MPCs and Liquidity Constraints in Emerging Economies*†

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Abstract

For the first time in the literature, this paper estimates the marginal propensity to consume (MPC) out of transitory income shocks using micro data for an emerging economy. To this end, I employ a nationally representative Peruvian household survey. Two striking differences emerge when the Peruvian MPC estimates are compared with U.S. MPC estimates obtained by the same method. First, the mean MPC of Peruvian income deciles (0.632) is much higher than that of U.S. deciles (0.089). Second, within-country MPC heterogeneity over the deciles is substantially stronger in Peru. Patterns in the consumption growth of the deciles and the MPCs of unconstrained top income groups delineated by an MPC homogeneity test suggest that liquidity constraints are important for explaining both the higher mean MPC and the stronger MPC heterogeneity in Peru.

***JEL classification*:** D12, D31, E21, F41

***Keywords*:** consumption, MPC, emerging economy, liquidity constraint

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I Introduction

There is an extensive literature devoted to estimating the marginal propensity to consume (MPC) out of transitory income shocks using micro data for developed economies. However, no such evidence is available for emerging economies. This paper represents the first attempt to estimate the MPC using micro data for an emerging economy. To this end, I employ a nationally representative Peruvian household survey (Encuesta Nacional de Hogares, ENAHO[1]) and estimate the MPC of each income decile using Blundell et al. (2008)'s method.

When the MPC estimates are compared with U.S. MPC estimates obtained by the same method, two striking differences emerge. First, the MPCs of the Peruvian deciles are substantially higher overall than those of the U.S. deciles. The mean MPC of the Peruvian deciles (63.2 percent) is 54.3 percentage points higher than that of the U.S. deciles (8.9 percent). Second, in both countries, lower income deciles tend to have higher MPCs, but the within-country MPC heterogeneity over the income deciles is substantially stronger in Peru than in the U.S. The MPC of the bottom decile (94.2 percent) is 64.3 percentage points higher than that of the top decile (29.9 percent) in Peru, while in the U.S., the MPC of the bottom decile (16.0 percent) is 12.4 percentage points higher than that of the top decile (3.6 percent).

When we see the results through the lens of the standard incomplete-market precautionary-saving models, there are three possible explanations for the stronger MPC heterogeneity over the income distribution in Peru than in the U.S. First, households in lower income deciles could exhibit higher MPC because they are more likely to be constrained than those in higher income deciles. The likelihood of being constrained could increase substantially faster in Peru than in the U.S. as households move from higher to lower income deciles. Second, households in lower income deciles could exhibit higher MPC in the absence of liquidity constraints when they tend to front-load their consumption more heavily in their consumption path governed by the Euler equation. The tendency of lower-income households to front-load consumption more heavily could be stronger in Peru than in the U.S. Third, even when households' consumption path follows the Euler equation and the degree of front-loading is similar across the income deciles, households in lower income deciles could exhibit higher MPC by facing higher interest rates. The tendency of lower-income households to face higher interest rates could be stronger in Peru than in the U.S.

I try to disentangle these three theory-guided explanations using data. The last ex-

[1] Instituto Nacional de Estadística e Informática (2004-2016).

planation with heterogeneous interest rates makes sense only when the effective interest rates used by lower-income households for their consumption-saving decision are borrowing interest rates. In the Peruvian sample, however, the share of households participating in borrowing activities is low (13.3 percent), and this share is even smaller in lower income deciles. Based on this observation, I eliminate the heterogeneous interest rate explanation.

The remaining two explanations, one with liquidity constraints and the other with front-loading behavior, are distinguishable by examining the consumption growth in the following period. Under the explanation with liquidity constraints, households in lower income deciles should exhibit higher consumption growth in the following period because when they become constrained, they fail to bring future resources to current consumption, and therefore, their consumption jumps in the following period. Under the explanation with front-loading behavior, households in lower income deciles should exhibit lower consumption growth in the following period exactly because they front-load consumption more heavily. Under either one of these explanations, the described pattern of the consumption growth should be stronger in Peru than in the U.S.

The group-average consumption growth of the deciles in Peru and the U.S. exhibit two clear patterns. First, lower income deciles exhibit higher consumption growth in the following period in both countries. Second, the tendency of lower income deciles to have higher consumption growth is substantially stronger in Peru than in the U.S. In the U.S., the average two-year-over-two-year growth of annual consumption in the bottom decile is 7.8 percentage points higher than that in the top decile, while the standard deviation of the consumption growth is 38.7 percent for the whole sample. In Peru, the year-over-year growth of quarterly consumption in the bottom decile is 30.2 percentage points higher than that in the top decile, while the standard deviation of the consumption growth is 45.3 percent for the whole sample. These patterns suggest that liquidity constraints are the main driver of the stronger MPC heterogeneity in Peru than in the U.S.

Once we accept that liquidity constraints are the main cause for the stronger MPC heterogeneity over the income distribution in Peru, we can decompose the cross-country MPC gap into two parts: (i) the gap caused by households being more affected by liquidity constraints in Peru than in the U.S. and (ii) the gap caused by factors unrelated to liquidity constraints, such as cross-country differences in preferences and interest rates. We can conduct this decomposition by identifying a top income group composed of households that are not only currently unconstrained but also highly unlikely to be constrained in the future (forwardly unconstrained households hereafter) in each country. The MPC gap between forwardly unconstrained households in Peru and those in the U.S. captures the gap caused by factors unrelated to liquidity constraints.

To delineate a top income group composed of forwardly unconstrained households, I exploit the fact that MPC should be homogeneous over the income within this group. I test whether MPC is homogeneous for the top $(10n)\%$ income groups for $n = 1, \cdots, 10$ by employing a test suggested by Davies (1977) and Davies (1987). This test shows that the top 20% or larger income groups in Peru reject the null hypothesis that MPC is homogeneous over the income, and the top 60% or larger income groups in the U.S. reject the null hypothesis.

Based on this result, I delineate a top income group composed of forwardly unconstrained households in each country by the top 10% of households in Peru and the top 50% of households in the U.S., which are the largest top $(10n)\%$ income groups in each country that fail to reject the null hypothesis of the test. Under this delineation, 56.0 percent of the cross-country MPC gap is attributable to households being more affected by liquidity constraints in Peru than in the U.S. This finding is a conservative estimate of the role of liquidity constraints in the MPC gap because the delineation is likely to overrate the size of a true forwardly unconstrained top income group, which can cause an overestimation of the MPC of forwardly unconstrained households in Peru.

Methodologically, this paper employs one of the main approaches from the extensive literature on MPC estimation in developed economies. In this literature, the key to estimating the MPC is to identify unexpected transitory income shocks and to measure consumption responses to such shocks. Three approaches have been widely accepted: (i) exploiting natural experiments of income shocks, (ii) imposing a theory-guided covariance structure on joint dynamics of income and consumption, and (iii) directly using answers to survey questions asking how much households would spend out of hypothetical income shocks. Well-known works in each of the approaches include Johnson et al. (2006) and Parker et al. (2013) for the first approach, Blundell et al. (2008) and Kaplan et al. (2014b) for the second one, and Jappelli and Pistaferri (2014) for the third one, among many others. I use the second approach because its data requirements are met by ENAHO.

There is a burgeoning literature examining how macroeconomic dynamics or policy effects are affected by the presence of liquidity-poor households and their consumption behavior. For example, Krueger et al. (2016) show that in an environment where a sizable fraction of liquidity-poor households exist, aggregate consumption can drop far more severely during bad times largely due to their enhanced precautionary-saving behavior in the face of increased unemployment risk. Kaplan et al. (2018) show that in a heterogeneous agent New-Keynesian (HANK) model with a two-asset environment, monetary policy works through a different mechanism than a conventional representative agent New-Keynesian framework (RANK) because liquidity-constrained households do not intertemporally substitute consumption much in response to interest rate changes but instead respond sensitively to temporary income changes. McKay et al. (2016) show that the effect of forward guidance is much weaker in a HANK model than in a RANK model since households do not respond much to a news shock on the real interest rate because of their shortened effective planning horizon (due to the liquidity constraints) and precautionary-saving motives. Oh and Reis (2012) show that targeted transfers can be effective in mitigating recessions by reducing the wealth of marginal workers (thus incentivizing them to work) and by reallocating wealth from low-MPC to high-MPC households.

It is noteworthy that all these studies are based on quantitative models fitted to the U.S. economy. The findings of this paper suggest that all these recently discovered mechanisms, through which liquidity-poor households and their consumption behavior affect aggregate dynamics or policy effects, could play a significantly larger role in emerging economies than in developed economies. In this regard, the findings of this paper suggest a new direction for the macroeconomic modeling of emerging economies. At the heart of the workhorse models for emerging market business cycles, such as Neumeyer and Perri (2005), Aguiar and Gopinath (2007), and Garcia-Cicco et al. (2010), representative households can borrow frictionlessly in optimizing their consumption paths. There exist other types of emerging market models that have explicit borrowing limits, such as sudden stop models and sovereign default models.[2] In these models, however, borrowing constraints bind only infrequently because they aim at explaining macroeconomic dynamics during infrequent episodes such as financial crises or sovereign defaults. Instead, the findings of this paper call for a new macroeconomic model of emerging economies in which there is a substantial fraction of liquidity-poor households even in normal times, and their MPC is as large as the estimates from the data. Revisiting important macroeconomic questions for emerging economies – such as their distinctive business cycle features, aggregate dynamics during crises, and effects of various policies – through the lens of such a new model would be an important future avenue for the international macroeconomics literature.

[2]Sudden stop models such as Mendoza (2010) and Bianchi (2011) impose collateral constraints on representative households' borrowing. Sovereign default models such as Arellano (2008) and Mendoza and Yue (2012) limit the access of any domestic agent to the international financial market during periods of sovereign default.

II The Underlying Model and MPC Estimation

The key equation for the MPC estimation of this paper is a first-order-approximated consumption growth function derived from a version of the standard precautionary-saving models. I begin by presenting the model. After that, I discuss the first-order-approximated consumption growth function derived from the model. The derivation, which I provide in online Appendix A, is nearly identical to that of Blundell et al. (2008), except for the part that deals with liquidity constraints, which are absent in their underlying model. Then, I discuss how to estimate the MPC using the consumption growth function and the imposed income process.

A The Underlying Model

In period t, each household i solves the following optimization problem.

$$\max_{\{C_{i,t+j},A_{i,t+j}\}_{j=0}^{J_{i,t}}} E\left[\sum_{j=0}^{J_{i,t}} \beta^j e^{(Z'_{i,t+j}\varphi^p_{t+j})} \frac{C_{i,t+j}^{1-\sigma}}{1-\sigma} \middle| \mathbf{S}_{i,t}\right]$$

$$s.t.$$

$$C_{i,t+j} + A_{i,t+j} = Y_{i,t+j} + (1+r_{t+j-1})A_{i,t+j-1}, \quad 0 \le j \le J_{i,t}, \tag{SBC}$$

$$A_{i,t+j} \ge 0, \quad 0 \le j \le J_{i,t} - 1, \tag{LQC}$$

$$A_{i,t+J_{i,t}} \ge 0 \tag{NPG}$$

in which $J_{i,t}$ denotes the remaining periods of household i's lifetime after period t, $\mathbf{S}_{i,t}$ denotes the state vector of household i, $Z_{i,t+j}$ denotes a vector of dummy variables for observable characteristics of household i in period $t+j$, $e^{(Z'_{i,t+j}\varphi^p_{t+j})}$ denotes household i's preference shift in period $t+j$, $C_{i,t+j}$ denotes real consumption of household i in period $t+j$, $A_{i,t+j}$ denotes household i's one-period asset purchased in period $t+j$, r_{t+j} denotes the real interest rate associated with asset $A_{i,t+j}$, and $Y_{i,t+j}$ denotes household i's disposable income in period $t+j$. (SBC) represents sequential budget constraints, (LQC) represents liquidity constraints, and (NPG) represents the no-Ponzi-game constraint that households face.

As in Blundell et al. (2008) and Kaplan et al. (2014b), I assume that each household i's log real income $\log Y_{i,t}$ is composed of three components: a component explained by household i's observable characteristics and time $Z'_{i,t}\varphi^y_t$, a permanent component $P_{i,t}$, and a transitory component $\epsilon_{i,t}$. Specifically, I assume

$$\log Y_{i,t} = Z'_{i,t}\varphi^y_t + P_{i,t} + \epsilon_{i,t},$$
$$P_{i,t} = P_{i,t-1} + \zeta_{i,t},$$
$$\zeta_{i,t} \sim_{iid} (0, \sigma^2_{pm}), \quad \epsilon_{i,t} \sim_{iid} (0, \sigma^2_{tr}), \quad (\zeta_{i,t})_t \perp (\epsilon_{i,t})_t, \quad \text{and}$$
$$(Z_{i,t})_t \perp (\zeta_{i,t}, \epsilon_{i,t})_t$$

in which $(x_t)_t$ represents time series $(\cdots, x_{t-2}, x_{t-1}, x_t, x_{t+1}, x_{t+2}, \cdots)$.

Let $y_{i,t}$ denote the unpredictable component of log income:

$$y_{i,t} := \log Y_{i,t} - Z'_{i,t}\varphi^y_t = P_{i,t} + \epsilon_{i,t}.$$

Then, we have

$$\Delta y_{i,t} = \zeta_{i,t} + \epsilon_{i,t} - \epsilon_{i,t-1}. \tag{1}$$

The vector of observable characteristics $Z_{i,t}$ appears in two places in the model: one in the preference shift $Z'_{i,t}\varphi^p_t$ and the other in the predictable component of income $Z'_{i,t}\varphi^y_t$. They appear in these places to make the model consistent with the data pattern that a sizable portion of income and consumption variations are explained by observable characteristics.[3] Specifically, $Z_{i,t}$ includes dummy variables for education, ethnicity, employment status, region, cohort, household size, number of children, urban area, the existence of members other than heads and spouses earning income, and the existence of persons who do not live with but are financially supported by the household. Among these characteristics, education, ethnicity, employment status, and region are allowed to have time-varying effects.

Let $Z'_{i,t}\varphi^p_t$ and $Z'_{i,t}\varphi^y_t$ be

$$Z'_{i,t}\varphi^p_t = [(Z^1_{i,t})', (Z^2_{i,t})'] \begin{bmatrix} \varphi^{p1}_t \\ \varphi^{p2} \end{bmatrix}, \quad Z'_{i,t}\varphi^y_t = [(Z^1_{i,t})', (Z^2_{i,t})'] \begin{bmatrix} \varphi^{y1}_t \\ \varphi^{y2} \end{bmatrix}$$

in which $Z^1_{i,t}$ and $Z^2_{i,t}$ are the vectors of dummies for household characteristics with time-varying effects and time-invariant effects, respectively, φ^{p1}_t and φ^{p2} are the elements of φ^p_t

[3]Some studies such as Guvenen and Smith (2014) do not have these terms in the model but instead assume that the residuals of income and consumption after controlling for observable characteristics are income and consumption of per-adult equivalent units, and the residuals should be explained by the model. This alternative approach does not affect the estimation of Blundell et al. (2008)'s partial insurance parameters but affects which consumption-to-income ratio to be multiplied in converting the partial insurance parameters to MPC. I report the MPC estimates under this alternative approach in online Appendix D.1.8. The main findings do not change.

associated with $Z^1_{i,t}$ and $Z^2_{i,t}$, respectively, and φ^{y1}_t and φ^{y2} are the elements of φ^y_t associated with $Z^1_{i,t}$ and $Z^2_{i,t}$, respectively. The model is general enough to incorporate aggregate uncertainty by allowing $(\varphi^{p1}_t)_t$ and $(\varphi^{y1}_t)_t$ to be stochastic.

The stochastic processes $(Z_{i,t})_t$, $(\zeta_{i,t})_t$, $(\epsilon_{i,t})_t$, $(\varphi^{p1}_t)_t$, $(\varphi^{y1}_t)_t$, $(r_t)_t$ are all exogenous in the model. I assume that households' idiosyncratic income shocks are independent of other exogenous variables:

$$(\zeta_{i,t}, \epsilon_{i,t})_t \perp (Z_{i,t}, \varphi^{p1}_t, \varphi^{y1}_t, r_t)_t.$$

Moreover, I assume that $(Z_{i,t})_t$ follows a Markov chain with transition probabilities that can be affected by aggregate states. Then, $(Z_{i,t})_t$ satisfies

$$P(Z_{i,t+j}|\mathbf{S}_{i,t}) = P(Z_{i,t+j}|Z_{i,t}, \mathbf{S}^{agg}_t), \quad j \geq 0$$

in which $\mathbf{S}^{agg}_t$ denotes the aggregate state of the economy.

In the model, household i's state vector $\mathbf{S}_{i,t}$ is composed of individual state $\mathbf{S}^{ind}_{i,t}$ and aggregate state $\mathbf{S}^{agg}_t$ as follows.

$$\mathbf{S}_{i,t} = (\mathbf{S}^{ind}_{i,t}, \mathbf{S}^{agg}_t),$$
$$\mathbf{S}^{ind}_{i,t} = \big(A_{i,t-1}, Z_{i,t}, P_{i,t}, \epsilon_{i,t}\big), \quad \mathbf{S}^{agg}_t = \big((\varphi^{p1}_{t-j})_{j\geq 0}, (\varphi^{y1}_{t-j})_{j\geq 0}, (r_{t-j})_{j\geq 0}\big)$$

in which $(x_{t-j})_{j\geq 0} := (x_t, x_{t-1}, x_{t-2}, \cdots)$ denotes the history of time series $(x_s)_s$ up to time t.[4]

Given the assumptions on the exogenous processes, equation '$\log Y_{i,t} = Z'_{i,t}\varphi^y_t + y_{i,t}$' is equivalent to the following decomposition.

$$\log Y_{i,t} = E[\log Y_{i,t}|Z_{i,t}, \mathbf{S}^{agg}_t] + \big\{\log Y_{i,t} - E[\log Y_{i,t}|Z_{i,t}, \mathbf{S}^{agg}_t]\big\},$$
$$E[\log Y_{i,t}|Z_{i,t}, \mathbf{S}^{agg}_t] = Z'_{i,t}\varphi^y_t, \quad \log Y_{i,t} - E[\log Y_{i,t}|Z_{i,t}, \mathbf{S}^{agg}_t] = y_{i,t}.$$

In the same way, any variable $x_{i,t}$ can be decomposed as follows:

$$x_{i,t} = E[x_{i,t}|Z_{i,t}, \mathbf{S}^{agg}_t] + \big\{x_{i,t} - E[x_{i,t}|Z_{i,t}, \mathbf{S}^{agg}_t]\big\},$$
$$E[x_{i,t}|Z_{i,t}, \mathbf{S}^{agg}_t] = Z_{i,t}\varphi^x_t, \quad x_{i,t} - E[x_{i,t}|Z_{i,t}, \mathbf{S}^{agg}_t] = x_{i,t} - Z_{i,t}\varphi^x_t$$

for some φ^x_t, of which elements corresponding to $Z^1_{i,t}$ are time-varying. From this point on,

[4] The reason why $\mathbf{S}^{agg}_t$ includes the whole history of exogenous aggregate variables is because I do not specify their processes. If I assume that $(r_t)_t$ follows an AR(1) process and has no effect on other aggregate variables, for example, $\mathbf{S}^{agg}_t$ needs to include only r_t, not the whole history $(r_{t-j})_{j\geq 0}$.

I describe $E[x_{i,t}|Z_{i,t},\mathbf{S}_t^{agg}]$ as 'part of $x_{i,t}$ explained (or picked up) by $Z_{i,t}$ and time' or 'predictable component of $x_{i,t}$', and $\left\{x_{i,t}-E[x_{i,t}|Z_{i,t},\mathbf{S}_t^{agg}]\right\}$ as 'part of $x_{i,t}$ unexplained (or not picked up) by $Z_{i,t}$ and time' or 'unpredictable component of $x_{i,t}$'. If $x_{i,t}=E[x_{i,t}|Z_{i,t},\mathbf{S}_t^{agg}]$, I describe this equation as '$x_{i,t}$ is explained (or picked up) by Z_{it} and time'.

Equations (2), (3), (4), and (5) below constitute the optimality conditions of the model.

$$e^{(Z'_{i,t+j}\varphi^p_{t+j})}C_{i,t+j}^{-\sigma}=\beta(1+r_{t+j})E_{t+j}\left[e^{(Z'_{i,t+j+1}\varphi^p_{t+j+1})}C_{i,t+j+1}^{-\sigma}\right]+\mu_{i,t+j},\ 0\leq j\leq J_{i,t}-1, \quad (2)$$

$$\mu_{i,t+j}\geq 0,\quad A_{i,t+j}\geq 0,\quad \mu_{i,t+j}A_{i,t+j}=0,\quad 0\leq j\leq J_{i,t}-1, \quad (3)$$

$$A_{i,t+J_{i,t}}=0,\quad \text{and} \quad (4)$$

$$\sum_{j=0}^{J_{i,t}-s}Q_{t+s,t+s+j}C_{i,t+s+j}=\sum_{j=0}^{J_{i,t}-s}Q_{t+s,t+s+j}Y_{i,t+s+j}+(1+r_{t+s-1})A_{i,t+s-1},\ 0\leq s\leq J_{i,t} \quad (5)$$

in which

$$Q_{t,t+j}=\begin{cases}1 & \text{if } j=0,\\ \frac{1}{(1+r_t)\cdots(1+r_{t+j-1})} & \text{if } j\geq 1\end{cases}$$

and $\mu_{i,t+j}$ is the Lagrangian multiplier associated with the liquidity constraint in period $t+j$.

The definition of 'households being liquidity-constrained in period $t+j$' is '$\mu_{i,t+j}>0$' in this paper. Equation (2) shows that the ratio between today's marginal utility and tomorrow's expected marginal utility is greater than what the Euler equation would dictate when $\mu_{i,t+j}$ is strictly positive. This occurs because households cannot transform their future resources into current consumption completely enough to smooth consumption when they are currently liquidity-constrained.

B The Consumption Growth Function

Let $Z'_{i,t}\varphi^c_t := E(\log C_{i,t}|Z_{i,t},\mathbf{S}_t^{agg})$ be the component of log consumption explained by $Z_{i,t}$ and time and $c_{i,t}:=\log C_{i,t}-Z'_{i,t}\varphi^c_t$ be the component unexplained by them.[5] The consumption growth function used throughout the empirical analyses of this paper is the following equation.

$$\Delta c_{i,t}=\tilde{\mu}_{i,t-1}+\phi^{PIH}_{i,t}\zeta_{i,t}+\psi^{PIH}_{i,t}\epsilon_{i,t}+\tilde{M}_{i,t}+\xi_{i,t}. \quad (6)$$

[5]Note that $Z'_{i,t}\varphi^c_t$ is not equal to $Z'_{i,t}\varphi^p_t$ because the optimal consumption path is affected not only by the preference shift but also by many other factors. For example, interest rates affect the intertemporal allocation of consumption. Moreover, $Z_{i,t}$ affects the expectation error in equation (2). See online Appendix A for details.

The consumption growth function (6) is derived by first-order-approximating the optimality conditions (2) and (5).[6] (See online Appendix A for the derivation.) Therefore, each term in the equation has a structural interpretation.

$\phi^{PIH}_{i,t}\zeta_{i,t}$ and $\psi^{PIH}_{i,t}\epsilon_{i,t}$ are the consumption responses to income shocks that households would make if liquidity constraints were not imposed in the model. For example, Blundell et al. (2008) consider the same model but without liquidity constraints. In such a model, households' consumption decisions follow the permanent income hypothesis (PIH) with CRRA utilities. From the model, they derive the following consumption function.

$$\Delta c_{i,t} = \phi^{PIH}_{i,t}\zeta_{i,t} + \psi^{PIH}_{i,t}\epsilon_{i,t} + \xi_{i,t}. \tag{7}$$

As a result of imposing the liquidity constraints in my model, equation (6) has two more terms, $\tilde{\mu}_{i,t-1}$ and $\tilde{M}_{i,t}$, compared to equation (7). Term $\tilde{\mu}_{i,t-1}$ is the component of $\{-(1/\sigma)\log(1-\hat{\mu}_{i,t-1})\}$ unexplained by the history of observable characteristics and aggregate states in which $\hat{\mu}_{i,t-1} := \mu_{i,t-1}/(e^{(Z'_{i,t-1}\varphi^p_{t-1})}C^{-\sigma}_{i,t-1})$ is the shadow cost of the liquidity constraint in terms of consumption goods in period $t-1$. Therefore, the more household i is constrained in period $t-1$, the greater the value of $\tilde{\mu}_{i,t-1}$ is. Term $\tilde{\mu}_{i,t-1}$ appearing on the right-hand side of equation (6) shows that when households are liquidity-constrained in the current period $t-1$, they cannot transform their future resources into current consumption completely enough to smooth consumption, and therefore, their consumption jumps in the following period t.

Term $\tilde{M}_{i,t}$ is the part of M_t unexplained by the history of observable characteristics and aggregate states, and M_t is the weighted sum of $[E_t \log(1-\hat{\mu}_{i,t+j}) - E_{t-1}\log(1-\hat{\mu}_{i,t+j})]$'s for $0 \le j \le J_{i,t}-1$, which is the expectation change in the effects of the current and future liquidity constraints on the current consumption growth. Term $\tilde{M}_{i,t}$ is positively correlated with transitory income shock $\epsilon_{i,t}$ because it relaxes the current liquidity constraint for currently constrained households and reduces the precautionary-saving motive for households that are currently unconstrained but are concerned about being constrained in the future. The correlation becomes stronger as households approach the liquidity constraint. If households are far away from the liquidity constraint such that the probability of hitting the constraint in the future is negligible, the correlation should be close to zero.

The last term $\xi_{i,t}$ captures the part of $\Delta \log C_{i,t}$ that is explained by the history of observable characteristics and aggregate states but is not picked up by $\Delta Z'_{i,t}\varphi^c_t$. $E\xi_{i,t} = 0$

[6]The underlying model features nonlinearity generated by the liquidity constraints. In the system of equations (2), (3), (4), and (5), the nonlinearity manifests through $\mu_{i,t+j}$, $0 \le j \le J_{i,t}-1$. The first-order approximation implemented to derive equation (6) preserves the nonlinearity because any term including $\mu_{i,t+j}$ is not approximated.

holds by construction, and $\xi_{i,t}$ can be autocorrelated. Since $(\zeta_{i,t}, \epsilon_{i,t})_t \perp (Z_{i,t}, \mathbf{S}_t^{agg})_t$, we have $(\xi_{i,t})_t \perp (\zeta_{it}, \epsilon_{it})_t$.[7]

C MPC Estimation

I estimate the MPC of each income decile in Peru and the U.S., separately. As in Blundell et al. (2008), I assume the partial insurance parameters under PIH, $\phi_{i,t}^{PIH}$ and $\psi_{i,t}^{PIH}$ are constant within each group but can vary across different groups. Under this assumption, equation (6) becomes

$$\Delta c_{i,t} = \tilde{\mu}_{i,t-1} + \phi_G^{PIH}\zeta_{i,t} + \psi_G^{PIH}\epsilon_{i,t} + \tilde{M}_{i,t} + \xi_{i,t}, \quad (i,t) \in G \tag{8}$$

in which G denotes a group of observation (i,t)'s.

As we shall see in section III, households are interviewed annually and one quarterly income and consumption are available per interview in the Peruvian data. Thus, we have year-over-year growth of quarterly consumption and income for the Peruvian sample. On the other hand, households are interviewed biannually and one annual income and consumption are available per interview in the U.S. data. Therefore, we have two-year-over-two-year growth of annual consumption and income for the U.S. sample. To examine equations (1) and (8) with these data, I sum each of the equations over multiple periods as follows.

$$\Delta^K y_{i,t} = \sum_{j=0}^{K-1} \zeta_{i,t-j} + \epsilon_{i,t} - \epsilon_{i,t-K}, \tag{9}$$

$$\begin{aligned}\Delta^K c_{i,t} = &\sum_{j=0}^{K-1} \tilde{\mu}_{i,t-j-1} + \phi_G^{PIH} \sum_{j=0}^{K-1} \zeta_{i,t-j} + \psi_G^{PIH} \sum_{j=0}^{K-1} \epsilon_{i,t-j} \\ &+ \sum_{j=0}^{K-1} \tilde{M}_{i,t-j} + \sum_{j=0}^{K-1} \xi_{i,t-j}, \quad (i,t) \in G\end{aligned} \tag{10}$$

in which $\Delta^K x_t := x_t - x_{t-K}$ for time series $(x_t)_t$. For the Peruvian sample, I set the period as a quarter and $K = 4$. For the U.S. sample, I set the period as a year and $K = 2$.

As in Blundell et al. (2008) and Kaplan et al. (2014b), I define the partial insurance parameter to transitory income shocks ψ_G for each group G as follows.

$$\psi_G := \frac{cov[\Delta c_{i,t}, \epsilon_{i,t} | (i,t) \in G]}{cov[\Delta y_{i,t}, \epsilon_{i,t} | (i,t) \in G]}. \tag{11}$$

[7] These features of $\xi_{i,t}$ remain unchanged even when we allow $\xi_{i,t}$ to include measurement errors that are mean-zero, autocorrelated, but uncorrelated with $(\zeta_{i,t}, \epsilon_{i,t})_t$.

Parameter ψ_G is the elasticity of consumption with regard to income when the income change is caused by a transitory income shock. When the grouping of observation (i,t)'s is independent of $\epsilon_{i,t}$, we can obtain

$$\psi_G = \psi_G^{PIH} + \frac{cov[\epsilon_{i,t}, \tilde{M}_{i,t} | (i,t) \in G]}{var[\epsilon_{i,t} | (i,t) \in G]} \tag{12}$$

by substituting equations (1) and (8) into equation (11). Note that ψ_G is equal to ψ_G^{PIH} when the liquidity constraints are removed from the model.

When the grouping of observation (i,t)'s is independent of $(\zeta_{i,t+j}, \epsilon_{i,t+j})_{j \geq 0}$ (the income shocks from period t onward), we can derive

$$\psi_G = \frac{cov[\Delta^K c_{it}, \Delta^K y_{i,t+K} | (i,t) \in G]}{cov[\Delta^K y_{it}, \Delta^K y_{i,t+K} | (i,t) \in G]}, \quad K \geq 1 \tag{13}$$

from equations (9) and (10).[8] Intuitively, ψ_G can be identified by running an IV regression in which $\Delta^K c_{i,t}$ is the dependent variable, $\Delta^K y_{i,t}$ is the endogenous regressor, and $\Delta^K y_{i,t+K}$ is the instrumental variable.

I use equation (13) to identify ψ_G. I group observation (i,t)'s based on their unpredictable component of income in period $t-K$, $y_{i,t-K}$, so that the grouping is independent of $(\zeta_{i,t+j}, \epsilon_{i,t+j})_{j \geq 0}$. Since ψ_G is an elasticity, I identify the MPC out of a transitory income shock by multiplying ψ_G by the ratio of the average consumption to the average income of group G in period $t-K$ as follows.

$$MPC_G = \psi_G \frac{E[C_{i,t-K} | (i,t) \in G]}{E[Y_{i,t-K} | (i,t) \in G]}. \tag{14}$$

Let $\kappa_G := \frac{E[C_{i,t-K} | (i,t) \in G]}{E[Y_{i,t-K} | (i,t) \in G]}$. To estimate MPC_G using equations (13) and (14), I estimate $(\kappa_G, \alpha_G, \psi_G)$ from the following moment conditions using the GMM method.

$$\begin{gathered} E[\kappa_G Y_{i,t-K} - C_{i,t-K} | (i,t) \in G] = 0, \\ E[\Delta^K c_{i,t} - \alpha_G - \psi_G \Delta^K y_{i,t} | (i,t) \in G] = 0, \quad \text{and} \\ E[\Delta^K y_{i,t+K} (\Delta^K c_{i,t} - \alpha_G - \psi_G \Delta^K y_{i,t}) | (i,t) \in G] = 0. \end{gathered} \tag{15}$$

[8] We can also verify from equations (9) and (10) that Blundell et al. (2008)'s formula for the partial insurance parameter to permanent income shocks, $\phi = \frac{cov(\Delta^K c_{it}, \Delta^K y_{i,t-K} + \Delta^K y_{it} + \Delta^K y_{i,t+K})}{cov(\Delta^K y_{it}, \Delta^K y_{i,t-K} + \Delta^K y_{it} + \Delta^K y_{i,t+K})}$ provides a biased estimate in the presence of liquidity constraints. This is consistent with Kaplan and Violante (2010)'s finding that Blundell et al. (2008)'s estimator for ϕ is biased while their estimator for ψ is unbiased when data are simulated from a model with borrowing constraints.

Standard errors are clustered within each household.[9] Once we have the GMM estimates and the variance-covariance matrix of $(\kappa_G, \alpha_G, \psi_G)$, we can obtain the estimate of MPC_G and its standard error using equation (14) or, equivalently,

$$MPC_G = \psi_G \kappa_G.$$

Since one period is a quarter for the Peruvian sample and a year for the U.S. sample, equation (14) yields quarterly MPCs for Peru and annual MPCs for the U.S. To compare the quarterly MPC estimates with the annual MPC estimates, I convert the quarterly MPCs of Peruvian households to annual MPCs by adopting Auclert (2019)'s conversion formula, which the author uses for the same purpose of comparing quarterly MPC estimates with annual MPC estimates. The conversion formula is

$$MPC_G^A = 1 - (1 - MPC_G^Q)^4 \tag{16}$$

in which MPC_G^A denotes the annual MPC and MPC_G^Q denotes the quarterly MPC of group G.[10] [11]

III Data

A Data Source

The MPC estimation for emerging economies using Blundell et al. (2008)'s method requires a micro dataset that satisfies four requirements. First, the dataset should include both the income and expenditure of households. Second, the dataset should have a panel structure of at least three consecutive surveys. Third, the sample should be representative of a country. Fourth, the dataset should be for an emerging economy. ENAHO is one of the rare datasets, if not the only one, that satisfies all four requirements. It is the major information source of the quantity indices for the final household expenditure in Peru's national accounts (Instituto Nacional de Estadística e Informática, n.d.) and thus is nationally representative and includes detailed categories of household expenditure. Moreover, ENAHO also collects information on detailed sources of household income. ENAHO tracks a subset of annual cross-sectional observations in the following

[9] The standard error clustering within each household is important because (i) the error term $(\Delta^K c_{i,t} - \alpha_G - \psi_G \Delta^K y_{i,t})$ is autocorrelated as it includes $\sum_{j=0}^{K-1} \tilde{\mu}_{i,t-j-1}$ and $\sum_{j=0}^{K-1} \xi_{i,t-j}$, and (ii) the instrumental variable $\Delta^K y_{i,t+K}$ of observation (i,t) can also be correlated with the error term of observation $(i, t+K)$.

[10] Auclert (2019) derives equation (16) under the assumption that the quarterly consumption response in period $t+j$ to a shock in period t decays exponentially in j and the interest rate is close to zero. The author finds that this conversion formula is a good approximation in partial equilibrium Bewley models.

[11] The standard errors are also converted using equation (16) and the Delta method.

year and possibly more. The panel households are also nationally representative. Most panel households appear two or three times in the data, while the maximum number of appearances is six. I use 2004-2016 waves of ENAHO. These waves give 11 years of consumption and income growth because the survey is annually conducted and there is no panel structure between the 2006 wave and the 2007 wave. Online Appendix B.1 provides more details about ENAHO including its coverage and and non-response rates.

For the MPC comparison between emerging and developed economies, I need another micro dataset that satisfies the first, second, and third conditions discussed above, but for a developed economy. I choose Kaplan et al. (2014b)'s replication dataset for U.S. households[12]. For the purpose of cross-country comparison, their dataset is relevant for two reasons. First, their sample years are not too different from the sample years of the Peruvian dataset I use in this paper. Specifically, they use the 1999-2011 waves from the Panel Study of Income Dynamics (PSID), which overlap significantly with my Peruvian sample (waves 2004-2016). Second, they prepare the dataset to estimate Blundell et al. (2008)'s partial insurance parameter with regard to transitory income shocks, which is the same object upon which I base my MPC estimates.

B Variable Construction

The baseline consumption measure for both Peruvian and U.S. households includes nondurable goods and a subset of services, as in many other studies on household consumption, such as Attanasio and Weber (1995) and Kocherlakota and Pistaferri (2009). Following these studies, I exclude health and education expenses from the consumption due to their durable nature. I exclude non-purchased consumption such as donations, food stamps, in-kind income, and self-production from the consumption. Including these items does not change the results in any meaningful way, as reported in online Appendix D.1.1 and D.2.1. Due to the lack of coverage in the early waves in the U.S. sample, the consumption of U.S. households does not include clothing, recreation, alcohol, and tobacco, while the consumption of Peruvian households includes them. In online Appendix D.1.2 and D.2.2, I conduct a robustness check by consistently excluding these expenses from the consumption of Peruvian households and verify that the main findings are robust. The constructed consumption of households in each country is deflated with the Consumer Price Index (CPI) series.

The income measure for both countries is composed of disposable labor income and transfers, as in Blundell et al. (2008) and Kaplan et al. (2014b). Capital income is excluded because we do not want to falsely attribute endogenous capital income changes to

[12] Kaplan et al. (2014a)

unexpected income shocks. In ENAHO, labor income and capital income are not distinguishable in self-employment income. Following Diaz-Gimenez et al. (1997) and Krueger and Perri (2006), I split the self-employment income into a labor income component and a capital income component using the ratio of unambiguous labor income to the sum of unambiguous labor income and unambiguous capital income in the sample.[13] Imputed components of missing income are excluded from the income measure for ENAHO, as these components might blur the identification of income shocks. I cannot do the same for the income of U.S. households, as the imputed income components are not distinguishable in Kaplan et al. (2014b)'s dataset. In online Appendix D.1.3, I conduct a robustness check by consistently including the imputed components of Peruvian households' income and verify that it does not change the results in any meaningful way. The income of Peruvian households includes two expense items that are also included in their consumption: rental equivalence of housing provided by work (as labor income) and rental equivalence of donated housing (as transfers).[14] On the other hand, the income of U.S. households does not include any expense items that are included in their consumption. In online Appendix D.1.4 and D.2.3, I conduct a robustness check by consistently excluding the two expense items from Peruvian households' income and verify that the main findings are robust. The constructed income of households in each country is deflated with the CPI series.

In ENAHO, reference periods vary over both expense items and income items. More importantly, individual households report more than 97 percent (in value) of expense items and income items, respectively, with reference periods shorter than or equal to the previous three months, on average. Given this feature of the data, I construct quarterly consumption and income by excluding expense and income items with reference periods longer than the previous three months. Expense and income items with reference periods shorter than the previous three months are scaled up to the quarterly expense and income, respectively. Since panel households are tracked only annually, we can only obtain the year-over-year growth of quarterly consumption and income from ENAHO. In the PSID, the reference period is fixed to one year, while households are tracked only biannually during the sample years of Kaplan et al. (2014b)'s dataset. Therefore, we can only obtain two-year-over-two-year growth of annual consumption and income from their dataset. [15]

[13]In my ENAHO sample, the ratio is 0.819. This ratio is slightly lower but quite similar to the ratio in the U.S., 0.864, which Diaz-Gimenez et al. (1997) and Krueger and Perri (2006) use.

[14]However, the income measure does not include rental equivalence of owned housing because it is categorized as capital income.

[15]Both the PSID and ENAHO are not free from the problem of time inconsistency between the reference period for consumption and that for income. In the PSID, the reference period for income is firmly fixed to a calendar year, but the reference period for consumption can depend on an interpretation, as pointed

Online Appendix B.2 provides more details of the variable construction.

C Sample Selection

Provided that the empirical analyses of this paper require multiple appearances by households, it is convenient to define different units of observation for the sake of discussion. I define an observation of a household in n consecutive surveys as a type-n observation. If a household appears in three consecutive surveys, this household provides three type-1 observations, two type-2 observations, and one type-3 observation.

Sample selection is implemented for either type-1 observations or type-2 observations. When I drop some type-1 observations, type-2 and type-3 observations that contain the dropped type-1 observations are also dropped. When I drop some type-2 observations, type-1 observations that do not have any selected type-2 observations to belong to are also dropped, and type-3 observations that contain the dropped type-2 observations are also dropped.

The sample selection for ENAHO proceeds as follows. First, I begin with type-1 observations that belong to at least one type-2 observation. Second, I drop type-2 observations if the interview months are not matched between the two consecutive surveys. Moreover, there are type-2 observations that are likely to falsely connect two different households. Such type-2 observations are detected and dropped.[16] Type-2 observations are also dropped if the head of the household changes. Third, type-1 observations are dropped if a survey response is categorized as incomplete by interviewers. Fourth, type-1 observations are dropped if the household heads are younger than 25 or older than 65. Fifth, type-1 observations are dropped if any of the observable characteristics needed to control income and consumption are missing. Sixth, type-1 observations are dropped if they have non-positive income or consumption. Seventh, type-1 observations are dropped if they have too much value in imputed income components. Similarly, type-1 observations are dropped if they report too much value in expense items or income items with reference

out by Crawley (2019). For example, the reference period for food consumption in the PSID questionnaire can be interpreted either as average weekly consumption during the reference year of income or as the consumption in the last week of the survey. In the baseline analysis, I accept the former interpretation, as many other studies implicitly do. Under the alternative interpretation, however, the time inconsistency problem arises in such a way that the reference period for income is longer than that for consumption. In ENAHO, the reference periods for both consumption and income are restricted to be no longer than the previous three months, as discussed above. Within these three months, however, the time inconsistency problem exists in both ways: some expense items have longer reference periods than some income items, while some expense items have shorter reference periods than some income items. In a robustness check conducted in online Appendix D.1.9, I address this time inconsistency problem using a continuous-time model and find that the main findings are robust to correcting the problem.

[16] Online Appendix B.4 provides details of the procedure.

periods longer than the previous three months. Eighth, all type-1 observations on households categorized as an income outlier are dropped.[17] This sample selection leaves 47,210 type-1 observations, 21,988 type-2 observations, and 7,509 type-3 observations. Online Appendix B.3 provides more details of the sample selection procedure including how many observations of each type are dropped in each step.

For the U.S. households, I adopt Kaplan et al. (2014b)'s sample selection with only a few minor revisions because their sample selection procedure is similar to mine. Online Appendix B.3 discusses details of the minor revisions and a remaining difference between my sample selection for ENAHO and their sample selection for the PSID, as well as a robustness check regarding the difference.

D Income Grouping

I estimate the MPC of each income decile in each country. The income distribution for the deciles is constructed by sorting type-1 observations with their unpredictable component of log real income, $y_{i,t}$. In accordance with the unit time length of each sample (a year for the U.S. sample and a quarter for the Peruvian sample), I sort the U.S. type-1 observations within each calendar year and the Peruvian type-1 observations within each calendar quarter.[18] The survey weights are used to compute the quantile of each observation.

The unit of observation in the MPC estimation is the type-3 observation. The observation that I denote as (i, t) in subsection II.C is the type-3 observation of household i in period $t - K$, t, and $t + K$ in which $K = 4$ in the Peruvian sample and $K = 2$ in the U.S. sample. The income decile of the type-3 observation is determined by its unpredictable component of log real income in the initial period $t - K$, $y_{i,t-K}$.

My baseline income measure for the Peruvian sample does not include items with reference periods longer than the previous three months and imputed income components, and I drop type-1 observations that have too much value in these components in the sample selection. If the proportion of these components in household income is correlated with the income level, this sample selection can cause a selection bias. Dropping observations with too much value in expense items with reference periods longer than the previous three months can cause the same issue.

[17] Income growth is used for the criterion of income outliers. See online Appendix B.3 for details.

[18] Because I already remove the time-fixed effect when controlling for the predictable components (annually for the U.S. sample, quarterly for the Peruvian sample), it should also be fine to sort unpredictable component of income $y_{i,t}$ in a larger observation pool than the pool of the unit time length. In online Appendix D.1.5 and D.2.4, I conduct a robustness check by sorting income in different observation pools and find that the main results are robust.

To resolve this concern, when constructing the income distribution and determining the income quantiles of the selected observations in the Peruvian sample, I include the dropped observations due to having too much value in income or expense items with reference periods longer than the previous three months or to having too much value in imputed income components. To sort these dropped observations and the selected observations together, I use the unpredictable component of the log real income of a comprehensive income measure that includes not only the baseline measure of income but also the income items with reference periods longer than the previous three months and the imputed components of income. Although these income components are bad because they can blur the measurement of income growth, they are helpful in determining the income quantiles of the selected observations.

IV Results

A Cross-Country MPC Comparison

Figure 1 plots the annual MPC estimates and the 95% confidence intervals of the income deciles in Peru and the U.S.[19] The result shows two striking differences between the two countries' MPCs. First, the MPCs of the Peruvian deciles are substantially higher

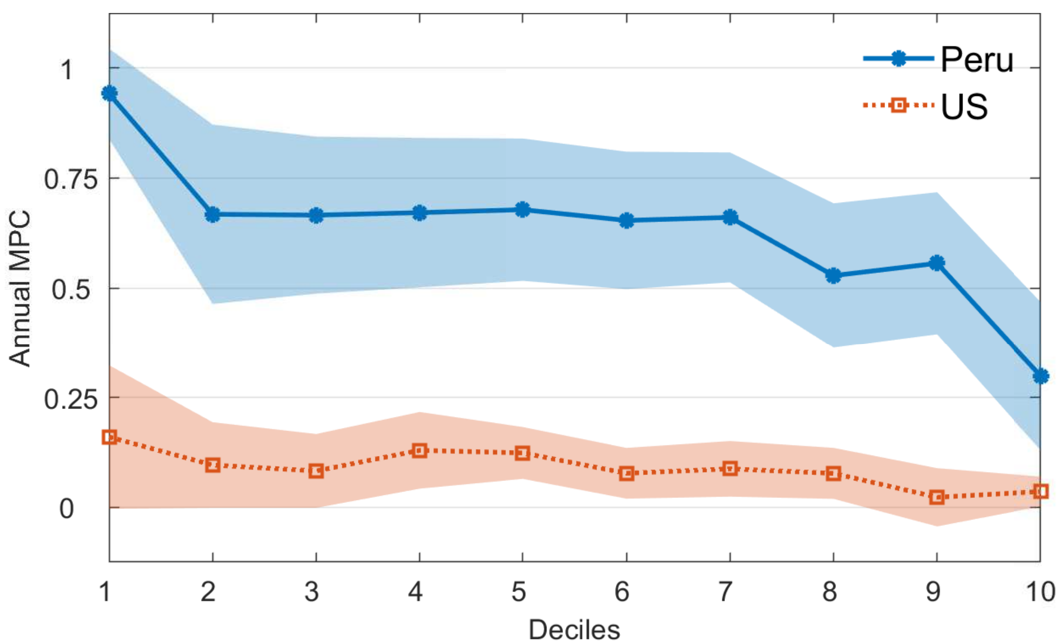


Figure 1: Annual MPCs of the Income Deciles in Peru and the U.S.

Notes: In the x-axis, 1 is the bottom decile. Shaded areas represent 95% confidence intervals.

[19]Online Appendix C reports the estimates and standard errors in a table for interested readers.

overall than those of the U.S. deciles. The mean MPC of the Peruvian deciles (63.2 percent) is 54.3 percentage points higher than that of the U.S. deciles (8.9 percent).[20] Second, in both countries, lower income deciles tend to have higher MPC, but the within-country MPC heterogeneity over the income deciles is substantially stronger in Peru than in the U.S. The MPC of the bottom decile (94.2 percent) is 64.3 percentage points higher than that of the top decile (29.9 percent) in Peru, while in the U.S., the MPC of the bottom decile (16.0 percent) is 12.4 percentage points higher than that of the top decile (3.6 percent).

I also find that these two differences consistently appear in an extensive list of robustness checks in online Appendix D. The list of robustness checks includes (i) alternative measures of consumption and income, (ii) alternative choices of observation pools in sorting income, (iii) alternative underlying models such as a model with persistent (not permanent) income shocks, a model with a subsistence point[21], a model with per-adult equivalent units, and a model in continuous time[22], and (iv) alternative sample selections.

Figure 1 compares the two economies' MPC graphs over the income deciles (not over the income levels). The null hypothesis underlying this comparison is that the U.S. is a scaled-up version of Peru. In other words, the U.S. and Peru follow the same model economy with the same parameter values, but all the quantity variables in the U.S. are proportionally scaled up compared to those in Peru.[23] Under the null hypothesis, we should observe identical MPC graphs over the income deciles between Peru and the U.S. By re-

[20]The average U.S. MPC estimate in this paper, 8.9 percent is in the same ballpark as the estimates of other studies which also apply Blundell et al. (2008)'s method to the PSID. Auclert (2019) estimates the U.S. MPCs of income terciles using the 1999-2013 waves of the PSID and plots them. In the plot, the author's MPC estimates are located around 2 percent, 10 percent, and 13 percent for the top, middle, and bottom terciles, respectively. Blundell et al. (2008) estimates ψ_G (the partial insurance parameter with regard to transitory income shocks, before converting it to MPC by multiplying income-to-consumption ratio) using the 1978-1992 waves of the PSID. Due to the insufficient coverage of expense items in the PSID during their sample period, they impute consumption based on the food demand estimated from the Consumer Expenditure Survey (CEX). They report 5.3 percent as the estimate of ψ_G for the whole sample.

[21]Specifically, I replace the household utility function with the one developed by Stone (1954) and Geary (1950) under which households obtain utility only from consumption beyond a subsistence point.

[22]As Crawley (2019) notes, continuous-time models are useful in dealing with two possible issues in discrete time models: the time aggregation problem and the time inconsistency problem. The time aggregation problem means that a completely transitory shock in a continuous-time process can generate an autocorrelation in a discrete-time process constructed by aggregating the continuous-time process over a specified period. The time inconsistency problem means that the reference period for consumption could be inconsistent with the reference period for income because of the intended design of a survey, unclear description of the questionnaires, or greater difficulties in recalling memory regarding expenses. As in Crawley (2019), I address these issues using a continuous-time model in online Appendix D.1.9.

[23]For the null hypothesis to be not self-contradictory, the model economy under the null hypothesis should be scale-free, *i.e.*, the model dynamics do not change when all quantities are proportionally scaled up. For example, the model in subsection II.A is scale-free. The model remains scale-free when the lower bound of $A_{i,t}$ in equation (LQC) is replaced with a constant fraction of the household's income. However, the model becomes non-scale-free if the lower bound is replaced with a non-zero constant.

jecting this null hypothesis, Figure 1 suggests that whenever we discipline a model using MPC estimates, the parameters governing the MPCs in the model should be significantly different between emerging and developed economies, and thus generate a significantly different macroeconomic outcome.

Separately from the relevance of this income-decile comparison in the context of disciplining a model with MPC estimates, it could also be intuitively appealing to compare the MPC estimates over income levels. The null hypothesis underlying this income-level comparison can be formalized as follows: MPC is a function of the Purchasing Power Parity(PPP)-converted level of income $Y_{i,t}$ (including both predictable and unpredictable components) regardless of whether households live in Peru or in the U.S. To test this null hypothesis, in online Appendix E, I sort households by $Y_{i,t}$ (instead of $y_{i,t}$) to construct income deciles, estimate MPCs of the deciles, and plot them over the x-axis of the PPP-converted group-average values of $Y_{i,t}$. It turns out that the top three deciles in Peru and the bottom three deciles in the U.S. overlap in their PPP-converted income, and in the overlapped region, the mean MPC of the top three deciles in Peru (0.442) is significantly greater than the mean MPC of the bottom three deciles in the U.S. (0.173). This result rejects the null hypothesis that MPC is determined by the PPP-converted level of income.

B The Main Driver of the Stronger MPC Heterogeneity in Peru

Why do we observe the differences between the MPC graph over the income deciles of Peruvian households and that of U.S. households in Figure 1? I begin an investigation to answer this question by attempting to determine the main driver of the stronger within-country MPC heterogeneity over the income deciles in Peru.

When we see Figure 1 through the lens of the standard incomplete-market precautionary-saving models such as the underlying model discussed in subsection II.A, there are three possible explanations for the stronger MPC heterogeneity over the income distribution in Peru.

First, households in lower income deciles could exhibit higher MPC because they are more likely to be constrained. In the underlying model, households that receive negative transitory income shocks would want to bring their future resources to current consumption by running down their asset position.[24] As a result, they become more likely to be constrained. Since lower-income households are more likely to have received negative transitory income shocks and want to run down their asset position, they are more

[24]When the income process is composed of a persistent (not permanent) component and a transitory component, such as the sum of an AR(1) process and an i.i.d. process as given in online Appendix D.1.6, negative income shocks to the persistent component can also induce households to run down their asset position.

likely to be constrained than higher-income households. The likelihood of being constrained could increase substantially faster in Peru than in the U.S. as households move from higher to lower income deciles, and this difference can explain the stronger MPC heterogeneity in Peru.

Second, households in lower income deciles could exhibit higher MPC in the absence of liquidity constraints if they tend to front-load consumption more heavily in their consumption path governed by the Euler equation. For example, consider a variant of the underlying model in which (i) liquidity constraints are removed, (ii) preference heterogeneity in patience β_i and intertemporal elasticity of substitution (IES) $1/\sigma_i$ is allowed, and (iii) $(\beta_i, 1/\sigma_i)$ can be correlated with the unpredictable component of income $y_{i,t}$. Moreover, assume that $\beta_i(1+r) < 1$ in the steady state, as in Aiyagari (1994). In such a model, household i's consumption is governed by the following Euler equation.

$$E_{t+j}\left[e^{\Delta Z'_{i,t+j+1}\varphi^{p}_{t+j+1}}\beta_i(1+r_{t+j})(C_{i,t+j+1}/C_{i,t+j})^{-\sigma_i}\right] = 1, \quad 0 \le j \le J_{i,t-1}.$$

In this model, households in lower income deciles could exhibit higher MPC if they tend to be less patient (lower β_i) or have higher IES (higher $1/\sigma_i$) because they front-load consumption more heavily, as Aguiar et al. (2019) note. If the tendency of lower-income households to front-load consumption more heavily is stronger in Peru than in the U.S., it could explain the stronger MPC heterogeneity in Peru.

Third, even when households' consumption path follows the Euler equation and the degree of front-loading is similar across the income deciles, households in lower income deciles could exhibit higher MPC by facing higher interest rates. When interest rates are different over the income deciles, the relative prices of consumption between today and tomorrow are also different, and these different relative prices generate different substitution effects and wealth effects. I eliminate the difference in the substitution effects by assuming that households' front-loading behavior is similar across the income deciles. The different wealth effects remain: when lower-income households face higher interest rates, they face relatively cheaper prices of future consumption, and thus, they consume more today. As a result, they exhibit higher MPC.[25] If the tendency of lower-income

[25] For example, consider a textbook example in which households optimize their lifetime utility $\sum_{t=0}^{\infty}\beta^t C_t^{1-\sigma}/(1-\sigma)$ subject to sequential budget constraints $C_t + A_t = Y_t + (1+r)A_{t-1}$, the no-Ponzi game constraint, and a perfectly foresighted path of $\{Y_t\}$ under a parametric restriction, $\beta(1+r) = 1$. The optimized consumption path is flat (no front-loading), and the MPC out of a one-time transitory income shock is the annuity value of the shock, $r/(1+r)$. If patience β_i and interest rate r_i are allowed to be heterogeneous in such a way that i) $\beta_i(1+r_i) = 1$ always holds for each household i and ii) r_i tends to be higher in lower income deciles, the MPC in this model, $r_i/(1+r_i)$ is higher in lower income deciles even if their consumption path follows an Euler equation and the degree of front-loading is the same across all income deciles.

households to face higher interest rates is stronger in Peru than in the U.S., this stronger heterogeneity in interest rates could explain the stronger MPC heterogeneity in Peru.

In the rest of this subsection, I try to disentangle these three theory-guided explanations using data. I begin with the last explanation with heterogeneous interest rates. This explanation makes sense only when the effective interest rates used by low-income households for their consumption-saving decision are borrowing interest rates.[26] To see if this is the case, I examine which fraction of households participate in borrowing activities in each of the income deciles in Peru.

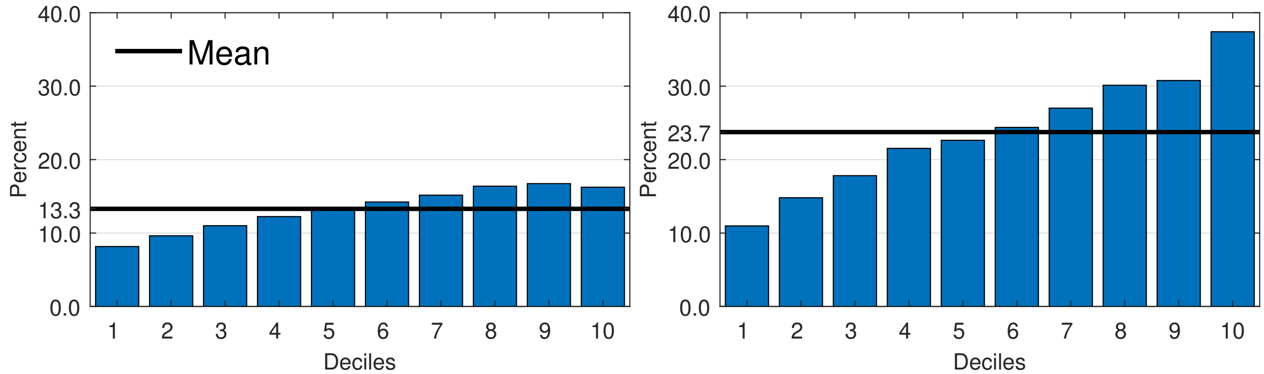
In the sample years of 2015 and 2016, ENAHO includes survey questionnaires that make it possible to identify households that borrowed during the previous twelve months. Using these questionnaires, I identify type-1 observations as participants of borrowing activities if they fall into one of the two categories: (i) a household that has at least one member who reports in a member-level questionnaire that the member borrowed in the previous twelve months or (ii) a household that reports in a household-level questionnaire that it obtained loans or credit in the previous twelve months for the purpose of buying, extending or constructing housing. Figure 2a plots the share of type-1 observations identified as participants in borrowing activities in each of the income deciles from the 2015-2016 sample.[27] The income deciles are again constructed using the unpredictable (with observable characteristics) component of log income. Figure 2a shows that the share of households participating in borrowing activities is only 13.3 percent on average in the Peruvian sample. Moreover, the share is even smaller in lower income deciles.

In Figure 2b, I add one more category of households when defining participants of borrowing activities: a household that has at least one member who holds a credit card. This definition may be excessively broad because some households might use credit cards only for transaction purposes rather than borrowing purposes. Even with this wide definition, the average share of households participating in borrowing activities is only 23.7 percent. Moreover, the tendency of lower-income households to be less likely to borrow than higher-income households is even stronger under this definition.[28]

[26]Saving interest rates are unlikely to be higher for lower-income households. Interest rates on liquid assets such as checking accounts should be close to risk-free interest rates regardless of who holds them. Interest rates on illiquid assets can be substantially heterogeneous in such a way that rich households are more accessible to higher returns than poor households. See Fagereng et al. (2020) for recent empirical evidence on heterogeneous returns to wealth.

[27]Although I use only two years of the sample, the number of type-1 observations used in plotting Figure 2a is large. After implementing the sample selection applicable to type-1 observations discussed in subsection III.C, the 2015 sample and the 2016 sample provide 21,675 and 23,552 observations of type-1, respectively.

[28]Demirguc-Kunt et al. (2015) and Demirguc-Kunt et al. (2018) compute similar statistics using their own surveys over a wide range of countries. They report that in Peru, the share of persons who '[b]orrowed from



(a) Baseline

(b) Including All Credit Card Holders

Figure 2: The Share of Peruvian Households Participating in Borrowing Activities in Each Income Decile from the 2015-2016 Sample

Notes: Figure 2a plots the share of type-1 observations identified as participants in borrowing activities in each of the income deciles from the 2015-2016 ENAHO sample. Figure 2b extends the definition of participants in borrowing activities by including credit card holders. In the x-axis of each figure, 1 is the bottom decile.

Provided that the share of households participating in borrowing activities is as small as 13.3 percent - 23.7 percent in Peru and that the shares are even smaller in lower-income (higher-MPC) groups, it is unlikely that higher-MPC households face higher interest rates for their consumption-saving problem. Based on this observation, I eliminate the explanation with heterogeneous interest rates.

The remaining two explanations, one with liquidity constraints and the other with front-loading behavior, are distinguishable by examining the consumption growth in the following period. Under the explanation with liquidity constraints, households in lower income deciles should exhibit higher consumption growth in the following period because when they become constrained, they fail to bring future resources to current consumption, and therefore, their consumption jumps in the following period. In equation (10), households constrained in period $t-K$ have higher values of $\sum_{j=0}^{K-1} \tilde{\mu}_{i,t-j-1}$ and thus tend to exhibit higher values of $\Delta^K c_{i,t}$. Moreover, for this explanation to be able to account for the stronger heterogeneity in Peru, the tendency of lower income deciles to exhibit higher consumption growth should be stronger in Peru.

Under the explanation with front-loading behavior, households in lower income deciles

a financial institution (% age 15+)' is 11.2 percent, the share of persons who '[b]orrowed from a financial institution or used a credit card (% age 15+)' is 18.0 percent, and the share of persons who '[b]orrowed any money in the past year (% age 15+) ' including informal borrowings such as borrowing from family and friends is 32.2 percent in the 2014 survey. The shares are 14.7 percent, 19.1 percent, and 36.5 percent, respectively, in the 2017 survey.

should exhibit lower consumption growth in the following period exactly because they front-load consumption more heavily than households in higher income deciles. In equation (10), when group G is composed of heavy front-loading households, the front-loading behavior manifests as $E(\sum_{j=0}^{K-1} \xi_{i,t-j}|G) < 0$[29], and thus, the group average $\Delta^K c_{i,t}$ is low. Moreover, for this explanation to be able to account for the stronger heterogeneity in Peru, the tendency of lower income deciles to exhibit lower consumption growth should be stronger in Peru.

To compare the following-period consumption growth among the income deciles of each country, I run the following regression using type-2 observations.

$$\Delta^K c_{i,t} = \alpha + \sum_{j=1}^{9} \delta_j I_{D_j}(i,t) + u_{i,t} \tag{17}$$

in which $I_{D_j}(i,t)$ is a dummy variable on whether a type-2 observation of household i observed in period t and $t-K$ belongs to the j-th income decile in period $t-K$. Parameter δ_j represents the difference in the average consumption growth between the j-th income decile and the top income decile. Standard errors are clustered within each household. Figure 3 plots the estimated values of δ_j, $1 \leq j \leq 9$ in Peru and the U.S., respectively.[30]

Figure 3 exhibits two clear patterns. First, lower income deciles exhibit higher consumption growth in the following period in both countries.[31] Second, the tendency of lower income deciles to have higher consumption growth is substantially stronger in Peru than in the U.S. In the U.S., the average two-year-over-two-year growth of annual consumption of the bottom decile is 7.8 percentage points higher than that of the top decile, while the standard deviation of the consumption growth is 38.7 percent for the whole sample. In Peru, the year-over-year growth of quarterly consumption of the bottom decile is 30.2 percentage points higher than that of the top decile, while the standard deviation of the consumption growth is 45.3 percent for the whole sample.[32]

[29]Term $\xi_{i,t-j}$ captures this front-loading behavior by including term $\frac{1}{\sigma_i} \log \beta_i$. See online Appendix A for details on which terms are included in $\xi_{i,t-j}$.

[30]Online Appendix C reports the estimates and standard errors in a table for interested readers.

[31]In the context of the U.S. economy, this paper is not the first to document the evidence of liquidity constraints using the negative relationship between consumption growth and lagged income. For example, Zeldes (1989) detects the presence of liquidity constraints for low-wealth households by regressing consumption growth on lagged income with other control variables.

[32]We observe the year-over-year growth of quarterly consumption in the Peruvian sample and two-year-over-two-year growth of annual consumption in the U.S. sample. Despite this difference in the growth units, the fact that the standard deviation of the observed consumption growth in the Peruvian sample (45.3 percent) is in the same ballpark as the standard deviation in the U.S. sample (38.7 percent) justifies the direct visual comparison of the two graphs in Figure 3. To illustrate this point, in online Appendix D.2.12, I plot δ_j, $1 \leq j \leq 9$ in the unit of the standard deviations. The figure appears quite similar to Figure 3 and

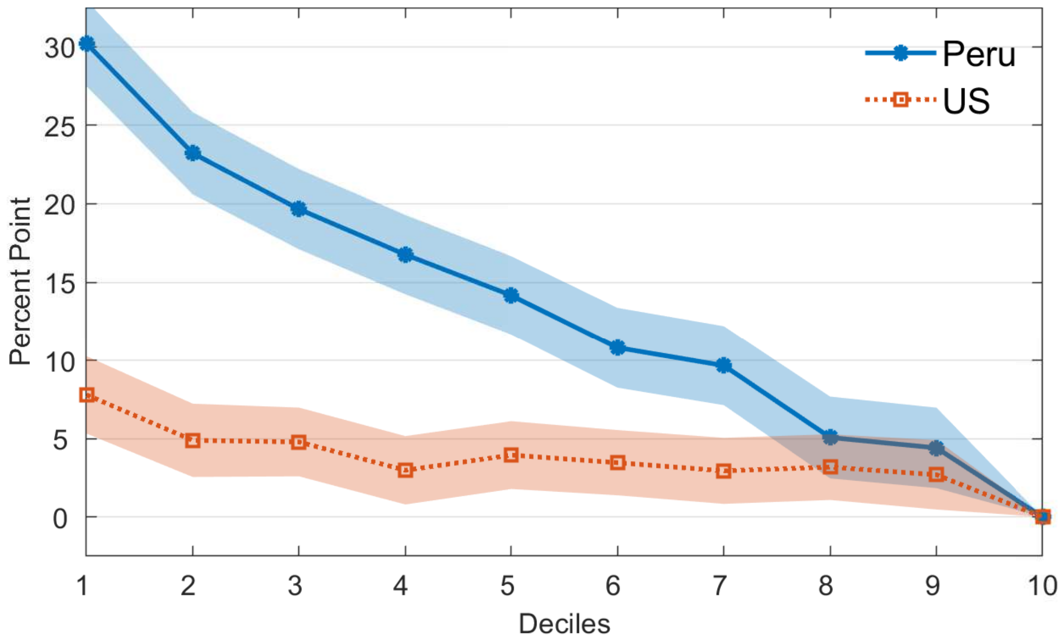


Figure 3: Group Average Consumption Growth Difference against the Top Income Decile

Notes: In the x-axis, 1 is the bottom decile. Shaded areas represent 95% confidence intervals.

These patterns support that liquidity constraints, rather than front-loading behavior, are the main driver of the stronger MPC heterogeneity over the income deciles in Peru.[33] [34]

exhibits the same two main patterns discussed above.

[33] As discussed above, lower-income households are more likely to be constrained than higher-income households because the former are more likely to have received negative transitory income shocks and want to run down their asset position. If this is indeed the reason why we observe the two main patterns in Figure 3, we should observe the same patterns when we group observations by income growth $\Delta^K y_{i,t}$ instead of income level $y_{i,t}$ because the income growth also includes temporary income shock $\epsilon_{i,t}$, as seen in equation (9). In online Appendix D.2.11, I verify that this is indeed the case. This robustness check can reduce the concern that the patterns in Figure 3 might be caused by some omitted factors correlated with both the income level and the consumption growth. For example, if poor households tend to experience higher inflation, the practice of deflating all nominal variables with the same CPI series can mechanically generate the pattern of lower-income households exhibiting higher consumption growth. However, this explanation cannot account for the fact that the same patterns emerge when observations are sorted by the income growth instead of the income level.

[34] Admittedly, this paper uses income grouping instead of wealth or liquid-wealth grouping (which are more common grouping strategies in the literature) because ENAHO does not collect wealth information. However, it is also noteworthy that the income grouping I use in this paper might have an advantage in detecting the effect of liquidity constraints compared to wealth or liquid-wealth grouping. In accordance with Aguiar et al. (2019)'s finding, I find that the consumption growth of hand-to-mouth households in Kaplan et al. (2014b)'s dataset is not significantly greater than that of non-hand-to-mouth households, indicating that the former might not be necessarily more constrained than the latter. In contrast, under the income grouping, we observe clear patterns in the same U.S. sample that lower income deciles exhibit higher consumption growth than higher income deciles. Online Appendix F provides further details of the discussion.

C The Role of Liquidity Constraints in the Cross-Country Mean MPC Gap

Once we accept that liquidity constraints are the main cause for the stronger MPC heterogeneity over the income distribution in Peru, we can decompose the cross-country mean MPC gap into two parts: (i) the gap caused by households being more affected by liquidity constraints in Peru than in the U.S. and (ii) the gap caused by factors unrelated to liquidity constraints, such as cross-country differences in preferences and interest rates. This decomposition can be conducted by identifying a top income group composed of forwardly unconstrained households in each country. The MPC gap between forwardly unconstrained households in Peru and those in the U.S. captures the gap caused by factors unrelated to liquidity constraints.

To delineate a top income group composed of forwardly unconstrained households, I exploit the fact that MPC should be homogeneous over the income within this group. I test whether MPC is homogeneous for the top $(10n)\%$ income groups for $n = 1, \cdots, 10$ by employing a statistical test suggested by Davies (1977) and Davies (1987) as follows. Let G be the top $x\%$ income group. For any $\omega \in [\underline{\omega}, \bar{\omega}] \subsetneq [0, 1]$, let $G_u(\omega)$ be the top $(\omega x)\%$ income group and $G_l(\omega)$ be $G_l(\omega) := G \backslash G_u(\omega)$. Let $z_G(\omega)$ be

$$z_G(\omega) := \frac{MPC_{G_l(\omega)} - MPC_{G_u(\omega)}}{s.e.\big(MPC_{G_l(\omega)} - MPC_{G_u(\omega)}\big)}$$

in which $s.e.(X)$ represents the standard error of statistic X. The test statistic for MPC homogeneity within group G, $z_G^{\sup}$, is defined as follows.

$$z_G^{\sup} := \sup_{\omega \in [\underline{\omega}, \bar{\omega}]} z_G(\omega).$$

The null hypothesis, '$H_0 : MPC_{G_l(\omega)} = MPC_{G_u(\omega)}, \forall \omega \in [\underline{\omega}, \bar{\omega}]$' is rejected in favor of the alternative hypothesis, '$H_1 : \exists \omega \in [\underline{\omega}, \bar{\omega}]$ such that $MPC_{G_l(\omega)} > MPC_{G_u(\omega)}$' when the value of $z_G^{\sup}$ is high enough.[35]

For the implementation of the test, three specific details need to be discussed. First, in estimating $z_G(\omega)$ for a given value of ω, we cannot assume that $MPC_{G_l(\omega)}$ and $MPC_{G_u(\omega)}$ are independent because observations for the same household at different times are correlated and can belong to different groups. Therefore, I estimate them jointly. Specifically, I estimate $\big(\kappa^{\omega}_{G_u}, \alpha^{\omega}_{G_u}, \psi^{\omega}_{G_u}, \kappa^{\omega}_{G_l}, \alpha^{\omega}_{G_l}, \psi^{\omega}_{G_l}\big)$ from the following moment conditions using the

[35]Here, I restrict the alternative hypothesis to be one-sided instead of two-sided. This restriction can be supported by both theory and the empirical evidence of this paper.

GMM method.

$$
\begin{aligned}
E\big[\{\kappa^{\omega}_{G_s} Y_{i,t-K} - C_{i,t-K}\} \cdot I^{\omega}_{G_s}(i,t)\big|(i,t) \in G\big] = 0, \quad s = u,l \\
E\big[\{\Delta^K c_{i,t} - \alpha^{\omega}_{G_s} - \psi^{\omega}_{G_s}\Delta^K y_{i,t}\} \cdot I^{\omega}_{G_s}(i,t)\big|(i,t) \in G\big] = 0, \quad s = u,l, \quad \text{and} \\
E\big[\{\Delta^K y_{i,t+K}(\Delta^K c_{i,t} - \alpha^{\omega}_{G_s} - \psi^{\omega}_{G_s}\Delta^K y_{i,t})\} \cdot I^{\omega}_{G_s}(i,t)\big|(i,t) \in G\big] = 0, \quad s = u,l.
\end{aligned}
\tag{18}
$$

in which $I^{\omega}_{G_s}(i,t)$ $(s = u,l)$ is a dummy variable indicating whether observation (i,t) belongs to $G_s(\omega)$ or not. Standard errors are clustered within each household.

Second, we need to set the boundary of $[\underline{\omega}, \bar{\omega}]$ and discretize it to compute z^{sup}_G. I set $\underline{\omega} = 0.1$, $\bar{\omega} = 0.9$ and discretize it by the interval size of 0.01.

Third, we need to set a rejection region. Davies (1977) provides a tight upper bound of significance probability ($P[\sup_{\omega\in[\underline{\omega},\bar{\omega}]} z_G(\omega) > c]$) under the null hypothesis, and Davies (1987) provides a way to approximate the upper bound with the data in use. Moreover, Davies (1987) shows that the p-value computed by the approximated upper bound performs well in the author's simulation example in terms of the rejection probability being close to the targeted significance level under the null hypothesis. Adopting Davies (1987)'s suggestion, I compute the p-value of the test as follows.

$$
p = \Phi(-z^{\text{sup}}_G) + V \exp\big(-\frac{1}{2}(z^{\text{sup}}_G)^2\big)/(8\pi)^{1/2} \tag{19}
$$

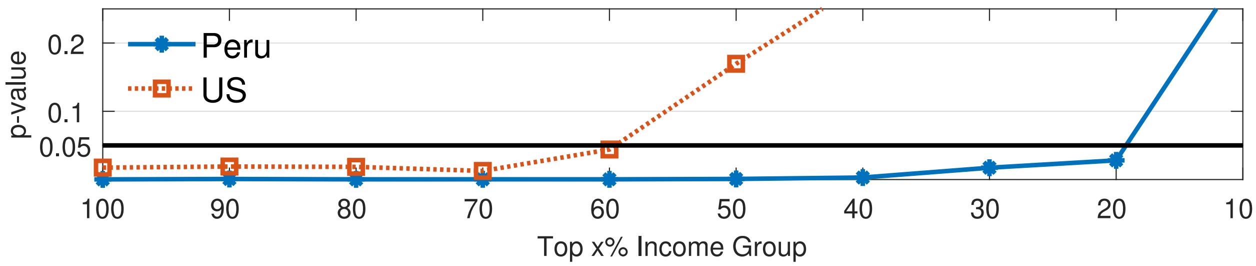
in which Φ is the cumulative normal distribution function, and

$$
V = |z_G(\omega_1) - z_G(\underline{\omega})| + |z_G(\omega_2) - z_G(\omega_1)| + \cdots + |z_G(\bar{\omega}) - z_G(\omega_n)|
$$

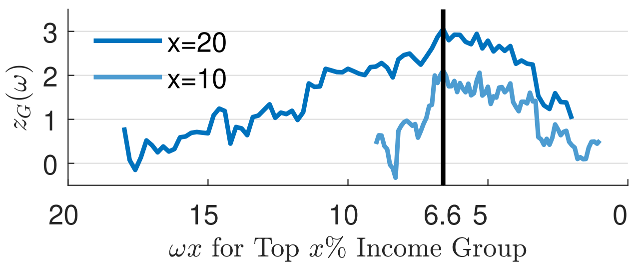
in which $\omega_1, \cdots, \omega_n$ are the discretized points within $[\underline{\omega}, \bar{\omega}]$. I reject the null hypothesis that MPC is homogeneous in group G if the p-value computed by equation (19) is smaller than 0.05.[36]

Figure 4a plots the p-values computed using equation (19) for the top $(10n)\%$ income groups, $n = 1, \cdots, 10$. This figure shows that in Peru, the top 10% income group fails to reject the null hypothesis of the MPC homogeneity test, while the top 20% or larger income groups reject it. In the U.S., the top 50% or smaller income groups fail to reject the

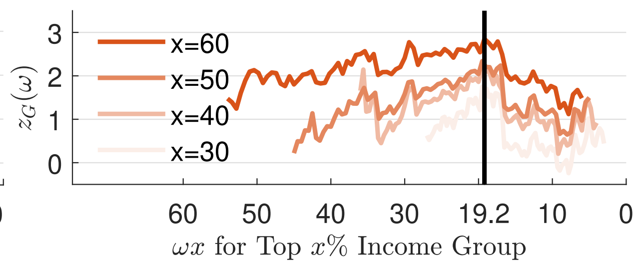
[36] Some econometric studies investigate similar problems with Davies (1977) and Davies (1987) in a specific econometric framework and draw an asymptotic distribution of the test statistic for the sup test. The most closely related setups to my econometric setup are those in Caner and Hansen (2004) and Andrews (1993). However, they require assumptions that do not fit my econometric setup. Caner and Hansen (2004) study an IV estimation method of a threshold model with endogenous regressors. Their method requires the threshold variable to be exogenous, but in my setup, the threshold variable $y_{i,t-K}$ is endogenous. Andrews (1993) studies tests for the parameter instability of the GMM estimators. The method is for a change-point model or, equivalently, a threshold model in which the threshold variable is time.



(a) p-value of the MPC Homogeneity Test for the Top x% Income Group



(b) $z_G(\omega)$, $\omega \in [0.1, 0.9]$ in Peru



(c) $z_G(\omega)$, $\omega \in [0.1, 0.9]$ in U.S.

Figure 4: MPC Homogeneity Test for Top Income Groups

Notes: Figure 4a plots the p-values of the MPC homogeneity test for the top x% income groups, $x = 10, 20, \cdots, 100$. Figure 4b and Figure 4c plot $z_G(\omega)$'s with varying values of $\omega \in [0.1, 0.9]$ for different top income groups in Peru and the U.S., respectively. The vertical black line indicates where $z_G(\omega)$ is at its maximum for the Peruvian top 20% income group in Figure 4b and for the U.S. top 60% income group in Figure 4c.

null hypothesis, while the top 60% or larger income groups reject it. Based on this result, in my baseline decomposition, I delineate a top income group composed of forwardly unconstrained households in each country by the Peruvian top 10% and the U.S. top 50% income groups, which are the largest top $(10n)$% income groups in each country that fail to reject the null hypothesis.

It is worth noting, however, that the Peruvian top 10% and the U.S. top 50% income groups are likely to be strictly larger than the true largest MPC-homogeneous top income group. Figure 4b plots $z_G(\omega)$'s with various values of $\omega \in [0.1, 0.9]$ used in the MPC homogeneity test for the Peruvian top 20% income group, which is the smallest top $(10n)$% income group that rejects the null in Peru. In the test, $z_G(\omega)$ is maximized at the 6.6 percentile from the top, which is located within the top 10% income group. Moreover, Figure 4b plots $z_G(\omega)$'s used in the MPC homogeneity test for the Peruvian top 10% income group and shows that $z_G(\omega)$ is maximized around the 6.6 percentile from the top, again. These patterns suggest that the threshold for MPC homogeneity is located around the 6.6 percentile from the top, which is located within the top 10% income group, but the top

10% income group fails to reject the null hypothesis due to a lack of power.

Similarly, Figure 4c plots $z_G(\omega)$'s with various values of $\omega \in [0.1, 0.9]$ used in the MPC homogeneity test for the U.S. top 60% income group, which is the smallest top $(10n)$% income group that rejects the null in the U.S. In the test, $z_G(\omega)$ is maximized at the 19.2 percentile from the top, which is located within the top 50%, top 40%, and top 30% income groups. Moreover, in the test for these smaller top income groups (the top 50%, top 40%, and top 30%), $z_G(\omega)$ is maximized around the 19.2 percentile from the top, again. These patterns suggest that the threshold for the MPC homogeneity is located around the 19.2 percentile from the top, which is located within the top 50%, top 40%, and top 30% income groups, but these groups fail to reject the null hypothesis due to a lack of power.

Overrating the size of a forwardly unconstrained top income group can cause an overestimation of the MPC of forwardly unconstrained households in Peru and a consequent underestimation of the role of liquidity constraints in the cross-country mean MPC gap decomposition. In this sense, the baseline decomposition provides a conservative estimate for the role of liquidity constraints. To illustrate this point, I also conduct the mean MPC gap decomposition under an alternative delineation of forwardly unconstrained top income groups, the Peruvian top 5% and the U.S. top 15%. These top income groups are chosen to be above the income percentile cutoffs that maximize $z_G(\omega)$ in Figure 4b and Figure 4c, respectively.

Under each delineation of forwardly unconstrained top income groups, I decompose the cross-country mean MPC gap into two parts (the gap between the two countries' forwardly unconstrained households and the gap caused by households being more affected by liquidity constraints in Peru than in the U.S.) as follows.

Let $\mathcal{G} = \{G_1, G_2, \cdots, G_{n_\mathcal{G}}\}$ be a partition of the sample over the income distribution. For example, when I split the sample by the income deciles, $n_\mathcal{G} = 10$ and $G_1, \cdots, G_{10}$ represent the income deciles, $D_1, \cdots, D_{10}$. The mean MPC of the sample, MPC_{mean}, is computed by

$$MPC_{mean} = \sum_{G_j \in \mathcal{G}} \frac{w_{G_j}}{\sum_{G_{j'} \in \mathcal{G}} w_{G_{j'}}} MPC_{G_j} \tag{20}$$

in which w_{G_j} is the population weight of G_j and MPC_{G_j} is the MPC estimate of G_j. Let $\mathcal{U}$ be a subset of $\mathcal{G}$ that is composed of forwardly unconstrained groups. The MPC of forwardly unconstrained households, MPC_{uncon}, is computed by

$$MPC_{uncon} = \sum_{G_j \in \mathcal{U}} \frac{w_{G_j}}{\sum_{G_{j'} \in \mathcal{U}} w_{G_{j'}}} MPC_{G_j}. \tag{21}$$

Let MPC_{liq} be the difference between MPC_{mean} and MPC_{uncon}:

$$MPC_{liq} := MPC_{mean} - MPC_{uncon}. \tag{22}$$

Let MPC^{PR}_{mean}, MPC^{PR}_{uncon}, and MPC^{PR}_{liq} be the statistics computed using equations (20), (21), and (22), respectively, from the Peruvian sample, and MPC^{US}_{mean}, MPC^{US}_{uncon}, and MPC^{US}_{liq} be those from the U.S. sample. The cross-country mean MPC gap between Peru and the U.S., MPC^{gap}_{mean}, is computed by

$$MPC^{gap}_{mean} = MPC^{PR}_{mean} - MPC^{US}_{mean}. \tag{23}$$

The MPC gap between forwardly unconstrained households in Peru and those in the U.S., MPC^{gap}_{uncon}, is computed by

$$MPC^{gap}_{uncon} = MPC^{PR}_{uncon} - MPC^{US}_{uncon}. \tag{24}$$

Under the assumption that liquidity constraints are the sole source of the stronger MPC heterogeneity over the income distribution in Peru, the MPC gap caused by liquidity constraints, MPC^{gap}_{liq}, can be computed by

$$MPC^{gap}_{liq} = MPC^{gap}_{mean} - MPC^{gap}_{uncon} = MPC^{PR}_{liq} - MPC^{US}_{liq}. \tag{25}$$

In computing the standard errors of each country's MPC_{mean}, MPC_{uncon}, and MPC_{liq} in equations (20), (21), and (22), we cannot assume independence among MPC_{G_j}'s, $G_j \in \mathcal{G}$ because observations for the same household at different times are correlated and can belong to different groups. Therefore, I estimate them jointly using the GMM method in the same way that I jointly estimate $MPC_{G_u(\omega)}$ and $MPC_{G_l(\omega)}$ using moment conditions (18) for the MPC homogeneity test. Standard errors are clustered within each household in the GMM estimation. In computing the standard errors of MPC^{gap}_{mean}, MPC^{gap}_{uncon}, and MPC^{gap}_{liq} in equation (23), (24), and (25), I assume independence between the Peruvian sample and the U.S. sample.

In the baseline mean MPC gap decomposition, I partition each country's sample by the income deciles and delineate a forwardly unconstrained top income group by the Peruvian top 10% and the U.S. top 50%, as discussed above. Panel A of Table 1 reports the results. The gap between the mean MPC of Peru (63.2 percent) and that of the U.S.(8.9 percent) is 54.3 percentage points. The gap between the MPC of forwardly unconstrained households in Peru (29.9 percent) and that in the U.S.(6.0 percent) is 23.9

Table 1: Decomposition of the Cross-Country Mean MPC Gap

A.	Grouping by Income Deciles, Peru Top 10% and U.S. Top 50% as Forwardly Unconstrained Income Groups		
	MPC_{mean}	MPC_{uncon}	MPC_{liq}
Peru	0.632	0.299	0.333
	(0.028)	(0.086)	(0.081)
U.S.	0.089	0.060	0.029
	(0.014)	(0.014)	(0.014)
Gap	0.543	0.239	0.304
	(0.031)	(0.087)	(0.082)
B.	**Grouping by Income Vigintiles, Peru Top 10% and U.S. Top 50% as Forwardly Unconstrained Income Groups**		
	MPC_{mean}	MPC_{uncon}	MPC_{liq}
Peru	0.627	0.319	0.308
	(0.028)	(0.083)	(0.079)
U.S.	0.089	0.060	0.029
	(0.015)	(0.014)	(0.014)
Gap	0.538	0.259	0.279
	(0.032)	(0.084)	(0.080)
C.	**Grouping by Income Vigintiles, Peru Top 5% and U.S. Top 15% as Forwardly Unconstrained Income Groups**		
	MPC_{mean}	MPC_{uncon}	MPC_{liq}
Peru	0.627	0.172	0.455
	(0.028)	(0.118)	(0.114)
U.S.	0.089	0.039	0.051
	(0.015)	(0.018)	(0.020)
Gap	0.538	0.133	0.405
	(0.032)	(0.119)	(0.116)

percentage points. As a result, 30.4 percentage points, which accounts for 56.0 percent of the mean MPC gap (54.3 percentage points), is attributable to Peruvian households being more affected by liquidity constraints than U.S. households.

Under the alternative delineation of forwardly unconstrained top income groups by the Peruvian top 5% and the U.S. top 15%, the mean MPC gap decomposition requires a finer partition than deciles. For the finer partition, I group observations by vigintiles of the income. To see whether the change in the partition itself affects the decomposition, in Panel B of Table 1, I conduct the decomposition under the baseline delineation of forwardly unconstrained top income groups (the Peruvian top 10%, the U.S. top 50%) and grouping by the income vigintiles. The numbers reported in Panel B are quite similar to those in Panel A, indicating that the change in the partition itself does not affect the decomposition in a meaningful way.

Panel C of Table 1 reports the decomposition results under the alternative delineation (the Peruvian top 5%, the U.S. top 15%) and grouping by the income vigintiles. The mean MPC gap in Panel C (53.8 percentage points) is similar to that in Panel A (54.3 percentage points). However, the MPC gap between forwardly unconstrained households in Peru and those in the U.S. in Panel C (13.3 percentage points) is substantially smaller than the gap in Panel A (23.9 percentage points). This is because the MPC of forwardly unconstrained Peruvian households in Panel C (17.2 percent) is substantially smaller than the MPC in Panel A (29.9 percent) by 12.7 percentage points, while the MPC of forwardly unconstrained U.S. households in Panel C (3.9 percent) is only 2.1 percentage points smaller than the MPC in Panel A (6.0 percent). As a result, 40.5 percentage points, which accounts for 75.2 percent of the mean MPC gap (53.8 percentage points), is attributable to Peruvian households being more affected by liquidity constraints than U.S. households. The results in Panel C verify that the MPC gap decomposition can underestimate the role of liquidity constraints when the size of the forwardly unconstrained top income group is overrated. In this sense, attributing 56.0 percent of the mean MPC gap to liquidity constraints in the baseline decomposition is a conservative estimation of its role.

V Conclusion

This paper estimates the MPC out of transitory income shocks using micro data for an emerging economy, Peru. Then, the Peruvian MPC estimates are compared with U.S. MPC estimates obtained by the same method. This comparison yields three main conclusions. First, the mean MPC level of Peru is substantially higher than that of the U.S. Second, within-country MPC heterogeneity in income distribution is substantially stronger in Peru than in the U.S. Third, liquidity constraints are important for explaining both the higher mean MPC level and the stronger MPC heterogeneity in Peru.

In a growing literature examining how micro heterogeneity matters for the macroeconomy, researchers have discovered novel mechanisms through which liquidity-poor households and their consumption behavior affect macroeconomic dynamics or policy effects in the context of developed economies. The results of this paper suggest that these mechanisms could play a significantly larger role in emerging economies. In this regard, this paper also suggests that we need a new macroeconomic model of emerging economies in which a large fraction of households are affected by liquidity constraints not only during infrequent sudden-stop or sovereign-default episodes but also even during normal times, and their consumption responses are as strong as the empirical estimates of this paper. Examining the macroeconomic consequences of the liquidity-poor households' consumption behavior through the lens of such a new model would be an important topic for future research in the field of international macroeconomics.

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[Online Appendix]

MPCs and Liquidity Constraints
in Emerging Economies

Seungki Hong

A Derivation of the Consumption Growth Function

In this section, I derive the consumption growth function (6) from the optimality conditions of the underlying model discussed in subsection II.A. The derivation is nearly identical to that of Blundell et al. (2008), except for the part that deals with liquidity constraints, which are absent in their underlying model.

Let $\hat{\mu}_{i,t+j} := \mu_{i,t+j}/(e^{(Z'_{i,t+j}\varphi^p_{t+j})}C^{-\sigma}_{i,t+j})$ be the shadow cost of liquidity constraint in terms of consumption goods in period $t+j$. Equation (2) can be re-written as

$$\begin{aligned}\exp\big(-\sigma\log C_{i,t+j} + Z'_{i,t+j}\varphi^p_{t+j} - \log\beta - \log(1+r_{t+j}) + \log(1-\hat{\mu}_{i,t+j})\big)\\ = E_{t+j}\big[\exp(-\sigma\log C_{i,t+j+1} + Z'_{i,t+j+1}\varphi^p_{t+j+1})\big].\end{aligned} \tag{A.1}$$

By log-linearizing the marginal utility in period $t+j+1$,

$$\exp(-\sigma\log C_{i,t+j+1} + Z'_{i,t+j+1}\varphi^p_{t+j+1}),$$

around its expected value in period $t+j$,

$$\exp\big(-\sigma\log C_{i,t+j} + Z'_{i,t+j}\varphi^p_{t+j} - \log\beta - \log(1+r_{t+j}) + \log(1-\hat{\mu}_{i,t+j})\big)$$

in equation (A.1)[37], we can obtain

$$\Delta\log C_{i,t+j+1} = \frac{1}{\sigma}\Delta(Z'_{i,t+j+1}\varphi^p_{t+j+1}) + \frac{1}{\sigma}\log\beta + \frac{1}{\sigma}\log(1+r_{t+j}) - \frac{1}{\sigma}\log(1-\hat{\mu}_{i,t+j}) + \eta^c_{i,t+j+1} \tag{A.2}$$

in which $\eta^c_{i,t+j+1}$ is an expectation error satisfying $E_{t+j}\eta^c_{i,t+j+1} = 0$.

[37] In other words, first-order-Taylor-approximate

$$-\sigma\log C_{i,t+j+1} + Z'_{i,t+j+1}\varphi^p_{t+j+1}$$

around

$$-\sigma\log C_{i,t+j} + Z'_{i,t+j}\varphi^p_{t+j} - \log\beta - \log(1+r_{t+j}) + \log(1-\hat{\mu}_{i,t+j}).$$

Note that

$$E_t \log C_{i,t+j} - E_{t-1} \log C_{i,t+j} = E_t\big(\sum_{s=0}^{j} \Delta \log C_{i,t+s}\big) - E_{t-1}\big(\sum_{s=0}^{j} \Delta \log C_{i,t+s}\big). \tag{A.3}$$

From equation (A.2), we have

$$\begin{aligned}\sum_{s=0}^{j} \Delta \log C_{i,t+s} =& \frac{1}{\sigma}(Z'_{i,t+j}\varphi^p_{t+j} - Z'_{i,t-1}\varphi^p_{t-1}) + \frac{j+1}{\sigma}\log\beta + \frac{1}{\sigma}\sum_{s=0}^{j}\log(1+r_{t+s-1}) \\ & - \frac{1}{\sigma}\sum_{s=0}^{j}\log(1-\hat{\mu}_{i,t+s-1}) + \sum_{s=0}^{j}\eta^c_{i,t+s}.\end{aligned} \tag{A.4}$$

By substituting equation (A.4) into equation (A.3), we can obtain

$$\begin{aligned}E_t \log C_{i,t+j} - E_{t-1}\log C_{i,t+j} =& \frac{1}{\sigma}(E_t Z'_{i,t+j}\varphi^p_{t+j} - E_{t-1}Z'_{i,t+j}\varphi^p_{t+j}) \\ & - \frac{1}{\sigma}(E_t \log Q_{t,t+j} - E_{t-1}\log Q_{t,t+j}) \\ & - \frac{1}{\sigma}\sum_{s=0}^{j}\big(E_t\log(1-\hat{\mu}_{i,t+s-1}) - E_{t-1}\log(1-\hat{\mu}_{i,t+s-1})\big) + \eta^c_{i,t}, \quad 0 \le j \le J_{i,t}.\end{aligned} \tag{A.5}$$

The intertemporal budget constraint (5) in period t is

$$\sum_{j=0}^{J_{i,t}} Q_{t,t+j}C_{i,t+j} = \sum_{j=0}^{J_{i,t}} Q_{t,t+j}Y_{i,t+j} + (1+r_{t-1})A_{i,t-1}, \tag{A.6}$$

which can be re-written as

$$\begin{aligned}&\log\Big(\sum_{j=0}^{J_{i,t}} \exp\big(\log Q_{t,t+j}C_{i,t+j}\big)\Big) \\ &= \log\Big(\sum_{j=0}^{J_{i,t}} \exp\big(\log Q_{t,t+j}Y_{i,t+j}\big) + (1+r_{t-1})\exp\big(\log A_{i,t-1}\big)\Big).\end{aligned} \tag{A.7}$$

The first-order approximation of the intertemporal budget constraint is conducted around the lifetime path of individual variables predicted by the history of observable characteristics and aggregate states. I choose this path as the path around which the variables are log-linearized because i) I want the coefficients evaluated on the path to be independent of individual income shocks $\epsilon_{i,t}$ and $\zeta_{i,t}$, and ii) I want the path to be the most accurate prediction among those satisfying the first condition.

Let $\hat{E}_t[\cdot]$ be the expectation conditional on the history of observable characteristics and aggregate shocks (or, equivalently, the history of all exogenous variables except individual households' idiosyncratic income shocks, $(\epsilon_{t-s})_{s\geq 0}$ and $(\zeta_{t-s})_{s\geq 0}$). In other words,

$$\hat{E}_t[x_{i,t+j}] := E\left[x_{i,t+j}|(Z_{i,t-s})_{s\geq 0},\ (\varphi^{p1}_{t-s})_{s\geq 0},\ (\varphi^{y1}_{t-s})_{s\geq 0},\ (r_{t-s})_{s\geq 0}\right]$$

for any stochastic time series $(x_{i,t})_t$.

By taking $\hat{E}_{t-1}[\cdot]$ on both sides of equation (A.6), we can obtain

$$\sum_{j=0}^{J_{i,t}} \hat{E}_{t-1}[Q_{t,t+j}C_{i,t+j}] = \sum_{j=0}^{J_{i,t}} \hat{E}_{t-1}[Q_{t,t+j}Y_{i,t+j}] + (1+r_{t-1})\hat{E}_{t-1}[A_{i,t-1}].$$

By log-linearizing

$$\left\{(Q_{t,t+j}C_{i,t+j})_{0\leq j\leq J_{i,t}},\ (Q_{t,t+j}Y_{i,t+j})_{0\leq j\leq J_{i,t}},\ A_{i,t-1}\right\}$$

around

$$\left\{\left(\hat{E}_{t-1}[Q_{t,t+j}C_{i,t+j}]\right)_{0\leq j\leq J_{i,t}},\ \left(\hat{E}_{t-1}[Q_{t,t+j}Y_{i,t+j}]\right)_{0\leq j\leq J_{i,t}},\ \hat{E}_{t-1}[A_{i,t-1}]\right\}$$

in equation (A.6)[38], we can obtain

$$\begin{aligned}
&\sum_{j=0}^{J_{i,t}} \theta_{i,t,t+j}(\log Q_{t,t+j}C_{i,t+j} - \log \hat{E}_{t-1}[Q_{t,t+j}C_{i,t+j}]) \\
&\qquad = \pi_{i,t}\sum_{j=0}^{J_{i,t}} \gamma_{i,t,t+j}(\log Q_{t,t+j}Y_{i,t+j} - \log \hat{E}_{t-1}[Q_{t,t+j}Y_{i,t+j}]) \\
&\qquad\quad + (1-\pi_{i,t})(\log A_{i,t-1} - \log \hat{E}_{t-1}[A_{i,t-1}])
\end{aligned} \tag{A.8}$$

[38]In other words, first-order-Taylor-approximate

$$\left\{(\log Q_{t,t+j}C_{i,t+j})_{0\leq j\leq J_{i,t}}, (\log Q_{t,t+j}Y_{i,t+j})_{0\leq j\leq J_{i,t}}, \log A_{i,t-1}\right\}$$

around

$$\left\{\left(\log \hat{E}_{t-1}[Q_{t,t+j}C_{i,t+j}]\right)_{0\leq j\leq J_{i,t}},\ \left(\log \hat{E}_{t-1}[Q_{t,t+j}Y_{i,t+j}]\right)_{0\leq j\leq J_{i,t}},\ \log \hat{E}_{t-1}[A_{i,t-1}]\right\}$$

in equation (A.7).

in which

$$\theta_{i,t,t+j} = \frac{\hat{E}_{t-1}[Q_{t,t+j}C_{i,t+j}]}{\sum_{j'=0}^{J_{i,t}} \hat{E}_{t-1}[Q_{t,t+j'}C_{i,t+j'}]}, 0 \leq j \leq J_{i,t},$$

$$\pi_{i,t} = \frac{\sum_{j'=0}^{J_{i,t}} \hat{E}_{t-1}[Q_{t,t+j'}Y_{i,t+j'}]}{\sum_{j'=0}^{J_{i,t}} \hat{E}_{t-1}[Q_{t,t+j'}Y_{i,t+j'}] + (1+r_{t-1})\hat{E}_{t-1}A_{i,t-1}}, \text{ and}$$

$$\gamma_{i,t,t+j} = \frac{\hat{E}_{t-1}[Q_{t,t+j}Y_{i,t+j}]}{\sum_{j'=0}^{J_{i,t}} \hat{E}_{t-1}[Q_{t,t+j'}Y_{i,t+j'}]}, 0 \leq j \leq J_{i,t}.$$

Note that

$$\sum_{j=0}^{J_{i,t}} \theta_{i,t,t+j} = \sum_{j=0}^{J_{i,t}} \gamma_{i,t,t+j} = 1.$$

Moreover, $(\theta_{i,t,t+j}, \pi_{i,t}, \gamma_{i,t,t+j})_{t,0\leq j\leq J_{i,t}}$ are independent of the household's idiosyncratic income shocks $(\zeta_{i,t}, \epsilon_{i,t})_t$ because they are functions of $(Z_{i,t-s})_{s\geq 0}$, $(\varphi^{p1}_{t-s})_{s\geq 0}$, $(\varphi^{y1}_{t-s})_{s\geq 0}$, and $(r_{t-s})_{s\geq 0}$.

By taking the first difference in expectations without hat (*i.e.*, $E_t[\cdot] - E_{t-1}[\cdot]$) on both sides of equation (A.8), we can obtain

$$\sum_{j=0}^{J_{i,t}} \theta_{i,t,t+j}(E_t \log Q_{t,t+j}C_{i,t+j} - E_{t-1} \log Q_{t,t+j}C_{i,t+j})$$
$$= \pi_{i,t} \sum_{j=0}^{J_{i,t}} \gamma_{i,t,t+j}(E_t \log Q_{t,t+j}Y_{i,t+j} - E_{t-1} \log Q_{t,t+j}Y_{i,t+j})$$

or, equivalently,

$$\begin{aligned}
&\sum_{j=0}^{J_{i,t}} \theta_{i,t,t+j}(E_t \log C_{i,t+j} - E_{t-1} \log C_{i,t+j}) \\
&= \sum_{j=0}^{J_{i,t}} (\pi_{i,t}\gamma_{i,t,t+j} - \theta_{i,t,t+j})(E_t \log Q_{t,t+j} - E_{t-1} \log Q_{t,t+j}) \\
&+ \sum_{j=0}^{J_{i,t}} \pi_{i,t}\gamma_{i,t,t+j}(E_t \log Y_{i,t+j} - E_{t-1} \log Y_{i,t+j}).
\end{aligned} \tag{A.9}$$

By substituting equation (A.5) into equation (A.9) and replacing $Y_{i,t+j}$ with $Z'_{i,t+j}\varphi^{y}_{t}$ +

$P_{i,t+j} + \epsilon_{i,t+j}$, we can obtain

$$\begin{aligned}
\eta^c_{i,t} = &-\frac{1}{\sigma}\sum_{j=0}^{J_{i,t}} \theta_{i,t,t+j}(E_t Z'_{i,t+j}\varphi^p_{t+j} - E_{t-1} Z'_{i,t+j}\varphi^p_{t+j}) \\
&+ \sum_{j=0}^{J_{i,t}} \pi_{i,t}\gamma_{i,t,t+j}(E_t Z'_{i,t+j}\varphi^y_{t+j} - E_{t-1} Z'_{i,t+j}\varphi^y_{t+j}) \\
&+ \sum_{j=0}^{J_{i,t}} (\pi_{i,t}\gamma_{i,t,t+j} - (1-\frac{1}{\sigma})\theta_{i,t,t+j})(E_t \log Q_{t,t+j} - E_{t-1}\log Q_{t,t+j}) \\
&+ \sum_{j=0}^{J_{i,t}} \pi_{i,t}\gamma_{i,t,t+j}(E_t(P_{i,t+j} + \epsilon_{i,t+j}) - E_{t-1}(P_{i,t+j} + \epsilon_{i,t+j})) \\
&+ \frac{1}{\sigma}\sum_{j=0}^{J_{i,t}-1}\left(\sum_{s=j+1}^{J_{i,t}} \theta_{i,t,t+s}\right)(E_t \log(1-\hat{\mu}_{i,t+j}) - E_{t-1}\log(1-\hat{\mu}_{i,t+j})).
\end{aligned} \tag{A.10}$$

By substituting equation (A.10) into equation (A.2), we can obtain

$$\begin{aligned}
\Delta \log C_{i,t} = &\frac{1}{\sigma}\Delta(Z'_{i,t}\varphi^p_t) + \frac{1}{\sigma}\log\beta + \frac{1}{\sigma}\log(1+r_{t-1}) - \frac{1}{\sigma}\log(1-\hat{\mu}_{i,t-1}) \\
&- \frac{1}{\sigma}\sum_{j=0}^{J_{i,t}} \theta_{i,t,t+j}(E_t Z'_{i,t+j}\varphi^p_{t+j} - E_{t-1} Z'_{i,t+j}\varphi^p_{t+j}) \\
&+ \sum_{j=0}^{J_{i,t}} \pi_{i,t}\gamma_{i,t,t+j}(E_t Z'_{i,t+j}\varphi^y_{t+j} - E_{t-1} Z'_{i,t+j}\varphi^y_{t+j}) \\
&+ \sum_{j=0}^{J_{i,t}} (\pi_{i,t}\gamma_{i,t,t+j} - (1-\frac{1}{\sigma})\theta_{i,t,t+j})(E_t \log Q_{t,t+j} - E_{t-1}\log Q_{t,t+j}) \\
&+ \sum_{j=0}^{J_{i,t}} \pi_{i,t}\gamma_{i,t,t+j}(E_t(P_{i,t+j} + \epsilon_{i,t+j}) - E_{t-1}(P_{i,t+j} + \epsilon_{i,t+j})) \\
&+ \frac{1}{\sigma}\sum_{j=0}^{J_{i,t}-1}\left(\sum_{s=j+1}^{J_{i,t}} \theta_{i,t,t+s}\right)(E_t \log(1-\hat{\mu}_{i,t+j}) - E_{t-1}\log(1-\hat{\mu}_{i,t+j})).
\end{aligned} \tag{A.11}$$

I re-write equation (A.11) as follows.

- The first line of equation (A.11) includes $\Delta \log C_{i,t}$ on its left-hand-side. I decompose $\log C_{i,t}$ into the part explained by current observable characteristics and time, $Z'_{i,t}\varphi^c_t$, and the residual part, $c_{i,t}$. Then, $\Delta \log C_{i,t}$ can be re-written as $\Delta c_{i,t} + \Delta(Z'_{i,t}\varphi^c_t)$.
- In the first line of equation (A.11), $\frac{1}{\sigma}\log\beta + \frac{1}{\sigma}\log(1+r_{t-1})$ can be picked up by

$Z_{i,t-1}$ and time. Therefore, I re-write this term as $Z'_{i,t-1}\varphi^{\beta,r}_{t-1}$.

- The first line of equation (A.11) includes $-\frac{1}{\sigma}\log(1-\hat{\mu}_{i,t-1})$. I decompose this term into the part explained by the history of aggregate shocks and observable characteristics up to period $t-1$, $\hat{E}_{t-1}[-\frac{1}{\sigma}\log(1-\hat{\mu}_{i,t-1})]$, and the residual part $\tilde{\mu}_{i,t-1}$, which can be written as

$$\tilde{\mu}_{i,t-1} := -\frac{1}{\sigma}\big\{\log(1-\hat{\mu}_{i,t-1}) - \hat{E}_{t-1}[\log(1-\hat{\mu}_{i,t-1})]\big\}.$$

- The second line of equation (A.11) is equal to

$$-\frac{1}{\sigma}\sum_{j=0}^{J_{i,t}}\theta_{i,t,t+j}(\hat{E}_t Z'_{i,t+j}\varphi^{p}_{t+j} - \hat{E}_{t-1}Z'_{i,t+j}\varphi^{p}_{t+j})$$

because $(\epsilon_t,\zeta_t)_t \perp (Z_{it},\varphi^{p1}_t,\varphi^{y1}_t,\varphi^{r}_t)_t$. By the same reason, the third and the fourth lines of equation (A.11) can be re-written as

$$\sum_{j=0}^{J_{i,t}}\pi_{i,t}\gamma_{i,t,t+j}(\hat{E}_t Z'_{i,t+j}\varphi^{y}_{t+j} - \hat{E}_{t-1}Z'_{i,t+j}\varphi^{y}_{t+j})$$

and

$$\sum_{j=0}^{J_{i,t}}(\pi_{i,t}\gamma_{i,t,t+j} - (1-\frac{1}{\sigma})\theta_{i,t,t+j})(\hat{E}_t \log Q_{t,t+j} - \hat{E}_{t-1}\log Q_{t,t+j}),$$

respectively.

- In the fifth line of equation (A.11),

$$E_t(P_{i,t}+\epsilon_{i,t}) - E_{t-1}(P_{i,t}+\epsilon_{i,t}) = \zeta_{i,t}+\epsilon_{i,t}$$

and

$$E_t(P_{i,t+j}+\epsilon_{i,t+j}) - E_{t-1}(P_{i,t+j}+\epsilon_{i,t+j}) = \zeta_{i,t}, \quad j \geq 1.$$

Therefore, the fifth line of equation (A.11) can be re-written as $\pi_{i,t}\zeta_{i,t} + \pi_{i,t}\gamma_{i,t,t}\epsilon_{i,t}$.

- I denote the whole term in the sixth line of equation (A.11) as M_t, *i.e.*,

$$M_t := \frac{1}{\sigma}\sum_{j=0}^{J_{i,t}-1}\Big(\sum_{s=j+1}^{J_{i,t}}\theta_{i,t,t+s}\Big)(E_t\log(1-\hat{\mu}_{i,t+j}) - E_{t-1}\log(1-\hat{\mu}_{i,t+j})).$$

I decompose this term into the part explained by the history of aggregate shocks and observable characteristics up to period t, $\hat{E}_t M_t$, and the residual part $\tilde{M}_{i,t} := M_t - \hat{E}_t M_t$.

Then, equation (A.11) becomes

$$\Delta c_{i,t} = \tilde{\mu}_{i,t-1} + \pi_{i,t}\zeta_{i,t} + \pi_{i,t}\gamma_{i,t,t}\epsilon_{i,t} + \tilde{M}_{i,t} + \xi_{i,t} \tag{A.12}$$

in which

$$\begin{aligned}
\xi_{i,t} =& - \Delta(Z'_{i,t}\varphi^c_t) + \frac{1}{\sigma}\Delta(Z'_{i,t}\varphi^p_t) + Z'_{i,t-1}\varphi^{\beta,r}_{t-1} - \frac{1}{\sigma}\hat{E}_{t-1}[\log(1-\hat{\mu}_{i,t-1})] \\
& - \frac{1}{\sigma}\sum_{j=0}^{J_{i,t}} \theta_{i,t,t+j}(\hat{E}_t Z'_{i,t+j}\varphi^p_{t+j} - \hat{E}_{t-1} Z'_{i,t+j}\varphi^p_{t+j}) \\
& + \sum_{j=0}^{J_{i,t}} \pi_{i,t}\gamma_{i,t,t+j}(\hat{E}_t Z'_{i,t+j}\varphi^y_{t+j} - \hat{E}_{t-1} Z'_{i,t+j}\varphi^y_{t+j}) \\
& + \sum_{j=0}^{J_{i,t}} (\pi_{i,t}\gamma_{i,t,t+j} - (1-\frac{1}{\sigma})\theta_{i,t,t+j})(\hat{E}_t \log Q_{t,t+j} - \hat{E}_{t-1} \log Q_{t,t+j}) \\
& + \hat{E}_t M_t.
\end{aligned}$$

By construction, we have $Ec_{i,t} = Ec_{i,t-1} = E\tilde{\mu}_{i,t-1} = E\tilde{M}_{i,t} = 0$ (since they are defined as residuals). We also have $E[\pi_{i,t}\zeta_{i,t}] = E[\hat{E}_{t-1}[\pi_{i,t}\zeta_{i,t}]] = E[\pi_{i,t}\hat{E}_{t-1}[\zeta_{i,t}]] = E[\pi_{i,t}E[\zeta_{i,t}]] = 0$. In the same way, we can show $E[\pi_{i,t}\gamma_{i,t,t}\epsilon_{i,t}] = 0$. Therefore, from equation (A.12), we have

$$E\xi_{i,t} = 0.$$

Moreover, because $\xi_{i,t}$ is a function of $(Z_{i,t-s})_{s\geq 0}$, $(\varphi^{p1}_{t-s})_{s\geq 0}$, $(\varphi^{y1}_{t-s})_{s\geq 0}$, and $(r_{t-s})_{s\geq 0}$, we have

$$(\zeta_{i,t}, \epsilon_{i,t})_t \perp (\xi_{i,t})_t.$$

B Details on Data

In this section, I provide details of the ENAHO survey, variable construction, and sample selection that are omitted in the main text for the sake of conciseness.

B.1 ENAHO Survey

ENAHO is a nationally representative household survey in Peru conducted by Instituto Nacional de Estadística e Informática (INEI), the national statistical office of Peru. This survey is conducted nationwide, covering both urban and rural areas. ENAHO targets people living in private dwellings but excludes inhabitants living in collective housing (such as people living in hospitals, barracks, police stations, hotels, asylums, religious cloisters, and detention centers, and armed forces living in barraks, camps, and boats).

In ENAHO, sample dwellings are selected from census data through multiple stages of stratified sampling. For the selected addresses, trained interviewers visit and collect data via face-to-face interview with the interviewees. ENAHO's manuals for pollsters (Instituto Nacional de Estadística e Informática, 2004, 2007, 2010-2016) indicate that interviewers make multiple visits whenever necessary to correct mistakes or recover missing information.

Table B.1 reports the non-response rates of each year documented in ENAHO's quality reports (Instituto Nacional de Estadística e Informática, 2009-2016) in which non-response rates are defined as 'the proportion of occupied dwellings of which informants do not want to be interviewed or are absent at the time of visit'. The average non-response rate during the sample years (2004-2016) is 7.5%. According to the quality reports, the non-response rates tend to be higher in urban areas than rural areas. Moreover, socioeconomic strata with higher income tend to exhibit higher non-response rates. These patterns raise a usual concern for surveys of this kind that rich households in urban areas are under-represented. In ENAHO, this concern is at least partially addressed by adjusting weights at a certain level of sampling strata reflecting geographic regions, urbanity, and socioeconomic status.

Table B.1: Non-response Rates in ENAHO

2004	2005	2006	2007	2008	2009	2010
9.0%	13.3%	7.9%	5.2%	6.8%	6.4%	7.2%
2011	2012	2013	2014	2015	2016	average
8.3%	6.8%	6.8%	6.6%	7.2%	6.6%	7.5%

Notes: The non-response rates of each year in this table are from ENAHO's quality reports (Instituto Nacional de Estadística e Informática, 2009-2016).

B.2 Variable Construction

My consumption measure for ENAHO builds on Kocherlakota and Pistaferri (2009)'s expenditure categories for Consumer Expenditure (CEX) Interview Survey. Most of their categories – such as food at home, food away from home, alcohol, apparel and footwear, clothing services, tobacco, heating, utilities, public transportation, gasoline and oil, vehicle maintenance and repairs, parking fees, newspapers and magazines, club membership fees, ticket admissions, miscellaneous entertainment expenses, home rent, home maintenance and repairs, telephone and cable, domestic services, other home services, personal care services, and miscellaneous rentals and repair – have corresponding expenditure items in ENANO.[39] In addition to them, I add two more expenditure categories including rental equivalence of owned or donated housing and daily nondurable goods.[40] Following Attanasio and Weber (1995) and Kocherlakota and Pistaferri (2009), I exclude health and education expenses from the consumption measure due to their durable nature.

The consumption measure of Kaplan et al. (2014b) is consistent with my consumption measure for ENAHO in that it is also composed of nondurable goods and a subset of services and that it also includes home rent and housing service from owned or donated housing. One notable difference between the two consumption measures is that their consumption measure includes health and education expenses. Therefore, I adopt their consumption measure with one revision that health and education expenses are excluded.

Like many other household surveys, missing information is imputed in both expense and income items in ENAHO. Imputed components of income could be particularly problematic in identifying income shocks given that many households rely only on a small number of income sources. Therefore, I exclude the imputed income components from the income of Peruvian households. As discussed in subsection III.B, I cannot do the same for the income of U.S. households, and therefore, I conduct a robustness check by consistently including the imputed components of Peruvian households' income in online Appendix D.1.3.

Unlike the imputed components of income, I do not remove the imputed components of expense from the consumption of Peruvian households. Note that imputation is conducted only when households report that they obtain some items but do not report their values. Given that households obtain a variety of expense items, when households miss the values on a subset of expense items, reflecting the fact that households obtain these

[39] Among Kocherlakota and Pistaferri (2009)'s expenditure categories, vehicle expenses, books, home insurance, and babysitting do not have corresponding expenditure items in ENAHO.

[40] Daily nondurable goods include laundry items such as detergent and bleach, bathroom items such as toilet papers and cleaning supplies, and daily care items such as soap, toothpaste, and shampoo. These items are not in CEX Interview Survey which Kocherlakota and Pistaferri (2009) use.

items using imputed values could still be helpful in measuring consumption responses.

In ENAHO, some expense items require judgment calls on determining their reference periods. ENAHO's questionnaires on expenditure proceed as follows. For each expense item, households are asked if they obtain it during period A. If the answer is yes, households are asked to report how much they spent on the item per period B. For most expense items, period A is equal to period B. Then, this period becomes the reference period for the expense item. However, there are cases in which period A and period B differ. For example, many food items have 'last 15 days' as period A, but households can choose period B. When period A and period B differ, I use the longer period between period A and period B as the reference period for the expense item.

As discussed in subsection III.B, in ENAHO, individual households report more than 97 percent (in value) of expense items and income items, respectively, with reference periods shorter than or equal to the previous three months, on average. Specifically, individual households' ratio between 'items with reference periods longer than the previous three months' and 'items with all reference periods' for the baseline measure of consumption is 1.74 percent, on average. The ratio for the baseline measure of income is 2.51 percent, on average.

Both countries' income and consumption are deflated with CPI series. Regarding the deflation of Peruvian households' income and consumption, ENAHO provides within-year-deflated values of income and expense items (or, equivalently, values in terms of the CPI index of the survey year). For example, ENAHO provides the value of a household's food expense spent on February, 2004 in terms of the 2004 price level. In constructing the real income and consumption of Peruvian households, I aggregate these within-year-deflated values of income and expense items, respectively, and then, deflate the aggregated values using annual CPI series of Peru.

B.3 Sample Selection

Here, I provide details of the sample selection omitted in the main text. In the second step, gender and age are used as the criteria for determining whether the head of the household changes. In the sixth step, type-1 observations are dropped if any of their (i) baseline consumption measure, (ii) baseline income measure, and (iii) comprehensive income measure including imputed income components and income items with reference periods longer than the previous three months are zero or negative. In the seventh step, the criterion for 'having too much value' is set as follows. For each $(x, y) \in \{$(expense items with reference periods longer than the previous three months, baseline consumption measure), (income items with reference periods longer than the

Table B.2: Baseline Sample Selection for ENAHO

	type-1	type-2	type-3
initial sample	113,329	74,667	36,005
months not matched, fake type-2 obs., or head changed	100,282	64,103	27,924
incomplete survey	86,396	49,738	20,295
age restriction, 25-65	67,681	38,380	15,496
observable characteristics missing	67,384	38,314	15,493
non-positive Y and C	66,961	37,863	15, 244
too much imputation in Y or 3ml in Y, C	47,819	22,354	7,666
outliers on income growth	47, 210	21, 988	7,509

Notes: In the penultimate line of the table, '3ml' is an abbreviation for 'items with reference periods longer than the previous three months'.

previous three months, baseline income measure), (income imputation, baseline income measure)}, observations are dropped if $x/(x+y) > 0.05$. In the eighth step, I define income outliers as households whose income growth is in the range of the extreme 1 percent (0.5 percent at the top and 0.5 percent at the bottom) in the calendar-year subsamples at least one time. Table B.2 reports how many observations of each type are dropped in each step.

For the U.S. households, I adopt Kaplan et al. (2014b)'s sample selection with three minor revisions. First, they restrict household heads' ages to be between 25 and 55. I revise this age restriction to be between 25 and 65 for the sake of consistent sample selection with the Peruvian sample. In online Appendix D.1.10 and D.2.6, I conduct a robustness check by revising the age restriction of both the U.S. and Peruvian samples to be between 25 and 55. Second, when controlling consumption and income with observable characteristics, Kaplan et al. (2014b) use only type-1 observations that belong to at least one type-3 observation. I additionally use type-1 observations that belong to at least one type-2 observation when controlling consumption and income with observable characteristics and constructing income distribution. Third, there are type-1 observations that miss either income or consumption, but not both. Kaplan et al. (2014b) allow them to be used when controlling income and consumption with observable characteristics. For example, if a type-1 observation misses income but does not miss consumption, it is used in controlling consumption. Instead, I use only type-1 observations that do not miss both income and consumption when controlling income and consumption with observable characteristics.

A remaining difference between Kaplan et al. (2014b)'s sample selection and my ENAHO sample selection is the criteria for income outliers. Kaplan et al. (2014b) categorize households as income outliers if their nominal income is below 100 Dollars or their income growth is greater than 5 or less than -0.8 at least one time. I do not use this criteria in my baseline selection for the Peruvian sample because it is not straightforward to determine the right cutoffs for Peruvian households reflecting cross-country differences including the difference in growth units (the two-year-over-two-year growth of annual income for U.S. households, the year-over-year growth of quarterly income for Peruvian households). In online Appendix D.1.11 and D.2.7, I conduct a robustness check by defining Peruvian income outliers in a more similar fashion with Kaplan et al. (2014b), despite the difficulty of finding the right corresponding cutoffs.

B.4 Detecting Potentially Fake Type-2 Observations

In ENAHO, panel observations are selected based on addresses. When an old household moves away and a new household moves into an address selected for a panel interview, ENAHO's manuals for pollsters (Instituto Nacional de Estadística e Informática, 2004, 2007, 2010-2016) indicate that the interview proceeds with the new household. However, the manual does not specify whether the observation on the new household will be distinguished from the previous observations on the old household or it will be falsely linked to the observations and create a fake type-2 observation. The latter case is problematic for the analyses of this paper.

Fortunately, there is an effective way to identify type-2 observations that are subject to this problem. ENAHO tracks not only households but also their members over time. Specifically, variable 'p215' records each household member's year-specific identification number (the unique number assigned in each year's survey to enumerate each member from 1 onward) in the previous year. This variable makes it possible to track household members over time. When two different households are falsely linked as a type-2 observation, we will observe that either household members are not linked by variable 'p215' or different persons are falsely linked by variable 'p215'. At persons' level, it is easier to determine whether the two persons linked by variable 'p215' are the same person since ENAHO collects household members' date of birth (dd/mm/yyyy) and gender. If two persons linked by variable 'p215' have the same birth date and gender, it is highly likely that they are the same person. And if the same person appears in the two households linked as a type-2 observation, it is highly likely that this type-2 observation is correctly tracking the same household over time. On the other hand, if we cannot verify any common person appearing in two households linked as a type-2 observation, it is not free from the problem of linking two different households.

Based on this logic, I link household members over time using variable 'p215', and identify linked persons whose date of birth and gender are exactly equal in the two interviews. I name them 'verified same members'. Despite a nontrivial chance that household members' birth dates are not exactly reported, it turns out that most type-2 observations do have at least one verified same member. I identify type-2 observations that do not have any verified same member, and define them as 'potentially fake type-2 observations'. I drop them in the sample selection.

Combined with the other steps of the sample selection, a selected type-2 observation satisfies the following conditions: it connects households that (i) live in the same address, (ii) have at least one verified same member, and (iii) have heads with the same age and gender. It is highly likely that such a type-2 observation correctly tracks the same household over time. In online Appendix D.1.13 and D.2.9, I apply even a stricter rule in detecting potentially fake type-2 observations at the cost of a smaller sample size as follows: if the number of verified same members of a type-2 observation is less than half of the household size for any of the two households connected as the type-2 observation, I identify it as a potentially fake type-2 observation and drop it.[41] The main findings are robust to applying this stricter rule.

C Estimates and Standard Errors in Tables

In this section, I report in tables the estimates and the standard errors that are used to plot figures in the main text.

Table C.1: Annual MPCs of the Income Deciles in Peru and the U.S.

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
Peru	0.942	0.668	0.666	0.671	0.678	0.654	0.660	0.528	0.556	0.299
	(0.052)	(0.104)	(0.091)	(0.087)	(0.083)	(0.080)	(0.075)	(0.084)	(0.082)	(0.086)
N	758	827	833	787	730	699	724	743	704	704
U.S.	0.160	0.096	0.083	0.129	0.123	0.077	0.087	0.077	0.023	0.036
	(0.083)	(0.050)	(0.043)	(0.045)	(0.030)	(0.029)	(0.032)	(0.030)	(0.034)	(0.017)
N	1,332	1,467	1,504	1,539	1,573	1,560	1,567	1,472	1,413	1,363

Notes: The estimates and the standard errors reported in this table are used to plot Figure 1.

[41]Under the stricter rule, the number of type-3 observations shrinks from 7,509 to 6,324.

Table C.2: Group Average Consumption Growth Difference against the Top Income Decile

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
Peru	0.302	0.232	0.197	0.168	0.142	0.108	0.097	0.051	0.044	0
	(0.014)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(n.a.)
N	2,364	2,375	2,309	2,230	2,177	2,080	2,116	2,116	2,134	2,087
U.S.	0.078	0.049	0.048	0.030	0.039	0.035	0.029	0.032	0.027	0
	(0.013)	(0.012)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(n.a.)
N	1,811	1,949	2,031	2,058	2,076	2,091	2,055	1,978	1,938	1,859

Notes: The estimates and the standard errors reported in this table are used to plot Figure 3.

D Robustness

D.1 Robustness for the MPC Estimation

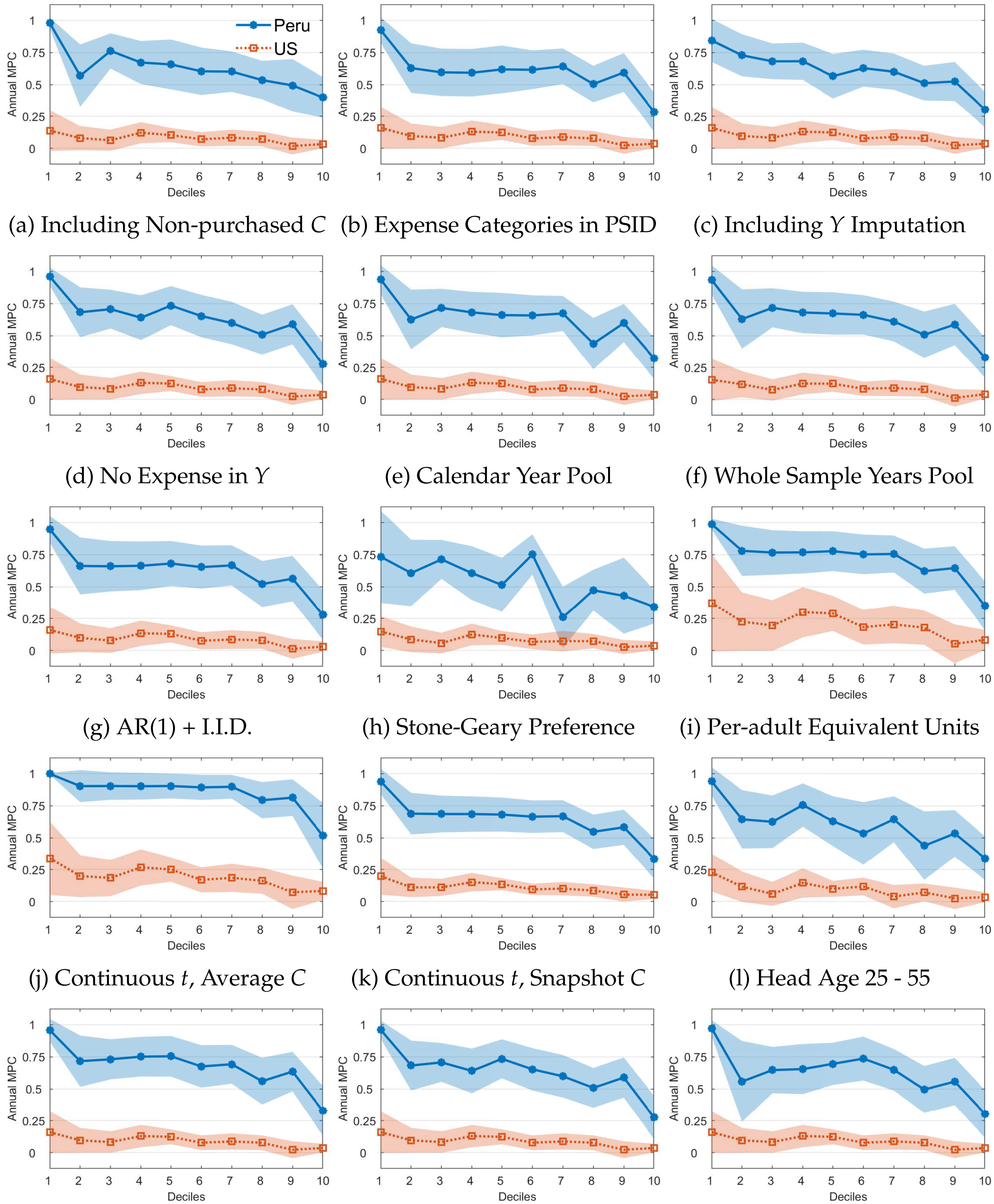
In this subsection, I present the results of the robustness checks that I conduct regarding the MPC estimation. Each panel of Figure D.1 plots the result of each robustness check. These panels in Figure D.1 verify that the main findings in Figure 1 – (i) the mean MPC being substantially higher and (ii) within-country MPC heterogeneity over the income distribution being substantially stronger in Peru than in the U.S.– are robust to the following alternative setups.

D.1.1 Including Non-purchased Consumption

In the baseline consumption measure, I exclude non-purchased consumption such as donations, food stamps, in-kind income, and self-production. In this robustness check, I use an alternative consumption measure that includes the non-purchased consumption. Figure D.1a plots the result.

D.1.2 Restricting Expense Categories to Those Available in the PSID

Due to the lack of coverage in the early waves in the U.S. sample, the baseline consumption of U.S. households does not include clothing, recreation, alcohol, and tobacco, while the baseline consumption of Peruvian households includes them. Here, I conduct a robustness check by consistently excluding these expenses from the consumption of Peruvian households. Figure D.1b plots the result.



(a) Including Non-purchased C (b) Expense Categories in PSID (c) Including Y Imputation

(d) No Expense in Y (e) Calendar Year Pool (f) Whole Sample Years Pool

(g) AR(1) + I.I.D. (h) Stone-Geary Preference (i) Per-adult Equivalent Units

(j) Continuous t, Average C (k) Continuous t, Snapshot C (l) Head Age 25 - 55

(m) Alternative Income Outliers (n) Male Heads Only (o) Stricter Rule for Fake Type-2

Figure D.1: Robustness – Annual MPCs

Notes: In the x-axis of each panel, 1 is the bottom decile. Shaded areas represent 95% confidence intervals.

D.1.3 Including Imputed Income Components

The baseline income measure for the Peruvian sample excludes imputed income components. Moreover, I drop observations that include too much value in the imputed income components in the Peruvian sample selection. These treatments are not available in the U.S. sample because the imputed components of income are not distinguishable in Kaplan et al. (2014b)'s dataset. Here, I conduct a robustness check by consistently including the imputed components of Peruvian households' income. Moreover, the observations with too much value in the imputed income components are not dropped. Figure D.1c plots the result.

D.1.4 Excluding Expense Items from Income

The income measure for ENAHO includes two expense items that are also included in the consumption of Peruvian households: rental equivalence of housing provided by work and rental equivalence of donated housing. On the other hand, the income of U.S. households does not include any expense items that are included in their consumption. Here, I conduct a robustness check by consistently excluding the two expense items from Peruvian households' income. Figure D.1d plots the result.

D.1.5 Sorting Income ($y_{i,t}$) in Different Observation Pools

In the baseline analysis, I sort unpredictable component of income $y_{i,t}$ within each calendar year for the U.S. sample and within each calendar quarter for the Peruvian sample, in accordance with the unit time length of each sample (a year for the U.S. sample, a quarter for the Peruvian sample). However, because I already remove the time-fixed effect when controlling for the predictable components (annually for the U.S. sample, quarterly for the Peruvian sample), it should also be fine to sort unpredictable component of income $y_{i,t}$ in a larger observation pool than the pool of the unit time length. In this robustness check, I sort income in different observation pools such as (i) the pool of each calender year (not only for the U.S. sample, but also for the Peruvian sample), and (ii) the pool of the whole sample years. Figure D.1e and Figure D.1f plot the MPC estimation results under the pool of each calendar year and the pool of the whole sample years, respectively.

D.1.6 Replacing the Permanent Component of Income with an AR(1) Process

In the baseline analysis, the unpredictable component of income $y_{i,t}$ is assumed to be composed of a permanent component and a transitory component, following Blundell et al. (2008) and Kaplan et al. (2014b). This income process is restrictive in that an income shock cannot have a persistent effect without being permanent. Kaplan and Violante (2010) propose a way to identify Blundell et al. (2008)'s partial insurance parameters under an alternative income process composed of an AR(1) component and a transitory component. Adopting their identification strategy, I estimate the MPCs under the alternative income process.

The identification strategy works as follows. Assume that households' income $Y_{i,t}$ is determined by

$$\log Y_{i,t} = Z'_{i,t}\varphi^y_t + P_{i,t} + \epsilon_{i,t},$$

$$P_{i,t} = \rho P_{i,t-1} + \zeta_{i,t},$$

$$\zeta_{i,t} \sim_{iid} (0, \sigma^2_{ps}), \quad \epsilon_{i,t} \sim_{iid} (0, \sigma^2_{tr}), \quad (\zeta_{i,t})_t \perp (\epsilon_{i,t})_t, \quad \text{and}$$

$$(Z_{i,t})_t \perp (\zeta_{i,t}, \epsilon_{i,t})_t.$$

As before, $y_{i,t} := \log Y_{i,t} - Z'_{i,t}\varphi^y_t$ represents the unpredictable component of income. Let

$$\tilde{\Delta}^K y_{i,t} := y_{i,t} - \rho^K y_{i,t-K}.$$

Then we have

$$\tilde{\Delta}^K y_{i,t} = \sum_{s=0}^{K-1} \rho^s \zeta_{i,t-s} + \epsilon_{i,t} - \rho^K \epsilon_{i,t-K} \tag{D.1}$$

for any $K \geq 1$. As in equation (11), the partial insurance parameter to transitory income shocks ψ_G for each group G is defined as follows.

$$\psi_G := \frac{cov[\Delta c_{i,t}, \epsilon_{i,t} | (i,t) \in G]}{cov[\Delta y_{i,t}, \epsilon_{i,t} | (i,t) \in G]}.$$

When the grouping of observation (i,t)'s is independent of $\epsilon_{i,t}$, the characterization of ψ_G in equation (12) still holds under the alternative income process as follows.

$$\psi_G = \psi_G^{PIH} + \frac{cov[\epsilon_{i,t}, \tilde{M}_{i,t} | (i,t) \in G]}{var[\epsilon_{i,t} | (i,t) \in G]}.$$

When the grouping of observation (i,t)'s is independent of $(\zeta_{i,t+j}, \epsilon_{t+j})_{j \geq 0}$, we can derive

$$\psi_G = \frac{cov[\Delta^K c_{it}, \tilde{\Delta}^K y_{i,t+K} | (i,t) \in G]}{cov[\tilde{\Delta}^K y_{it}, \tilde{\Delta}^K y_{i,t+K} | (i,t) \in G]} \tag{D.2}$$

from equations (10) and (D.1).

To identify ψ_G using equation (D.2), we need to know the value of ρ^K to compute $\tilde{\Delta}^K y_{i,t}$ and $\tilde{\Delta}^K y_{i,t+K}$. I estimate ρ^K using the following equation.

$$\rho^K = \frac{cov[y_{i,t}, y_{i,t-2K}]}{cov[y_{i,t-K}, y_{i,t-2K}]} = \frac{\rho^{2K} var(P_{i,t-2K})}{\rho^K var(P_{i,t-2K})}. \tag{D.3}$$

In the Peruvian sample, the estimate (standard error[42]) of ρ^4 is 0.939 (0.020). Since the time unit is a quarter, the estimate of ρ^4 represents Peruvian households' annual autocorrelation coefficient for their persistent income shocks. In the U.S. sample, the estimate (standard error) of ρ^2 is 0.923 (0.010). Since the time unit is a year, the estimate of ρ^2 represents U.S. households' biannual autocorrelation coefficient for their persistent income shocks. The fact that the estimates of ρ^K for both countries are close to 1 assures that the specification of the income process imposed in the baseline analysis (random walk + i.i.d) is not seriously flawed.

Figure D.1g plots the MPCs I estimate using equation (D.2), the estimates of ρ^K from equation (D.3), and equation (14).

D.1.7 Incorporating a Subsistence Point into the Preference

Consumption being close to a subsistence level is more likely in Peru than in the U.S. In this robustness check, I estimate MPCs after incorporating a subsistence level into the model. Specifically, I replace the household uitility function of the baseline model with the one developed by Stone (1954) and Geary (1950) under which households obtain utility only from consumption beyond a subsistence point. Under the Stone-Geary preference, households solve the following problem.

$$\max_{\{C_{i,t+j}, A_{i,t+j}\}_{j=0}^{J_{i,t}}} E\left[\sum_{j=0}^{J_{i,t}} \beta^j e^{(Z'_{i,t+j}\varphi^p_{t+j})} \frac{(C_{i,t+j} - \underline{C})^{1-\sigma}}{1-\sigma} \middle| \mathbf{S}_{i,t} \right]$$

$$s.t.$$

$$C_{i,t+j} + A_{i,t+j} = Y_{i,t+j} + (1 + r_{t+j-1}) A_{i,t+j-1}, \quad 0 \le j \le J_{i,t}, \tag{SBC}$$

$$A_{i,t+j} \ge 0, \quad 0 \le j \le J_{i,t} - 1, \tag{LQC}$$

$$A_{i,t+J_{i,t}} \ge 0 \tag{NPG}$$

in which $\underline{C}$ represents the subsistence point of consumption. To make sure the problem is well-defined, I assume that households' income $Y_{i,t}$ is always greater than $\underline{C}$ and is

[42] In the estimation, standard errors are clustered within each household.

determined by

$$\log(Y_{i,t} - \underline{C}) = Z'_{i,t}\varphi_t^{y*} + P_{i,t} + \epsilon_{i,t},$$

$$P_{i,t} = P_{i,t-1} + \zeta_{i,t},$$

$$\zeta_{i,t} \sim_{iid} (0, \sigma_{pm}^2), \quad \epsilon_{i,t} \sim_{iid} (0, \sigma_{tr}^2), \quad (\zeta_{i,t})_t \perp (\epsilon_{i,t})_t, \quad \text{and}$$

$$(Z_{i,t})_t \perp (\zeta_{i,t}, \epsilon_{i,t})_t.$$

Let

$$\begin{aligned} C^*_{i,t} &:= C_{i,t} - \underline{C}, \quad \text{and} \\ Y^*_{i,t} &:= Y_{i,t} - \underline{C}. \end{aligned} \tag{D.4}$$

By substituting equation (D.4) into the households' problem and the income process specified above, we can observe that the model with Stone-Geary preference is isomorphic to the baseline model in subsection II.A, except for $(C_{i,t}, Y_{i,t})$ of the baseline model being replaced with $(C^*_{i,t}, Y^*_{i,t})$. Exploiting this isomorphism, we can estimate the annual MPC using the following equations.

$$\psi_G = \frac{cov[\Delta^K c^*_{it}, \Delta^K y^*_{i,t+K} | (i,t) \in G]}{cov[\Delta^K y^*_{it}, \Delta^K y^*_{i,t+K} | (i,t) \in G]}, \quad K \geq 1, \quad \text{and} \tag{D.5}$$

$$MPC_G = \psi_G \frac{E[C^*_{i,t-K} | (i,t) \in G]}{E[Y^*_{i,t-K} | (i,t) \in G]}. \tag{D.6}$$

in which $c^*_{i,t} := \log C^*_{i,t} - Z'_{i,t}\varphi_t^{c*}$ is the unpredictable component of $\log C^*_{i,t}$ and $y^*_{i,t} := \log Y^*_{i,t} - Z'_{i,t}\varphi_t^{y*}$ is the unpredictable component of $\log Y^*_{i,t}$.

When computing $C^*_{i,t}$ and $Y^*_{i,t}$ using equation (D.4), I use the consumption measure including non-purchased consumption for $C_{i,t}$ and the baseline measure of income for $Y_{i,t}$. I calibrate the subsistence point $\underline{C}$ to be equal to one of the poverty lines that World Bank uses, \$ 3.20 per day in 2011 International Dollar. Observations with $C_{i,t} \leq \underline{C}$ or $Y_{i,t} \leq \underline{C}$ are dropped. The unpredictable components, $c^*_{i,t}$ and $y^*_{i,t}$ are constructed by controlling for the predictable components from $\log C^*_{i,t}$ and $\log Y^*_{i,t}$. As in the baseline analysis, when constructing income groups I include observations dropped due to having too much value in imputed income components or to having too much value in items with reference periods longer than the previous three months. For the purpose of income sorting, I use the unpredictable component of the comprehensive income measure (which includes not only the baseline measure of income but also the income items with reference periods longer than the previous three months and the imputed income components) minus the subsistence point, $\underline{C}$. Figure D.1h plots the result of the MPC estimation.

D.1.8 Treating Unpredictable Components as Per-Adult Equivalent Units

In the model discussed in subsection II.A, the vector of observable characteristics $Z_{i,t}$ appears in two places: one in the preference shift $Z'_{i,t}\varphi^p_t$ and the other in the predictable component of income $Z'_{i,t}\varphi^y_t$. They appear in these places to make the model consistent with the data pattern that a sizable portion of income and consumption variations are explained by observable characteristics.

Some studies such as Guvenen and Smith (2014) do not have these terms in the model and instead assume that the residuals of income and consumption after controlling for observable characteristics are income and consumption of per-adult equivalent units, and the residuals should be explained by the model. This alternative approach does not affect the estimation of Blundell et al. (2008)'s partial insurance parameters, but affects which consumption-to-income ratio to be multiplied in converting the partial insurance parameters to MPC. In the baseline analysis, I use $\frac{E[C_{i,t-K}|(i,t)\in G]}{E[Y_{i,t-K}|(i,t)\in G]}$, as described in equation (14). Note that both $C_{i,t-K}$ and $Y_{i,t-K}$ include the predictable components $Z'_{i,t-K}\varphi^c_{t-K}$ and $Z'_{i,t-K}\varphi^y_{t-K}$. On the other hand, in the approach of treating $c_{i,t}$ and $y_{i,t}$ as the log consumption and log income of per-adult equivalent units, $\frac{E[\exp(c_{i,t-K})|(i,t)\in G]}{E[\exp(y_{i,t-K})|(i,t)\in G]}$ should be multiplied, instead.

In this robustness check, I take this alternative approach and estimate MPCs by multiplying the Blundell et al. (2008)'s partial insurance parameters with $\frac{E[\exp(c_{i,t-K})|(i,t)\in G]}{E[\exp(y_{i,t-K})|(i,t)\in G]}$. Figure D.1i plots the MPC estimation result under this approach.

D.1.9 Addressing the Time Aggregation Problem and the Time Inconsistency Problem in a Continuous Time Model

As Crawley (2019) notes, continuous-time models are useful in dealing with two possible issues in discrete time models: the time aggregation problem and the time inconsistency problem. The time aggregation problem means that a completely transitory shock in a continuous-time process can generate an autocorrelation in a discrete-time process constructed by aggregating the continuous-time process over a specified period. The time inconsistency problem means the reference period for consumption could be inconsistent with the reference period for income because of the intended design of a survey, unclear description of questionnaires, and greater difficulties in recalling memory regarding expenses. In this robustness check, I address these issues using a continuous-time model, as in Crawley (2019).

Crawley (2019) presents a continuous-time model in which a level income process and a level consumption function are specified (instead of a log income process and a log consumption function) because level variables are more convenient to aggregate over time than log variables. In the model, the level consumption follows a random walk that moves only in response to current shocks on the level income. Then, the author shows in appendix that the identifying equations in the continuous-time model with the level specifications become equal to the identifying equations in a discrete-time model with log specifitaions under a first-order approximation as the discrete timeframe approaches to a continuous one in a limit. However, the income process specified in the author's discrete-time model is different from the income process in Blundell et al. (2008). Moreover, it is not clear how the consumption function should be specified in the discrete-time model for the equivalence of the identifying equations between the discrete-time model and the continuous-time model.[43]

The model presented here is borrowed from Crawley (2019) but with two modificiations. First, as in the appendix of Crawley (2019), I begin from a discrete-time model with log specifications, derive the identifying equations under a first-order approximation, and obtain their limits as the discrete timeframe approaches to a continuous one, but I use a different first-order approximation which allows my discrete-time model to have the same income process as the one in Blundell et al. (2008). Second, I specify the consumption function in such a way that the dynamic consumption responses to a transitory income shock decay exponentially over time.[44]

As in the appendix of Crawley (2019), I begin with a discrete-time model with m sub-periods. I enumerate the discrete time index for the sub-periods t as $t = \frac{1}{m}, \frac{2}{m}, \cdots, \frac{m-1}{m}, 1, 1 + \frac{1}{m}, \cdots$. The time length of 1 in the t-axis (*i.e.*, $\Delta t = 1$) corresponds to the unit time length of the observations. It is a quarter in the Peruvian sample and a year in the U.S. sample. $Y_{i,t}$ and $C_{i,t}$ represent income and consumption during sub-period t. $\bar{Y}_T$ and $\bar{C}_T$ represent the total income and consumption during the period of the unit time length ($\Delta t = 1$) ending at $t = T$. In other words,

$$\bar{Y}_T := Y_{i,T-1+\frac{1}{m}} + Y_{i,T-1+\frac{2}{m}} + \cdots + Y_{i,T} \tag{D.7}$$

[43] Crawley (2019)'s appendix only shows the equivalence of the identifying equation for the variance in income growth.

[44] This specification is consistent with Auclert (2019)'s conversion formula between quarterly MPC and annual MPC. Admittedly, however, the consumption function is not derived from the optimality condition of households' problem. Deriving testable implications from the optimality conditions of a continuous-time model (or from the optimality conditions of a discrete-time model in a continuous-time limit), would be an interesting extension in this line of investigation.

and

$$\bar{C}_T := C_{i,T-1+\frac{1}{m}} + C_{i,T-1+\frac{2}{m}} + \cdots + C_{i,T}. \tag{D.8}$$

The log income process and the log consumption function are specified as follows.

$$\log Y_{i,t} = P_{i,t} + \epsilon_{i,t} \tag{D.9}$$

in which

$$P_{i,t} = P_{i,t-\frac{1}{m}} + \zeta_{i,t},$$

$$\zeta_{i,t} \sim_{iid} (0, \sigma^2_{pm,m}), \quad \epsilon_{i,t} \sim_{iid} (0, \sigma^2_{tr,m}), \quad (\zeta_{i,t})_t \perp (\epsilon_{i,t})_t.$$

$$\Delta^{\frac{1}{m}} \log C_{i,t} = \phi\zeta_{i,t} + \sum_{k=0}^{\infty} \psi_{\frac{k}{m}} \epsilon_{i,t-\frac{k}{m}} \tag{D.10}$$

in which $\Delta^s x_t := x_t - x_{t-s}$ for any time-series $(x_t)_t$ and any $s > 0$. As in the main text, I omit s from Δ^s when $s = 1$.

Let

$$\Psi_{\frac{j}{m}} := \psi_0 + \psi_{\frac{1}{m}} + \cdots + \psi_{\frac{j}{m}}$$

and

$$\overrightarrow{\Psi}_{\frac{j}{m}} := \Psi_{\frac{0}{m}} + \Psi_{\frac{1}{m}} + \cdots + \Psi_{\frac{j}{m}}.$$

By summing up equation (D.10) over j sub-periods, we get

$$\Delta^{\frac{j}{m}} \log C_{i,t+j} = \big(\psi_0 + \psi_{\frac{1}{m}} + \cdots + \psi_{\frac{j}{m}}\big)\epsilon_{i,t} + \big(\text{other terms unrelated with } \epsilon_{i,t}\big).$$

Therefore, the dynamic consumption response in sub-period $t + j$ to a transitory income shock in sub-period t is $\left(\Psi_{\frac{j}{m}} \cdot \frac{E[C]}{E[Y]}\right)$. The MPC out of a transitory income shock during the period of the unit length ($\Delta t = 1$) after the shock (or, equivalently, the cumulative consumption response to the shock during the period) is

$$MPC = \overrightarrow{\Psi}_{\frac{m-1}{m}} \cdot \frac{E[C]}{E[Y]}. \tag{D.11}$$

From equation (D.7), we have

$$\log(\bar{Y}_{i,T}) = \log\Big(\sum_{j=1}^{m} \exp(\log Y_{i,T-1+\frac{j}{m}})\Big).$$

By first-order-Taylor-approximating $\log Y_{i,T-1+\frac{j}{m}}$ around $E_{T-1}\log(\frac{1}{m}\bar{Y}_{i,T})$ for $j = 1, \cdots, m$ in this equation, we can obtain

$$\log(\bar{Y}_{i,T}) \approx \frac{1}{m}\sum_{j=1}^{m}\log Y_{i,T-1+\frac{j}{m}} + \log m. \tag{D.12}$$

In the same way, equation (D.8) can be re-written as

$$\log(\bar{C}_{i,T}) = \log\Big(\sum_{j=1}^{m}\exp(\log C_{i,T-1+\frac{j}{m}})\Big).$$

By first-order-Taylor-approximating $\log C_{i,T-1+\frac{j}{m}}$ around $E_{T-1}\log(\frac{1}{m}\bar{C}_{i,T})$ for $j = 1, \cdots, m$ in this equation, we can get

$$\log(\bar{C}_{i,T}) \approx \frac{1}{m}\sum_{j=1}^{m}\log C_{i,T-1+\frac{j}{m}} + \log m. \tag{D.13}$$

Let $Y_{i,T}^{obs}$ and $C_{i,T}^{obs}$ be the observed income and consumption in the data during period T. In terms of the relationship between the variables in the model and the variables observed in the data, I consider three cases: (i) $(Y_{i,T}^{obs}, C_{i,T}^{obs}) = (\bar{Y}_{i,T}, \bar{C}_{i,T})$, (ii) $(Y_{i,T}^{obs}, C_{i,T}^{obs}) = (\bar{Y}_{i,T}, C_{i,T})$, and (iii) $(Y_{i,T}^{obs}, C_{i,T}^{obs}) = (Y_{i,T}, \bar{C}_{i,T})$.

Regarding the time inconsistency problem, the first case does not have it as the reference period of the observed income matches that of the observed consumption. In the second case, the observed consumption is the consumption flow during the last sub-period of the reference period for the observed income. This case has the time inconsistency problem in such a way that the reference period for the observed income is longer than that of the observed consumption. In the third case, the observed income is the income flow during the last sub-period of the reference period for the observed consumption. In this case, the time inconsistency problem is present in such a way that the reference period for the observed income is shorter than that for the observed consumption. As discussed in footnote 15 of subsection III.B, the PSID is subject to the time inconsistency problem of the second case, while ENAHO is subject to the time inconsistency problems of both the second and third cases.

The time aggregation problem is present when the observed income is an aggregated income over multiple sub-periods. Therefore, the first and the second cases have the time aggregation problem, while the third case does not.

Case 1. When $(Y_{i,T}^{obs}, C_{i,T}^{obs}) = (\bar{Y}_{i,T}, \bar{C}_{i,T})$

Let

$$y_{i,T}^{obs} := \log Y_{i,T}^{obs}, \quad \text{and}$$
$$c_{i,T}^{obs} := \log C_{i,T}^{obs}.$$

From equation (D.12) and (D.13), we have

$$\Delta y_{i,T}^{obs} = \Delta \log Y_{i,T}^{obs} = \frac{1}{m}\sum_{j=1}^{m}\left(\log Y_{i,T-1+\frac{j}{m}} - \log Y_{i,T-2+\frac{j}{m}}\right) \tag{D.14}$$

and

$$\Delta c_{i,T}^{obs} = \Delta \log C_{i,T}^{obs} = \frac{1}{m}\sum_{j=1}^{m}\left(\log C_{i,T-1+\frac{j}{m}} - \log C_{i,T-2+\frac{j}{m}}\right) \tag{D.15}$$

By substituting equations (D.9) and (D.10) into (D.14) and (D.15) and computing variances and covariances of the observed income growth $\Delta y_{i,T}^{obs}$ and consumption growth $\Delta c_{i,T}^{obs}$, we can obtain the following equations.

$$var[\Delta y_{i,T}^{obs}] = \left(\frac{1}{m} + \frac{(m-1)(2m-1)}{3m^2}\right)(m\sigma_{pm,m}^2) + 2\left(\frac{\sigma_{tr,m}^2}{m}\right),$$

$$cov[\Delta y_{i,T}^{obs}, \Delta y_{i,T+1}^{obs}] = \frac{m^2-1}{6m^2}(m\sigma_{pm,m}^2) - \left(\frac{\sigma_{tr,m}^2}{m}\right),$$

$$cov[\Delta y_{i,T}^{obs}, \Delta y_{i,T+N}^{obs}] = 0, \quad N \geq 2,$$

$$cov[\Delta c_{i,T}^{obs}, \Delta y_{i,T}^{obs}] = \phi\frac{2m^2+1}{3m^2}(m\sigma_{pm,m}^2) + \frac{1}{m}\left\{\sum_{j=0}^{m-1}(3\overrightarrow{\Psi}_{\frac{j}{m}} - \overrightarrow{\Psi}_{1+\frac{j}{m}})\right\}\left(\frac{\sigma_{tr,m}^2}{m}\right),$$

$$cov[\Delta c_{i,T}^{obs}, \Delta y_{i,T+1}^{obs}] = \phi\frac{m^2-1}{6m^2}(m\sigma_{pm,m}^2) - \frac{1}{m}(\sum_{j=0}^{m-1}\overrightarrow{\Psi}_{\frac{j}{m}})\left(\frac{\sigma_{tr,m}^2}{m}\right),$$

$$cov[\Delta c_{i,T}^{obs}, \Delta y_{i,T+N}^{obs}] = 0, \quad N \geq 2,$$

$$\begin{aligned} cov[\Delta c_{i,T}^{obs}, \Delta y_{i,T-1}^{obs}] = \frac{m^2-1}{6m^2}\phi(m\sigma_{pm.m}^2) + \frac{1}{m}\Bigg\{\sum_{j=0}^{m-1}(\overrightarrow{\Psi}_{1+\frac{j}{m}} - 2\overrightarrow{\Psi}_{\frac{j}{m}}) \\ - \sum_{j=0}^{m-1}(\overrightarrow{\Psi}_{2+\frac{j}{m}} - 2\overrightarrow{\Psi}_{1+\frac{j}{m}} + \overrightarrow{\Psi}_{\frac{j}{m}})\Bigg\}\left(\frac{\sigma_{tr,m}^2}{m}\right), \end{aligned}$$

$$cov[\Delta c^{obs}_{i,T}, \Delta y^{obs}_{i,T-N}] = \frac{1}{m}\Big\{ \sum_{j=0}^{m-1}(\overrightarrow{\Psi}_{N+\frac{j}{m}} - 2\overrightarrow{\Psi}_{N-1+\frac{j}{m}} + \overrightarrow{\Psi}_{N-2+\frac{j}{m}}) - \sum_{j=0}^{m-1}(\overrightarrow{\Psi}_{N+1+\frac{j}{m}} - 2\overrightarrow{\Psi}_{N+\frac{j}{m}} + \overrightarrow{\Psi}_{N-1+\frac{j}{m}})\Big\}\left(\frac{\sigma^2_{tr,m}}{m}\right), \quad N \geq 2.$$

Now let's consider a limit in which m approaches infinity, *i.e.*, the discrete-time model approaches a continuous-time model. For the model in the limit to be stationary, we should have

$$\sigma^2_{pm} := \lim_{m\to\infty} m\sigma^2_{pm,m} < \infty \tag{D.16}$$

and

$$\sigma^2_{tr} := \lim_{m\to\infty} \frac{\sigma^2_{tr,m}}{m} < \infty \tag{D.17}$$

Moreover, I assume that the dynamic consumption response to a past transitory shock $\Psi_{\frac{j}{m}}$ decays exponentially over time. In the continuous-time model, this assumption becomes

$$\Psi_t = \tau\lambda e^{-\lambda t}, \quad t \in [0, \infty) \tag{D.18}$$

for $\lambda > 0$ and $\tau > 0$, and

$$\overrightarrow{\Psi}_t = \int_0^t \Psi_t dt = \tau(1 - e^{-\lambda t}), \quad t \in [0, \infty). \tag{D.19}$$

Under equations (D.16), (D.17), (D.18), and (D.19), we have the following equations for variances and covariances of the continuous-time model in the limit.

$$var[\Delta y^{obs}_{i,T}] = \frac{2}{3}\sigma^2_{pm} + 2\sigma^2_{tr}, \tag{D.20}$$

$$cov[\Delta y^{obs}_{i,T}, \Delta y^{obs}_{i,T+1}] = \frac{1}{6}\sigma^2_{pm} - \sigma^2_{tr}, \tag{D.21}$$

$$cov[\Delta y^{obs}_{i,T}, \Delta y^{obs}_{i,T+N}] = 0, \quad N \geq 2, \tag{D.22}$$

$$cov[\Delta c^{obs}_{i,T}, \Delta y^{obs}_{i,T}] = \frac{2}{3}\phi\sigma^2_{pm} + \tau\{2 - \frac{1}{\lambda}(1 - e^{-\lambda})(3 - e^{-\lambda})\}\sigma^2_{tr}, \tag{D.23}$$

$$cov[\Delta c^{obs}_{i,T}, \Delta y^{obs}_{i,T+1}] = \frac{\phi}{6}\sigma^2_{pm} - \tau\{1 - \frac{1}{\lambda}(1 - e^{-\lambda})\}\sigma^2_{tr}, \tag{D.24}$$

$$cov[\Delta c^{obs}_{i,T}, \Delta y^{obs}_{i,T+N}] = 0, \quad N \geq 2, \tag{D.25}$$

$$cov[\Delta c^{obs}_{i,T}, \Delta y^{obs}_{i,T-1}] = \frac{\phi}{6}\sigma^2_{pm} + \tau\{-1 + \frac{1}{\lambda}(1 - e^{-\lambda})(e^{-2\lambda} - 3e^{-\lambda} + 3)\}\sigma^2_{tr}, \tag{D.26}$$

$$cov[\Delta c_{i,T}^{obs}, \Delta y_{i,T-N}^{obs}] = -\tau \frac{1}{\lambda} e^{-\lambda(N-2)}(1-e^{-\lambda})^4 \sigma_{tr}^2, \quad N \geq 2. \tag{D.27}$$

From equations (D.20), (D.21), (D.22), (D.23), (D.24), (D.25), (D.26), and (D.27), we can obtain the variances and covariances of $\Delta^K c_{i,T}^{obs}$ and $\Delta^K y_{i,T}^{obs}$ for $K = 2$ and $K = 4$ as follows.

$$var[\Delta^2 y_{i,T+2}^{obs}] = \frac{5}{3}\sigma_{pm}^2 + 2\sigma_{tr}^2, \tag{D.28}$$

$$cov[\Delta^2 y_{i,T}^{obs}, \Delta^2 y_{i,T+2}^{obs}] = \frac{1}{6}\sigma_{pm}^2 - \sigma_{tr}^2, \tag{D.29}$$

$$cov[\Delta^2 c_{i,T+2}^{obs}, \Delta^2 y_{i,T+2}^{obs}] = \frac{5}{3}\phi\sigma_{pm}^2 + \tau\{2 + \frac{1}{\lambda}(1-e^{-\lambda})(e^{-2\lambda} - e^{-\lambda} - 2)\}\sigma_{tr}^2, \tag{D.30}$$

$$cov[\Delta^2 c_{i,T}^{obs}, \Delta^2 y_{i,T+2}^{obs}] = \frac{\phi}{6}\sigma_{pm}^2 + \tau\{-1 + \frac{1}{\lambda}(1-e^{-\lambda})\}\sigma_{tr}^2 \tag{D.31}$$

for $K = 2$.

$$var[\Delta^4 y_{i,T+4}^{obs}] = \frac{11}{3}\sigma_{pm}^2 + 2\sigma_{tr}^2, \tag{D.32}$$

$$cov[\Delta^4 y_{i,T}^{obs}, \Delta^4 y_{i,T+4}^{obs}] = \frac{1}{6}\sigma_{pm}^2 - \sigma_{tr}^2, \tag{D.33}$$

$$cov[\Delta^4 c_{i,T+4}^{obs}, \Delta^4 y_{i,T+4}^{obs}] = \frac{11}{3}\phi\sigma_{pm}^2 + \tau\{2 + \frac{1}{\lambda}(1-e^{-\lambda})(e^{-4\lambda} - e^{-3\lambda} - 2)\}\sigma_{tr}^2, \tag{D.34}$$

$$cov[\Delta^4 c_{i,T}^{obs}, \Delta^4 y_{i,T+4}^{obs}] = \frac{\phi}{6}\sigma_{pm}^2 + \tau\{-1 + \frac{1}{\lambda}(1-e^{-\lambda})\}\sigma_{tr}^2 \tag{D.35}$$

for $K = 4$.

To estimate the MPC using these equations, we need to identify τ. To do so, I exploit the following fact: when the real interest rate is close to zero, the cumulative consumption response to a temporary income shock after a long enough time should be equal to the size of the shock itself, *i.e.*,

$$\lim_{t\to\infty} \overrightarrow{\Psi}_t \cdot \frac{E[C]}{E[Y]} = \tau \cdot \frac{E[C]}{E[Y]} \approx 1.$$

Under the assumption that the effective real interest rates for households' consumption-saving problem are close to zero in both Peru and the U.S.[45], I use the following equation to identify τ.

$$E[\tau C_{i,t-K} - Y_{i,t-K}] = 0. \tag{D.36}$$

[45]In the real world, the real interest rates in Peru are noticeably higher than those in the U.S. Reflecting this fact will widen the gap between the MPC estimates of the two countries.

Under the assumption, the MPC after the unit time length ($\Delta t = 1$) becomes

$$MPC = 1 - e^{-\lambda}.$$

For the Peruvian sample, I estimate the quarterly MPC ($= 1 - e^{-\lambda}$) together with σ^2_{pm}, σ^2_{tr}, ϕ, and τ using equations (D.32), (D.33), (D.34), (D.35), and (D.36). For the U.S. sample, I estimate the annual MPC ($= 1 - e^{-\lambda}$) with the other four parameters using equations (D.28), (D.29), (D.30), (D.31), and (D.36). As in the baseline analysis, the estimation is separately conducted for each of the income deciles. The income deciles are constructed by sorting type-3 observations of period $t - K$, t, and $t + K$ by y_{t-K}. For the estimation, I use the GMM method. For comparison between the quarterly MPCs and the annual MPCs, again I convert the Peruvian quarterly MPCs into annual MPCs using Auclert (2019)'s conversion formula (16).

Figure D.1j plots the annual MPC estimates of Peru and the U.S. We can see from this figure that the two main patterns – (i) the mean MPC being substantially higher and (ii) within-country MPC heterogeneity over the income distribution being substantially stronger in Peru than in the U.S.– robustly appear in the continuous-time model in which the time aggregation problem does not exist any more.

Case 2. When $(Y^{obs}_{i,T}, C^{obs}_{i,T}) = (\bar{Y}_{i,T}, C_{i,T})$
When $(Y^{obs}_{i,T}, C^{obs}_{i,T}) = (\bar{Y}_{i,T}, C_{i,T})$, we have the following variances and covariances in the discrete-time model.

$$var[\Delta y^{obs}_{i,T}] = \left(\frac{1}{m} + \frac{(m-1)(2m-1)}{3m^2}\right)(m\sigma^2_{pm,m}) + 2\left(\frac{\sigma^2_{tr,m}}{m}\right), \tag{D.37}$$

$$cov[\Delta y^{obs}_{i,T}, \Delta y^{obs}_{i,T+1}] = \frac{m^2-1}{6m^2}(m\sigma^2_{pm,m}) - \left(\frac{\sigma^2_{tr,m}}{m}\right), \tag{D.38}$$

$$cov[\Delta y^{obs}_{i,T}, \Delta y^{obs}_{i,T+N}] = 0, \quad N \geq 2, \tag{D.39}$$

$$cov[\Delta c^{obs}_{i,T}, \Delta y^{obs}_{i,T}] = \phi\frac{m+1}{2m}(m\sigma^2_{pm,m}) + (3\overrightarrow{\Psi}_{\frac{m-1}{m}} - \overrightarrow{\Psi}_{1+\frac{m-1}{m}})\left(\frac{\sigma^2_{tr,m}}{m}\right), \tag{D.40}$$

$$cov[\Delta c^{obs}_{i,T}, \Delta y^{obs}_{i,T+1}] = \phi\frac{m-1}{2m}(m\sigma^2_{pm,m}) - \overrightarrow{\Psi}_{\frac{m-1}{m}}\left(\frac{\sigma^2_{tr,m}}{m}\right), \tag{D.41}$$

$$cov[\Delta c^{obs}_{i,T}, \Delta y^{obs}_{i,T+N}] = 0, \quad N \geq 2, \tag{D.42}$$

$$cov[\Delta c^{obs}_{i,T}, \Delta y^{obs}_{i,T-N}] = \Big\{ (\overrightarrow{\Psi}_{N+\frac{m-1}{m}} - 2\overrightarrow{\Psi}_{N-1+\frac{m-1}{m}} + \overrightarrow{\Psi}_{N-2+\frac{m-1}{m}}) - (\overrightarrow{\Psi}_{N+1+\frac{m-1}{m}} - 2\overrightarrow{\Psi}_{N+\frac{m-1}{m}} + \overrightarrow{\Psi}_{N-1+\frac{m-1}{m}}) \Big\} \left(\frac{\sigma^2_{tr,m}}{m} \right), \quad N \geq 1. \tag{D.43}$$

As m approaches infinity satisfying equations (D.16), (D.17), (D.18), and (D.19), the continuous-time model in the limit has the following equations for the variances and covariances.

$$var[\Delta y^{obs}_{i,T}] = \frac{2}{3}\sigma^2_{pm} + 2\sigma^2_{tr}, \tag{D.44}$$

$$cov[\Delta y^{obs}_{i,T}, \Delta y^{obs}_{i,T+1}] = \frac{1}{6}\sigma^2_{pm} - \sigma^2_{tr}, \tag{D.45}$$

$$cov[\Delta y^{obs}_{i,T}, \Delta y^{obs}_{i,T+N}] = 0, \quad N \geq 2, \tag{D.46}$$

$$cov[\Delta c^{obs}_{i,T}, \Delta y^{obs}_{i,T}] = \frac{\phi}{2}\sigma^2_{pm} + \{2\tau(1-e^{-\lambda}) - \tau e^{-\lambda}(1-e^{-\lambda})\}\sigma^2_{tr}, \tag{D.47}$$

$$cov[\Delta c^{obs}_{i,T}, \Delta y^{obs}_{i,T+1}] = \frac{\phi}{2}\sigma^2_{pm} - \tau(1-e^{-\lambda})\sigma^2_{tr}, \tag{D.48}$$

$$cov[\Delta c^{obs}_{i,T}, \Delta y^{obs}_{i,T+N}] = 0, \quad N \geq 2, \tag{D.49}$$

$$cov[\Delta c^{obs}_{i,T}, \Delta y^{obs}_{i,T-N}] = \{-\tau e^{-\lambda(N-1)}(1-e^{-\lambda})^2 + \tau e^{-\lambda N}(1-e^{-\lambda})^2\}\sigma^2_{tr}, \quad N \geq 1. \tag{D.50}$$

From equations (D.44), (D.45), (D.46), (D.47), (D.48), (D.49), and (D.50), we can obtain the variances and covariances of $\Delta^K c^{obs}_{i,T}$ and $\Delta^K y^{obs}_{i,T}$ for $K = 2$ and $K = 4$ as follows.

$$var[\Delta^2 y^{obs}_{i,T+2}] = \frac{5}{3}\sigma^2_{pm} + 2\sigma^2_{tr}, \tag{D.51}$$

$$cov[\Delta^2 y^{obs}_{i,T}, \Delta^2 y^{obs}_{i,T+2}] = \frac{1}{6}\sigma^2_{pm} - \sigma^2_{tr}, \tag{D.52}$$

$$cov[\Delta^2 c^{obs}_{i,T+2}, \Delta^2 y^{obs}_{i,T+2}] = \frac{3}{2}\phi\sigma^2_{pm} + \tau(1-e^{-\lambda})(2-e^{-2\lambda})\sigma^2_{tr}, \tag{D.53}$$

$$cov[\Delta^2 c^{obs}_{i,T}, \Delta^2 y^{obs}_{i,T+2}] = \frac{\phi}{2}\sigma^2_{pm} - \tau(1-e^{-\lambda})\sigma^2_{tr} \tag{D.54}$$

for $K = 2$.

$$var[\Delta^4 y^{obs}_{i,T+4}] = \frac{11}{3}\sigma^2_{pm} + 2\sigma^2_{tr}, \tag{D.55}$$

$$cov[\Delta^4 y^{obs}_{i,T}, \Delta^4 y^{obs}_{i,T+4}] = \frac{1}{6}\sigma^2_{pm} - \sigma^2_{tr}, \tag{D.56}$$

$$cov[\Delta^4 c^{obs}_{i,T+4}, \Delta^4 y^{obs}_{i,T+4}] = \frac{7}{2}\phi\sigma^2_{pm} + \tau(1-e^{-\lambda})(2-e^{-4\lambda})\sigma^2_{tr}, \tag{D.57}$$

$$cov[\Delta^4 c_{i,T}^{obs}, \Delta^4 y_{i,T+4}^{obs}] = \frac{\phi}{2}\sigma_{pm}^2 - \tau(1-e^{-\lambda})\sigma_{tr}^2 \tag{D.58}$$

for $K = 4$.

Under the identification of τ by equation (D.36) as in the first case, I estimate Peruvian households' quarterly MPC ($= 1 - e^{-\lambda}$) together with σ_{pm}^2, σ_{tr}^2, ϕ, and τ using equations (D.55), (D.56), (D.57), (D.58), and (D.36). For the U.S. sample, I estimate annual MPC ($= 1 - e^{-\lambda}$) with the other four parameters using equation (D.51), (D.52), (D.53), (D.54), and (D.36). Again, the estimation is separately conducted for each of the income deciles, and the income deciles are constructed by sorting type-3 observations of period $t-K$, t, and $t+K$ by y_{t-K}. As in the first case, I use the GMM estimation method, and the quarterly MPCs of the Peruvian households are converted into annual MPCs using Auclert (2019)'s conversion formula (16).

Figure D.1k plots the annual MPC estimates of Peru and the U.S. This figure verifies that the two main findings – (i) the mean MPC being substantially higher and (ii) within-country MPC heterogeneity over the income distribution being substantially stronger in Peru than in the U.S.– are robust in the continuous-time model in which both the time aggregation problem and the time inconsistency problem with a longer reference period for income than that for consumption are explicitly addressed.

It is noteworthy that the time inconsistency problem with a reference period for income being longer than that for consumption could be more serious in the PSID than in ENAHO. In ENAHO, both the reference periods for income and expense items included in the baseline measures of income and consumption are restricted to be within the previous three months. On the other hand, in the PSID, the reference periods for income items are fixed at a year, while the reference periods for expense items could be as short as a week, depending on the interpretation of the questionnaires. (See the discussion in footnote 15 of the main text.) As another robustness check for the concern that this time inconsistency problem is more serious in the PSID than in ENAHO, we can consider a case in which this time inconsistency problem is present only in the U.S. In this case, the relevant comparison should be between the MPC estimates of Peruvian households in Figure D.1j and those of U.S. households in Figure D.1k. The two main findings robustly appear even in this comparison.

Case 3. When $(Y_{i,T}^{obs}, C_{i,T}^{obs}) = (Y_{i,T}, \bar{C}_{i,T})$

When $(Y_{i,T}^{obs}, C_{i,T}^{obs}) = (Y_{i,T}, \bar{C}_{i,T})$, the discrete-time model has the following equations.

$$cov[\Delta y_{i,T}^{obs}, \Delta y_{i,T+1}^{obs}] = -\sigma_{tr,m}^2,$$

$$cov[\Delta y_{i,T}^{obs}, \Delta y_{i,T+N}^{obs}] = 0, \quad N \geq 2,$$

$$cov[\Delta c_{i,T}^{obs}, \Delta y_{i,T+1}^{obs}] = -\frac{1}{m} \overrightarrow{\Psi}_0 \, \sigma_{tr,m}^2,$$

$$cov[\Delta c_{i,T}^{obs}, \Delta y_{i,T+N}^{obs}] = 0, \quad N \geq 2.$$

From these four equations, we can derive

$$cov[\Delta^K y_{i,T}^{obs}, \Delta^K y_{i,T+K}^{obs}] = -\sigma_{tr,m}^2, \tag{D.59}$$

$$cov[\Delta^K c_{i,T}^{obs}, \Delta^K y_{i,T+K}^{obs}] = -\frac{1}{m} \overrightarrow{\Psi}_0 \, \sigma_{tr,m}^2. \tag{D.60}$$

for any $K \geq 1$. From equations (D.59) and (D.60), we have

$$MPC = \overrightarrow{\Psi}_1 > \overrightarrow{\Psi}_0 = m \cdot \frac{cov[\Delta^K c_{i,T}^{obs}, \Delta^K y_{i,T+K}^{obs}]}{cov[\Delta^K y_{i,T}^{obs}, \Delta^K y_{i,T+K}^{obs}]}. \tag{D.61}$$

Therefore, when

$$\frac{cov[\Delta^K c_{i,T}^{obs}, \Delta^K y_{i,T+K}^{obs}]}{cov[\Delta^K y_{i,T}^{obs}, \Delta^K y_{i,T+K}^{obs}]} > 0, \tag{D.62}$$

the MPC out of a transitory income shock approaches infinity as m goes to infinity. This conclusion is contradictory to any continuous-time model with finite interest rates. In other words, the continuous-time model with $(Y_{i,T}^{obs}, C_{i,T}^{obs}) = (Y_{i,T}, \bar{C}_{i,T})$ cannot explain data that exhibits inequality (D.62).

However, as long as m is finite and satisfies

$$m \cdot \frac{cov[\Delta^K c_{i,T}^{obs}, \Delta^K y_{i,T+K}^{obs}]}{cov[\Delta^K y_{i,T}^{obs}, \Delta^K y_{i,T+K}^{obs}]} < 1,$$

equation (D.61) is not necessarily inconsistent with the discrete-time model. More importantly, equation (D.61) is helpful to understand the bias caused by the time-inconsistency problem with a longer reference period for consumption. When the true lengths of the reference periods for consumption and income are 1 and $\frac{1}{m}$, respectively, and we falsely treat the length for the reference periods for both income and consumption as 1 in the estimation, there is a time inconsistency problem in such a way that the true reference period for income is shorter than that for consumption. In this situation, we will estimate MPC by $\frac{cov[\Delta^K c_{i,T}^{obs}, \Delta^K y_{i,T+K}^{obs}]}{cov[\Delta^K y_{i,T}^{obs}, \Delta^K y_{i,T+K}^{obs}]}$. As equation (D.61) shows, this is an underestimation.

It is worth noting that the time inconsistency problem with a longer reference period for consumption can be present in the Peruvian sample but not in the U.S. sample, as discussed in footnote 15. In other words, the MPCs of Peruvian households are underestimated, while those of U.S. households are not, if any significant bias is generated by this problem. In this case, correcting this problem will only widen the MPC gap between Peru and the U.S.

D.1.10 Using a Different Age Restriction for Household Heads in the Sample Selection

In the baseline sample selection, I restrict the ages of household heads to be between 25 and 65 in both the Peruvian and U.S. samples. Kaplan et al. (2014b) uses a narrower selection by restricting the ages of household heads to be between 25 and 55. Here, I conduct a robustness check by adopting Kaplan et al. (2014b)'s age restriction (or, equivalently, dropping observations with household heads younger than 25 or older than 55). Figure D.1l plots the result.

D.1.11 Using an Alternative Definition of Income Outliers in the Sample Selection

As discussed in online Appendix B.3, there is a difference in the definition of income outliers in the Peruvian sample selection and the U.S. sample selection. In the Peruvian sample selection, I define income outliers as households whose income growth is in the range of the extreme 1 percent (0.5 percent at the top and 0.5 percent at the bottom) in the calendar-year sub-samples at least one time. In the U.S. sample selection, I adopt Kaplan et al. (2014b)'s definition of income outliers. They categorize households as income outliers if their nominal income is below 100 Dollars or their income growth is greater than 5 or less than -0.8 at least one time. I do not use this criteria for the Peruvian sample selection because it is not straightforward to determine the right cutoffs for Peruvian households reflecting cross-country differences including the difference in growth units (the two-year-over-two-year growth of annual income for U.S. households, the year-over-year growth of quarterly income for Peruvian households).

Regarding the difference in the definition of outliers, I conduct a robustness check by defining Peruvian income outliers in a more similar fashion with Kaplan et al. (2014b), despite the difficulty of finding the right corresponding cutoffs. Specifically, I categorize Peruvian households as income outliers if their nominal income is below 150 Sols[46] or their income growth is greater than 5 or less than -0.8 at least one time. Figure D.1m plots the MPC estimates under the alternative definition of income outliers in the Peruvian sample selection.

[46]The cutoff of 150 Sols is chosen by reflecting the fact that the 'PPP conversion factor, GDP (LCU per international $)' of World Development Indicators (WDI) varies from 1.34 to 1.56 during 2004-2016.

D.1.12 Selecting Male Heads Only in the Sample Selection

In the baseline sample selection, I include both households with male heads and those with female heads in both the Peruvian and U.S. samples. In this robustness check, I drop households with female heads. Figure D.1n plots the result.

D.1.13 Applying a Stricter Rule in Detecting Potentially Fake Type-2 Observations

In the sample selection for the Peruvian sample, I detect and drop potentially fake type-2 observations, which are likely to connect two different households. As discussed in online Appendix B.4, I identify them by type-2 observations that do not have any verified same member. In this robustness check, I apply a stricter rule in detecting them at the cost of a smaller sample size as follows: if the number of verified same members of a type-2 observation is less than half of the household size for any of the two households connected as the type-2 observation, I identify it as a potentially fake type-2 observation and drop it. Figure D.1o plots the MPC estimation result under the stricter rule.

D.2 Robustness for the Group Average Consumption Growth Difference against the Top Income Decile

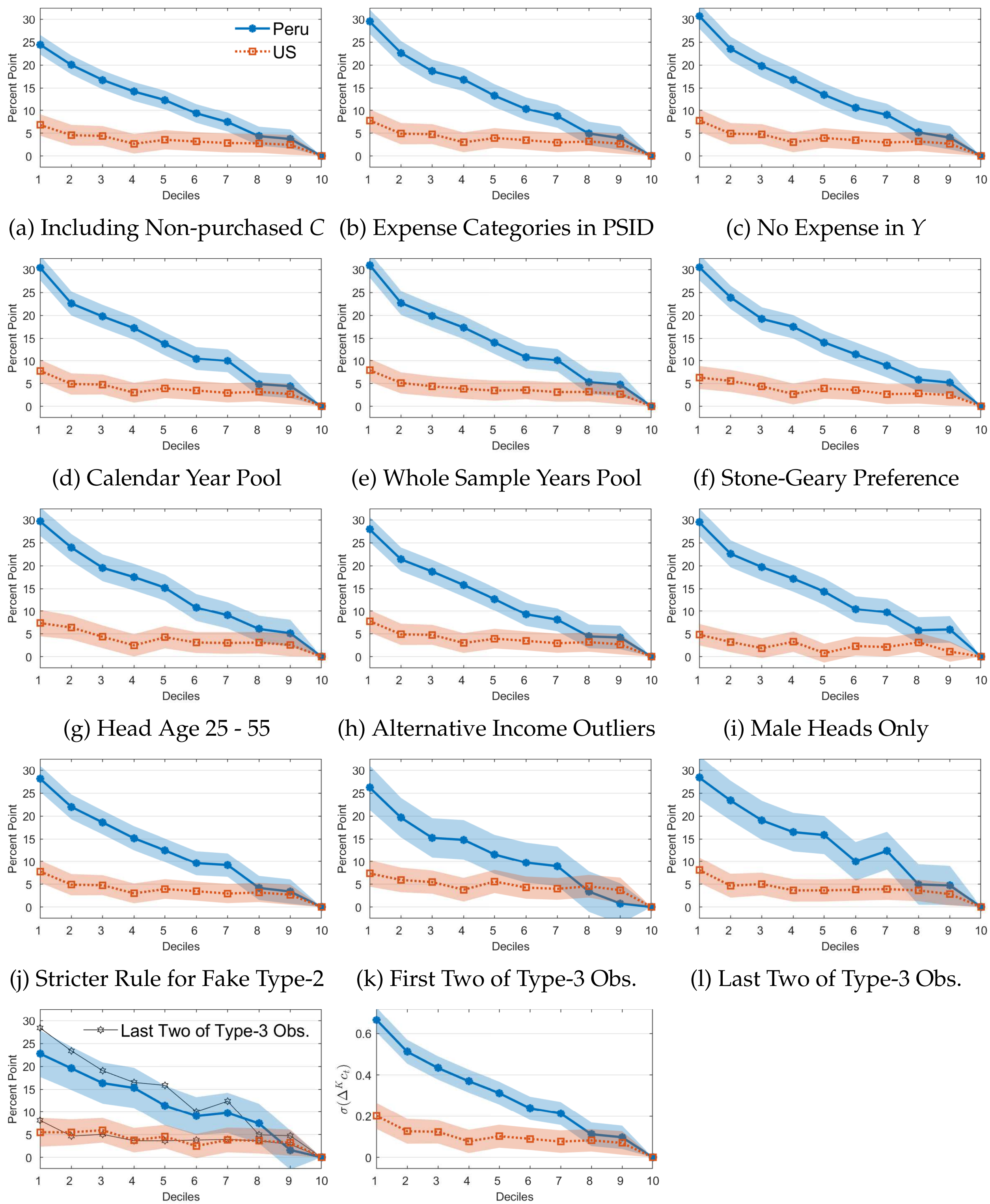
This subsection presents robustness checks for the patterns in the group-average consumption growth difference against the top income decile. Each panel of Figure D.2 plots the consumption growth differences of each robustness check. From the panels in Figure D.2, we can observe that the two main patterns in Figure 3 – (i) lower income deciles exhibiting higher consumption growth in both countries and (ii) the first pattern being substantially stronger in Peru than in the U.S. – robustly appear in the following alternative setups.

D.2.1 Including Non-purchased Consumption

As in online Appendix D.1.1, I include non-purchased consumption in the measures of consumption in both the Peruvian and U.S. samples. Figure D.2a plots the result.

D.2.2 Restricting Expense Categories to Those Available in the PSID

As in online Appendix D.1.2, I exclude clothing, recreation, alcohol, and tobacco from the consumption of Peruvian households. Figure D.2b plots the result.



(a) Including Non-purchased C (b) Expense Categories in PSID (c) No Expense in Y

(d) Calendar Year Pool (e) Whole Sample Years Pool (f) Stone-Geary Preference

(g) Head Age 25 - 55 (h) Alternative Income Outliers (i) Male Heads Only

(j) Stricter Rule for Fake Type-2 (k) First Two of Type-3 Obs. (l) Last Two of Type-3 Obs.

(m) Sorted by $\Delta^K y_t$ (n) Normalized by $\sigma(\Delta^K c_t)$

Figure D.2: Robustness – Group-average Consumption Growth Difference against the Top Income Decile

Notes: In the x-axis of each panel, 1 is the bottom decile. Shaded areas represent 95% confidence intervals.

D.2.3 Excluding Expense Items from Income

As in online Appendix D.1.4, I exclude rental equivalence of housing provided by work and rental equivalence of donated housing from the income of Peruvian households. In principle, this change of income definition can affect the group-average consumption growth by changing the income quantiles of the households. Figure D.2c plots the result.

D.2.4 Sorting Income ($y_{i,t}$) in Different Observation Pools

As in online Appendix D.1.5, I sort income in different observation pools from the baseline analysis, including (i) the pool of each calendar year (not only for the U.S. sample, but also for the Peruvian sample), and (ii) the pool of the whole sample years. Figure D.2d and Figure D.2e plot the results under the pool of each calendar year and the pool of the whole sample years, respectively.

D.2.5 Incorporating a Subsistence Point into the Preference

As in online Appendix D.1.7, I incorporate the subsistence point in the form of Stone-Geary preference into the model. Figure D.2f plots the result.

D.2.6 Using a Different Age Restriction for Household Heads in the Sample Selection

As in online Appendix D.1.10, I change the age restriction from 25 - 65 to 25-55 in the sample selection for both the Peruvian and U.S. samples. Figure D.2g plots the result.

D.2.7 Using an Alternative Definition of Income Outliers in the Sample Selection

In this robustness check, I use the alternative definition of income outliers for the Peruvian sample selection discussed in online Appendix D.1.11. Figure D.2h plots the result.

D.2.8 Selecting Male Heads Only in the Sample Selection

As in online Appendix D.1.12, I drop households with female heads in both the Peruvian and U.S. samples. Figure D.2i plots the result.

D.2.9 Applying a Stricter Rule in Detecting Potentially Fake Type-2 Observations

As in online Appendix D.1.13, I apply the stricter rule in detecting potentially fake type-2 observations in the sample selection for the Peruvian sample. Figure D.2j plots the result.

D.2.10 Using Type-3 Observations Only

In the main text, the analysis of comparing group-average consumption growth of the income deciles against the top decile uses type-2 observations, while the MPC estimation uses type-3 observations. As a consequence, the former uses a far larger number of observations than the latter. The larger number of observations in the consumption growth comparison improves the precision of the estimates but can also cause a concern of not using the same set of observations as the MPC estimation. To resolve this concern, I conduct the consumption growth comparison using only the type-3 observations that are used in the MPC estimation. Specifically, a type-3 observation of household i in $t-K$, t, and $t+K$ is sorted by its unpredictable component of income in period $t-K$, and the consumption growth $\Delta^K c_{i,t}$ is used for the group-average consumption growth comparison. Figure D.2k plots the result. Although the confidence intervals are wider than Figure 3 due to a smaller sample size, we can robustly observe the two main patterns – (i) lower income deciles exhibiting higher consumption growth in both countries and (ii) the first pattern being substantially stronger in Peru than in the U.S.

Each type-3 observation includes two type-2 observations: the first two and last two survey responses. In Figure D.2k, I use the former type-2 observation of each type-3 observation. In Figure D.2l, I instead use the latter type-2 observation of each type-3 observation. Specifically, when a type-3 observation is composed of a household's survey responses in period $t-K$, t, and $t+K$, I sort it by its unpredictable component of income in period t, and the consumption growth $\Delta^K c_{i,t+K}$ is used for the group-average consumption growth comparison. Again, the confidence intervals are wider than Figure 3, but we can robustly observe the two main patterns.

D.2.11 Sorting Observations with $\Delta^K y_{i,t}$

As discussed in subsection IV.B, households with lower income are more likely to be constrained because they are more likely to have received negative transitory income shocks and want to run down their asset position. If this is indeed the main reason why we observe the two main patterns – (i) lower income deciles exhibiting higher consumption growth in both countries and (ii) the first pattern being substantially stronger in Peru – in Figure 3, we should observe the same patterns when we group observations based on income growth $\Delta^K y_{i,t}$ instead of income level $y_{i,t}$ because the income growth also includes temporary income shock $\epsilon_{i,t}$, as seen in equation (9). To verify whether it is the case, I group type-3 observations of household i appearing in period $t-K$, t, and $t+K$ using income growth $\Delta^K y_{i,t}$, and compare the group averages of consumption growth

$\Delta^K c_{i,t+K}$. Figure D.2m plots the result. The two main patterns of Figure 3 robustly appear in this figure.

For the comparison between the income growth grouping and the income level grouping, the right point of comparison against Figure D.2m is Figure D.2l. This is because both figures use the consumption growth of the second type-2 observation of each type-3 observation (*i.e.*, $\Delta^K c_{i,t+K}$ for each type-3 observation of period $t-K$, t, and $t+K$) and the only difference between the two figures is that one figure groups observations by $\Delta^K y_t$, while the other one groups them by y_t. For the sake of comparison, I plot the point estimates of Figure D.2l in Figure D.2m as black thin lines with star markers. As the comparison shows, the degree of within-country heterogeneity in the consumption growth under the income growth grouping is similar to that under the income level grouping in both countries.

D.2.12 Normalizing the Consumption Growth Differences with Standard Deviations

We observe the year-over-year growth of quarterly consumption in the Peruvian sample and the two-year-over-two-year growth of annual consumption in the U.S. sample. Despite this difference in growth units, in Figure 3, I plot the graphs of both countries for the consumption growth differences against the top income decile in percent points and make visual comparison. This comparison is justifiable because the standard deviation of the observed consumption growth in the Peruvian sample (45.3 percent) is in the same ballpark as the standard deviation in the U.S. sample (38.7 percent). To illustrate this point, I plot the consumption growth differences in the unit of the standard deviation in Figure D.2n. The graphs in this figure do not look much different from those in Figure 3, and the two main patterns – (i) lower income deciles exhibiting higher consumption growth and (ii) the first pattern being substantially stronger in Peru than in the U.S.– robustly appear in this figure.

E MPC Comparison over the PPP-converted level of income $Y_{i,t}$

In this section, I test a null hypothesis that MPC is a function of the PPP-converted level of income $Y_{i,t}$ (including both predictable and unpredictable components), regardless of whether households live in Peru or in the U.S. To this end, I sort households by $Y_{i,t}$ (instead of $y_{i,t}$) to construct income deciles, estimate MPCs of the deciles, and plot them over the x-axis of the PPP-converted group-average values of $Y_{i,t}$ in Figure E.1.[47]

[47] For the PPP conversion, I use WDI's data series, 'PPP conversion factor, GDP (LCU per international $)'.

It turns out that the top three deciles in Peru and the bottom three deciles in the U.S. overlap in their PPP-converted income, and in the overlapped region, the MPC estimates of the Peruvian top three deciles are substantially higher than those of the U.S. bottom three deciles. To see if the cross-country MPC gap in the overlapped region is statistically significant, I conduct a two-sided test on the null hypothesis that the mean MPC of the Peruvian top three deciles is equal to that of the U.S. bottom three deciles. As Table E.1 reports, the mean MPC of the Peruvian top three deciles (44.2 percent) is significantly different from the mean MPC of the U.S. bottom three deciles (17.3 percent) at the 1% confidence level.

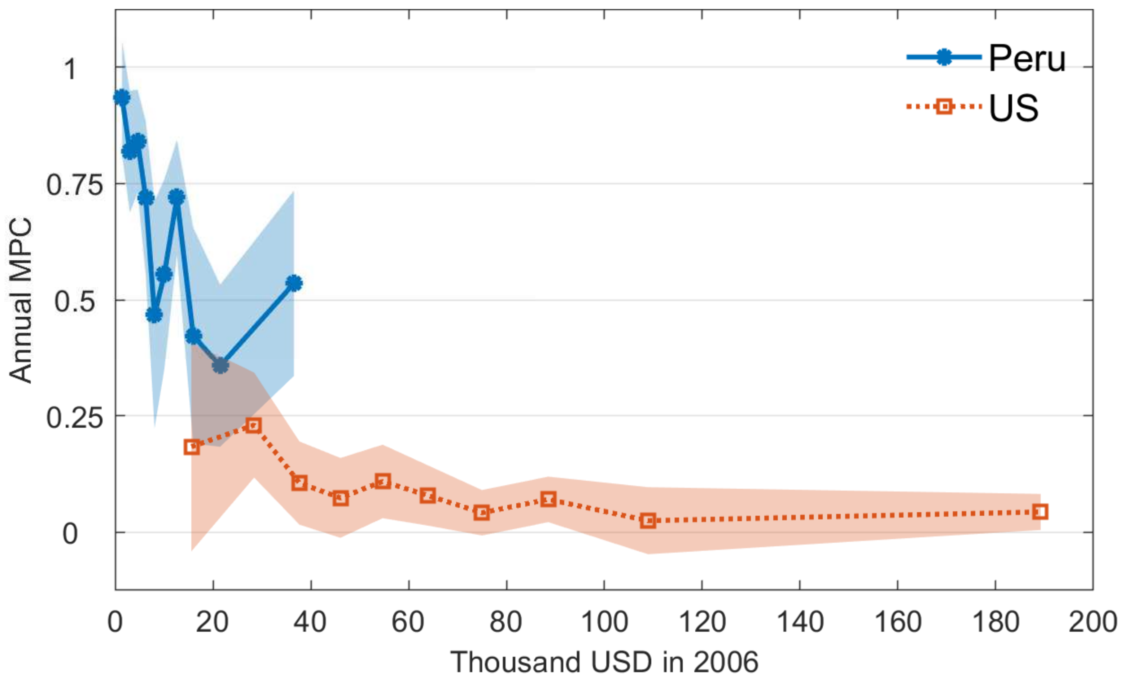


Figure E.1: Annual MPCs of $Y_{i,t}$-deciles on the x-axis of PPP-converted group-average $Y_{i,t}$

Notes: Shaded areas represent 95% confidence intervals.

Table E.1: Mean MPC Comparison in the Overlapped Region

	Peruvian Top Three Deciles	U.S. Bottom Three Deciles
mean MPC	0.442	0.173
	(0.062)	(0.046)
p-value	0.00048	

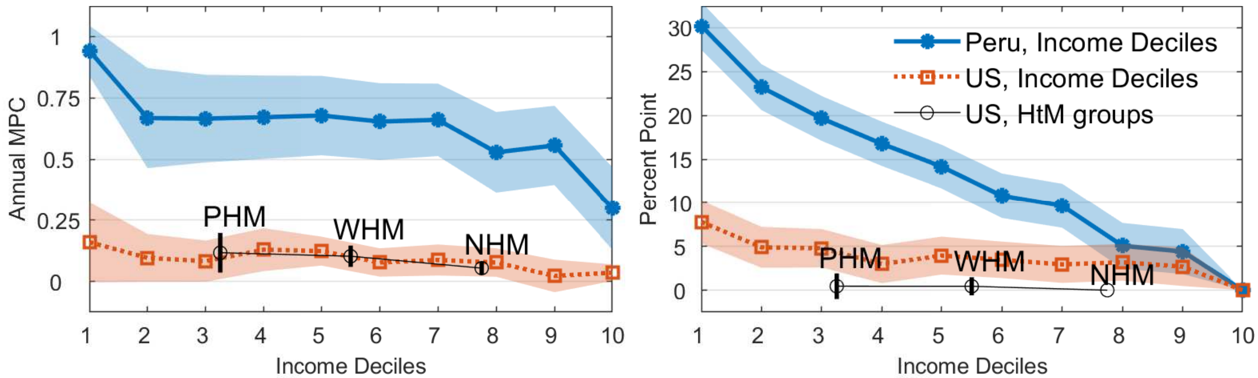
Notes: The last row of the table reports the p-value of the two-sided test on the null hypothesis that the mean MPC of the top three income($Y_{i,t}$) deciles in Peru is equal to that of the bottom three deciles in the U.S.

F The Advantage of Income Grouping in Detecting Liquidity Constraints

I use income deciles to split the sample into groups. The income measure I use to construct the income deciles is the unpredictable (by observable characteristics) component of labor income and transfers. As discussed in subsection IV.B, the standard incomplete-market precautionary-saving models predict that this income grouping can pick up the effect of liquidity constraints since lower-income households are more likely to be constrained than higher-income households. This paper is not the first to exploit this fact. For example, Zeldes (1989) tests for the presence of liquidity constraints for groups of households using lagged income as an instrument.

In the literature, wealth grouping or liquid-wealth grouping are more common grouping strategies for the identification of households that are at or close to liquidity constraints. For example, Zeldes (1989) uses net worth to split the sample into groups. Kaplan et al. (2014b) focus on households that hold little liquid wealth. In particular, they emphasize the existence of wealthy hand-to-mouth households, who are wealthy in illiquid assets but hold little liquid wealth, and find that their consumption response to transitory income shocks is as sensitive as that of poor hand-to-mouth households, who are poor in both illiquid and liquid assets.

Admittedly, I choose income grouping because wealth grouping or liquid-wealth grouping are not available for the Peruvian sample, as ENAHO does not collect detailed information on wealth. However, it is also noteworthy that the income grouping I use in this paper might have an advantage in detecting the effect of liquidity constraints compared to wealth grouping or liquid-wealth grouping. As Aguiar et al. (2019) point out, low-wealth or low-liquid-wealth households may exhibit high MPC not because they are at or close to liquidity constraints but because they have preferences for low wealth targets. If preference heterogeneity is allowed in the standard incomplete-market precautionary-



(a) Annual MPCs (b) Average Consumption Growth Differences

Figure F.1: Comparison with U.S. Hand-to-Mouth Groups

Notes: Figure F.1a plots the annual MPCs of the poor hand-to-mouth (PHM), wealthy hand-to-mouth (WHM), and non-hand-to-mouth (NHM) groups defined in Kaplan et al. (2014b) on top of Figure 1. The unfilled circle markers represent the point estimates for these groups, and the vertical lines passing the markers represent 95% confidence intervals. Figure F.1b plots the difference between the group-average consumption growth of PHM and WHM against that of NHM on top of Figure 3.

saving models, households with a low degree of patience (β_i) or a high degree of IES ($1/\sigma_i$) will have low wealth targets because they front-load consumption. At the same time, they would exhibit high MPC even in the absence of liquidity constraints exactly because of their front-loading behavior.

In supporting their argument that wealth-poor or liquid-wealth-poor households are not necessarily at or close to liquidity constraints, Aguiar et al. (2019) show that the average consumption growth of U.S. hand-to-mouth households is not greater than that of non-hand-to-mouth households. To see if this is also the case in the U.S. sample I use in this paper, I repeat the analyses of subsection IV.A and IV.B but using the U.S. hand-to-mouth groups. In doing so, I adopt Kaplan et al. (2014b)'s definition of poor-hand-to-mouth (PHM), wealthy-hand-to-mouth (WHM), and non-hand-to-mouth (NHM) households and use the identifiers of these groups included in their dataset.

Figure F.1a plots the annual MPC estimates for the U.S. PHM, WHM, and NHM groups. For the sake of comparison, Figure F.1a also plots the MPC estimates for the U.S. income deciles and the Peruvian income deciles presented in Figure 1.

Two patterns are worth noting from Figure F.1a. First, as Kaplan et al. (2014b) highlight, the consumption of PHM and WHM households responds more sensitively to transitory income shocks than that of NHM households in their dataset. The annual MPCs of PHM (11.7 percent) and WHM (10.3 percent) are approximately twice as large as that of

NHM (5.4 percent).[48] Second, even when compared with PHM and WHM in the U.S., the MPCs of Peruvian income deciles are substantially higher.

Figure F.1b plots the difference between the average consumption growth in the following period of PHM and WHM against that of NHM. For the sake of comparison, Figure F.1b also plots the difference between the average consumption growth of the income deciles against that of the top income decile in Peru and the U.S. presented in Figure 3.

In accordance with Aguiar et al. (2019)'s finding, Figure F.1b shows that the following-period consumption growth of PHM households and that of WHM households are not significantly greater than that of NHM households in Kaplan et al. (2014b)'s dataset. This result suggests that PHM and WHM households might not necessarily be more constrained than NHM households in the U.S. In contrast, under the income grouping, we can observe clear patterns in the same U.S. sample that lower income deciles tend to exhibit higher consumption growth and all the other nine deciles exhibit significantly greater consumption growth than the top income decile. This result suggests that unlike the wealth grouping, the income grouping used in this paper successfully picks up the effect of liquidity constraints.

Theoretically, this outcome may arise because labor income and transfers are less affected by preference heterogeneity than wealth. For example, when preference heterogeneity is introduced into the standard models in such a way that it is independent of the labor income process and transfers (which is a common assumption in such models with preference heterogeneity), preference heterogeneity affects individual wealth levels by changing the target wealth, while it does not affect individual levels of labor income and transfers.

[48]The annual MPC estimates I report here are different from the numbers reported in Kaplan et al. (2014b) for the following reasons. First, they report estimates on Blundell et al. (2008)'s partial insurance parameter ψ, while I compute MPC by multiplying ψ with the consumption-output ratio. Second, I revise their consumption measure and sample selection procedure as discussed in section III.