

# Emerging Market Business Cycles with Heterogeneous Agents\*

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January 16, 2023

## Abstract

This paper explains emerging market business cycles by estimating a heterogeneous-agent small open economy model where the marginal propensity to consume (MPC) is as high as the estimates from emerging market micro data. A conventional mechanism through which a representative-agent model explains the business cycles does not operate in the heterogeneous-agent model because precautionary saving interrupts it. Instead, emerging market business cycles are explained by a new mechanism in which high MPC and correspondingly strong precautionary saving play essential roles. When MPC is lowered to the U.S. level via recalibration, excess consumption volatility disappears in most of the posterior distribution.

**JEL classification:** E21, E32, F41, D31

**Keywords:** emerging economy, business cycle, heterogeneous agents, MPC, precautionary saving

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\*This paper is a revised version of Chapter 3 of my Ph.D. dissertation at Columbia University. I am highly indebted to Martin Uribe, Stephanie Schmitt-Grohe, and Andres Drenik for their constant guidance, support, and suggestions. I am also grateful to Hassan Afrouzi, Mario Crucini, Nils Gornemann, Emilien Gouin-Bonenfant, Ryan Kim, Christian Moser, Tommaso Porzio, Jesse Schreger, Shang-Jin Wei, Stephen Zeldes, and seminar participants at the Bank of Korea, the Central Bank of Chile, Columbia University, the Federal Reserve Bank of Chicago, the Hong Kong University of Science and Technology, KDI, KIET, KIEP, KIF, KIPF, Purdue University, Seoul National University, the University of British Columbia, and the University of Hong Kong for their helpful comments and discussions. All errors are my own.

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# 1 Introduction

One of the most salient patterns of emerging market business cycles is the phenomenon of ‘excess consumption volatility’: consumption is more volatile than output in emerging economies, while it is not in developed economies. Extensive literature is devoted to explaining excess consumption volatility, and the dominant modeling framework is representative-agent small open economy (RASOE) models. At the heart of these models, representative households optimize according to the permanent income hypothesis (PIH). Importantly, widely accepted mechanisms for excess consumption volatility in the literature, such as the permanent income effect of a trend shock (Aguiar and Gopinath, 2007) and the intertemporal substitution effect of interest rate fluctuations (Neumeyer and Perri, 2005), crucially depend on the household PIH behavior.

However, micro data suggest that household consumption behavior deviates significantly from the PIH in emerging economies, and the deviation is greater than that in developed economies. Under the PIH, the marginal propensity to consume (MPC) out of a transitory income shock is essentially zero. However, when Hong (2022) estimates the MPC by applying a standard method (developed by Blundell, Pistaferri, and Preston (2008)) to a Peruvian household survey, he finds that Peruvian MPCs are substantially higher than U.S. MPCs, which are already greater than zero.

Motivated by this observation, this paper revisits emerging market business cycles through the lens of a heterogeneous-agent small open economy (HASOE) model in which household MPCs are as high as the empirical estimates. To this end, I incorporate Kaplan, Moll, and Violante (2018)’s two-asset household heterogeneity over liquid and illiquid assets into a standard RASOE model. The financial friction in illiquid asset trading is calibrated (jointly with the time discount factor) such that both household MPC and wealth are empirically realistic.<sup>1</sup> Then, I take the HASOE model to Peruvian macro data through Bayesian estimation to explain emerging market business cycles. For comparison, I also estimate the corresponding RASOE model.

I report three main findings. First, the RASOE model explains Peruvian macro data through the conventional Aguiar and Gopinath (2007) mechanism, while this mechanism does not operate in the HASOE model. In the RASOE model, the Aguiar and Gopinath (2007) mechanism operates as follows: when a trend shock hits the economy, earnings mildly jump on impact but grow strongly in the future; the permanent income effect of the future earnings growth drives a strong consumption response, generating excess consumption volatility. In the HASOE model, the future aggregate earnings growth also means that households must face a greater idiosyncratic income risk in the future and thus enhance their precautionary saving. The enhanced precautionary saving effect offsets the permanent income effect, and the consumption response to a trend shock is muted.

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<sup>1</sup>The two-asset structure allows me to capture both realistically high MPCs and the correct amount of aggregate wealth. In a one-asset model, on the other hand, households must hold a small amount of assets to yield high MPCs. This leads to an insufficient amount of aggregate capital, which is problematic for a business cycle analysis.

Second, the HASOE model, once augmented with a financial friction shock, can successfully explain emerging market business cycles through a new mechanism in which households' high MPC and correspondingly strong precautionary saving motive play essential roles. Specifically, large consumption fluctuations are mainly driven by two channels: (i) in the face of heightened financial friction, households substantially reduce their consumption either because of an aggravated consumption smoothing failure or because of enhanced precautionary saving<sup>2</sup>; (ii) when a stationary productivity shock hits the economy, households' individual income fluctuates, and the income fluctuations are strongly translated into consumption fluctuations due to their high MPC.

Third, to evaluate the quantitative importance of the high MPC and strong precautionary saving, I conduct a counterfactual experiment in which household MPCs are adjusted to the U.S. level, which is substantially lower than the Peruvian level, via recalibration. In the counterfactual experiment, I find that excess consumption volatility disappears in most of the posterior distribution, including the posterior mean, median, and mode.

My paper is related to multiple strands of literature. First, there is rapidly growing literature examining how microlevel household behavior and its heterogeneity affect macroeconomic outcomes. Well-known works in this literature include [Kaplan et al. \(2018\)](#), [Auclert \(2019\)](#), [Krueger, Mitman, and Perri \(2016\)](#), [McKay, Nakamura, and Steinsson \(2016\)](#), [Auclert, Rognlie, and Straub \(2018\)](#), [Bayer, Luetticke, Pham-Dao, and Tjaden \(2019\)](#), and [Oh and Reis \(2012\)](#), among many others. Many studies in this literature focus on the fact that even in advanced economies such as the U.S., a sizable fraction of households exhibit significantly higher MPC than what the PIH predicts. This paper contributes to this literature by exploiting a different margin: MPC is substantially higher in emerging economies than in developed economies. It finds that the difference in microlevel consumption behavior matters for aggregate dynamics to the extent that it can explain one of the most salient patterns of emerging market business cycles, excess consumption volatility.

Second, there have been recent efforts to expand the first literature to open and emerging economies, such as [Auclert, Rognlie, Souchier, and Straub \(2021\)](#), [De Ferra, Mitman, and Romei \(2020\)](#), [Zhou \(2021\)](#), [Ferrante and Gornemann \(2022\)](#), [Guntin, Ottonello, and Perez \(2022\)](#), [Guo, Ottonello, and Perez \(2022\)](#), [Oskolkov \(2022\)](#), [Villalvazo \(2021\)](#), and [Sunel \(2018\)](#). My paper contributes to this literature by studying emerging market business cycles through a HASOE model disciplined by micro moments. Among the abovementioned papers, my paper is most closely related to [Guntin et al. \(2022\)](#). These two papers share the view that micro data, when interpreted through a heterogeneous-agent model, provide important information about what drives

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<sup>2</sup>Those facing a bad idiosyncratic income shock need to cash out their assets to smooth consumption. When financial friction is heightened, however, it becomes more costly to cash out assets, and they fail to smooth consumption more significantly. Those who do not face an immediate need to cash out their assets at the moment of heightened financial friction recognize that it will be more expensive to cash out their assets for a while. Therefore, they prepare themselves by accumulating more buffer stocks and reducing consumption.

large consumption fluctuations. However, they come to different conclusions: [Guntin et al. \(2022\)](#) find that the permanent income effect of a trend shock drives large consumption swings, while I find that a financial friction shock and a stationary productivity shock mainly drive consumption fluctuations. In this sense, a long-standing debate on what drives consumption fluctuations in emerging economies, particularly between a trend shift and financial frictions<sup>3</sup>, continues in the heterogeneous-agent open economy landscape.<sup>4</sup>

Third, there is rich literature devoted to explaining emerging market business cycles, in which representative-agent models are dominantly used. Important examples include [Neumeyer and Perri \(2005\)](#), [Aguiar and Gopinath \(2007\)](#), [Uribe and Yue \(2006\)](#), [Garcia-Cicco et al. \(2010\)](#), [Chang and Fernández \(2013\)](#), [Chen and Crucini \(2016\)](#), and [Fernández-Villaverde, Guerrón-Quintana, Rubio-Ramirez, and Uribe \(2011\)](#), among many others. My paper contributes to this literature by bringing new intuitions and tools from the first literature regarding how household heterogeneity and microlevel behavior affect aggregate dynamics, applying them in the context of emerging market business cycles, and deriving new explanations.

Fourth, in terms of methodology, this paper has a commonality with [Bayer, Born, and Luetticke \(2022\)](#) and [Auclert, Rognlie, and Straub \(2020\)](#) in that Bayesian methods are applied to estimate a heterogeneous-agent model. Bayesian estimation requires a model to be solved many times. It only recently became possible to solve heterogeneous-agent models fast enough to conduct Bayesian estimation due to the development of new computational methods. The main contributors to this recent computational development include [Auclert, Bardóczy, Rognlie, and Straub \(2021\)](#), [Boppart, Krusell, and Mitman \(2018\)](#), [Ahn, Kaplan, Moll, Winberry, and Wolf \(2018\)](#), [Bayer and Luetticke \(2020\)](#), [Winberry \(2018\)](#), and [Reiter \(2009\)](#). Among the new methods, I use the one developed by [Auclert et al. \(2021\)](#).

The remainder of this paper is organized as follows. Section 2 specifies models. Section 3 takes the models to data through a two-step procedure composed of calibration and Bayesian estimation. Section 4 augments the HASOE model with a financial friction shock. Section 5 conducts a counterfactual experiment in which Peruvian households are replaced with those exhibiting U.S. MPCs. Section 6 concludes.

## 2 Model

One of the goals of this paper is to compare the ways in which the RASOE and HASOE models explain emerging market business cycles. In this section, I introduce a standard RASOE model that

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<sup>3</sup>For a trend shift, see [Aguiar and Gopinath \(2007\)](#). For financial frictions, see [Neumeyer and Perri \(2005\)](#), [Garcia-Cicco, Pancrazi, and Uribe \(2010\)](#), [Chang and Fernández \(2013\)](#), [Mendoza \(2010\)](#), and [Bianchi \(2011\)](#).

<sup>4</sup>For interested readers, I discuss key differences between the two papers (in both micro moments and macro models) and how they come to different conclusions in Online Appendix J.

is widely used in the literature (Neumeyer and Perri (2005), Aguiar and Gopinath (2007), Garcia-Cicco et al. (2010), and Chang and Fernández (2013)) and a HASOE model that I construct by incorporating household heterogeneity into the RASOE model.

## 2.1 Representative-Agent Small Open Economy (RASOE) Model

In this subsection, I present a decentralized version of a standard RASOE model.<sup>5</sup> Consider an economy composed of representative households, firms, and banks.

**Households.** Households trade assets  $A_t$ , which are the shares of firms, and supply labor  $L_t$ . They optimize Greenwood, Hercowitz, and Huffman (1988)'s preference (GHH preference hereafter) subject to budget constraints and the no-Ponzi-game constraint as follows.

$$\begin{aligned} \max_{\{C_t, A_t, L_t\}_{t=0}^{\infty}} E_0 \sum_{t=0}^{\infty} (\beta_R)^t \frac{(C_t - \kappa_R X_{t-1} L_t^{1+\omega})^{1-\gamma}}{1-\gamma} \\ s.t. \quad C_t + A_t = w_t L_t + (1 + r_t^a) A_{t-1}, \quad t \geq 0, \text{ and} \\ \lim_{j \rightarrow \infty} E_t \left[ A_{t+j} / \left( \prod_{s=1}^j (1 + r_{t+s}^a) \right) \right] \geq 0, \end{aligned}$$

where  $C_t$  is consumption,  $w_t$  is wage,  $(1 + r_t^a)$  is the gross return on  $A_{t-1}$ , and  $X_{t-1}$  is the stochastic trend of the economy. As a result of imposing the GHH preference, the wealth effect is removed in the labor supply decision, as  $L_t$  is determined by  $w_t = (1 + \omega) \kappa_R X_{t-1} L_t^\omega$ .<sup>6</sup>

**Firms.** Competitive firms produce output  $Y_t$  using capital  $K_{t-1}$  and labor  $L_t$ , make investment  $I_t$ , and borrow funds  $F_t$  from domestic banks. They solve the following optimization problem.

$$\begin{aligned} \max_{\{K_t, F_t, L_t, Y_t, I_t, \Pi_t\}_{t=0}^{\infty}} E_0 \sum_{t=0}^{\infty} Q_{0,t} \Pi_t \tag{1} \\ s.t. \quad \Pi_t = Y_t - w_t L_t - I_t - \Phi(K_t, K_{t-1}) + F_t - (1 + r_{t-1}) F_{t-1}, \\ Y_t = z_t K_{t-1}^\alpha (X_t L_t)^{1-\alpha}, \\ I_t = K_t - (1 - \delta) K_{t-1}, \\ \Phi(K_t, K_{t-1}) = \frac{\phi}{2} \left( \frac{K_t}{K_{t-1}} - g^* \right)^2 K_{t-1}, \end{aligned}$$

<sup>5</sup>In Online Appendix A.4, I present an equivalent, centralized version of the RASOE model, which appears far more frequently in related studies. Here, I intentionally present a decentralized version because I will construct a HASOE model by incorporating household heterogeneity into this version.

<sup>6</sup>The wealth effect removal is an important reason why the GHH preference is common in emerging market business cycle models; if it is not removed, the wealth effect can create a countercyclical labor supply, which is inconsistent with data, particularly when a model is fitted to an emerging economy with large consumption fluctuations.

$$Q_{0,t} = \begin{cases} 1 & \text{if } t = 0, \\ 1/(\prod_{s=1}^t (1+r_s^a)) & \text{if } t \geq 1, \end{cases} \quad \text{and}$$

$$\lim_{j \rightarrow \infty} E_t \left[ F_{t+j} / \left( \prod_{s=1}^j (1+r_{t+s}^a) \right) \right] \leq 0,$$

where  $\Pi_t$  is the per-period profit,  $\Phi(K_t, K_{t-1})$  is an adjustment cost for capital accumulation,  $z_t$  is the stationary component of firms' productivity, and  $X_t$  is the nonstationary component (or stochastic trend) of firms' productivity. Firms discount profit flows using return rates on their shares. As we shall see below, the firms' objective function is the total value of the firms.

**Asset Return and Price.** Let  $s_t$  be the shares of firms that each representative household holds when the total shares are normalized to 1. Let  $q_t$  be the price of the shares after the current profits are distributed as dividends. Since total shares are normalized to 1,  $q_t$  also represents the total value of the firms after distributing current profits. By construction, we have the following equations.

$$A_t = s_t q_t, \quad (1+r_t^a)A_{t-1} = s_{t-1}(\Pi_t/s_{t-1} + q_t), \quad \text{and} \quad s_t = 1, \quad \forall t$$

$$\Rightarrow A_t = q_t, \quad t \geq 0, \quad \text{and} \tag{2}$$

$$1+r_t^a = (\Pi_t + q_t)/q_{t-1}, \quad t \geq 0. \tag{3}$$

By iterating equation (3) forward to solve  $q_0$  and taking an expectation, we can verify that the firms' objective function  $E_0 \sum_{t=0}^{\infty} Q_{0,t} \Pi_t$  is equal to  $\Pi_0 + q_0$ . In other words, firms maximize their total value before distributing current profits. This explains why firms discount profit flows with asset returns in their optimization.

It is worth noting how  $\{r_t^a\}_{t=0}^{\infty}$  are determined in equilibrium. From period 1 onward,  $\{r_t^a\}_{t=1}^{\infty}$  are subject to the following optimality condition for firms.

$$E_t [(1+r_t)/(1+r_{t+1}^a)] = 1, \quad t \geq 0. \tag{4}$$

When we consider impulse responses to an MIT shock (*i.e.*, without aggregate uncertainty), this equation becomes  $r_{t+1}^a = r_t$ ,  $t \geq 0$ . On the other hand, the return in period 0,  $r_0^a$ , is not determined by equation (4). Instead,  $r_0^a$  is solely determined by  $\Pi_0$ ,  $q_0$ , and  $q_{-1}$  through equation (3).

**Banks.** Banks in this economy play a passive role. They lend funds  $F_t$  to firms by issuing debt  $D_t$  in the international financial market. Since they are competitive, they charge an interest rate on  $F_t$  that is equal to the financing cost, which is the interest rate in the international financial market,  $r_t$ . Moreover,  $F_t$  and  $D_t$  should be balanced in each period or, equivalently,

$$F_t = D_t, \quad t \geq 0. \tag{5}$$

**International Financial Market.** The interest rate  $r_t$  in the international financial market is specified as follows.

$$r_t = r^* + \psi \left\{ \exp \left( \frac{\bar{D}_t/X_t - \tilde{D}^*}{\tilde{Y}^*} \right) - 1 \right\} - \theta_z(z_t - 1) - \theta_g \left( \frac{g_t}{g^*} - 1 \right) + \mu_t - 1, \quad t \geq 0, \quad (6)$$

where  $\psi > 0$ ,  $\theta_z > 0$ , and  $\theta_g > 0$ .  $\bar{D}_t$  is the cross-sectional average of banks' international debt. Individual banks and firms regard  $\bar{D}_t$  as exogenous, but at equilibrium, individual banks' international debt  $D_t$  is equal to  $\bar{D}_t$ .  $\tilde{D}^*$ ,  $\tilde{Y}^*$ ,  $g^*$ , and  $r^*$  are the long-run averages of  $\bar{D}_t/X_t$ ,  $Y_t/X_{t-1}$ ,  $g_t := X_t/X_{t-1}$ , and  $r_t$ , respectively, and  $\mu_t$  is an exogenous disturbance to interest rates.<sup>7</sup>

**Aggregate Shocks.** Three aggregate shocks hit the economy: a stationary productivity shock  $z_t$ , a trend shock  $g_t$ , and an interest rate shock  $\mu_t$ . I assume that each shock follows an AR(1) process:

$$\begin{aligned} \log z_t &= \rho_z \log z_{t-1} + \varepsilon_t^z, & \varepsilon_t^z &\sim N(0, \sigma_z^2), \\ \log(g_t/g^*) &= \rho_g \log(g_{t-1}/g^*) + \varepsilon_t^g, & \varepsilon_t^g &\sim N(0, \sigma_g^2), \quad \text{and} \\ \log \mu_t &= \rho_\mu \log \mu_{t-1} + \varepsilon_t^\mu, & \varepsilon_t^\mu &\sim N(0, \sigma_\mu^2). \end{aligned} \quad (7)$$

**Trade Balance.** The trade balance of the economy,  $TB_t$ , is determined as follows.

$$TB_t = -D_t + (1 + r_{t-1})D_{t-1}, \quad t \geq 0. \quad (8)$$

In Online Appendix A.1, I present the complete set of equilibrium conditions.

## 2.2 Heterogeneous-Agent Small Open Economy (HASOE) Model

I construct a HASOE model by incorporating Kaplan et al. (2018)'s two-asset household heterogeneity over liquid and illiquid assets into the RASOE model presented in section 2.1.<sup>8</sup> I adopt two-asset heterogeneity (instead of one-asset heterogeneity) because it allows my model to capture both realistically high MPC and the correct amount of aggregate capital.<sup>9</sup> Consider an economy composed of heterogeneous households and representative firms and banks.

**Working Households.** Almost all households (with fraction  $p$ ) work and earn labor income (work-

<sup>7</sup>A reduced-form specification of the interest rate in the international financial market, such as equation (6), is widely used in emerging market business cycle studies, particularly when models are intended to be first-order approximated with respect to aggregate shocks. (See, for instance, Neumeier and Perri (2005), Garcia-Cicco et al. (2010), and Chang and Fernández (2013).) In equation (6), interest rates are higher when the international debt  $\bar{D}_t$  is larger and the productivities  $z_t$  and  $g_t$  are lower. In this aspect, equation (6) reflects the theoretical implication of sovereign default models such as Arellano (2008) and Mendoza and Yue (2012) in a reduced-form manner.

<sup>8</sup>However, I do not incorporate the nominal rigidity in Kaplan et al. (2018)'s model because my model is intended to be as close as possible to the conventional real models of emerging economies except for household heterogeneity.

<sup>9</sup>See footnote 1. Additionally, see Kaplan and Violante (2018) for a more detailed discussion.



ers hereafter). Workers face idiosyncratic earnings risk and trade liquid and illiquid assets. Liquid assets are bank deposits, and illiquid assets are the shares of firms. Compared to liquid assets, illiquid assets yield higher returns but are more expensive to trade. Workers exhibit idiosyncratic labor productivity, which can be decomposed into a component predictable with their observable characteristics ( $\Gamma$ ) and an unpredictable component bearing earnings risk ( $e$ ). Workers cannot take short positions in both liquid and illiquid assets. Each worker  $i$  solves the following problem.<sup>10</sup>

$$\max_{\{c_{i,t}, b_{i,t}, a_{i,t}, v_{i,t}\}_{t=0}^{\infty}} E_0 \sum_{t=0}^{\infty} \beta^t \frac{c_{i,t}^{1-\gamma}}{1-\gamma} \quad (9)$$

$$\begin{aligned} s.t. \quad & c_{i,t} + b_{i,t} + v_{i,t} + \chi_t(v_{i,t}, a_{i,t-1}; \Gamma_i) = w_t \Gamma_i e_{i,t} \bar{l}_t + (1 - \xi)(1 + r_t^b) b_{i,t-1}, \\ & v_{i,t} = a_{i,t} - (1 + r_t^a) a_{i,t-1}, \quad \text{and} \\ & b_{i,t} \geq 0, \quad a_{i,t} \geq 0. \end{aligned} \quad (10)$$

In the budget constraint (10),  $b_{i,t}$  and  $a_{i,t}$  are liquid and illiquid asset holdings, respectively, and  $(1 - \xi)(1 + r_t^b)$  and  $(1 + r_t^a)$  are their gross return rates. Since  $r^a = r^b$  on the balanced growth path and  $\xi > 0$ , illiquid assets yield higher returns than liquid assets.<sup>11</sup> To trade illiquid assets, workers must pay adjustment cost  $\chi_t(v_{i,t}, a_{i,t-1}; \Gamma_i)$ .

For the functional form of the illiquid asset adjustment cost, I closely follow [Auclert et al. \(2021\)](#)'s discrete-time version of [Kaplan et al. \(2018\)](#)'s model as follows.

$$\chi_t(v_{i,t}, a_{i,t-1}; \Gamma_i) = \chi_1 \left| \frac{v_{i,t}}{(1 + r_t^a) a_{i,t-1} + \chi_0 \Upsilon(\Gamma_i) X_{t-1}} \right|^{\chi_2} \left( (1 + r_t^a) a_{i,t-1} + \chi_0 \Upsilon(\Gamma_i) X_{t-1} \right),$$

where  $\chi_0 > 0$ ,  $\chi_1 > 0$ , and  $\chi_2 > 1$ .  $X_{t-1}$  is the stochastic trend of the economy, and  $\Upsilon(\Gamma_i)$  is the predictable component of earnings in a detrended steady state,  $E[w_t \Gamma_i e_{i,t} \bar{l}_t / X_{t-1} | \Gamma_i]$ .

Parameter  $\chi_1$  is the scaling factor for the adjustment cost and determines the overall importance

<sup>10</sup>Unlike in the RASOE model in subsection 2.1, I do not let households choose labor supply under the GHH preference. Instead, I delegate the labor supply decision to a labor union and write its optimization problem such that the labor supply equation coincides with that of the RASOE model. The reason is as follows: when individual households facing idiosyncratic earnings risk choose labor supply under the GHH preference, they exhibit abnormally high MPC compared to data. Under the GHH preference, households try to smooth  $(c - h(l))$  rather than  $c$ , where  $h(l)$  is labor disutility. As a result, consumption comoves too strongly with earnings, yielding excessively high MPC.

Alternatively, one might consider imposing separable labor disutility instead of the GHH preference on individual households. Then, the issue discussed in footnote 6 returns; the wealth effect can create a countercyclical labor supply pattern when the model is fitted to emerging economies' large consumption swings.

In the heterogeneous-agent New Keynesian (HANK) literature, researchers also find that imposing the GHH preference creates problems, although in different dimensions. Some researchers prefer to circumvent these problems by introducing a labor union to which the labor supply decision is delegated. (See [Auclert, Bardóczy, and Rognlie \(2021\)](#) for a detailed discussion.) In the same spirit, I introduce a labor union to circumvent the problem caused by individual labor supply decisions under the GHH preference.

<sup>11</sup>As we shall see later, the liquid assets are bank deposits, and  $\xi(1 + r_t^b)$  is a deposit service fee that banks charge.



of the adjustment cost in workers' optimization. When  $\chi_1$  increases, workers i) save more and ii) exhibit higher MPC for two reasons. First, workers exhibit stronger precautionary saving behavior because they fear the realization of a low-earnings path more intensely, as illiquid assets become more expensive to cash out. Second, workers who are currently facing a bad earnings shock fail to smooth consumption more significantly; thus, they save more (as they cash out their assets less), and their consumption responds more strongly to a transitory income shock.

Parameter  $\chi_2$  captures how less costly it is for wealthier households to adjust illiquid asset positions. When  $\chi_2 = 1$ , the adjustment cost becomes proportional to the absolute amount of illiquid asset position adjustment,  $v_{i,t}$ . As  $\chi_2$  increases above one, the adjustment cost becomes less costly for wealthier households, who have higher values of  $(1 + r_t^a)a_{i,t-1}$ . For this reason, parameter  $\chi_2$  is useful to make wealthy and poor households face different degrees of financial frictions and thus exhibit different MPCs. Later, I calibrate  $\chi_1$  and  $\chi_2$  (jointly with  $\beta$ ) by targeting ten MPC moments over earnings deciles and workers' aggregate wealth.<sup>12</sup>

In the budget constraint (10), workers' earnings are  $w_t \Gamma_i e_{i,t} \bar{l}_t$ , where  $w_t$  is a wage rate per efficiency unit of labor,  $\Gamma_i$  and  $e_{i,t}$  are the predictable and unpredictable components of idiosyncratic labor productivity, respectively, and  $\bar{l}_t$  is a common labor supply determined by a labor union. The labor union makes a labor supply decision by linearly weighting the aggregate labor income  $w_t L_t$  and labor disutility  $X_{t-1} \frac{1}{1+\omega} \bar{l}_t^{1+\omega}$  as follows.

$$\begin{aligned} \max_{\bar{l}_t, L_t} \quad & w_t L_t - \kappa \left( X_{t-1} \frac{1}{1+\omega} \bar{l}_t^{1+\omega} \right) \\ \text{s.t.} \quad & L_t = p \bar{\Gamma} \bar{e} \bar{l}_t, \end{aligned} \quad (11)$$

where  $\kappa > 0$ ,  $L_t$  is aggregate labor supply (in efficiency units), and  $\bar{\Gamma} (:= E[\Gamma_i])$  and  $\bar{e} (:= E[e_{i,t}])$  are the cross-sectional average of the predictable and unpredictable components of workers' idiosyncratic productivity, respectively. As a result of the optimization, the labor supply is determined as follows.

$$w_t (p \bar{\Gamma} \bar{e})^{1+\omega} = \kappa X_{t-1} L_t^\omega, \quad t \geq 0. \quad (12)$$

This labor supply equation is identical to that in the RASOE model under  $(1 + \omega) \kappa_R = \frac{\kappa}{(p \bar{\Gamma} \bar{e})^{1+\omega}}$ . In other words, the HASOE model does not deviate from the RASOE model in the dimension of the aggregate labor supply.

The predictable component of idiosyncratic labor productivity,  $\Gamma_i$ , follows a lognormal distribution:  $\log \Gamma_i \sim N(0, \sigma_\Gamma)$ . The unpredictable component of idiosyncratic labor productivity,  $e_{i,t}$ , is

<sup>12</sup>What about  $\chi_0$ ? The term  $\chi_0 \Upsilon(\Gamma_i) X_{t-1}$  appears in the functional form of  $\chi_i(v_{i,t}, a_{i,t-1}; \Gamma_i)$  only to ensure that the denominator of  $[v_{i,t} / \{(1 + r_t^a) a_{i,t-1} + \chi_0 \Upsilon(\Gamma_i) X_{t-1}\}]$  is nonzero. (Reflecting its purpose, in calibration, I assign an arbitrary small number, 0.01, to  $\chi_0$ .) In this term,  $\chi_0$  is augmented with  $\Upsilon(\Gamma_i) X_{t-1}$  to make workers' problem i) stationary after detrending and ii) identical across different  $\Gamma_i$ 's after normalization. See Online Appendix B.3.

composed of a persistent component ( $e_{1,i,t}$ ) and a transitory component ( $e_{2,i,t}$ ) as follows.<sup>13</sup>

$$\begin{aligned}\log e_{i,t} &= \log e_{1,i,t} + \log e_{2,i,t}, \\ \log e_{1,i,t} &= \rho_{e_1} \log e_{1,i,t-1} + \varepsilon_{1,i,t}, \quad \varepsilon_{1,i,t} \sim N(0, \sigma_{\varepsilon_1}^2), \quad \text{and} \\ \log e_{2,i,t} &= \varepsilon_{2,i,t}, \quad \varepsilon_{2,i,t} \sim N(0, \sigma_{\varepsilon_2}^2).\end{aligned}$$

Let  $G(\Gamma)$  denote the cumulative distribution function (CDF) of  $\Gamma$ , and  $\Psi_t(e_1, e_2, b_-, a_- | \Gamma)$  denote the CDF of  $(e_1, e_2, b_-, a_-)$  conditional on  $\Gamma$  in period  $t$  among workers. Moreover, let  $c_t(e_1, e_2, b_-, a_-; \Gamma)$ ,  $b_t(e_1, e_2, b_-, a_-; \Gamma)$ , and  $a_t(e_1, e_2, b_-, a_-; \Gamma)$  denote the policy functions of workers with  $\Gamma$  in period  $t$ .<sup>14</sup> The law of motion for  $\Psi_t(e_1, e_2, b_-, a_- | \Gamma)$  is determined as follows.

$$\begin{aligned}\Psi_{t+1}(e'_1, e'_2, b, a | \Gamma) &= \int_{e_1, e_2, b_-, a_-} [P(e_{1,t+1} \leq e'_1 | e_{1,t} = e_1) P(e_{2,t+1} \leq e'_2) \\ &\quad I_{\{b_t(e_1, e_2, b_-, a_-; \Gamma) \leq b, a_t(e_1, e_2, b_-, a_-; \Gamma) \leq a\}}(e_1, e_2, b_-, a_-)] d\Psi_t(e_1, e_2, b_-, a_- | \Gamma),\end{aligned}\tag{13}$$

where  $I_{\{X\}}(x)$  is an indicator function (*i.e.*,  $I_{\{X\}}(x) = 1$  if  $x \in X$ , 0 otherwise).

**Entrepreneurial Households** A tiny fraction  $(1 - p)$  of households do not work and earn income only from the returns on firm share holdings and pure rents from banks (entrepreneurs hereafter). Unlike workers, entrepreneurs do not face idiosyncratic earnings risk and do not pay adjustment cost when trading firm shares. Entrepreneurs solve the following optimization problem.

$$\begin{aligned}\max_{\{C_t^E, A_t^E\}_{t=0}^{\infty}} \quad & E_0 \sum_{t=0}^{\infty} (\beta_E)^t \frac{(C_t^E)^{1-\gamma}}{1-\gamma} \\ \text{s.t.} \quad & C_t^E + A_t^E = R_t^E + (1 + r_t^a) A_{t-1}^E, \quad \text{and} \\ & \lim_{j \rightarrow \infty} E_t \left[ A_{t+j}^E / \left( \prod_{s=1}^j (1 + r_{t+s}^a) \right) \right] \geq 0,\end{aligned}\tag{14}$$

where  $C_t^E$ ,  $A_t^E$ , and  $R_t^E$  are entrepreneurs' consumption, shareholdings, and pure rents, respectively.

I introduce entrepreneurs in my model for three reasons. First, as Bayer et al. (2019) note, the presence of entrepreneurs allows the model to have a more realistic wealth distribution, in which a tiny fraction of the richest households hold a significant fraction of wealth. Second, the top wealth share is unlikely to be accumulated by a precautionary saving motive. By introducing entrepreneurs, the aggregate precautionary savings can exclude the top wealth share in the model

<sup>13</sup>The labor productivity process specification in the model is consistent with the income process specification imposed in the MPC estimation. See Online Appendix F.1.

<sup>14</sup> I attach the time subscript to the policy functions because they depend on the state vector  $\mathbf{S}_t$ , which includes conditional distribution  $\Psi_t(e_1, e_2, b_-, a_- | \Gamma)$ , stochastic trend  $X_{t-1}$ , and other predetermined and exogenous variables in the economy. See footnote 16 for details on the state vector  $\mathbf{S}_t$ .

(as it is held by entrepreneurs) and be calibrated by matching a relevant empirical target.<sup>15</sup> Third, as also noted by Bayer et al. (2019), the pure rents of the economy can be allocated back to households without distorting factor returns or introducing a new asset.

**Banks.** As in the RASOE model, banks lend funds  $F_t$  to firms and finance part of the funds by issuing debt  $D_t$  in the international financial market. In addition, banks in the HASOE model play two more roles. First, they also finance funds by intermediating household deposits,  $B_t$ . Thus, equation (5) in the RASOE model is replaced with the following equation in the HASOE model:

$$F_t = D_t + B_t, \quad t \geq 0. \quad (15)$$

The gross rate of banks' financing cost for the intermediation of household deposit  $B_{t-1}$  is  $(1 + r_t^b)$ . This financing cost consists of a gross return on household deposits  $(1 - \xi)(1 + r_t^b)$  and a service charge  $\xi(1 + r_t^b)$ . Banks can frictionlessly adjust the sources of financing, and thus, the financing cost is equalized between the two sources, household deposits and international debt, as follows.

$$1 + r_t^b = 1 + r_{t-1}, \quad t \geq 0. \quad (16)$$

Second, banks facilitate trades in firm shares among workers and earn facilitation fees  $\chi_t^{agg}$ . Through these two new roles, banks now create pure rents,  $\xi(1 + r_t^b)B_{t-1}$  and  $\chi_t^{agg}$ . As discussed above, entrepreneurs hold the right to claim these pure rents:

$$(1 - p)R_t^E = \xi(1 + r_t^b)B_{t-1} + \chi_t^{agg}. \quad (17)$$

**Other Parts.** Other parts of the economy are identical to the corresponding parts in the RASOE model. Specifically, firms solve the problem (1). Asset return  $r_t^a$  and price  $q_t$  satisfy

$$\begin{aligned} a_{i,t} &= s_{i,t}q_t, & (1 + r_t^a)a_{i,t-1} &= s_{i,t-1}(\Pi_t/s_{t-1} + q_t), \\ A_t^E &= s_t^E q_t, & \text{and } (1 + r_t^a)A_{t-1}^E &= s_{t-1}^E(\Pi_t/s_{t-1} + q_t), \quad \forall t, \end{aligned}$$

where  $s_{i,t}$ ,  $s_t^E$ , and  $s_t$  are worker  $i$ 's shares of firms, an entrepreneur's shares of firms, and the total shares of firms, respectively. Under the normalization that  $s_t = 1$ , asset return  $r_t^a$  and price  $q_t$  again satisfy equations (2) and (3). The interest rate  $r_t$  in the international financial market is determined by equation (6). Three aggregate shocks,  $z_t$ ,  $g_t$ , and  $\mu_t$ , hit the economy and are assumed to follow an AR(1) process, as specified in equation (7). Trade balance is determined by equation (8).

**Aggregation.** Let  $C_t$ ,  $A_t$ ,  $B_t$ , and  $\chi_t^{agg}$  denote the aggregate consumption, firm value, deposit, and

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<sup>15</sup>As we shall see later, the power of precautionary saving plays several important roles in the main results of this paper. Without having entrepreneurs in the model, the power of precautionary saving can be significantly overrated.

illiquid asset adjustment cost, respectively, and  $C_t^W$ ,  $A_t^W$ ,  $B_t^W$ , and  $\chi_t^W$  denote the cross-sectional average of workers' consumption, illiquid asset holdings, liquid asset holdings, and illiquid asset adjustment cost, respectively. The aggregate quantities are constructed as follows.

$$C_t = pC_t^W + (1-p)C_t^E, \quad C_t^W = \int_{\Gamma} \int_{e_1, e_2, b_-, a_-} c_t(e_1, e_2, b_-, a_-; \Gamma) d\Psi_t dG. \quad (18)$$

$$A_t = pA_t^W + (1-p)A_t^E, \quad A_t^W = \int_{\Gamma} \int_{e_1, e_2, b_-, a_-} a_t(e_1, e_2, b_-, a_-; \Gamma) d\Psi_t dG. \quad (19)$$

$$B_t = pB_t^W, \quad B_t^W = \int_{\Gamma} \int_{e_1, e_2, b_-, a_-} b_t(e_1, e_2, b_-, a_-; \Gamma) d\Psi_t dG. \quad (20)$$

$$\chi_t^{agg} = p\chi_t^W, \quad \chi_t^W = \int_{\Gamma} \int_{e_1, e_2, b_-, a_-} \chi_t(a_t(e_1, e_2, b_-, a_-; \Gamma) - (1+r_t^a)a_{-, a_-}; \Gamma) d\Psi_t dG. \quad (21)$$

**Equilibrium.** Given the initial conditions on  $\Psi_0(e_1, e_2, b_-, a_- | \Gamma)$ ,  $X_{-1}$ ,  $A_{-1}$ ,  $A_{-1}^E$ ,  $K_{-1}$ ,  $D_{-1}$ ,  $B_{-1}$ ,  $F_{-1}$ , and  $r_{-1}$ ,<sup>16</sup> (i) individual workers' policy functions  $\{c_t(e_1, e_2, b_-, a_-; \Gamma), b_t(e_1, e_2, b_-, a_-; \Gamma), a_t(e_1, e_2, b_-, a_-; \Gamma)\}_{t=0}^{\infty}$  that solve workers' problem (9), (ii) conditional cumulative distributions  $\{\Psi_t(e_1, e_2, b_-, a_- | \Gamma)\}_{t=1}^{\infty}$  that evolve over time according to equation (13), (iii) prices and aggregate variables  $\{r_t^b, r_t^a, r_t, w_t, q_t, \bar{l}_t, L_t, \Pi_t, Y_t, I_t, K_t, F_t, D_t, TB_t, C_t, C_t^E, A_t, A_t^E, R_t^E, B_t, \chi_t^{agg}\}_{t=0}^{\infty}$  satisfying the optimality conditions for entrepreneurs' problem (14), the optimality conditions for firms' problem (1), aggregation equations (18)-(21), and other equilibrium conditions (2), (3), (6), (8), (11), (12), (15), (16), and (17), and (iv) aggregate shocks  $\{z_t, g_t, \mu_t\}_{t=0}^{\infty}$  that follow the stochastic processes specified in equation (7) constitute the equilibrium of the economy.

### 2.3 Solving the Models

To study business cycles using Bayesian estimation, a model needs to be solved fast enough. There is well-established literature on the Bayesian estimation of representative-agent models, but for heterogeneous-agent models, it only recently became possible to solve these models fast enough to conduct Bayesian estimation due to the development of new solution methods.<sup>17</sup>

Among the new methods, I adopt Auclert et al. (2021)'s method, which computes linearized aggregate dynamics based on Boppart et al. (2018)'s finding that the MA( $\infty$ ) representation of a linearized model regarding aggregate uncertainty can be fully recovered from impulse responses to an MIT shock due to certainty equivalence. Since this method exploits impulse responses to an MIT shock, in Online Appendices A.1 and B.1, I characterize the equilibrium of the RASOE and HASOE models, respectively, when the economy is subject to deterministic paths of aggregate

<sup>16</sup>The initial conditions given here specify the predetermined objects in state vector  $\mathbf{S}_0$ . Referring back to footnote 14, state vector  $\mathbf{S}_t$  is composed of predetermined objects  $\Psi_t(e_1, e_2, b_-, a_- | \Gamma)$ ,  $X_{t-1}$ ,  $A_{t-1}$ ,  $A_{t-1}^E$ ,  $K_{t-1}$ ,  $D_{t-1}$ ,  $B_{t-1}$ ,  $F_{t-1}$ , and  $r_{t-1}$  and aggregate exogenous variables  $z_t$ ,  $g_t$ , and  $\mu_t$ .

<sup>17</sup>The main contributors to this recent development include Auclert et al. (2021), Boppart et al. (2018), Ahn et al. (2018), Bayer and Luetticke (2020), Winberry (2018), and Reiter (2009).

exogenous variables  $\{z_t, g_t, \mu_t\}_{t=0}^{\infty}$ .

Both my RASOE and HASOE models exhibit a stochastic trend, and thus, the equilibrium needs to be detrended to become stationary. In Online Appendices A.2 and B.2, I present a detrended stationary equilibrium of the RASOE and HASOE models, respectively. I solve the detrended equilibrium using Auclert et al. (2021)’s method. Online Appendix C discusses how this method is applied to the detrended equilibrium. Then, in Online Appendix D, I discuss how to recover the original equilibrium from the detrended equilibrium.

### 3 Taking Models to Data

Both the RASOE and HASOE models are fitted to the Peruvian economy. Specifically, I take the models to Peruvian data through two steps. First, I calibrate parameters determining key moments on the balanced growth path. Second, I estimate parameters governing aggregate dynamics around the balanced growth path using Bayesian methods. This two-step procedure is possible because the parameters estimated in the second step do not affect the balanced growth path.

#### 3.1 Calibration

In both the RASOE and HASOE models, the time unit is a quarter. Table 1 reports the calibrated parameter values and target moments or information sources used for the calibration. For parameters  $g^*$ ,  $r^*$ ,  $\alpha$ ,  $\delta$ ,  $\tilde{D}^*$ ,  $\gamma$ , and  $\omega$ , I assign the same parameter values to the RASOE and HASOE models. Parameters  $g^*$  and  $r^*$  are calibrated to the long-run average output growth rate and real lending interest rate in data, respectively. Parameters  $\alpha$ ,  $\delta$ , and  $\tilde{D}^*$  are calibrated by matching the long-run average capital-output ratio (10.91), investment-output ratio (0.191), and trade-balance-to-output ratio (0.043) from data in the related equilibrium conditions.<sup>18,19</sup> Parameters  $\gamma$  and  $\omega$  are

<sup>18</sup>The output growth, investment-output ratio, and trade-balance-to-output ratio are computed using Banco Central de Reserva del Perú (BCRP)’s national account data from 1980–2018. (Specifically, real quarterly national account data are obtained, seasonally adjusted, and transformed to a per capita term.) The capital-output ratio is computed using Feenstra, Inklaar, and Timmer (2015)’s Penn World Table (version 9.1) capital and output data from 1980–2017. The real lending interest rates are computed by deflating BCRP’s data on lending rates in foreign currency (TAMEX) from 1992–2018 with the expected inflation on U.S. CPIs. The expected inflation is constructed by taking an average inflation rate over the current and past three quarters, following Neumeyer and Perri (2005) and Uribe and Yue (2006). (Atkeson and Ohanian (2001) empirically support this approximation of expected inflation.)

<sup>19</sup>In the literature, interest rates are often constructed by adding J.P. Morgan’s EMBIG sovereign bond spreads with U.S. interest rates. (‘EMBIG interest rates’ hereafter). Instead, I construct interest rates based on BCRP data series (‘BCRP interest rates’ hereafter). I find that these two interest rates are highly correlated (correlation 0.863), but their means are substantially different; the average nonannualized quarterly EMBIG interest rate is 0.007, while that of the BCRP interest rate is 0.021. Given that the long-run average value of  $TB_t/Y_t$  is calibrated to its data counterpart, there is a one-to-one relationship between  $r^*$  and  $D_t/Y_t$  on the balanced growth path through an equilibrium condition  $r^* = \frac{TB_t/Y_t}{D_t/Y_t} g^* + (g^* - 1)$ . Using this equation, I recover the value of  $r^*$  that corresponds to the long-run average value of  $D_t/Y_t$  in Milesi-Ferretti and Lane (2017)’s dataset. The value of such  $r^*$  is 0.025, which is far closer to the average BCRP rate than the average EMBIG rate. Based on this observation, I use BCRP interest rates rather than EMBIG

Table 1: Calibration for the Peruvian Economy

Description	Value	Target / Source
<i>Common in RASOE and HASOE</i>		
$g^*$ long-run average gross growth rate	1.004	$E[Y_t/Y_{t-1}]$
$r^*$ long-run average lending rate	0.021	BCRP, U.S. CPI
$\alpha$ capital income share	0.378	$(K/Y)(r^* + \delta)/g^*$
$\delta$ depreciation rate	0.014	$g^*(I/Y)/(K/Y) - (g^* - 1)$
$\tilde{D}^*$ international debt	10.57	$(TB/Y)\tilde{Y}^*/(1 + r^* - g^*)$
$\gamma$ inverse of IES	2.000	Garcia-Cicco et al. (2010)
$\omega$ inverse of labor supply elasticity	0.600	Garcia-Cicco et al. (2010)
<i>RASOE only</i>		
$\beta_R$ representative households' discount factor	0.987	$(g^*)^\gamma/(1 + r^*)$
$\kappa_R$ scale parameter for labor disutility	1.660	$L = 1$ on the b.g.p
<i>HASOE only - earnings process</i>		
$\sigma_\Gamma$ S.D. of the predictable component	0.656	} ENAHO
$\rho_{e_1}$ persistence of the unpredictable, AR(1) component	0.968	
$\sigma_{e_1}$ S.D. of shocks to the unpredictable, AR(1) component	0.134	
$\sigma_{e_2}$ S.D. of shocks to the unpredictable, <i>i.i.d.</i> component	0.464	
<i>HASOE only - targeting MPCs &amp; Workers' Aggregate Wealth</i>		
$\beta$ workers' discount factor	0.948	} MPC estimates & earnings-income ratio in ENAHO
$\chi_1$ scale parameter for illiquid asset adjustment cost	6.694	
$\chi_2$ convexity parameter for illiquid asset adjustment cost	1.724	
$\chi_0$ non-zero denominator in illiquid asset adjustment cost	0.010	
<i>HASOE only - other parameters</i>		
$\kappa$ scale parameter for labor disutility	5.449	$L = 1$ on the b.g.p
$\xi$ long-run average spread	0.020	BCRP, U.S. CPI
$\beta_E$ entrepreneurs' discount factor	0.987	$(g^*)^\gamma/(1 + r^*)$
$p$ share of workers (= 1 – share of entrepreneurs)	0.987	WID

Notes: The time unit is a quarter. 'b.g.p' in the 'Target/Source' column represents the balanced growth path.

assigned the values used in Garcia-Cicco et al. (2010), which are common in the related literature.

Parameters  $\beta_R$  and  $\kappa_R$  appear only in the RASOE model. Parameter  $\beta_R$  is calibrated such that representative households' Euler equation holds on the balanced growth path. Parameter  $\kappa_R$  is calibrated such that the aggregate labor supply is normalized to 1 on the balanced growth path.

Parameters  $\sigma_\Gamma$ ,  $\rho_{e_1}$ ,  $\sigma_{e_1}$ ,  $\sigma_{e_2}$ ,  $\beta$ ,  $\chi_1$ ,  $\chi_2$ ,  $\chi_0$ ,  $\kappa$ ,  $\xi$ ,  $\beta_E$ , and  $p$  appear only in the HASOE model. Parameters  $\sigma_\Gamma$ ,  $\rho_{e_1}$ ,  $\sigma_{e_1}$ , and  $\sigma_{e_2}$  govern workers' earnings process. I calibrate them using earnings data from the 2011–2018 waves of a nationally representative Peruvian household survey, Encuesta

interest rates so that the model generates  $D_t/Y_t$  close to Milesi-Ferretti and Lane (2017)'s debt data.



Nacional de Hogares (ENAHO). I first remove predictable components from household earnings using observable characteristics. Then, I calibrate  $\sigma_{\Gamma}$  using the predictable components and  $\rho_{e_1}$ ,  $\sigma_{e_1}$ , and  $\sigma_{e_2}$  by applying [Floden and Lindé \(2001\)](#)'s method to the residual components.<sup>20</sup>

Parameters  $\beta$ ,  $\chi_1$ , and  $\chi_2$  are calibrated by targeting MPC moments and workers' aggregate wealth.<sup>21</sup> For the target MPC moments, I estimate the Peruvian quarterly MPC at each residual earnings ( $e_{i,t}$ ) decile by applying [Blundell et al. \(2008\)](#)'s method to the ENAHO data, as in [Hong \(2022\)](#).<sup>22,23</sup> To target the correct amount of workers' aggregate wealth, I match the earnings-income ratio (or, equivalently, (labor income) / (labor income + capital income)) on the balanced growth path of the model with the ratio in the ENAHO data, 0.817.<sup>24</sup> I implement this joint calibration by minimizing the following objective function  $J$ :

$$J = \varpi \left\{ \frac{w_t \bar{\Gamma} \bar{e}_t}{w_t \bar{\Gamma} \bar{e}_t + [r_t^a A_{t-1}^W + \{(1 - \xi)(1 + r_t^b) - 1\} B_{t-1}^W]} \text{ on the balanced growth path} - 0.817 \right\}^2 + (1 - \varpi) \left\{ (MPC_{model} - MPC_{data}) \cdot V_{mpc} \cdot (MPC_{model} - MPC_{data})' \right\},$$

where  $\varpi$  denotes a weight on the first target (workers' earnings-income ratio),  $MPC_{model}$  and  $MPC_{data}$  denote a 10-by-1 vector of the model-predicted MPC on the balanced growth path and the estimated MPC at each earnings decile, respectively, and  $V_{mpc}$  is a weight matrix, which I choose to be a diagonal matrix whose diagonal elements equal the earnings share of each decile.

The joint calibration matches targets well, even though only three parameters are used to target eleven moments. First, workers' earnings-income ratio is 0.832 in the model, and its data counterpart is 0.817. Second, [Figure 1](#) plots the model-predicted MPC (labeled 'Model') and the estimated MPC (labeled 'Data') at each earnings decile and shows that the former tracks the latter closely. Importantly, the data strongly suggest that households significantly deviate from the PIH, as the mean quarterly MPC estimate across deciles (0.209) is substantially greater than zero, and

<sup>20</sup>See [Online Appendix F.1](#) for details.

<sup>21</sup>For  $\chi_0$ , I assign an arbitrary small number, 0.01, as discussed in [footnote 12](#).

<sup>22</sup>In estimating and targeting MPCs, observations are grouped by residual earnings  $e_{i,t}$  (or, equivalently, unpredictable component of earnings) instead of total earnings ( $w_t \Gamma_i e_{i,t} \bar{l}_t$ ) because  $e_{i,t}$  bears risk and thus induces precautionary saving and MPC heterogeneity, while  $\Gamma_i$  does not.

<sup>23</sup>Compared to [Hong \(2022\)](#), the consumption measure is changed from nondurable consumption to total consumption (including durable consumption) to be consistent with the aggregate consumption measure. The sample period is also changed to 2011–2018. Some of the early waves (2004–2010) used in [Hong \(2022\)](#) are not used here because quarterly expenses of some key durable goods are unavailable in these waves. [Online Appendix F](#) provides further details of the MPC estimation and data processing procedures.

<sup>24</sup>In ENAHO, labor and capital incomes are not distinguishable within self-employment income. As in [Diaz-Gimenez, Quadrini, and Rios-Rull \(1997\)](#), [Krueger and Perri \(2006\)](#), and [Hong \(2022\)](#), I split self-employment income into labor and capital income parts using the ratio between unambiguous labor and capital incomes. In ENAHO, the ratio of (unambiguous labor income) / (unambiguous labor income + unambiguous capital income) is 0.817, and it becomes the earnings-income ratio once self-employment income is split according to this ratio. This ratio is close to the ratio that [Diaz-Gimenez et al. \(1997\)](#) and [Krueger and Perri \(2006\)](#) use for their U.S. sample, 0.864.



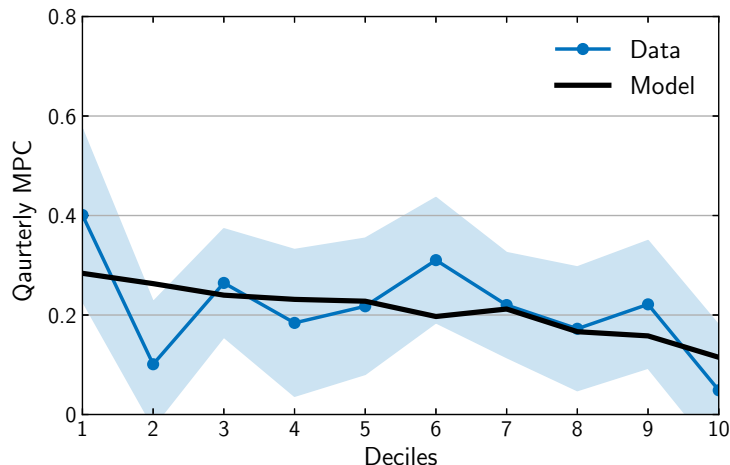


Figure 1: Quarterly MPCs in Peru: Data vs. Model

*Notes:* This figure plots the model-predicted MPC (labeled ‘Model’) and the estimated MPC (labeled ‘Data’) at each earnings decile. Integer 1 on the  $x$ -axis denotes the bottom decile. Shaded areas represent 95% confidence intervals.

the model successfully captures such deviation by matching the MPC moments.

The rest of the HASOE-specific parameters ( $\kappa$ ,  $\xi$ ,  $\beta_E$ , and  $p$ ) are calibrated as follows. Parameter  $\kappa$  is calibrated such that the aggregate labor supply is normalized to 1 on the balanced growth path. Parameter  $\xi$  is calibrated to a spread between long-run average lending and deposit interest rates in data.<sup>25</sup> Parameter  $\beta_E$  is calibrated such that entrepreneurs’ Euler equation holds on the balanced growth path. Parameter  $p$  is calibrated such that the entrepreneurs’ wealth share matches the top  $100(1 - p)\%$  share of wealth in data.<sup>26</sup>

Among the calibration targets used for the HASOE model, only three are distributional moments: the top 1.3% ( $= 100(1 - p)\%$ ) share of wealth and the standard deviations of predictable and unpredictable earnings components. The model, however, predicts many more distributional moments than the three targets. Table 2 compares some key moments for wealth, earnings, and consumption distributions between the model and data. All the moments compared in the table are untargeted except for the top 1.3% wealth share. Table 2 suggests that the HASOE model overall captures Peruvian wealth, earnings, and consumption distributions reasonably well, even though

<sup>25</sup>The real deposit interest rates are computed by deflating BCRP’s data on deposit rates in foreign currency (TIP-MEX) during 1992–2018 with the expected inflation on U.S. CPIs, which are constructed as in footnote 18.

<sup>26</sup>For this purpose, I use wealth inequality data from the World Inequality Database (WID). Since Peru does not have micro wealth data, the WID imputes the wealth inequality of Peru based on its income inequality and the wealth inequality of other countries that exhibit a similar degree of income inequality with Peru and have micro wealth data (Bajard, Chancel, Moshrif, and Piketty, 2022). As Alvarado, Atkinson, et al. (2021) note, the WID’s wealth concept is a market value of wealth, which includes financial assets yielding nonproductive pure rents, such as entrepreneurs’ claims to rents  $R_t^E$  in the model. Thus, I evaluate the market value of the claims assuming that entrepreneurs can trade the claims among themselves and include this value as part of entrepreneurs’ wealth. See Online Appendix G for details.

Table 2: Distributional Moments: Model (HASOE) vs. Data

Moment	Model	Data	Note	Data Source
<i>Wealth distribution</i>				
top 1.3% share	0.458	0.458	targeted	WID
top 5% share	0.532	0.644	untargeted	WID
top 10% share	0.594	0.760	untargeted	WID
Gini	0.642	0.874	untargeted	WID
<i>Earnings distribution of workers (residualized)</i>				
top 5% share	0.172	0.172	untargeted	ENAHO
top 10% share	0.279	0.273	untargeted	ENAHO
Gini	0.380	0.362	untargeted	ENAHO
<i>Earnings distribution of workers (unresidualized)</i>				
top 5% share	0.246	0.197	untargeted	ENAHO
top 10% share	0.373	0.311	untargeted	ENAHO
Gini	0.503	0.446	untargeted	ENAHO
<i>Consumption distribution of workers (residualized)</i>				
top 5% share	0.119	0.149	untargeted	ENAHO
top 10% share	0.211	0.238	untargeted	ENAHO
Gini	0.270	0.298	untargeted	ENAHO
<i>Consumption distribution of workers (unresidualized)</i>				
top 5% share	0.203	0.178	untargeted	ENAHO
top 10% share	0.320	0.283	untargeted	ENAHO
Gini	0.436	0.396	untargeted	ENAHO

Notes: ‘Residualized’ means that predictable components are removed, and ‘unresidualized’ means they are not.

only a small number of distributional moments are targeted.

Table 3 reports the size of stock variables in the RASOE and HASOE models. The two models exhibit the same values of  $K/Y$  (10.91) and  $D/Y$  (2.487) as a result of calibration. The value of  $D/Y$  (2.487) is close to its data counterpart in Milesi-Ferretti and Lane (2017)’s dataset (1.783), although not directly targeted.<sup>27</sup> As formally shown in Online Appendices A.3 and B.4, on the

Table 3: The Size of Stock Variables

	$(K/Y)$	$(A/Y)$	$(A^W/Y)$	$(A^E/Y)$	$(B/Y)$	$(B^W/Y)$	$(D/Y)$
RASOE	10.91	8.419	-	-	-	-	2.487
HASOE	10.91	7.785	6.016	142.2	0.633	0.642	2.487

<sup>27</sup>See footnote 19 for a related discussion.

balanced growth path, the stock variables satisfy ‘ $K/Y = A/Y + D/Y$ ’ in the RASOE model and ‘ $K/Y = A/Y + B/Y + D/Y$ ’ in the HASOE model.<sup>28</sup> It is also worth noting that  $B/Y$  (0.633) is very small in the HASOE model. This is because workers barely save in liquid assets in the model under the low deposit interest rate observed in data.

### 3.2 Bayesian Estimation

Parameters  $\psi, \phi, \theta_z, \theta_g, \rho_z, \sigma_z, \rho_g, \sigma_g, \rho_\mu$ , and  $\sigma_\mu$  govern the aggregate dynamics around the balanced growth path in both the RASOE and HASOE models. I estimate these parameters using standard Bayesian methods and macro data. For the macro data, I use output, consumption, investment, and trade-balance-to-output ratio, following the existing studies that conduct Bayesian estimation to examine emerging market business cycles. Specifically, I use the time series of  $[\Delta \log Y_t, \Delta \log C_t, \Delta \log I_t, \Delta(TB_t/Y_t)]$ , as in [Chang and Fernández \(2013\)](#).<sup>29</sup> I construct these data series using BCRP’s national account data from 1980–2018.<sup>30</sup> In the estimation, I allow *i.i.d.* measurement errors on each data series and estimate their standard errors,  $\sigma_y^{me}$ ,  $\sigma_c^{me}$ ,  $\sigma_i^{me}$ , and  $\sigma_{tby}^{me}$ .

I construct a posterior distribution by sampling 300,000 draws through the Random Walk Metropolis Hastings (RWMH) algorithm described in [Herbst and Schorfheide \(2015\)](#) and burning the initial 50,000 draws. A successful implementation of the algorithm requires i) a variance-covariance matrix of the proposal distribution that is close to the variance-covariance matrix of the posterior distribution after scaling and ii) a scaling factor for the matrix that achieves an acceptance rate in the range 0.2–0.4. To this end, I run multiple preliminary stages of the RWMH algorithm and its variant before the main RWMH algorithm, through which i) the draws of the chain move close to the posterior mode, ii) the variance-covariance matrix of the proposal distribution is updated to become close to the variance-covariance matrix of the posterior distribution after scaling, and iii) the scaling factor is updated to achieve an acceptance rate close to 0.27.<sup>31</sup>

Table 4 presents the prior and posterior distributions. I impose a fairly flat prior distribution, as reported in the ‘Prior’ panel. Measurement errors are allowed to explain up to 6.25% of the observed variances. Parameters  $\rho_z$ ,  $\rho_g$ , and  $\rho_\mu$  in the prior distribution follow a beta distribution

<sup>28</sup>In the HASOE model, the wealth-output ratio is 12.13, which is greater than the capital-output ratio because the market value of entrepreneurs’ claims to pure rents is included in wealth. See footnote 26 for a related discussion.

<sup>29</sup>[Garcia-Cicco et al. \(2010\)](#) use the same set of statistics except for using  $TB_t/Y_t$  instead of  $\Delta(TB_t/Y_t)$ . Both choices are acceptable from a statistical perspective, as neither inherits a trend in the data and the model. I choose  $\Delta(TB_t/Y_t)$  over  $TB_t/Y_t$  because the countercyclicality of trade balance, a stylized pattern for both emerging and developed economies, is better captured when  $\Delta \log Y_t$  is correlated with  $\Delta(TB_t/Y_t)$  rather than with  $TB_t/Y_t$ .

<sup>30</sup>As described in footnote 18, I obtain BCRP’s real quarterly national account data, seasonally adjust them, and transform them to a per capita term. For the last step (transformation to a per capita term), I construct quarterly population series by linearly interpolating BCRP’s annual population data.

<sup>31</sup>As a result, I obtain the acceptance rates of 0.278, 0.264, and 0.297 in the main RWMH algorithm for the estimation of the RASOE model in subsection 2.1, the HASOE model in subsection 2.2, and the HASOE model revised by augmenting a financial friction shock in section 4, respectively.

Table 4: Prior and Posterior Distributions in the Bayesian Estimation

Density	Prior		Posterior - RASOE ( $z, g, \mu$ )		Posterior - HASOE ( $z, g, \mu$ )		Posterior - HASOE ( $z, g, \mu, \eta$ )				
	[Meta1,Meta2]	Mode	Mean	[0.05 ,0.95 ]	Mode	Mean	[0.05 ,0.95 ]	Mode	Mean	[0.05 ,0.95 ]	
$\psi$	Uniform	[0.000,4.000]	0.513	2.471	[0.864,3.851]	0.005	0.004	[0.002,0.007]	1.472	3.154	[1.860,3.944]
$\phi$	Gamma	[15.00,15.00]	1.661	2.364	[1.095,3.976]	7.126	7.307	[5.823,8.970]	3.094	1.731	[0.288,3.143]
$\theta_z$	Uniform	[0.000,2.000]	0.017	0.245	[0.017,0.672]	0.000	0.001	[0.000,0.004]	0.000	0.090	[0.005,0.279]
$\theta_g$	Uniform	[0.000,2.000]	0.006	0.079	[0.003,0.255]	0.350	0.360	[0.270,0.456]	0.084	0.476	[0.023,1.446]
$\rho_z$	0.99·Beta	[0.500,0.200]	0.931	0.919	[0.873,0.954]	0.988	0.986	[0.979,0.989]	0.942	0.943	[0.899,0.974]
$\sigma_z$	Invgamma	[0.010,0.020]	0.017	0.017	[0.015,0.019]	0.029	0.030	[0.027,0.034]	0.017	0.017	[0.015,0.019]
$\rho_g$	0.99·Beta	[0.500,0.200]	0.988	0.988	[0.985,0.989]	0.044	0.065	[0.018,0.128]	0.795	0.809	[0.691,0.900]
$\sigma_g$	Invgamma	[0.010,0.020]	0.006	0.006	[0.006,0.007]	0.039	0.039	[0.034,0.045]	0.006	0.006	[0.005,0.007]
$\rho_\mu$	0.99·Beta	[0.500,0.200]	0.919	0.878	[0.746,0.961]	0.694	0.749	[0.609,0.868]	0.488	0.522	[0.184,0.835]
$\sigma_\mu$	Invgamma	[0.010,0.020]	0.011	0.047	[0.018,0.073]	0.003	0.003	[0.002,0.004]	0.004	0.006	[0.002,0.013]
$\rho_\eta$	0.99·Beta	[0.500,0.200]	-	-	-	-	-	-	0.904	0.555	[0.150,0.927]
$\sigma_\eta$	Invgamma	[0.010,0.020]	-	-	-	-	-	-	0.404	0.822	[0.344,1.323]
$\sigma_y^{me}$	Uniform	[0.000,0.007]	0.007	0.006	[0.006,0.007]	0.007	0.007	[0.006,0.007]	0.006	0.006	[0.006,0.007]
$\sigma_c^{me}$	Uniform	[0.000,0.009]	0.009	0.009	[0.008,0.009]	0.009	0.009	[0.008,0.009]	0.009	0.009	[0.008,0.009]
$\sigma_i^{me}$	Uniform	[0.000,0.045]	0.045	0.044	[0.043,0.045]	0.045	0.044	[0.043,0.045]	0.045	0.044	[0.043,0.045]
$\sigma_{tby}^{me}$	Uniform	[0.000,0.004]	0.004	0.004	[0.004,0.004]	0.004	0.004	[0.004,0.004]	0.004	0.004	[0.004,0.004]

Notes: Estimation is based on the Peruvian quarterly national account data from 1980–2018. In the prior density column, ‘0.99 · Beta’ means that the corresponding parameter multiplied by (1/0.99) follows a beta distribution. The column labeled ‘[Meta1,Meta2]’ reports the meta parameters of the prior distributions. For the uniform distribution, [Meta1,Meta2] is [lower bound, upper bound]. For the inverse gamma distribution and gamma distribution, [Meta1,Meta2] is [mean, standard deviation]. For ‘0.99 · Beta’, [Meta1,Meta2] is [mean, standard deviation] of the beta distribution part. Posterior statistics are based on 300,000 posterior draws from the RWMH algorithm, of which the initial 50,000 draws are burned.

after being scaled by  $(1/0.99)$ . This scaling is to ensure that these parameters do not exceed 0.99 under any posterior draw, as the precision of Auclert et al. (2021)'s computation method can be compromised when the economy becomes too persistent.<sup>32</sup> The 'Posterior - RASOE  $(z, g, \mu)$ ' and 'Posterior - HASOE  $(z, g, \mu)$ ' panels report key statistics of the posterior distributions for the RASOE and HASOE models introduced in subsections 2.1 and 2.2, respectively.

### 3.3 Model Performance

Table 5 compares key business cycle moments between models and data after the Bayesian estimation. Starting from the data, the Peruvian national accounts exhibit the stylized patterns of emerging market business cycles well. First, Peruvian output is substantially more volatile than that of typical developed economies:  $\sigma(\Delta \log Y_t)$  is 0.027 in Peru, which far exceeds the average in rich economies, 0.008, as reported in Table 1.6 of Uribe and Schmitt-Grohé (2017). Second, consumption is more volatile than output in Peru (excess consumption volatility):  $\sigma(\Delta \log C_t)$  is 0.036, which is substantially greater than  $\sigma(\Delta \log Y_t)$ , 0.027. Third, trade balance is countercyclical in Peru:  $\text{corr}(\Delta(TB_t/Y_t), \Delta \log Y_t)$  is -0.346. I highlight one more moment for later discussion, although it has received less attention in the literature;  $\text{corr}(\Delta \log C_t, \Delta \log I_t)$  is substantially less than one.<sup>33</sup> Moreover, the low correlation is not an abnormal phenomenon of the Peruvian data: the correlation is 0.189 for emerging countries and 0.278 for developed countries, on average.<sup>34</sup>

How successful are the models at explaining these data patterns? Table 5 reports the business cycle moments predicted by the RASOE model described in subsection 2.1 in the rows labeled 'RASOE  $(z, g, \mu)$  model' and suggests that the RASOE model explains the data patterns reasonably well: consumption is more volatile than output ( $\sigma(\Delta \log C_t)/\sigma(\Delta \log Y_t) = 0.046/0.040 = 1.144$ ), trade balance is countercyclical ( $\text{corr}(\Delta(TB_t/Y_t), \Delta \log Y_t) = -0.111$ ), and the correlation between consumption and investment is low ( $\text{corr}(\Delta \log C_t, \Delta \log I_t) = 0.287$ ). The RASOE model exhibits a few discrepancies against data, as well: the output and consumption volatilities are noticeably greater than the data counterparts, and the output and consumption autocorrelations with two- and three-quarter lags are as substantial as those with one-quarter lag.

Table 5 also reports the moments predicted by the HASOE model described in subsection 2.2 in

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<sup>32</sup> Auclert et al. (2021)'s sequence space approach requires a truncation of sequences, and truncation errors can be nontrivial when the economy is extremely persistent. In this paper, I truncate sequences at  $T = 700$  when solving models and drop the last seven periods further when evaluating moments. In Online Appendix E, I verify that at the posterior mode, truncation errors are negligible in the model statistics used in this paper.

<sup>33</sup> It is indeed negative, but as we shall see later, what matters in this paper is that this value is substantially less than one.

<sup>34</sup> In computing the correlation for emerging and developed countries, I use the quarterly macro data series and country categorization used for the business cycle statistics in Chapter 1 of Uribe and Schmitt-Grohé (2017). From the dataset, sample countries are selected if all five data series of output, investment, exports, imports, and consumption are available for at least twenty consecutive years. After the sample selection, 16 emerging countries and 17 rich countries remain in the sample. In averaging the correlation across multiple countries, I use population weights.

Table 5: Business Cycle Moments: Model vs. Data

		$\Delta \log Y_t$	$\Delta \log C_t$	$\Delta \log I_t$	$\Delta(TB_t/Y_t)$
<i>Standard deviation</i>					
	RASOE ( $z, g, \mu$ ) model	0.040	0.046	0.143	0.029
	HASOE ( $z, g, \mu$ ) model	0.066	0.059	0.288	0.036
	HASOE ( $z, g, \mu, \eta$ ) model	0.029	0.036	0.167	0.018
	Data	0.027	0.036	0.179	0.017
<i>Contemporaneous correlation</i>					
<i>with <math>\Delta \log Y_t</math></i>	RASOE ( $z, g, \mu$ ) model		0.776	0.520	-0.111
	HASOE ( $z, g, \mu$ ) model		0.938	0.913	-0.824
	HASOE ( $z, g, \mu, \eta$ ) model		0.598	0.509	-0.248
	Data		0.681	0.437	-0.346
<i>with <math>\Delta(TB_t/Y_t)</math></i>	RASOE ( $z, g, \mu$ ) model		-0.461	-0.610	
	HASOE ( $z, g, \mu$ ) model		-0.821	-0.921	
	HASOE ( $z, g, \mu, \eta$ ) model		-0.180	-0.632	
	Data		-0.318	-0.460	
<i>with <math>\Delta \log C_t</math></i>	RASOE ( $z, g, \mu$ ) model			0.287	
	HASOE ( $z, g, \mu$ ) model			0.788	
	HASOE ( $z, g, \mu, \eta$ ) model			-0.223	
	Data			-0.158	
<i>Autocorrelation</i>					
<i>with lag 1</i>	RASOE ( $z, g, \mu$ ) model	0.474	0.312	-0.202	-0.229
	HASOE ( $z, g, \mu$ ) model	-0.165	-0.028	-0.280	-0.126
	HASOE ( $z, g, \mu, \eta$ ) model	0.036	-0.048	-0.080	-0.131
	Data	0.404	0.078	-0.304	0.023
<i>with lag 2</i>	RASOE ( $z, g, \mu$ ) model	0.472	0.312	-0.046	-0.079
	HASOE ( $z, g, \mu$ ) model	0.006	0.008	-0.032	-0.044
	HASOE ( $z, g, \mu, \eta$ ) model	0.027	-0.039	-0.067	-0.078
	Data	0.009	0.036	-0.094	-0.077
<i>with lag 3</i>	RASOE ( $z, g, \mu$ ) model	0.471	0.312	0.006	-0.028
	HASOE ( $z, g, \mu$ ) model	0.015	0.001	-0.015	-0.041
	HASOE ( $z, g, \mu, \eta$ ) model	0.022	-0.025	-0.053	-0.058
	Data	-0.090	-0.112	0.026	-0.061

*Notes:* The model statistics are computed under each posterior draw, and the means across the posterior distribution are reported.

the rows labeled ‘HASOE ( $z, g, \mu$ ) model.’ The reported numbers suggest that the HASOE model fails to explain the data patterns in several important dimensions: output and consumption are far

greater than the data counterparts, consumption is less volatile than output ( $\sigma(\Delta \log C_t)/\sigma(\Delta \log Y_t) = 0.059/0.066 = 0.897$ ), and the correlation between consumption and investment is close to 1 ( $\text{corr}(\Delta \log C_t, \Delta \log I_t) = 0.788$ ).

How does the RASOE model explain the data patterns? Why does the HASOE model fail to do so, on the other hand? The following subsection addresses these questions.

### 3.4 How RASOE Works and Why HASOE Does Not

I start by examining the driving mechanism of the RASOE model. The ‘RASOE ( $z, g, \mu$ ) model’ panel in Table 6 presents variance decomposition in the RASOE model and shows that trend shocks are the main driver of output and consumption fluctuations: 50.8% of output fluctuations and 83.6% of consumption fluctuations are driven by trend shocks. This result is consistent with [Aguiar and Gopinath \(2007\)](#)’s finding that trend shocks drive emerging market business cycles.

In Figure 2a, I examine the consumption response to a trend shock in the RASOE model and verify that the permanent income effect of a trend shock drives excess consumption volatility, exactly as [Aguiar and Gopinath \(2007\)](#) argue. The first panel shows that the impact effect of a trend shock on consumption is greater than that on output. The RASOE model imposes the GHH preference, under which households smooth per-period utility  $GHH_t := C_t - h_t(L_t)$  subject to budget constraints, where  $h_t(L_t) := \kappa_R X_{t-1} L_t^{1+\omega}$  is labor disutility. Since  $C_t = GHH_t + h_t(L_t)$ , the strong impact effect of a trend shock on consumption can come either from  $GHH_t$  or from  $h_t(L_t)$ . In the second panel, I decompose the consumption response into the responses of  $GHH_t$  and  $h_t(L_t)$  and find that almost all the impact effect on consumption comes from the impact effect on  $GHH_t$ . A trend shock affects  $GHH_t$  by affecting  $w_t$  and  $r_t^a$  in the budget constraints as well as labor disutility function  $h_t(\cdot)$  via  $X_{t-1}$ . In particular, the effects on  $w_t$  and  $h_t(\cdot)$  transmit to  $GHH_t$  through earnings  $w_t L_t$  in the budget constraints, as labor supply  $L_t$  is determined by wage  $w_t$  and labor disutility  $h_t(\cdot)$ . In the third panel, I decompose the response of  $GHH_t$  into the response driven by  $w_t$  and  $h_t(\cdot)$  and the response driven by  $r_t^a$  and find that it is dominantly driven by the former.<sup>35</sup> The last panel plots the impulse response of earnings  $w_t L_t$ , which mildly jumps on impact but grows strongly in the future.<sup>36</sup> These panels show that the permanent income effect of the future growth of earnings generates a strong impact effect on  $GHH_t$  and thus on  $C_t$ .

In the literature, a competing hypothesis exists on the driving mechanism of emerging market business cycles: emerging economies face volatile interest rates, and they cause excess consumption volatility because households respond to them by intertemporally substituting consumption ([Neumeier and Perri, 2005](#)). This mechanism is muted in explaining the Peruvian data largely be-

<sup>35</sup>The consumption response decomposition into driving factors in the RASOE model requires an extra computational step in addition to solving the model (unlike that in the HASOE model). See Online Appendix H for details.

<sup>36</sup>In fact, the impulse response of  $w_t L_t$  is the same as that of  $Y_t$  because  $w_t L_t = (1 - \alpha)Y_t$  at equilibrium.



Table 6: Variance Decomposition

	$\Delta \log Y_t$	$\Delta \log C_t$	$\Delta \log I_t$	$\Delta(TB_t/Y_t)$
<i>RASOE (z, g, <math>\mu</math>) model</i>				
stationary productivity shock (z)	0.492 (0.048)	0.163 (0.026)	0.341 (0.053)	0.020 (0.015)
trend shock (g)	0.508 (0.048)	0.836 (0.026)	0.056 (0.013)	0.353 (0.041)
interest rate shock ( $\mu$ )	0.001 (0.000)	0.001 (0.001)	0.603 (0.054)	0.627 (0.042)
<i>HASOE (z, g, <math>\mu</math>) model</i>				
stationary productivity shock (z)	0.547 (0.043)	0.826 (0.030)	0.236 (0.033)	0.370 (0.045)
trend shock (g)	0.452 (0.043)	0.164 (0.030)	0.708 (0.036)	0.380 (0.046)
interest rate shock ( $\mu$ )	0.000 (0.000)	0.010 (0.002)	0.056 (0.011)	0.251 (0.038)
<i>HASOE (z, g, <math>\mu</math>, <math>\eta</math>) model</i>				
stationary productivity shock (z)	0.918 (0.024)	0.318 (0.052)	0.189 (0.039)	0.021 (0.011)
trend shock (g)	0.078 (0.023)	0.030 (0.013)	0.379 (0.048)	0.929 (0.044)
interest rate shock ( $\mu$ )	0.000 (0.000)	0.000 (0.000)	0.009 (0.012)	0.034 (0.042)
financial friction shock ( $\eta$ )	0.004 (0.002)	0.652 (0.051)	0.423 (0.043)	0.016 (0.015)

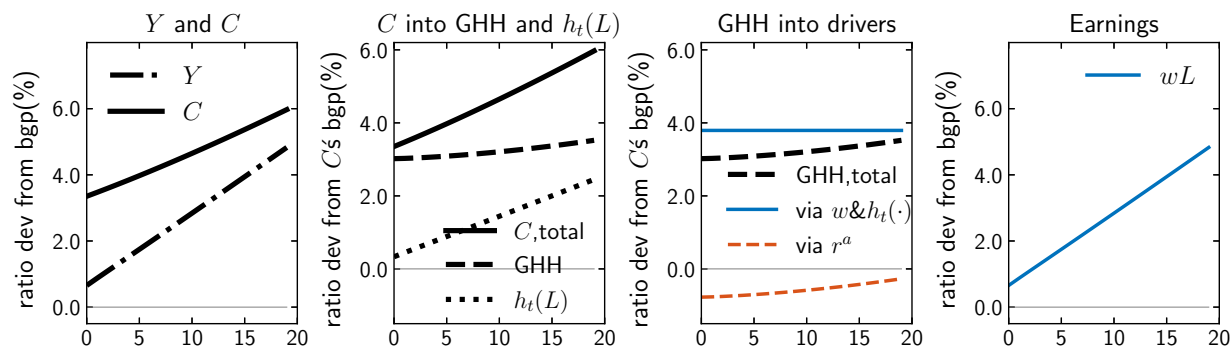
*Notes:* The decomposed shares are computed under each posterior draw, and their means and standard deviations across the posterior distribution are reported. The numbers in parentheses are the posterior standard deviations.

cause of the low correlation between consumption and investment; when the interest rate increases, both consumption and investment plunge<sup>37</sup>; thus, if interest rates drove the business cycles, consumption and investment would be strongly positively correlated.<sup>38</sup>

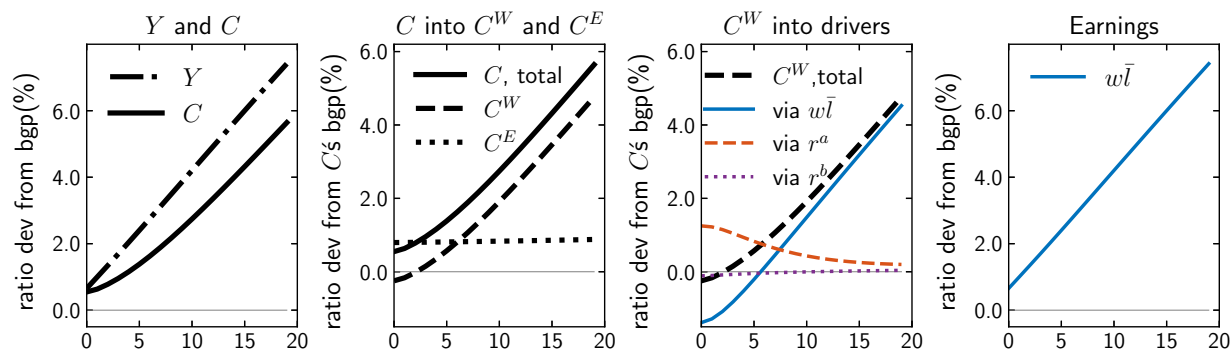
Now, I turn to the failure of the HASOE model. The ‘HASOE ( $z, g, \mu$ ) model’ panel in Table 6 presents variance decomposition in the HASOE model and shows that trend shocks do not play an important role in generating consumption fluctuations. Instead, stationary productivity shocks

<sup>37</sup>Investment decreases because the marginal rate of capital should increase toward the interest rate after reflecting capital adjustment costs. See equation (A.8) in Online Appendix A.

<sup>38</sup>Rather, low  $corr(\Delta \log C_t, \Delta \log I_t)$  is achieved in the RASOE model by appointing two different shocks,  $g$  and  $\mu$  shocks, as the main drivers of consumption and investment fluctuations, respectively.



(a) RASOE Model Prediction under the RASOE Posterior



(b) HASOE Model Prediction under the RASOE Posterior

Figure 2: Consumption Response to  $g$  Shock: RASOE vs. HASOE under the RASOE Posterior

Notes: Figures 2a and 2b plot the impulse response of consumption and other related variables to a one-standard-deviation trend shock in the RASOE and HASOE models, respectively, evaluated at the same parameter draws from the RASOE model's posterior distribution. The model statistics are computed at each posterior draw, and their means across the posterior distribution are plotted. The unit of the y-axis is either 'ratio dev from bgp(%)', which represents the deviation from the balanced growth path (b.g.p) of the variable of interest divided by its value on the b.g.p, or 'ratio dev from  $C$ 's bgp(%)', which represents the deviation of the variable of interest divided by the value of  $C_t$  on the b.g.p.

(z) generate most consumption fluctuations (82.6%). As we see in Table 5, however, stationary productivity shocks cannot generate excess consumption volatility.

Why can't the Aguiar and Gopinath (2007) mechanism operate in the HASOE model as it does in the RASOE model? To answer this question, I feed the RASOE model's posterior parameter draws into the HASOE model and examine how consumption responds to a trend shock. The first panel in Figure 2b plots the consumption and output responses in this experiment. The impact effect on output is similar between the RASOE and HASOE models, but output grows more strongly in the HASOE model. Despite this stronger future output growth (and a consequent stronger permanent income effect), the impact effect on consumption in the HASOE model is much weaker than that in the RASOE model and is only as much as the impact effect on output. Since

$C_t = pC_t^W + (1 - p)C_t^E$  in the HASOE model, the muted initial response of consumption might come from either  $C_t^W$  or  $C_t^E$ . In the second panel, I decompose the consumption response into the responses of  $C_t^W$  and  $C_t^E$  and find that the muted impact effect on consumption comes entirely from the muted initial response of  $C_t^W$ . A trend shock affects workers' consumption by affecting  $w_t\bar{l}_t$ ,  $r_t^a$ , and  $r_t^b$  in their budget constraints. In the third panel, I decompose the response of  $C_t^W$  into the responses driven by  $w_t\bar{l}_t$ ,  $r_t^a$ , and  $r_t^b$  and find that the muted initial response of  $C^W$  is entirely driven by its response to aggregate earnings,  $w\bar{l}$ .<sup>39</sup> The last panel plots the impulse response of  $w\bar{l}$ , which mildly jumps on impact, as in the RASOE model, but grows more rapidly in the following periods than it does in the RASOE model.

At first, it may be surprising that workers do not increase consumption despite a strong future growth of aggregate earnings and a consequent permanent income increase. The economic mechanism behind this result is as follows. Individual workers' earnings are determined by aggregate earnings  $w_t\bar{l}_t$  multiplied by idiosyncratic productivity  $\Gamma_i e_{i,t}$ , where  $e_{i,t}$  bears idiosyncratic earnings risk. Thus, the future growth of aggregate earnings due to a trend shift means not only a greater permanent income but also a greater idiosyncratic earnings risk that workers must face in the future. The greater future idiosyncratic risk enhances workers' precautionary saving, and the enhanced precautionary saving effect offsets the permanent income effect. In short, the presence of a strong precautionary saving motive hinders the [Aguiar and Gopinath \(2007\)](#) mechanism in the HASOE model.<sup>40</sup>

## 4 Reviving the HASOE Model

Thus far, I have shown the following: i) a RASOE model can explain stylized patterns of emerging market business cycles, consistent with conventional wisdom; ii) however, the driving mechanism in the RASOE model crucially hinges on the PIH behavior of representative households, which are inconsistent with the consumption behavior observed in micro data; iii) a HASOE model that successfully captures the microlevel consumption behavior (by incorporating household heterogeneity into the RASOE model) fails to explain the business cycle patterns. In this section, I show that by adding one aggregate shock to the HASOE model, we can revive it such that it accounts for the business cycle patterns well through a new mechanism.

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<sup>39</sup>To be precise, aggregate earnings of the economy are  $w_t L_t = (p\bar{l}\bar{e})w_t\bar{l}_t$ , and  $w_t\bar{l}$  should be named an 'aggregate earnings per efficiency unit.' Given that  $w_t L_t$  is a scaled-up version of  $w_t\bar{l}_t$  and they exhibit the same impulse responses, I refer to both terms as 'aggregate earnings' for brevity unless a distinction between the two is necessary.

<sup>40</sup>Another way to understand this result is to focus on aggregate savings. For simplicity, assume for a moment that the economy does not grow in the long-run (*i.e.*,  $g_{ss} = 1$ ), there is no aggregate shock, and the economy is in a steady state. Then, a one-time trend shock hits the economy, and after certain periods, the economy reaches a new steady state in which all the quantity variables are 10% greater than the old steady state. The aggregate savings must also be 10% greater in the new steady state, and the greater aggregate savings are achieved by enhanced precautionary saving over the transition periods (and after reaching the new steady state, as well) due to a greater idiosyncratic risk.

I consider a financial friction shock that directly interrupts workers' consumption smoothing.<sup>41</sup> Given that workers barely use liquid assets as a saving vehicle (see Table 3), I impose a shock to the trading cost of illiquid assets. Specifically, workers' budget constraint (10) is revised as follows.

$$c_{i,t} + b_{i,t} + v_{i,t} + \eta_t \chi_t(v_{i,t}, a_{i,t-1}; \Gamma_i) = w_t \Gamma_i e_{i,t} \bar{l}_t + (1 - \xi)(1 + r_t^b) b_{i,t-1}, \quad (22)$$

where  $\eta_t$  is the financial friction shock. The aggregation equation (21) is revised accordingly:

$$\chi_t^{agg} = p \chi_t^W, \quad \chi_t^W = \int_{\Gamma} \int_{e_1, e_2, b_-, a_-} \eta_t \chi_t(a_t(e_1, e_2, b_-, a_-; \Gamma) - (1 + r_t^a) a_-, a_-; \Gamma) d\Psi_t dG. \quad (23)$$

The balanced-growth-path value of  $\eta_t$  is 1, and  $\log \eta_t$  follows an AR(1) process:

$$\log \eta_t = \rho_\eta \log \eta_{t-1} + \varepsilon_t^\eta, \quad \varepsilon_t^\eta \sim N(0, \sigma_\eta^2). \quad (24)$$

For the Bayesian estimation of the revised HASOE model, I impose the same prior distribution as before on all the parameters to be estimated except two newly added parameters,  $\rho_\eta$  and  $\sigma_\eta$ . For  $\rho_\eta$  and  $\sigma_\eta$ , I impose the same prior distribution as the one imposed on the other exogenous shock processes. See the 'Prior' panel in Table 4 for details. The 'Posterior - HASOE ( $z, g, \mu, \eta$ )' panel in Table 4 reports key statistics of the posterior distribution for the revised HASOE model.

Table 5 reports the business cycle moments predicted by the revised HASOE model in the rows labeled 'HASOE ( $z, g, \mu, \eta$ ) model' and suggests that the revised HASOE model explains the stylized patterns of emerging market business cycles quite well: consumption is more volatile than output ( $\sigma(\Delta \log C_t) / \sigma(\Delta \log Y_t) = 0.036 / 0.029 = 1.215$ ), trade balance is countercyclical ( $\text{corr}(\Delta(TB_t / Y_t), \Delta \log Y_t) = -0.248$ ), and the correlation between consumption and investment is low ( $\text{corr}(\Delta \log C_t, \Delta \log I_t) = -0.223$ ). Moreover, even better than the RASOE model, the revised HASOE model predicts output and consumption volatilities that are close to their data counterparts ( $\sigma(\Delta \log Y_t) = 0.029$  in the model, 0.027 in data;  $\sigma(\Delta \log C_t) = 0.036$  in the model, 0.036 in data). The revised HASOE model also closely matches other business cycle moments reported in Table 5 except the autocorrelation of  $\Delta \log Y_t$  with a one-quarter lag (0.036 in the model, 0.404 in data).<sup>42</sup>

<sup>41</sup>Consideration of such a shock is partly motivated by studies emphasizing the role of financial frictions in the international financial market, such as  $\psi$ ,  $\theta_z$ , and  $\theta_g$  in equation (6) (see Neumeyer and Perri (2005), Garcia-Cicco et al. (2010), and Chang and Fernández (2013), for instance). These frictions translate shocks or other variables' fluctuations into interest rate fluctuations, which then strongly affect representative households' consumption via intertemporal substitution. In heterogeneous-agent models, however, households are less affected by intertemporal substitution and more affected by a precautionary saving motive. Thus, in addition to the financial frictions in the international financial market that only affect interest rates, I consider a financial friction shock that households face when trading assets so that it directly affects the precautionary saving motive.

<sup>42</sup>This discrepancy in output autocorrelation quickly dissipates from a two-quarter lag forward. Given that the discrepancy survives only one quarter and that output fluctuations mostly come from stationary productivity shocks (see the 'HASOE( $z, g, \mu, \eta$ ) model' in Table 6), it is likely that replacing the conventional AR(1) process of stationary

The ‘HASOE ( $z, g, \mu, \eta$ ) model’ panel in Table 6 presents variance decomposition in the revised HASOE model. Most output fluctuations (91.8%) are driven by stationary productivity shocks, while trend shocks play only a limited role (7.8%). Consumption fluctuations are almost entirely driven by financial friction shocks (65.2%) and stationary productivity shocks (31.8%), while trend shocks play essentially no role.<sup>43</sup>

The addition of the financial friction shock is effective at reviving the HASOE model for two reasons. First, the  $\eta$  shock generates large consumption fluctuations without causing output fluctuations much (see Table 6), resolving the absence of excess consumption volatility in the initial HASOE model. Second, the  $\eta$  shock also generates large investment fluctuations (see Table 6), and importantly, the consumption and investment responses are in the opposite direction (see Figure L.8 in Online Appendix L.2), generating a negative correlation between consumption and investment and thus fixing the strongly positive  $corr(\Delta \log C_t, \Delta \log I_t)$  in the initial HASOE model.<sup>44</sup>

To identify the driving mechanism of consumption fluctuations, I examine the consumption responses to financial friction shocks and stationary productivity shocks. Since  $C_t = pC_t^W + (1 - p)C_t^E$  in the revised HASOE model, the total consumption response can be decomposed into the responses of  $C_t^E$  and  $C_t^W$ . Moreover, since aggregate shocks affect workers’ consumption by affecting  $w_t \bar{l}_t$ ,  $r_t^a$ ,  $r_t^b$ , and  $\eta_t$  in their budget constraints, the response of  $C_t^W$  can be further decomposed into the responses driven by each of them.

Figure 3a plots the total consumption response to a financial friction shock and decomposes it into entrepreneurs’ consumption response and workers’ responses driven by  $w_t \bar{l}_t$ ,  $r_t^a$ ,  $r_t^b$ , and  $\eta_t$  in their budget constraints. This figure shows that the total consumption response to a financial friction shock almost entirely comes from workers’ consumption response to the change in  $\eta_t$  in their budget constraints. Workers reduce consumption when the asset trading cost increases for the following economic reasons. Workers facing a bad idiosyncratic earnings shock need to cash out their assets to smooth consumption. When the financial friction shock is realized, however, it becomes more costly to cash out their assets, and they fail to smooth consumption more significantly. For workers who do not face an immediate need to cash out their assets at the moment of

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productivity shocks with an ARMA(1,1) process can fix this discrepancy. However, I do not impose this rather unconventional assumption because the model aims to minimize changes from conventional representative-agent models other than the heterogeneous household block with high MPCs.

<sup>43</sup>The ‘HASOE ( $z, g, \mu, \eta$ ) model’ panel in Table 6 also reports the variance decomposition of investment and trade-balance-to-output ratio fluctuations in the revised HASOE model. Notably, trend shocks play an important role in these fluctuations. When firms expect future productivity growth in the model, they can increase investment without a precautionary saving concern, unlike workers’ consumption decisions. Moreover, given the limited output response to a trend shock, firms finance investment by rapidly increasing international debt through banks.

<sup>44</sup>Consumption and investment respond to an  $\eta$  shock in the opposite direction for the following reason. When financial friction is heightened, workers reduce consumption and increase saving due to either consumption smoothing disruption or enhanced precautionary saving, as will be discussed further in a later part of this section. As aggregate saving increases, the interest rate decreases, and the lower interest rate boosts investment.

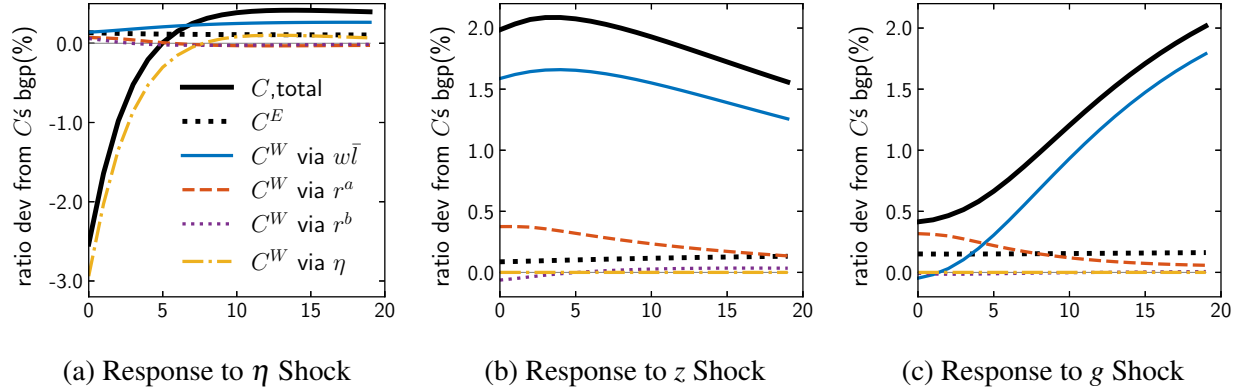


Figure 3: Consumption Response Decomposition in the HASOE ( $z, g, \mu, \eta$ ) Model

*Notes:* Figures 3a, 3b, and 3c plot the impulse responses of consumption to one-standard-deviation  $\eta$ ,  $z$ , and  $g$  shocks, respectively, in the revised HASOE model. In each figure, the consumption response is decomposed into entrepreneurs' consumption response and workers' responses driven by  $w\bar{l}$ ,  $r^a$ ,  $r^b$ , and  $\eta$  in their budget constraints. The model statistics are computed at each posterior draw, and their means across the posterior distribution are plotted. The unit of the y-axis is 'ratio dev from  $C_t$ 's b.g.p.(%)', which represents the deviation from the balanced growth path (b.g.p) of the variable of interest divided by the value of  $C_t$  on the b.g.p.

heightened financial friction, they recognize that it will be more expensive to cash out their assets for a while. Therefore, they prepare themselves by accumulating more buffer stocks and reducing consumption.

Figure 3b plots the total consumption response to a stationary productivity shock and its decomposed responses. This figure shows that the total consumption response mostly comes from workers' consumption response driven by aggregate earnings  $w_t\bar{l}_t$ . Workers' consumption response driven by  $r_t^a$  also nontrivially contributes to the total response. The economic mechanism behind this result is as follows. When a positive stationary productivity shock hits the economy, both labor and investment demands increase, and thus, aggregate earnings ( $w_t\bar{l}_t$ ,  $t \geq 0$ ) and interest rates ( $r_t = r_{t+1}^a$ ,  $t \geq 0$ ) increase. Moreover, the asset price ( $q_0$ ) jumps on impact (due to the higher future productivity), and so does the rate of asset return ( $r_0^a$ ). As a result, workers' income, including their earnings and asset returns, increases. Importantly, because workers exhibit high MPC, they strongly translate these income fluctuations into consumption fluctuations.

In addition to the consumption responses to the main shocks ( $z$  and  $\eta$ ), I also examine the consumption response to a trend shock. Figure 3c plots the total consumption response to a trend shock and its decomposed responses and reconfirms the economic intuition obtained in the previous section: the consumption response to a trend shock is muted in the HASOE model because in the face of a future growth of aggregate earnings, workers' precautionary saving becomes enhanced due to a greater future idiosyncratic risk.



## 5 Counterfactual Experiment

As discussed in the previous section, Peruvian households’ high MPC and correspondingly strong precautionary saving play key roles in the transmission mechanism of  $\eta$  and  $z$  shocks to generate consumption volatility in the HASOE model. In this section, I quantify their role by running a counterfactual experiment under which household MPC is adjusted to the U.S. level, which is substantially lower than the Peruvian level (Hong, 2022).

For the counterfactual experiment, I recalibrate  $\beta$ ,  $\chi_1$ , and  $\chi_2$  by targeting U.S. MPC moments and workers’ aggregate wealth. For the target MPC moments, I estimate U.S. MPC at each earnings decile by applying Blundell et al. (2008)’s method to the 2005–2017 waves of the Panel Study of Income Dynamics (PSID). Since the reference period of the PSID data is a year, I obtain annual U.S. MPC estimates, while my HASOE model is a quarterly model. Given the frequency mismatch between the model and data, I target the annual MPC estimates as follows: I first simulate individual workers’ quarterly earnings and consumption series from the model; then, I convert the quarterly series to annual series by summing them over every four quarters; using the simulated annual data, I compute the model counterparts of the MPC estimates by applying the same MPC estimation procedure applied to the PSID; I calibrate  $\beta$ ,  $\chi_1$ , and  $\chi_2$  such that the model counterparts are as close as possible to the MPC moments.<sup>45</sup> For the workers’ aggregate wealth, I target its value in the benchmark Peruvian economy  $((A^W + B^W)/Y = 6.658$ , as reported in Table 3).

Table 7 reports the recalibrated parameter values. The value of  $\chi_1$  (0.716) in the counterfactual economy is markedly lower than the value (6.694) in the benchmark economy. This means that the U.S. MPC estimates discipline the model to exhibit lower MPC and weaker precautionary saving than the Peruvian MPC estimates do. The value of  $\beta$  (0.974) in the counterfactual economy is noticeably greater than the value (0.948) in the benchmark economy. This is because workers have a weaker precautionary saving motive in the counterfactual economy than in the benchmark economy and thus must be more patient to achieve the same amount of their aggregate wealth.

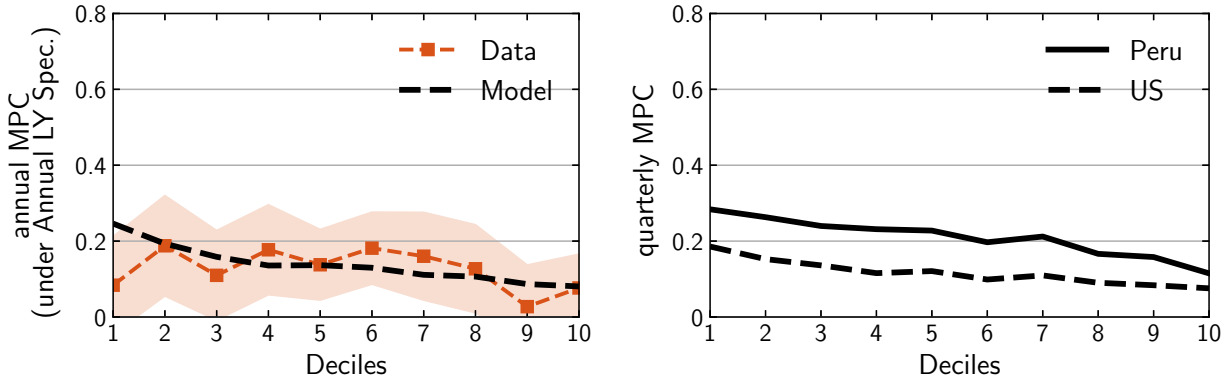
The joint recalibration again matches targets well, even though only three parameters are used to target eleven moments. First, workers’ aggregate wealth  $(A^W + B^W)/Y$  in the counterfactual economy is 6.564, which is close to the target, 6.658. Second, Figure 4a plots the annual MPC es-

Table 7: Recalibrated Parameters for the Counterfactual Economy

Description	Value	Target / source
$\beta$ workers’ discount factor	0.974	} MPC estimates (from PSID) & ( $A^W + B^W$ )/ $Y$ in Table 3
$\chi_1$ scale parameter for illiquid asset adjustment cost	0.716	
$\chi_2$ convexity parameter for illiquid asset adjustment cost	1.788	

<sup>45</sup>The same targeting method is used in Hong (2022) when comparing Peruvian and U.S. MPCs using a model.





(a) U.S. Annual MPC Estimates: Data vs. Model (b) Model-Predicted Quarterly MPCs: Peru vs. U.S.

Figure 4: MPCs in the Counterfactual Economy

*Notes:* Figure 4a plots the annual MPC estimates obtained from the PSID (labeled ‘Data’) and its model counterpart in the counterfactual economy (labeled ‘Model’). Shaded areas are 95% confidence intervals. Figure 4b plots the model-predicted quarterly MPC in the benchmark and counterfactual economies (labeled ‘Peru’ and ‘US’, respectively).

timates obtained from the PSID (labeled ‘Data’) and their model counterparts in the counterfactual economy (labeled ‘Model’) and shows that the latter tracks the former closely.

Figure 4b compares the model-predicted quarterly MPCs in the benchmark and counterfactual economies and shows that there is a substantial MPC gap between the two economies: the mean quarterly MPC across deciles in the benchmark economy is 0.209, which is approximately twice as large as that in the counterfactual economy, 0.117. This figure suggests that when we interpret the Peruvian and U.S. MPC estimates reflecting the different reference periods of the underlying surveys through the lens of the HASOE model, the estimates tell us that Peruvian households exhibit substantially higher MPCs than U.S. households.<sup>46,47</sup>

Now, we are ready to examine the business cycle implication of this MPC gap. In Figure 5, I plot the posterior distributions of output volatility  $\sigma(\Delta \log Y_t)$ , consumption volatility  $\sigma(\Delta \log C_t)$ , and their ratio in the benchmark economy and compare them with the corresponding distributions in the counterfactual economy, which are obtained by evaluating the recalibrated model at each parameter draw from the benchmark economy’s posterior distribution. Figure 5a shows that the

<sup>46</sup>This result is consistent with the result of the model-based MPC comparison in Hong (2022), where I employ a standard one-asset incomplete-market model to interpret the MPC estimates reflecting different reference periods.

<sup>47</sup>Annual and quarterly MPCs mean a consumption response within a year and a quarter, respectively, after the realization of a shock. By definition, annual MPC should be greater than quarterly MPC. However, the annual MPC estimates (and their model counterparts) in Figure 4a are not much greater than the model-predicted quarterly MPC in Figure 4b. This is because the annual MPC estimates (and their model counterparts) in Figure 4a underestimate the true annual MPC in the model due to a ‘time aggregation problem’ noted by Crawley (2020): when households receive earnings shocks and make consumption decisions at a certain frequency while Blundell et al. (2008)’s method is applied to data aggregated over a longer time period, the method significantly underestimates the consumption sensitivity to transitory shocks. See Hong (2022) for a detailed discussion.

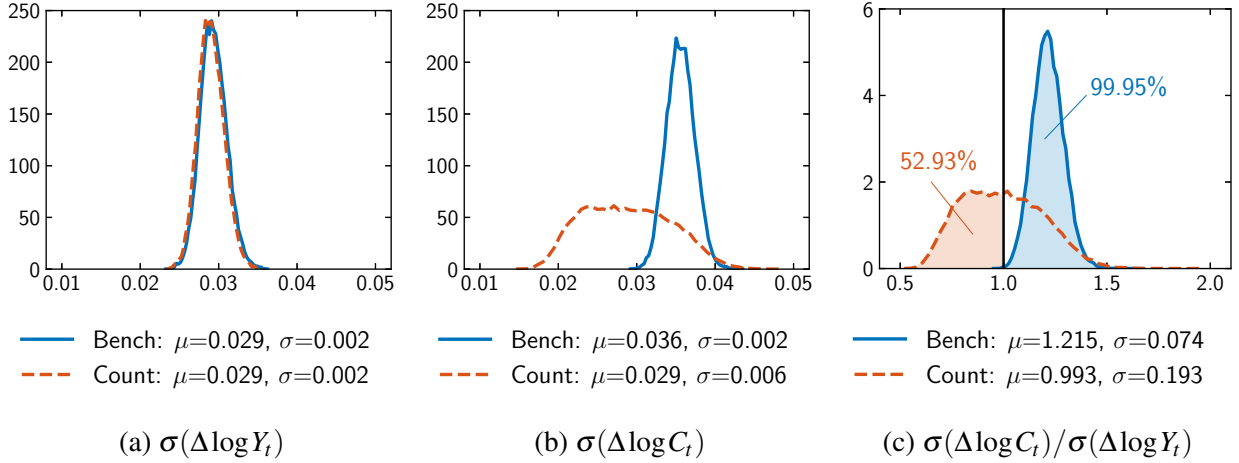


Figure 5: Consumption and Output Volatilities and Their Ratio: Benchmark vs. Counterfactual

*Notes:* Figures 5a, 5b, and 5c plot the posterior distributions of  $\sigma(\Delta \log Y_t)$ ,  $\sigma(\Delta \log C_t)$ , and  $\frac{\sigma(\Delta \log C_t)}{\sigma(\Delta \log Y_t)}$  in the benchmark economy, respectively (labeled ‘Bench’), and compare them with the corresponding distributions in the counterfactual economy (labeled ‘Count’), which are obtained by evaluating the recalibrated model at each parameter draw from the benchmark economy’s posterior distribution. The legend reports the mean and standard deviation of each distribution.

output volatility distribution is nearly identical between the two economies.<sup>48</sup> On the other hand, Figure 5b shows that the consumption volatility distribution changes substantially. In particular, the distribution in the counterfactual economy exhibits a lower mean (0.029) and greater standard deviation (0.006) than that in the benchmark economy (mean 0.036 and standard deviation 0.002). Figure 5c compares the distribution of the consumption-output volatility ratio. On average, the ratio is 1.215 in the benchmark economy (excess consumption volatility) and 0.993 in the counterfactual economy (the absence of excess consumption volatility). Moreover, unlike in the benchmark economy where consumption is more volatile than output in nearly the entire part (99.95%) of the posterior distribution, the excess consumption volatility disappears in the counterfactual economy in most (52.93%) of the posterior distribution, including the posterior median and mode.<sup>49</sup>

To understand the consumption volatility change, I compute consumption impulse responses in the counterfactual economy by evaluating the recalibrated model at each parameter draw from the benchmark economy’s posterior distribution. Then, I decompose the consumption responses into entrepreneurs’ responses and workers’ responses driven by  $w\bar{l}$ ,  $r^a$ ,  $r^b$ , and  $\eta$ , as in Figure 3 for the benchmark economy. Figure 6 plots the mean responses across the posterior distribution.

<sup>48</sup>In the model, output is determined by firms’ Cobb–Douglas production,  $Y_t = z_t K_{t-1}^\alpha (X_t L_t)^{1-\alpha}$ . Because  $K_{t-1}$  is a slow-moving variable and  $L_t$  is determined by  $z_t$ ,  $X_t$ ,  $X_{t-1}$ , and  $K_{t-1}$  (through labor supply (12) and labor demand (A.10)), aggregate shocks  $z_t$  and  $g_t$  almost entirely determine the output volatility. Given this supply-side feature of the model, it is not surprising that the two economies exhibit similar output volatilities.

<sup>49</sup>At the posterior mode,  $\frac{\sigma(\Delta \log C_t)}{\sigma(\Delta \log Y_t)}$  is 1.232 and 0.746 in the benchmark and counterfactual economies, respectively.

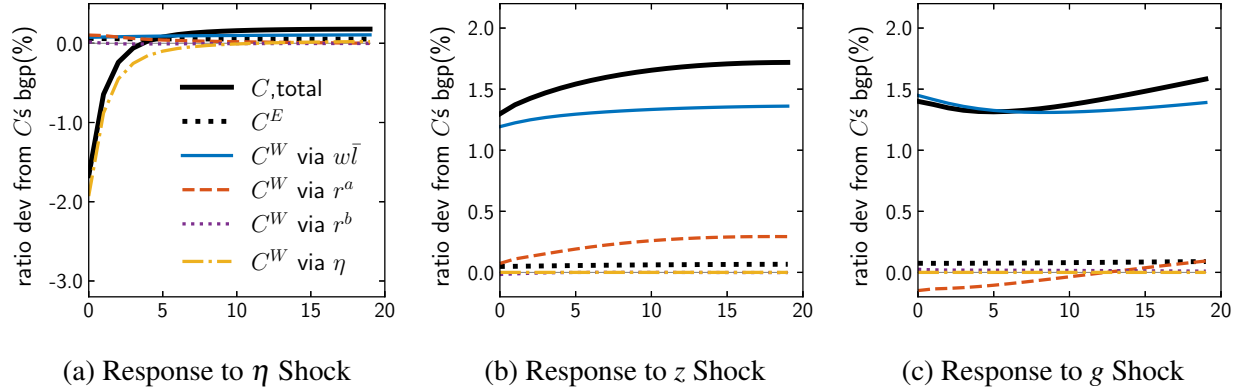


Figure 6: Consumption Response Decomposition in the Counterfactual Economy

Notes: Figures 6a, 6b, and 6c plot the impulse responses of consumption to one-standard-deviation  $\eta$ ,  $z$ , and  $g$  shocks, respectively, in the counterfactual economy evaluated at the parameter draws from the benchmark economy's posterior distribution. In each figure, the consumption response is decomposed into entrepreneurs' consumption response and workers' responses driven by  $w_t \bar{l}_t$ ,  $r_t^a$ ,  $r_t^b$ , and  $\eta$  in their budget constraints. The model statistics are computed at each posterior draw, and their means across the posterior distribution are plotted. The unit of the y-axis, 'ratio dev from  $C_t$ 's bgp(%)', represents the deviation from the balanced growth path (b.g.p) of the variable of interest divided by  $C_t$  on the b.g.p.

Figure 6a shows that the mean consumption response to a financial friction shock is substantially weaker in the counterfactual economy than that in the benchmark economy (which is plotted in Figure 3a), and the weaker total response is driven by workers' weaker response to the change of  $\eta_t$  in their budget constraint. Economically, workers have a weaker precautionary saving motive in the counterfactual economy than in the benchmark economy, and thus, in the face of heightened financial friction, precautionary saving is also less enhanced in the counterfactual economy.

Figure 6b shows that the mean consumption response to a stationary productivity shock is also substantially weaker in the counterfactual economy than that in the benchmark economy (which is plotted in Figure 3b), and the weaker total response is driven by workers' weaker responses to  $w_t \bar{l}_t$  and  $r_t^a$  in their budget constraint. However, as Online Appendix L.1 shows, the impulse responses of the drivers ( $w_t \bar{l}_t$  and  $r_t^a$ ) to a  $z$  shock are very similar between the two economies. This means that when a  $z$  shock is realized, workers face a similar degree of income fluctuations between the benchmark and counterfactual economies, but those in the counterfactual economy exhibit much smaller MPC and thus translate the income fluctuations far less into consumption fluctuations.

The weak consumption responses to  $\eta$  and  $z$  shocks observed in Figures 6a and 6b and the underlying economic mechanisms explain why the mean consumption volatility is smaller in the counterfactual economy than in the benchmark economy, as presented in Figure 5b.

In the rest of this section, I discuss two other interesting observations regarding the counterfactual economy. First, unlike  $\eta$  and  $z$  shocks, a trend shock generates more consumption fluctuations

in the counterfactual economy than in the benchmark economy.<sup>50</sup> Figures 6c and 3c reveal the reason why: the consumption response to a  $g$  shock is stronger in the counterfactual economy than in the benchmark economy. This is because a precautionary saving motive is weak in the counterfactual economy, and thus, Aguiar and Gopinath (2007)'s permanent income effect is revived.

Second, the consumption volatility distribution is more dispersed in the counterfactual economy than in the benchmark economy in Figure 5b for the following reason. The Bayesian estimation does not sharply pin down  $\rho_\eta$  and  $\sigma_\eta$  because both a relatively small but persistent  $\eta$  shock and a large but transitory  $\eta$  shock can generate a strong and sharp consumption response in the model (see Figure L.8 in Online Appendix L.2) and thus can explain macro data well. However, when these shocks are fed into the counterfactual economy, the consumption response varies substantially depending on the types of the  $\eta$  shock: the response becomes much weaker in the counterfactual economy than in the benchmark economy when the shock is relatively small but persistent (as in the posterior mode), while it becomes not much weaker (and sometimes becomes even stronger) when the shock is large but transitory. Economically, this is because the main transmission mechanism is different depending on the types of the  $\eta$  shock. As discussed in section 4, the financial friction shock generates consumption fluctuations through i) consumption smoothing disruption for those who face an immediate need to cash out their assets and ii) enhanced precautionary saving for those who do not. A relatively small but persistent  $\eta$  shock works more through enhanced precautionary saving for the future, while a large but transitory  $\eta$  shock works more through immediate consumption smoothing disruption. In the counterfactual economy, the enhanced precautionary saving effect becomes substantially weaker, while the consumption smoothing disruption does not.

## 6 Conclusion

This paper explains emerging market business cycles using a HASOE model disciplined by MPC estimates from Peruvian micro data. I find that a conventional mechanism through which the corresponding RASOE model explains emerging market business cycles does not operate in the HASOE model because it is hindered by household precautionary saving. Instead, the HASOE model explains emerging market business cycles through a new mechanism in which households' high MPC and correspondingly strong precautionary saving play important roles. When household MPCs are adjusted to the U.S. level, which is substantially lower than the Peruvian level, via recalibration, excess consumption volatility disappears in most of the posterior distribution.

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<sup>50</sup>In Online Appendix I, I decompose the change in consumption variance (from the benchmark to the counterfactual economies) into the changes originating from each shock. In terms of the posterior mean,  $\sigma^2(\Delta \log C_t)$  decreases by 32.2% in the counterfactual economy. Out of this -32.2% change, -27.9%p and -18.0%p come from  $\eta$  and  $z$  shocks generating fluctuations less, respectively, while +13.7%p comes from a  $g$  shock generating fluctuations more.

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