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

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Abstract

I assess sources of aggregate fluctuations for 12 emerging markets in a small open economy model, focusing on the importance of permanent versus transitory technology shocks. These countries present short quarterly national accounts data, usually since 1990, but much longer annual series, since 1950. To use this information efficiently, I estimate the model using a Bayesian mixed frequency strategy combining 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 quarterly series, addressing potential temporal-aggregation bias of annual 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%. In contrast, estimates for 6 developed countries indicate that permanent technology shocks play a predominant role. To assess the relative merits of the mixed frequency strategy, I perform a Monte Carlo experiment 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. Finally, the mixed strategy also does a better job than annual estimation in several dimensions.

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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 particular, emerging countries present short quarterly national accounts data, usually since 1990, but much longer annual series, for most cases since 1950. To use this data more efficiently I propose a Bayesian mixed frequency 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 excess volatility of macroeconomic variables with respect to developed countries (henceforth, DC), countercyclicality of the trade balance, 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). In this framework, they argue that the countercyclicality of the trade balance and the excess volatility of consumption indicate that permanent technology shocks are relatively more important in EM than in DC. Finally, the authors estimate the model for Mexico and Canada, finding evidence in favor of their hypothesis.[1]

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

[1] They estimate the model through GMM, using quarterly data since 1980.

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 methodology contrasts with the most standard practice in the related literature that uses only quarterly data in estimations (see e.g. AG, Chang et.al. (2010)). Unfortunately, for EM quarterly national accounts are normally available for relatively short periods of time, typically since the early nineties, 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 is likely to deliver more precise estimates in particular for extremely persistent shock processes.

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). Accordingly, estimates may suffer from temporal-aggregation bias as emphazised by Christiano, Eichenbaum and Marshall (1991) for permanent income hypothesis implications, Aadland (2001) for labor market predictions of RBC models and Galles and Portier (2005) for identification of monetary shocks.[2] More recently, Kim (2010) shows that assuming a model period of lower frequency than the true one leads to biased estimates of the Calvo price-adjustment parameter in a New Keynesian model. Last but not least, many EM countries simply do not present reliable annual data for such a long period.[3]

One of the main contributions of this paper is of empirical nature. In short, I explore sources of fluctuations in EM and DC in 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 shocks (transitory and permanent) and three non-technology shocks (to time preference, government spending and interest rate). I estimate the model with

[2] For more mechanical temporal-bias on autoregresive process see Working (1960) seminal paper.

[3] In fact, for most countries national accounts series are available since 1950's. When data is available before 1950's 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.

Bayesian methods for 12 EM and 6 DC using mixed frequency data (annual and quarterly) for the period 1950-2010.[4] In particular, this study pays special attention to the relative importance of permanent and transitory technology shocks and to differences between EM and DC.

The main empirical findings can be summarized as follows. First, 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. In turn, 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. Second, PTS are in fact relatively less important in EM than in DC. For instance, PTS contribution to output variance falls from 55% in DC to 35% in EM. This finding contrasts with the AG result that PTS are more relevant in EM. Third, interest rate shocks are the primary source of investment and trade balance fluctuations in EM.

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 and the excess volatility of consumption, showing lack of support for the AG hypothesis. Instead, I find that the contribution of PTS is positively associated with the persistence of output, consumption and investment growth (first order autocorrelations).

The mixed frequency estimation technique employed here is primarily based on well-established state-space methods (see e.g. Durbin and Koopman (2001)). In fact, there is a large body of empirical literature implementing mixed frequency estimation, in particular 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

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

primarily focused on estimation efficiency.[5,6] In practice, this study also presents a 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.

Finally, to illustrate potential gains of the mixed frequency strategy, I conduct a Monte Carlo experiment (generating artificial data) for a representative emerging market and assess efficiency properties of alternative estimation strategies. I find that, on the one hand, the single frequency estimators based on either short quarterly series or annual data present large bias. In particular, quarterly estimation severely overpredicts the relative importance of PTS and understates that of TTS up to the point of reversing the order of importance.[7] On the other hand, the proposed mixed frequency estimations deliver substantial efficiency gains and bias reductions, sorting structural shocks in the correct order of importance. Finally, mixed frequency estimation also does a better job in assessing sources of fluctuations than coarser annual estimation.

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 (still PTS are relatively more important in EM than in DC). Interestingly, the differences between mixed frequency and quarterly data estimates are in line with many predictions of the Monte Carlo experiment, including the upward bias of PTS.

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 perform the Monte Carlo experiment to study the relative performance of mixed and single frequency estimation strategies. In section 5, I study the sensitivity of main estimation results to alternative estimation strategies and parameter values. Finally, section 6 concludes.

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

[6] 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.

[7] Estimation based on annual estimation, as in GPU, also overpredicts the relative importance of PTS but the bias is smaller than with short quarterly series. This strategy also presents severe problems to identify the contribution of preference and interest rate shocks, sharply overpredicting the importance of the latter to explain trade balance fluctuations.

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 in accounting for EM business cycles facts than a model with only technology shocks, as shown in GPU.

The representative household faces the following sequential budget constraint:

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

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:

$$Y_t = a_t K_t^{\alpha} \left(X_t h_t\right)^{1-\alpha}, \tag{2}$$

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:

$$K_{t+1} = (1-\delta) K_t + I_t, \tag{3}$$

with depreciation rate $\delta \in [0,1)$. The country interest rate is assumed to be elastic to aggregate debt-to-gdp ratio (gdp trend), 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 detrended output respectively (detrended) and, thus, $\bar{y}X_t$ denotes the output trend.[8] 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:

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

All five structural shocks follow a first-order autoregressive process. 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:

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

This shock is governed by the following autoregressive process:

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

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 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:

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

[8] 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.

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.

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. The least standard features of the estimation strategy, namely accommodating mixed frequency data in the model and the treatment of missing observations, are described in detail below.

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

3.1 Calibration

I calibrate the structural parameters α, β, δ, γ, θ, ω, $\bar{g}$, $\bar{d}$ 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 elastiticy	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 and steady state values of debt-to-gdp, government spending-to-gdp and gdp growth are calibrated to match corresponding long-run ratios for each country.

On the one hand, parameters $\delta, \bar{g}, \bar{d}$ 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 $\bar{g}$, $\bar{d}$ 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).[9] 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.

3.2 Estimation Strategy

The Bayesian estimation procedure is primarily based on Markov Chain Monte Carlo methods as described in detail in Ann & 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.

[9] Unlike this paper where 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.

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

I estimate 12 structural parameters and 8 parameters associated with 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). All parameters are assumed to 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-output ratio, both at quarterly and annual frequency.[10] 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 when quarterly and annual data are available simultaneously, I use both in the estimation (henceforth, overlapping strategy).

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

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-output ratio and the 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.[11] 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). This step allows us to keep the state space as small as possible, minimizing computing time. Finally, combining 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 $G(\Theta)$ and $H(\Theta)$ 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).[12]

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.[13] I deal with this issue implementing a Kalman Filter adapted to missing values following Aruoba et.al. (2009), which extend Durbin-Koopman (2001) methodology. In essence, the Kalman filter is updated using only the sub-set of available observations each period (see Appendix).[14]

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

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

[13] 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.

[14] 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 2 to 3 times.

3.3 Data

I estimate the model for 12 emerging countries: 6 are from Latin-America (Argentina, Brazil, Chile, Colombia, Mexico and Peru), 5 are from Asia (Indonesia, Malaysia, Philippines, Thailand and Turkey) and 1 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 that start at 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 in the estimation are seasonally adjusted. Main data sources and sample periods are detailed in the Appendix.

3.4 Estimation Results

This section presents main estimation results. 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, in particular of permanent and transitory technology shocks (henceforth, PTS and TTS respectively). I also compare main findings with the existing literature. In particular, I attempt to answer the following questions: 1) Are PTS relatively more important in EM than in DC, as AG findings? 2) Are PTS a negligible source of fluctuations in EM as GPU findings for Argentina? 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.

3.4.1 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). Tables 3-4 display parameter estimates (posterior median and standard errors) for each country 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. In particular, note that permanent technology shocks estimates exhibit a large dispersion and standard errors relative to 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.[15] It is also observed 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 less extent by TTS. In turn, PTS exhibit a persistence significantly larger than zero, of around 0.58 (relatively homogeneous across countries), well above AG estimates and in line with GPU results.[16] 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 (-.41) while the correlation of σ_g with other non-technology shocks is positive. This appears

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

[16] 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 to explain some results in the Monte Carlo Experiment.

to indicate that PTS and TTS compete intensely with each other to explain fluctuations.

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.

Importantly, estimates assign a relevant role to financial frictions. In effect, the median estimate 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 approximately by 36 basis points. This elasticity value lies within the range of estimates in related papers, from around 10 basis points in Akitoby et.al. (2006) to 50 basis points in GPU. 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 assigned a larger interest rate-debt elasticity (the correlation between these two concepts is -0.52 in the cross section).

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.

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.

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 in particular, interest rate-debt elasticity ψ turn out to be surprisingly similar for both groups.[17] Finally,

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

note that in general EM estimates display larger standard errors and dispersion, especially for volatilities.

3.4.2 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).[18]

Before assessing the model fit it is useful to outline most salient empirical moments for our 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 trade balance is acyclical. In light of this, empirical

[18] 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.

second moments of EM and DC are closer than expected.[19]

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. In particular, it correctly ranks both volatility and first order autocorrelations for output, consumption, investment and the trade balance, both for EM and DC. 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 one. 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 discussed in Schmitt-Grohe and Uribe (2003). Finally,

[19] 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)). 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.

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 than emerges here is how the model implies a similar negative correlation of output and trade balance for both group of countries despite the predominance of TTS in EM.[20] This is in part explained by the fact that TTS are in fact more persistent in EM, reducing the positive impact on trade balance procyclicality.

3.4.3 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).[21] 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 shock is 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 accounts for 55% and 34% of output and consumption variability respectively. Similar to EM, interest rate shocks explain the bulk of investment

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

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

volatility, 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 above, I find huge differences in the relative importance of shocks in EM and DC, especially about 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.[22]

Finally, 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). Looking at non-technology shocks, the importance of spending shocks declines substantially from DC to EM, possibly due to

[22] In light of this, the ratio of output variance accounted 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.

the smaller size of government spending to gdp 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.[23]

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 facts combined suggest potential identification issues between permanent versus transitory technology shocks but precise estimates of the joint importance of technology versus non-technology shocks.[24]

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. 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).

The main results about sources of fluctuations so far present strong differences and some similarities with closely related papers. First of all, the finding that TTS are relatively more important than PTS in EM compared to DC is clearly at odds with the main findings of AG for Mexico and Canada.[25] Further, 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).[26]

[23]This apparently contradictory behavior may be explained by the larger degree of capital adjustment cost φ in EM that leads to a more persistent impact of interest rates on investment that its captured by the trade balance-to-gdp ratio, variable expressed in levels, but not that much in investement, that is expressed in first differences.

[24]In the Monte Carlo experiment, 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 is difficult to identify these shocks.

[25]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.

[26]This difference is in part explained by the fact that our Argentina estimates assigns a smaller role for PTS than the average EM (e.g. the output variance share of PTS for Argentina is 17%, half that of EM). The remainder difference is likely to be explained by the different sample period. In fact, I re-estimated the model with a longer sample for Argentina for the period and data cosidered in GPU (1900-2005) and the estimated share of PTS is very similar to GPU result.

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 (including both EM and DC) 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 particular, it is worth exploring the relevance of AG argument that the countercyclicality of the trade balance and the excess volatility of consumption in EM are informative of the presence of PTS.

Surprisingly, the only set of 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.[27] 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 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 countercylicality 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).[28]

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 presence of transitory technology shocks. To test this hypothesis I remove sudden stop episodes from EM and DC samples (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 remain practically unchanged, in particular regarding the sources of output growth fluctuations. Therefore, the main findings appear to be robust to the exclusion of sudden stops.

[27] It is also observed significant negative correlations 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 than 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.

[28] 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, in turn, shows a small and positive correlation (wrong sign).

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 remainder EM countries. But further analysis of this hypothesis is out of the scope of this paper.

In sum, baseline estimations assign a predominant role to TTS in EM and to PTS in DC for the period 1950-2010. Further, the contribution of PTS in EM is considerable, though relatively less important than in DC. There is no obvious explanation for these differences in sources of fluctuations between EM and DC based only on usual second moments.

4 Monte Carlo Experiment

The goal of this section is to explore potential efficiency gains of mixed frequency series 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 before where 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 (see first column of table 8). 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.[29] I henceforth assume that the econometrician observes only the last 21 years of quarterly data for each sample, as it is typically the case for an EM economy.[30]

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

[29] 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.

[30] Accordingly, the first 89 years of quarterly data are replaced by not available observations.

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 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 focus on efficiency gains regarding the contribution of shocks to economic fluctuations, paying special attention to the relative importance of permanent and transitory productivity shocks.

4.1 Mixed Frequency vs Quarterly Estimation

The first set of estimation methodologies correctly assumes that the decision period is one quarter (quarterly model). 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 (as in a typical EM). The second estimation strategy employs mixed frequency series and assumes that only the last 60 years of annual data is observed, together with the 21 years of quarterly data (henceforth, MF1). This resembles the baseline estimation strategy. The third estimation strategy also considers MF, but assumes that all 110 years of annual data are observed (henceforth, MF2). The latter is an attempt to illustrate 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 3 alternative strategies proposed following essentially the same Bayesian methodology described in the empirical section.[31] Tables 8 and 9 present estimation results for MF1, MF2 and quarterly estimation strategies. Table 8 shows average parameter estimates across samples and root mean square errors (RMSE) with respect to true parameter vector Θ.[32]

[31] 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 in the true parameter vector used in the data generating process.

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

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

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 bias. 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 bias (see table 8). 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 bias.

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, last panel of table 8 shows 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 second panel table 8).[33] In particular, bias associated with TTS is substantially reduced under MF, which leads to a more accurate assessment of the importance of this shock to economic fluctuations, which is

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 $J = 100,000$) .

[33] 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.

verified later through variance decompositions.[34]

Table 8: Monte Carlo Experiment. MF & Quarterly Estimation

Param	True	Posterior Mean MF2	Posterior Mean MF1	Posterior Mean Quart	RMSE MF2	RMSE MF1	RMSE Quart	Gain % MF2-Q	Gain % 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: 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 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 MF strategy with respect to quarterly estimation.

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 9 displays average variance decompositions under the three estimation strategies considered so far and under the true parameter vector generating the data.

Before exploring efficiency properties of MF, I summarize main inefficiencies and bias of quarterly estimation. Strikingly, quarterly estimation yields a huge upward bias on the contribution of PTS to output growth variance, estimated to be 48% compared to a true value of 29%.[35] This 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.[36] Not surprisingly, the contribution of each technology shock to output is particularly imprecisely estimated (RMSE are in the range of 34-37 percentage

[34] Uconditional 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).

[35] Similar results hold for consumption and to a less extent for investment growth.

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

points out of 100). In sum, these statistics suggest that there is really hard to identify the relative importance of the two technology shocks using a small sample of quarterly data.

Table 9: 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: 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 estimation under MF compared to quarterly data estimation. The small sample biases of quarterly estimation are significantly reduced under MF methodologies, in particular, 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 (a symmetric result holds for TTS). This takes the PTS/TTS 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, placing TTS as more important.

Similarly, the RMSE of 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 last two columns of table 9). 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.

4.2 Mixed Frequency vs Annual Estimation

The goal of this section is to assess the efficiency properties of the annual estimation procedure performed in GPU and explore potential gains of incorporating quarterly data through MF strategy.

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 MF2.[37]

Given that previous strategies and annual estimation assume different model periods, it is not straightforward to compare efficiency properties of parameter estimators. Consequently, to assess the relative merits of these strategies I focus on variance decompositions at the annual frequency. To facilitate comparisons, table 10 reports variance decomposition statistics not only for annual estimation but also for MF2 (it reports entries only 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

[37] As stated below, there is annual data available for most countries since 1950, but I decided not to run annual estimation with only 60 observations for convergence reasons.

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 very similar bias qualitatively speaking as the other estimation procedures. In particular, 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, as it overstates the contribution of preference shocks to the detriment of interest rate shocks. Again, I find that mixed frequency strategy provides more accurate 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 7%. 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).

The extremely poor relative performance of annual estimation to account for trade balance fluctuations is related with implied moments for investment. Specifically, annual estimation presents a large downward bias for the first order autocorrelation of investment growth, implying a negative value of 0.06 compared to a true positive value of 0.12 (instead, MF and quarterly estimation correctly predict this moment).[38] This suggests 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.[39]

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

[39] This, in turn, may potentially contribute to the upward bias of PTS since a lower perceived capital adjustment 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 10: Monte Carlo Experiment. Variance Decomp. MF & 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: Variance decomposition at annual frequency (does not include measurement errors). MF2 and Annual 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.

Though 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 estimations, in particular about the importance of permanent versus stationary technology shocks.

5 Sensitivity Analysis

This section analyzes the sensitivity and robustness of main results. First, I assess the sensitivity of main empirical findings to different estimation strategies, in particular about the importance of trend versus transitory technology shocks in EM and DC. Second, I examine the sensitivity of results obtained in the Monte Carlo experiment with respect to alternative parameter values and estimation strategies, focusing on efficiency gains of MF estimation.

5.1 Empirical Results

This section studies the sensitivity of main empirical findings (obtained under baseline estimation) to different estimation strategies. Specifically, I consider the alternatives of quarterly estimation and MF estimation with non-overlapping data. I concentrate on the sensitivity of variance decomposition results, especially on the relative importance of PTS and TTS.

5.1.1 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 11 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. Note this is consistent with the bias predicted in the Monte Carlo experiment. It is also observed a substantial decline in the volatility of preference shocks.

Table 12 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 in detriment to transitory technology shocks (compare tables 12 and 7). As a result, quarterly estimations indicate that PTS and TTS play a similar role in explaining fluctuations in EM[40]. 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 Monte Carlo experiment.[41] A similar rebalance in sources of fluctuations is obtained for DC, reinforcing the predominance of PTS for this group.[42] Consequently,

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

[41] 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 obbey 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). Additionaly, we cannot rule out the possibility of structural breaks.

[42] Keep in mind that quarterly series for DC are available for a longer period than for EM (on average about 13 years more). Therefore, it is reasobale to expect smaller differences between MF and quarterly estimates for DC.

the result that PTS is relatively more important in EM than in DC still holds for quarterly estimation. Note also that the contribution of preference shocks in EM falls substantially from MF to quarterly estimation.

Table 11: 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 (1.5)	6.6 (1.5)	6.0 (1.3)	5.2 (1.2)	4.9 (1.2)	5.8 (1.3)
ψ	Int rate debt-elasticity	0.36 (0.13)	0.38 (0.16)	0.19 (0.09)	0.36 (0.11)	0.29 (0.10)	0.33 (0.10)
ρ_a	Autocorr transitory tech	0.92 (0.09)	0.91 (0.10)	0.88 (0.15)	0.81 (0.19)	0.68 (0.23)	0.60 (0.21)
ρ_g	Autocorr permanent tech	0.58 (0.14)	0.59 (0.13)	0.55 (0.18)	0.59 (0.06)	0.54 (0.07)	0.55 (0.08)
ρ_v	Autocorr preference shock	0.97 (0.02)	0.97 (0.02)	0.90 (0.13)	0.97 (0.02)	0.96 (0.02)	0.97 (0.02)
ρ_s	Autocorr spending shock	0.76 (0.06)	0.76 (0.06)	0.77 (0.08)	0.88 (0.02)	0.87 (0.03)	0.82 (0.04)
ρ_μ	Autocorr int rate shock	0.97 (0.02)	0.96 (0.02)	0.96 (0.03)	0.96 (0.02)	0.96 (0.02)	0.96 (0.03)
σ_a	Std Dev transitory tech	0.91 (0.17)	0.88 (0.20)	0.80 (0.22)	0.28 (0.13)	0.24 (0.12)	0.24 (0.12)
σ_g	Std Dev permanent tech	0.88 (0.35)	0.79 (0.34)	0.75 (0.33)	0.70 (0.12)	0.77 (0.13)	0.72 (0.11)
σ_v	Std Dev preference shock	23.6 (7.0)	20.4 (6.5)	11.4 (5.2)	20.1 (5.1)	18.4 (5.3)	19.0 (5.9)
σ_s	Std Dev spending shock	12.2 (1.5)	14.8 (1.7)	14.1 (2.0)	4.7 (0.4)	4.8 (0.5)	4.9 (0.6)
σ_μ	Std Dev int rate shock	0.35 (0.09)	0.36 (0.12)	0.26 (0.10)	0.23 (0.04)	0.20 (0.04)	0.20 (0.06)

Notes: Posterior estimates based on a 3-million MCMC chain (first 1 million draws are discarded). 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). Estimates of standard deviation of shocks are in percentage points.

Table 12: 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: 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 OF standard errors across countries). Variance does not include measurement errors.

5.1.2 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 11). 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 results country by country are also quite similar.[43]

5.2 Monte Carlo Experiment

This section analyzes the robustness and sensitivity of main results obtained in the Monte Carlo experiment to different parameter values and alternative estimation strategies. In particular, I study the robustness of efficiency gains and bias reductions of MF estimation.

[43] Country by country estimates are available upon request to the author.

5.2.1 Sensitivity to Parameter Values

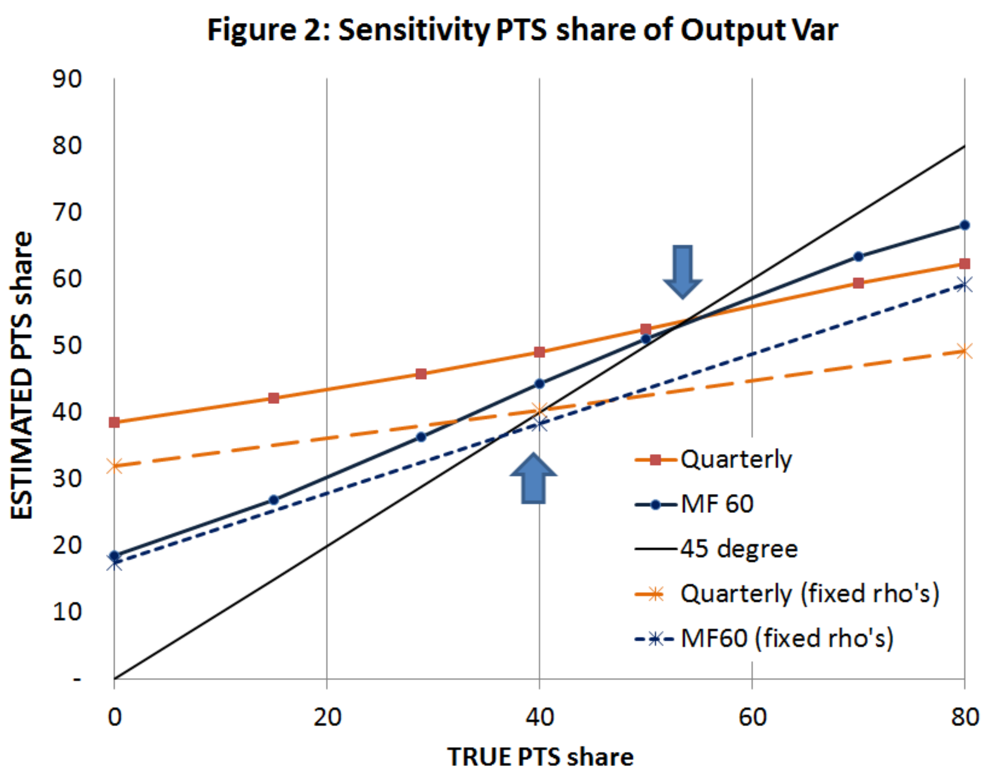
First, I explore the sensitivity of results to different calibrations of the true data generating process, focusing on the relative important of PTS and TTS.

Sensitivity to σ_g/σ_a: I study the sensitivity of the results to different values of the relative volatility of permanent with respect to transitory technology shocks, but keeping constant the sum of 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 13 presents the share of output growth variance attributed to PTS under MF1 and quarterly estimation (and corresponding bias and efficiency 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 2 shows the same information in a scatter plot with the true PTS share in the horizontal axis and the estimated 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.

Ideally, PTS shares lines in figure 2 should be close to the 45 degree line (unbiased estimator of PTS shares). Instead, the two PTS share lines exhibit a positive intersect in the vertical axes (38% and 19% for quarterly and MF1 respectively) and slopes smaller than one (about 3/10 and 5/8 for quarterly and MF1 respectively). These two lines appear to cross the 45 degree line at around 53%; therefore, PTS share bias is positive for true shares of less than 53% and negative for larger values. Given that MF1 slope is bigger, MF1 is always closer to the 45 degree line, and thus presents smaller (absolute) bias than quarterly estimation for all values of σ_g/σ_a considered (see also table 13). The bias gain (absolute terms) of MF1 are convex presenting larger gains for extreme values of the true PTS share away from the crossing point (similar for the RMSE gains, see table 13).

How can we explain the shape of the PTS contribution bias? First, there is a sort of attenuation effect, where PTS share is upward biased for small values of the true PTS and downward biased for large true values (centripetal force). This attenuation effect seems to be related to the identification issues between PTS and TTS in small sample bias discussed before (the relative shares of these shocks are extremely sensitive to the realization of shocks). 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 45 degree line in 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 (persistence effect) contributing to an upward bias of PTS in all cases. More specifically, the shorter the sample, the larger the downward bias estimates 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. At the point 53% it is possible that the attenuation (downward bias in this case) and persistence effect (upward bias) offset each other exactly. To investigate the plausibility of the persistence effect I repeat the Monte-Carlo experiment but calibrating all $\rho's$ coefficients to the true values, so that to eliminate the persistence effect. Figure 2, shows the estimated PTS shares lines for MF1 and quarterly (dashed blue and dotted orange lines respectively), which cross the 45 degree line at 38% and 40% respectively, much close to the middle (40%) once we eliminate the persistence-bias effect. Further, both curves are located below the corresponding PTS lines that estimated all parameters, indicating that the persistence effect always implies an upward PTS bias.

Are the two estimation strategies ranking the technology shocks correctly? To this end, the lower panel of table 13 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). Strikingly, quarterly estimation incorrectly predicts that PTS is larger than TTS for the wide interval [-50%, 0%], that is even when TTS share is 50 percentage points larger. In contrast, mixed frequency estimates are always closer to the true difference and incorrectly rank PTS in first place only for the interval [-10%,0%].

It must be stressed the extremely poor performance of quarterly estimation for low values of PTS. In effect, when we shut down PTS (set $\sigma_g = 0$), quarterly estimate assigns 38% of output variance to it, identifying an 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, and that the attenuation intensity is maximum since PTS is at the largest distance from the middle. In conclusion, quarterly estimation may be specially 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.

Table 13: Share of Output Var Explained by PTS

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

5.2.2 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 before, that 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.[44]

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[45]. 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 result of extending the sample backwards.

5.2.3 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 3 times as large as for the last 21 years. Then, I implement the same MF estimation 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 2/3 of the gains of baseline MF). In sum, efficiency gains of MF with respect to quarterly estimation are robust to noisier early annual data.

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

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

6 Conclusions

This study explores the sources of fluctuations in an small open economy model estimated for 12 emerging and 6 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 while, in contrast, permanent productivity shocks are predominant in developed economies. This result is at odds with Aguiar and Gopinath (2007) finding that permanent shocks are relatively more relevant in emerging countries (based on quarterly estimations for Canada and Mexico). Note that even if permanent technology shocks are not predominant in emerging economies, still they account for a substantial fraction of output variance, far above the negligible role assigned by Garcia-Cicco et.al. (2010) annual estimation for Argentina.

I also perform a Monte Carlo experiment for a representative emerging market to assess the performance of alternative estimation strategies. Importantly, estimations with only 21 years of quarterly data present huge small sample bias, severely overpredicting the relative role of permanent over transitory technology shocks, reversing the true order of importance. Further, mixed frequency estimations strongly reduce this bias and yield much more precise estimates. I also find that mixed frequency estimation delivers a more accurate assessment of sources of fluctuations than the annual estimation strategy followed in GPU.

Another interesting result is that estimations, both empirical and with artificial data, yield a wide dispersion for the relative importance of shocks across EM. This highlights the importance of conducting estimation with many countries to draw conclusions for EM group as a whole.

Interestingly, for the period used in estimation, from 1950 to 2010, many empirical second moments are pretty similar for emerging and developed economies. Accordingly, it is difficult to associate the different role assigned to permanent technology shocks to differences in these moments. Therefore, more work needs to be done to explore which data dynamics is behind the estimated heterogeneity in sources of fluctuations.

Finally, in future research it would be interesting to investigate the robustness of results to structural breaks and different filtering of observables.

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7 Appendix

7.1 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:

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

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

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

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

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

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

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

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

7.2 Estimation

7.2.1 Mixed Frequency Data State-Space Representation

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

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

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:

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

where $\Delta\tilde{y}_t^A$, $\Delta\tilde{c}_t^A$, $\Delta\tilde{i}_t^A$ 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 $\bar{g}=1$):

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

for $w=y,c,$ and i, where L denotes the lag operator. 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 approximations are valid for values of $\bar{g}$ 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:

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

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 $\Delta w_t \equiv [\Delta y_t,\ \Delta c_t, \Delta i_t]^{\prime}$. 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:

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

7.2.2 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 in practice we 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 $\mathcal{Z}^t \equiv \{Z_1^*, Z_2^*, ..., Z_t^*\}$, $a_{t|t} \equiv E(X_t \mid \mathcal{Z}^t)$, $P_{t|t} \equiv V(X_t \mid \mathcal{Z}^t)$, $a_t \equiv E(X_t \mid \mathcal{Z}^{t-1})$ and $P_t \equiv V(X_t \mid \mathcal{Z}^{t-1})$. 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.

7.2.3 Data

Variables expressed in per capita terms using UN population daabase (available only at annual frequency). To obtain quarterly series in per capita terms I first linearly intrapolated annual population observations. All quarterly series used in the estimation are seasonally adjusted. When original time series were available both non-seasonally and seasonally adjusted, I used 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.[46] 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.

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

Developed Countries Data When available, DC annual national accounts data is from OCDE stat online database. For early periods, I complemented 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 extended the sample backwards with discontinued series from OCDE but downloaded through Datastream).

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

7.2.4 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.

7.2.5 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.

7.2.6 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.

7.3 Sensitivity Analysis

7.3.1 Empirical Results

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.