[Online Appendix]

MPCs in an Emerging Economy: Evidence from Peru

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A Approximated Consumption Function from a Model with Borrowing Constraints

To justify their partial insurance parameters as a good measure of consumption responses to income shocks, Blundell et al. (2008) use a first-order-approximated consumption function derived from a standard incomplete-market, life-cycle model without borrowing constraints. In this section, I show that this justification can be extended to the case with borrowing constraints by deriving a first-order-approximated consumption function from the same model but with borrowing constraints. The derivation is nearly identical to that of Blundell et al. (2008), except for the part that deals with borrowing constraints. As pointed out in subsection 2.1, however, both Blundell et al. (2008)'s and my approximated consumption functions have a critical limitation that they ignore households' precautionary saving due to prudence as defined by Kimball (1990).

A.1 Underlying Model

I start by specifying the underlying model.[1] In period t, each household i solves the following optimization problem.

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

$$s.t.$$

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

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

$$A_{i,t+J_{i,t}} \ge 0 \tag{A.TML}$$

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, $e^{(Z'_{i,t+j}\varphi^p_{t+j})}$ denotes a preference shift, $C_{i,t+j}$ denotes real consumption, $A_{i,t+j}$ denotes household i's bond holdings, r_{t+j} denotes the real interest rate associated with asset $A_{i,t+j}$, and $Y_{i,t+j}$ denotes disposable labor income. (A.SBC) , (A.LQC), and (A.TML) represent sequential budget constraints, liquidity constraints, and a terminal condition, respectively.

Households' labor income $Y_{i,t}$ is composed of three components in logs, namely, a component predictable with observable characteristics and time $Z'_{i,t}\varphi^y_t$, a permanent component $P_{i,t}$, and a

[1] Compared to the model used for simulation, the model specified here has additional features, such as a preference shift (predicted by observable characteristics), stochastic evolution of the observable characteristics, and aggregate uncertainty. These features are added here to maximize the generality of the derivation described in this section.

transitory component $\epsilon_{i,t}$ as follows.

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

By construction, we have

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

$Z_{i,t}$ includes dummy variables for observable characteristics. I allow some of the characteristics 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 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.

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.

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

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.

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

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

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

for some φ_t^x, of which elements corresponding to $Z_{i,t}^1$ are time-varying. 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 $\{x_{i,t} - E[x_{i,t}|Z_{i,t}, \mathbf{S}_t^{agg}]\}$ 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 (A.2), (A.3), (A.4), and (A.5) below constitute the optimal conditions of the model.

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

$$\mu_{i,t+j} \ge 0, \quad (A_{i,t+j} + \bar{B}) \ge 0, \quad \mu_{i,t+j}(A_{i,t+j} + \bar{B}) = 0, \quad 0 \le j \le J_{i,t}-1, \tag{A.3}$$

$$A_{i,t+J_{i,t}} = 0, \quad \text{and} \tag{A.4}$$

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

in which

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

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

A.2 Derivation of the Approximated Consumption Function

In this subsection, I derive an approximated consumption growth function (A.21) from the model specified in Online Appendix A.1 by first-order-approximating optimal conditions (A.2) and (A.5).

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

$$\begin{aligned}\exp\big(-\sigma\log C_{i,t+j} + Z'_{i,t+j}\varphi^p_{t+j} - \log\beta - \log(1+r_{t+j}) + \log(1-\hat{\mu}_{i,t+j})\big) \\ = E_{t+j}\big[\exp(-\sigma\log C_{i,t+j+1} + Z'_{i,t+j+1}\varphi^p_{t+j+1})\big].\end{aligned} \tag{A.6}$$

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.6)[2], we can obtain

$$\Delta \log C_{i,t+j+1} = \frac{1}{\sigma}\Delta(Z'_{i,t+j+1}\varphi^p_{t+j+1}) + \frac{1}{\sigma}\log\beta + \frac{1}{\sigma}\log(1+r_{t+j}) - \frac{1}{\sigma}\log(1-\hat{\mu}_{i,t+j}) + \eta^c_{i,t+j+1} \quad \text{(A.7)}$$

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

Note that

$$E_t \log C_{i,t+j} - E_{t-1}\log C_{i,t+j} = E_t\Big(\sum_{s=0}^{j}\Delta\log C_{i,t+s}\Big) - E_{t-1}\Big(\sum_{s=0}^{j}\Delta\log C_{i,t+s}\Big). \quad \text{(A.8)}$$

From equation (A.7), we have

$$\begin{aligned}\sum_{s=0}^{j}\Delta\log C_{i,t+s} =& \frac{1}{\sigma}(Z'_{i,t+j}\varphi^p_{t+j} - Z'_{i,t-1}\varphi^p_{t-1}) + \frac{j+1}{\sigma}\log\beta + \frac{1}{\sigma}\sum_{s=0}^{j}\log(1+r_{t+s-1}) \\ & - \frac{1}{\sigma}\sum_{s=0}^{j}\log(1-\hat{\mu}_{i,t+s-1}) + \sum_{s=0}^{j}\eta^c_{i,t+s}.\end{aligned} \quad \text{(A.9)}$$

By substituting equation (A.9) into equation (A.8), we can obtain

$$\begin{aligned}E_t\log C_{i,t+j} - E_{t-1}\log C_{i,t+j} =& \frac{1}{\sigma}(E_t Z'_{i,t+j}\varphi^p_{t+j} - E_{t-1}Z'_{i,t+j}\varphi^p_{t+j}) \\ & - \frac{1}{\sigma}(E_t\log Q_{t,t+j} - E_{t-1}\log Q_{t,t+j}) \\ & - \frac{1}{\sigma}\sum_{s=0}^{j}\big(E_t\log(1-\hat{\mu}_{i,t+s-1}) - E_{t-1}\log(1-\hat{\mu}_{i,t+s-1})\big) + \eta^c_{i,t}, \quad 0 \le j \le J_{i,t}.\end{aligned} \quad \text{(A.10)}$$

The intertemporal budget constraint (A.5) in period t is

$$\sum_{j=0}^{J_{i,t}} Q_{t,t+j}C_{i,t+j} = \sum_{j=0}^{J_{i,t}} Q_{t,t+j}Y_{i,t+j} + (1+r_{t-1})A_{i,t-1}, \quad \text{(A.11)}$$

[2] 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

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

which can be re-written as

$$\begin{aligned}&\log\bigg(\sum_{j=0}^{J_{i,t}}\exp\big(\log Q_{t,t+j}C_{i,t+j}\big)\bigg)\\&=\log\bigg(\sum_{j=0}^{J_{i,t}}\exp\big(\log Q_{t,t+j}Y_{i,t+j}\big)+(1+r_{t-1})\exp\big(\log A_{i,t-1}\big)\bigg).\end{aligned}\tag{A.12}$$

A 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,

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

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

By taking $\hat{E}_{t-1}[\cdot]$ on both sides of equation (A.11), 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

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

around

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

in equation (A.11)[3], we can obtain

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

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

around

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

in equation (A.12).

$$\sum_{j=0}^{J_{i,t}} \theta_{i,t,t+j}(\log Q_{t,t+j}C_{i,t+j} - \log \hat{E}_{t-1}[Q_{t,t+j}C_{i,t+j}])$$
$$= \pi_{i,t} \sum_{j=0}^{J_{i,t}} \gamma_{i,t,t+j}(\log Q_{t,t+j}Y_{i,t+j} - \log \hat{E}_{t-1}[Q_{t,t+j}Y_{i,t+j}])$$
$$+ (1-\pi_{i,t})(\log A_{i,t-1} - \log \hat{E}_{t-1}[A_{i,t-1}]) \tag{A.13}$$

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.13), 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,

$$\sum_{j=0}^{J_{i,t}} \theta_{i,t,t+j}(E_t \log C_{i,t+j} - E_{t-1} \log C_{i,t+j})$$
$$= \sum_{j=0}^{J_{i,t}} (\pi_{i,t}\gamma_{i,t,t+j} - \theta_{i,t,t+j})(E_t \log Q_{t,t+j} - E_{t-1} \log Q_{t,t+j}) \tag{A.14}$$
$$+ \sum_{j=0}^{J_{i,t}} \pi_{i,t}\gamma_{i,t,t+j}(E_t \log Y_{i,t+j} - E_{t-1} \log Y_{i,t+j}).$$

By substituting equation (A.10) into equation (A.14) 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

$$
\begin{aligned}
\eta^c_{i,t} = &-\frac{1}{\sigma}\sum_{j=0}^{J_{i,t}}\theta_{i,t,t+j}(E_t Z'_{i,t+j}\varphi^p_{t+j} - E_{t-1}Z'_{i,t+j}\varphi^p_{t+j}) \\
&+\sum_{j=0}^{J_{i,t}}\pi_{i,t}\gamma_{i,t,t+j}(E_t Z'_{i,t+j}\varphi^y_{t+j} - E_{t-1}Z'_{i,t+j}\varphi^y_{t+j}) \\
&+\sum_{j=0}^{J_{i,t}}(\pi_{i,t}\gamma_{i,t,t+j} - (1-\frac{1}{\sigma})\theta_{i,t,t+j})(E_t \log Q_{t,t+j} - E_{t-1}\log Q_{t,t+j}) \\
&+\sum_{j=0}^{J_{i,t}}\pi_{i,t}\gamma_{i,t,t+j}(E_t(P_{i,t+j}+\epsilon_{i,t+j}) - E_{t-1}(P_{i,t+j}+\epsilon_{i,t+j})) \\
&+\frac{1}{\sigma}\sum_{j=0}^{J_{i,t}-1}\left(\sum_{s=j+1}^{J_{i,t}}\theta_{i,t,t+s}\right)(E_t\log(1-\hat{\mu}_{i,t+j}) - E_{t-1}\log(1-\hat{\mu}_{i,t+j})).
\end{aligned}
\tag{A.15}
$$

By substituting equation (A.15) into equation (A.7), we can obtain

$$
\begin{aligned}
\Delta\log C_{i,t} = &\frac{1}{\sigma}\Delta(Z'_{i,t}\varphi^p_t) + \frac{1}{\sigma}\log\beta + \frac{1}{\sigma}\log(1+r_{t-1}) - \frac{1}{\sigma}\log(1-\hat{\mu}_{i,t-1}) \\
&-\frac{1}{\sigma}\sum_{j=0}^{J_{i,t}}\theta_{i,t,t+j}(E_t Z'_{i,t+j}\varphi^p_{t+j} - E_{t-1}Z'_{i,t+j}\varphi^p_{t+j}) \\
&+\sum_{j=0}^{J_{i,t}}\pi_{i,t}\gamma_{i,t,t+j}(E_t Z'_{i,t+j}\varphi^y_{t+j} - E_{t-1}Z'_{i,t+j}\varphi^y_{t+j}) \\
&+\sum_{j=0}^{J_{i,t}}(\pi_{i,t}\gamma_{i,t,t+j} - (1-\frac{1}{\sigma})\theta_{i,t,t+j})(E_t \log Q_{t,t+j} - E_{t-1}\log Q_{t,t+j}) \\
&+\sum_{j=0}^{J_{i,t}}\pi_{i,t}\gamma_{i,t,t+j}(E_t(P_{i,t+j}+\epsilon_{i,t+j}) - E_{t-1}(P_{i,t+j}+\epsilon_{i,t+j})) \\
&+\frac{1}{\sigma}\sum_{j=0}^{J_{i,t}-1}\left(\sum_{s=j+1}^{J_{i,t}}\theta_{i,t,t+s}\right)(E_t\log(1-\hat{\mu}_{i,t+j}) - E_{t-1}\log(1-\hat{\mu}_{i,t+j})).
\end{aligned}
\tag{A.16}
$$

I re-write equation (A.16) as follows.

- The first line of equation (A.16) 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, $c_{i,t}$.[4] 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.16), $\frac{1}{\sigma}\log\beta + \frac{1}{\sigma}\log(1+r_{t-1})$ can be picked up by $Z_{i,t-1}$ and

[4]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 (A.2), as shown in equation (A.15).

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

- The first line of equation (A.16) 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 $\tilde{\mu}_{i,t-1}$. Term $\tilde{\mu}_{i,t-1}$ can be written as

$$\tilde{\mu}_{i,t-1} := -\frac{1}{\sigma}\left\{\log(1-\hat{\mu}_{i,t-1}) - \hat{E}_{t-1}[\log(1-\hat{\mu}_{i,t-1})]\right\}. \tag{A.17}$$

- The second line of equation (A.16) 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.16) 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.16),

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

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.16) 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.16) as M_t, *i.e.*,

$$M_t := \frac{1}{\sigma}\sum_{j=0}^{J_{i,t}-1}\left(\sum_{s=j+1}^{J_{i,t}}\theta_{i,t,t+s}\right)(E_t\log(1-\hat{\mu}_{i,t+j}) - E_{t-1}\log(1-\hat{\mu}_{i,t+j})). \tag{A.18}$$

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 $\tilde{M}_{i,t}$. Term $\tilde{M}_{i,t}$ can be written as

$$\tilde{M}_{i,t} := M_t - \hat{E}_t M_t. \tag{A.19}$$

Then, equation (A.16) becomes

$$\Delta c_{i,t} = \tilde{\mu}_{i,t-1} + \pi_{i,t}\zeta_{i,t} + \pi_{i,t}\gamma_{i,t,t}\epsilon_{i,t} + \tilde{M}_{i,t} + \xi_{i,t} \tag{A.20}$$

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.20), 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

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

In addition, $\xi_{i,t}$ can be autocorrelated.[5]

By relabeling $\pi_{i,t}$ and $\pi_{i,t}\gamma_{i,t}$ in equation (A.20) as ϕ^{PIH} and ψ^{PIH}, we obtain the following approximated consumption function.

$$\Delta c_{i,t} = \tilde{\mu}_{i,t-1} + \phi^{PIH}_{i,t}\zeta_{i,t} + \psi^{PIH}_{i,t}\epsilon_{i,t} + \tilde{M}_{i,t} + \xi_{i,t}. \tag{A.21}$$

As defined in equation (A.17), $\tilde{\mu}_{i,t-1}$ is the component of $\{-(1/\sigma)\log(1-\hat{\mu}_{i,t-1})\}$ unexplained by the history of observable characteristics and aggregate states where $\hat{\mu}_{i,t-1} := \mu_{i,t-1}/(e^{(Z'_{i,t-1}\varphi^{p}_{t-1})}C^{-\sigma}_{i,t-1})$ 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 (A.21) 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 consump-

[5]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 $(\zeta_{i,t}, \epsilon_{i,t})_t$.

tion jumps in the following period t.

As defined in equation (A.19), $\tilde{M}_{i,t}$ is the part of M_t unexplained by the history of observable characteristics and aggregate states where M_t is a weighted sum of $[E_t \log(1-\hat{\mu}_{i,t+j}) - E_{t-1}\log(1-\hat{\mu}_{i,t+j})]$'s for $0 \leq j \leq J_{i,t}-1$ (as given in equation (A.18)). Thus, $\tilde{M}_{i,t}$ captures the expectation change in the effects of the current and future liquidity constraints on the current consumption growth. $\tilde{M}_{i,t}$ is positively correlated with transitory income shock $\epsilon_{i,t}$ because a positive transitory shock relaxes the current liquidity constraint for constrained households and reduces a precautionary-saving motive for households who are unconstrained but concerned about being constrained in the future. The correlation becomes stronger as households approach the liquidity constraint.

$\phi^{PIH}_{i,t}\zeta_{i,t}$ 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 an approximated consumption function, which is the same as equation (A.21), except for the absence of the two terms, $\tilde{\mu}_{i,t-1}$ and $\tilde{M}_{i,t}$. In other words, these two terms are added as a result of imposing liquidity constraints in the model.

A.3 Partial Insurance Parameter to Transitory Shocks

As in Blundell et al. (2008), assume the partial insurance parameters under PIH, $\phi^{PIH}_{i,t}$ and $\psi^{PIH}_{i,t}$ are constant within each group but can vary across different groups. Under this assumption, equation (A.21) becomes

$$\Delta c_{i,t} = \tilde{\mu}_{i,t-1} + \phi^{PIH}_{G}\zeta_{i,t} + \psi^{PIH}_{G}\epsilon_{i,t} + \tilde{M}_{i,t} + \xi_{i,t}, \quad (i,t) \in G \tag{A.22}$$

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

By substituting equations (A.1) and (A.22) into the definition of Blundell et al. (2008)'s partial insurance parameter to transitory shocks in equation (1), we obtain

$$\psi_G = \psi^{PIH}_G + \frac{cov[\epsilon_{i,t}, \tilde{M}_{i,t} | (i,t) \in G]}{var[\epsilon_{i,t} | (i,t) \in G]}. \tag{A.23}$$

Two observations are noteworthy. First, when there is no liquidity constraint in the model, the partial insurance parameter ψ_G defined in equation (1) measures ψ^{PIH}_G in equation (A.22), as pointed out by Blundell et al. (2008). Second, when liquidity constraints are imposed in the model, the partial insurance parameter ψ_G is greater than ψ^{PIH}_G by $\frac{cov[\epsilon_{i,t}, \tilde{M}_{i,t}|(i,t)\in G]}{var[\epsilon_{i,t}|(i,t)\in G]}$, which captures the effect of liquidity constraints on the current consumption. This effect includes both i) the effect of the current liquidity constraint for constrained households and ii) the effect of a precautionary saving motive to avoid future liquidity constraints for unconstrained households.

A.4 Limitation

As pointed out in subsection 2.1, the approximated consumption function ignores households' precautionary saving due to prudence as defined by Kimball (1990). This is because when we first-order-Taylor-approximate log marginal utility in equation (A.6), we drop the second-order terms, while prudence manifests through these second-order terms, as discussed in Carroll (1997) and Jappelli and Pistaferri (2017). Blundell et al. (2008)'s original approximated consumption function has the same problem.

Because of this reason, the approximated consumption function approach has a critical limitation in justifying the use of the partial insurance parameter or an MPC estimator based on it. This limitation motivates me to conduct numerical simulation in which the model is non-linearly solved and thus prudence is well preserved.

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 each year's non-response rate documented by 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: This table reports each year's non-response rate documented by ENAHO's quality reports (Instituto Nacional de Estadística e Informática, 2009-2016).

B.2 Variable Construction

My consumption measure for the ENAHO sample 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.[6] In addition to them, I add two more expenditure categories, including rental equivalence of owned or donated housing and daily nondurable goods.[7] 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.

Both Kaplan et al. (2014)'s consumption measure for the PSID sample and my consumption measure for the ENAHO sample are composed of nondurable goods and a subset of services. Moreover, both measures include home rent and housing service from owned or donated housing. One notable difference is that Kaplan et al. (2014)'s consumption measure includes health and education expenses. Therefore, for the consumption measure of the PSID sample, I adopt their consumption measure with one revision that health and education expenses are excluded.

Like many other household surveys, missing information is imputed for 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 7.3.1, I cannot do the same for the income of U.S. households and thus conduct a robustness check by consistently including the imputed components in the Peruvian income.

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

[7] 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.

Unlike the imputed components of income, I do not remove the imputed components of expense from the Peruvian consumption. Note that imputation is conducted only when households report that they earn or obtain some items but do not report their values. Given that households obtain a variety of expense items, when a subset of households' expense items have missing values, reflecting the fact that households obtain these items using imputed values could still be helpful in measuring consumption responses.

In ENAHO, some expense items require judgment calls when determining their reference periods. ENAHO's questionnaires on expenditure proceed as follows. For each expense item, households are asked whether 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 them as the reference period for the expense item.

As noted in subsection 3.2, in ENAHO, individual households report more than 97 percent (in value) of expense items and income items, respectively, under reference periods shorter than or equal to the previous three months, on average. Specifically, individual households' ratio between 'the value of items with a longer reference period than the previous three months' and 'the value of items with all reference periods' for expense items is 1.74 percent, on average. The ratio for income items is 2.51 percent, on average.

As discussed in subsection 3.2, when constructing quarterly Peruvian consumption and income, i) expense and income items with a longer reference period than the previous three months are excluded, ii) expense and income items with a shorter reference period than the previous three months are scaled up to quarterly expense and income, respectively, and iii) nominal values are deflated. In implementation, I achieve these tasks i), ii), and iii) using certain features of the EHAHO data as follows.

In ENAHO, the values of expenses and incomes are recorded in three different variables, namely, a p-variable, a d-variable, and an i-variable. For example, the value of food purchase is recorded in variables p601c, d601c, and i601c. P-variables record a raw value (or, equivalently, an actual value reported by a survey respondent), while d-variables record an annualized and within-year-deflated value. For example, when a monthly purchased value of a certain food item spent on February 2004 is reported in p601c, the value is annualized by being multiplied by 12, deflated such that the value is expressed in terms of the 2004 price level, and then recorded in d601c. I-variables record an annualized, within-year-deflated, and imputed value by adding any imputation to the corresponding d-variables.

Using these features of the data, I construct quarterly Peruvian consumption and income according to the following three steps. First, I collect all the expense and income items with a reference period shorter than or equal to the previous three months. This step achieves task i) above. Second, I aggregate the annualized values recorded in d-variables or i-variables (depending on whether to include imputation). This step achieves task ii) above.[8] Third, I deflate the aggregated within-year-deflated values of incomes and expenses using the annual CPI series. This step achieves task iii) above.

B.3 Sample Selection

In this subsection, I provide details of the sample selection omitted in the main text. I start with Peruvian sample selection. In the fourth step, gender and age are used as criteria to determine whether household heads are replaced. In the eighth step, observations are dropped if any of their (i) baseline consumption, (ii) baseline income, and (iii) comprehensive income, which include not only the baseline income but also income items with a longer reference period than the previous three months and imputed incomes, are zero or negative. Table B.2 shows how many observations are dropped in each step. Specifically, the columns labeled N_1, N_2, and N_3 in the table report the number of remaining observations, pairs of two consecutive observations, and triplets of three consecutive observations, respectively, in each step.

For the U.S. sample, I adopt Kaplan et al. (2014)'s sample selection with three minor revisions. First, they restrict household heads' ages to be between 25 and 55. This age range compares to Blundell et al. (2008)'s age range in their sample selection, 30-65. Given this difference, I choose to use the age range of 25-65, which includes the age ranges of both studies.[9] Second, when controlling consumption and income with observable characteristics, Kaplan et al. (2014) use only observations that belong to at least one triplet of three consecutive observations. I additionally use observations that belong to at least one pair of two consecutive observations when controlling

Table B.2: Baseline sample selection for ENAHO

	N_1	N_2	N_3
initial sample (obs. made over at least two consecutive surveys)	113,329	74,667	36,005
months not matched, fake panel 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
nonpositive 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
income outliers	$47,210$	$21,988$	7,509

Notes: In the penultimate line of the table, '3ml' is an abbreviation for 'items with a longer reference period than the previous three months.' The columns labeled N_1, N_2, and N_3 in the table report the number of remaining observations, pairs of two consecutive observations, and triplets of three consecutive observations, respectively, in each step.

[8] Since d-variables and i-variables contain annualized values, they have to be divided by four to be expressed in terms of quarterly values. For the purpose of this paper, however, this quarterization is unnecessary because the factor of four cancels out in my MPC estimation procedure, as it uses the first differences of log quarterly consumption and income and the consumption-income ratio.

[9] In subsection 7.3.4, I conduct a robustness check by revising the age restriction of both the U.S. and Peruvian samples to be 25-55, following that of Kaplan et al. (2014).

consumption and income with observable characteristics and constructing income distribution. Third, there are observations that miss either income or consumption, but not both. Kaplan et al. (2014) allow them to be used when controlling income and consumption with observable characteristics. For example, if an observation misses income but does not miss consumption, it is used when controlling consumption. Instead, I use only observations that do not miss both income and consumption when controlling income and consumption with observable characteristics.

A remaining difference between the Peruvian and U.S. sample selections is the criteria for income outliers. Kaplan et al. (2014) 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 once. These criteria are inherited in my U.S. sample. However, I do not use these criteria in my baseline 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 (two-year-over-two-year growth of annual income for U.S. households, year-over-year growth of quarterly income for Peruvian households). In subsection 7.3.4, I conduct a robustness check by defining Peruvian income outliers in a more similar fashion as in Kaplan et al. (2014), despite the difficulty of finding the right corresponding cutoffs.

B.4 Detecting Potentially Fake Panel 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 previous observations, creating a fake panel observation. The latter case is problematic for the analyses of this paper.

Fortunately, there is an effective way to identify panel 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 panel 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 panel observation, it is highly likely that this panel 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 panel 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' exact birth dates are missing or misreported, it turns out that most panel observations do have at least one verified same member. I identify pairs of two consecutive observations that do not have any verified same member, and define them as 'potentially fake panel observations.' I drop them in the sample selection.

After the whole steps of sample selection, any pair of two consecutive observations in the sample 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 panel observation correctly tracks the same household.[10]

[10]In subsection 7.3.4, I apply even a stricter rule when detecting potentially fake panel observations at the cost of a smaller sample size as follows: if the number of verified same members is less than half of the household size for any of the two households connected as a panel observation, I identify it as a potentially fake panel observation and drop it. Under the stricter rule, the number of triplets of three consecutive observations shrinks from 7,509 to 6,324. The main findings are robust to applying this stricter rule.

C Estimates and Standard Errors in Tables

In this section, I report MPC estimates and standard errors in tables for interested readers. In each table, 'ALL' represents the MPC estimate within the ungrouped sample, 'D1'-'D10' represent the MPC estimate within each residual income decile, and 'AVG' represents the mean of the ten MPC estimates across deciles.[11]

Table C.1: Peruvian quarterly MPC estimates

	ALL	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	AVG
MPC^Q	0.195	0.280	0.183	0.188	0.213	0.237	0.219	0.239	0.183	0.197	0.106	0.204
	(0.015)	(0.062)	(0.045)	(0.041)	(0.044)	(0.047)	(0.042)	(0.043)	(0.039)	(0.041)	(0.035)	(0.015)
N	7,509	758	827	833	787	730	699	724	743	704	704	7,509

Notes: 'ALL' represents the MPC estimate within the ungrouped sample, 'D1'-'D10' represent the MPC estimate within each residual income decile, and 'AVG' represents the mean of the ten MPC estimates across deciles. Numbers in parentheses are standard errors. The estimates and standard errors reported in this table are used in Figure 1.

Table C.2: Peruvian annual MPC estimates under Auclert (2019)'s model-free annualization

	ALL	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	AVG
MPC^A	0.580	0.731	0.555	0.566	0.616	0.661	0.628	0.664	0.554	0.585	0.361	0.592
	(0.031)	(0.092)	(0.099)	(0.088)	(0.085)	(0.083)	(0.080)	(0.076)	(0.085)	(0.085)	(0.100)	(0.029)
N	7,509	758	827	833	787	730	699	724	743	704	704	7,509

Notes: 'ALL' represents the MPC estimate within the ungrouped sample, 'D1'-'D10' represent the MPC estimate within each residual income decile, and 'AVG' represents the mean of the ten MPC estimates across deciles. Numbers in parentheses are standard errors. The estimates and standard errors reported in this table are used in Figure 3.

Table C.3: U.S. annual MPC estimates

	ALL	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	AVG
MPC^A	0.078	0.113	0.085	0.073	0.111	0.126	0.083	0.090	0.081	0.024	0.040	0.083
	(0.013)	(0.059)	(0.044)	(0.038)	(0.033)	(0.031)	(0.031)	(0.033)	(0.031)	(0.036)	(0.020)	(0.013)
N	14,790	1,332	1,467	1,504	1,539	1,573	1,560	1,567	1,472	1,413	1,363	14,790

Notes: 'ALL' represents the MPC estimate within the ungrouped sample, 'D1'-'D10' represent the MPC estimate witin each residual income decile, and 'AVG' represents the mean of the ten MPC estimates across deciles. Numbers in parentheses are standard errors. The estimates and standard errors reported in this table are used in Figures 4 and 5.

[11] To compute the standard error of the mean MPC in the 'AVG' column, we need the variance-covariance matrix of all the ten deciles' parameters (κ_G, α_G, and ψ_G). To obtain this variance-covariance matrix, I conduct joint GMM estimation of the ten deciles as in footnote 31.

D Details on Annualization

Annual MPC to a transitory income shock means the ratio of consumption change to income change caused by the shock within a year after its realization. In the quarterly model specified in subsection 2.2, the annual MPC of household i to a transitory shock $\epsilon_{i,t}$ is

$$MPC^A_{true}(i,t) = \frac{\partial C_{i,t}/\partial \epsilon_{i,t}}{\partial Y_{i,t}/\partial \epsilon_{i,t}} + \frac{\partial C_{i,t+1}/\partial \epsilon_{i,t}}{\partial Y_{i,t}/\partial \epsilon_{i,t}} + \frac{\partial C_{i,t+2}/\partial \epsilon_{i,t}}{\partial Y_{i,t}/\partial \epsilon_{i,t}} + \frac{\partial C_{i,t+3}/\partial \epsilon_{i,t}}{\partial Y_{i,t}/\partial \epsilon_{i,t}}, \tag{D.1}$$

or more formally,[12]

$$\begin{aligned} MPC^A_{true}(i,t) = & \frac{C_t(A_{i,t-1}, P_{i,t}, \epsilon_{i,t}) - C_t(A_{i,t-1}, P_{i,t}, 0)}{Y_t(P_{i,t}, \epsilon_{i,t}) - Y_t(P_{i,t}, 0)} \\ & + \frac{C_{t+1}(A_{i,t}, P_{i,t+1}, \epsilon_{i,t+1}) - C_{t+1}(A^*_{i,t}, P_{i,t+1}, \epsilon_{i,t+1})}{Y_t(P_{i,t}, \epsilon_{i,t}) - Y_t(P_{i,t}, 0)} \\ & + \frac{C_{t+2}(A_{i,t+1}, P_{i,t+2}, \epsilon_{i,t+2}) - C_{t+2}(A^*_{i,t+1}, P_{i,t+2}, \epsilon_{i,t+2})}{Y_t(P_{i,t}, \epsilon_{i,t}) - Y_t(P_{i,t}, 0)} \\ & + \frac{C_{t+3}(A_{i,t+2}, P_{i,t+3}, \epsilon_{i,t+3}) - C_{t+3}(A^*_{i,t+2}, P_{i,t+3}, \epsilon_{i,t+3})}{Y_t(P_{i,t}, \epsilon_{i,t}) - Y_t(P_{i,t}, 0)} \end{aligned} \tag{D.2}$$

in which $A^*_{i,t}$, $A^*_{i,t+1}$, and $A^*_{i,t+2}$ are household i's asset positions in quarterly age t, $t+1$, and $t+2$ when the transitory shock $\epsilon_{i,t}$ in age t is counterfactually set equal to zero.

Note that the first term on the right-hand side of equation (D.1) is quarterly MPC and that the second, third, and fourth terms are households' dynamic consumption responses to a transitory shock $\epsilon_{i,t}$ in the following three quarters ($t+1$, $t+2$, and $t+3$). As long as these dynamic consumption responses are positive, annual MPC is greater than quarterly MPC.

Both the model-free and model-based MPC annualization methods discussed in subsection 4.4 compute annual MPC by recovering the second, third, and fourth terms based on the first term on the right-hand side of equation (D.1). First, Auclert (2019) derives the model-free annualization formula (6) under the assumption that $\frac{\partial C_{i,t+j}/\partial \epsilon_{i,t}}{\partial Y_{i,t}/\partial \epsilon_{i,t}}$ dies out exponentially over time (or, equivalently, $\frac{\partial C_{i,t+j}/\partial \epsilon_{i,t}}{\partial Y_{i,t}/\partial \epsilon_{i,t}} = \lambda^j \frac{\partial C_{i,t}/\partial \epsilon_{i,t}}{\partial Y_{i,t}/\partial \epsilon_{i,t}}$ for some $\lambda > 0$) and that the interest rate is zero. Second, the model-based annualization method calibrates a standard incomplete-market model by targeting quarterly MPC and then computes model-predicted dynamic consumption responses to a transitory shock in the subsequent quarters.

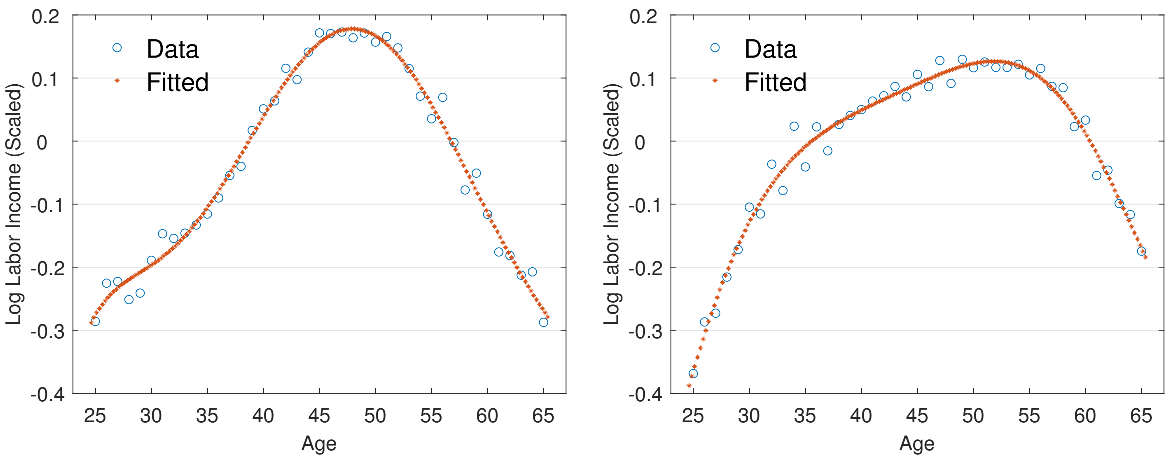
As discussed in footnote 36, one might instead consider annualizing ahead of time the quarterly income and consumption data by multiplying both by four and then applying the MPC estimation method to the annualized data. This ahead-of-time annualization yields an annual MPC that is exactly equal to the quarterly MPC and thus essentially ignores the second, third, and fourth terms on the right-hand side of equation (D.1).

[12] In equation (D.1), I slightly abuse partial derivative notation ∂ in that the size of transitory shock $\epsilon_{i,t}$ is not necessarily infinitesimal.

E Income Process Calibration

E.1 Age-Specific Deterministic Component of Income ω_t

As discussed in subsections 4.2 and 5.2, the age-specific deterministic income component ω_t is computed as follows. First, I compute the means of the predictable components of income conditional on households' yearly ages in the data and normalize them by subtracting the unconditional mean. Then, I fit a sixth-order polynomial curve to these normalized yearly-age-specific means. Lastly, I use this fitted curve to interpolate quarterly-age-specific component ω_t. Figures E.1a and E.1b plot the data points of normalized yearly-age-specific means and the fitted curve in Peru and the U.S., respectively.



(a) Peru (b) U.S.

Figure E.1: Age-specific deterministic component of income ω_t

E.2 Stochastic Process for $y_{i,t}$ (Benchmark Case: AR(1) + I.I.D.)

E.2.1 Peru

In the model, residual income $y_{i,t}$ evolves according to the following stochastic process.

$$
\begin{gathered}
y_{i,t} = P_{i,t} + \epsilon_{i,t}, \quad 0 \le t \le T, \\
P_{i,t} = \rho P_{i,t-1} + \zeta_{i,t}, \quad 1 \le t \le T, \\
\zeta_{i,t} \sim_{iid} (0, \sigma^2_{ps}), \quad \epsilon_{i,t} \sim_{iid} (0, \sigma^2_{tr}), \quad P_{i,0} \sim_{iid} (0, \sigma^2_{P_0}), \\
(\zeta_{i,t})_t \perp (\epsilon_{i,t})_t, \quad (\epsilon_{i,t})_t \perp P_{i,0}, \quad \text{and} \quad P_{i,0} \perp (\zeta_{i,t})_t.
\end{gathered}
$$

Under this specification, the following equations hold.

$$
var[P_{i,t}|t] = \begin{cases} \sigma^2_{P_0} & \text{if } t = 0, \\ \rho^{2t}\sigma^2_{P_0} + \{1 + \rho^2 + \cdots + \rho^{2(t-2)} + \rho^{2(t-1)}\}\sigma^2_{ps} & \text{if } 1 \le t \le T. \end{cases} \tag{E.1}
$$

$$var[y_{i,t}|t] = var[P_{i,t}|t] + \sigma_{tr}^2, \quad 0 \le t \le T. \tag{E.2}$$

$$cov[y_{i,t}, y_{i,t+4k}|t] = \rho^{4k} var[P_{i,t}|t], \quad 0 \le t \le T - 4k, \quad k \ge 1. \tag{E.3}$$

Equations (E.2) and (E.3) specify the quarterly-age-specific variances and covariances of $y_{i,t}$. Given that households do not die between $t = 0$ and $t = T$ in the model, we can also derive the yearly-age-specific variances and covariances of $y_{i,t}$ for any given annual age a as follows.

$$var[y_{i,t}|4a \le t \le 4a+3] = \frac{1}{4}\sum_{j=0}^{3} var[y_{i,t}|t = 4a+j], \quad 0 \le a \le \frac{T-3}{4}. \tag{E.4}$$

$$cov[y_{i,t}, y_{i,t+4k}|4a \le t \le 4a+3] = \frac{1}{4}\sum_{j=0}^{3} cov[y_{i,t}, y_{i,t+4k}|t = 4a+j], \quad 0 \le a \le \frac{T-3-4k}{4}, \quad k \ge 1. \tag{E.5}$$

I estimate Peruvian ρ, σ_{ps}^2, σ_{tr}^2, and $\sigma_{P_0}^2$ using the moment conditions of yearly-age-specific variances and covariances of $y_{i,t}$ in equations (E.4) and (E.5). Specifically, I use moments that have at least 100 observations in the data.

The estimation procedure is very similar to that of Blundell et al. (2008) (described in their Appendix D) except that they deal with the first differences of residual income and consumption ($\Delta y_{i,t}$, $\Delta c_{i,t}$), while I deal with residual income ($y_{i,t}$). Let x_i and d_i be

$$x_i = \begin{pmatrix} \text{household } i\text{'s residual income observed at age 25} \\ \vdots \\ \text{household } i\text{'s residual income observed at age 65} \end{pmatrix}, \; d_i = \begin{pmatrix} 1\{\text{household } i \text{ is in the sample at age 25}\} \\ \vdots \\ 1\{\text{household } i \text{ is in the sample at age 65}\} \end{pmatrix}.$$

The missing elements in x_i are set equal to zero. Let

$$m_i := vech(x_i x_i'), \quad s_i := vech(d_i d_i'), \quad m := vech(\sum_{i=1}^{N} x_i x_i' \oslash \sum_{i=1}^{N} d_i d_i'), \quad \text{and} \quad s := vech(\sum_{i=1}^{N} d_i d_i')$$

in which $\oslash$ denotes an element-wise division. m is a vector composed of yearly-age-specific variances and covariances of $y_{i,t}$. Let

$$\tilde{m}_i = selec(m_i), \quad \tilde{s}_i = selec(s_i), \quad \tilde{m} = selec(m), \quad \text{and} \quad \tilde{s} := selec(s)$$

where $selec(\cdot)$ is a function that removes elements at positions in which s's elements are less than 100. (I use only moments that have at least 100 observations in the data.)

Let θ be $\theta := (\rho, \sigma_{ps}^2, \sigma_{tr}^2, \sigma_{P_0}^2)$, and $f(\theta)$ be the function of parameters corresponding to the vector of moments $\tilde{m}$ in the model. I estimate θ by minimizing $(\tilde{m} - f(\theta))'\Omega^{\tilde{m}}(\tilde{m} - f(\theta))$ in which $\Omega^{\tilde{m}}$ is a weight matrix. For $\Omega^{\tilde{m}}$, I use a diagonal matrix whose diagonal elements are equal to

$diag((V^{\tilde{m}})^{-1})$ where $V^{\tilde{m}}$ is the variance-covariance matrix of $\tilde{m}$ to avoid small-sample bias that optimal weight matrix $(V^{\tilde{m}})^{-1}$ causes, as recommended by Altonji and Segal (1996). $V^{\tilde{m}}$ is estimated by

$$V^{\tilde{m}} = \left[\sum_{i=1}^{N} ((\tilde{m}_i - \tilde{m}) \otimes \tilde{s}_i)((\tilde{m}_i - \tilde{m}) \otimes \tilde{s}_i)' \right] \oslash (\tilde{s}\tilde{s}')$$

in which $\otimes$ denotes an element-wise product.

Lastly, as Chamberlain (1984) shows, the variance-covariance matrix of θ can be obtained by

$$V^{\theta} = (G'\Omega^{\tilde{m}}G)^{-1}G'\Omega^{\tilde{m}}V^{\tilde{m}}\Omega^{\tilde{m}}G(G'\Omega^{\tilde{m}}G)^{-1} \tag{E.6}$$

in which $G := \partial f(\theta)/\partial\theta$ is the Jacobian of f with regard to θ.

Table E.1 reports the estimates and standard errors of ρ, σ^2_{ps}, σ^2_{tr}, and $\sigma^2_{P_0}$, and Figure E.2 illustrates the moment matching outcome by comparing the yearly-age-specific variances and covariances of $y_{i,t}$ between the model (labeled 'model') and the data (labeled 'data'). Two observations are noteworthy. First, ρ is estimated to be substantially lower than 1. (In terms of an

Table E.1: Peruvian quarterly income process: AR(1)+I.I.D.

ρ	σ^2_{ps}	σ^2_{tr}	$\sigma^2_{P_0}$
0.963	0.021	0.196	0.296
(0.005)	(0.003)	(0.008)	(0.037)

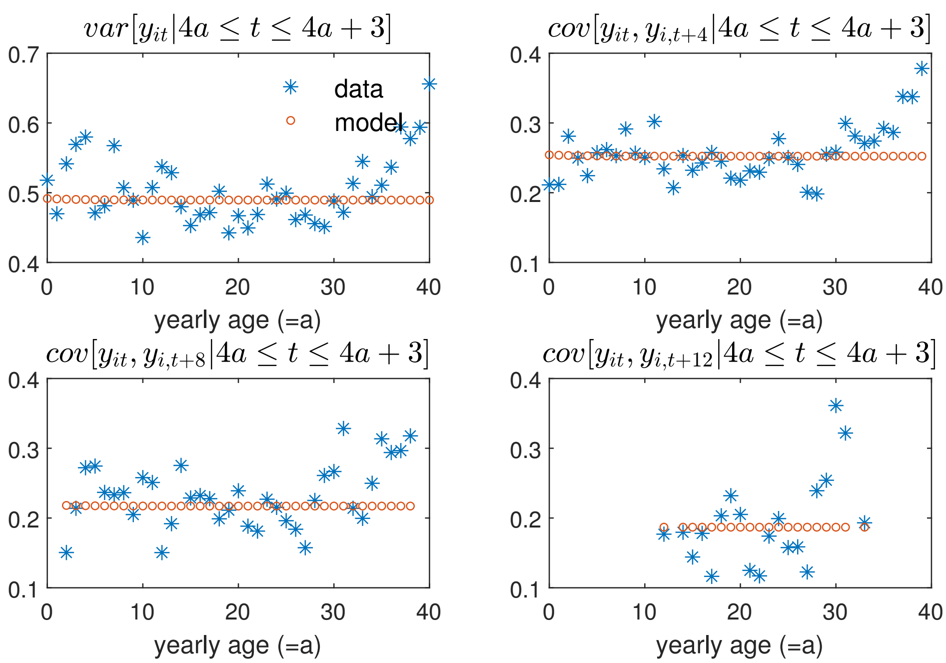


Figure E.2: Income moment matching, AR(1)+I.I.D., Peru

Notes: This figure compares the yearly-age-specific variances and covariances of quarterly residual incomes (denoted by $y_{i,t}$) between the model (labeled 'model') and the data (labeled 'data').

annual rate, $\rho^4 = 0.861$.) This result is driven by the Peruvian data pattern observed in Figure E.2 that yearly-age-specific covariances $cov[y_{i,t}, y_{i,t+4}|4a \leq t \leq 4a+3]$'s (in which a is a yearly age) are significantly greater than $cov[y_{i,t}, y_{i,t+4k}|4a \leq t \leq 4a+3]$'s, $k \geq 2$. Note that $cov[y_{i,t}, y_{i,t+4k}|t] = \rho^{4k} var[P_{i,t}|t]$ in the model, as shown in equation (E.3). Second, $\sigma^2_{P_0}$ (0.296) is very close to $\frac{\sigma^2_{ps}}{1-\rho^2}$ (0.293). This result reflects the Peruvian data pattern observed in Figure E.2 that yearly-age-specific variances $var[y_{i,t}|4a \leq t \leq 4a+3]$'s are flat over ages. Note that $var[y_{i,t}|t] = \sum_{s=0}^{t-1} \rho^{2s}\sigma^2_{ps} + \rho^{2t}\sigma^2_{P_0} + \sigma^2_{tr}$ for $1 \leq t \leq T$, as shown in equations (E.1) and (E.2).

E.2.2 U.S.

In the case of the U.S., the time unit in the model (quarter) is different from the reference period in the data (year). So, as discussed in subsection 5.2, I estimate the parameters governing the stochastic process of the quarterly residual income $y_{i,t}$ (ρ, σ_{ps}, σ_{tr}, and σ_{P_0}) using the SMM (Simulated Method of Moments) method as follows. First, for a given set of parameters, I simulate quarterly income series and convert them into annual series by aggregating them over every four quarters. Specifically, I simulate quarterly residual incomes $y_{i,t}$, convert them into quarterly actual incomes $Y_{i,t}$ using age-specific deterministic components ω_t, and then convert them into annual actual incomes by aggregating them over every four quarters. After residualizing the simulated annual incomes, I compute their age-specific variances and covariances. Then, I find parameters that minimize the distance between these simulated moments and their data counterparts. For the minimum distance estimation, as in the Peruvian case (Online Appendix E.2.1), I use a diagonal weight matrix whose diagonal elements are equal to those of the optimal weight matrix (*i.e.*, the inverse of the variance-covariance matrix of the moments of interest). Also, as in the Peruvian case, I use only moments with at least 100 observations. Standard errors are again computed using Chamberlain (1984)'s equation (E.6).[13]

Table E.2 reports the estimates and standard errors of ρ, σ^2_{ps}, σ^2_{tr}, and $\sigma^2_{P_0}$, and Figure E.3 illustrates the moment matching outcome by comparing the yearly-age-specific variances and covariances of annual residual incomes between the model (labeled 'model') and the data (labeled 'data'). In the figure, $\hat{y}_{i,a}$ denotes residual annual income at yearly age a.

Two observations are noteworthy. First, unlike in Peru, ρ is very close to 1 in the U.S. (In terms of an annual rate, $\rho^4 = 0.958$.) It reflects the U.S. data pattern observed in Figure E.3 that $cov[\hat{y}_{i,a}, \hat{y}_{i,a+2}|a]$'s are not substantially greater than $cov[\hat{y}_{i,a}, \hat{y}_{i,a+2k}|a]$'s , $k \geq 2$. Second, $\sigma^2_{P_0}$ (0.130)

Table E.2: U.S. quarterly income process: AR(1)+I.I.D.

ρ	σ^2_{ps}	σ^2_{tr}	$\sigma^2_{P_0}$
0.989	0.005	0.263	0.130
(0.002)	(0.001)	(0.017)	(0.013)

[13] Unlike the Peruvian case, $f(\theta)$ does not have an analytic form. Therefore, the Jacobian G is computed numerically.

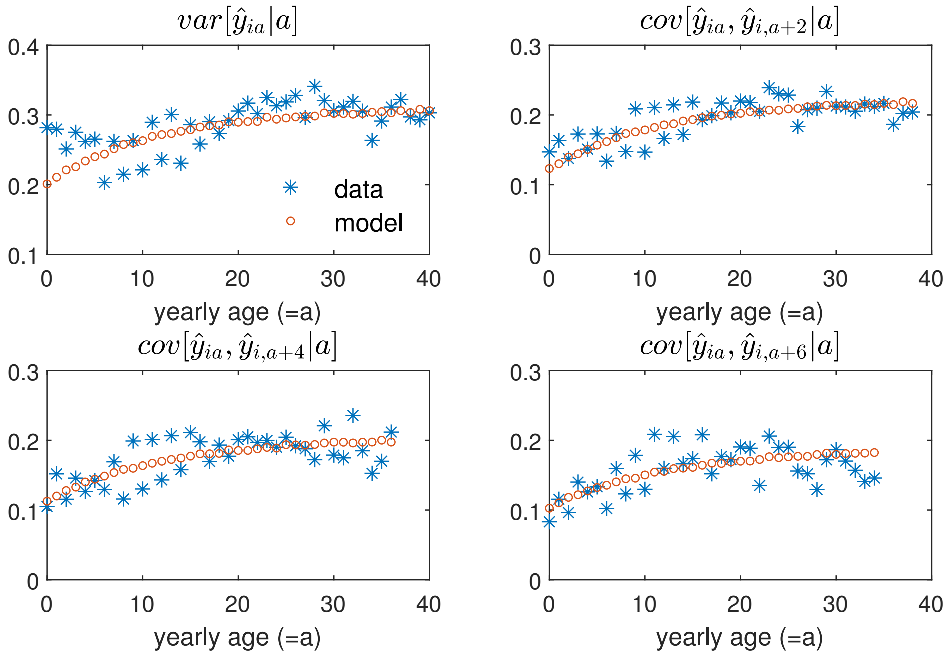


Figure E.3: Income moment matching, AR(1)+I.I.D., U.S.

Notes: This figure compares the yearly-age-specific variances and covariances of annual residual incomes (denoted by $\hat{y}_{i,a}$) between the model (labeled 'model') and the data (labeled 'data').

is noticeably smaller than $\frac{\sigma_{ps}^2}{1-\rho^2}$ (0.241). This result reflects the U.S. data pattern observed in Figure E.3 that $var[\hat{y}_{i,a}|a]$'s increase with age.

E.3 Stochastic Process for $y_{i,t}$ (Alternative Case: RW + I.I.D.)

E.3.1 Peru

In subsection 7.1, I consider an alternative model specification in which $P_{i,t}$ follows a random walk instead of an AR(1) process. I re-estimate the Peruvian income process using the same procedure as the one described in Online Appendix E.2.1 but under the restriction that $\rho = 1$. Table E.3 reports the estimates and standard errors of σ_{ps}^2, σ_{tr}^2, and $\sigma_{P_0}^2$, and Figure E.4 illustrates the moment matching outcome by comparing the yearly-age-specific variances and covariances of $y_{i,t}$ between the model (labeled 'model') and the data (labeled 'data'). Two observations are noteworthy. First, as a consequence of assuming $\rho = 1$, the estimated Peruvian income process fails to capture the data pattern that yearly-age-specific covariances $cov[y_{i,t}, y_{i,t+4}|4a \leq t \leq 4a+3]$'s are significantly greater than $cov[y_{i,t}, y_{i,t+4k}|4a \leq t \leq 4a+3]$'s, $k \geq 2$ in Peru. Second, $(\sigma_{ps}^2/\sigma_{P_0}^2)$ is very small in Peru (0.0015). This result reflects the data pattern that the yearly-age-specific variances $var[y_{i,t}|4a \leq t \leq 4a+3]$'s are flat over ages in Peru.

Table E.3: Peruvian quarterly income process: RW+I.I.D.

σ^2_{ps}	σ^2_{tr}	$\sigma^2_{P_0}$
0.0003	0.251	0.212
(0.0001)	(0.004)	(0.011)

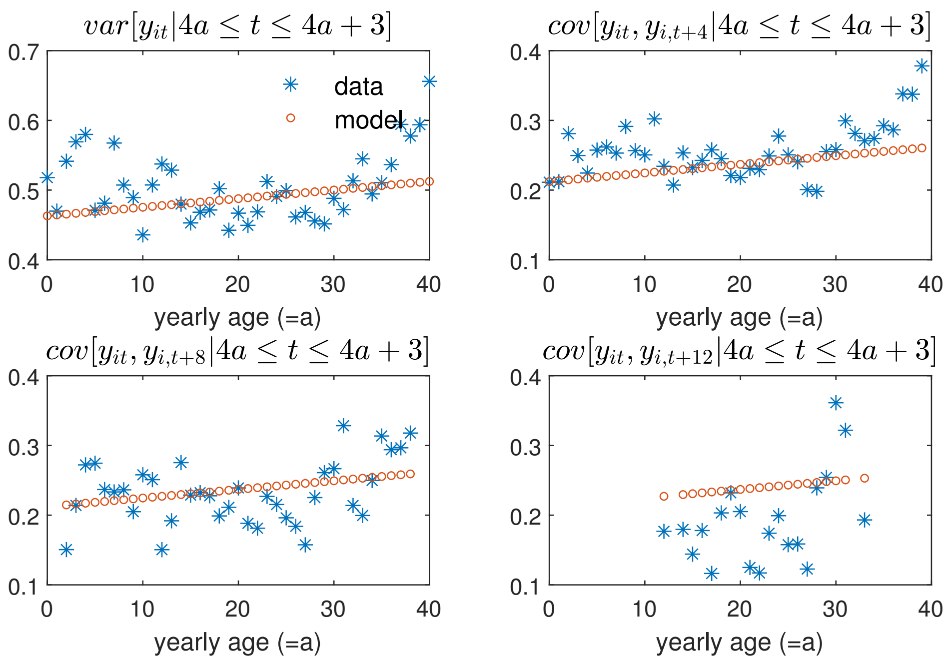


Figure E.4: Income moment matching, RW+I.I.D., Peru

Notes: This figure compares the yearly-age-specific variances and covariances of quarterly residual incomes (denoted by $y_{i,t}$) between the model (labeled 'model') and the data (labeled 'data').

E.3.2 U.S.

Similarly, I re-estimate the U.S. income process using the same procedure as the one described in Online Appendix E.2.2 but under the restriction that $\rho = 1$. Table E.4 reports the estimates and standard errors of σ^2_{ps}, σ^2_{tr}, and $\sigma^2_{P_0}$, and Figure E.5 illustrates the moment matching outcome by comparing the yearly-age-specific variances and covariances of annual residual incomes between the model (labeled 'model') and the data (labeled 'data'). Two observations are noteworthy. First, Figure E.5 suggests that unlike the Peruvian case, the restriction $\rho = 1$ does not significantly compromise the moment-matching outcome. This is because ρ is close to 1 anyway even when it is estimated without the restriction. (See Table E.2.) Second, $(\sigma^2_{ps}/\sigma^2_{P_0})$ is much larger in the U.S. (0.0041) than in Peru (0.0015). This result reflects the data pattern observed in Figures E.4 and E.5 that the yearly-age-specific variances of residual income noticeably increase with age in the U.S., while they do not in Peru.

Table E.4: U.S. quarterly income process: RW+I.I.D.

σ^2_{ps}	σ^2_{tr}	$\sigma^2_{P_0}$
0.0005	0.370	0.133
(0.0001)	(0.010)	(0.009)

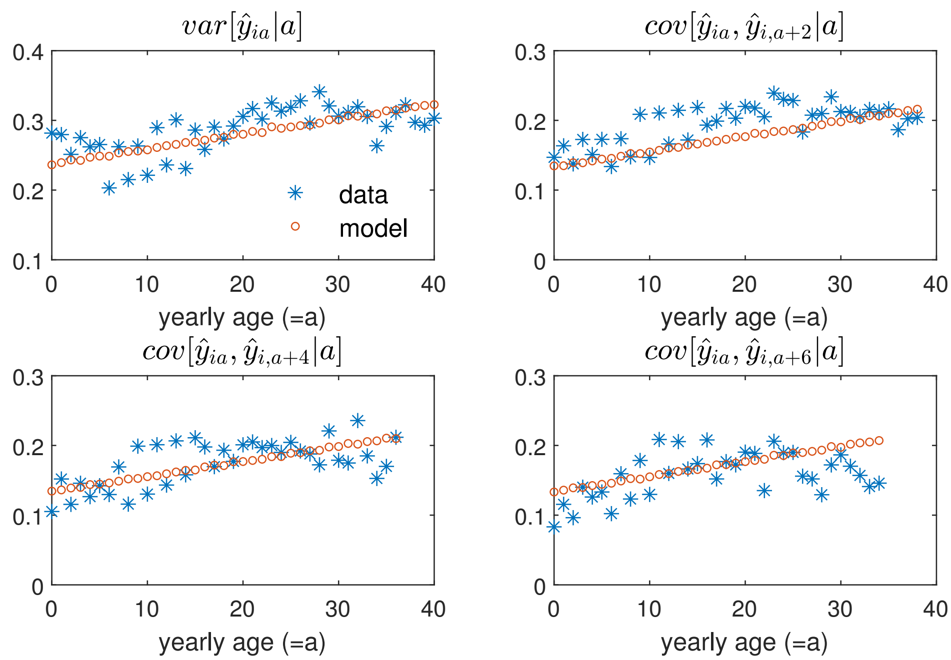


Figure E.5: Income moment matching, RW+I.I.D., U.S.

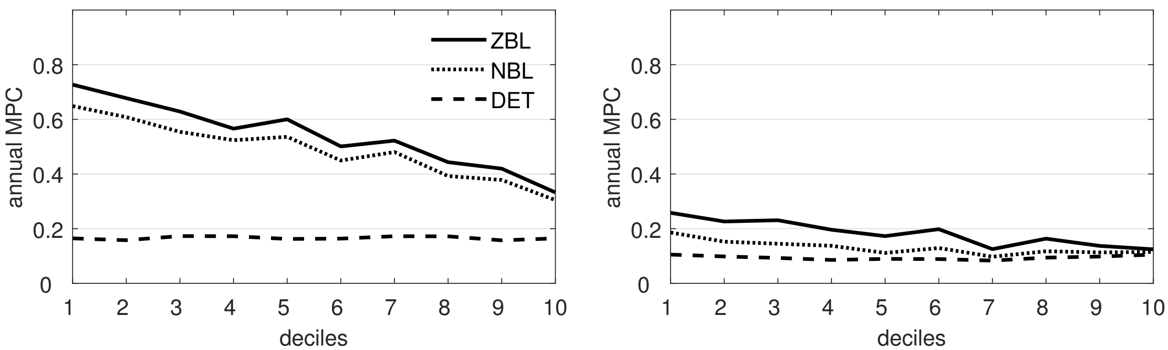
Notes: This figure compares the yearly-age-specific variances and covariances of annual residual incomes (denoted by $\hat{y}_{i,a}$) between the model (labeled 'model') and the data (labeled 'data').

F The Role of Borrowing Constraints under a Larger Natural Borrowing Limit

As discussed in section 6, the role of zero borrowing limits is negligible in both Peruvian and U.S. benchmark economies because the natural borrowing limits are formed very close to zero. One of the reasons for the small natural borrowing limits in the benchmark economy is due to the wide range of the income grid. In the baseline income process discretization (Rouwenhorst (1995) for $\epsilon_{i,t}$, Fella et al. (2019)'s extended version of Rouwenhorst (1995) for $P_{i,t}$), gridpoints for transitory and persistent components are equally spaced in the range of $[-\sqrt{N_{tr}-1}\sigma_{tr}, \sqrt{N_{tr}-1}\sigma_{tr}]$ and $[-\sqrt{N_{ps}-1}\sigma_{P_t}, \sqrt{N_{ps}-1}\sigma_{P_t}]$, respectively, where N_{tr} and N_{ps} are the number of grid points and $\sigma^2_{P_t} = var[P_{i,t}|t]$. Since I use $N_{tr} = N_{ps} = 20$, the minimum possible realization of $Y_{i,t}$ is $\exp(\omega_t - \sqrt{19}\sigma_{tr} - \sqrt{19}\sigma_{P_t})$.

In this section, I use a smaller number of gridpoints, $N_{tr} = N_{ps} = 9$. The minimum possible realization of $Y_{i,t}$ increases to $\exp(\omega_t - 3\sigma_{tr} - 3\sigma_{P_t})$, and thus, the natural borrowing limits also become larger.[14] Under the new income grids, β is recalibrated by targeting MPC estimates.

Figures F.1a and F.1b plot the same graphs as Figures 7a and 7b but under the coarse income grids and recalibrated β's. These figures show that unlike in the benchmark economies, the zero borrowing limits now increase the MPCs by nonnegligible margins in both Peru and the U.S. (5.4%p in Peru and 5.3%p in the U.S. in terms of the mean annual MPC) as the natural borrowing limits become larger. This result suggests that to have a fair evaluation of the role of borrowing constraints on MPCs, an evidence-based calibration for the minimum possible income levels needs to be performed.



(a) Peru (b) U.S.

Figure F.1: Annual MPCs (ZBL, NBL, and DET) under a coarse income grid

Notes: Figures F.1a and F.1b plot the same graphs as Figures 7a and 7b but under coarse income grids and recalibrated β's for the Peruvian and U.S. economies.

[14] In the benchmark Peruvian economy, the natural borrowing limit is 1.4 times the average quarterly labor income ($E[Y_{i,t}]$) at $t = 0$ and monotonically decreases to 0.008 times the average quarterly labor income at $t = T - 1$. In the Peruvian economy with the coarse income grid, the natural borrowing limit is 5.2 times the average quarterly labor income at $t = 0$ and monotonically decreases to 0.03 times the average quarterly labor income at $t = T - 1$. In the benchmark U.S. economy, the natural borrowing limit is 1.7 times the average quarterly labor income ($E[Y_{i,t}]$) at $t = 0$ and monotonically decreases to 0.008 times the average quarterly labor income at $t = T - 1$. In the U.S. economy with the coarse income grid, the natural borrowing limit is 6.5 times the average quarterly labor income at $t = 0$ and monotonically decreases to 0.03 times the average quarterly labor income at $t = T - 1$.

G Robustness under Alternative Data Treatments

This section provides detailed descriptions and the results of the alternative data treatments that are briefly discussed in subsection 7.3. For each case, I plot four graphs in the corresponding panel in Figure G.1: annualized Peruvian MPC estimates under model-free annualization (labeled 'PR, model-free'), annual U.S. MPC estimates (labeled 'US, model-free'), true annual MPCs in the Peruvian model economy (or, equivalently, annualized Peruvian MPCs under model-based annualization, labeled 'PR, model-base'), and true annual MPCs in the U.S. model economy (labeled 'US, model-base'). The former two graphs correspond to the graphs in Figure 4 under the baseline case, and the latter two graphs correspond to the graphs in Figure 6 under the baseline case. To plot the latter two graphs, I calibrate the quarterly model specified in subsection 2.2.[15] In the model calibration, the income process is also recalibrated whenever the alternative data treatment revises the income measure or changes the sample.[16]

Figure G.1 shows that in each case, the following results robustly emerge. i) When annualizing Peruvian MPC estimates, the model-free and model-based methods yield similar outcomes. ii) The annual U.S. MPC estimates have a time aggregation problem in the quarterly model. iii) Under both model-free and model-based comparisons, Peruvian MPCs are substantially higher overall than U.S. MPCs, and iv) MPCs are also more heterogeneous over residual income deciles in Peru than in the U.S.

In the rest of this section, I provide a description of each alternative data treatment.

G.1 Including Nonpurchased Consumption

In the baseline consumption measure, I exclude nonpurchased 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 nonpurchased consumption. Figure G.1a plots the result.

G.2 Restricting Expense Categories to Those Available in the PSID

Due to a narrow coverage on expense items in the early waves of the PSID, the U.S. baseline consumption does not include clothing, recreation, alcohol, and tobacco, while the Peruvian baseline consumption includes them. In this robustness check, I consistently exclude these expense items from the Peruvian consumption. Figure G.1b plots the result.

[15] In the cases of a continuous time model, there is no distinction between model-free and model-based estimates. (See Online Appendix G.8 for details.) Thus, the latter two graphs ('PR, model-base' and 'US, model-base') are not plotted.

[16] Even in the cases without a direct revision of the sample selection procedure, the sample can change whenever the consumption or income measures are revised because they are used in some steps of the sample selection.

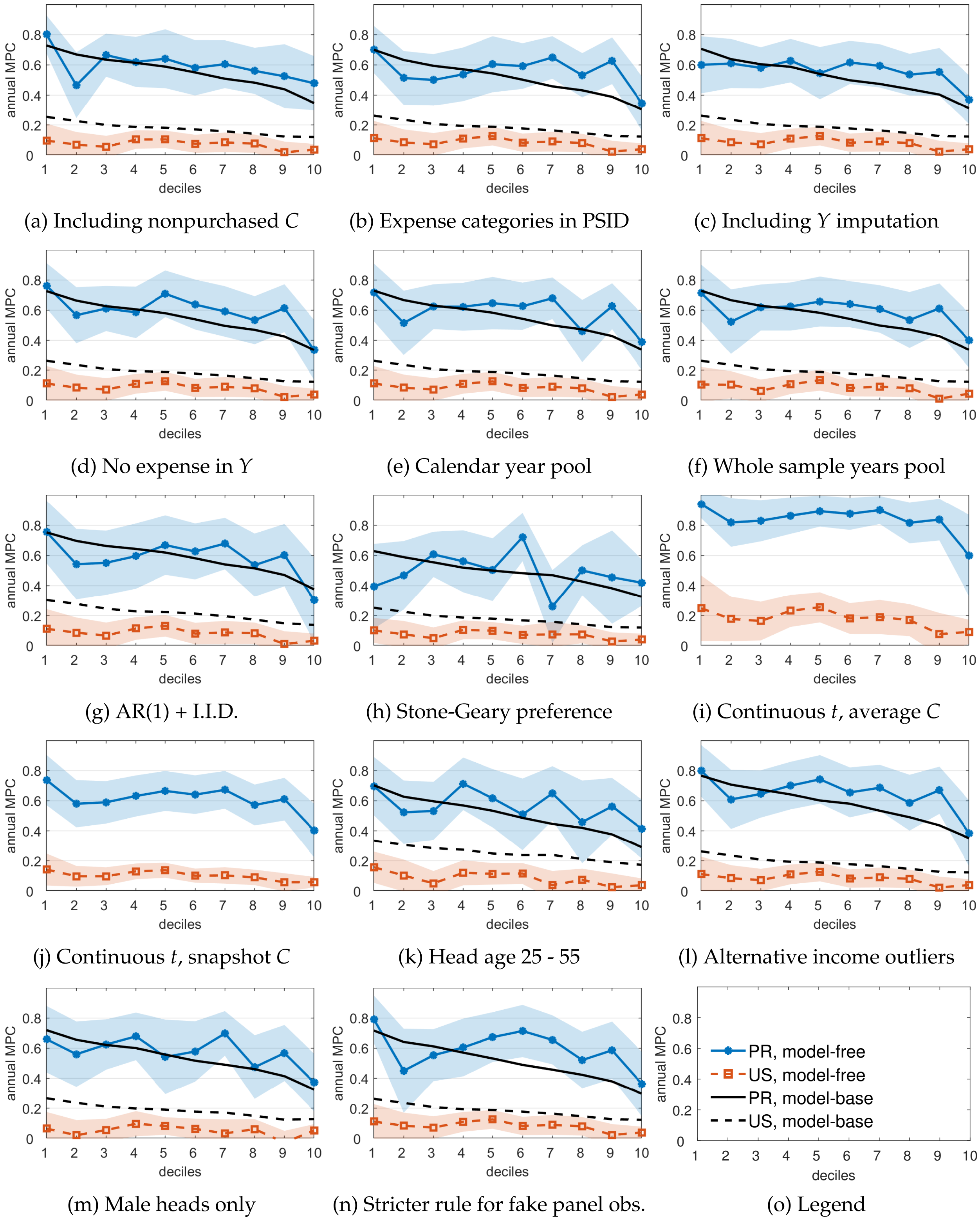


Figure G.1: Robustness under alternative data treatments

G.3 Including Imputed Components of Missing Income

The Peruvian baseline income excludes the imputed components of missing income. Moreover, I drop observations that have too much value in the imputed income components during the Peruvian sample selection. These treatments are not available for the U.S. sample because imputed income components are not distinguishable in Kaplan et al. (2014)'s dataset. In this robustness check, I consistently include the imputed components of missing income in the Peruvian income. Moreover, the observations with too much value in the imputed components of missing income are also included in the Peruvian sample. Figure G.1c plots the result.

G.4 Excluding Expense Items from Income

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

G.5 Sorting Residual Incomes in Different Observation Pools

In the baseline analysis, I sort residual income $y_{i,t}$'s within each calendar year for the U.S. sample and within each calendar quarter for the Peruvian sample, in accordance with the reference period of each sample (a year for the U.S. sample and 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 residual incomes in a larger observation pool than the pool of the reference period. So, I conduct a robustness check by sorting residual incomes in different observation pools. First, I sort Peruvian observations within each calendar year, in accordance with how U.S. observations are sorted in the baseline analysis. Second, I sort observations in the pool of the whole sample years both in the Peruvian and U.S. samples. Figures G.1e and G.1f plot the results under the pools of each calendar year and the whole sample years, respectively.

G.6 Replacing the Permanent Component of Income with a Persistent Component

In the baseline MPC estimation, I assume that the income process is composed of a permanent (random walk) component and a transitory component, following the original specification of Blundell et al. (2008). Kaplan and Violante (2010) propose a way to identify Blundell et al. (2008)'s partial insurance parameters under an alternative income process in which the permanent component is replaced with a persistent component following an AR(1) process. Adopting their identification strategy, I re-estimate MPCs using a revised estimator of ψ_G that replaces $\Delta^K y_{i,t}$ with $\tilde{\Delta}^K y_{i,t}$ where $\tilde{\Delta} y_{i,t} = y_{i,t} - \tilde{\rho}^K y_{i,t-K}$. For Peruvian quarterly MPC estimation, $\rho = 0.963$ reported in Table 1 is used as the value of $\tilde{\rho}$. For U.S. annual MPC estimation, t is a year, and thus,

$\tilde{\rho}$ is an annual autocorrelation coefficient. I obtain $\tilde{\rho}$ by estimating the annual income process (assumed in the U.S. annual MPC estimation) using age-specific variances and covariances of annual residual incomes. As a result, I obtain the annual autocorrelation coefficient of 0.958. This value turns out to be very close to 0.989^4 where 0.989 is the value of quarterly autocorrelation coefficient reported in Table 2. After obtaining the revised estimate of ψ_G, I again convert it to MPC by multiplying it with the mean-consumption-to-mean-income ratio of each group. Figure G.1g plots the result.

G.7 Incorporating a Subsistence Point into Household 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 MPC estimation equation. To this end, I revise the model specified in Online Appendix A by replacing 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. Under the Stone-Geary preference, households solve the following problem.

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

$$s.t.$$

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

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

$$A_{i,t+J_{i,t}} \ge 0 \tag{E.TML}$$

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

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

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

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

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

Let

$$\begin{aligned} C^*_{i,t} &:= C_{i,t} - \underline{C}, \quad \text{and} \\ Y^*_{i,t} &:= Y_{i,t} - \underline{C}. \end{aligned} \tag{G.1}$$

By substituting equation (G.1) into the households' problem and the income process specified above, we can observe that the model with Stone-Geary preference is isomorphic to the original model in Online Appendix A, except for $(C_{i,t}, Y_{i,t})$ being replaced with $(C^*_{i,t}, Y^*_{i,t})$. Exploiting this isomorphism, we can estimate MPC using the following equations.

$$\psi_G = \frac{cov[\Delta^K c^*_{it}, \Delta^K y^*_{i,t+K} | (i,t) \in G]}{cov[\Delta^K y^*_{it}, \Delta^K y^*_{i,t+K} | (i,t) \in G]}, \quad K \geq 1, \quad \text{and} \tag{G.2}$$

$$MPC_G = \psi_G \frac{E[C^*_{i,t} | (i,t) \in G]}{E[Y^*_{i,t} | (i,t) \in G]} \tag{G.3}$$

in which $c^*_{i,t} := \log C^*_{i,t} - Z'_{i,t}\varphi^{c*}_t$ is the unpredictable component of $\log C^*_{i,t}$ and $y^*_{i,t} := \log Y^*_{i,t} - Z'_{i,t}\varphi^{y*}_t$ is the unpredictable component of $\log Y^*_{i,t}$.[17]

When computing $C^*_{i,t}$ and $Y^*_{i,t}$ using equation (G.1), I use the consumption measure including nonpurchased consumption for $C_{i,t}$ and the baseline measure of income for $Y_{i,t}$. I calibrate the subsistence point $\underline{C}$ to one of the poverty lines that World Bank uses, \$ 3.20 per day in 2011 International dollar.[18] 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 due to having too much value in items with a longer reference period 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 a longer reference period than the previous three months and the imputed incomes) minus the subsistence point, $\underline{C}$. Figure G.1h plots the result.

G.8 Addressing a Time Aggregation Problem in a Continuous-Time Model

In the spirit of Crawley (2020), I also consider a continuous-time model as a way to obtain and compare MPC estimates without a time aggregation problem. As in Crawley (2020), moment conditions are derived from the model and used for the MPC estimation.

The continuous-time model is borrowed from Crawley (2020) but with two modificiations. First, Crawley (2020) assumes a random walk consumption function under which consumption responds only to current transitory and permanent shocks as in Blundell et al. (2008), while I specify a consumption function such that dynamic consumption responses to a transitory income shock decay exponentially over time. My specification is motivated by the observation in subsection 4.4 that Auclert (2019)'s model-free annualization formula (6), which is derived from an assumption that dynamic consumption responses to a transitory shock die out exponentially over

[17]This isomorphism is also exploited when I calibrate the quarterly model specified in subsection 2.2 to obtain the model-based outcomes.

[18]For Peru, this subsistence point (\$ 3.20 per day in 2011 International dollar) is PPP-converted into 2011 Peruvian sols using the 2011 data point of the data series 'PPP Conversion Factor, Private Consumption (LCU per International \$)' in World Bank's WDI database.

time in a quarterly model, provides a good approximation. Second, as in the online appendix B1 of Crawley (2020), I begin from a discrete-time model with log income specifications, derive moment conditions under a first-order approximation, and obtain their limits as the discrete time-frame approaches 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).

As in the online appendix B1 of Crawley (2020), I begin from a discrete-time model with m sub-periods within each period. I enumerate the discrete time index for sub-period 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,

$$\bar{Y}_T := Y_{i,T-1+\frac{1}{m}} + Y_{i,T-1+\frac{2}{m}} + \cdots + Y_{i,T} \tag{G.4}$$

and

$$\bar{C}_T := C_{i,T-1+\frac{1}{m}} + C_{i,T-1+\frac{2}{m}} + \cdots + C_{i,T}. \tag{G.5}$$

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

$$\log Y_{i,t} = P_{i,t} + \epsilon_{i,t} \tag{G.6}$$

in which

$$P_{i,t} = P_{i,t-\frac{1}{m}} + \zeta_{i,t},$$
$$\zeta_{i,t} \sim_{iid} (0, \sigma^2_{ps,m}), \quad \epsilon_{i,t} \sim_{iid} (0, \sigma^2_{tr,m}), \quad (\zeta_{i,t})_t \perp (\epsilon_{i,t})_t.$$

$$\Delta^{\frac{1}{m}} \log C_{i,t} = \phi\zeta_{i,t} + \sum_{k=0}^{\infty} \psi_{\frac{k}{m}} \epsilon_{i,t-\frac{k}{m}} \tag{G.7}$$

in which $\Delta^s x_t := x_t - x_{t-s}$ for any time-series $(x_t)_t$ and $s > 0$. 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 (G.7) over j sub-periods, we obtain

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

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 time length ($\Delta t = 1$) after the shock (or, equivalently, the sum of consumption responses to the shock during the period) is

$$MPC = \overrightarrow{\Psi}_{\frac{m-1}{m}} \cdot \frac{E[C]}{E[Y]}. \tag{G.8}$$

From equation (G.4), 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

$$\log(\bar{Y}_{i,T}) \approx \frac{1}{m}\sum_{j=1}^{m} \log Y_{i,T-1+\frac{j}{m}} + \log m. \tag{G.9}$$

In the same way, equation (G.5) 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 obtain

$$\log(\bar{C}_{i,T}) \approx \frac{1}{m}\sum_{j=1}^{m} \log C_{i,T-1+\frac{j}{m}} + \log m. \tag{G.10}$$

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) $(Y_{i,T}^{obs}, C_{i,T}^{obs}) = (Y_{i,T}, \bar{C}_{i,T})$. The second and third cases are motivated by the fact that both the PSID and ENAHO are not free from the problem of inconsistent reference periods between consumption and income. In the PSID, the reference period of income is firmly fixed to a calendar year, but the reference period of consumption can depend on an interpretation, as pointed out by Crawley (2020). For example, 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 previous week of the survey. In the baseline analysis, I accept the former interpretation, as many other studies implicitly do. Under the latter interpretation, however, the reference period of income is longer than that of consumption, as in the second case.[19] In ENAHO, the reference periods of both consumption and income are restricted to be no longer than the previous three months. Within these three months, however, some income items have longer reference periods than some expense items, as in the second case, while some income items have shorter reference periods than some expense items, as in the third case.

[19] Crawley (2020) uses the interpretation of the second case when bringing data to his estimation equations in his benchmark estimation.

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

Let

$$y^{obs}_{i,T} := \log Y^{obs}_{i,T}, \quad \text{and}$$
$$c^{obs}_{i,T} := \log C^{obs}_{i,T}.$$

From equations (G.9) and (G.10), we have

$$\Delta y^{obs}_{i,T} = \Delta \log Y^{obs}_{i,T} = \frac{1}{m}\sum_{j=1}^{m}\left(\log Y_{i,T-1+\frac{j}{m}} - \log Y_{i,T-2+\frac{j}{m}}\right) \tag{G.11}$$

and

$$\Delta c^{obs}_{i,T} = \Delta \log C^{obs}_{i,T} = \frac{1}{m}\sum_{j=1}^{m}\left(\log C_{i,T-1+\frac{j}{m}} - \log C_{i,T-2+\frac{j}{m}}\right) \tag{G.12}$$

By substituting equations (G.6) and (G.7) into (G.11) and (G.12) and computing variances and covariances of the observed income growth $\Delta y^{obs}_{i,T}$ and consumption growth $\Delta c^{obs}_{i,T}$, we can obtain the following equations.

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

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

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

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

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

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

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

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

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

$$\sigma_{ps}^2 := \lim_{m\to\infty} m\sigma_{ps,m}^2 < \infty \tag{G.13}$$

and

$$\sigma_{tr}^2 := \lim_{m\to\infty} \frac{\sigma_{tr,m}^2}{m} < \infty \tag{G.14}$$

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

$$\Psi_t = \tau\lambda e^{-\lambda t}, \quad t \in [0,\infty) \tag{G.15}$$

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

$$\overrightarrow{\Psi}_t = \int_0^t \Psi_s ds = \tau(1 - e^{-\lambda t}), \quad t \in [0,\infty). \tag{G.16}$$

Under equations (G.13), (G.14), (G.15), and (G.16), we have the following equations for variances and covariances of the continuous-time model in the limit.

$$var[\Delta y_{i,T}^{obs}] = \frac{2}{3}\sigma_{ps}^2 + 2\sigma_{tr}^2, \tag{G.17}$$

$$cov[\Delta y_{i,T}^{obs}, \Delta y_{i,T+1}^{obs}] = \frac{1}{6}\sigma_{ps}^2 - \sigma_{tr}^2, \tag{G.18}$$

$$cov[\Delta y_{i,T}^{obs}, \Delta y_{i,T+N}^{obs}] = 0, \quad N \geq 2, \tag{G.19}$$

$$cov[\Delta c_{i,T}^{obs}, \Delta y_{i,T}^{obs}] = \frac{2}{3}\phi\sigma_{ps}^2 + \tau\{2 - \frac{1}{\lambda}(1-e^{-\lambda})(3-e^{-\lambda})\}\sigma_{tr}^2, \tag{G.20}$$

$$cov[\Delta c_{i,T}^{obs}, \Delta y_{i,T+1}^{obs}] = \frac{\phi}{6}\sigma_{ps}^2 - \tau\{1 - \frac{1}{\lambda}(1-e^{-\lambda})\}\sigma_{tr}^2, \tag{G.21}$$

$$cov[\Delta c_{i,T}^{obs}, \Delta y_{i,T+N}^{obs}] = 0, \quad N \geq 2, \tag{G.22}$$

$$cov[\Delta c_{i,T}^{obs}, \Delta y_{i,T-1}^{obs}] = \frac{\phi}{6}\sigma_{ps}^2 + \tau\{-1 + \frac{1}{\lambda}(1-e^{-\lambda})(e^{-2\lambda} - 3e^{-\lambda} + 3)\}\sigma_{tr}^2, \tag{G.23}$$

$$cov[\Delta c_{i,T}^{obs}, \Delta y_{i,T-N}^{obs}] = -\tau\frac{1}{\lambda}e^{-\lambda(N-2)}(1-e^{-\lambda})^4\sigma_{tr}^2, \quad N \geq 2. \tag{G.24}$$

From equations (G.17), (G.18), (G.19), (G.20), (G.21), (G.22), (G.23), and (G.24), 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.

$$var[\Delta^2 y_{i,T+2}^{obs}] = \frac{5}{3}\sigma_{ps}^2 + 2\sigma_{tr}^2, \tag{G.25}$$

$$cov[\Delta^2 y_{i,T}^{obs}, \Delta^2 y_{i,T+2}^{obs}] = \frac{1}{6}\sigma_{ps}^2 - \sigma_{tr}^2, \tag{G.26}$$

$$cov[\Delta^2 c^{obs}_{i,T+2}, \Delta^2 y^{obs}_{i,T+2}] = \frac{5}{3}\phi\sigma^2_{ps} + \tau\{2 + \frac{1}{\lambda}(1-e^{-\lambda})(e^{-2\lambda} - e^{-\lambda} - 2)\}\sigma^2_{tr}, \tag{G.27}$$

$$cov[\Delta^2 c^{obs}_{i,T}, \Delta^2 y^{obs}_{i,T+2}] = \frac{\phi}{6}\sigma^2_{ps} + \tau\{-1 + \frac{1}{\lambda}(1-e^{-\lambda})\}\sigma^2_{tr} \tag{G.28}$$

for $K = 2$.

$$var[\Delta^4 y^{obs}_{i,T+4}] = \frac{11}{3}\sigma^2_{ps} + 2\sigma^2_{tr}, \tag{G.29}$$

$$cov[\Delta^4 y^{obs}_{i,T}, \Delta^4 y^{obs}_{i,T+4}] = \frac{1}{6}\sigma^2_{ps} - \sigma^2_{tr}, \tag{G.30}$$

$$cov[\Delta^4 c^{obs}_{i,T+4}, \Delta^4 y^{obs}_{i,T+4}] = \frac{11}{3}\phi\sigma^2_{ps} + \tau\{2 + \frac{1}{\lambda}(1-e^{-\lambda})(e^{-4\lambda} - e^{-3\lambda} - 2)\}\sigma^2_{tr}, \tag{G.31}$$

$$cov[\Delta^4 c^{obs}_{i,T}, \Delta^4 y^{obs}_{i,T+4}] = \frac{\phi}{6}\sigma^2_{ps} + \tau\{-1 + \frac{1}{\lambda}(1-e^{-\lambda})\}\sigma^2_{tr} \tag{G.32}$$

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 zero, the total consumption response to a temporary income shock after a long enough time should be equal to the size of the shock itself, *i.e.*,

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

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.[20], I use the following equation to identify τ.

$$E[\tau C_{i,t} - Y_{i,t}] = 0. \tag{G.33}$$

Under the assumption, the MPC during the period of 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_{ps}, σ^2_{tr}, ϕ, and τ using equations (G.29), (G.30), (G.31), (G.32), and (G.33). For the U.S. sample, I estimate the annual MPC ($= 1 - e^{-\lambda}$) with the other four parameters using equations (G.25), (G.26), (G.27), (G.28), and (G.33). As in the baseline analysis, the estimation is separately conducted for each residual income decile. For the estimation, I use the GMM method. Lastly, the Peruvian quarterly MPCs are converted into annual MPCs as follows. In this continuous-time model for Peru, $\Delta t = 1$ corresponds to a quarter, and thus, we have

$$MPC^Q = 1 - e^{-\lambda}, \quad MPC^A = 1 - e^{-4\lambda} \quad \Rightarrow \quad 1 - MPC^A = (1 - MPC^Q)^4.$$

[20] This assumption can be supported by the long-run-average real interest rates in Peru and the U.S. reported in Tables 1 and 2.

In other words, Auclert (2019)'s conversion formula (6) holds true in my continuous time model. So, I convert Peruvian quarterly MPCs to annual MPCs using this equation.

Figure G.1i plots the annual MPC estimates of Peru and the U.S.

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.

$$var[\Delta y^{obs}_{i,T}] = \left(\frac{1}{m} + \frac{(m-1)(2m-1)}{3m^2}\right)(m\sigma^2_{ps,m}) + 2\left(\frac{\sigma^2_{tr,m}}{m}\right), \tag{G.34}$$

$$cov[\Delta y^{obs}_{i,T}, \Delta y^{obs}_{i,T+1}] = \frac{m^2-1}{6m^2}(m\sigma^2_{ps,m}) - \left(\frac{\sigma^2_{tr,m}}{m}\right), \tag{G.35}$$

$$cov[\Delta y^{obs}_{i,T}, \Delta y^{obs}_{i,T+N}] = 0, \quad N \geq 2, \tag{G.36}$$

$$cov[\Delta c^{obs}_{i,T}, \Delta y^{obs}_{i,T}] = \phi\frac{m+1}{2m}(m\sigma^2_{ps,m}) + (3\overrightarrow{\Psi}_{\frac{m-1}{m}} - \overrightarrow{\Psi}_{1+\frac{m-1}{m}})\left(\frac{\sigma^2_{tr,m}}{m}\right), \tag{G.37}$$

$$cov[\Delta c^{obs}_{i,T}, \Delta y^{obs}_{i,T+1}] = \phi\frac{m-1}{2m}(m\sigma^2_{ps,m}) - \overrightarrow{\Psi}_{\frac{m-1}{m}}\left(\frac{\sigma^2_{tr,m}}{m}\right), \tag{G.38}$$

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

$$\begin{aligned} cov[\Delta c^{obs}_{i,T}, \Delta y^{obs}_{i,T-N}] = &\Big\{(\overrightarrow{\Psi}_{N+\frac{m-1}{m}} - 2\overrightarrow{\Psi}_{N-1+\frac{m-1}{m}} + \overrightarrow{\Psi}_{N-2+\frac{m-1}{m}}) \\ &- (\overrightarrow{\Psi}_{N+1+\frac{m-1}{m}} - 2\overrightarrow{\Psi}_{N+\frac{m-1}{m}} + \overrightarrow{\Psi}_{N-1+\frac{m-1}{m}})\Big\}\left(\frac{\sigma^2_{tr,m}}{m}\right), \quad N \geq 1. \end{aligned} \tag{G.40}$$

As m approaches infinity satisfying equations (G.13), (G.14), (G.15), and (G.16), the continuous-time model in the limit has the following equations for the variances and covariances.

$$var[\Delta y^{obs}_{i,T}] = \frac{2}{3}\sigma^2_{ps} + 2\sigma^2_{tr}, \tag{G.41}$$

$$cov[\Delta y^{obs}_{i,T}, \Delta y^{obs}_{i,T+1}] = \frac{1}{6}\sigma^2_{ps} - \sigma^2_{tr}, \tag{G.42}$$

$$cov[\Delta y^{obs}_{i,T}, \Delta y^{obs}_{i,T+N}] = 0, \quad N \geq 2, \tag{G.43}$$

$$cov[\Delta c^{obs}_{i,T}, \Delta y^{obs}_{i,T}] = \frac{\phi}{2}\sigma^2_{ps} + \{2\tau(1-e^{-\lambda}) - \tau e^{-\lambda}(1-e^{-\lambda})\}\sigma^2_{tr}, \tag{G.44}$$

$$cov[\Delta c^{obs}_{i,T}, \Delta y^{obs}_{i,T+1}] = \frac{\phi}{2}\sigma^2_{ps} - \tau(1-e^{-\lambda})\sigma^2_{tr}, \tag{G.45}$$

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

$$cov[\Delta c^{obs}_{i,T}, \Delta y^{obs}_{i,T-N}] = \{-\tau e^{-\lambda(N-1)}(1-e^{-\lambda})^2 + \tau e^{-\lambda N}(1-e^{-\lambda})^2\}\sigma^2_{tr}, \quad N \geq 1. \tag{G.47}$$

From equations (G.41), (G.42), (G.43), (G.44), (G.45), (G.46), and (G.47), 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.

$$var[\Delta^2 y_{i,T+2}^{obs}] = \frac{5}{3}\sigma_{ps}^2 + 2\sigma_{tr}^2, \tag{G.48}$$

$$cov[\Delta^2 y_{i,T}^{obs}, \Delta^2 y_{i,T+2}^{obs}] = \frac{1}{6}\sigma_{ps}^2 - \sigma_{tr}^2, \tag{G.49}$$

$$cov[\Delta^2 c_{i,T+2}^{obs}, \Delta^2 y_{i,T+2}^{obs}] = \frac{3}{2}\phi\sigma_{ps}^2 + \tau(1-e^{-\lambda})(2-e^{-2\lambda})\sigma_{tr}^2, \tag{G.50}$$

$$cov[\Delta^2 c_{i,T}^{obs}, \Delta^2 y_{i,T+2}^{obs}] = \frac{\phi}{2}\sigma_{ps}^2 - \tau(1-e^{-\lambda})\sigma_{tr}^2 \tag{G.51}$$

for $K = 2$.

$$var[\Delta^4 y_{i,T+4}^{obs}] = \frac{11}{3}\sigma_{ps}^2 + 2\sigma_{tr}^2, \tag{G.52}$$

$$cov[\Delta^4 y_{i,T}^{obs}, \Delta^4 y_{i,T+4}^{obs}] = \frac{1}{6}\sigma_{ps}^2 - \sigma_{tr}^2, \tag{G.53}$$

$$cov[\Delta^4 c_{i,T+4}^{obs}, \Delta^4 y_{i,T+4}^{obs}] = \frac{7}{2}\phi\sigma_{ps}^2 + \tau(1-e^{-\lambda})(2-e^{-4\lambda})\sigma_{tr}^2, \tag{G.54}$$

$$cov[\Delta^4 c_{i,T}^{obs}, \Delta^4 y_{i,T+4}^{obs}] = \frac{\phi}{2}\sigma_{ps}^2 - \tau(1-e^{-\lambda})\sigma_{tr}^2 \tag{G.55}$$

for $K = 4$.

Under the identification of τ by equation (G.33) as in the first case, I estimate Peruvian households' quarterly MPC ($= 1 - e^{-\lambda}$) together with σ_{ps}^2, σ_{tr}^2, ϕ, and τ using equations (G.52), (G.53), (G.54), (G.55), and (G.33). For the U.S. sample, I estimate annual MPC ($= 1 - e^{-\lambda}$) with the other four parameters using equations (G.48), (G.49), (G.50), (G.51), and (G.33). Again, the estimation is separately conducted for each residual income decile. 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 equation (6).

Figure G.1j plots the annual MPC estimates of Peru and the U.S.

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

$$cov[\Delta^K y^{obs}_{i,T}, \Delta^K y^{obs}_{i,T+K}] = -\sigma^2_{tr,m}, \tag{G.56}$$

$$cov[\Delta^K c^{obs}_{i,T}, \Delta^K y^{obs}_{i,T+K}] = -\frac{1}{m} \overrightarrow{\Psi}_0 \, \sigma^2_{tr,m}. \tag{G.57}$$

for any $K \geq 1$. From equations (G.56) and (G.57), we have

$$MPC \cdot \frac{E[Y]}{E[C]} = \overrightarrow{\Psi}_1 > \overrightarrow{\Psi}_0 = m \cdot \frac{cov[\Delta^K c^{obs}_{i,T}, \Delta^K y^{obs}_{i,T+K}]}{cov[\Delta^K y^{obs}_{i,T}, \Delta^K y^{obs}_{i,T+K}]}. \tag{G.58}$$

Therefore, when

$$\frac{cov[\Delta^K c^{obs}_{i,T}, \Delta^K y^{obs}_{i,T+K}]}{cov[\Delta^K y^{obs}_{i,T}, \Delta^K y^{obs}_{i,T+K}]} > 0, \tag{G.59}$$

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 $(Y^{obs}_{i,T}, C^{obs}_{i,T}) = (Y_{i,T}, \bar{C}_{i,T})$ cannot explain data that exhibits inequality (G.59).

However, as long as m is finite and satisfies

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

equation (G.58) is not necessarily inconsistent with the discrete-time model. More importantly, equation (G.58) is helpful to understand the bias that arises when consumption has a longer reference period than income. If the true lengths of the reference periods for consumption and income are 1 and $\frac{1}{m}$ in the data, respectively, and if we falsely treat the length of the reference periods for both income and consumption as 1 in the estimation, we will estimate MPC by $\frac{cov[\Delta^K c^{obs}_{i,T}, \Delta^K y^{obs}_{i,T+K}]}{cov[\Delta^K y^{obs}_{i,T}, \Delta^K y^{obs}_{i,T+K}]} \cdot \frac{E[C]}{E[Y]}$, while the true MPC is $\overrightarrow{\Psi}_1 \cdot \frac{E[C]}{E[Y]}$. As equation (G.58) shows, this is an underestimation.

Notably, a situation in which some expense items have longer reference periods than some income items can occur in ENAHO, but not in the PSID, as discussed above (right before the beginning of Case 1). In other words, if any significant bias is generated by this problem, Peruvian MPCs are underestimated, while U.S. MPCs are not. Correcting this problem will only widen the MPC gap between Peru and the U.S.

G.9 Using a Different Age Restriction in the Sample Selection

Kaplan et al. (2014) restrict household heads' ages to be between 25 and 55. This age range compares to Blundell et al. (2008)'s age range, 30-65. Given this difference, I choose to use the age range of 25-65 in my baseline sample selection, which includes the age ranges of both studies. In this robustness check, I revise the age restriction for both the U.S. and Peruvian samples to be

25-55, following that of Kaplan et al. (2014). Figure G.1k plots the result.

G.10 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 between Peruvian and U.S. sample selections. 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 once. In the U.S. sample selection, I adopt Kaplan et al. (2014)'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 once. 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 (two-year-over-two-year growth of annual income for U.S. households, year-over-year growth of quarterly income for Peruvian households).

Regarding this difference in the definition of income outliers, I conduct a robustness check by defining Peruvian income outliers in a more similar fashion as Kaplan et al. (2014), despite the difficulty of finding the right corresponding cutoffs. Specifically, I categorize Peruvian households as income outliers if their nominal income is below 150 Peruvian sols[21] or their income growth is greater than 5 or less than -0.8 at least once. Figure G.1l plots the result.

G.11 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 this robustness check, I drop households with female heads. Figure G.1m plots the result.

G.12 Applying a Stricter Rule in Detecting Potentially Fake Panel Observations

In the Peruvian sample selection, I detect and drop potentially fake panel observations, which are likely to connect two different households. As discussed in online Appendix B.4, I define them as pairs of two consecutive 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 is less than half of the household size for any of the two households connected as a panel observation, I identify it as a potentially fake panel observation and drop it. Under the stricter rule, the number of triplets of three consecutive observations shrinks from 7,509 to 6,324. Figure G.1n plots the result.

[21] The cutoff of 150 sols is chosen by reflecting the fact that World Bank's WDI data on 'PPP conversion factor, GDP (LCU per international $)' varies from 1.34 to 1.56 during 2004-2016.

H MPCs on Other Axes

H.1 MPCs on the Residual Income ($y_{i,t}$) Axis

One natural hypothesis arising from Figure 4 is that Peruvian MPCs might be more heterogeneous simply because their residual incomes are more heterogeneous. As a way to examine this hypothesis, in Figure H.1, I re-plot the MPC estimates in Figure 4 on the axis of group-average residual income $E[y_{i,t}|(i,t) \in G]$'s where G represents residual income deciles. Figure H.1 verifies that the group-averages of Peruvian quarterly residual incomes are indeed more heterogeneous than those of U.S. annual residual incomes.

This hypothesis is, however, subject to two problems. First, the fact that U.S. annual residual incomes are less dispersed than Peruvian quarterly residual incomes does not necessarily mean that U.S. households face smaller income risks because annual residual incomes tend to be less dispersed than quarterly residual incomes. In the U.S. model economy calibrated in subsection 5.2, for example, the unconditional variance of quarterly residual income is 0.474, while that of annual residual income is 0.272. Second, comparing only the residual income dispersion ignores the relative contribution of persistent and transitory risks, while households respond to them very differently.

Reflecting these two problems, the simple hypothesis above can be refined into the following question: how do the differences in the income process between Peru and the U.S. contribute to their differences in MPCs? I examine this question in subsection 7.2.

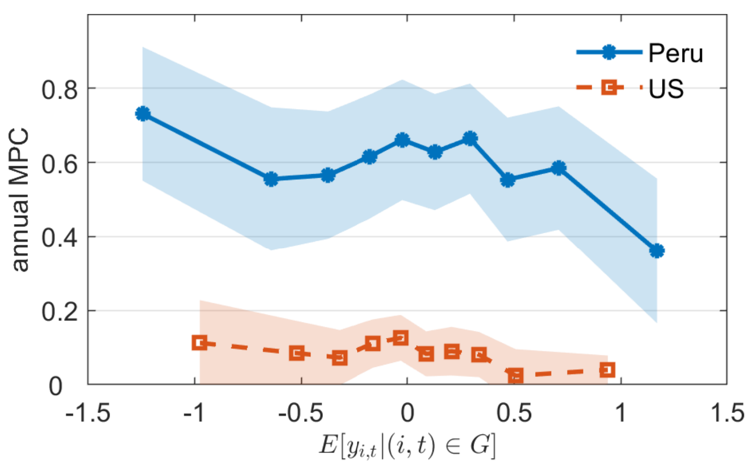


Figure H.1: Re-plotting Figure 4 on the axis of the group-average reisidual income

Notes: This figure re-plots Figure 4 on the axis of group-average residual income $E[y_{i,t}|(i,t) \in G]$'s where G represents residual income deciles.

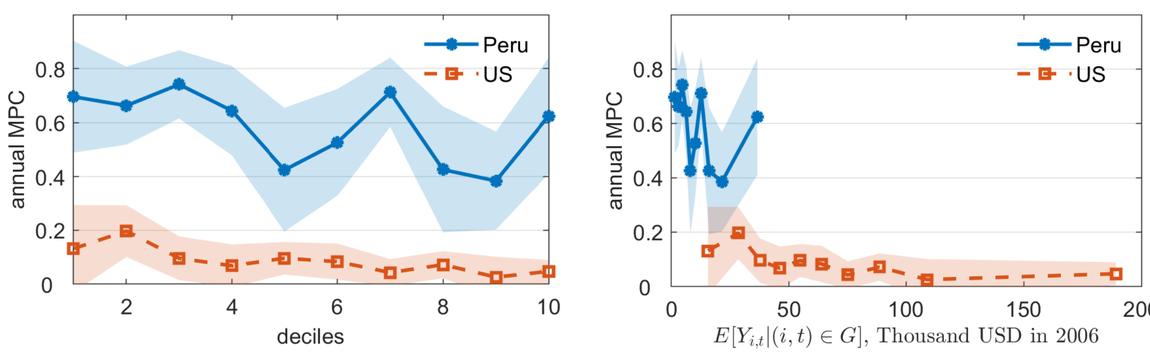
H.2 MPCs on the Actual Income ($Y_{i,t}$) Axis

In the baseline estimation, I estimate the MPC within each residual income decile because precautionary saving theory predicts MPC heterogeneity over residual income, as discussed in subsection 3.4. The theory further predicts that the permanent income heterogeneity captured by the predictable components $Z'_{i,t}\varphi^y_t$ does not create MPC heterogeneity, and thus, the monotone MPC heterogeneity over residual income should be diluted by the predictable components when groups are instead formed by actual income ($Y_{i,t}$).

To examine this prediction, I re-estimate MPCs by grouping households based on their actual income ($Y_{i,t}$). Figure H.2a plots the annualized Peruvian MPC estimates under the model-free annualization and the annual U.S. MPC estimates on the axis of the deciles. This figure verifies that the monotone MPC heterogeneity observed under the residual income ($y_{i,t}$) grouping almost disappears under the actual income ($Y_{i,t}$) grouping in Peru. In the U.S. where MPC heterogeneity over the residual income ($y_{i,t}$) grouping is weak in the first place, the dilution is also not vivid.

Separately from precautionary saving theory, it is also of natural interest to examine whether U.S. and Peruvian households earning a similar level of income exhibit similar MPCs. To examine this question, I plot the MPC estimate within each actual income ($Y_{i,t}$) decile on the axis of group-average actual income $E[Y_{i,t}|(i,t) \in G]$ after PPP conversion.[22]

Figure H.2b shows the result. This figure shows that the top three deciles in Peru and the bottom three deciles in the U.S. overlap in their PPP-converted income. In the overlapped region, however, the Peruvian top three deciles exhibit substantially higher MPCs than the U.S. bottom three deciles. Specifically, the mean annual MPC across the Peruvian top three deciles is 47.8%, while the mean annual MPC across the U.S. bottom three deciles is 14.1%.



(a) On the axis of the deciles (b) On the axis of group-average actual income

Figure H.2: MPCs of the actual income ($Y_{i,t}$) deciles

Notes: In this figure, I plot the MPC estimate within each actual income ($Y_{i,t}$) decile. Figure H.2a plots the estimates on the axis of the deciles, while Figure H.2b plots them on the axis of the group-average actual income $E[Y_{i,t}|(i,t) \in G]$ after PPP conversion. In each figure, I plot the annualized Peruvian MPC estimates under the model-free annualization (labeled 'Peru') and the annual U.S. MPC estimates (labeled 'U.S.').

[22]Specifically, Peruvian nominal incomes are PPP-converted into U.S. dollar values using the data series 'PPP conversion factor, GDP (LCU per international $)' in World Bank's WDI database, and then deflated with the U.S. CPI series obtained from the Federal Reserve Bank of St. Louis.

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