the financial friction model in Chapter I, suggesting that the PTS is arguably easier to identify in the RBC

[17] Table 4, in addition to RBC baseline estimations, includes median estimates for an alternative calibration of ψ as in AG(2004) (RBC-AG).

[18] This median autocorrelation ρ_a is somewhat smalle than the median autocorrelation of the TTS estimated in chapter I for the FF model (0.92).

model.

Table 3: Posterior Distribution Emerging Markets

Param	Arg	Bra	Chi	Col	Mex	Peru	Indo	Mal	Phil	Thai	Tur	S.Afr	**Median**
φ	3.9	12.7	2.4	0.6	3.0	2.7	2.5	1.8	0.8	0.4	6.4	4.4	**2.6**
	(0.2)	(1.2)	(0.2)	(0.1)	(0.3)	(0.2)	(0.4)	(0.2)	(0.1)	(0.1)	(0.5)	(0.4)	**(0.2)**
ρ_a	0.96	0.93	0.90	0.73	0.76	0.93	0.77	0.79	0.94	0.66	0.97	0.81	**0.86**
	(0.00)	(0.02)	(0.02)	(0.03)	(0.03)	(0.01)	(0.04)	(0.03)	(0.01)	(0.03)	(0.00)	(0.02)	**(0.02)**
ρ_g	0.27	0.70	0.02	0.02	0.56	0.20	0.72	0.85	0.99	0.01	0.24	0.86	**0.42**
	(0.03)	(0.06)	(0.02)	(0.02)	(0.05)	(0.03)	(0.06)	(0.02)	(0.00)	(0.01)	(0.04)	(0.02)	**(0.03)**
σ_a	1.59	1.05	1.55	1.39	0.77	2.32	1.57	2.02	0.93	2.81	2.28	0.79	**1.56**
	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.2)	(0.2)	(0.2)	(0.1)	(0.3)	(0.2)	(0.0)	**(0.1)**
σ_g	3.15	1.05	3.03	1.85	1.20	4.37	0.88	1.04	0.18	3.75	3.90	0.44	**1.53**
	(0.2)	(0.2)	(0.2)	(0.2)	(0.1)	(0.3)	(0.2)	(0.2)	(0.0)	(0.3)	(0.4)	(0.1)	**(0.2)**

Notes:Each column displays posterior median and standard deviation (between parenthesis) for a given country. Last column displays median across countries of posterior medians and standard deviations respectively. Posterior estimates are based on a 2-million MCMC chain (first 1 million draws are discarded). Estimates of standard deviation of shocks are in percentage points. Countries from left to right: Argentina, Brazil, Chile, Colombia, Mexico, Peru, Indonesia, Malaysia, Philippines, Thailand, Turkey and South Africa.

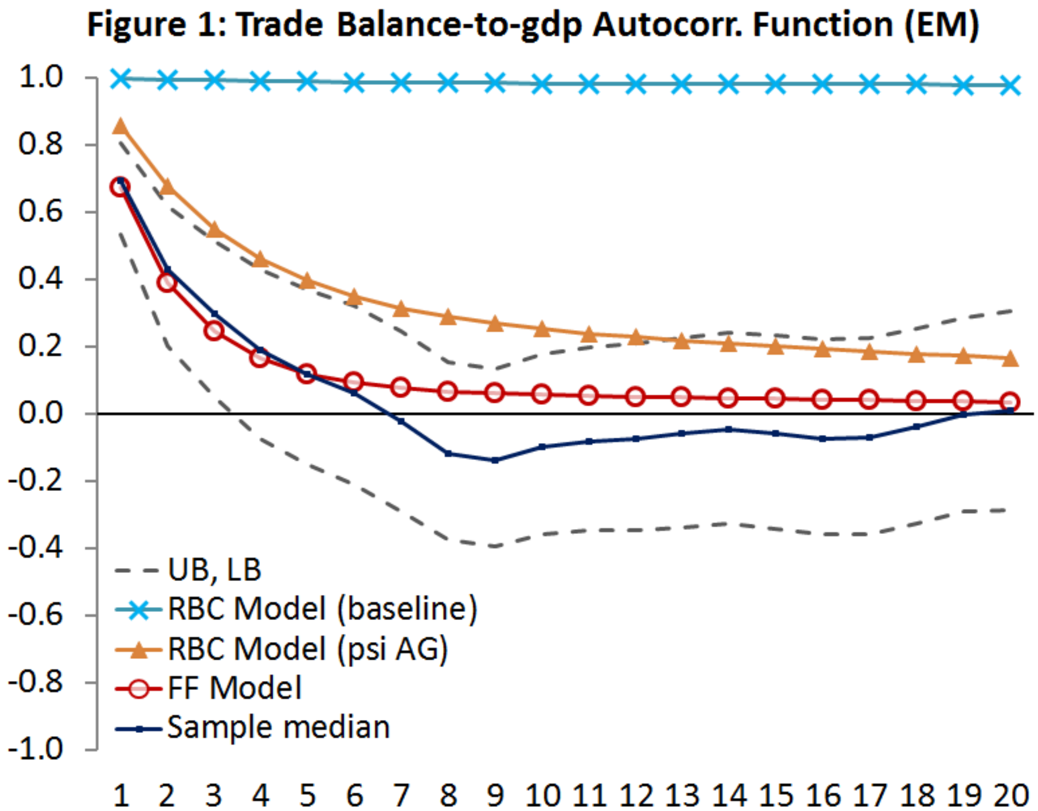
Table 4: Posterior Distribution (median across countries)

		EM countries		DC countries	
Param	Concept	Baseline	RBC-AG	Baseline	RBC-AG
φ	Capital Adj Costs	2.6	2.8	0.5	0.5
		(0.2)	(0.3)	(0.1)	(0.1)
ρ_a	Autocorr transitory tech	0.86	0.85	0.84	0.81
		(0.02)	(0.02)	(0.02)	(0.02)
ρ_g	Autocorr permanent tech	0.42	0.46	0.03	0.03
		(0.03)	(0.02)	(0.02)	(0.02)
σ_a	Std Dev transitory tech	1.56	1.75	1.29	1.46
		(0.14)	(0.14)	(0.11)	(0.12)
σ_g	Std Dev permanent tech	1.53	2.00	1.71	1.77
		(0.20)	(0.23)	(0.11)	(0.11)

Notes:Each column displays median (across countries) of posterior median and standard deviation (between parenthesis) respectively. Baseline and AG denote estimates under baseline estimation and estimation with a larger debt-elasticity of interest rate equivalent to AG(2004) respectively. Posterior estimates are based on a 2-million MCMC chain (first 1 million draws are discarded). Estimates of standard deviation of shocks are in percentage points.

Now, I analyze the ability of the estimated model to replicate observed business cycle moments for emerging countries during 1950-2010. For that purpose, table 5 presents empirical and implied second moments for the rate of growth of output, consumption, investment and the trade balance-to-gdp ratio. The moments are computed at the annual frequency because annual data are only available for the whole estimation period 1950-2010 and because it makes it easier to compare with GPU results. Table 5 presents implied moments for the baseline RBC, but also estimates under an alternative strategy that calibrates a larger interest rate elasticity equivalent to AG(2004) (RBC-AG). To facilitate comparisons, I reproduce the moments implied by the financial frictions model from Chapter I.

Here, I analyze the main predictions of the RBC model regarding standard business cycle moments in EM. The RBC model does an extremely poor job in reproducing trade balance facts as highlighted in GPU. To illustrate this, figure 1 displays the trade balance-to-gdp (*tby*) autocorrelation function from 1 to 20 lags (at the annual frequency), both in the data and in the model (evaluated at the mean of parameter estimates across countries). In the data, most countries show a downward-sloping trade balance-to gdp ratio autocorrelation function that starts at a value significantly smaller than one and that, for many countries, converges relatively quickly to zero (see median across the 12 EM, solid line, and 95% confidence intervals, dashed lines). The baseline RBC model (starred line) evidently fails to reproduce this fact, as it predicts an autocorrelation function close to one and extremely persistent (it stays at least above 0.95 after 20 years for all countries), a feature that holds for all EM countries without exception. Moreover, the model implied autocorrelation function lies completely outside confidence intervals, for all lags and countries.



The excessively persistent trade balance-to-output ratio predicted by the RBC is explained by the extremely small calibrated debt-interest rate elasticity ψ which results in consumption and debt processes that are very close to a random walk, typical of a small open economy with incomplete markets without frictions (see Schmitt-Grohe Uribe (2003)).[19] Notably, this high implied persistence of the trade balance cannot be explained by the presence of the permanent technology shock. Indeed, if we shut this shock off the implied autocorrelation function remains essentially unchanged,

[19] GPU discusses the importance of the ψ value to characterize the persistence of the *tby* in the RBC model, stressing that for any set of the remainder parameter values one can find a sufficiently small value of ψ that implies an autocorrelation function of the *tby* flat and close to unity. In this sense, from the estimates obtained in this chapter is clear that the calibrated ψ in the baseline strategy is small enough to imply a flat and close to one autocorrelation for all countries.

flat and close to one for all countries.

It is worth recalling that the financial frictions model, for which this interest rate elasticity is estimated (to be much larger) and not just calibrated to a small value, generates an autocorrelation of *tby* close to the data and inside the confidence bands (see circled line, figure 1).[20] Moreover, later, when I re-estimate the RBC model setting the elasticity to a larger value as in AG(2004), still small compared to realistic estimates, the autocorrelation function gets closer to the data (see line with triangles), though the fit is not as good as in the FF model.[21] As these two examples suggest, one way to achieve a downward-sloping tby autocorrelation function in the small open economy model is to set a larger interest rate debt-elasticity. The intuition for this result is as follows. If the economy is running a trade balance deficit, the external debt increases, leading to higher borrowing costs. This, in turn, discourages domestic demand and provokes and improvement in the external balance that gradually reverts to its mean.

A larger ψ is not the only avenue to obtain stationarity and, in particular, a downward-sloping trade balance autocorrelation function in a small open economy model with incomplete markets. This could also be achieved by specifying a subjective discount factor sufficiently sensitive to consumption or significant portfolio adjustment costs, as discussed in Schmitt-Grohe and Uribe (2003).

The RBC model also predicts an unrealistically large volatility of the trade balance-to-gdp ratio. Table 5 (see baseline RBC model) shows that the model implies a standard deviation of the trade-balance-to gdp ratio of about 32% (median across EM countries), almost ten times the volatility observed in the data, of 3.4% (smaller than output volatility). This excess unconditional volatility is to a large extent a consequence of the extremely persistent trade balance highlighted above. In

[20] GPU find a similar improvement in the model fit of the trade balance, from the RBC to the FF model with estimates for Argentina with annual data for 1900-2005.

[21] The autocorrelation is smaller than in the baseline RBC, downward-sloping and lies closer to the upper limit of the confidence interval (see line with triangles).

fact, the volatility of the trade balance-to-gdp ratio in differences (average 2.3%) is smaller than the observed in the data (average 3.2%), and thus, the persistence of this variable is ultimately responsible for the predicted high unconditional variance. And given that the small interest rate-debt elasticity accounts for the excess persistence of the tby, it is also likely to explain the excess trade balance volatility, premise that is confirmed later.

Table 5: Second Moments (annual frequency)

	Emerging Markets			
	Y	C	I	TBY
Std Dev %				
- Data	4.4	4.7	14.4	3.4
- Financial frictions model	4.4	5.4	11.2	3.9
- RBC model (AG)	6.7	6.0	15.6	4.2
- RBC model (baseline)	5.7	4.8	16.1	32.2
	(0.30)	(0.35)	(0.59)	(0.77)
Correl w/Y				
- Data	-.-	0.76	0.70	-0.18
- Financial frictions model		0.83	0.55	-0.13
- RBC model (AG)		0.91	0.79	-0.27
- RBC model (baseline)		0.90	0.76	-0.04
		(0.03)	(0.03)	(0.05)
Correl w/TBY				
- Data	-.-	-0.14	-0.24	-.-
- Financial frictions model		-0.17	-0.13	
- RBC model (AG)		-0.29	-0.32	
- RBC model (baseline)		-0.05	-0.05	
		(0.05)	(0.05)	
Autocorrel				
- Data	0.25	0.20	0.10	0.69
- Financial frictions model	0.39	0.29	0.12	0.77
- RBC model (AG)	0.25	0.24	0.07	0.80
- RBC model (baseline)	0.28	0.25	0.07	1.00
	(0.05)	(0.04)	(0.03)	(0.06)

Notes: Median across countries of model and empirical moments. Model implied moments based on 100,000 draws from posterior distribution (posterior median) (standard errors between parenthesis). Empirical moments for the period 1950-2010. Variables Y, C and I denote rate of growth of output, consumption and investment. TBY denotes trade balance-to-output ratio.

There are other features that also contribute to the predicted excess volatility of the external balance, in particular the significant serial correlation of the permanent shock ρ_g for some countries. The intuition for this result is that a larger ρ_g generates a stronger reaction of consumption to current income movements in response to permanent technology shocks, which results in a more volatile trade balance. For example, if we reduce this coefficient to zero for all countries (from and average of 0.4), keeping the other parameters unchanged, the standard deviation of *tby* falls around 1/3 on average (or about 10% points).[22]

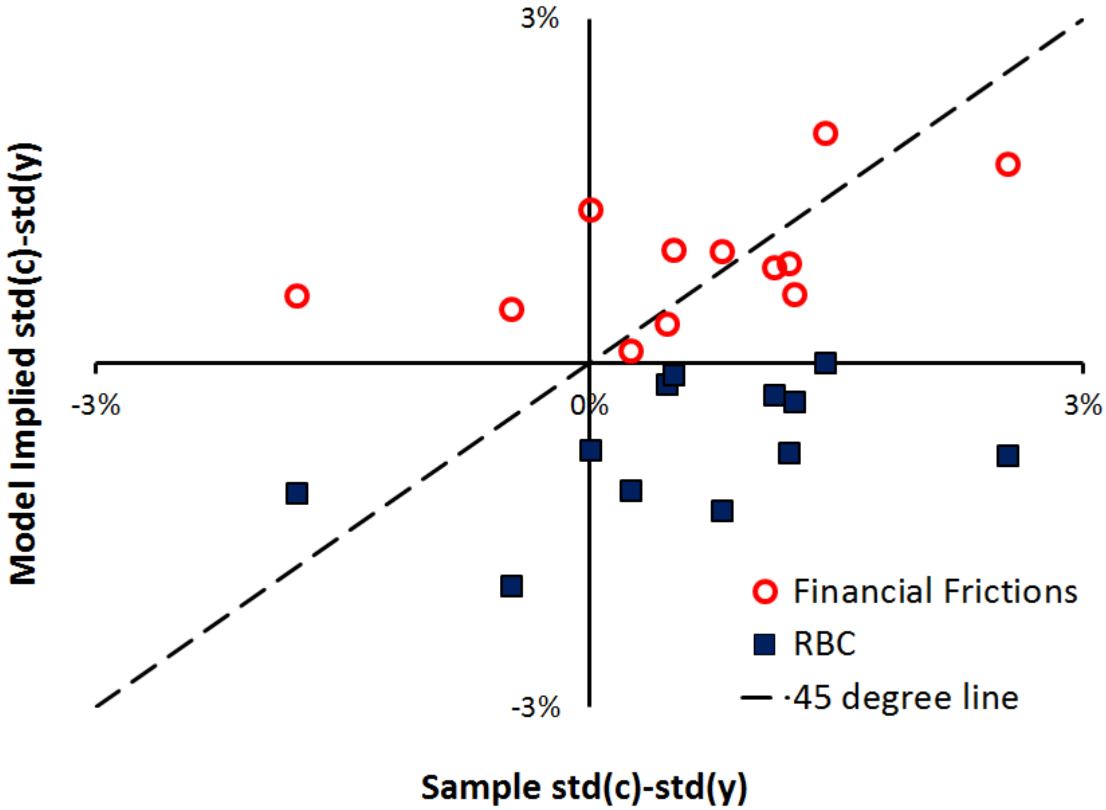
Now, I analyze the model implications for the other variables. Strikingly, the baseline RBC model predicts a consumption growth less volatile than output for all EM countries, in contrast with the excess volatility observed in the data. On average, implied consumption standard deviation is almost 1% smaller than output, while in the data consumption is in fact 0.3% more volatile (see table 5). This is not because the model does not predict sufficiently volatile consumption (the absolute standard deviation is close to the data) but because it clearly overstates the volatility of output (by 1.3% on average).

The predicted excess smoothness of consumption relative to output holds for most EM countries one by one (see tables C1 and C2 in the appendix). To illustrate this point, figure 2 plots the difference between the standard deviation of consumption and that of output implied by the model (vertical axis) against the same quantity observed in the data (horizontal axis) country by country (squares indicate RBC model predictions). Ideally, we would like to observe points close to the 45 degree line so that model predictions are in line with the data and, at least, points either in the upper-right or in the lower-left quadrants (predicting the right sign for the country). Unfortunately, the RBC model locates most of the countries in the lower-right quadrant, predicting that consumption is less volatile than output when in the data consumption is indeed more volatile.

[22] The clearest example is Philippines that shows both the largest ρ_g (0.99) and the highest predicted volatility of *tby* (2.60). If we instead set $\rho_g = 0$ for this country, the standard deviation of *tby* drops to 0.18, closer to the data (though still very large).

Notably, all countries but one are below the 45 degree line, which suggests that the RBC systematically underpredicts consumption relative volatility. These results are in line with GPU (RBC) estimations for Argentina and Mexico.[23]

Figure 2: Excess Consumption Volatility (over Output)



Within the RBC model, it is possible to generate consumption more volatile than output if we increase the relative volatility of the permanent shock (σ_g/σ_a), or if we raise its persistence (ρ_g). For example, if we set $\rho_g = 0.95$ for all countries (compared to a median of 0.41), other things equal, the relative standard deviation of consumption versus output increases, on average, from

[23] GPU estimated RBC model does not predict enough excess volatility of consumption over output as in the data for both countries, though there are some differences: while for Argentina the model implies that consumption is indeed more volatile than output, yet not as much as in the data, for Mexico the model counterfactually implies that consumption is significantly less volatile than output.

0.89 to 1.02, closer to the data (1.07).[24] However, this change comes at a significant costs in other dimensions, as it produces an even higher *tby* volatility and unrealistically large output growth persistence. Similar consequences arise if we increase σ_g.

As discussed in Chapter I, the financial frictions model does in general a better job in replicating excess volatility of consumption. For comparison, figure 2 also includes the predictions of the FF model (red circles), which correctly places most countries in the upper-right quadrant and close to the 45 degree line.[25] However, it is not always the case that the FF model performs better than the RBC along this dimension. In effect, for the two countries that show consumption smoother than output in the data (Philippines and Thailand), the FF model is unable to place them in the lower-left corner while, on the contrary, the RBC model predicts the right sign. In sum, the RBC is unable to correctly sign countries with excess consumption volatility and the FF model, in turn, is unable to fit the countries displaying excess consumption smoothness.

The RBC also presents some limitations to reproduce other empirical facts in EM but the distance with the data is not as long as for the moments analyzed so far. For example, the RBC implies that the *tby* is countercyclical on average, but the median correlation with output is just -0.05, smaller in absolute value than the median of -0.18 observed in the data. Similarly, the model does not generate enough negative correlation between consumption and investment with the trade balance. Besides, the RBC overstates the correlation of consumption with output, arguably because the economy is uniquely driven by technology shocks. Not surprisingly, the FF model performs better along these correlations, which is likely the consequence of the presence of demand and

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[24] The excess volatility of consumption over output rises with ρ_g but the sensisitivty is relatively small at the annual frequency which makes it hard to generate substantial excess volatility at this frequency for reasonable parameter values. By contrast, the excess volatility of consumption at the quarterly frequency is much more sensitive to ρ_g than at annual frequency. This is because most of the response of consumption to permanent shock is processed on impact (first quarter).

[25] The FF model, unlike the RBC, also correctly predicts the absolute volatility of consumption and output.

interest rate shocks that effectively weaken the link between consumption and output.[26]

Despite all of its flaws, the RBC performs relatively well in some dimensions like the autocorrelation of output, consumption and investment growth, the large correlation of investment with output and the excess volatility of investment, displaying an even better fit than the FF model (see table 5, RBC baseline).

Interestingly, most shortcomings of the RBC to explain business cycles facts in EM also hold for DC estimations for the period 1950-2010, including trade balance-to-gdp issues and relatively consumption smoothness. See tables C4 and C5 in the appendix for empirical and model implied moments for DC (country by country and group median respectively).

Comparison with GPU RBC Estimations In this brief section I show that the main shortcomings of the baseline RBC model are robust to different estimations periods considered in GPU and AG.

Recall that GPU presents RBC estimations for Mexico and Argentina with data for 1900-2005. For comparison, I also re-estimate the RBC model with MF data for the period 1900-2010, but only for the six Latin-American countries.[27] For this longer period, business cycles turn out to be qualitatively similar to those found for the period 1950-2010. In effect, I find that the main RBC flaws outlined above also hold for the model estimated for the period 1900-2010, including those involving trade balance and consumption dynamics.

Finally, GPU argue that the reasonable fit of the estimated RBC model in AG is because the model does an acceptable job for the short recent period (1980-2003) used in AG for Mexico but

[26] As a result of this better fit, the modified likelihood of the FF model is significantly larger than that obtained for the RBC-AG for most countries, so we tend to select the former over alternative RBC models.

[27] Reliable annual data for 1900-1949 is not available for the remainder EM countries and DC data exhibit a sharp structural change in moments in the post-war period.

is unable to reproduce data facts for a longer period, 1900-2005.[28] To check this possibility, I re-estimate the baseline RBC model with quarterly data for the period used in AG, for 4 EM and 6 DC, for which quarterly national accounts are available for the whole period. I find that, in contrast to GPU, the main flaws of the baseline RBC model also hold for this shorter period.

Small Departure from the Frictionless RBC

This section analyzes the sensitivity of main results with respect to the degree of financial frictions. So far, in the baseline estimated RBC model I have calibrated the interest rate-debt elasticity to an extremely small value as in GPU just for the sake of inducing stationarity of the system. By contrast, in this section, I re-estimate the model under essentially the same estimation strategy but calibrating a larger elasticity equivalent to the one used in AG(2004) (henceforth RBC-AG). This stronger sensitivity of the interest rate represents a departure from the frictionless RBC paradigm but it is still a small value compared with estimates in the literature. Importantly, I find that after this only modification the estimated model fit improves substantially in many dimensions that are problematic in the frictionless RBC, in particular for trade balance facts. However, the model still struggles to reproduce the excess consumption volatility in the data.

Table 4 reports parameter estimates of the RBC-AG model both for EM and DC (median across countries).[29] At first sight, median parameter estimates are quite similar to those obtained for the baseline RBC model. However, note that there is an increase in the volatility of both shocks, especially for the permanent shock, and a slight increase in the persistence of the permanent shock.

Notably, the RBC-AG exhibits a much better data fit than the baseline RBC in many dimensions. Table 5 includes the second moments implied by the RBC-AG. In particular, the RBC-AG predicts a realistic volatility of *tby*, smaller than the volatility of output, as in the data, while

[28] For this, GPU provide GMM estimates for Mexico using the same data as AG for the period 1980-2003.

[29] See parameter estimates country by country in table C-6 in the appendix.

the baseline RBC implied a *tby* many times larger than its empirical counterpart. At the same time, as anticipated above, the RBC-AG generates a more realistic shape of the autocorrelation of *tby*, downward-sloping and closer to the upper limit of the confidence interval (see line with triangles, figure 1). This is explained by the larger sensitivity of the interest rate to indebtedness as discussed in the previous section. Even if this relatively small departure from the frictionless RBC represents a remarkable improvement with respect to the autocorrelation curve implied by the frictionless RBC, still the function lies outside the confidence bands for several lags and the fit is not as good as in the FF model.

The RBC-AG also make progress in other dimensions, as it implies more realistic negative correlations between the trade balance and output, consumption and investment. This is likely the consequence of more volatile and persistent PTS with respect to the baseline RBC estimations. Arguably, RBC-AG estimates end up in a more volatile permanent shock because it gives rise to a more realistic countercyclical trade balance without producing the side-effect of an extremely volatile *tby* that we observed in the presence of a smaller ψ. Unfortunately, the RBC-AG still overstates the correlation between output and consumption, reflecting once more the absence of demand shocks.

Despite the improvements enumerated above, the RBC-AG still generates a consumption that is counterfactually less volatile than output in EM (about 0.7% on average), which is explained as before by excessive output volatility and not by insufficiently volatile consumption (in general, implied consumption standard deviation is in fact larger than in the data).

It is worth highlighting that AG(2004) show that their estimated RBC model also does a reasonable job in explaining tby facts in the data, at least for its volatility and first order autocorrelation (they did not report higher order autocorrelations). Therefore, the fit improvement of the RBC-AG over the baseline RBC it does not come as a complete surprise. Precisely, one of the contributions of this chapter is to assess the RBC model performance for several countries and for a longer data span than AG implementing the mixed frequency Bayesian estimation.

Variance Decomposition

This section reports variance decomposition statistics of main aggregate variables, focusing on the contribution of the permanent technology shock in emerging markets. I compare EM results with DC in the spirit of AG. Also, I contrast the results with AG(2004) estimations and also with the predictions of the FF model of Chapter I.

Table 6-7 reports variance decompositions of the rate of growth of output, consumption and investment and the trade balance-to-output ratio implied by the baseline RBC estimates for EM and DC respectively country by country (at the annual frequency). Given that the RBC model is driven by just two shocks, I only report the contribution of the permanent shock (the share of the transitory shock is 100% minus the share of PTS). In turn, table 8 displays average variance decompositions (across countries) for EM and DC corresponding to the baseline RBC and also for the RBC-AG estimates respectively.

Table 6: RBC Variance Decomposition Emerging Markets

Variable	Arg	Bra	Chi	Col	Mex	Peru	Indo	Mal	Phil	Thai	Tur	S.Afr	**Mean**
Y	45.9	47.4	38.8	33.8	70.3	42.7	40.3	61.4	64.5	36.5	36.5	62.3	**48.4**
	(4.6)	(8.7)	(4.7)	(5.0)	(4.1)	(4.4)	(5.7)	(4.9)	(4.5)	(5.2)	(4.8)	(3.5)	**(5.0)**
C	59.7	68.6	57.7	56.8	87.4	60.1	64.7	79.5	74.3	59.0	46.2	82.8	**66.4**
	(4.5)	(9.4)	(4.7)	(5.4)	(2.3)	(4.3)	(5.5)	(3.3)	(3.7)	(5.4)	(5.6)	(2.1)	**(4.7)**
I	50.4	80.0	51.9	52.0	93.8	50.2	76.9	80.6	28.3	50.2	39.9	92.0	**62.2**
	(4.7)	(9.4)	(5.0)	(5.5)	(1.9)	(4.5)	(6.0)	(3.8)	(3.9)	(5.6)	(5.5)	(1.6)	**(4.8)**
TBY	31.1	80.6	53.1	77.4	93.9	45.2	70.2	44.8	99.5	46.0	29.6	93.0	**63.7**
	(4.6)	(8.5)	(6.0)	(3.9)	(1.6)	(5.1)	(5.6)	(12.0)	(0.2)	(5.8)	(5.7)	(1.4)	**(5.0)**

Notes: Table displays the contribution of the permanent technology shock to each variable variance. Each column displays posterior mean and standard deviation (between parenthesis) for a given country. The variables Y,C,I denote the rate of growth of output, consumption and investment and tby denotes the trade balance-to-gdp ratio. Posterior estimates based on 100,000 draws from the posterior distribution. Last column displays mean across countries. Countries from left to right: Argentina, Brazil, Chile, Colombia, Mexico, Peru, Indonesia, Malaysia, Philippines, Thailand, Turkey and South Africa.

Main estimates indicate that the permanent shock explains about 48% of output growth fluctuations in emerging markets. Thus, permanent and transitory technology shocks play a similar role in output movements. However, the permanent shock plays a predominant role for consumption and investment growth and for *tby*, accounting for 66%, 62% and 64% of their variance respectively. The relatively larger importance of the permanent shock for consumption and investment with respect to output is explained by the fact that demand variables strongly react to persistent shocks as discussed before.[30]

Interestingly, I find a considerable variation across countries in the role assigned to PTS (though dispersion is not as high as the one observed in Chapter I for the FF model). For example, the fraction of output variance explained by PTS goes from a minimum of 34% in Colombia to a maximum of 70% in Mexico. Interestingly, the standard errors of the PTS share of output variance are only 5% on average, which represents a sharp decrease from those obtained for the FF model (about 16%). This suggests that the relative importance of PTS and TTS is easier to identify in the RBC than in the FF model. Arguably, this is explained by the fact that in the RBC the permanent technology is the only shock able to generate excess volatility of consumption and countercyclicality of the trade balance, while in contrast, in the FF model other non-technology shocks are also able to reproduce those facts, making identification more challenging in the latter.

A comparison with the results of Chapter I for EM reveals that PTS present a more modest role in the FF than in the RBC. Specifically, the PTS share of output variance in EM decreases from almost 50% in the RBC to 35% in the FF model, which is explained by the presence of non-technology shocks in the FF model (not included in the RBC). An even larger decrease is observed in the contribution of PTS to consumption, investment and tby (falls around 44%, 49% and 60% respectively) in the FF model. These reductions are fully explained by the emerging share of non-technology shocks, as the transitory shock also exhibit a smaller importance. These results reveal that the predominance of PTS shocks to explain main EM in the RBC weakens considerably once

[30] For robustness, I also computed variance decompositions implied by the RBC-AG estimations, which yield very similar results both for EM and DC on average (see table 8). The only noticeable difference is that the RBC-AG implies a moderately higher contribution of PTS to tby, for both groups.

we include other demand shocks.

Emerging Markets versus Developed Countries Tables 6 and 7 indicate that the permanent shock is more relevant in EM than in DC for the period 1950-2010, explaining almost 50% and 30% of output variance in each group respectively. Strikingly, all six DC countries exhibit a PTS share of output variance smaller than the EM mean. In DC, as in EM, the permanent shock is more important for consumption and investment fluctuations than for output (see table 7).

Table 7: RBC Variance Decomposition Developed Countries

Variable	Australia	Belgium	Canada	Netherlands	Norway	Sweden	**Mean**
Y	47.4	11.7	29.8	25.9	27.1	35.2	**29.5**
	(4.3)	(2.2)	(3.0)	(3.8)	(4.2)	(4.1)	**(3.6)**
C	69.6	26.7	48.3	45.1	45.4	54.6	**48.3**
	(3.6)	(4.2)	(3.5)	(4.9)	(5.0)	(4.4)	**(4.3)**
I	60.1	62.7	40.0	32.3	26.5	47.2	**44.8**
	(4.3)	(6.3)	(3.4)	(4.3)	(3.9)	(4.5)	**(4.4)**
TBY	54.0	41.0	28.3	18.5	0.8	25.7	**28.1**
	(4.5)	(5.2)	(3.4)	(3.6)	(0.2)	(3.9)	**(3.5)**

Notes: Table displays the contribution of the permanent technology shock to each variable variance. Each column displays posterior mean and standard deviation (between parenthesis) for a given country. The variables Y,C,I denote the rate of growth of output, consumption and investment and tby denotes the trade balance-to-gdp ratio. Posterior estimates based on 100,000 draws from the posterior distribution. Last column displays mean across countries.

The larger importance of permanent shocks in EM is in line with the qualitative results of AG for the period 1980-2003 for Mexico and Canada. However, note that Mexico, the country used in AG as a representative EM, exhibits a larger role for PTS (70% of output variance) than the average EM (50%)[31]. This fact, together with the high variability of PTS shares across countries, highlights the need to analyze several countries to extract conclusions for EM as a whole, as argued

[31] In my estimates, Canada variance decomposition is similar to the average EM.

in Chapters I and II.

Table 8: Variance Decomposition (PTS share)

	EM countries		DC countries	
Variable	Baseline	RBC-AG	Baseline	RBC-AG
Y	48.4	49.9	29.5	29.4
	(5.0)	(5.0)	(3.6)	(3.5)
C	66.4	66.1	48.3	45.9
	(4.7)	(4.6)	(4.3)	(4.2)
I	62.2	61.5	44.8	43.3
	(4.8)	(4.7)	(4.4)	(4.5)
TBY	63.7	73.6	28.1	43.5
	(5.0)	(3.6)	(3.5)	(4.5)

Notes: Table displays the contribution of the permanent technology shock to each variable variance. Baseline and RBC-AG denote RBC baseline and AG interest rate-debt elasticity calibration. Each column displays average across countries of posterior mean and standard deviation (between parenthesis) respectively. The variables Y,C,I denote the rate of growth of output, consumption and investment and tby denotes the trade balance-to-gdp ratio. Posterior estimates based on 100,000 draws from the posterior distribution.

Comparison with AG(2004) To take the comparison with AG(2004) a step further, I re-estimate the model using a calibration strategy closer to AG(2004). For that, I calibrate $\theta = 1.4$ and $\delta = 0.03$ and $\bar{d} = 0.1$ quarterly and $\psi = 0.0363$ (annual) for all countries as in AG(2004) (henceforth "AG strategy", see table 1). Then, I re-estimate the model both using MF for 1950-2010 for all countries and quarterly data for 1980-2003 (the same period used in AG(2004)) for the countries with data available for that period. Tables 9 and 10 present corresponding variance decompositions (annual frequency) for Mexico and Canada respectively under alternative estimation strategies and periods.

Unfortunately, AG(2004) do not report variance decompositions of the estimated model which makes it difficult to compare. To overcome this problem, I compute the variance decomposition evaluating the RBC model at point parameter estimates taken from AG(2004) (GHH model).[32]

[32] Note, however, that I do not compute standard errors for this variance decomposition.

Note that the qualitative results about the larger role for PTS in Mexico (EM) than in Canada (DC) holds for both AG(2004) and my estimates. In particular, variance decompositions using AG(2004) parameter estimates for the period 1980-2003 show that the contribution of PTS to output in Mexico is as high as 95%, almost 2.5 times the share in Canada (39%).

Table 9: Mexico Variance Decomp. (PTS share, annual freq)

	MF 1950-2010		Quart 1980-2003		
Variable	Baseline	AG strategy	Baseline	AG strategy	**AG(2004)**
Y	70.3	68.3	68.0	56.5	**95.9**
	(4.1)	(4.5)	(9.3)	(8.6)	
C	87.4	84.6	84.1	68.0	**98.7**
	(2.3)	(2.9)	(9.0)	(9.5)	
I	93.8	90.6	87.4	55.0	**99.9**
	(1.9)	(2.9)	(13.0)	(18.2)	
TBY	93.9	91.8	91.9	95.0	**99.5**
	(1.6)	(1.4)	(5.3)	(3.0)	

Notes: Table displays the contribution of the permanent technology shock to each variable variance under the baseline and AG estimation strategies respectively. Last column displays the variance decomposition evaluating the RBC model (AG strategy) using point parameter estimates from AG(2004). Each column displays average across countries of posterior mean and standard deviation (between parenthesis) respectively. The variables Y,C,I denote the rate of growth of output, consumption and investment and tby denotes the trade balance-to-gdp ratio. Posterior estimates based on 100,000 draws from the posterior distribution.

However, there are important quantitative differences. In particular, AG(2004) estimates for Mexico imply than the PTS explains an overwhelming 95% of output variance, while my estimates never surpass 70%. As it is clear from table 9, this difference is not explained by the estimation period and calibration strategy, and it is likely to be the result of the different estimation techniques and strategies (I use Bayesian estimation, AG implement GMM estimation). The bigger role assigned to the permanent shock by AG(2004) is the consequence of larger estimates of its relative volatility σ_g/σ_a.As for Canada, also AG(2004) estimates imply a slightly larger role for PTS on output fluctuations than my estimates (see table 10), but the differences are smaller than for Mexico.

Table 10: Canada Variance Decomp. (PTS share, annual freq)

	MF 1950-2010		Quart 1980-2003		
Variable	Baseline	AG strategy	Baseline	AG strategy	**AG(2004)**
Y	29.8	30.5	27.4	27.7	**39.1**
	(3.0)	(3.0)	(4.2)	(4.3)	
C	48.3	46.3	45.4	41.5	**58.3**
	(3.5)	(3.5)	(5.3)	(5.1)	
I	40.0	40.0	36.7	37.4	**44.6**
	(3.4)	(3.4)	(5.1)	(5.0)	
TBY	28.3	48.3	26.9	57.0	**95.4**
	(3.4)	(3.9)	(5.3)	(5.8)	

Notes: Table displays the contribution of the permanent technology shock to each variable variance under the baseline and AG estimation strategies respectively. Last column displays the variance decomposition evaluating the RBC model (AG strategy) using point parameter estimates from AG(2004). Each column displays average across countries of posterior mean and standard deviation (between parenthesis) respectively. The variables Y,C,I denote the rate of growth of output, consumption and investment and tby denotes the trade balance-to-gdp ratio. Posterior estimates based on 100,000 draws from the posterior distribution.

3.4 Monte Carlo Experiment

In this section, I perform a Monte Carlo experiment to assess the small sample properties of the MF and quarterly data estimators following the same methodology of Chapter II.

I first simulate 200 samples of 61 years each of quarterly data using the RBC-AG model evaluated at the mean of parameter estimates for EM from previous section. I generate data for the eight observables used in MF estimation in previous section .Then, I add independent measurement errors of 5% of empirical variance for each series. Finally, I estimate the RBC-AG model both using baseline MF estimation with 61 years or quarterly data estimation with 20 years. I compare mean estimates across samples and RMSE (both for parameter and variance decompositions). Table 11 reports parameter estimates and true values of the DGP.

Table 11: MC Experiment MF vs Quart Estimation

		Posterior mean		RMSE		
Param	True	MF1	Quart	MF1	Quart	MF1-Q
φ	3.5	3.5	3.6	0.4	0.6	-34
ρ_a	0.83	0.83	0.84	0.03	0.05	-33
ρ_g	0.45	0.46	0.48	0.08	0.11	-31
σ_a	1.72	1.77	1.80	0.23	0.33	-32
σ_g	2.24	2.16	2.12	0.39	0.54	-28

Notes: Monte Carlo experiment estimations based on 200 samples, 1,000,000 MCMC draws each (first 500,000 are discarded). MF and Quart denote mixed frequency and quarterly data estimation respectively. MF1 estimation includes 60 years of annual observations. Both estimation strategies include 84 observations of quarterly series (21 years). Last column displays RMSE percentage change from quarterly to MF estimation.

I find that the MF estimation strategy presents large efficiency gains as RMSE for parameters fall across the board and 30% on average, and slight bias reductions. Note, however, that the bias both for MF and quarterly estimation are markedly smaller than those observed in Chapter II for the FF model. Similarly, RMSE for variance decompositions fall about 5 percentage points (out of 100%) from quarterly to MF estimation, though bias are moderate for both strategies compared to those obtained in Chapter II for the FF model.

Strikingly, RMSE for both technology shocks contributions to output fluctuations are roughly 60% smaller than those calculated in Chapter II (see table 12). These facts confirm that the technology shocks are better identified in the RBC than in the FF model, as discussed in previous section. Plausibly, this is explained by the fact that the permanent technology in the RBC is the only shock able to generate excess volatility of consumption and trade balance countercyclicality. Consequently, the permanent technology shock is more easily identified in the RBC than in the FF model in which it competes with other non-technology shocks that also generated these salient moments. To further explore this hypothesis, using the simulated data I analyzed which empirical moments are associated with the estimated importance of the PTS on output fluctuations across samples. In short, I find that the excess volatility of consumption and PTS share present a significantly positive correlation of almost 0.5, providing support to AG hypothesis that this moment is informative about the presence of PTS in EM. Recall, nonetheless, that I perform the same exercise in Chapter II obtaining the opposite results: in the FF model the sample excess volatility of consumption is not positively associated with PTS importance (on the contrary, the correlation is small and negative). Instead, the excess volatility is in fact positively associated with non-technology shocks. These competing shocks make it harder to identify PTS in the FF model, and, thus, extending the data span is vital to precisely estimate the relative importance of technology shocks in that model.

Table 12: MCE Var Decomp PTS shock

		Posterior mean		RMSE		
Variable	True	MF1	Quart	MF1	Quart	MF1-Q
Y	48.0	46.3	45.5	9.6	13.7	-4
C	68.2	66.0	64.2	9.6	14.7	-5
I	73.7	71.5	69.2	10.6	16.4	-6
TBY	73.7	72.0	70.3	8.3	12.9	-5

Notes: Table displays share of PTS shock to aggregate fluctuations (annual frequency). Monte Carlo experiment estimations based on 200 samples, 1,000,000 MCMC draws each (first 500,000 are discarded). MF and Quart denote mixed frequency and quarterly data estimation respectively. MF1 estimation includes 60 years of annual observations. Both estimation strategies include 84 observations of quarterly series (21 years). Last column displays RMSE absolute difference from quarterly to MF estimation.

3.5 Conclusions

In this chapter, I analyze the ability of the real business cycle (RBC) paradigm to account for salient business cycle facts in emerging markets. For that purpose, I estimate an standard small open economy RBC model with permanent and transitory technology shocks, proposed in AG(2004) and GPU(2010), for twelve emerging markets for the period 1950-2010, using the Bayesian mixed frequency technique proposed in Chapter I.

One of the paper main findings is that the different calibration of the debt-elasticity of the interest rate in AG and GPU goes a long way in explaining the fairly different results about the RBC performance in these two papers.

First, I estimate the RBC model calibrating a extremely small debt-elasticity equivalent to GPU, which they considered a "frictionless" RBC. Notably, I find that the shortcomings of the RBC documented in GPU for Argentina and Mexico also hold for all countries in my sample and for different estimation periods. Specifically, the estimated RBC model counterfactually predicts a very persistent and volatile *tby* and it does not generate enough volatility of consumption relative to output as in the data

Second, I analyze the robustness of the failures of the RBC to relatively small departures from the frictionless RBC paradigm. More precisely, I re-estimate the RBC model calibrating a larger debt-elasticity of the interest rate equivalent to that used in AG(2004), much higher than in GPU, but still small compared to empirical estimates. Interestingly, I find that after this unique modification the RBC-AG model exhibits a remarkable improvement in fitting the data for most EM. In particular, the model implies more realistic tby dynamics including a volatility similar to that of output and an autocorrelation function downward-sloping and much closer to the data. Still, the RBC-AG model is unable to generate the observed excess volatility of consumption, because it overpredicts the volatility of output.

Despite the improvements of the RBC-AG compared to the baseline RBC, its performance is not as good as that of the financial frictions model of Chapter I, in which the debt-elasticity of the interest rate is actually estimated. In this regard, the behavior of consumption relative to output in the data (the excess volatility and a correlation quite smaller than one) suggests that demand shocks are a plausible source of fluctuations. This fact is likely to account for the success of the FF model, which includes preference, spending and interest rate shocks, unlike the RBC model, which is uniquely driven by technology shocks.

Finally, I use artificial data to show that the mixed frequency strategy delivers large efficiency gains (fall in RMSE) with respect to estimations with short quarterly series. However, the efficiency gains are not as large as those obtained in Chapter II, mainly because quarterly estimation biases and, in particular, regarding variance decompositions, are much smaller than in the FF model This is explained by the fact that the permanent technology in the RBC is the only shock able to generate excess volatility of consumption and trade balance countercyclicality. Consequently, this shock is more easily identified in the RBC than in the FF model, in which it competes with other non-technology shocks that also generate these salient moments.

For future research, I plan to directly estimate the degree of financial frictions within the RBC model, so as to see how far it goes in fitting the data in EM. Then, in light of the improvement of the RBC fit after relaxing the interest rate-debt elasticity, it would be interesting to explore whether a variant of the RBC, uniquely driven by the two technology shocks, is able to get even closer to the data, especially to explain the observed consumption facts.ether the MF estimator is indeed more efficient that alternative strategies.

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Appendix A

Appendix

A.1 Appendix for Chapter I

A.1.1 Model

Household problem optimality conditions:

$$\theta X_{t-1} h_t^{\omega} = (1-\alpha) Y_t$$

$$\Lambda_t = \beta (1+r_t) E_t \Lambda_{t+1}$$

$$\Lambda_t \left[1 + \phi \left(\frac{K_{t+1}}{K_t} - g \right) \right] = \beta E_t \Lambda_{t+1} \left[\alpha \frac{Y_{t+1}}{K_{t+1}} + 1 - \delta + \phi \left(\frac{K_{t+2}}{K_{t+1}} - g \right) \frac{K_{t+2}}{K_{t+1}} - \frac{\phi}{2} \left(\frac{K_{t+2}}{K_{t+1}} - g \right)^2 \right]$$

where Γ_t is the Lagrange multiplier of the budget constraint given by:

$$\Lambda_t = \nu_t \left(C_t - \theta \omega^{-1} X_{t-1} h_t^{\omega} \right)^{-\gamma}.$$

Equilibrium Equations with Stationary Variables

Let me define stationary variables $y_t \equiv Y_t/X_{t-1}$, $c_t \equiv C_t/X_{t-1}$, $i_t \equiv I_t/X_{t-1}$, $k_t \equiv K_t/X_{t-1}$, $d_t \equiv D_t/X_{t-1}$ and $\lambda_t \equiv \Lambda_t/X_{t-1}^{-\gamma}$. A stationary competitive equlibrium is characterized by the following equations:

$$\theta h_t^{\omega-1} = (1-\alpha) \frac{y_t}{h_t}$$

$$\lambda_t = \beta (1+r_t) g_t^{-\gamma} E_t \lambda_{t+1}$$

$$\lambda_t\left[1+\phi\left(\frac{k_{t+1}}{k_t}g_t-g\right)\right] = \beta g_t^{-\gamma}E_t\lambda_{t+1}\left[\alpha\frac{y_{t+1}}{k_{t+1}}+1-\delta+\phi\left(\frac{k_{t+2}}{k_{t+1}}g_{t+1}-g\right)\frac{k_{t+2}}{k_{t+1}}g_{t+1}-... \right.$$
$$\left.\frac{\phi}{2}\left(\frac{k_{t+2}}{k_{t+1}}g_{t+1}-g\right)^2\right]$$

$$\frac{d_{t+1}}{1+r_t}g_t+y_t=d_t+i_t+c_t+\frac{\phi}{2}\left(\frac{k_{t+1}}{k_t}g_t-g\right)^2k_t+s_t$$

$$i_t=k_{t+1}g_t-(1-\delta)\,k_t$$

$$y_t=a_tk_t^{\alpha}h_t^{1-\alpha}g_t^{1-\alpha}$$

$$r_t=r^*+\psi\left[\exp\left(\frac{\bar{d}_{t+1}}{\bar{y}}-\bar{d}\right)\right]+\exp\left(\mu_t-1\right)-1$$

together with the 5 law of motions of shocks described in the main text.

A.1.2 Estimation

Mixed Frequency Data State-Space Representation

First, let me define the model counterpart of observed variables at quarterly frequency as follows:

$$Z_t^Q\equiv\left[\Delta y_t,\ \Delta c_t,\Delta i_t,tby_t\right]',$$

where Δy_t, Δc_t and Δi_t denote the quarterly rate of growth of output, consumption and investment (expressed in log-differences) respectively and tby_t indicates the quarterly trade balance to output ratio. For a given vector of structural parameters, I solve the model numerically up to a first order approximation for quarterly and cast it in state-space form as follows:

$$Z_t^Q=\hat{G}\hat{X}_t,$$

$$\hat{X}_{t+1}=\hat{H}\hat{X}_t+\hat{\varepsilon}_{t+1},$$

where X_t is a state vector (comprised of 5 exogenous shocks and 3 endogenous state variables), ε_{t+1} is a vector of innovations, and $\hat{G}$ and $\hat{H}$ are matrices, which entries are highly nonlinear functions of the structural parameters. Now, let me define $\tilde{Z}_t^A$, the annual counterpart of Z_t^Q as follows:

$$\tilde{Z}_t^A\equiv\left[\Delta\tilde{y}_t^A,\Delta\tilde{c}_t^A,\Delta\tilde{i}_t^A,\tilde{t}by_t^A\right],$$

where $\Delta\tilde{y}_t^A$, $\Delta\tilde{c}_t^A$, $\Delta\tilde{\imath}_t^A$ are the annual rate of growth of output, consumption and investment in log-differences and $\tilde{tby}_t$ denotes the annual trade balance-to-gdp ratio. More precisely, in the model the annual rate of growth in log-differences can be written as a function of quarterly variables as follows:

$$\Delta\tilde{w}_t^A \equiv \log\left(\frac{w_t + w_{t-1} + w_{t-2} + w_{t-3}}{w_{t-4} + w_{t-5} + w_{t-6} + w_{t-7}}\right), \text{ for } w = y, c, i.$$

Similarly, the variable $\tilde{tby}_t^A$ is defined as follows:

$$\tilde{tby}_t^A \equiv \frac{tb_t + tb_{t-1} + tb_{t-2} + tb_{t-3}}{y_t + y_{t-1} + y_{t-2} + y_{t-3}},$$

where tb_t denotes the trade balance at quarterly frequency. However, note that these annualized variables are non-linear functions of quarterly variables and, thus, we need to take a first order approximation to obtain a linear state-space representation to accomodate both frequencies. For convenience, I find a first order approximation of the annual variables as a function only of their quarterly counterparts (current values and lags). This approach allows us to keep the size of the state vector needed to characterize the dynamics of annual data as small as possible, and consequently, to minimize computing time. On the one hand, variables in log differences can be approximated around steady state as follows (setting $g = 1$):

$$\Delta\tilde{w}_t^A \simeq \left(1 + 2L + 3L^2 + 4L^3 - 3L^4 - 2L^5 - L^6\right)\frac{\Delta w_t}{4} \equiv \Delta w_t^A,$$

for $w = y, c$, and i, where L denotes the lag operator. I obtain this approximation as follows: first, I write $\Delta\tilde{w}_t^A$ in log-deviations from w_{t-7}; second, I differentiate $\Delta\tilde{w}_t^A$ with respect to each argument from the vector $\{\Delta w_t, ...\Delta w_{t-6}\}$. Finally, in the resulting expression I set $g = 1$, obtaining the expression given above for Δw_t^A.

On the other hand, the annual trade balance-to-gdp ratio is approximated as follows:

$$\tilde{tby}_t \simeq \frac{(tby_t + tby_{t-1} + tby_{t-2} + tby_{t-3})}{4} \equiv tby_t^A$$

This approximation is derived in a similiar way as for Δw_t^A. These approximations are valid for values of g close to one, which is true in our sample. Now, let Z_t denote the vector that collects series both at quarterly and annual frequency as follows:

$$Z_t \equiv \left[Z_t^{Q'}, Z_t^{A\prime} \right]',$$

with $Z_t^{A\prime} = \left[\Delta y_t^A, \Delta c_t^A, \Delta i_t^A, tby_t^A \right]$. Finally, combining previous steps we obtain a state-space representation for both variables at quarterly and annual frequencies as follows:

$$Z_t = GX_t,$$

$$X_{t+1} = HX_t + \varepsilon_{t+1},$$

where G and H are companion matrices to $\hat{G}$ and $\hat{H}$ presented below. The state vector X_t for the mixed frequency representation is given by:

$$X_t \equiv \begin{pmatrix} \hat{X}_t \\ \Delta w_{t-1} \\ \Delta w_{t-2} \\ \vdots \\ \Delta w_{t-6} \\ tby_{t-1} \\ tby_{t-2} \\ tby_{t-3} \end{pmatrix},$$

with $\Delta w_t \equiv [\Delta y_t,\ \Delta c_t, \Delta i_t]'$. Then, transition matrix H is given by:

$$H = \begin{pmatrix} \hat{H} & O & O & O \\ G_\Delta & O & O & O \\ O & I_9 & O & O \\ G_{tby} & O & O & O \\ O & O & I_3 & O \end{pmatrix},$$

where matrix G_Δ is given by the first 3 rows of $\hat{G}$, matrix G_{tby} is given by the last row of $\hat{G}$ and

I_N is an identity matrix of dimension N. In turn, matrix G is given by:

$$G = \begin{pmatrix} \hat{G} & O & O \\ \frac{G_{\Delta}}{4} & \frac{A}{4} & O \\ \frac{G_{tby}}{4} & O & \frac{B}{4} \end{pmatrix},$$

where $B = [1, 1, 1]$; and A is a 3x18 matrix given by:

$$A = [2I_3 \; 3I_3 \; 4I_3 \; 3I_3 \; 2I_3 \; I_3].$$

Kalman Filter for Missing Observations

Here, I describe the Kalman filter and likelihood evaluation adapted to missing observations following Aruoba et.al. (2009). The model variables Z_t are potentially observed in the data with measurement error:

$$\bar{Z}_t = Z_t + u_t, \quad u_t \sim N(0, Q),$$

where u_t is a vector of measurement errors serially uncorrelated. Thus, the model state-space form including all N variables potentially observed is given by:

$$\bar{Z}_t = GX_t + u_t,$$

$$X_{t+1} = HX_t + \varepsilon_{t+1}, \quad \varepsilon_{t+1} \sim N(0, R)$$

However, at period t we generally observe a subset Z_t^* of Z_t with N_t^* elements ($0 \leq N_t^* \leq N$). For a period t presenting at least one observation ($N_t^* > 0$), we can re-write the measurement equation adjusted to missing observations as follows:

$$Z_t^* = G_t^* X_t + u_t^*, \quad u_t^* \sim N(0, Q_t^*),$$

where G_t^* and u_t^* are obtained after removing the rows of G and u_t corresponding to missing values at time t.

Now, let $\mathcal{Z}^t \equiv \{Z_1^*, Z_2^*, ..., Z_t^*\}$, $a_{t|t} \equiv E\left(X_t \mid \mathcal{Z}^t\right)$, $P_{t|t} \equiv V\left(X_t \mid \mathcal{Z}^t\right)$, $a_t \equiv E\left(X_t \mid \mathcal{Z}^{t-1}\right)$ and $P_t \equiv V\left(X_t \mid \mathcal{Z}^{t-1}\right)$. As usual, the Kalman filter is initialized using the unconditional mean and variance of the state vector The prediction equations are exactly the same as in the standard Kalman filter:

$$a_{t+1} = Ha_{t|t}$$

$$P_{t+1} = HP_{t|t}H' + R.$$

In turn, the updating equations adapted to missing values are given by:

$$a_{t|t} = \begin{cases} a_t + P_t G_t^* F_t^{-1} v_t^* & \text{if } N_t^* > 0 \\ a_t & \text{if } N_t^* = 0 \end{cases}$$

$$P_{t|t} = \begin{cases} P_t - P_t G_t^* F_t^{-1} P_t' G_t'^* & \text{if } N_t^* > 0 \\ P_t & \text{if } N_t^* = 0 \end{cases}$$

where $F_t = G_t^* P_t G_t'^* + Q_t^*$ and $v_t^* = Z_t^* - G_t^* a_t$. These equations reflect the fact that the set of elements of $\bar{Z}_t$ observed is time varying (including the case when $N_t^* = 0$).

Finally, the log-likelihood of the data given a vector of structural parameters is given by:

$$\log L = -\frac{1}{2}\sum_{t=1}^{T} l_t,$$

where T denotes the sample size and l_t is given by:

$$l_t = \begin{cases} N_t^* \log 2\pi + \log |F_t| + v_t'^* F_t^{-1} v_t^* & \text{if } N_t^* > 0 \\ 0 & \text{if } N_t^* = 0 \end{cases}$$

If all elements of $\bar{Z}_t$ are missing, the contribution of period t to the likelihood is zero.

Data

Variables are expressed in per capita terms using UN population database (available only at annual frequency). To obtain quarterly series in per capita terms I first linearly intrapolate annual population observations. All quarterly series used in the estimation are seasonally adjusted. When original time series are available both non-seasonally and seasonally adjusted, I use the non-seasonally adjusted series and then filtered it with X-12 Arima from Census Bureau. For the sake of data quality, I only include economies with at least 4 million inhabitants in 2009. Table A1 displays the first quarterly observation available for each country and variable.

Emerging Markets Data Annual national accounts data for EM comes mainly from Penn World Tables 7 (PWT). When data is not available from PWT, time series are from Barro-Ursua (2008) or Oxford Latin-America Historical Database (the latter is just available for Latin-American countries). Annual observation for 2010 is from World Bank WDI. In turn, EM quarterly data is obtained from national sources.[1] Argentina quarterly series for the period 1980Q1-1992Q4 are from Neumeyer and Perri (2006). For the sake of comparison, annual data for Argentina and Mexico before 2005 is from GPU.

Developed Countries Data When available, DC annual national accounts data is from OCDE stat online database. For early periods, I complement OCDE data with PWT (using multiple series splice ratio methodology). In turn, quarterly time series are mainly from OCDE stats online (for some countries I extend the sample backwards with discontinued series from OCDE but downloaded through Datastream).

[1] All EM quarterly data was retrieved from Datastream. In some cases I constructed a longer series using multiple series through multiple splice ratio methodololgy.

Table A1: First Observation by Country (Quarterly Data)

	Y	C	I	TBY
Emerging Markets				
Argentina	1980Q2	1980Q2	1980Q2	1980Q1
Brazil	1990Q2	1991Q2	1991Q2	1993Q1
Chile	1980Q2	1996Q2	1990Q2	1996Q1
Colombia	1994Q2	1994Q2	1994Q2	1994Q1
Mexico	1980Q2	1980Q2	1980Q2	1981Q2
Peru	1979Q2	1979Q2	1979Q2	1979Q1
Indonesia	1997Q2	2000Q2	1997Q2	1990Q1
Malaysia	1988Q2	1991Q2	1991Q2	1991Q1
Philippines	1981Q2	1981Q2	1981Q2	1981Q1
Thailand	1993Q2	1993Q2	1993Q2	1993Q1
Turkey	1987Q2	1987Q2	1987Q2	1987Q1
South Africa	1960Q2	1960Q2	1960Q2	1960Q1
Developed Countries				
Australia	1959Q4	1959Q4	1959Q4	1959Q3
Belgium	1980Q2	1980Q2	1980Q2	1980Q1
Canada	1955Q2	1955Q2	1955Q2	1955Q1
Netherlands	1977Q2	1977Q2	1977Q2	1977Q1
Norway	1978Q2	1978Q2	1978Q2	1978Q1
Sweden	1980Q2	1980Q2	1980Q2	1980Q1

Estimation Results

Table A2: Measurement Errors and Likelihood Emerging Markets

Variable	Arg	Bra	Chi	Col	Mex	Peru	Indo	Mal	Phil	Thai	Tur	S.Afr	**Median**
Y_Q	0.2	5.5	3.6	4.5	5.8	2.1	5.1	3.2	6.0	4.0	3.5	6.1	4.2
C_Q	2.2	2.1	3.5	3.8	5.1	4.8	3.1	4.4	4.4	4.1	0.9	5.9	3.9
I_Q	1.9	4.3	3.7	4.4	5.9	4.1	5.7	5.3	5.2	5.7	5.6	6.1	5.3
TBY_Q	5.5	5.7	5.8	5.7	6.0	2.5	4.4	5.7	5.2	6.0	6.1	3.4	5.7
Y_A	0.5	5.3	3.1	5.0	5.7	1.5	5.6	3.8	6.2	5.7	0.6	6.2	5.2
C_A	4.1	4.0	5.8	5.3	4.7	5.0	5.3	5.5	1.9	0.5	0.3	6.1	4.8
I_A	1.2	5.6	5.7	5.3	6.0	6.0	6.1	5.9	5.0	6.0	6.0	6.2	5.9
TBY_A	6.1	5.7	6.1	6.2	6.2	5.9	6.1	6.1	5.6	6.2	6.2	0.3	6.1
Like	1791.0	1277.4	1074.3	1237.0	1785.0	1496.8	868.2	1040.7	1534.8	996.3	1266.4	2510.6	

Notes: Baseline estimation results. Each column displays measurement error estimates (posterior median) for each country and log-marginal likelihood. Measurement errors are expressed as a fraction of the sample variance of the corresponding variable. Subscript Q and A denote quarterly and annual data respectively. Log-marginal likelihood (Like) is calculated using Geweke's modified harmonic mean methodology with truncation parameter 0.1.

Table A3: Measurement Errors and Likelihood Developed Countries

Variable	Australia	Belgium	Canada	Netherl.	Norway	Sweden	**Median**
Y_Q	0.0	5.5	1.7	1.6	5.9	4.9	3.3
C_Q	0.2	5.7	3.9	5.9	3.7	4.8	4.4
I_Q	0.5	5.2	5.4	1.8	4.4	2.5	3.5
TBY_Q	0.2	6.0	0.2	5.7	5.6	5.6	5.6
Y_A	0.0	6.1	0.9	5.8	5.8	4.4	5.1
C_A	0.0	6.0	5.7	5.2	1.9	0.5	3.5
I_A	0.0	4.1	6.1	0.5	5.9	2.5	3.3
TBY_A	0.0	6.0	0.1	6.1	6.2	6.2	6.1
Like	3555.9	2132.0	3712.6	2094.7	1706.7	2087.4	

Notes: Baseline estimation results. Each column displays measurement error estimates (posterior median) for each country and log-marginal likelihood. Measurement errors are expressed as a fraction of the sample variance of the corresponding variable. Subscript Q and A denote quarterly and annual data respectively. Log-marginal likelihood (Like) is calculated using Geweke's modified harmonic mean methodology with truncation parameter 0.1.

Second Moments

Table A4: Second Moments EM Latin-America (annual frequency)

	Argentina		Brazil		Chile		Colombia		Mexico		Peru		**Median**	
	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model
Std deviation %														
- Y	5.1	4.8	3.7	3.5	4.9	4.5	2.4	2.4	3.5	2.9	5.5	6.2	3.7	3.5
- C	6.4	5.4	4.9	4.4	7.5	6.2	2.7	2.5	3.9	3.3	6.3	7.2	4.9	4.4
- I	16.3	11.6	11.5	9.1	24.3	15.3	12.5	8.8	10.7	7.1	20.2	13.1	12.5	9.1
- TBY	3.1	4.2	1.9	2.0	4.2	4.7	2.7	2.1	3.3	3.2	4.7	4.0	3.1	3.2
Correlation w/Y														
- C	0.90	0.91	0.77	0.86	0.67	0.75	0.86	0.83	0.88	0.84	0.72	0.83	0.77	0.83
- I	0.86	0.74	0.63	0.55	0.71	0.50	0.78	0.50	0.83	0.71	0.70	0.58	0.71	0.55
- TBY	-0.13	-0.14	-0.31	-0.07	0.10	-0.07	-0.02	-0.20	-0.46	-0.20	0.09	0.03	-0.02	-0.07
Correlation w/TBY														
- C	-0.15	-0.20	-0.24	-0.20	0.03	-0.19	-0.06	-0.21	-0.47	-0.15	0.04	-0.02	-0.06	-0.19
- I	-0.26	-0.17	-0.18	0.07	0.04	0.07	-0.12	-0.43	-0.43	-0.26	0.01	0.07	-0.12	0.00
Autrocorrelation														
- Y	0.16	0.32	0.36	0.28	0.13	0.37	0.30	0.26	0.27	0.37	0.40	0.48	0.27	0.32
- C	0.14	0.29	-0.02	0.19	0.12	0.30	0.06	0.23	0.28	0.27	0.38	0.38	0.12	0.27
- I	0.05	0.10	0.03	0.12	-0.19	0.17	0.17	-0.03	0.11	0.09	0.13	0.22	0.05	0.10
- TBY	0.62	0.88	0.82	0.50	0.70	0.84	0.70	0.60	0.78	0.86	0.64	0.70	0.70	0.70

Notes: Model implied moments based on 500,000 draws from posterior distribution (posterior median). Empirical moments calculated for the period 1950-2010. Variables Y, C and I denote rate of growth of output, consumption and investment. TBY denotes trade balance to output ratio.

Table A5: Second Moments EM Asia and Africa (annual frequency)

	Indonesia		Malaysia		Philippines		Thailand		Turkey		S. Africa		**Median**	
	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model
Std deviation %														
- Y	4.5	4.4	4.3	4.4	4.4	3.5	5.1	4.9	5.2	5.3	2.5	2.3	4.4	4.4
- C	4.5	5.7	5.7	6.4	2.6	4.0	4.6	5.4	6.4	6.2	3.0	3.3	4.5	5.4
- I	13.6	11.1	15.8	13.2	12.5	11.3	15.2	10.6	17.2	13.2	13.3	6.8	13.6	11.1
- TBY	4.1	5.8	8.6	14.5	3.2	3.1	5.1	3.8	2.0	2.0	3.6	4.9	3.6	3.8
Correlation w/Y														
- C	0.46	0.80	0.65	0.75	0.24	0.75	0.82	0.86	0.87	0.87	0.75	0.74	0.65	0.75
- I	0.81	0.60	0.70	0.45	0.60	0.38	0.58	0.55	0.48	0.56	0.50	0.47	0.58	0.47
- TBY	-0.23	-0.12	-0.26	-0.15	0.16	0.04	-0.34	-0.17	-0.23	0.00	-0.08	-0.27	-0.23	-0.12
Correlation w/TBY														
- C	0.05	-0.11	-0.01	-0.12	-0.12	-0.04	-0.36	-0.25	-0.26	-0.14	-0.27	-0.27	-0.12	-0.12
- I	-0.31	0.07	-0.33	-0.17	-0.09	-0.09	-0.44	-0.36	-0.23	0.01	-0.25	-0.17	-0.25	-0.09
Autrocorrelation														
- Y	0.23	0.42	0.16	0.40	0.03	0.46	0.26	0.42	-0.07	0.29	0.34	0.55	0.16	0.42
- C	0.26	0.33	0.24	0.28	0.54	0.36	0.16	0.33	-0.11	0.24	0.29	0.37	0.24	0.33
- I	0.21	0.20	0.09	0.08	0.21	0.10	0.14	0.13	-0.17	0.16	0.02	0.21	0.09	0.13
- TBY	0.69	0.87	0.84	0.95	0.60	0.57	0.77	0.62	0.50	0.45	0.64	0.85	0.64	0.62

Notes: Model implied moments based on 500,000 draws from posterior distribution (posterior median). Empirical moments calculated for the period 1950-2010. Variables Y, C and I denote rate of growth of output, consumption and investment. TBY denotes trade balance to output ratio.

Table A6: Second Moments Developed Countries (annual frequency)

	Australia		Belgium		Canada		Netherlands		Norway		Sweden		**Median**	
	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model
Std deviation %														
- Y	2.3	3.2	1.9	1.8	2.3	2.1	2.5	2.9	1.8	3.6	2.2	2.0	2.2	2.1
- C	2.4	3.4	1.9	2.3	1.9	2.6	2.6	3.8	2.3	4.8	2.3	2.9	2.3	2.9
- I	9.9	6.0	6.4	5.0	7.3	4.6	9.0	8.0	7.3	9.4	6.2	4.4	7.3	5.0
- TBY	2.1	1.6	2.1	2.5	2.0	1.7	2.9	4.1	6.9	9.6	3.0	3.3	2.1	2.5
Correlation w/Y														
- C	0.77	0.87	0.60	0.74	0.67	0.80	0.78	0.80	0.52	0.79	0.71	0.75	0.67	0.79
- I	0.78	0.58	0.67	0.50	0.75	0.57	0.78	0.60	0.39	0.45	0.74	0.57	0.74	0.57
- TBY	-0.19	-0.09	-0.20	-0.12	0.14	-0.20	-0.25	-0.21	-0.43	-0.11	-0.02	0.02	-0.19	-0.11
Correlation w/TBY														
- C	-0.20	-0.09	-0.14	-0.08	0.06	-0.16	-0.36	-0.24	-0.04	-0.08	0.03	-0.01	-0.04	-0.08
- I	-0.50	-0.30	-0.08	-0.04	0.04	-0.05	-0.24	-0.11	-0.17	-0.18	0.05	0.04	-0.08	-0.05
Autrocorrelation														
- Y	0.06	0.47	0.30	0.47	0.28	0.52	0.24	0.49	0.50	0.36	0.32	0.22	0.28	0.47
- C	-0.04	0.38	0.26	0.38	0.20	0.38	0.42	0.42	0.12	0.26	0.16	0.26	0.16	0.38
- I	-0.26	0.13	0.00	0.14	0.00	0.19	0.11	0.12	0.28	-0.03	0.28	0.17	0.00	0.13
- TBY	-0.16	0.46	0.84	0.82	0.81	0.78	0.79	0.89	0.88	0.90	0.93	0.90	0.81	0.82

Notes: Model implied moments based on 500,000 draws from posterior distribution (posterior median). Empirical moments calculated for the period 1950-2010. Variables Y, C and I denote rate of growth of output, consumption and investment. TBY denotes trade balance to output ratio.

Variance Decomposition

Table A7: Variance Decomposition EM Latin-America (annual frequency)

	Argentina		Brazil		Chile		Colombia		Mexico		Peru		Average	
Output growth														
- Transitory Tech	76.5	(10.2)	62.0	(20.5)	57.8	(20.4)	82.3	(5.7)	41.7	(34.8)	12.8	(21.0)	**55.5**	**(18.8)**
- Permanent Tech	17.8	(10.3)	35.6	(20.5)	20.8	(20.4)	3.2	(5.0)	52.8	(35.4)	71.3	(22.7)	**33.6**	**(19.0)**
- Preference	3.3	(1.4)	1.7	(1.3)	17.2	(6.6)	3.8	(2.7)	0.4	(0.4)	11.6	(3.1)	**6.3**	**(2.5)**
- Spending	0.0	(0.0)	0.1	(0.1)	1.2	(0.5)	1.3	(0.5)	0.5	(0.4)	1.6	(0.6)	**0.8**	**(0.3)**
- Interest rate	2.5	(0.5)	0.6	(0.2)	3.0	(0.8)	9.4	(2.0)	4.6	(1.2)	2.7	(0.6)	**3.8**	**(0.9)**
Consumption growth														
- Transitory Tech	64.5	(8.2)	50.4	(14.2)	28.5	(10.2)	57.6	(6.4)	28.5	(25.5)	8.7	(14.4)	**39.7**	**(13.2)**
- Permanent Tech	12.5	(7.6)	20.0	(13.4)	9.7	(10.0)	2.3	(3.7)	39.3	(26.2)	46.7	(16.0)	**21.8**	**(12.8)**
- Preference	20.9	(3.3)	25.4	(4.5)	55.9	(5.7)	29.3	(4.8)	17.0	(3.6)	36.2	(5.0)	**30.8**	**(4.5)**
- Spending	0.0	(0.1)	1.4	(0.8)	4.0	(1.9)	6.1	(2.4)	12.4	(4.7)	6.5	(2.9)	**5.1**	**(2.1)**
- Interest rate	1.9	(0.4)	2.7	(1.4)	2.0	(0.5)	4.6	(1.2)	2.9	(1.0)	1.9	(0.4)	**2.7**	**(0.8)**
Investment growth														
- Transitory Tech	46.7	(7.7)	20.3	(8.9)	16.4	(7.2)	27.5	(5.5)	23.5	(21.2)	4.6	(7.7)	**23.2**	**(9.7)**
- Permanent Tech	13.1	(7.7)	12.7	(7.9)	7.8	(7.8)	0.6	(1.1)	35.4	(24.5)	23.8	(9.4)	**15.6**	**(9.7)**
- Preference	8.2	(2.8)	31.0	(10.8)	36.1	(8.1)	6.2	(3.0)	1.1	(0.9)	27.1	(5.4)	**18.3**	**(5.2)**
- Spending	0.0	(0.1)	6.0	(2.4)	6.2	(1.9)	2.7	(1.3)	1.2	(0.9)	8.9	(2.2)	**4.2**	**(1.4)**
- Interest rate	31.9	(4.2)	30.0	(6.0)	33.4	(5.9)	62.9	(5.4)	38.7	(6.5)	35.6	(4.1)	**38.8**	**(5.3)**
Trade balance (%gdp)														
- Transitory Tech	12.2	(5.1)	2.0	(1.4)	1.9	(1.2)	4.3	(2.3)	8.0	(8.4)	0.6	(0.7)	**4.8**	**(3.2)**
- Permanent Tech	5.3	(3.7)	3.7	(2.5)	2.6	(2.9)	0.2	(0.6)	16.2	(12.0)	3.0	(2.0)	**5.2**	**(3.9)**
- Preference	51.6	(14.8)	20.2	(5.2)	55.0	(16.4)	8.2	(4.9)	14.5	(9.0)	27.7	(9.2)	**29.5**	**(9.9)**
- Spending	0.2	(0.3)	19.7	(4.1)	6.2	(2.6)	3.6	(1.8)	24.8	(10.5)	16.3	(3.6)	**11.8**	**(3.8)**
- Interest rate	30.7	(11.7)	54.4	(7.8)	34.3	(14.1)	83.7	(7.1)	36.6	(17.3)	52.4	(10.7)	**48.7**	**(11.4)**

Notes: Estimations based on 500,000 draws from posterior distribution. Variance decomposition at annual frequency (does not include measurement errors). For each country, first and second columns display posterior mean and standard deviation (between parenthesis) respectively. Last two columns display average mean and average standard deviation across countries respectively. Values are expressed in percentage points.

Table A8: Variance Decomposition EM Asia and Africa (annual frequency)

	Indonesia		Malaysia		Philippines		Thailand		Turkey		S. Africa		Average	
Output growth														
- Transitory Tech	27.6	(21.2)	53.9	(15.4)	33.3	(12.6)	34.5	(19.4)	88.3	(5.2)	5.2	(6.7)	**40.5**	**(13.4)**
- Permanent Tech	50.8	(21.3)	15.7	(17.6)	40.8	(12.9)	35.1	(21.1)	2.6	(3.9)	69.4	(8.2)	**35.7**	**(14.1)**
- Preference	13.9	(5.0)	0.1	(0.2)	18.4	(4.4)	12.1	(4.0)	8.3	(3.6)	10.7	(4.3)	**10.6**	**(3.6)**
- Spending	4.0	(1.3)	0.2	(0.3)	1.3	(0.5)	1.2	(0.7)	0.2	(0.1)	1.0	(0.4)	**1.3**	**(0.6)**
- Interest rate	3.8	(1.1)	30.1	(5.6)	6.3	(1.3)	17.1	(3.6)	0.7	(0.2)	13.7	(2.5)	**11.9**	**(2.4)**
Consumption growth														
- Transitory Tech	14.1	(12.1)	28.4	(9.3)	14.3	(6.1)	25.7	(14.9)	66.6	(5.4)	2.0	(3.0)	**25.2**	**(8.5)**
- Permanent Tech	31.7	(13.5)	9.8	(11.4)	26.7	(7.9)	28.2	(17.1)	1.6	(2.6)	36.3	(5.5)	**22.4**	**(9.7)**
- Preference	36.4	(6.3)	19.6	(4.8)	53.3	(5.4)	29.9	(4.7)	29.6	(4.7)	40.2	(4.3)	**34.8**	**(5.0)**
- Spending	14.3	(4.6)	13.7	(4.7)	2.9	(1.2)	2.8	(1.7)	0.7	(0.3)	4.6	(1.5)	**6.5**	**(2.3)**
- Interest rate	3.5	(0.9)	28.5	(5.3)	2.8	(0.6)	13.4	(2.6)	1.5	(0.6)	16.9	(2.4)	**11.1**	**(2.1)**
Investment growth														
- Transitory Tech	7.9	(7.9)	12.4	(5.7)	6.5	(3.4)	9.6	(5.9)	28.6	(5.0)	0.3	(0.6)	**10.9**	**(4.8)**
- Permanent Tech	25.2	(10.5)	6.7	(7.9)	5.4	(2.6)	9.4	(6.5)	0.4	(0.7)	18.7	(3.5)	**11.0**	**(5.3)**
- Preference	23.1	(6.7)	0.1	(0.2)	25.7	(4.4)	15.6	(4.9)	45.3	(6.9)	12.1	(4.1)	**20.3**	**(4.5)**
- Spending	15.4	(4.0)	0.2	(0.3)	7.3	(2.3)	3.5	(1.7)	3.4	(1.4)	3.7	(1.6)	**5.6**	**(1.9)**
- Interest rate	28.4	(6.2)	80.6	(6.1)	55.1	(4.8)	61.9	(5.7)	22.2	(3.6)	65.2	(5.1)	**52.3**	**(5.2)**
Trade balance (%gdp)														
- Transitory Tech	1.1	(1.0)	10.6	(6.0)	1.4	(0.6)	1.1	(0.7)	2.2	(1.2)	0.2	(0.2)	**2.8**	**(1.6)**
- Permanent Tech	5.1	(3.0)	0.7	(1.2)	1.8	(1.7)	0.9	(0.9)	0.2	(0.3)	3.8	(1.5)	**2.1**	**(1.4)**
- Preference	59.9	(14.2)	11.9	(12.9)	16.4	(4.3)	10.2	(6.7)	13.1	(4.0)	47.2	(15.1)	**26.5**	**(9.5)**
- Spending	15.6	(6.3)	59.0	(13.6)	15.9	(3.3)	5.8	(2.0)	9.9	(2.5)	10.7	(3.6)	**19.5**	**(5.2)**
- Interest rate	18.3	(7.7)	17.7	(8.7)	64.4	(6.5)	82.0	(8.2)	74.6	(5.6)	38.1	(11.5)	**49.2**	**(8.0)**

Notes: Estimations based on 500,000 draws from posterior distribution. Variance decomposition at annual frequency (does not include measurement errors). For each country, first and second columns display posterior mean and standard deviation (between parenthesis) respectively. Last two columns display average mean and average standard deviation across countries respectively. Values are expressed in percentage points.

Table A9: Variance Decomposition Developed Countries (annual frequency)

	Australia		Belgium		Canada		Netherlands		Norway		Sweden		Average	
Output growth														
- Transitory Tech	5.1	(6.9)	11.6	(12.4)	4.1	(5.2)	10.9	(8.7)	26.2	(13.7)	66.5	(11.3)	**20.7**	**(9.7)**
- Permanent Tech	68.8	(8.8)	66.7	(13.4)	84.4	(5.9)	63.5	(11.5)	31.3	(14.2)	16.4	(10.9)	**55.2**	**(10.8)**
- Preference	7.2	(2.9)	9.5	(3.3)	5.6	(2.4)	16.9	(6.5)	0.1	(0.2)	8.6	(4.0)	**8.0**	**(3.2)**
- Spending	5.2	(1.1)	4.0	(1.1)	2.3	(0.5)	1.8	(0.7)	0.1	(0.2)	2.7	(1.0)	**2.7**	**(0.8)**
- Interest rate	13.8	(2.3)	8.2	(1.8)	3.6	(0.7)	6.8	(1.4)	42.3	(5.2)	5.8	(1.2)	**13.4**	**(2.1)**
Consumption growth														
- Transitory Tech	4.0	(5.4)	7.0	(7.7)	2.6	(3.6)	7.4	(5.8)	14.9	(8.4)	37.4	(6.6)	**12.2**	**(6.2)**
- Permanent Tech	53.1	(7.7)	34.6	(8.7)	53.0	(5.6)	34.4	(8.4)	20.1	(9.5)	6.2	(4.5)	**33.6**	**(7.4)**
- Preference	23.8	(3.3)	37.9	(4.5)	29.0	(3.5)	48.1	(6.3)	24.3	(3.8)	37.7	(5.0)	**33.5**	**(4.4)**
- Spending	11.0	(2.3)	15.0	(3.1)	11.1	(2.2)	4.4	(1.9)	9.7	(2.6)	15.2	(4.0)	**11.1**	**(2.7)**
- Interest rate	8.1	(1.5)	5.4	(1.2)	4.2	(0.8)	5.7	(1.1)	31.0	(4.1)	3.5	(0.8)	**9.6**	**(1.6)**
Investment growth														
- Transitory Tech	1.5	(2.2)	2.4	(3.2)	0.6	(1.1)	3.0	(2.7)	4.6	(3.3)	21.0	(5.8)	**5.5**	**(3.0)**
- Permanent Tech	19.8	(4.0)	26.6	(6.1)	36.9	(4.5)	40.7	(6.7)	10.4	(5.3)	9.9	(6.5)	**24.0**	**(5.5)**
- Preference	11.6	(3.5)	11.0	(3.2)	14.5	(3.8)	18.3	(4.9)	0.1	(0.2)	16.0	(5.1)	**11.9**	**(3.4)**
- Spending	11.9	(2.3)	10.6	(3.0)	11.2	(2.1)	4.9	(1.5)	0.1	(0.2)	6.2	(2.6)	**7.5**	**(2.0)**
- Interest rate	55.3	(4.0)	49.4	(5.7)	36.7	(3.7)	33.1	(4.7)	84.8	(3.8)	46.9	(6.8)	**51.0**	**(4.8)**
Trade balance (%gdp)														
- Transitory Tech	0.5	(0.6)	0.5	(0.6)	0.6	(0.6)	0.6	(0.7)	4.0	(3.1)	5.0	(2.5)	**1.9**	**(1.4)**
- Permanent Tech	0.8	(0.3)	5.7	(2.2)	10.4	(2.6)	7.8	(4.8)	0.7	(0.7)	1.5	(1.3)	**4.5**	**(2.0)**
- Preference	9.6	(2.9)	53.4	(13.7)	30.3	(11.5)	73.4	(15.3)	15.9	(12.4)	64.1	(15.5)	**41.1**	**(11.9)**
- Spending	14.3	(2.5)	18.1	(5.6)	20.3	(4.3)	4.2	(2.8)	65.7	(12.1)	18.4	(8.6)	**23.5**	**(6.0)**
- Interest rate	74.8	(4.5)	22.3	(9.3)	38.5	(9.3)	14.0	(8.3)	13.7	(4.6)	10.9	(5.8)	**29.0**	**(7.0)**

Notes: Estimations based on 500,000 draws from posterior distribution. Variance decomposition at annual frequency (does not include measurement errors). For each country, first and second columns display posterior mean and standard deviation (between parenthesis) respectively. Last two columns display average mean and average standard deviation across countries respectively. Values are expressed in percentage points.

A.1.3 Sensitivity Analysis

Table A10: Variance Decomposition MF Non-Overlapping Estimation

	Emerging Markets				Developed Countries			
	Y	C	I	TBY	Y	C	I	TBY
Transitory tech	47.4	31.4	16.2	3.3	17.0	9.1	3.0	1.4
	(14.4)	(9.8)	(6.0)	(2.0)	(12.0)	(7.5)	(3.4)	(1.3)
Permanent tech	36.6	23.2	13.1	3.2	61.7	35.6	27.8	6.0
	(14.8)	(10.1)	(6.1)	(2.2)	(13.1)	(8.5)	(6.5)	(2.8)
Preference	7.4	32.9	18.6	25.5	6.7	36.6	11.1	38.0
	(3.2)	(4.8)	(5.2)	(9.3)	(3.3)	(4.9)	(3.8)	(12.8)
Spending	1.5	6.4	6.3	16.4	2.8	10.9	8.5	28.2
	(0.6)	(2.3)	(2.1)	(4.5)	(0.9)	(2.9)	(2.3)	(6.5)
Interest rate	7.2	6.0	45.7	51.6	11.8	7.8	49.7	26.4
	(1.5)	(1.3)	(5.3)	(9.0)	(2.3)	(1.6)	(5.0)	(7.4)

Notes: Posterior estimates are based on 500,000 draws from posterior distribution. Variables Y, C and I denote rate of growth of output, consumption and investment, annual frequency. TBY denotes trade balance to output ratio. Each entry displays the contribution of a given structural shock to the corresponding variable (average across countries). For each country the point estimate is the mean of the posterior distribution. Standard errors between parenthesis (average standard errors across countries). Variance does not include measurement errors.

Table A11: Variance Decomposition EM Latin-America MF estim. 1901-2010

	Argentina		Brazil		Chile		Colombia		Mexico		Peru		Average	
Output growth														
- Transitory Tech	80.5	(5.3)	57.9	(23.3)	84.9	(6.1)	65.8	(10.1)	71.8	(11.7)	4.7	(9.2)	**60.9**	**(11.0)**
- Permanent Tech	3.4	(4.3)	20.9	(23.2)	4.2	(6.0)	5.7	(9.3)	8.5	(12.4)	80.2	(9.9)	**20.5**	**(10.9)**
- Preference	11.9	(3.6)	19.5	(6.0)	3.7	(1.6)	17.0	(6.6)	14.1	(5.2)	10.3	(2.0)	**12.8**	**(4.2)**
- Spending	0.1	(0.1)	1.0	(0.4)	3.8	(1.3)	4.3	(1.2)	2.1	(0.5)	1.8	(0.5)	**2.2**	**(0.7)**
- Interest rate	4.1	(0.8)	0.7	(0.2)	3.4	(0.9)	7.1	(1.6)	3.4	(0.7)	2.9	(0.5)	**3.6**	**(0.8)**
Consumption growth														
- Transitory Tech	55.6	(4.5)	29.0	(11.9)	40.4	(5.0)	20.4	(4.5)	42.3	(7.0)	3.0	(6.2)	**31.8**	**(6.5)**
- Permanent Tech	2.0	(2.6)	7.9	(9.3)	1.9	(2.9)	1.7	(3.0)	5.0	(7.7)	52.0	(7.8)	**11.8**	**(5.5)**
- Preference	36.0	(3.7)	43.6	(4.1)	37.0	(5.1)	31.7	(5.6)	42.9	(4.6)	35.0	(4.0)	**37.7**	**(4.5)**
- Spending	0.4	(0.3)	11.9	(3.9)	16.6	(5.8)	44.6	(6.9)	7.0	(1.8)	8.1	(3.0)	**14.8**	**(3.6)**
- Interest rate	6.1	(1.1)	7.7	(1.5)	4.1	(1.4)	1.6	(0.4)	2.7	(0.5)	1.8	(0.4)	**4.0**	**(0.9)**
Investment growth														
- Transitory Tech	19.3	(2.9)	4.3	(1.9)	18.0	(3.4)	13.9	(3.1)	19.6	(3.8)	1.8	(3.9)	**12.8**	**(3.2)**
- Permanent Tech	1.0	(1.3)	1.7	(2.1)	1.2	(1.8)	0.4	(0.8)	1.3	(2.1)	30.1	(5.6)	**6.0**	**(2.3)**
- Preference	29.7	(5.6)	65.6	(5.1)	23.1	(6.3)	27.6	(6.4)	37.2	(5.9)	22.9	(3.7)	**34.4**	**(5.5)**
- Spending	0.4	(0.3)	11.4	(2.6)	14.7	(5.1)	4.5	(1.4)	8.7	(1.9)	8.9	(1.9)	**8.1**	**(2.2)**
- Interest rate	49.5	(4.6)	17.0	(3.0)	43.0	(7.9)	53.5	(5.9)	33.3	(3.8)	36.3	(3.7)	**38.8**	**(4.8)**
Trade balance (%gdp)														
- Transitory Tech	2.8	(0.6)	0.7	(0.3)	2.7	(0.6)	1.8	(0.8)	1.2	(0.5)	0.3	(0.5)	**1.6**	**(0.6)**
- Permanent Tech	0.3	(0.5)	0.7	(0.8)	0.6	(1.0)	0.1	(0.3)	0.1	(0.3)	4.9	(1.6)	**1.2**	**(0.8)**
- Preference	31.1	(9.8)	21.9	(5.6)	13.6	(2.9)	14.3	(5.7)	13.2	(2.6)	35.1	(8.5)	**21.5**	**(5.8)**
- Spending	0.4	(0.3)	9.1	(2.4)	7.6	(2.9)	4.1	(1.6)	4.9	(1.4)	15.7	(3.3)	**7.0**	**(2.0)**
- Interest rate	65.4	(9.6)	67.5	(5.8)	75.5	(5.1)	79.7	(6.1)	80.4	(3.3)	44.0	(10.0)	**68.7**	**(6.6)**

Notes: Variance decompositions for Latin-American coutrnies using MF for 1901-2010. Estimations based on 500,000 draws from posterior distribution. Variance decomposition at annual frequency (does not include measurement errors). For each country, first and second columns display posterior mean and standard deviation (between parenthesis) respectively. Last two columns display average mean and average standard deviation across countries respectively. Values are expressed in percentage points.

Table A12: Variance Decomposition EM Latin-America Annual estim. 1901-2010

	Argentina		Brazil		Chile		Colombia		Mexico		Peru		Average	
Output growth														
- Transitory Tech	82.2	(6.3)	20.2	(23.9)	78.7	(14.9)	70.3	(10.5)	78.6	(5.9)	15.0	(19.0)	**57.5**	**(13.4)**
- Permanent Tech	5.2	(5.7)	61.2	(24.1)	14.0	(14.9)	6.8	(10.0)	3.3	(4.5)	70.1	(19.7)	**26.8**	**(13.2)**
- Preference	9.1	(2.8)	15.3	(4.9)	2.1	(1.0)	10.7	(4.5)	12.5	(4.3)	8.7	(2.3)	**9.7**	**(3.3)**
- Spending	0.0	(0.0)	1.7	(0.5)	2.4	(0.9)	3.5	(1.0)	1.6	(0.4)	1.6	(0.6)	**1.8**	**(0.6)**
- Interest rate	3.5	(0.8)	1.6	(0.4)	2.8	(0.8)	8.7	(2.0)	3.9	(0.8)	4.6	(1.0)	**4.2**	**(1.0)**
Consumption growth														
- Transitory Tech	56.5	(5.6)	8.5	(10.9)	41.2	(9.0)	23.2	(5.0)	44.8	(5.4)	9.8	(12.9)	**30.7**	**(8.2)**
- Permanent Tech	3.2	(3.6)	25.4	(10.9)	7.9	(8.3)	2.2	(3.4)	1.8	(2.6)	47.6	(14.0)	**14.7**	**(7.1)**
- Preference	34.3	(4.5)	49.7	(5.5)	36.8	(5.7)	28.4	(5.4)	47.4	(4.9)	35.5	(4.8)	**38.7**	**(5.2)**
- Spending	0.2	(0.2)	14.9	(4.7)	12.0	(4.8)	44.9	(6.7)	4.4	(1.3)	5.6	(2.7)	**13.7**	**(3.4)**
- Interest rate	5.8	(1.7)	1.5	(0.6)	2.1	(1.0)	1.3	(0.4)	1.7	(0.5)	1.5	(0.3)	**2.3**	**(0.7)**
Investment growth														
- Transitory Tech	15.8	(3.0)	2.9	(3.8)	19.2	(5.3)	14.2	(3.8)	21.0	(4.0)	5.6	(7.6)	**13.1**	**(4.6)**
- Permanent Tech	1.4	(1.6)	13.5	(6.0)	5.1	(5.9)	1.0	(1.8)	0.6	(0.9)	31.3	(10.5)	**8.8**	**(4.4)**
- Preference	31.4	(6.2)	46.4	(5.6)	19.7	(5.8)	20.2	(5.8)	34.7	(5.9)	15.4	(4.1)	**28.0**	**(5.6)**
- Spending	0.3	(0.3)	6.7	(2.5)	12.7	(5.1)	4.3	(1.4)	7.4	(1.7)	6.5	(2.1)	**6.3**	**(2.2)**
- Interest rate	51.1	(5.8)	30.5	(4.6)	43.2	(8.1)	60.4	(5.9)	36.3	(4.5)	41.2	(5.0)	**43.8**	**(5.7)**
Trade balance (%gdp)														
- Transitory Tech	2.4	(0.6)	0.5	(0.5)	2.5	(0.9)	1.6	(0.7)	1.3	(0.5)	0.7	(0.8)	**1.5**	**(0.7)**
- Permanent Tech	0.3	(0.4)	2.1	(1.3)	1.1	(1.3)	0.2	(0.3)	0.1	(0.2)	1.4	(0.9)	**0.9**	**(0.7)**
- Preference	18.9	(6.9)	26.9	(8.8)	9.8	(3.2)	9.5	(4.3)	11.4	(2.9)	26.5	(12.2)	**17.2**	**(6.4)**
- Spending	0.2	(0.2)	3.3	(1.2)	5.4	(2.9)	3.3	(1.3)	4.2	(1.4)	10.4	(3.3)	**4.5**	**(1.7)**
- Interest rate	78.2	(7.0)	67.2	(8.8)	81.1	(6.0)	85.5	(4.8)	83.0	(3.6)	61.1	(13.9)	**76.0**	**(7.3)**

Notes: Variance decompositions for Latin-American coutrnies under annual estimation for 1901-2010. Estimations based on 500,000 draws from posterior distribution. Variance decomposition at annual frequency (does not include measurement errors). For each country, first and second columns display posterior mean and standard deviation (between parenthesis) respectively. Last two columns display average mean and average standard deviation across countries respectively. Values are expressed in percentage points.

A.2 Appendix for Chapter II

Table B1: Monte Carlo Exp. MF & Full Info Quarterly Estimation

		Posterior Mean			RMSE			Gain %	
Param	True	FullQ	MF1	Quart	FullQ	MF1	Quart	FullQ-Q	MF1-Q
φ	6.1	7.2	8.5	10.0	2.5	4.3	6.2	-60	-31
ψ	0.02	0.03	0.04	0.07	0.02	0.04	0.07	-70	-43
ρ_a	0.92	0.84	0.81	0.76	0.19	0.22	0.27	-31	-19
ρ_g	0.58	0.54	0.53	0.54	0.20	0.20	0.20	-4	0
ρ_v	0.97	0.96	0.95	0.93	0.03	0.04	0.07	-62	-50
ρ_s	0.76	0.72	0.70	0.64	0.10	0.13	0.21	-52	-36
ρ_μ	0.97	0.94	0.93	0.88	0.05	0.06	0.14	-63	-58
σ_a	0.91	0.82	0.81	0.73	0.31	0.33	0.39	-20	-15
σ_g	0.88	0.85	0.88	0.98	0.48	0.50	0.53	-10	-6
σ_v	23.6	22.6	21.2	21.1	8.0	8.2	10.2	-22	-20
σ_s	12.2	12.7	13.0	13.7	1.5	2.1	2.8	-46	-23
σ_μ	0.35	0.47	0.59	0.83	0.20	0.36	0.64	-69	-44

Notes: Table displays parameter estimates (posterior mean and RMSE) under alternative estimation strategies. MF and Quart denote mixed frequency and standard quarterly data estimation respectively. FullQ denotes quarterly estimation with full information. MF1 includes 60 years of annual observations. MF1 and Quart estimation strategies include only 84 observations of quarterly series (21 years). FullQ includes 61 years of quarterly data (244 observations). Last two columns display the RMSE percentage change of FullQ and MF1 strategies with respect to quarterly estimation. Monte Carlo experiment estimations based on 200 samples, 1,000,000 MCMC draws each (first 500,000 are discarded).

Table B2: Variance Decomp. Noisy early data MF vs Q Estim.

	True	Posterior Mean MF1	Posterior Mean Quart	Bias MF1	Bias Quart	RMSE MF1-Quart
Output growth						
- Transitory Tech	51.4	42.0	38.2	-9.4	-13.2	-2.9
- Permanent Tech	28.8	39.7	45.7	11.0	17.0	-4.6
- Preference	11.8	10.6	10.2	-1.2	-1.6	-1.9
Consumption growth						
- Transitory Tech	31.2	24.0	22.2	-7.3	-9.0	-2.1
- Permanent Tech	17.7	24.5	29.2	6.8	11.6	-4.7
- Preference	43.2	40.6	39.7	-2.6	-3.5	-2.9
Investment growth						
- Transitory Tech	14.4	9.7	9.1	-4.7	-5.3	-1.3
- Permanent Tech	9.8	11.6	14.8	1.8	5.0	-4.8
- Preference	19.1	20.2	22.0	1.1	2.8	-3.3
- Interest rate	51.8	50.3	46.8	-1.5	-5.0	-4.2
Trade balance (%gdp)						
- Preference	36.3	26.6	26.8	-9.7	-9.4	-3.6
- Spending	9.5	14.0	14.0	4.5	4.5	-1.5
- Interest rate	50.4	54.3	51.9	3.9	1.6	-4.9

Notes: Table displays variance decomposition at annual frequency (does not include measurement errors). MF1 and Quart denote mixed frequency and quarterly estimation respectively. MF1 strategy includes 84 observations of quarterly series (21 years) and 61 years of annual data. In the DGP the first 40 annual observations present 4 times larger measurement error. Quarterly estimation includes last 21 years of quarterly data. Monte Carlo experiment estimations based on 200 samples, 1,000,000 MCMC draws each (first 500,000 are discarded). Variance decompositions calculated based on 100,000 draws from posterior. Last column displays the difference between RMSE of MF1 vs Q.

A.3 Appendix for Chapter III

A.3.1 EM estimates country by country

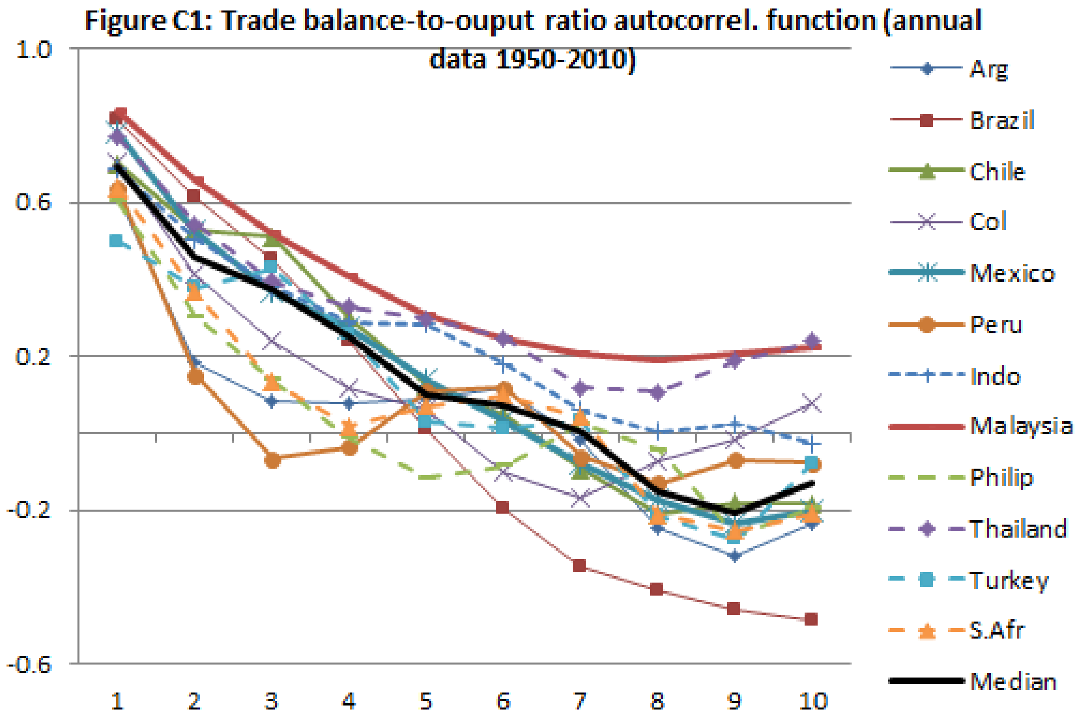

Table C1: Second Moments EM Latin-America (annual frequency)

	Argentina		Brazil		Chile		Colombia		Mexico		Peru		**Median**	
	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model
Std deviation %														
- Y	5.1	6.8	3.7	4.0	4.9	5.7	2.4	4.2	3.5	3.4	5.5	9.5	3.7	4.2
- C	6.4	6.5	4.9	3.8	7.5	4.9	2.7	3.1	3.9	3.2	6.3	8.2	4.9	3.8
- I	16.3	16.6	11.5	8.9	24.3	17.9	12.5	14.7	10.7	7.7	20.2	21.7	12.5	14.7
- TBY	3.1	50.6	1.9	46.4	4.2	34.2	2.7	17.5	3.3	22.3	4.7	58.7	3.1	34.2
Correlation w/Y														
- C	0.90	0.95	0.77	0.88	0.67	0.88	0.86	0.94	0.88	0.89	0.72	0.95	0.77	0.89
- I	0.86	0.88	0.63	0.80	0.71	0.80	0.78	0.76	0.83	0.75	0.70	0.86	0.71	0.80
- TBY	-0.13	-0.04	-0.31	-0.01	0.10	-0.04	-0.02	-0.07	-0.46	-0.05	0.09	-0.03	-0.02	-0.04
Correlation w/TBY														
- C	-0.15	-0.04	-0.24	-0.01	0.03	-0.04	-0.06	-0.08	-0.47	-0.05	0.04	-0.03	-0.06	-0.04
- I	-0.26	-0.04	-0.18	-0.02	0.04	-0.04	-0.12	-0.08	-0.43	-0.05	0.01	-0.04	-0.12	-0.04
Autrocorrelation														
- Y	0.16	0.31	0.36	0.28	0.13	0.18	0.30	0.06	0.27	0.29	0.40	0.27	0.27	0.27
- C	0.14	0.25	-0.02	0.24	0.12	0.18	0.06	0.14	0.28	0.27	0.38	0.25	0.12	0.24
- I	0.05	0.10	0.03	0.17	-0.19	0.02	0.17	-0.20	0.11	0.08	0.13	0.05	0.05	0.05
- TBY	0.62	1.00	0.82	1.00	0.70	1.00	0.70	0.99	0.78	1.00	0.64	1.00	0.70	1.00

Notes: Table displays second moments implied by the RBC model (baseline estimation) and empirical moments. Empirical moments calculated for the period 1950-2010. Variables Y, C and I denote rate of growth of output, consumption and investment. TBY denotes trade balance to output ratio. Model implied moments based on 100,000 draws from posterior distribution (posterior median).

Table C2: Second Moments EM Asia and Africa (annual frequency)

	Indonesia		Malaysia		Philippines		Thailand		Turkey		S. Africa		**Median**	
	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model
Std deviation %														
- Y	4.5	5.0	4.3	8.3	4.4	5.7	5.1	8.8	5.2	8.8	2.5	3.2	4.4	5.7
- C	4.5	4.2	5.7	8.3	2.6	4.6	4.6	6.9	6.4	8.1	3.0	3.1	4.5	4.6
- I	13.6	10.1	15.8	15.9	12.5	16.2	15.2	17.7	17.2	19.6	13.3	7.2	13.6	15.9
- TBY	4.1	25.9	8.6	30.2	3.2	296.7	5.1	25.0	2.0	92.8	3.6	25.0	3.6	25.9
Correlation w/Y														
- C	0.46	0.89	0.65	0.90	0.24	0.81	0.82	0.95	0.87	0.96	0.75	0.85	0.65	0.89
- I	0.81	0.70	0.70	0.68	0.60	0.58	0.58	0.77	0.48	0.90	0.50	0.58	0.58	0.68
- TBY	-0.23	-0.04	-0.26	-0.14	0.16	0.04	-0.34	-0.04	-0.23	-0.01	-0.08	-0.07	-0.23	-0.04
Correlation w/TBY														
- C	0.05	-0.05	-0.01	-0.16	-0.12	0.05	-0.36	-0.05	-0.26	-0.01	-0.27	-0.08	-0.12	-0.05
- I	-0.31	-0.06	-0.33	-0.13	-0.09	0.00	-0.44	-0.07	-0.23	-0.02	-0.25	-0.07	-0.25	-0.06
Autrocorrelation														
- Y	0.23	0.18	0.16	0.45	0.03	0.72	0.26	0.05	-0.07	0.27	0.34	0.45	0.16	0.27
- C	0.26	0.24	0.24	0.41	0.54	0.53	0.16	0.13	-0.11	0.24	0.29	0.39	0.24	0.24
- I	0.21	0.05	0.09	0.12	0.21	0.04	0.14	-0.26	-0.17	0.14	0.02	0.18	0.09	0.05
- TBY	0.69	0.99	0.84	0.98	0.60	1.00	0.77	0.99	0.50	1.00	0.64	1.00	0.64	0.99

Notes: Table displays second moments implied by the RBC model (baseline estimation) and empirical moments. Empirical moments calculated for the period 1950-2010. Variables Y, C and I denote rate of growth of output, consumption and investment. TBY denotes trade balance to output ratio. Model implied moments based on 100,000 draws from posterior distribution (posterior median).

A.3.2 DC estimates

Table C3: Posterior Distribution Developed Countries

Param	Australia	Belgium	Canada	Netherlands	Norway	Sweden	**Median**
φ	0.4	0.2	2.3	0.6	0.2	2.3	**0.5**
	(0.04)	(0.03)	(0.16)	(0.07)	(0.04)	(0.20)	**(0.1)**
ρ_a	0.67	0.24	0.90	0.84	0.84	0.89	**0.84**
	(0.02)	(0.03)	(0.01)	(0.02)	(0.03)	(0.01)	**(0.02)**
ρ_g	0.01	0.03	0.09	0.32	0.03	0.02	**0.03**
	(0.01)	(0.04)	(0.03)	(0.02)	(0.02)	(0.02)	**(0.02)**
σ_a	1.1	1.7	0.8	2.3	1.5	0.9	**1.3**
	(0.1)	(0.1)	(0.1)	(0.2)	(0.2)	(0.1)	**(0.1)**
σ_g	1.9	0.6	1.2	2.2	2.2	1.5	**1.7**
	(0.1)	(0.1)	(0.1)	(0.1)	(0.2)	(0.1)	**(0.1)**

Notes:Each column displays posterior median and standard deviation (between parenthesis) for a given country. Last column displays median across countries of posterior medians and standard deviations respectively. Posterior estimates are based on a 2-million MCMC chain (first 1 million draws are discarded). Estimates of standard deviation of shocks are in percentage points.

Table C4: Second Moments Developed Countries (annual frequency)

	Y	C	I	TBY
Std Dev %				
- Data	2.2	2.3	7.3	2.5
- Financial frictions model	2.5	3.2	5.5	2.9
- RBC model (AG)	3.2	2.7	6.7	1.8
- RBC model (baseline)	3.1	2.6	6.5	14.5
	(0.16)	(0.17)	(0.25)	(0.76)
Correl w/Y				
- Data	-.-	0.69	0.74	-0.20
- Financial frictions model		0.79	0.57	-0.12
- RBC model (AG)		0.95	0.76	-0.23
- RBC model (baseline)		0.94	0.76	-0.04
		(0.02)	(0.03)	(0.05)
Correl w/TBY				
- Data	-.-	-0.09	-0.12	-.-
- Financial frictions model		-0.08	-0.08	
- RBC model (AG)		-0.25	-0.28	
- RBC model (baseline)		-0.04	-0.07	
		(0.05)	(0.05)	
Autocorrel				
- Data	0.29	0.18	0.05	0.82
- Financial frictions model	0.47	0.38	0.13	0.85
- RBC model (AG)	0.15	0.18	-0.21	0.59
- RBC model (baseline)	0.19	0.20	-0.19	0.99
	(0.05)	(0.04)	(0.04)	(0.05)

Notes: Median across countries of model and empirical moments. Model implied moments based on 100,000 draws from posterior distribution (posterior median) (standard errors between parenthesis). Empirical moments for the period 1950-2010. Variables Y, C and I denote rate of growth of output, consumption and investment. TBY denotes trade balance-to-output ratio.

Table C5: Second Moments Developed Countries (annual frequency)

	Australia		Belgium		Canada		Netherlands		Norway		Sweden		**Median**	
	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model
Std deviation %														
- Y	2.3	4.0	1.9	2.7	2.3	2.9	2.5	8.0	1.8	6.7	2.2	3.1	2.2	3.1
- C	2.4	3.3	1.9	1.8	1.9	2.3	2.6	6.3	2.3	5.4	2.3	2.6	2.3	2.6
- I	9.9	7.4	6.4	5.9	7.3	6.3	9.0	23.6	7.3	14.2	6.2	6.5	7.3	6.5
- TBY	2.1	9.3	2.1	5.7	2.0	14.4	2.9	27.6	6.9	18.7	3.0	14.5	2.1	14.4
Correlation w/Y														
- C	0.77	0.94	0.60	0.93	0.67	0.94	0.78	0.97	0.52	0.97	0.71	0.93	0.67	0.94
- I	0.78	0.77	0.67	0.61	0.75	0.84	0.78	0.76	0.39	0.67	0.74	0.85	0.74	0.76
- TBY	-0.19	-0.05	-0.20	0.01	0.14	-0.03	-0.25	-0.09	-0.43	-0.06	-0.02	-0.04	-0.19	-0.04
Correlation w/TBY														
- C	-0.20	-0.06	-0.14	-0.01	0.06	-0.03	-0.36	-0.10	-0.04	-0.06	0.03	-0.04	-0.04	-0.04
- I	-0.50	-0.08	-0.08	-0.07	0.04	-0.04	-0.24	-0.10	-0.17	-0.10	0.05	-0.04	-0.08	-0.07
Autocorrelation														
- Y	0.06	0.11	0.30	-0.33	0.28	0.20	0.24	0.19	0.50	0.15	0.32	0.19	0.28	0.15
- C	-0.04	0.18	0.26	-0.21	0.20	0.21	0.42	0.20	0.12	0.18	0.16	0.20	0.16	0.18
- I	-0.26	-0.19	0.00	-0.36	0.00	0.01	0.11	-0.19	0.28	-0.30	0.28	0.01	0.00	-0.19
- TBY	-0.16	0.99	0.84	0.97	0.81	1.00	0.79	0.99	0.88	0.98	0.93	1.00	0.81	0.99

Notes: Table displays second moments implied by the RBC model (baseline estimation) and empirical moments. Empirical moments calculated for the period 1950-2010. Variables Y, C and I denote rate of growth of output, consumption and investment. TBY denotes trade balance to output ratio. Model implied moments based on 100,000 draws from posterior distribution (posterior median).

A.3.3 RBC-AG estimates

Table C6: RBC-AG Posterior Distribution Emerging Markets

Param	Arg	Bra	Chi	Col	Mex	Peru	Indo	Mal	Phil	Thai	Tur	S.Afr	**Median**
φ	3.6	12.6	2.3	0.5	3.1	3.5	2.5	1.9	0.8	0.4	5.8	4.7	**2.8**
	(0.2)	(1.1)	(0.2)	(0.1)	(0.3)	(0.3)	(0.3)	(0.2)	(0.1)	(0.1)	(0.6)	(0.4)	**(0.3)**
ρ_a	0.95	0.92	0.88	0.66	0.77	0.75	0.93	0.80	0.94	0.65	0.96	0.81	**0.85**
	(0.01)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.01)	(0.03)	(0.01)	(0.03)	(0.01)	(0.02)	**(0.02)**
ρ_g	0.27	0.74	0.02	0.03	0.64	0.65	0.02	0.84	0.99	0.01	0.29	0.86	**0.46**
	(0.03)	(0.05)	(0.02)	(0.02)	(0.06)	(0.05)	(0.02)	(0.03)	(0.00)	(0.01)	(0.04)	(0.02)	**(0.02)**
σ_a	1.75	1.11	1.75	1.75	0.87	2.04	1.72	2.05	0.99	3.15	2.61	0.86	**1.75**
	(0.1)	(0.1)	(0.1)	(0.2)	(0.1)	(0.1)	(0.2)	(0.2)	(0.1)	(0.3)	(0.3)	(0.1)	**(0.1)**
σ_g	3.48	1.04	3.31	2.19	1.14	1.80	3.48	1.13	0.27	4.02	4.56	0.51	**2.00**
	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.3)	(0.3)	(0.2)	(0.0)	(0.3)	(0.5)	(0.1)	**(0.2)**

Notes:Each column displays posterior median and standard deviation (between parenthesis) for a given country. Last column displays median across countries of posterior medians and standard deviations respectively. Posterior estimates are based on a 2-million MCMC chain (first 1 million draws are discarded). Estimates of standard deviation of shocks are in percentage points. Countries from left to right: Argentina, Brazil, Chile, Colombia, Mexico, Peru, Indonesia, Malaysia, Philippines, Thailand, Turkey and South Africa.

Table C7: RBC-AG Posterior Distribution Developed Countries

Param	Australia	Belgium	Canada	Netherlands	Norway	Sweden	**Median**
φ	0.4	0.2	2.2	0.6	0.2	2.2	**0.5**
	(0.04)	(0.04)	(0.16)	(0.06)	(0.04)	(0.20)	**(0.1)**
ρ_a	0.65	0.26	0.88	0.84	0.79	0.88	**0.81**
	(0.02)	(0.03)	(0.01)	(0.02)	(0.04)	(0.01)	**(0.02)**
ρ_g	0.01	0.04	0.08	0.33	0.02	0.02	**0.03**
	(0.01)	(0.11)	(0.03)	(0.02)	(0.02)	(0.02)	**(0.02)**
σ_a	1.2	1.9	0.9	2.5	1.7	0.9	**1.5**
	(0.1)	(0.2)	(0.1)	(0.2)	(0.2)	(0.1)	**(0.1)**
σ_g	2.0	0.7	1.3	2.5	2.3	1.5	**1.8**
	(0.1)	(0.1)	(0.1)	(0.2)	(0.2)	(0.1)	**(0.1)**

Notes:Each column displays posterior median and standard deviation (between parenthesis) for a given country. Last column displays median across countries of posterior medians and standard deviations respectively. Posterior estimates are based on a 2-million MCMC chain (first 1 million draws are discarded). Estimates of standard deviation of shocks are in percentage points.

Table C8: RBC-AG Variance Decomposition Emerging Markets

Variable	Arg	Bra	Chi	Col	Mex	Peru	Indo	Mal	Phil	Thai	Tur	S.Afr	**Mean**
Y	47.4	49.4	38.9	33.3	68.3	51.1	38.0	61.8	73.1	35.1	40.2	62.8	**49.9**
	(4.5)	(7.9)	(4.6)	(4.9)	(4.5)	(4.7)	(5.4)	(4.9)	(4.4)	(5.0)	(5.0)	(3.6)	**(5.0)**
C	59.1	68.3	55.6	54.3	84.6	73.4	50.5	77.9	83.9	55.7	48.9	80.9	**66.1**
	(4.4)	(8.3)	(4.6)	(5.4)	(2.9)	(3.8)	(5.6)	(3.5)	(3.1)	(5.4)	(5.7)	(2.3)	**(4.6)**
I	51.5	75.9	51.9	51.1	90.6	85.5	42.5	80.1	29.0	48.7	41.1	89.7	**61.5**
	(4.6)	(9.2)	(4.9)	(5.4)	(2.9)	(3.3)	(5.5)	(3.8)	(3.9)	(5.5)	(5.5)	(1.9)	**(4.7)**
TBY	58.8	84.3	73.2	77.0	91.8	83.6	40.3	83.5	98.6	46.7	52.0	94.0	**73.6**
	(4.8)	(3.3)	(4.3)	(3.9)	(1.4)	(2.5)	(6.1)	(3.4)	(0.5)	(5.5)	(6.7)	(1.2)	**(3.6)**

Notes: Table displays the contribution of the permanent technology shock to each variable variance. Each column displays posterior mean and standard deviation (between parenthesis) for a given country. The variables Y,C,I denote the rate of growth of output, consumption and investment and tby denotes the trade balance-to-gdp ratio. Posterior estimates based on 100,000 draws from the posterior distribution. Last column displays mean across countries. Countries from left to right: Argentina, Brazil, Chile, Colombia, Mexico, Peru, Indonesia, Malaysia, Philippines, Thailand, Turkey and South Africa.

Table C9: RBC-AG Variance Decomposition Developed Countries

Variable	Australia	Belgium	Canada	Netherlands	Norway	Sweden	**Mean**
Y	47.9	10.1	30.5	28.8	26.2	32.8	**29.4**
	(4.3)	(2.1)	(3.0)	(4.0)	(3.9)	(4.0)	**(3.5)**
C	68.3	22.1	46.3	45.9	43.6	49.2	**45.9**
	(3.7)	(3.9)	(3.5)	(4.9)	(4.8)	(4.5)	**(4.2)**
I	60.5	51.8	40.0	35.3	27.2	44.7	**43.3**
	(4.3)	(6.4)	(3.4)	(4.5)	(3.7)	(4.4)	**(4.5)**
TBY	52.7	47.9	48.3	44.5	19.2	48.3	**43.5**
	(4.3)	(5.5)	(3.9)	(5.2)	(3.1)	(4.9)	**(4.5)**

Notes: Table displays the contribution of the permanent technology shock to each variable variance. Each column displays posterior mean and standard deviation (between parenthesis) for a given country. The variables Y,C,I denote the rate of growth of output, consumption and investment and tby denotes the trade balance-to-gdp ratio. Posterior estimates based on 100,000 draws from the posterior distribution. Last column displays mean across countries.