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Emerging Market Business Cycles Revisited: Learning about the Trend*

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Abstract

We build an equilibrium business cycle model in which agents cannot perfectly distinguish between the permanent and transitory components of TFP shocks and learn about those components using the Kalman filter. Calibrated to Mexico, the model predicts a higher variability of consumption relative to output and a strongly negative correlation between the trade balance and output for a wide range of variability and persistence of permanent shocks vis-à-vis the transitory shocks. Moreover, our estimation for Mexico and Canada suggests more severe informational frictions in emerging markets than in developed economies.

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1 Introduction

This paper underscores learning about the "nature" of shocks in explaining salient features of emerging market economy (EME) business cycles–the higher variability of consumption relative to output and the negative correlation between the cyclical components of the trade balance and output. To do so, it builds a small open economy model in which the representative agent observes all the past and current total factor productivity (TFP) shocks and knows the stochastic properties of the distributions of trend growth and transitory components, but does not observe the realizations of the individual components. Using the available information, she forms expectations about trend growth (or permanent) and transitory (or cycle) components of TFP shocks using the Kalman filter.[1]

To reconcile the key differences between emerging and developed economy business cycles, we study a model in which two different signals reveal information about the permanent and transitory components of TFP. The first signal is total TFP growth and therefore, in addition to revealing information, it determines the productivity of the economy. The second one is an additional noisy signal that reveals information about the permanent component of TFP which is modeled as the trend growth shock plus i.i.d. noise. This trend growth signal allows us to vary the degree of information imperfection while keeping all other structural parameters unchanged including for the TFP and the size of permanent or transitory shocks.

Our structural estimation suggests that the accuracy of the trend growth signals for Mexico is significantly lower than that for Canada. Starting from the baseline imperfect information model for Mexico and reducing the noisiness (variance) of the trend growth signal, we find that the model moments move closer to those of developed economies regarding variability of consumption and cyclical behavior of the trade balance. This structural analysis shows that the degree of uncertainty that agents face while formulating expectations can help explain key differences of EME business cycles compared to developed countries.

Earlier research found that the predominance of trend growth shocks is crucial to explain salient features of emerging market business cycles. In our setup, however, two key mechanisms are sufficient for the model to generate "permanent-like" responses even when trend growth shocks are not predominant. First, under perfect information, in response to a positive and persistent trend

[1] Apart from the imperfect information and associated learning, our model is a canonical small open economy RBC model with trend growth shocks featuring production with endogenous capital and labor, with capital adjustment costs.

growth shock, the agent reduces her labor supply due to the wealth effect while increasing her investment. When the persistence of the trend growth shock is higher than a threshold (around 0.2 in our calibration), the decline in labor supply leads to a fall in output even after capital starts to accumulate. This leads the model to generate low correlations of output with consumption and investment. Under imperfect information, when a positive, persistent trend growth shock hits, the agent only gradually realizes that the economy was hit by such a shock. This, in turn, contains the fall in hours worked, preventing a decline in output.

The second key mechanism that helps explain EME regularities is related to the TFP being modeled as *trend plus cycle*. In this case, the beliefs about the contemporaneous trend growth shock relative to the cycle shock can be higher even when the variability of the trend growth shock is lower than that of the cycle shock. This is because, under imperfect information, the agent optimally decomposes the TFP growth into *trend growth*, and *change in the cycle*. This, in turn, implies that when updating the beliefs about the changes in the cycle, she updates her beliefs not only about the contemporaneous cycle shock but also its first lag. This backward revision has no implications for the already executed decisions in the previous period. However, it implies that in response to a positive signal, the agent may improve her beliefs about the change in the cycle by not only improving her beliefs about the contemporaneous cycle shock, but also by lowering her beliefs about its first lag. Therefore, a given upward updating of the change in the cycle can be attained by improving the beliefs about a contemporaneous cycle shock by less than she would in a setting without the backward revision of the cycle shock.[2]

We interpret the permanent component of TFP shocks as capturing major structural changes in the economy driven by policy regime switches such as trade or financial reforms (as in Aguiar and Gopinath (2007)). These changes are likely to have permanent effects on TFP, as opposed to business cycles that do not alter trend growth but simply are mean reverting fluctuations around a stable trend. Capturing these policy regime switches adequately requires an explicit modeling of these two components separately. In addition, Baxter and Crucini (1995) find that, in an incomplete markets environment, the effects of an international business cycle shock vary greatly depending on whether shocks are permanent or transitory. Their findings provide an additional rationale for the modeling of trend-cycle decomposition explicitly and a reason for why the agents would want to know about this decomposition for their economy as well as for foreign economies that they have financial linkages with.

[2]Under learning with trend plus pure noise, for example, such a backward revision does not happen.

Our main motivation for introducing a learning problem to decompose total TFP into trend and cycle relies on the uncertainty surrounding the duration of structural changes in EMEs. Once a reform takes place in an EME, agents face a high degree of uncertainty as to when and if the next government will undo the reform.[3] This view is also supported by the earlier literature on emerging market business cycles that hinged on uncertain duration of reforms particularly in the context of exchange rate based stabilization programs (see, for instance, Calvo and Drazen (1998), Calvo and Mendoza (1996), and Mendoza and Uribe (2000), among others). In this context, our paper underscores that the *uncertainty* regarding the duration of these structural breaks contribute significantly to the salient differences between emerging and developed economy business cycles.

Most time series data (particularly at high frequency) in EMEs are shorter than in developed economies making the informational frictions more acute. For example, the median length of quarterly GDP series available for EMEs is 96 while that in developed economies is 164 quarters (see International Financial Statistics of the IMF). Looking at employment, the median length for EMEs is about half of that for developed economies (44 vs. 80 quarters).[4] For EMEs, series such as EMBI spreads start as late as mid 1990s or early 2000s. Moreover, yield curves are also short since most EME government bonds have at most 10 year maturity. Some series such as hours worked are missing altogether for many EMEs.

The lack of long time series data in emerging markets makes it more difficult to measure TFP exacerbating the difficulty of decomposing TFP into trend and cycle. To see how the measurement problem can feed into the decomposition problem define $TFP^m = TFP^t + \epsilon$ where TFP^m is measured TFP, TFP^t is true TFP while ϵ is a noise term capturing the measurement problem. The standard deviation of ϵ pins down the severity of the measurement problem which we conjecture to be larger in EMEs than developed economies. With this more general formulation, the agents could be assumed to decompose first the measured TFP into noise and true TFP, and second, true TFP into trend and cycle. A large standard deviation for ϵ would make it harder to decompose trend and cycle since the true TFP would be observed less accurately. In this sense, the measurement problem would add yet another layer of uncertainty making the trend-cycle decomposition problem more challenging for the agent.

[3]EMEs are surrounded by greater uncertainty in general and not only with regards to duration of reforms. This greater uncertainty can be due to several intertwined characteristics of these economies such as lack of transparency, lower institutional quality, and greater political uncertainty. Acemoglu et al. (2003) and references therein document that EMEs are characterized by poorer institutional quality and greater political uncertainty compared with developed countries.

[4]In these calculations, the set of EMEs and advanced economies follow the sample choice of Aguiar and Gopinath (2007).

Finally, if TFP primarily measures idiosyncratic technological shocks at the firm level, one could argue that at the micro level, agents could have perfect information about the type of shocks they receive and that imperfect information is just a statistical problem for the econometrician. In other words, since trend shocks capture the importance of regime changes, they may not be perfectly distinguishable at the firm or household level.

Our paper primarily contributes to the emerging market business cycles literature including Aguiar and Gopinath (2007), Garcia-Cicco, Pancrazzi and Uribe (2010), Mendoza (1995, 2010), Neumeyer and Perri (2005), and Uribe and Yue (2006), among others.[5] Aguiar and Gopinath (2007) show that introducing trend shocks to an, otherwise, standard small open economy real business cycle model can account for the salient features of economic fluctuations in EMEs.[6] In order for the perfect information model to account for the two key features of EME business cycles, a high variability of innovation to trend shocks and a low autocorrelation of the trend growth shocks are necessary. Our imperfect information model relaxes these assumptions considerably.

Our paper makes an important methodological contribution to a vast literature on macro models with learning. To our knowledge, ours is the first paper to incorporate a learning problem with permanent shocks as well as persistent AR(1) transitory shocks into a dynamic stochastic general equilibrium growth model. In this literature, Boz (2009) investigates the business cycle implications of learning about persistent productivity shocks in the context of emerging market business cycles. Her model does not allow for both permanent and transitory shocks. In a related paper, Nieuwerburgh and Veldkamp (2004) study U.S. business cycle asymmetries in an RBC framework with asymmetric learning regarding transitory TFP shocks. Their analysis focuses on whether learning regarding transitory TFP shocks can induce asymmetries in output growth over the business cycle. Another study on U.S. business cycles is Edge, Laubach and Williams (2007) who show that uncertainty regarding the nature of productivity shocks (permanent shifts versus transitory shocks) helps explain some of the U.S. business cycle characteristics. They model signals as trend plus iid shocks, whereas we model signals as trend plus AR(1) cycle shocks. Similarly, Guvenen (2007) studies learning about earnings utilizing a signal extraction problem with AR(1)

[5] An early contribution in this literature includes Mendoza (1991), who provides a workhorse real business cycle model for small open economies. Mendoza's model calibrated to Canada proves successful in explaining the observed persistence and variability of output fluctuations as well as counter-cyclicality of trade balance.

[6] The intuition for this result relies on the permanent-income theory of consumption. If faced with a positive trend growth shock to output, the agent increases her consumption by more than the increase in current output since she expects an even higher output in the following period. This mechanism generates a consumption profile that is more volatile than output and also a trade balance deficit in response to a positive trend growth shock for the agent to finance a consumption level above output.

plus noise shocks. In a parallel work to ours, Blanchard, L'Huillier and Lorenzoni (2008) follow a similar modeling strategy with trend growth and transitory shocks to explore the contribution of news and noise shocks to macroeconomic volatility.

Similar to our paper, the literature on "news shocks" (e.g., Cochrane (1994), Jaimovich and Rebelo (2009) and Lorenzoni (2006), Schmitt-Grohe and Uribe (2008), among others) emphasizes the role of expectations. As shown by these studies, the standard RBC model with Cobb-Douglas preferences implies counterfactual dynamics on labor supply in response to positive news shocks; labor supply drops on impact due to positive wealth effect–similar to the dynamics of labor supply in response to highly persistent trend growth shocks. Many of the recent studies have focused on building frameworks that deliver empirically-plausible dynamics of labor. Jaimovich and Rebelo (2009), for example, propose "quasi-GHH preferences" to contain the large wealth effect. Our analysis shows that an alternative modeling approach could be the introduction of learning in an environment with trend growth shocks. Highly persistent trend growth shocks have similar economic interpretation as news shocks and the gradual learning in our framework leads to realistic dynamics of labor supply.

Finally, our paper relates to Quah (1990) who aims to resolve the dispute about whether consumption is excessively smooth in the U.S. data. The main intuition of Aguiar and Gopinath (2007) builds on the permanent income hypothesis. Since shocks to trend growth generate larger fluctuations in consumption, a model with larger trend growth shocks is consistent with EME facts (higher consumption volatility) while the opposite is true for developed economies. Quah (1990) argues that one way to resolve this excessive smoothness observed in the U.S. data is to assume that the labor income as an integrated process plus a trend stationary one. Unlike us, he assumes that the econometrician is imperfectly informed while the agents are fully informed. He finds that consumption will appear excessively smooth to the imperfectly informed econometrician since the consumption decisions were made by the economic agents who were in fact fully informed.

The rest of the paper is structured as follows. The next section introduces our model as well as the information structure and the consequent learning process. Section 3 presents our baseline quantitative analysis and sensitivity. Section 4 concludes and discusses extensions for further research.

2 Model

Motivated by the observations outlined in the last section, we consider a standard small open economy real business cycle model with trend shocks similar to that utilized by Aguiar and Gopinath (2007) and Garcia-Cicco et al. (2010). Unlike these two studies, in our emerging market economy model, the representative agent is imperfectly informed about the trend-cycle decomposition of the TFP shocks and, thereby, solves a signal extraction problem as explained in detail below.

The model features production with endogenous capital and labor. There are costs associated with adjusting capital, which are typically introduced in the literature to match the variability and persistence of investment. The agent can borrow and lend in international capital markets. We assume incomplete asset markets, such that the only financial instrument available is a one-period non-contingent bond that pays an interest rate that increases with the debt level. At the beginning of every period, the agent observes TFP and the trend growth signal, updates expectations regarding the components of TFP, makes investment, labor, debt, and consumption decisions.

The production function takes a standard Cobb-Douglas form,

$$Y_t = e^{z_t} K_t^{1-\alpha} (\Gamma_t L_t)^{\alpha},$$

where $\alpha \in (0,1)$ is the labor's share of output. z_t is the transitory shock that follows an AR(1) process

$$z_t = \rho_z z_{t-1} + \varepsilon_t^z$$

with $|\rho_z| < 1$, and ε_t^z is independently, identically, and normally distributed, $\varepsilon_t^z \sim N(0, \sigma_z^2)$. Γ_t represents the cumulative product of growth shocks and is defined by

$$\Gamma_t = e^{g_t} \Gamma_{t-1} = \prod_{s=0}^{t} e^{g_s},$$

and

$$g_t = (1 - \rho_g)\mu_g + \rho_g g_{t-1} + \varepsilon_t^g,$$

where $|\rho_g| < 1$, and ε_t^g is independently, identically, and normally distributed with $\varepsilon_t^g \sim N(0, \sigma_g^2)$. The term μ_g represents the long run mean growth rate. Combining trend growth and transitory shocks, we define a single productivity shock A:[7]

$$\ln(A_t) \equiv z_t + \alpha \ln(\Gamma_t),$$

and growth rate of A as g^A:

$$\ln(g_t^A) \equiv \ln\left(\frac{A_t}{A_{t-1}}\right) = z_t - z_{t-1} + \alpha g_t. \tag{1}$$

The representative agent's utility function is in Cobb-Douglas form:

$$u_t = \frac{(C_t^{\gamma}(1-L_t)^{1-\gamma})^{1-\sigma}}{1-\sigma}.^{8}$$

The agent maximizes expected present discounted value of utility subject to the following resource constraint:

$$C_t + K_{t+1} = Y_t + (1-\delta)K_t - \frac{\phi}{2}\left(\frac{K_{t+1}}{K_t} - \mu_g\right)^2 K_t - B_t + q_t B_{t+1}.$$

C_t, K_t, q_t, and B_t denote consumption, the capital stock, the price of debt and the level of debt, respectively. We assume that capital depreciates at the rate δ, and adjustments to capital stock requires quadratic adjustment cost with the adjustment cost parameter ϕ. μ_g denotes the unconditional mean of the growth rate of A.

We assume that the small open economy faces a debt-elastic interest-rate premium, such that the interest rate paid is given by:

$$\frac{1}{q_t} = 1 + r_t = 1 + r^* + \psi\left[e^{\frac{B_{t+1}}{A_t} - b} - 1\right],$$

where b is the aggregate level of debt that the representative agent takes as given. The specification of the interest rate is aimed to account for possible risk premia charged due to a higher default risk when debt increases.[9]

[7]This follows directly from the fact that the production function could be written alternatively as $Y_t = A_t K_t^{1-\alpha}(L_t)^{\alpha}$, where $A_t = e^{z_t}\Gamma_t^{\alpha}$.

[8]We also explore the case with Jaimovich-Rebelo preferences in Section 3.3.

[9]The debt elastic interest rate premium is introduced so as to induce stationarity to the asset holdings in the stochastic steady state. Other formulations used in the literature for this purpose include Mendoza (1991)'s endogenous discounting, and Aiyagari (1994)'s preferences with the rate of time preference higher than the interest rate. Schmitt-Grohé and Uribe (2003) survey some of the alternative methods used for this purpose and concludes that quantitative differences among the approaches applied to linearized systems are negligible.

Since realizations of shock g_t permanently affect Γ_t, output is nonstationary. To induce stationarity, we normalize all the variables by A_{t-1}.[10] We use the notation that a variable with a hat denotes its detrended counterpart.

After detrending, the recursive representation of the representative agent's problem can be formulated as follows:

$$V(\widehat{K}_t, \widehat{B}_t, \widetilde{z}_t, \ln(\widetilde{g}_t), g_t^A) = \max\left\{u(\widehat{C}_t, L_t) + \beta(g_t^A)^{\gamma(1-\sigma)} E_t V(\widehat{K}_t, \widehat{B}_{t+1}, \widetilde{z}_{t+1}, \ln(\widetilde{g}_{t+1}), g_{t+1}^A)\right\},$$

subject to the budget constraint:

$$\widehat{C}_t + \widehat{K}_{t+1} g_t^A = \widehat{Y}_t + (1-\delta)\widehat{K}_t - \frac{\phi}{2}\left(\frac{\widehat{K}_{t+1}}{\widehat{K}_t} g_t^A - \mu_g\right)^2 \widehat{K}_t - \widehat{B}_t + g_t^A q_t \widehat{B}_{t+1},$$

where $\widetilde{z}_t$ and $\ln(\widetilde{g}_t)$ are the beliefs regarding the transitory and permanent shock, respectively.

Defining investment as X_t, we can summarize the evolution of the capital stock as follows:

$$g_t^A \widehat{K}_{t+1} = (1-\delta)\widehat{K}_t + \widehat{X}_t - \frac{\phi}{2}\left(\frac{\widehat{K}_{t+1}}{\widehat{K}_t} g_t^A - \mu_g\right)^2 \widehat{K}_t.$$

The first order conditions for the competitive equilibrium are:

$$\gamma \widehat{C}^{\gamma(1-\sigma)-1}(1-L_t)^{(1-\gamma)(1-\sigma)}\left(g_t^A \phi\left(g_t^A \frac{\widehat{K}_{t+1}}{\widehat{K}_t} - \mu_g\right) + g_t^A\right) = -\beta g_t^{A\gamma(1-\sigma)} E_t \frac{\partial V}{\partial \widehat{K}_{t+1}}, \tag{2}$$

$$\gamma \widehat{C}^{\gamma(1-\sigma)-1}(1-L_t)^{(1-\gamma)(1-\sigma)} g_t^A q_t = \beta (g_t^A)^{\gamma(1-\sigma)} E_t \frac{\partial V}{\partial \widehat{B}_{t+1}}, \tag{3}$$

$$\frac{\widehat{C}_t}{1-L_t} = \frac{\gamma}{1-\gamma}\frac{\partial \widehat{Y}_t}{\partial L_t}. \tag{4}$$

Equation (2) is the Euler Equation that relates the marginal benefit of investing an additional unit of resource in capital to marginal cost of not consuming that unit. Equation (3) is the Euler Equation related to the level of debt and equation (4) is the first order condition concerning the labor-leisure choice.

[10] Note that perfect information model can be normalized by Γ_{t-1}. In our imperfect information setting, however, Γ_{t-1} is not in the information set of the agent. Y_{t-1} and A_{t-1} are other plausible candidates for normalization as they grow at the same rate as A and are in emerging market representative agent's information set. We choose to normalize by A_{t-1}, but normalizing by Y_{t-1} would yield identical results.

2.1 Filtering Problem

We assume that the representative agent is imperfectly informed about the true decomposition of the TFP shocks into its trend growth and cycle components and forms expectations about this decomposition using the Kalman filter. In addition to TFP shocks, the representative agent also receives an additional noisy signal regarding the trend growth shocks. In particular she observes s_t such that $s_t = g_t + \varepsilon_t^s$ where $\varepsilon^s \sim N(0, \sigma_s)$.[11] Her information set as of time t includes the entire history of TFP shocks and publicly observable signals s_t; $I_t \equiv \{A_t, s_t, A_{t-1}, s_{t-1}, ...\}$. We also assume that underlying probabilistic distributions of Γ and z are known to the agent. Thus, we abstract from any consideration regarding model uncertainty to concentrate exclusively on the implications of learning under imperfect information about the realizations of the shocks.

In order to use the Kalman filter, we express the filtering problem in state space form as described in Harvey (1989). This form consists of a measurement equation and a transition equation. The measurement equation includes a vector reformulation of Equation (1) and the definition of s_t:

$$\begin{bmatrix} \ln(g_t^A) \\ s_t \end{bmatrix} = \underbrace{\begin{bmatrix} 1 & -1 & \alpha & 0 \\ 0 & 0 & 1 & 1 \end{bmatrix}}_{\mathbf{Z}} \underbrace{\begin{bmatrix} z_t \\ z_{t-1} \\ g_t \\ \varepsilon_t^s \end{bmatrix}}_{\boldsymbol{\alpha}_t}.$$

The measurement equation includes the lagged value of transitory shock, z_{t-1}. Because, to make the learning problem stationary, the relationship between the observed and unobserved variables needs to be formulated in growth rates. The transition equation summarizes the evolution of unobserved variables and is given by:

$$\underbrace{\begin{bmatrix} z_t \\ z_{t-1} \\ g_t \\ \varepsilon_t^s \end{bmatrix}}_{\boldsymbol{\alpha}_t} = \underbrace{\begin{bmatrix} \rho_z & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & \rho_g & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}}_{\mathbf{T}} \underbrace{\begin{bmatrix} z_{t-1} \\ z_{t-2} \\ g_{t-1} \\ \varepsilon_{t-1}^s \end{bmatrix}}_{\boldsymbol{\alpha}_{t-1}} + \underbrace{\begin{bmatrix} 0 \\ 0 \\ (1-\rho_g)\mu_g \\ 0 \end{bmatrix}}_{\mathbf{c}} + \underbrace{\begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}}_{\mathbf{R}} \underbrace{\begin{bmatrix} \varepsilon_t^z \\ \varepsilon_t^g \\ \varepsilon_t^s \end{bmatrix}}_{\boldsymbol{\eta}_t} \tag{5}$$

[11] Note that we could also model this signal as one that reveals information about the cycle (z). This would yield similar results because a more accurate knowledge of g would transform into a more accurate knowledge of z and vice versa. This latter observation is due to the fact that the sum of g and Δz is actually observed (through the TFP growth).

where $\boldsymbol{\eta}_t \sim N(0, \mathbf{Q})$ and $\mathbf{Q} \equiv \begin{bmatrix} \sigma_z^2 & 0 & 0 \\ 0 & \sigma_g^2 & 0 \\ 0 & 0 & \sigma_s^2 \end{bmatrix}$. Equation (5) simply summarizes the autoregressive processes of trend growth and transitory components of TFP in matrix notation. Note that, in this setting, we can control the degree of information imperfection by varying σ_s without changing the TFP process. As $\sigma_s \to \infty$, s_t does not provide any additional information compared to the realizations of TFP shocks, thus, the model features full imperfect information environment. As $\sigma_s \to 0$, s_t fully reveals the components of TFP, hence the model becomes identical to the perfect information environment.

Given the normality of the disturbances, the optimal estimator that minimizes the mean squared error is linear. The matrices $\mathbf{Z}$, $\mathbf{T}$, $\mathbf{c}$, $\mathbf{R}$ and $\mathbf{Q}$ are the *system matrices*. Following the notation of Harvey (1989), we denote the optimal estimator of $\boldsymbol{\alpha}_t$ based on information set, I_t by $\mathbf{a}_t$:

$$\mathbf{a}_t \equiv E[\boldsymbol{\alpha}_t | I_t].$$

The covariance matrix of the estimation error is given by $\mathbf{P}_t$:

$$\mathbf{P}_t \equiv E[(\boldsymbol{\alpha}_t - \mathbf{a}_t)(\boldsymbol{\alpha}_t - \mathbf{a}_t)'].$$

In this setting, the updating rule converges monotonically to a time-invariant solution for the error covariance matrix.[12] The steady state error covariance matrix can be calculated as a solution to the following *algebraic Riccati equation*:

$$\mathbf{P} = \mathbf{TPT}' - \mathbf{TPZ}'(\mathbf{ZPZ}')^{-1}\mathbf{ZPT}' + \mathbf{RQR}'. \tag{6}$$

Finally, using I_{t-1} and the transition equation (5), we have:

$$\mathbf{a}_{t|t-1} = \mathbf{T}\mathbf{a}_{t-1} + \mathbf{c}.$$

The updating rule sets the posteriors $\mathbf{a}_t$ to be a convex combination of prior beliefs $\mathbf{a}_{t|t-1}$ and the new signal $\ln(g_t^A)$:

[12] See Harvey (1989) pp. 123 for a proof of this statement.

$$\mathbf{a}_t = \underbrace{[\mathbf{I} - \mathbf{PZ}'(\mathbf{ZPZ}')^{-1}\mathbf{Z}]}_{k^1}\mathbf{a}_{t|t-1} + \underbrace{[\mathbf{PZ}'(\mathbf{ZPZ}')^{-1}]}_{k^2}\begin{bmatrix} \ln(g_t^A) \\ s_t \end{bmatrix} \tag{7}$$

where $\mathbf{I}$ is an identity matrix of size 4×4. Equations (2.1) and (7) fully characterize learning.

Equation (7) deserves a closer look. This equation consists of two parts. The first part is priors, $\mathbf{a}_{t|t-1}$ or $E[\boldsymbol{\alpha}|I_{t-1}] = E[z_t, z_{t-1}, g_t|I_{t-1}]$, multiplied by their corresponding weights summarized in the matrix $k^1_{4\times4}$. The second part is the set of signals, g_t^A and s_t, multiplied by the *Kalman gain* $k^2_{4\times2}$. Weights assigned to the priors and the new signals (k^1 and k^2) depend mainly on the relative variance of trend to cycle shocks, σ_g/σ_z. As we will illustrate and explain in detail in the next section, the higher the relative variability of trend shocks, the larger the share of TFP shocks attributed to the permanent component.

3 Quantitative Analysis

This section explains the calibration and estimation procedure of the parameters and documents the business cycle moments for Mexico and Canada. Further, it plots impulse response functions and explains in detail the implications of introducing imperfect information. We solve our model using a first order approximation around the deterministic steady state following the "brute-force iterative procedure" proposed by Binder and Pesaran (1997).[13]

3.1 Business Cycle Dynamics

We calibrate our model to quarterly Mexican and Canadian data. We use a combination of calibrated and estimated parameters. For β, γ, b, ψ, α, σ, and δ, we use the same values for both Mexico and Canada; these values are standard in the literature (see e.g., Mendoza (1991); Aguiar and Gopinath (2007); Schmitt-Grohé and Uribe (2003); Neumeyer and Perri (2005)). γ is set to 0.36, which implies that around one-third of an agent's time is devoted to labor in the steady-state. The interest rate premium coefficient is set to a small value, 0.001. The full set of calibrated parameters is summarized in the upper panel of Table 1. We set μ_g to the average growth rate of output from the data and estimate the remaining structural parameters, σ_g, σ_z, ρ_g, ρ_z, ϕ, and σ_s using a GMM estimation applied to the baseline imperfect information model. We report our

[13]The log-linearized system is provided in an Appendix available upon request.

estimation results in the middle panel of Table 1.[14]

Table 1 reveals that the estimated standard deviation of the trend growth component (σ_s) for Mexico is about 20 times that for Canada. Put differently, the trend growth signals are less informative in Mexico suggesting more severe informational frictions in Mexico relative to Canada. To map these estimates to signal-to-noise ratios, we report two separate metrics; the ratio of standard deviation of trend growth shock to the standard deviation of the trend growth signal noise ($\frac{\sigma_g}{1-\rho_g^2}/\sigma_s$) and the ratio of standard deviation of TFP growth to the standard deviation of the trend growth signal noise (σ_{g^A}/σ_s). Both metrics point to the existence of markedly more informative signals in Canada relative to Mexico. The first signal-to-noise ratio metric indicates that the signals are about six times more informative in Canada. And, the second metric indicates that signals are about eight times more informative in Canada.

Next we compare the relative importance of trend shocks in our estimation. To do so, we examine two related metrics calculated based on our estimated parameters. The first metric is the variability of innovations to trend growth shocks relative to innovations to transitory shocks, σ_g/σ_z. This metric, however, does not incorporate any potential differences in the persistence of these two types of shocks. Therefore, we also examine another one that we calculate as follows. We decompose the first log-difference of TFP according to:

$$\Delta \ln A_t = \Delta z_t + \alpha g_t.$$

Computing the variance of this expression, and taking into account that trend and transitory shocks are uncorrelated in our model, we obtain

$$\sigma^2_{\Delta \ln A} = \underbrace{\frac{2\sigma_z^2}{1+\rho_z}}_{\sigma^2_{\Delta z}} + \underbrace{\frac{\alpha^2\sigma_g^2}{1-\rho_g^2}}_{\sigma^2_{\alpha g_t}}$$

[14] With these parameters, for the baseline case, the Kalman gains are

$$k^1 = \begin{bmatrix} 0.6391 & 0.3609 & -0.2437 & 0.0017 \\ 0.3765 & 0.6235 & 0.2559 & -0.0001 \\ -0.3862 & 0.3862 & 0.7348 & -0.0026 \\ 0.3862 & -0.3862 & -0.7348 & 0.0026 \end{bmatrix}$$

and

$$k^2 = \begin{bmatrix} 0.3609 & -0.0017 \\ -0.3765 & 0.0001 \\ 0.3862 & 0.0026 \\ -0.3862 & 0.9974 \end{bmatrix}.$$

and we define our measure of the relative importance of trend shocks simply as follows:

$$V = \frac{\frac{\alpha^2 \sigma_g^2}{1-\rho_g^2}}{\frac{2\sigma_z^2}{1+\rho_z} + \frac{\alpha^2 \sigma_g^2}{1-\rho_g^2}},$$

which is reported in the last row of Table 1. Note that this metric is bounded in the interval [0,1] where higher values imply higher importance of trend growth shocks.

This second metric has several advantages that make it an accurate measure of relative variability of trend shocks. First, it does not restrict the permanent shocks to follow a random walk. As pointed out by Campbell and Mankiw (1987), if trend growth shocks are persistent (remember that we estimate ρ_g to be 0.62 for Mexico), only a type of metric we use would preserve that trend and cycle shocks remain uncorrelated. This is an important aspect that is also highlighted by Campbell and Mankiw (1987).[15] Second, Quah (1990, 1992) shows that when the trend follows a more complicated process, as it does in our model, an unobserved component estimation of trend growth shocks should be pursued, as we do in our analysis.[16]

Using the two metrics described, we find that our baseline imperfect information model implies markedly similar relative variance of trend shocks for Mexico and Canada. Both metrics imply that the variance of trend shocks are lower than that of cycle shocks for both countries. As we discuss next, our model can account for the key differences between business cycles of Mexico and Canada with differences in the degree of informational imperfection reported in Table 1.

Table 2 shows the ability of our model to match the business cycle moments of Mexico and Canada (first two columns, respectively). The imperfect information model matches the key moments of the Mexican data closely as reported in the third column.[17] The ratio of consumption variability to income variability is 1.19, compared with 1.26 in the data. The correlation of net exports with output is -0.67, which compares quite well with the value of -0.75 in the data. The model also matches the other moments closely as illustrated in Table 2. Remember that the GMM estimation reveals $\sigma_g/\sigma_z = 0.79$ and $V = 0.27$, suggesting that the imperfect information model matches the Mexican business cycles without a predominance of trend growth shocks.

The model with a lower degree of informational imperfection matches the Canadian business

[15] Campell and Mankiw indicate that: "...But of course, one usually thinks of trend and cycle as having a low or zero correlation..."

[16] Similarly, Oh et al. (2008) also makes a case in favor of a use of type of metric we present when the trend is not a pure random walk.

[17] We calculate all moments using simulated data series. Simulated data are HP-filtered with a smoothing parameter of 1600, the standard value for quarterly data.

cycles well. As highlighted in the last column of Table 2, when the agent can accurately decompose TFP into trend and cycle, the dynamics of the model appear quite similar to what the permanent income hypothesis predicts. When there is a positive transitory shock to output, the representative agent increases her consumption but this increase is lower than the increase in output. Because the agent knows that the output will gradually decline back to its previous level, she saves a portion of the increase in output; in line with the standard consumption-smoothing effect in the presence of transitory shocks. When the shock is permanent, the agent observes an increase in output today but she also realizes that future output will be even higher. The agent's optimal response to such positive permanent shocks is to increase her consumption more than the increase in current output.

We, next, examine the impulse response functions for the imperfect information model estimated for Mexico. We also examine the impulse response functions, for the perfect information case using the same parameter values estimated for the imperfect information model.[18] Figures 1 and 2 show these impulse responses to a 1-percent transitory and 1-percent permanent shock, respectively. Under imperfect information, the model displays "permanent-like" behavior in response to a transitory shock (crossed-dashed lines in Figure 1). Consumption increases more than output; net exports decline significantly. Also notice that imperfect information introduces amplification driven by the fact that the agent assigns a positive probability to the event that the shock might be permanent and, therefore, increases investment and consumption by more than under the perfect information case. Under perfect information, the model displays standard consumption smoothing dynamics.

In response to a permanent shock (crossed-dashed lines in Figure 2), the model again displays permanent-like responses. Consumption responds more than output; net-exports decline significantly. Also notice that learning introduces persistence. Under perfect information, the response of hours to a *persistent trend growth shock* is quite strong. In response to a persistent, positive trend growth shock, hours decline significantly due to the wealth effect.[19] The decline in hours leads to a fall in output. Investment increases gradually due to the capital adjustment cost. Therefore, the increase in capital in response to positive trend growth shock is insufficient to offset the impact of the fall in hours on output.

The strong response of hours to persistent trend growth shocks makes it difficult for the perfect

[18]The perfect information scenario corresponds to the setup in which agents are fully informed about the trend-cycle decomposition which can be captured as $\sigma_s = 0$.

[19]The magnitude of this decline increases with the persistence of the trend growth shock. In our simulations that we discuss later, we find that when the persistence of trend growth shock is higher than a threshold, $\rho_g > 0.2$, the decline in hours becomes so large that it leads output to fall in response to a positive trend growth shock.

information model to match the correlations of aggregate variables with output observed in the Mexican data. This is evident in Figure 2 (remember that estimated ρ_g in this case is 0.62).[20] The graph shows that in response to a positive trend growth shock, hours and net exports fall while consumption and investment increase. Remember that output also falls in response to this positive trend growth shock. As a result, the model generates $\rho(c, y)$ and $\rho(I, y)$ that are lower compared with the case when $\rho_g = 0$. In addition, $\rho(nx, y)$ becomes positive because net exports move in the same direction with output both in the case of a cycle shock and a trend growth shock.

The imperfect information model can deliver high $\rho(c, y)$ and $\rho(I, y)$ consistent with the data. This is because learning leads the agent to realize only gradually that a trend growth shock hit. Since learning induces gradual realization, the decline in hours is not sufficient to lead to a decline in output. Therefore, the imperfect information model matches the correlations in the data quite well even with persistent trend growth shocks.

The dynamics of hours and output that arise due to gradual learning constitute a methodological contribution to the "news shocks" literature (e.g., Cochrane (1994), Jaimovich and Rebelo (2009) and Lorenzoni (2006), Schmitt-Grohe and Uribe (2008), among others). As shown by these studies, the standard RBC model with Cobb-Douglas preferences implies counterfactual dynamics on labor supply in response to positive news shocks; labor supply drops on impact due to positive wealth effect–similar to the dynamics of labor supply in response to highly persistent trend growth shocks. Many of the recent studies in this literature have focused on building frameworks that deliver empirically-plausible dynamics of labor. Jaimovich and Rebelo (2009), for example, propose "quasi-GHH preferences" to contain the large wealth effect. Our analysis shows that an alternative modeling approach could be the introduction of learning in an environment with trend growth shocks. Highly persistent trend growth shocks have a similar economic interpretation to news shocks and the gradual learning in our framework implies realistic dynamics of the labor supply.

3.2 Further Insights on Learning

To illustrate the learning dynamics implied by the model, in Figure 3, we plot beliefs for permanent and transitory components along with TFP that the agent directly observes. The crossed-solid line depicts TFP, the diamond-dashed line plots the evolution of the belief about the permanent

[20] In general, the perfect information model with $\rho_g > 0.2$ cannot generate $\rho(c, y)$ or $\rho(I, y)$ that is greater than 0.9 regardless of σ_g/σ_z.

component, while the starred-dashed line shows the evolution of the belief for the transitory component. In the left panel, the source of fluctuation in TFP is a 1-percent transitory component shock, whereas in the right panel, it is a trend growth shock of the same magnitude.[21]

A close investigation of the right panel of Figure 3 –the case of a trend growth shock– suggests that, on impact, beliefs regarding the trend growth shock, $\tilde{g}$, goes up by only half of the increase in the true value of g. The initial period in which a high TFP growth is observed is particularly confusing for the agent. Only after observing another signal, $\tilde{g}$ becomes significantly close to the true value of g in that period. This is because of the nature of learning about cycle and trend. A high TFP growth today can be either a positive trend growth shock or a positive cycle shock. Therefore, the observation of a high TFP growth by itself is not very informative. However, note that a cycle shock dies out very differently from a trend growth shock.[22] A positive cycle shock in period 2 leads to a negative TFP growth starting from period 3. This is because given that the trend does not change, an above trend growth in period 2 has to be followed by a below trend growth so that the economy converges back to the same trend as the shock dies out. On the contrary, a positive trend growth shock in period 2 dies out by leading to an even higher trend over time. Given these differences, after observing the initial high TFP growth in period 2, the TFP growth in period 3 becomes crucial for the agent to be able to decompose trend and cycle. Therefore, it is this initial uncertainty and its gradual disappearance that contains the decline in hours and prevents a potential decline in output in response to a persistent trend growth shock.

We simulate a case where both 1% permanent shock and 1% transitory shock are given at the same time in the perfect and the imperfect information models. Table 3 documents the true values of these shocks for the perfect information case and the beliefs calculated by the agent in the imperfect information case under baseline parameterization. As expected, under perfect information, the shocks are 1% each for g_t and z_t leading to 1.68% growth in TFP, given that $\alpha = 0.68$. Under imperfect information, however, while decomposing TFP between g_t and Δz_t, the agent assigns 0.65% to $\widetilde{g}_t$, 0.60% to $\widetilde{z}_t$, and -0.63% to $\widetilde{z}_{t-1}$. In other words, the agent, using the Kalman filter, increases $\widetilde{z}_t$ while decreasing $\widetilde{z}_{t-1}$, part of the increase in $\Delta\widetilde{z}_t$ coming from an

[21] In the right panel, interestingly, TFP shock turns negative after the initial positive shock. This is in fact intuitive. Rewriting Equation 1, we have: $\ln(g_t^A) = z_t - z_{t-1} + \alpha g_t$. Thus, g_t is zero as only the transitory component is shocked in the first panel, while z_t increases by 1-percent on impact and $z_{t-1} = 0$ because we start from the steady state. As the shock dies out after the first period, $z_t = \rho_z z_{t-1}$ becomes smaller than z_{t-1} implying a negative value for $z_t - z_{t-1}$. With $z_t - z_{t-1} < 0$ and $g_t = 0$, we have $\ln(g_t^A)$ turning negative after the initial period as depicted in the top panel of Figure 3.

[22] The comparison of "simulated TFP growth," solid blue line, in the lower and higher panels of Figure 3 reveals this.

update of $\widetilde{z}_{t-1}$. This leads to the increase in $\widetilde{g}_t$ to be larger than $\widetilde{z}_t$ inducing a dampening of the contemporaneous cyclical component in the imperfect information model. Considering that the policy decisions of time $t-1$ are already executed at the time when the signal $\ln(g_t^A)$ arrives, the reduction in $\widetilde{z}_{t-1}$ does not impact the imperfect information model's long run moments directly. However, as mentioned earlier, the reduction in $\widetilde{z}_{t-1}$ allows the agent to increase $\Delta\widetilde{z}_t$ by increasing $\widetilde{z}_t$ by a smaller amount than she would otherwise under perfect information scenario. This has a significant impact on the long run moments because it induces the agent to give more weight to permanent shocks relative to the contemporaneous cycle shocks in the imperfect information model.

In order to analyze the implications of learning using the Kalman filter, we conduct further experiments. We report implied beliefs attached to the components of TFP for various values of σ_g/σ_z (Table 4). These experiments reveal that the probability assigned to a given TFP shock being permanent ($\widetilde{g}_t$) monotonically increases with σ_g/σ_z, while that assigned to it being transitory ($\widetilde{z}_t$) decreases. The relative variability of trend shocks that equates $\widetilde{g}_t$ to $\widetilde{z}_t$ is 0.76, which is slightly lower than 0.78 under baseline parametrization.

This mechanism hinges on the revision of $\widetilde{z}_{t-1}$. This revision of $\widetilde{z}_{t-1}$ in case of a positive shock at time t is downwards. This is because the agent assigns positive probability to a scenario with a negative transitory shock in period $t-1$. A close investigation of the top panel of Figure 3 reveals that for example in the case of a positive transitory shock in period 1, $g_t^A = \alpha g_t + z_t - z_{t-1}$ increases in period 1 with unchanged z_{t-1} and g_t. However, starting with the second period, g_t^A turns negative with $z_t < z_{t-1}$ as the shock dies out gradually. The mirror image of these dynamics occur in the case of a negative shock. Going back to Table 3, observing a positive signal in period t, the agent realizes that a positive transitory or permanent shock might have hit at time t, or a negative transitory shock might have hit in period $t-1$ and g^A went up in period t as this negative shock dies out. Assigning some probability to each of these scenarios, the agent increases her belief about g_t, z_t, and reduces the one about z_{t-1}.

3.3 Sensitivity Analysis

3.3.1 The Role of Shock Processes

In this subsection, we investigate the role of the relative variability and persistence of trend growth shocks in accounting for the EME business cycles. In this regard, we compare two scenarios: our baseline imperfect information model with the trend growth signal shut down and also the perfect information model. For both, we focus on the case of Mexico in the interest of space.

The imperfect information model can match the key moments with different combinations of ρ_g and σ_g/σ_z as shown in the top panel of Figure 4. For a given value of ρ_g, the imperfect information model, in general, implies that $\sigma(c)/\sigma(y)$ increases with σ_g/σ_z. Hence, lower values of ρ_g combined with higher values of σ_g/σ_z deliver the desired key moments.[23] $\sigma(c)/\sigma(y)$ of 1.26 observed in the data can be matched with $(\sigma_g/\sigma_z, \rho_g) \in \{(5, 0), (3, 0.2), (2, 0.4), (1, 0.61), (0.5, 0.8)\}$. That is, the model can match this moment with higher relative variability of trend shocks if one allows for lower ρ_g. Similarly, the correlation between output and net exports, $\rho(nx, y)$ of -0.75, in the data is implied by the imperfect information model for $(\sigma_g/\sigma_z, \rho_g) \in \{(4.5, 0), (2.2, 0.2), (1.1, 0.4), (0.7, 0.61), (0.5, 0.8)\}$. Likewise, the model can match this moment with several values for relative variability of trend shocks and ρ_g combinations if lower ρ_g's are combined with higher relative variability of trend shocks.

In addition, with the imperfect information model, note that $\rho(nx, y)$ rarely turns positive as opposed to the perfect information model, where, for most calibrations, this correlation is positive. (Compare the right hand side panels of Figure 4.) This result arises due to the dynamics through hours and output as explained earlier in the discussion of the impulse response functions. Hence, it is not the trade balance that increases in response to a positive trend shock, but it is the output that declines.[24]

The perfect information model requires a low value of ρ_g and a high value of σ_g/σ_z to generate a consumption profile that is more variable than output and a trade balance profile that is strongly countercyclical. The lower panel of Figure 4 shows how those key moments change under perfect information. Notice that the perfect information model can generate those key moments only for low values of ρ_g ($\rho_g < 0.2$). For high values of ρ_g the strong response of hours to permanent shocks that we discussed above makes it difficult to generate the right signs for correlations. Since the perfect information model requires a low value of ρ_g to be able match the correlations, it automatically arises that it also requires a high value for σ_g/σ_z to be able to generate a response in consumption that is larger than output. It is only this kind of a combination for ρ_g and σ_g/σ_z

[23]We conducted similar analysis by allowing ρ_z and ϕ to vary along with the relative variability of trend shocks and found that variation in those parameters do not change the relationship between $\sigma(c)/\sigma(y)$, $\rho(nx, y)$, and the relative variability of trend shocks. In other words, regardless of ρ_z and ϕ, $\sigma(c)/\sigma(y)$ and $\rho(nx, y)$ increase with relative variability of trend shocks. Simulations are available upon request.

[24]Similar dynamics with decline in hours being sufficient to lead to a decline in output takes place in the imperfect information model only in the case of unrealistically high values for both ρ_g and σ_g/σ_z. Those values imply output variabilities that are larger than 3 percent – higher than that in the data.

in the perfect information model that can match the key moments.

3.3.2 The Role of the Severity of Informational Frictions

Next we explore how the changes in the degree of information imperfection affect our baseline results. In order to do so, we report the business cycle statistics for higher and lower values of σ_s in Table 5. The first column with $\sigma_s \to \infty$ is a scenario where the standard deviation of the trend growth signal is set to a large number. The second column reproduces the baseline scenario results. The following two columns report the moments of the cases with lower σ_s or higher precision for the trend growth signal. Note that the perfect information model is a particular case of our baseline model when the noisiness of the trend growth signal goes to zero and therefore it reveals the true trend shock entirely. All the structural parameters in this exercise are kept constant, which, in turn, implies merely the same σ_g/σ_z, and V across columns.

Two important findings arise from Table 5. First, $\sigma_s \to \infty$ scenario yields similar results to baseline. The marginal differences between these two scenarios suggest that with our baseline estimation, the trend growth signals already have almost no informativeness. Symmetrically, although not reported here, for the case of Canada, increasing the informativeness of the trend growth signals more than they are in the baseline estimation did not change the results significantly. We see these as evidence to support the view that informational frictions are more severe in emerging markets in that the best fit of the model is achieved when the trend growth signal reveals almost no information in the case of Mexico while for Canada, the best fit is when this signal eliminates the informational imperfection entirely.

Second, the third and fourth columns of Table 5 suggest that the moments get closer to those of developed economies as σ_s falls, i.e., consumption variability becomes lower than output variability and trade balance becomes procyclical. This observation reinforces the evidence elaborated earlier in this paper to support our main hypothesis that the differences in the degree of uncertainty faced by agents play a key role in accounting for the differences between emerging and developed economy business cycles.

3.3.3 The Role of Preferences

In this section, we explore the sensitivity of our baseline results to the preference specification re-estimating our model with Jaimovich-Rebelo preferences (Jaimovich and Rebelo, 2009), which take the following form:

$$u_t = \frac{(C_t - \tau N_t^{\nu} H_t)^{1-\sigma}}{1-\sigma},$$

where $\tau > 0$ and $\nu > 1$.[25] The elasticity of labor supply is given by $\left(\frac{1}{\nu-1}\right)$. H_t stands for habit as in Jaimovich and Rebelo (2009) and evolves according to:

$$H_{t+1} = C_t^{\gamma} H_t^{1-\gamma}. \tag{8}$$

With this formulation, habit is determined by the history of consumption and is updated every period as a geometric average of the previous period's habit and consumption.[26] The weights of this geometric average are determined by $0 \leq \gamma \leq 1$ and the case with $\gamma = 0$ corresponds to the well known Greenwood, Hercowitz and Huffman (1988) (GHH) preferences. When making consumption decisions, agents internalize the connection between habits and consumption. Put differently, a higher consumption today, for example, leads to a higher value of habits tomorrow, requiring a higher level of consumption tomorrow in order to enjoy a given level of utility. The budget constraint and the information structure remain the same as in our baseline model.

Table 6 lists the additional parameters required for the calibration and the associated new set of estimated parameters for exogenous shock processes. We set $\nu = 1.6$ in order to obtain a labor supply elasticity of 2.5. τ is listed as an estimated parameter since its value is pinned down such that the steady state value of labor is 0.28. This value is determined simultaneously with the other estimated parameters during the GMM estimation as the steady state labor is affected by other estimated parameters of the model. The final additional parameter that arises with J-R preferences is γ which determines the strength of the wealth effect on labor. The estimated value of γ is fairly low, implying that the best fit of the model is achieved with preferences that are close but not identical to GHH preferences. In this sensitivity exercise, we do not re-estimate the noisiness of the growth signal, σ_s, and retain its baseline value. This is to keep the level of the information friction the same as in baseline, focusing solely on the role of preferences in driving our results.

The last two columns of Table 5 report the business cycle moments with J-R preferences for imperfect and perfect information scenarios, respectively. With the aforementioned parameters, our imperfect information model does a remarkable job in matching the business cycle moments

[25] We assume that $\beta\mu_g^{1-\sigma} < 1$ to ensure that utility is well defined. Further, to have a well-behaved steady state consumption, we impose $\beta(1+r^*)^{1/\sigma} = \mu_g$.

[26] Note that these preferences are slightly different from Jaimovich and Rebelo preferences. In their specification, contemporaneous consumption is used in updating habits; C_{t+1} is on the right hand side of Equation (8) instead of C_t.

shown in the second to last column. Consumption is more variable than output, trade balance is strongly countercyclical, and the model matches the variability of output, investment and trade balance quite well. Further, similar to baseline Cobb-Douglas preferences, the model delivers these results when trend shock are not larger than transitory shocks.

When we feed in the same estimated parameters to the perfect information model with J-R preferences, reported in the last column of Table 5, we find weakly countercyclical trade balance and a consumption profile that is less variable than output; and the model overshoots the variability of investment and trade balance. Since perfect information model features a low wealth effect on labor supply with $\gamma = 0.11$, the counterfactual dynamics that we observed in the perfect information model with Cobb-Douglass preferences in response to highly persistent trend growth shocks do not arise. Therefore, the perfect information model with J-R preferences can generate a negative correlation between trade balance and output. However, without the predominance of trend growth shocks, the countercyclicality of the trade balance is weak and consumption variability is lower than output variability.

4 Conclusion

In this paper, we provided a framework to explain the key business cycle characteristics of emerging market economies. We showed that when the agents are imperfectly informed about the trend-cycle decomposition of productivity shocks, and they solve a learning problem using the Kalman filter to estimate the components of the TFP, the model performance in matching the emerging market business cycles improves greatly. The key ingredients for these results are: the existence of trend shocks, the existence of transitory but persistent cycle shocks, and uncertainty regarding the decomposition of TFP into its components.

Our analysis contributes to the emerging market business cycles literature, which has largely emphasized the role of financial frictions, terms of trade shocks, and trend shocks but largely overlooked the role of uncertainty and informational frictions. We fill this gap by highlighting the role of uncertainty that the agents face while formulating their expectations about the long-run implications of the shocks they face in explaining emerging market business cycles.

By introducing imperfect information and learning about the underlying fundamentals of the economy in a tractable manner, we open up a new line of research. For example, studying optimal policy (fiscal or monetary) in the framework we provide can deliver interesting insights. Another interesting application could be to build the signal extraction problem developed in this paper into a two-country environment allowing different levels of informational frictions across the two economies to explore cross country portfolio allocations, consumption correlations, etc.

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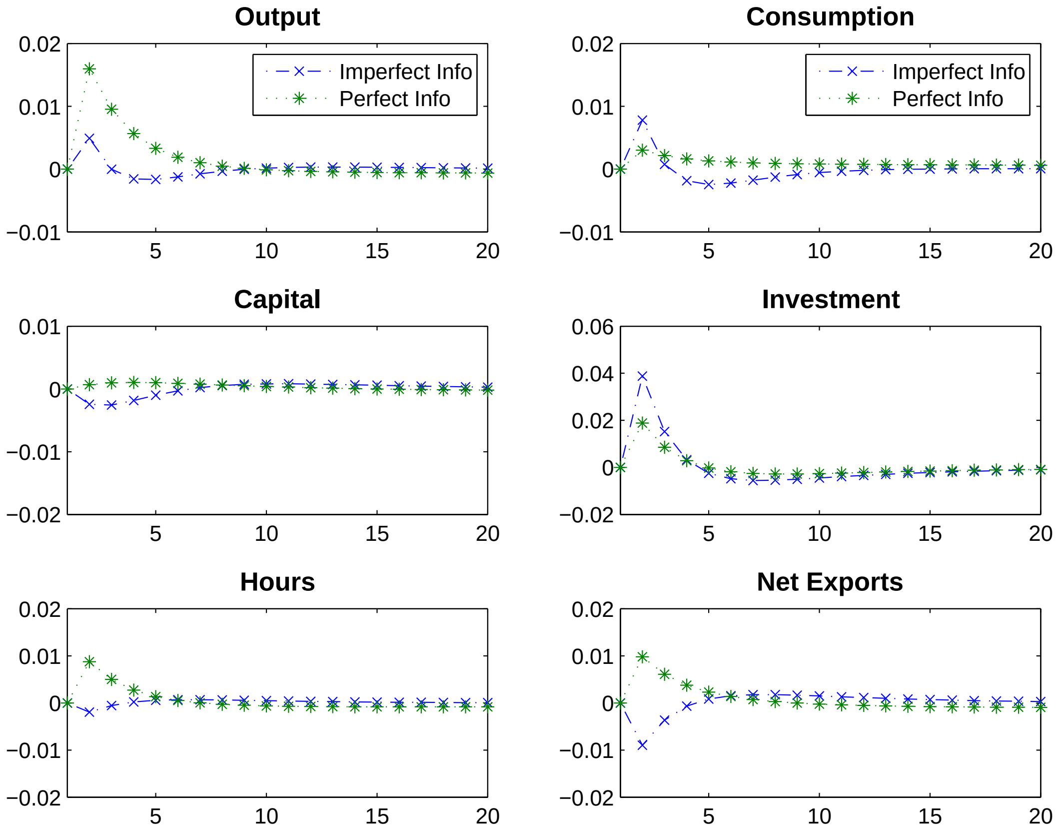
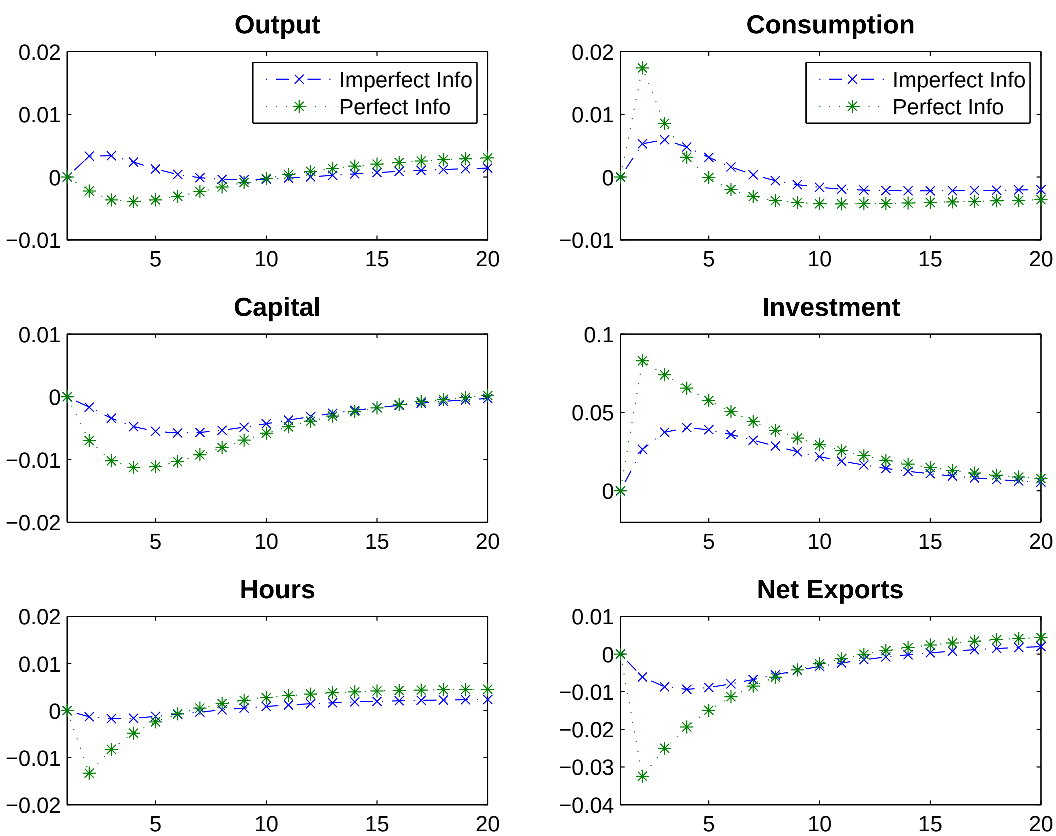
Figure 1: Impulse Responses to a Transitory Shock



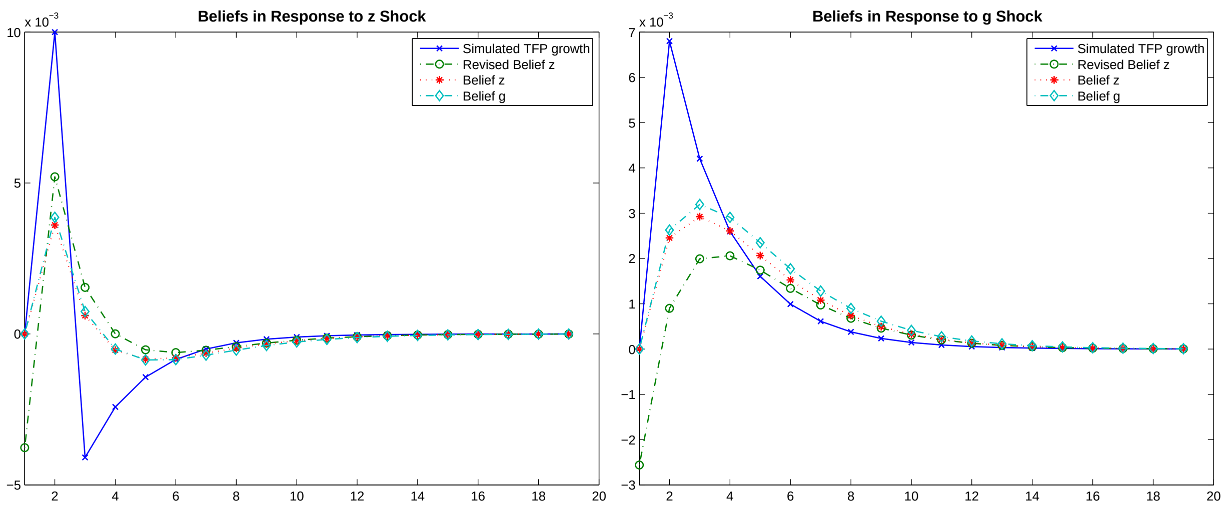
Note: This figure illustrates the response of the endogenous supply side (on the left) and demand side (on the right) variables to a 1-percent shock to the transitory component of the TFP.

Figure 2: Impulse Responses to a Trend Growth Shock



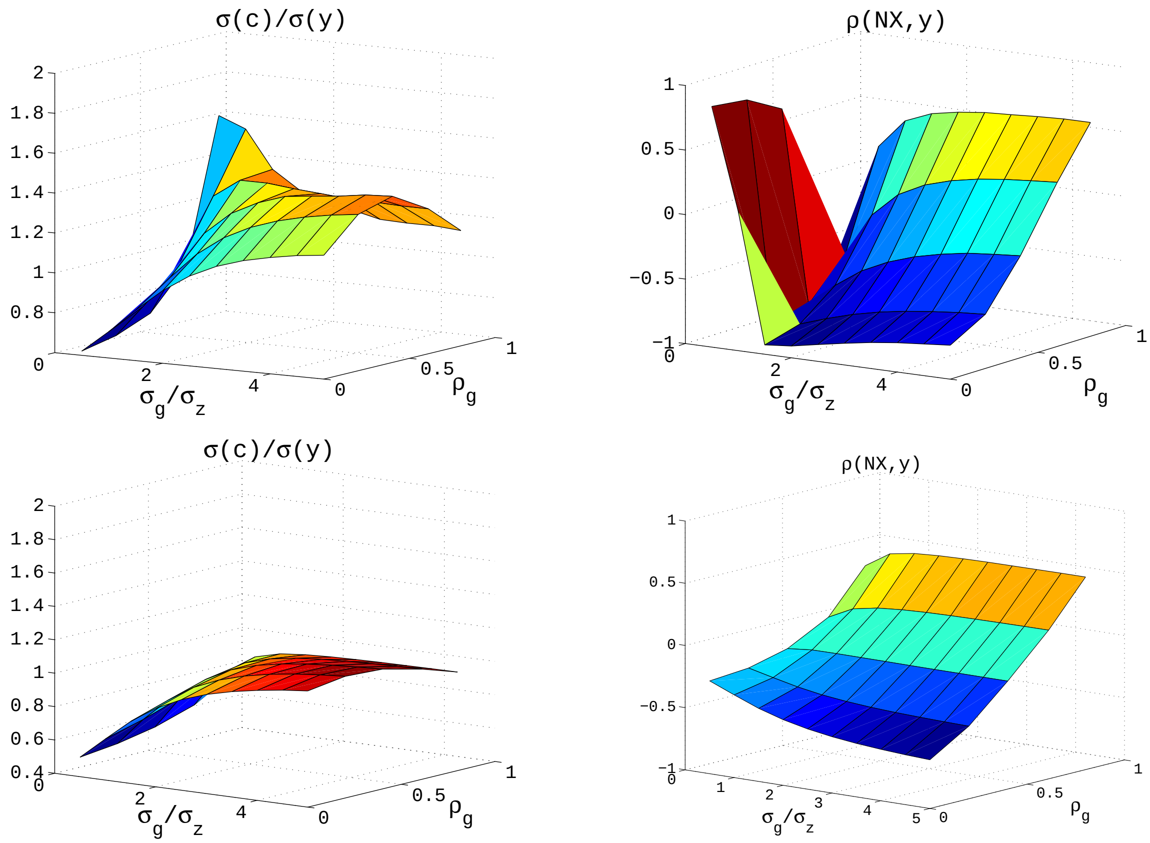
Note: This figure illustrates the response of the endogenous supply side (on the left) and demand side (on the right) variables to a 1-percent shock to the trend growth component of the TFP.

Figure 3: Beliefs Attached to TFP Components



Note: This figure illustrates the beliefs for permanent and transitory components along with TFP that the agent directly observes. The crossed-solid line depicts TFP, the diamond-dashed line plots the evolution of the belief about the permanent component, while the stared-dashed line shows the evolution of the belief for the transitory component. In the left panel, the source of fluctuation in TFP is a 1-percent transitory component shock, whereas in the right panel, it is a trend growth shock of the same magnitude.

Figure 4: Sensitivity of Moments to Shock Processes: Imperfect and Perfect Information



Notes: The figures show the sensitivity of standard deviation of consumption relative to output and the trade balance output correlation to different values of σ_g/σ_z and ρ_g. The top panel shows imperfect information while the bottom panel shows the perfect information scenario.

Table 1: Parameters of the Baseline Model

		Mexico	Canada
Calibrated Parameters			
β	Discount factor	0.98	0.98
γ	Consumption exponent of utility	0.36	0.36
b	Steady state normalized debt	10	10
ψ	Coefficient on interest rate premium	0.001	0.001
α	Labor exponent	0.68	0.68
σ	Risk aversion	2	2
δ	Depreciation rate	0.05	0.05
Estimated Parameters			
σ_g	Stdev of permanent component noise	1.06	0.56
σ_z	Stdev of transitory component noise	1.35	0.60
ρ_g	Persistence of permanent component	0.62	0.21
ρ_z	Persistence of transitory component	0.59	0.90
σ_s	Stdev of trend growth signal noise	20.03	1.07
ϕ	Capital adjustment cost	1.27	2.00
μ_g	Growth rate	0.66	0.73
Signal-to-noise Ratios			
$\frac{\sigma_g}{1-\rho_g^2}/\sigma_s$		0.09	0.58
σ_{g^A}/σ_s		8.50	72.00
Relative Variance of Trend Shocks			
σ_g/σ_z		0.79	0.93
V		0.27	0.28

Note: This table summarizes the parameter used in the baseline model. The calibrated parameters are directly taken from the literature and they are the same both for Mexico and Canada. The estimated parameters are derived using generalized method of moments. The table reports two different values of the signal-to-noise ratio for the signal s. The first one is the ratio of the standard deviation of permanent component to that of the signal s noise. The second one is the ratio of the standard deviation of the growth rate of TFP to that of signal s noise.

Table 2: Business Cycle Moments

	Data		Baseline Model	
	Mexico	Canada	Mexico	Canada
$\sigma(y)$	2.40	1.55	2.16	1.31
$\sigma(\Delta y)$	1.52	0.80	1.54	0.80
$\frac{\sigma(c)}{\sigma(y)}$	1.26	0.74	1.19	0.77
$\frac{\sigma(I)}{\sigma(y)}$	4.15	2.67	4.25	2.56
$\frac{\sigma(NX)}{\sigma(y)}$	0.90	0.57	0.93	0.31
$\rho(y)$	0.83	0.93	0.79	0.81
$\rho(\Delta y)$	0.27	0.55	0.27	0.44
$\rho(y, NX)$	-0.75	-0.12	-0.67	-0.15
$\rho(y, c)$	0.92	0.87	0.97	0.98
$\rho(y, I)$	0.91	0.74	0.84	0.86

Notes: Moments are calculated using the simulated and HP-filtered data generated by the corresponding model.

Table 3: Perfect vs Imperfect Information

	$ln(g_t^A) = \alpha g_t + \Delta z_t$	$\widetilde{g}_t$	$\widetilde{z}_t$	$\widetilde{z}_{t-1}$
PI	1.68 %	1 %	1 %	0 %
II	1.68 %	0.65 %	0.61 %	-0.63 %

Note: PI refers to the perfect information model and II refers to the imperfect information model. $\widetilde{g}_t$, $\widetilde{z}_t$, and $\widetilde{z}_{t-1}$ are equal to their true values in the perfect information case.

Table 4: Further Experiment on Kalman Learning

Model	σ_g/σ_z	$ln(g_t^A) = \alpha g_t + \Delta z_t$	$\widetilde{g}_t$	$\widetilde{z}_t$	$\widetilde{z}_{t-1}$
PI	**0.78**	**1.68 %**	**1 %**	**1 %**	**0 %**
II	0.5	1.68 %	0.36 %	0.83 %	-0.61 %
II	**0.78**	**1.68 %**	**0.65 %**	**0.61 %**	**-0.63 %**
II	1	1.68 %	0.85 %	0.49 %	-0.61 %
II	2	1.68 %	1.53 %	0.23 %	-0.41 %
II	3	1.68 %	1.89 %	0.13 %	-0.27 %
II	5	1.68 %	2.22 %	0.07 %	-0.13 %

Notes: This table illustrates the weights or beliefs attached to the components of TFP for various values of relative variability of permanent to transitory shock.

Table 5: Sensitivity Analysis

					J-R Pref	
	$\sigma_s \to \infty$	Baseline	$\sigma_s = 10$	$\sigma_s = 1$	II	PI
$\sigma(y)$	2.16	2.16	2.18	2.78	2.39	2.31
$\sigma(\Delta y)$	1.53	1.54	1.55	2.03	1.59	1.76
$\frac{\sigma(c)}{\sigma(y)}$	1.17	1.19	1.18	0.93	1.10	0.98
$\frac{\sigma(I)}{\sigma(y)}$	4.26	4.25	4.24	3.85	4.24	5.06
$\frac{\sigma(NX)}{\sigma(y)}$	0.92	0.93	0.94	1.22	0.79	1.18
$\rho(y)$	0.69	0.79	0.82	0.78	0.86	0.73
$\rho(\Delta y)$	0.30	0.27	0.46	0.32	0.22	0.12
$\rho(y, NX)$	-0.68	-0.67	-0.63	0.15	-0.67	-0.19
$\rho(y, c)$	0.97	0.97	0.96	0.66	0.98	0.69
$\rho(y, I)$	0.85	0.84	0.83	0.41	0.82	0.70

Notes: The table reports the business cycle statistics for higher and lower values of σ_s. The first column corresponds to the imperfect information setup. The second column reproduces the baseline scenario results. The following third and fourth columns reports the moments with σ_s set to 10 and 1, respectively. The last two columns show the moments with Jaimovich Rebelo (J-R) preferences. II refers to imperfect information and PI refers to perfect information.

Table 6: Parameters with Jaimovich-Rebelo (J-R) Preferences

Additional Calibrated Parameters		
ν	Labor exponent	1.60
Estimated Parameters		
γ	Habit parameter	0.11
σ_g	Stdev of permanent component noise	0.80
σ_z	Stdev of transitory component noise	0.81
ρ_g	Persistence of permanent component	0.70
ρ_z	Persistence of transitory component	0.76
σ_s	Stdev of trend growth signal noise	20.03
ϕ	Capital adjustment cost	1.05
μ_g	Growth rate	0.66
τ	Labor Coefficient	0.088
Relative Variance of Trend Shocks		
σ_g/σ_z		0.99
V		0.44
Signal-to-noise Ratios		
$\frac{\sigma_g}{1-\rho_g^2}/\sigma_s$		0.08
σ_{g^A}/σ_s		5.50

Note: This table summarizes the parameters used for the estimation of the imperfect information model with Jaimovich-Rebelo preferences.